TU UB

Die approbierte Originalversion dieser Diplom-/ Masterarbeit ist in der Hauptbibliothek der Technischen Universität Wien aufgestellt und zugänglich.



The approved original version of this diploma or master thesis is available at the main library of the Vienna University of Technology.

http://www.ub.tuwien.ac.at/eng

Unterschrift (Betreuer)



DIPLOMARBEIT

Adaptive Isogeometrische Randelementmethode

für die Hypersinguläre Integralgleichung

ausgeführt am Institut für Analysis und Scientific Computing der Technischen Universität Wien

unter der Anleitung von Ao.Univ.Prof. Dipl.Math. Dr.techn. Dirk Praetorius Dipl.-Ing. Gregor Gantner

> durch Stefan Schimanko Südhangsiedlung 9 3300 Amstetten

Datum

Unterschrift (Student)



${\rm D} \ {\rm I} \ {\rm P} \ {\rm L} \ {\rm O} \ {\rm M} \ {\rm A} \quad {\rm T} \ {\rm H} \ {\rm E} \ {\rm S} \ {\rm I} \ {\rm S}$

Adaptive Isogeometric Boundary Element Method

for the Hyper-Singular Integral Equation

written at the Institute for Analysis and Scientific Computing of the Vienna University of Technology

supervised by Ao.Univ.Prof. Dipl.Math. Dr.techn. Dirk Praetorius Dipl.-Ing. Gregor Gantner

> by Stefan Schimanko Südhangsiedlung 9 3300 Amstetten

Eidesstattliche Erklärung

Ich erkläre an Eides statt, dass ich die vorliegende Diplomarbeit nach den anerkannten Grundsätzen für wissenschaftliche Abhandlungen selbstständig ausgeführt habe und alle verwendeten Hilfsmittel, insbesondere die zugrunde gelegte Literatur, genannt habe.

Datum

Unterschrift

Abstract and Outline

The present work deals with the effective numerical solution of the hyper-singular integral equation

$$Wu = (1/2 - K')\phi$$
 on $\Gamma := \partial \Omega$

for given boundary data ϕ with integral mean zero and a bounded Lipschitz domain $\Omega \subset \mathbb{R}^2$. Here, W denotes the hyper-singular integral operator and K' is the adjoint double-layer integral operator, cf. Section 1. This integral equation is an equivalent formulation of the Neumann problem

$$\begin{aligned} -\Delta P &= 0 \quad \text{in } \Omega, \\ \partial_n P &= \phi \quad \text{on } \Gamma, \end{aligned}$$

where $\partial_n P$ denotes the normal derivative of P. Indeed, $P|_{\Gamma}$ conincides with u up to an additive constant. On the other hand, P can be regained by u and ϕ via the representation formula (or: third Green formula), cf. Subsection 1.3.

In this thesis, we present and analyze an adaptive isogeometric boundary element method for the hypersingular integral equation. The main principle of isogeometric analysis (IGA) is to use the same kind of functions, which represent the problem geometry, for the discretization of the partial differential equation at hand. Nowadays, the problem geometry Ω resp. its boundary Γ is usually represented in computer aided design (CAD) by so-called non-uniform rational B-splines (NURBS), T-splines, or hierarchical splines. The advantage of this approach is that, unlike standard approaches, no meshing of the geometry Ω resp. its boundary Γ is necessary in order to define suitable approximation spaces. Thomas Hughes and collaborators originally invented this concept for finite element methods (IGAFEM) for three dimensional geometries, cf. [CHB09] and [HCB05].

However, CAD typically describes only the boundary Γ , not the volume Ω itself. Hence, the most appealing approach is the boundary element method (BEM), if applicable, i.e., if the fundamental solution of the considered differential operator is explicitly known. In our case, the fundamental solution G of the Laplacian is given by

$$G(x, y) = -\frac{1}{2\pi} \log |x - y|.$$

We consider the variational formulation of the hypersingular integral equation, i.e.,

$$\langle Wu; v \rangle_{\Gamma} + \langle 1; u \rangle_{\Gamma} \langle 1; v \rangle_{\Gamma} = \langle (1/2 - K')\phi; v \rangle_{\Gamma} \text{ for all } v \in H^{1/2}(\Gamma),$$

cf. Subsection 1.3. The basic idea of BEM is to replace the trace space $H^{1/2}(\Gamma)$ in the variational formulation by a finite dimensional subspace. We end up with a discrete variational formulation, which is solvable numerically. Then, the discrete solution $U_{\star} \in \mathcal{X}_{\star}$ is an approximation of the (weak) solution uof the hypersingular integral equation.

Although there exists rich literature on IGAFEM, only little is found for isogeometric BEM (IGABEM). First, IGABEM was considered in [PGK⁺09] for two dimensions, and in [SSE⁺13] for three dimensions. Concerning a posteriori error estimation for IGABEM, the articles [FGHP16a], [FGHP16b], and [FGP15] consider simple two dimensional model problems for weakly-singular integral equations which are equivalent formulations of the Dirichlet problem.

This thesis now deals with the hyper-singular integral equation. To approximate the (weak) solution u of the hyper-singular integral equation, we employ an adaptive Galerkin IGABEM of the type

with ansatz spaces consisting of p-th order NURBS. Notice that the usually used piecewise polynomials for standard BEM are just special NURBS. Due to numerical reasons, we also incorporate an approximation of the given Neumann data ϕ into the adaptive scheme. To this end, we employ the L^2 -orthogonal projection to replace ϕ by some discrete data $\Pi_{\star}\phi$. As a consequence, we have to deal with oscillation terms in the analysis. However, the big advantage of this approach is that the appearing integrals can be computed with reliable quadratures. Especially the adjoint double-layer integral operator K' caused stability problems in the beginning, since possible singularities of ϕ as well as the singular kernel of the boundary integral operator K' had to be treated simultaneously. These severe stability issues are avoided by use of the approximation $\Pi_{\star}\phi$.

The outline of the thesis is as follows: In Section 1, we introduce the necessary Sobolev spaces on the boundary Γ . We also give the precise definitions of the hyper-singular integral operator W and the adjoint double-layer integral operator K'. In the adaptive scheme, we will compute discrete solutions. To this end, we introduce two equivalent variational formulations resp. their discrete counterparts. Additionally, we comment on the equivalence of the hyper-singular integral equation and the Neumann problem.

In Section 2, we first introduce B-splines. Based on these, NURBS are defined and some basic properties are deduced. Afterwards, the boundary discretization and the corresponding discretization spaces for the isogeometric boundary element method are discussed.

Section 3 introduces two locally equivalent weighted residual error estimators μ_{\star} and $\tilde{\rho}_{\star}$ which also include the data oscillation terms of the approximation $\Pi_{\star}\phi$ of ϕ . For standard BEM, [CS95] first proposed the weighted residual error estimator which was sharpened later in [Car97]. While the local contributions of μ_{\star} are related to the nodes of a partition of the boundary Γ , the local contributions of the auxiliary estimator $\tilde{\rho}_{\star}$ are related to elements of the partition. We note that we employ the node-based error estimator μ_{\star} to steer the adaptive IGABEM algorithm, while the auxiliary results which are used to analyse $\tilde{\rho}_{\star}$ and the oscillation terms derived from the approximation of the Neumann data ϕ .

Further, we formally state the adaptive Algorithm (1) steered by μ_{\star} . First, we compute the approximation $\Pi_{\ell}\phi$ and solve the discrete variational formulation of the hypersingular integral equation with the perturbed right-hand side $(1/2 - K')\Pi_{\ell}\phi$. The next step is to compute the local contributions of μ_{ℓ} and to mark the nodes with the largest contributions. Based on this a *posteriori* infomation, the refinement strategy steers both the local mesh-size of the underlying partition and the local smoothness of the NURBS, which leads to a refined mesh and a larger ansatz space. We repeat this loop until a given tolerance for the overall error μ_{\star} is reached.

Because of the local equivalence of μ_{\star} and $\tilde{\rho}_{\star}$, the mathematical results of $\tilde{\rho}_{\star}$ will transfer to μ_{\star} and will thus allow to analyze the adaptive strategy based on μ_{\star} . Our main results read as follow: First, the error estimator is linearly convergent with respect to the number of adaptive steps, cf. Section 4. This means that there exist constants $0 < q_{\text{lin}} < 1$ and $C_{\text{lin}} > 0$ such that

$$\mu_{\ell+k} \leq C_{\min} q_{\min}^k \mu_\ell$$
 for all $k, \ell \in \mathbb{N}_0$.

Second, cf. Section 5, the estimator μ_{ℓ} decays at optimal algebraic convergence rate. This means that if a convergence rate of s in the number of knots is possible for suitably chosen meshes which do not necessarily have to be nested, i.e., $\mathcal{O}(|\mathcal{K}_{\star}|^{-s})$, then the nested meshes generated by the adaptive algorithm lead to the same order of convergence of the estimator. Hence, there exists a constant $C_{\text{opt}} > 0$ such that

$$\mu_{\ell} \leq C_{\text{opt}} \left(|\mathcal{K}_{\ell}| - |\mathcal{K}_{0}| \right)^{-s} \text{ for all } \ell \in \mathbb{N}_{0},$$

where $|\mathcal{K}_{\ell}|$ denotes the number of knots of the the partition of the ℓ -th step of the adaptive algorithm.

In Section 6, numerical aspects of the implementation of the hyper-singular integral equation are discussed. To underline our analytical findings, numerical experiments are given in Section 7.

The codes of the implementation are given in Appendix A, which also concludes the thesis.

Danksagung

Mein Dank richtet sich an erster Stelle an meine Betreuer Dirk Praetorius und Gregor Gantner, die mir immer mit Rat und Tat zur Seite gestanden sind und auf diese Weise sehr zum Gelingen dieser Arbeit beigetragen haben. Ebenso darf natürlich die ganze Arbeitsgruppe nicht unerwähnt bleiben, mit der ich viele unterhaltsame und interessante Stunden verbringen und genießen durfte.

Des Weiteren möchte ich mich bei meinen Studienkollegen bedanken, im Speziellen vor allem bei Alexander Haberl und Fabian Mußnig, denen ich nicht nur diverse Übungsbeispiele, sowie Mitschriften und Lernunterlagen zu verdanken habe, sondern die besonders auch abseits der Universität zu echten Freunden geworden sind. Auch auf das jährliche Treffen in Weyregg bei Stefanie Renner freue ich mich jeden Sommer, genauso wie auf den regelmäßigen "Stammtisch" mit meinen Freunden.

Zu guter Letzt gilt mein Dank meiner Familie, die mich immer in meinen Bestrebungen unterstützt hat und für mich da gewesen ist. Egal was passiert, ich weiß, ich kann auf euch zählen, vielen Dank dafür.

Finanziell wurde diese Arbeit durch das FWF Projekt Optimal Isogeometric Boundary Element Method (P29096) unterstützt.

Contents

1	Intr 1.1	oduction Function spaces	13 13	
	$\begin{array}{c} 1.2 \\ 1.3 \end{array}$	Hyper-singular integral operator W \dots \dots \dots Neumann problem \dots \dots \dots	$\begin{array}{c} 14\\ 14 \end{array}$	
2	Disc	cretization	17	
_	2.1	B-splines	17	
	2.2	NURBS	18	
	2.3	Boundary discretization	19	
	2.4	Mesh-refinement	20	
	2.5	Discretization spaces	$\frac{1}{22}$	
3	Error estimators and adaptive algorithm 23			
	3.1	Error estimators	23	
	3.2	Auxiliary results	23	
		3.2.1 Scott-Zhang type operator J_{\star}	23	
		3.2.2 Convergence of uniform refinement	26	
		3.2.3 Inverse estimates	27	
		3.2.4 Approximation property of Π_{\star}	27	
	3.3	Data approximation error $\widetilde{\operatorname{osc}}_{\star}$	28	
	3.4	Error estimator $\tilde{\rho}_{\star}$	29	
	3.5	Adaptive algorithm	34	
4	Line	ear convergence of adaptive IGABEM	35	
5	Opt	imal convergence of adaptive IGABEM	39	
6	Nur	nerical approximation	43	
U	61	Approximation of W_{k}	45	
	6.2	Approximation of S_b .	49	
	6.3	Approximation of F_h	50	
	6.4	Numerical evaluation of $K'\phi_h$	53	
	6.5	Numerical evaluation of WU_h	55	
_				
7	Nur	nerical experiment	57	
	7.1		57	
	7.2	Indirect BEM	62	
	7.3	Neumann problem with singular right-hand side ϕ	65	
Appendix A Implementation			69	
	A.I	Functions.h	69	
	A.2	Structures.h	70	
	A.3	Spline.h and Spline.c	72	
	A.4	phi_approx.h and phi_approx.c	79	
	A.5	WMatrix.h and WMatrix.c	82	
	A.6	FVector.h and FVector.c.	90	
	A.7	res_RHS.h and res_RHS.c	98	
	A.8	mark.m	101	
	A.9 A 10	insert_cpoint.m, increase_Mult and refine_BoundaryMesh	102 106	
P	D-f			
Re	Keterences 109			

1 Introduction

Throughout, we assume that Ω is a bounded Lipschitz domain in \mathbb{R}^2 whose boundary $\Gamma := \partial \Omega$ can be parametrized by a fixed regular closed curve $\gamma : [a, b] \to \Gamma$. This means that γ is continuous, piecewise continuously differentiable, and $\gamma|_{[a,b]}$ is bijective. We also demand for the left and right derivative of γ , that $\gamma'^{\ell} \neq 0$ for $t \in (a, b]$ and $\gamma'^{r} \neq 0$ for $t \in [a, b)$. Additionally, we assume that

$$\gamma^{\prime}(t) + c\gamma^{\prime}(t) \neq 0 \quad \text{for all } c > 0 \text{ and all } t \in [a, b].$$

$$(1.1)$$

We consider the hyper-singular integral equation

$$Wu = (1/2 - K')\phi \quad \text{on } \Gamma, \tag{1.2}$$

for given Neumann data ϕ , the hyper-singular integral operator W, and the adjoint of the double-layer integral operator K. With the fundamental solution of the Laplacian

$$G(x,y) = -\frac{1}{2\pi} \log |x-y|,$$
(1.3)

these operators are defined by

$$Wu(x) := -\partial_{n_x} \int_{\Gamma} \partial_{n_y} G(x, y) u(y) \, ds_y,$$

$$Ku(x) := \int_{\Gamma} \partial_{n_y} G(x, y) u(y) \, ds_y,$$
(1.4)

where n_z denotes the outer unit normal vector at $z \in \Gamma$ and ∂_{n_z} is the normal derivative.

Throughout the work, $|\cdot|$ denotes the absolute value of scalars, the Euclidean norm of vectors in \mathbb{R}^2 , the measure of a set in \mathbb{R} , the cardinality of a discrete set, or the arclength of a curve in \mathbb{R}^2 , which will be clear from the context. The notation $A \leq B$ is an abbriviation for $A \leq cB$ with a generic constant c > 0. Moreover, $A \simeq B$ is an abbreviation for $A \leq B \leq A$. All mesh-related quantities have the same index, e.g., \mathcal{K}_{\star} is the set of knots of the partition $[\mathcal{T}_{\star}]$, and h_{\star} is the corresponding mesh-size etc. The analogous notation is used for partitions $[\mathcal{T}_{+}], [\mathcal{T}_{0}], [\mathcal{T}_{\ell}]$, etc.

1.1 Function spaces

For any measurable subset $\Gamma_0 \subseteq \Gamma$ resp. any interval $\Gamma_0 \subseteq \mathbb{R}$, we denote the Lebesgue space of all square integrable functions by $L^2(\Gamma_0)$. The corresponding norm is

$$\|u\|_{L^{2}(\Gamma_{0})}^{2} := \int_{\Gamma_{0}} |u(x)|^{2} dx,$$

and we define the Sobolev space $H^0(\Gamma_0) := L^2(\Gamma_0)$.

If $u \in L^2(\Gamma_0)$ is differentiable along the arc, ∇u denotes the arclength derivative. We define the Sobolev space $H^1(\Gamma_0) := \{ u \in L^2(\Gamma_0) : \nabla u \in L^2(\Gamma_0) \}$ with corresponding norm

$$\begin{aligned} \|u\|_{H^{1}(\Gamma_{0})}^{2} &:= \|u\|_{L^{2}(\Gamma_{0})}^{2} + |u|_{H^{1}(\Gamma_{0})}^{2}, \\ \|u\|_{H^{1}(\Gamma_{0})}^{2} &:= \int_{\Gamma_{0}} |\nabla u(x)|^{2} \, dx. \end{aligned}$$

Furthermore, we will also need the Sobolev space $H^{1/2}(\Gamma_0) := \left\{ u \in L^2(\Gamma_0) : ||u||_{H^{1/2}(\Gamma_0)} < \infty \right\}$ with corresponding norm

$$\begin{aligned} \|u\|_{H^{1/2}(\Gamma_0)}^2 &:= \|u\|_{L^2(\Gamma_0)}^2 + |u|_{H^{1/2}(\Gamma_0)}^2, \\ \|u\|_{H^{1/2}(\Gamma_0)}^2 &:= \int_{\Gamma_0} \int_{\Gamma_0} \frac{|u(x) - u(y)|^2}{|x - y|^2} \, dy \, dx. \end{aligned}$$

The dual space of $H^{1/2}(\Gamma)$ is denoted by $H^{-1/2}(\Gamma)$, where duality is understood with respect to the extended $L^2(\Gamma)$ -scalar product, i.e., for $u \in H^{1/2}(\Gamma)$ and $\phi \in L^2(\Gamma)$,

$$\langle \phi; u \rangle_{\Gamma} := \int_{\Gamma} \phi(x) u(x) \, dx.$$

We note that $H^{1/2}(\Gamma) \subseteq L^2(\Gamma) \subseteq H^{-1/2}(\Gamma)$ form a Gelfand triple and all inclusions are dense and compact, cf. [SS11, Proposition 2.5.2].

1.2 Hyper-singular integral operator W

The hyper-singular integral operator W is a well-defined linear and continuous operator

 $W \colon H^{1/2}(\Gamma) \to H^{-1/2}(\Gamma).$

Moreover, W is symmetric and positive semi-definite, i.e.,

 $\langle Wu; v \rangle_{\Gamma} = \langle u; Wv \rangle_{\Gamma}$ and $\langle Wu; u \rangle_{\Gamma} \ge 0$ for all $u, v \in H^{1/2}(\Gamma)$,

where $\langle \cdot; \cdot \rangle_{\Gamma}$ denotes the extended $L^2(\Gamma)$ scalar product. The bilinear form

$$\langle\!\langle u; v \rangle\!\rangle_W := \langle Wu; v \rangle_{\Gamma}$$

is a scalar product on $H^{1/2}_{\star}(\Gamma) := \{v \in H^{1/2} : \langle 1; v \rangle_{\Gamma} = 0\}$, see, e.g., [SS11, Section 3.5.1]. Therefore,

$$\langle\!\langle u; v \rangle\!\rangle_{W+S} := \langle Wu; v \rangle_{\Gamma} + \langle 1; u \rangle_{\Gamma} \langle 1; v \rangle_{\Gamma} \quad \text{for all } u, v \in H^{1/2}(\Gamma), \tag{1.5}$$

defines a scalar product on $H^{1/2}(\Gamma)$. Apparently, $\langle\!\langle \cdot; \cdot \rangle\!\rangle_{W+S}$ is bilinear and symmetric. Since W is positive semi-definite and $\langle\!\langle \cdot; \cdot \rangle\!\rangle_W$ is a scalar product on $H^{1/2}_{\star}(\Gamma)$, it follows, that $\langle\!\langle \cdot; \cdot \rangle\!\rangle_{W+S}$ is also positive definite on $H^{1/2}(\Gamma)$.

According to the Rellich compactness theorem, the induced norm $||| u |||_{W+S}^2 := \langle \langle u; u \rangle \rangle_{W+S}$ is an equivalent norm on $H^{1/2}(\Gamma)$.

1.3 Neumann problem

The double-layer integral operator K is a well-defined linear and continuous operator

$$K \colon H^{1/2}(\Gamma) \to H^{1/2}(\Gamma). \tag{1.6}$$

Moreover, its adjoint is a well-defined linear and continuous operator

$$K': H^{-1/2}(\Gamma) \to H^{-1/2}(\Gamma).$$
 (1.7)

The restriction of K' to $L^2(\Gamma)$ even maps to $L^2(\Gamma)$. Further details are found in, e.g., [Pra07, Theorem 4.26].

The hyper-singular integral equation (1.2) stems from the Neumann problem

$$-\Delta P = 0 \quad \text{in } \Omega, \partial_n P = \phi \quad \text{on } \Gamma.$$
(1.8)

Recall the first Green's formula

$$\langle \nabla P; \nabla Q \rangle_{\Omega} = \langle \phi; Q \rangle_{\Gamma} \text{ for } Q \in H^1(\Omega).$$

If we plug-in the constant function $Q \equiv 1$, we see that

$$0 = \langle \phi; 1 \rangle_{\Gamma} \tag{1.9}$$

has to be fulfilled to allow weak solutions of (1.8). Moreover, solutions can only be unique up to additive constants, i.e., if P is a solution of (1.8) and $\alpha \in \mathbb{R}$, then $P + \alpha$ is also a solution of (1.8). To fix additive constants, we use the Sobolev space

$$H^1_{\star}(\Omega) := \left\{ v \in H^1(\Omega) : \langle v; 1 \rangle_{\Gamma} = 0 \right\}.$$

It is well known, that there exists a unique solution $P \in H^1_{\star}(\Omega)$ of (1.8), if $\phi \in H^{-1/2}(\Gamma)$ satisfies (1.9), see, e.g., [Ste08, Theorem 4.9].

The Neumann problem (1.8) is equivalent to the hypersingular integral equation (1.2) in the following sense. If $P \in H^1(\Omega)$ solves (1.8), the trace $u := P|_{\Gamma}$ solves (1.2). Conversely, if $u \in H^{1/2}(\Gamma)$ solves (1.2), the function $P(x) := \int_{\Gamma} G(x, y)\phi(y) \, ds_y - \int_{\Gamma} \partial_{n_y} G(x, y)u(y) \, ds_y$ solves the Neumann problem (1.8), where G(x, y) is the fundamental solution of the Laplacian (1.3), see [Pra07, Theorem 4.13].

However, this equivalence does not state the unique solvability of the hypersingular integral equation (1.2).

We assume $\phi \in H_{\star}^{-1/2}(\Gamma) := \{v \in H^{-1/2}(\Gamma) : \langle \psi; 1 \rangle_{\Gamma} = 0\}$ due to (1.9). It holds that $\langle Wv; 1 \rangle_{\Gamma} = 0$ for all $v \in H^{1/2}(\Gamma)$, since W is symmetric and the constant functions are in the kernel of W, see [Pra07, Proposition 4.15]. Furthermore, from [Pra07, Proposition 4.15], it follows $\langle (1/2 - K')\phi; 1 \rangle_{\Gamma} = 0$ for all $\phi \in H_{\star}^{-1/2}(\Gamma)$.

Under the constraint, that the solution u of (1.2) is in $H^{1/2}_{\star}(\Gamma)$, the hyper-singular integral equation is recast into the variational formulation: Find $u \in H^{1/2}_{\star}(\Gamma)$ such that

$$\langle\!\langle u; v \rangle\!\rangle_W = \langle (1/2 - K')\phi; v \rangle_{\Gamma} \quad \text{for all } v \in H^{1/2}_{\star}(\Gamma).$$

$$(1.10)$$

Thereof, we can deduce the variational formulation: Find $u \in H^{1/2}(\Gamma)$ such that

$$\langle\!\langle u; v \rangle\!\rangle_{W+S} = \langle (1/2 - K')\phi; v \rangle_{\Gamma} \quad \text{for all } v \in H^{1/2}(\Gamma).$$

$$(1.11)$$

According to the Riesz theorem, the equation (1.10) admits a unique solution $u \in H^{1/2}_{\star}(\Gamma)$. On the other hand, if we look at the formulation (1.11), we also get from the Riesz theorem a unique solution $u \in H^{1/2}(\Gamma)$. From

$$|\Gamma|\langle u;1\rangle_{\Gamma} = \underbrace{\langle Wu;1\rangle_{\Gamma}}_{=0} + \langle 1;1\rangle_{\Gamma}\langle u;1\rangle_{\Gamma} = \langle \langle u;1\rangle \rangle_{W+S} = \langle (1/2 - K')\phi;1\rangle_{\Gamma} = 0,$$

it even follows that $u \in H^{1/2}_{\star}(\Gamma)$. Therefore, both variational formulations are equivalent.

To approximate u, we use a boundary element method. This means that we replace the space $H^{1/2}(\Gamma)$ in (1.11) by a finite dimensional subspace \mathcal{X}_{\star} and look for a solution $U_{\star} \in \mathcal{X}_{\star}$. Hence, we consider the discrete variational formulation: Find $U_{\star} \in \mathcal{X}_{\star}$ such that

$$\langle\!\langle U_{\star}; V_{\star} \rangle\!\rangle_{W+S} = \langle (1/2 - K')\phi; V_{\star} \rangle_{\Gamma} \quad \text{for all } V_{\star} \in \mathcal{X}_{\star}, \tag{1.12}$$

which can be solved numerically.

2 Discretization

In this section, we introduce B-splines as well as NURBS and deduce some basic properties. Additionally, the discretization of the boundary Γ is discussed and the ansatz spaces are defined.

2.1 B-splines

Consider $knots \check{\mathcal{K}} := (t_i)_{i \in \mathbb{Z}}$ on \mathbb{R} such that $t_{i-1} \leq t_i$ for $i \in \mathbb{Z}$ and $\lim_{i \to \pm \infty} t_i = \pm \infty$. The multiplicity of any knot t_i is denoted by $\#t_i$. We define the corresponding set of nodes $\check{\mathcal{N}} := \{t_i : i \in \mathbb{Z}\} = \{\check{z}_j : j \in \mathbb{Z}\}$ with $\check{z}_{j-1} < \check{z}_j$ for $j \in \mathbb{Z}$. For $i \in \mathbb{Z}$, the *i*-th *B*-spline of degree p is defined inductively by

$$B_{i,0} := \chi_{[t_{i-1},t_i)},$$

$$B_{i,p} := \beta_{i-1,p} B_{i,p-1} + (1 - \beta_{i,p}) B_{i+1,p-1} \quad \text{for } p \in \mathbb{N},$$
(2.1)

where, for $t \in \mathbb{R}$,

$$\beta_{i,p}(t) := \begin{cases} \frac{t-t_i}{t_{i+p}-t_i} & \text{if } t_i \neq t_{i+p} \\ 0 & \text{if } t_i = t_{i+p} \end{cases}$$

To stress the dependence on the knots $\check{\mathcal{K}}$, also the notation $B_{i,p}^{\check{\mathcal{K}}} := B_{i,p}$ and $\beta_{i,p}^{\check{\mathcal{K}}} := \beta_{i,p}$ is used.

Lemma 2.1 Let I = [a, b) be a finite interval and $p \in \mathbb{N}_0$. Then, the following assertions (i)–(vi) hold:

- (i) The set {B_{i,p}|_I : i ∈ Z, B_{i,p}|_I ≠ 0} is a basis for the space of all right-continuous N
 -piecewise polynomials of degree lower or equal p on I with break points N
 ∩ (a, b) and which are, at each break point t_i, p − #t_i times continuously differentiable if p − #t_i ≥ 0.
- (ii) For $i \in \mathbb{Z}$, the *i*-th *B*-spline $B_{i,p}$ of degree *p* vanishes outside the interval $[t_{i-1}, t_{i+p})$. It is positive on the open interval (t_{i-1}, t_{i+p}) .
- (iii) For $i \in \mathbb{Z}$, the *i*-th B-spline $B_{i,p}$ of degree p is completely determined by the p+2 knots t_{i-1}, \ldots, t_{i+p} .
- (iv) The B-splines of degree p form a (locally finite) partition of unity, i.e.,

$$\sum_{i\in\mathbb{Z}}B_{i,p}=1 \quad on \ \mathbb{R}$$

- (v) Let $i \in \mathbb{Z}$. For $z = t_{i-p} = \cdots = t_i < t_{i+1}$, it holds $B_{i+1-p,p}(z) = 1$.
- (vi) Let $i \in \mathbb{Z}$. For $t_{i-p-1} < z = t_{i-p} = \cdots = t_i$, it holds $\lim_{t \to z^-} B_{i-p,p}(t) = 1$.

Proof. The proof of (i) is found in [de 86, Theorem 6], and (ii)–(iii) are proved in [de 86, Section 2]. (iv) is proved in [de 86, page 9–10].

For (v) and (vi), we use induction on p.

(v) We show $B_{i+1-p,p}(z) = 1$ by induction on p. For p = 0 and $z = t_i < t_{i+1}$, it follows

$$B_{i+1,0}(z) = \chi_{[t_i, t_{i+1})}(z) = \chi_{[t_i, t_{i+1})}(t_i) = 1$$

In the induction step, we suppose that the claim is true up to p-1, i.e.,

$$z = t_{i-(p-1)} = \dots = t_i < t_{i+1} \implies B_{i+1-(p-1),p-1}(z) = 1.$$
(2.2)

Then, we need to prove the statement for p using (2.2). Let $z = t_{i-p} = \cdots = t_i < t_{i+1}$. Then, definition (2.1) shows

$$B_{i+1-p,p}(z) = \beta_{i-p,p}(z)B_{i+1-p,p-1}(z) + (1 - \beta_{i+1-p,p}(z))B_{i+1-(p-1),p-1}(z).$$

If we take a look at the specific factors, we see

$$\beta_{i-p,p}(z) = 0, \text{ since } t_{i-p} = t_i,$$

 $\beta_{i+1-p,p}(z) = \frac{z - t_{i+1-p}}{t_{i+1} - t_{i+1-p}} = 0.$

From the induction hypothesis (2.2), we derive

$$B_{i+1-(p-1),p-1}(z) = 1.$$

Hence, there holds

$$B_{i+1-p,p}(z) = 1,$$

which concludes the induction step.

(vi) We show $\lim_{t\to z^-} B_{i-p,p}(t) = 1$ by induction on p. Let p = 0 and $t_{i-1} < z = t_i$. Then,

$$\lim_{t \to z_{-}} B_{i,0}(t) = \lim_{t \to z_{-}} \chi_{[t_{i-1},t_i)}(t) = 1.$$

In the induction step, we suppose that the claim is true up to p-1, i.e.,

$$t_{i-p} < z = t_{i-(p-1)} = \dots = t_i \implies \lim_{t \to z-} B_{i-(p-1),p-1}(t) = 1.$$
 (2.3)

Let $t_{i-p-1} < z = t_{i-p} = \cdots = t_i$. Via the definition of B-splines (2.1), it follows, if the limits exist,

$$\lim_{t \to z_{-}} \beta_{i-p-1,p}(t) \lim_{t \to z_{-}} B_{i-p,p-1}(t) + \lim_{t \to z_{-}} (1 - \beta_{i-p,p}(t)) \lim_{t \to z_{-}} B_{i-(p-1),p-1}(t)$$
$$= \lim_{t \to z_{-}} \left(\beta_{i-p-1,p}(t) B_{i-p,p-1}(t) + (1 - \beta_{i-p,p}(t)) B_{i-(p-1),p-1}(t) \right)$$
$$= \lim_{t \to z_{-}} B_{i-p,p}(t).$$

As before, we consider the individual terms,

$$\lim_{t \to z_{-}} \beta_{i-p-1,p}(t) = \lim_{t \to z_{-}} \frac{t - t_{i-p-1}}{t_{i-1} - t_{i-p-1}} = 1,$$
$$\lim_{t \to z_{-}} \beta_{i-p,p}(t) = 0 \quad \text{since } t_{i-p} = t_{i}.$$

According to the induction hypothesis (2.3), it holds that

$$\lim_{t \to z-} B_{i-(p-1),p-1}(t) = 1.$$

Therefore,

$$\lim_{t \to z_{-}} B_{i-p,p}(t) = \lim_{t \to z_{-}} B_{i-p,p-1}(t) + 1.$$

From (ii) and (iv), it follows directly

$$0 \le \lim_{t \to z-} B_{i-p,p}(t) \le 1.$$

Hence, $\lim_{t\to z^-} B_{i-p,p-1}(t) = 0$ as well as $\lim_{t\to z^-} B_{i-p,p}(t) = 1$, which concludes the proof. \Box

2.2 NURBS

Additionally to the knots $\check{\mathcal{K}} = (t_i)_{i \in \mathbb{Z}}$, we consider positive weights $\mathcal{W} := (w_i)_{i \in \mathbb{Z}}$ with $w_i > 0$ and define for $i \in \mathbb{Z}$ and $p \in \mathbb{N}_0$ the *i*-th NURBS by

$$R_{i,p} := \frac{w_i B_{i,p}}{\sum_{\ell \in \mathbb{Z}} w_\ell B_{\ell,p}}.$$
(2.4)

We also use the notation $R_{i,p}^{\check{\mathcal{K}},\mathcal{W}} := R_{i,p}$. Note that the denominator is locally finite and positive. In addition, we define for $p \in \mathbb{N}_0$ the B-spline space

$$\mathscr{S}^{p}(\check{\mathcal{K}}) := \left\{ \sum_{i \in \mathbb{Z}} a_{i} B_{i,p}^{\check{\mathcal{K}}} : a_{i} \in \mathbb{R} \right\}$$

$$(2.5)$$

as well as the NURBS space

$$\mathcal{N}^{p}(\check{\mathcal{K}},\mathcal{W}) := \left\{ \sum_{i \in \mathbb{Z}} a_{i} R_{i,p}^{\check{\mathcal{K}},\mathcal{W}} : a_{i} \in \mathbb{R} \right\} = \frac{\mathscr{S}^{p}(\check{\mathcal{K}})}{\sum_{\ell \in \mathbb{Z}} w_{\ell} B_{\ell,p}^{\check{\mathcal{K}},\mathcal{W}}}.$$
(2.6)

2.3 Boundary discretization

We discuss the different quantities of the discretization of Γ and introduce some further notation.

- Nodes $z_j = \gamma(\check{z}_j) \in \check{\mathcal{N}}_{\star}$ Let $\mathcal{N}_{\star} := \{z_j : j = 1, \dots, n\}$ and $z_0 := z_n$ be a set of nodes. Suppose that $z_j = \gamma(\check{z}_j)$ for some $\check{z}_j \in [a, b]$ with $a = \check{z}_0 < \check{z}_1 < \check{z}_2 < \dots < \check{z}_n = b$ such that $\gamma|_{[\check{z}_{j-1}, \check{z}_j]} \in C^1([\check{z}_{j-1}, \check{z}_j])$.
- Multiplicity $\#z_j$ and knots $\mathcal{K}_{\star}, \mathcal{K}_{\star}$

Let $p \in \mathbb{N}_0$ be some fixed polynomial order. Each node z_j has a multiplicity $\#z_j \in \{1, 2, \dots, p+1\}$ with $\#z_0 = \#z_n = p+1$ and $\#z_j \leq p$ for $j = 1, \dots, n-1$. This induces knots

$$\mathcal{K}_{\star} = \underbrace{(z_1, \dots, z_1, \dots, z_n, \dots, z_n)}_{\#z_1 \text{ times}}$$
(2.7)

with corresponding knots $\check{\mathcal{K}}_{\star} := \gamma|_{(a,b]}^{-1}(\mathcal{K}_{\star})$ on the parameter domain [a,b].

• Elements T,[T] and partitions \mathcal{T}_{\star} , $[\mathcal{T}_{\star}]$ Let $\mathcal{T}_{\star} = \{T_1, \ldots, T_n\}$ be a partition of Γ into compact and connected segments $T_j = \gamma(\check{T}_j)$ with $\check{T}_j = [\check{z}_{j-1}, \check{z}_j]$. We define

$$[\mathcal{T}_{\star}] := \{ [T] : T \in \mathcal{T}_{\star} \} \quad \text{with} \quad [T] := (T, \# z_{T,1}, \# z_{T,2}),$$
(2.8)

where $z_{T,1} = z_{j-1}$ and $z_{T,2} = z_j$ are the two nodes of $T = T_j$.

• Local mesh-sizes $h_{\star,T}, \check{h}_{\star,T}$ and $h_{\star}, \check{h}_{\star}$

The arclength of each element $T \in \mathcal{T}_{\star}$ is denoted by $h_{\star,T}$. We define the local mesh-width function $h_{\star} \in L^{\infty}(\Gamma)$ by $h_{\star}|_{T} = h_{\star,T}$. Additionally, we define for each element $T \in \mathcal{T}_{\star}$ its length $\check{h}_{\star}|_{T} := |\gamma^{-1}(T)|$ with respect to the parameter domain [a, b]. This gives rise to $\check{h}_{\star} \in L^{\infty}(\Gamma)$ with $\check{h}_{\star}|_{T} = \check{h}_{\star,T}$. Note that the lengths $h_{\star,T}$ and $\check{h}_{\star,T}$ of an element T are equivalent, and the equivalence constants depend only on γ .

• Local mesh-ratios $\check{\kappa}_{\star}$

The local mesh-ratio is defined by

$$\check{\kappa}_{\star} := \max\left\{\check{h}_{\star,T}/\check{h}_{\star,T'} : T, T' \in \mathcal{T}_{\star} \text{ with } T \cap T' \neq \emptyset\right\}.$$
(2.9)

• Patches $\omega_{\star}(z), \omega_{\star}(\Gamma_0), \omega_{\star}(\mathcal{E}), [\omega_{\star}](\mathcal{E})$ and $\bigcup \mathcal{E}$

For each set $\Gamma_0 \subseteq \Gamma$ and $m \in \mathbb{N}_0$, we define inductively

$$\omega_{\star}^{m}(\Gamma_{0}) := \begin{cases} \Gamma_{0}, & \text{if } m = 0, \\ \omega_{\star}(\Gamma_{0}) := \bigcup \left\{ T \in \mathcal{T}_{\star} : T \cap \Gamma_{0} \neq \emptyset \right\}, & \text{if } m = 1, \\ \omega_{\star}(\omega_{\star}^{m-1}(\Gamma_{0})), & \text{if } m > 1. \end{cases}$$

$$(2.10)$$

For nodes $z \in \Gamma$, we abbreviate $\omega_{\star}(z) := \omega_{\star}(\{z\})$. Analogously, for each set $\mathcal{E} \subseteq [\mathcal{T}_{\star}]$ and $m \in \mathbb{N}_0$, we define inductively

$$[\omega_{\star}^{m}](\mathcal{E}) := \begin{cases} \mathcal{E}, & \text{if } m = 0, \\ [\omega_{\star}](\mathcal{E}) := \{ [T] \in [\mathcal{T}_{\star}] : \exists [T'] \in \mathcal{E}, \ T \cap T' \neq \emptyset \}, & \text{if } m = 1, \\ [\omega_{\star}]([\omega_{\star}^{m-1}](\mathcal{E})), & \text{if } m > 1. \end{cases}$$
(2.11)

We also need

$$\bigcup \mathcal{E} := \bigcup \{ T \in \mathcal{T}_{\star} : [T] \in \mathcal{E} \} \subseteq \Gamma$$
(2.12)

and

$$\omega_{\star}^{m}(\mathcal{E}) := \omega_{\star}^{m} \Big(\bigcup \mathcal{E}\Big).$$
(2.13)

2.4 Mesh-refinement

Let ref (·) be a given deterministic mesh-refinement strategy such that, for each mesh $[\mathcal{T}_{\star}]$ and an arbitrary set of marked nodes $\mathcal{M}_{\star} \subseteq \mathcal{N}_{\star}$ the refinement $[\mathcal{T}_{+}] := \operatorname{ref}([\mathcal{T}_{\star}], \mathcal{M}_{\star})$ is also a mesh in the same sense as above. Suppose that the marked nodes belong to the union of the refined elements, i.e., $\mathcal{M}_{\star} \subseteq \bigcup([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}])$, and that the knots \mathcal{K}_{\star} form a subsequence of the knots \mathcal{K}_{+} . This implies the following estimate

$$|[\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]| \le 2(|\mathcal{K}_{+}| - |\mathcal{K}_{\star}|), \tag{2.14}$$

since $[\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]$ is the set of all elements in which a new knot is inserted and one new knot can be inserted in at most 2 elements of the old mesh, i.e., at the intersection of 2 elements.

We write $[\mathcal{T}_+] \in \operatorname{ref}([\mathcal{T}_\star])$, if there exist finitely many meshes $[\mathcal{T}_1], \ldots, [\mathcal{T}_\ell]$ and subsets $\mathcal{M}_j \subseteq \mathcal{N}_j$ of the corresponding nodes such that $[\mathcal{T}_\star] = [\mathcal{T}_1], [\mathcal{T}_+] = [\mathcal{T}_\ell]$, and $[\mathcal{T}_j] = \operatorname{ref}([\mathcal{T}_{j-1}], \mathcal{M}_{j-1})$ for all $j = 2, \ldots, \ell$, where we formally allow $\ell = 1$, i.e., $[\mathcal{T}_\star] \in \operatorname{ref}([\mathcal{T}_\star])$.

Later on, we need some assumptions concerning the mesh-refinement strategy, which are as follows:

Assumption 2.2 Let $[\mathcal{T}_0]$ be an arbitrary initial mesh and $[\mathbb{T}] := \operatorname{ref}([\mathcal{T}_0])$ be the set of all possible refinements. Suppose that the mesh-refinement strategy satisfies the properties (M1)-(M3):

(M1) There exists a constant $\check{\kappa}_{max} \geq 1$ such that the local mesh-ratios (2.9) are uniformly bounded

$$\check{\kappa}_{\star} \leq \check{\kappa}_{\max} \quad \text{for all } [\mathcal{T}_{\star}] \in [\mathbb{T}].$$

$$(2.15)$$

(M2) There is a common refinement $[\mathcal{T}_{\star} \oplus \mathcal{T}_{+}] \in \operatorname{ref}([\mathcal{T}_{\star}]) \cap \operatorname{ref}([\mathcal{T}_{+}])$ for all $[\mathcal{T}_{\star}], [\mathcal{T}_{+}] \in [\mathbb{T}]$, such that the knots $\mathcal{K}_{\star} \oplus \mathcal{K}_{+}$ of $[\mathcal{T}_{\star} \oplus \mathcal{T}_{+}]$ satisfy the overlay estimate

$$|\mathcal{K}_{\star} \oplus \mathcal{K}_{+}| \le |\mathcal{K}_{\star}| + |\mathcal{K}_{+}| - |\mathcal{K}_{0}|.$$

$$(2.16)$$

(M3) There exists a constant $C_{\text{mesh}} > 0$ which depends only on $[\mathcal{T}_0]$, such that for each sequence $([\mathcal{T}_\ell])_{\ell \in \mathbb{N}_0}$ of meshes generated by successive mesh-refinement, i.e., $[\mathcal{T}_j] = \text{ref}([\mathcal{T}_{j-1}], \mathcal{M}_{j-1})$ for all $j \in \mathbb{N}$ and arbitrary $\mathcal{M}_j \subseteq \mathcal{N}_j$, the following closure estimate holds:

$$|\mathcal{K}_{\ell}| - |\mathcal{K}_{0}| \le C_{\text{mesh}} \sum_{j=0}^{\ell-1} |\mathcal{M}_{j}| \quad \text{for all } \ell \in \mathbb{N}.$$

$$(2.17)$$

In the implementation of the adaptive IGABEM Algorithm 3.5, one can use either pure *h*-refinement based on local biscection or a strategy, which also takes the multiplicity of the marked nodes into account and will be specified below.

The *h*-refinement strategy is rather simple: Let $[\mathcal{T}_{\star}] \in [\mathbb{T}]$ and let $\mathcal{M}_{\star} \subseteq \mathcal{N}_{\star}$ be a set of marked nodes. The refined mesh $[\mathcal{T}_{+}] := \operatorname{ref}([\mathcal{T}_{\star}], \mathcal{M}_{\star})$, is obtained the following way:

INPUT: mesh $[\mathcal{T}_{\star}]$, marked nodes \mathcal{M}_{\star} .

- (i) Mark every element $T \in \mathcal{T}_{\star}$ such that $T \cap \mathcal{M}_{\star} \neq \emptyset$.
- (ii) Recursively, mark further elements $T' \in \mathcal{T}_{\star}$, if there exists a marked element $T \in \mathcal{T}_{\star}$ with $T \cap T' \neq \emptyset$ and $\check{h}_{\star,T'} > 2\check{\kappa}_0 \check{h}_{\star,T}$.
- (iii) Refine all marked elements $T \in \mathcal{T}_{\star}$ via bisection in the parameter domain by insertion of a knot of multiplicity one, and obtain $[\mathcal{T}_{+}]$.

OUTPUT: refined mesh $[\mathcal{T}_+]$.

The second strategy used differs from the first one and also considers the node multiplicity:

INPUT: mesh $[\mathcal{T}_{\star}]$, marked nodes \mathcal{M}_{\star} .

- (i) Consider each element $T \in \mathcal{T}_{\star}$. If both nodes of T belong to \mathcal{M}_{\star} , the element T is marked.
- (ii) Define $\mathcal{M}^0_{\star} := \{T' \cap \mathcal{N}_{\star} : T' \in \mathcal{T}_{\star}, T' \cap \mathcal{N}_{\star} \subseteq \mathcal{M}_{\star}\}$. For all nodes $z \in \{z' \in \mathcal{M}_{\star} \setminus \mathcal{M}^0_{\star} : \#z' < p\}$, increase the multiplicity by one. For $z \in \{z' \in \mathcal{M}_{\star} \setminus \mathcal{M}^0_{\star} : \#z' = p\}$, mark all elements $T \in \mathcal{T}_{\star}$ with $z \in T$.
- (iii) Recursively, further elements $T' \in \mathcal{T}_{\star}$ will be marked if there exists a marked element $T \in \mathcal{T}_{\star}$ with $T \cap T' \neq \emptyset$ and $\check{h}_{\star,T'} > 2\check{\kappa}_0 \check{h}_{\star,T}$.
- (iv) Refine all marked elements $T \in \mathcal{T}_{\star}$ via bisection in the parameter domain and obtain $[\mathcal{T}_{+}]$.

OUTPUT: refined mesh $[\mathcal{T}_+]$.

According to [AFF⁺13], the first strategy satisfies the assumptions (M1)–(M3). [FGP, Proposition 2.2] shows that (M1)–(M3) also hold for the second strategy.

For the proof of the main result, i.e., the optimality of the proposed Algorithm 3.5, we use some auxiliary error estimator $\tilde{\rho}$, which relies on an equivalent mesh-size function \tilde{h} from [FGHP16b, Proposition 4.2], which also takes the knot multiplicities into account.

Proposition 2.3 Under the assumption (M1) there exists a modified mesh-size function $h: [\mathbb{T}] \to L^{\infty}(\Gamma)$ such that $\tilde{h}([\mathcal{T}_{\star}])$ is \mathcal{T}_{\star} -piecewise constant for $[\mathcal{T}_{\star}] \in [\mathbb{T}]$ with the following properties: There exist constants $C_{\text{wt}} > 0$ and $0 < q_{\text{ctr}} < 1$ such that for all $[\mathcal{T}_{\star}] \in [\mathbb{T}]$ and all refinements $[\mathcal{T}_{+}] \in \text{ref}([\mathcal{T}_{\star}])$, the corresponding mesh-sizes $\tilde{h}_{\star} := \tilde{h}([\mathcal{T}_{\star}])$ and $\tilde{h}_{+} := \tilde{h}([\mathcal{T}_{+}])$ satisfy equivalence

$$C_{\mathrm{wt}}^{-1}\check{h}_{\star} \le \check{h}_{\star} \le C_{\mathrm{wt}}\check{h}_{\star} \quad \mathrm{resp.} \quad C_{\mathrm{wt}}^{-1}\check{h}_{+} \le \check{h}_{+} \le C_{\mathrm{wt}}\check{h}_{+}, \tag{2.18}$$

as well as reduction,

 $\widetilde{h}_{+} \le \widetilde{h}_{\star},\tag{2.19}$

contraction on the patch of refined elements,

$$h_{+}|_{\omega_{+}([\mathcal{T}_{+}]\setminus[\mathcal{T}_{\star}])} \leq q_{\mathrm{ctr}} h_{\star}|_{\omega_{+}([\mathcal{T}_{+}]\setminus[\mathcal{T}_{\star}])},\tag{2.20}$$

and equality on the non-contracting part,

$$h_{+}|_{\Gamma \setminus \omega_{+}([\mathcal{T}_{+}] \setminus [\mathcal{T}_{\star}])} = h_{\star}|_{\Gamma \setminus \omega_{\star}([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}])}.$$
(2.21)

The constants $C_{\rm wt} > 0$ and $0 < q_{\rm ctr} < 1$ depend only on $\check{\kappa}_{\rm max}, p$, and γ .

Proof. For all $[\mathcal{T}_{\star}] \in [\mathbb{T}]$, the modified mesh-size $\widetilde{h}_{\star} \in L^{\infty}(\Gamma)$ is defined as

$$\widetilde{h}|_{T} = |\gamma^{-1}(\omega_{\star}(T))| \cdot q_{1}^{\sum_{z \in \mathcal{N}_{\star} \cap \omega_{\star}(T)} \# z} \quad \text{for all } T \in \mathcal{T}_{\star},$$

with a suitable constant $0 < q_1 < 1$. The proof of the properties can be found in [FGHP16b, Proposition 4.2].

2.5 Discretization spaces

Let $[\mathcal{T}_0]$ be a given initial mesh with corresponding knots \mathcal{K}_0 such that for each $\check{z}_j \in \check{\mathcal{N}}_0$ it holds $\#\check{z}_j \leq p$ for $j = 1, \ldots, n-1$ and $\#\check{z}_0 = \#\check{z}_n = p+1$. Suppose that $\mathcal{W}_0 = (w_i)_{i=1-p}^{N-p}$ are given initial weights with $N = |\mathcal{K}_0|$.

We extend the transformed knot sequence $\check{\mathcal{K}}_0 = (t_i)_{i=1}^N$ arbitrarily to $(t_i)_{i\in\mathbb{Z}}$ with $t_{-p} = \cdots = t_0 = a$, $t_i \leq t_{i+1}, \lim_{i\to\pm\infty} t_i = \pm\infty$ and $\mathcal{W}_0 = (w_i)_{i\in\mathbb{Z}}$ with $w_i > 0$ and assume $w_{1-p} = w_{N-p}$. Additionally, we define $w_{\min} := \min(\mathcal{W}_0)$ and $w_{\max} := \max(\mathcal{W}_0)$. For the extended sequences, we also write $\check{\mathcal{K}}_0$ and \mathcal{W}_0 and set

$$\mathcal{X}_{0} := \left\{ \sum_{i \in \mathbb{Z}} a_{i} R_{i,p} |_{[a,b)} \circ \gamma |_{[a,b)}^{-1} : a_{i} \in \mathbb{R} \text{ and } a_{1-p} = a_{N-p} \right\}$$

$$= \left\{ \sum_{i \in \mathbb{Z}} a_{i} R_{i,p} |_{[a,b)} \circ \gamma |_{[a,b)}^{-1} : a_{i} \in \mathbb{R} \right\} \cap C(\Gamma)$$

$$(2.22)$$

The equality in (2.22) holds, because for j = 1, ..., n-1 the multiplicity satisfies $\#\check{z}_j \leq p$ and therefore with Lemma 2.1 (i) we get at least continuity at each $\gamma(t_j)$. In combination with $a_{1-p} = a_{N-p}$ and $w_{1-p} = w_{N-p}$, Lemma 2.1 (v) shows the continuity at $\gamma(t_0) = \gamma(t_N)$.

We note that $\mathcal{X}_0 \subset H^1(\Gamma) \subset H^{1/2}(\Gamma)$ and that Lemma 2.1 implies that the set

$$\left\{R_{i,p}|_{[a,b)} \circ \gamma|_{[a,b)}^{-1} : i = 2 - p, \dots, N - p - 1\right\} \cup \left\{\left(R_{1-p,p}|_{[a,b)} + R_{N-p,p}|_{[a,b)}\right) \circ \gamma|_{[a,b)}^{-1}\right\}$$
(2.23)

is a basis of \mathcal{X}_0 . Due to Lemma 2.1, this basis does not depend on how the sequences \mathcal{K}_0 and \mathcal{W}_0 are extended.

Let $[\mathcal{T}_{\star}] \in [\mathbb{T}]$ be a mesh with knots \mathcal{K}_{\star} . Via *knot insertion* from \mathcal{K}_0 to \mathcal{K}_{\star} , one obtains unique corresponding weights \mathcal{W}_{\star} . These are chosen such that the denominators of the NURBS functions do not change. This implies nestedness

$$\mathcal{X}_{\star} \subseteq \mathcal{X}_{+} \text{ for all } [\mathcal{T}_{\star}] \in [\mathbb{T}] \text{ and all } [\mathcal{T}_{+}] \in \operatorname{ref} (\mathcal{T}_{\star}),$$

where the spaces \mathcal{X}_{\star} resp. \mathcal{X}_{+} are defined analogously to (2.22). A basis of \mathcal{X}_{\star} is given similarly as in (2.23). For further details, we refer, e.g., to [FGP15, Section 4.2].

To discretize the right-hand side ϕ of (1.2), we consider the space

$$\mathcal{P}^{p}(\mathcal{T}_{\star}) := \left\{ \check{\Psi}_{\star} \circ \gamma |_{[a,b)}^{-1} : \check{\Psi}_{\star} \in \mathcal{P}^{p}(\check{\mathcal{T}}_{\star}) \right\},$$
(2.24)

where $\mathcal{P}^{p}(\check{\mathcal{T}}_{\star})$ denotes the set of all $\check{\mathcal{N}}_{\star}$ -piecewise polynomials in the parameter domain. We define $\check{\mathcal{K}}_{\star,p+1}$ as the knots, which are obtained from $\check{\mathcal{K}}_{\star}$ by increasing all multiplicities to p+1. With this definition, Lemma 2.1 provides a basis of $\mathcal{P}^{p}(\mathcal{T}_{\star})$

$$\left\{B_{i,p}^{\check{\mathcal{K}}_{\star,p+1}}|_{[a,b)} \circ \gamma|_{[a,b)}^{-1} : i = 1 - p, \dots, N_{p+1} - p\right\},\tag{2.25}$$

where N_{p+1} denotes the number of knots $\check{\mathcal{K}}_{\star,p+1}$ in (a, b].

3 Error estimators and adaptive algorithm

Throughout, for given Neumann data ϕ with $\langle \phi; 1 \rangle_{\Gamma} = 0$ and additional regularity $\phi \in L^2(\Gamma)$, let $u \in H^{1/2}(\Gamma)$ and $U_{\star} \in \mathcal{X}_{\star}$ be the unique solutions to

$$\langle\!\langle u; v \rangle\!\rangle_{W+S} = \langle (1/2 - K')\phi; v \rangle_{\Gamma} \qquad \text{for all } v \in H^{1/2}(\Gamma),$$

$$\langle\!\langle U_{\star}; V_{\star} \rangle\!\rangle_{W+S} = \langle (1/2 - K')\phi_{\star}; V_{\star} \rangle_{\Gamma} \qquad \text{for all } V_{\star} \in \mathcal{X}_{\star},$$

$$(3.1)$$

$$(0.2)$$

where ϕ_{\star} is optionally defined either as $\phi_{\star} := \phi$ or $\phi_{\star} := \Pi_{\star} \phi$ for all $[\mathcal{T}_{\star}] \in [\mathbb{T}]$ with the L^2 -orthogonal projection $\Pi_{\star} : L^2(\Gamma) \to \mathcal{P}^p(\mathcal{T}_{\star})$ onto $\mathcal{P}^p(\mathcal{T}_{\star})$. The two possibilities are considered due to numerical reasons, which will become clear in Section 6, see Remark 6.2.

3.1 Error estimators

Note that $(1/2 - K')\phi_{\star}$ is in $L^2(\Gamma)$ due to $\phi \in L^2(\Gamma)$, wherefore the following estimators are well-defined. We define the node-based error estimator

$$\mu_{\star}(z) := \|h_{\star}^{1/2} \left((1/2 - K')\phi_{\star} - WU_{\star} \right)\|_{L^{2}(\omega_{\star}(z))} + \|h_{\star}^{1/2}(\phi - \phi_{\star})\|_{L^{2}(\omega_{\star}(z))} \quad \text{for all } z \in \mathcal{N}_{\star}, \tag{3.3}$$

and

$$\mu_{\star} := \mu_{\star}(\mathcal{N}_{\star}) \quad \text{with} \quad \mu_{\star}^{2}(\mathcal{E}_{\star}) := \sum_{z \in \mathcal{E}_{\star}} \mu_{\star}(z)^{2} \quad \text{for all } \mathcal{E}_{\star} \subseteq \mathcal{N}_{\star}.$$
(3.4)

Additionally, we define the auxiliary elementwise error estimator with local contributions

$$\widetilde{\rho}_{\star}([T]) := \|\widetilde{h}_{\star}^{1/2} \big((1/2 - K')\phi_{\star} - WU_{\star} \big)\|_{L^{2}(T)} + \|\widetilde{h}_{\star}^{1/2} (\phi - \phi_{\star})\|_{L^{2}(T)} \quad \text{for all } [T] \in [\mathcal{T}_{\star}], \tag{3.5}$$

and

$$\widetilde{\rho}_{\star} := \widetilde{\rho}_{\star}([\mathcal{T}_{\star}]) \quad \text{with} \quad \widetilde{\rho}_{\star}([\mathcal{E}_{\star}])^2 := \sum_{[T] \in [\mathcal{E}_{\star}]} \widetilde{\rho}_{\star}([T])^2 \quad \text{for all} \quad [\mathcal{E}_{\star}] \subseteq [\mathcal{T}_{\star}].$$
(3.6)

As a direct consequence of Proposition 2.3 and the equivalence $h_{\star} \simeq \dot{h}_{\star}$, there exists a constant $C_{\text{loc}} > 0$ such that

$$C_{\text{loc}}^{-1} \widetilde{\rho}_{\star}([T])^2 \le \mu_{\star}(z)^2 \le C_{\text{loc}} \sum_{\substack{T' \in \mathcal{T}_{\star} \\ z \in T'}} \widetilde{\rho}_{\star}([T'])^2 \quad \text{for all } z \in \mathcal{N}_{\star} \text{ and } T \in \mathcal{T}_{\star} \text{ with } z \in T,$$
(3.7)

as well as,

$$C_{\rm loc}^{-1} \,\widetilde{\rho}_{\star}^2 \le \mu_{\star}^2 \le C_{\rm loc} \,\widetilde{\rho}_{\star}^2. \tag{3.8}$$

The constant $C_{\text{loc}} > 0$ depends only on $\check{\kappa}_{\max}, p$, and γ .

3.2 Auxiliary results

Before we turn towards the properties of the auxiliary estimator $\tilde{\rho}_{\star}$, we collect some auxiliary results, which will be needed later.

3.2.1 Scott-Zhang type operator J_{\star}

To begin with, we introduce a Scott-Zhang type operator J_{\star} for $[\mathcal{T}_{\star}] \in [\mathbb{T}]$.

It holds $R_{i,p} = w_i B_{i,p}/w$, where $w = \sum_{\ell \in \mathbb{Z}} w_\ell B_{\ell,p}$ is the fixed denominator from Section 2.5. In [BdVBSV14, Section 2.1.5], it is shown that, for $i \in \{1 - p, \ldots, N - p\}$, there exist dual basis functions $B_{i,p}^* \in L^2([a, b])$ with $\operatorname{supp} B_{i,p}^* = \operatorname{supp} B_{i,p}$ and

$$\int_{[a,b]} B_{i,p}^*(t) B_{j,p}(t) dt = \delta_{ij} = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{else} \end{cases}$$

and

$$\|B_{i,p}^*\|_{L^2(\operatorname{supp}B_{i,p})} \le (2p+3)9^p |\operatorname{supp}B_{i,p}|^{-1/2}.$$
(3.9)

Define $R_{i,p}^* := B_{i,p}^* w/w_i$ with the denominator w from before, and $\widehat{R}_{i,p} := R_{i,p}|_{[a,b)} \circ \gamma|_{[a,b)}^{-1}$. For $[\mathcal{T}_{\star}] \in [\mathbb{T}]$, we define the following Scott-Zhang type operator

$$J_{\star}: L^{2}(\Gamma) \to \mathcal{X}_{\star},$$

$$J_{\star}(v) := \sum_{i \in \{1-p,\dots,N-p-1\}} \left(\int_{[a,b]} R^{*}_{i,p}(t) v(\gamma(t)) \, dt \right) \widehat{R}_{i,p} + \left(\int_{[a,b]} R^{*}_{1-p,p}(t) v(\gamma(t)) \, dt \right) \widehat{R}_{N-p,p}.$$
(3.10)

Lemma 3.1 Let $[\mathcal{T}_{\star}] \in [\mathbb{T}]$. The Scott-Zhang type operator (3.10) satisfies the following properties:

- (i) Local projection property: For $T \in \mathcal{T}_{\star}$ and $v \in L^2(\Gamma)$, the property $v|_{\omega_{\star}^p(T)} \in \mathcal{X}_{\star}|_{\omega_{\star}^p(T)} := \{\xi|_{\omega_{\star}^p(T)} : \xi \in \mathcal{X}_{\star}\}$ implies $v|_T = (J_{\star}v)|_T$.
- (ii) Local L²-stability: There exists a constant $C_{sz} > 0$ such that for $v \in L^2(\Gamma)$ and $T \in \mathcal{T}_*$, there holds

$$\|J_{\star}v\|_{L^{2}(T)} \leq C_{\mathrm{sz}}\|v\|_{L^{2}(\omega_{\star}^{p}(T))}.$$
(3.11)

The constant $C_{sz} > 0$ depends only on $\check{\kappa}_{max}, p, w_{max}$, and γ .

(iii) Local approximation properties: There exists a constant $C_{sz} > 0$ such that for all $v \in H^{1/2}(\Gamma)$

$$\|h_{\star}^{-1/2}(1-J_{\star})v\|_{L^{2}(\Gamma)} \leq C_{\rm sz}|v|_{H^{1/2}(\Gamma)},\tag{3.12}$$

and if v is even in $H^1(\Gamma)$

$$\|h_{\star}^{-1+\sigma}(1-J_{\star})v\|_{L^{2}(\Gamma)} \leq C_{\mathrm{sz}}\|h_{\star}^{\sigma}\nabla v\|_{L^{2}(\Gamma)} \quad \text{for all } \sigma \in \mathbb{R},$$

$$(3.13)$$

as well as,

$$|(1 - J_{\star})v|_{H^{1/2}(\Gamma)} \le C_{\rm sz} ||h_{\star}^{1/2} \nabla v||_{L^{2}(\Gamma)}.$$
(3.14)

The constant $\tilde{C}_{sz} > 0$ depends only on $\check{\kappa}_{max}, p, w_{max}$, and γ .

Proof. Let $I := \{1 - p, \dots, N - p - 1\}$ throughout the proof.

(i) As $v|_{\omega_{\star}^{p}(T)} \in \mathcal{X}_{\star}|_{\omega_{\star}^{p}(T)}$, it can be rewritten in terms of the NURBS-basis with coefficients $a_{j} \in \mathbb{R}$

$$v|_{\omega_*^p(T)} = \sum_{j \in \{2-p,\dots,N-p-1\}} a_j \widehat{R}_{j,p}|_{\omega_*^p(T)} + a_{1-p} (\widehat{R}_{1-p,p} + \widehat{R}_{N-p,p})|_{\omega_*^p(T)}.$$

Therefore, it holds for $i \in I$ with supp $\widehat{R}_{i,p} \subseteq \omega^p_{\star}(T)$

$$\begin{split} \int_{[a,b]} R_{i,p}^*(t) v(\gamma(t)) \, dt &= \sum_{j \in \{2-p,\dots,N-p-1\}} a_j \int_{[a,b]} R_{i,p}^*(t) R_{j,p}(t) \, dt + \\ & a_{1-p} \int_{[a,b]} R_{i,p}^*(t) (R_{1-p,p} + R_{N-p,p})(t) \, dt \\ &= \sum_{j \in \{2-p,\dots,N-p-1\}} a_j \int_{[a,b]} \frac{B_{i,p}^*(t) w(t)}{w_i} \frac{B_{j,p}(t) w_j}{w(t)} \, dt + \\ & a_{1-p} \int_{[a,b]} \frac{B_{i,p}^*(t) w(t)}{w_i} \left(\frac{B_{1-p,p}(t) w_{1-p}}{w(t)} + \frac{B_{N-p,p}(t) w_{N-p}}{w(t)} \right) \, dt \\ &= a_i. \end{split}$$

If $\widehat{R}_{i,p}|_T \neq 0$, it follows supp $\widehat{R}_{i,p} \subseteq \omega^p_{\star}(T)$. Together with the preceding identity, this implies

$$(J_{\star}v)|_{T} = \sum_{i \in I} \left(\int_{[a,b]} R_{i,p}^{*}(t)v(\gamma(t)) dt \right) \widehat{R}_{i,p}|_{T} + \left(\int_{[a,b]} R_{1-p,p}^{*}(t)v(\gamma(t)) dt \right) \widehat{R}_{N-p,p}|_{T}$$
$$= \sum_{i \in I} a_{i} \widehat{R}_{i,p}|_{T} + a_{1-p} \widehat{R}_{N-p,p}|_{T}$$
$$= v|_{T}$$

and concludes the proof of (i).

(ii) Recall supp $R_{i,p}^{\star} = \operatorname{supp} R_{i,p}$ and $\widehat{R}_{i,p} = R_{i,p}|_{[a,b)} \circ \gamma|_{[a,b)}^{-1}$. We use $0 \leq \widehat{R}_{i,p} \leq 1$ and (3.9) to see

$$\begin{split} \|J_{\star}v\|_{L^{2}(T)} &= \left\|\sum_{i\in I} \left(\int_{[a,b]} R_{i,p}^{*}(t)v(\gamma(t)) dt\right) \widehat{R}_{i,p} \\ &+ \left(\int_{[a,b]} R_{1-p,p}^{*}(t)v(\gamma(t)) dt\right) \widehat{R}_{N-p,p} \right\|_{L^{2}(T)} \\ &\leq \sum_{\substack{i\in I\\ |\mathrm{supp}\widehat{R}_{i,p}\cap T|>0}} \left|\int_{[a,b]} R_{i,p}^{*}(t)v(\gamma(t)) dt\right| \|\widehat{R}_{i,p}\|_{L^{2}(T)} \\ &+ \chi_{(0,\infty)}(|T\cap \mathrm{supp}\widehat{R}_{N-p,p}|) \left|\int_{[a,b]} R_{1-p,p}^{*}(t)v(\gamma(t)) dt\right| \|\widehat{R}_{N-p,p}\|_{L^{2}(T)} \\ &\lesssim \sum_{\substack{i\in I\\ |\mathrm{supp}\widehat{R}_{i,p}\cap T|>0}} \|R_{i,p}^{*}\|_{L^{2}(\mathrm{supp}R_{i,p})} \|v\|_{L^{2}(\mathrm{supp}\widehat{R}_{i,p})} h_{\star,T}^{1/2} \\ &\lesssim \sum_{\substack{i\in I\\ |\mathrm{supp}\widehat{R}_{i,p}\cap T|>0}} \|v\|_{L^{2}(\mathrm{supp}\widehat{R}_{i,p})} \lesssim \|v\|_{L^{2}(\omega_{\star}^{p}(T))}. \end{split}$$

The hidden constants depend only on $\check{\kappa}_{\max}, p, w_{\max}$, and γ .

(iii) Let $T \in \mathcal{T}_{\star}$. We define $v_{\omega_{\star}^{p}(T)} := \frac{1}{|\omega_{\star}^{p}(T)|} \int_{\omega_{\star}^{p}(T)} v(x) \, ds_{x}$. It holds

$$\begin{aligned} \|(1-J_{\star})v\|_{L^{2}(T)} &= \|v-J_{\star}v\|_{L^{2}(T)} \\ \stackrel{(i)}{=} \|v-v_{\omega_{\star}^{p}(T)} - J_{\star}(v-v_{\omega_{\star}^{p}(T)})\|_{L^{2}(T)} \\ &\leq \|v-v_{\omega_{\star}^{p}(T)}\|_{L^{2}(T)} + \underbrace{\|J_{\star}(v-v_{\omega_{\star}^{p}(T)})\|_{L^{2}(T)}}_{\stackrel{(3.11)}{\lesssim} \|v-v_{\omega_{\star}^{p}(T)}\|_{L^{2}(\omega_{\star}^{p}(T))}} \\ &\lesssim \|v-v_{\omega_{\star}^{p}(T)}\|_{L^{2}(\omega_{\star}^{p}(T))} \end{aligned}$$
(3.15)

Let $\sigma \in (0,1]$ and $w \in H^{\sigma}(\Gamma_0)$ for $\Gamma_0 \subseteq \Gamma$. Then, [Fae00, Lemma 2.5] states that the following inequality holds

$$\|w\|_{L^{2}(\Gamma_{0})}^{2} \leq \frac{1}{2}|\Gamma_{0}|^{2\sigma}|w|_{H^{\sigma}(\Gamma_{0})}^{2} + \frac{1}{|\Gamma_{0}|}\left|\int_{\Gamma_{0}} w\,ds\right|^{2}.$$
(3.16)

Hence, for $\sigma = 1/2$, it follows from (3.15) and (3.16)

$$\begin{split} \|(1-J_{\star})v\|_{L^{2}(T)}^{2} \lesssim \frac{1}{2} \underbrace{|\omega_{\star}^{p}(T)|}_{\simeq h_{\star,T}} \underbrace{|v-v_{\omega_{\star}^{p}(T)}|_{H^{1/2}(\omega_{\star}^{p}(T))}^{2}}_{\stackrel{\text{def.}}{=} |v|_{H^{1/2}(\omega_{\star}^{p}(T))}^{2}} + \frac{1}{|\omega_{\star}^{p}(T)|} \underbrace{\left|\int_{\omega_{\star}^{p}(T)}^{v-v_{\omega_{\star}^{p}(T)}} ds\right|^{2}}_{=0} \\ \lesssim h_{\star,T} |v|_{H^{1/2}(\omega_{\star}^{p}(T))}^{2}, \end{split}$$

which immediately shows (3.12).

Now, we assume that v is even in $H^1(\Gamma)$. We proceed as before and use (3.16) for $v \in H^1(\Gamma)$. This proves (3.13).

With the help of [Fae00, Lemma 2.3] and [FGHP16a, Lemma 4.5], we see

Together with (3.12) and (3.13), we finally see

$$|(1-J_{\star})v|_{H^{1/2}(\Gamma)} \lesssim ||h_{\star}^{1/2}\nabla v||_{L^{2}(\Gamma)}.$$

This proves the last point.

3.2.2 Convergence of uniform refinement

The next lemma states, that independently of the starting mesh $[\mathcal{T}_{\star}] \in [\mathbb{T}]$, uniform refinement always leads to convergence.

Lemma 3.2 Let $u \in H^{1/2}(\Gamma)$ be the solution to (1.11), let $\epsilon > 0$ and $[\mathcal{T}_{\star}] \in [\mathbb{T}]$. Then, there exists a refinement $[\mathcal{T}_{\bullet}] \in \operatorname{ref}([\mathcal{T}_{\star}])$ such that the corresponding Galerkin solution $U_{\bullet} \in \mathcal{X}_{\bullet}$ satisfies

$$\|u - U_{\bullet}\|_{H^{1/2}(\Gamma)} \le \epsilon. \tag{3.17}$$

Proof. We split the proof into three steps.

Step 1: We show a Céa-type quasi-optimality: Let $[\mathcal{T}_{\bullet}] \in [\mathbb{T}]$ be arbitrary. Since the energy norm $\|\cdot\|_{W+S}$ is an equivalent norm to $\|\cdot\|_{H^{1/2}(\Gamma)}$, the following inequality is satisfied

$$\|u - U_{\bullet}\|_{H^{1/2}(\Gamma)}^{2} \lesssim \|u - U_{\bullet}\|_{W+S}^{2} = \langle\!\langle u - U_{\bullet}; u - U_{\bullet}\rangle\!\rangle_{W+S}.$$

Due to the Galerkin orthogonality, it holds for all $V_{\bullet} \in \mathcal{X}_{\bullet}$

$$\langle\!\langle u - U_{\bullet}; u - U_{\bullet} \rangle\!\rangle_{W+S} = \langle\!\langle u - U_{\bullet}; u - V_{\bullet} \rangle\!\rangle_{W+S} \lesssim ||| u - U_{\bullet} |||_{W+S} ||| u - V_{\bullet} |||_{W+S}$$

Taking the infimum over all $V_{\bullet} \in \mathcal{X}_{\bullet}$ and using again the norm equivalence, we get the Céa-type quasioptimality

$$\|u - U_{\bullet}\|_{H^{1/2}(\Gamma)} \lesssim \min_{V_{\bullet} \in \mathcal{X}_{\bullet}} \|u - V_{\bullet}\|_{H^{1/2}(\Gamma)}.$$

Step 2: We use the Scott-Zhang type operator J_{\bullet} : Since $H^1(\Gamma)$ is a dense subset of $H^{1/2}(\Gamma)$, there exists a function $v \in H^1(\Gamma)$ with

$$||u - v||_{H^{1/2}(\Gamma)} \le \frac{\epsilon}{2},$$

and we can estimate

$$\min_{V_{\bullet} \in \mathcal{X}_{\bullet}} \|u - V_{\bullet}\|_{H^{1/2}(\Gamma)} \le \|u - v\|_{H^{1/2}(\Gamma)} + \|v - J_{\bullet}v\|_{H^{1/2}(\Gamma)} \le \frac{\epsilon}{2} + \|v - J_{\bullet}v\|_{H^{1/2}(\Gamma)}.$$

From (3.13) and (3.14), we get

$$\begin{aligned} \|v - J_{\bullet}v\|_{H^{1/2}(\Gamma)}^{2} &= \|v - J_{\bullet}v\|_{L^{2}(\Gamma)}^{2} + |v - J_{\bullet}v|_{H^{1/2}(\Gamma)}^{2} \\ &\lesssim \|h_{\bullet}^{1/2}\nabla v\|_{L^{2}(\Gamma)}^{2} \lesssim \|\widetilde{h}_{\bullet}\|_{L^{\infty}(\Gamma)} |\nabla v|_{H^{1}(\Gamma)}^{2} \end{aligned}$$

Step 3: We combine (i) and (ii): There exists $[T_{\bullet}] \in [\mathbb{T}]$ with $\|\tilde{h}_{\bullet}\|_{L^{\infty}(\Gamma)} \ll 1$ sufficiently small such that

$$\|u - U_{\bullet}\|_{H^{1/2}(\Gamma)} \leq \frac{\epsilon}{2} + \|v - J_{\bullet}v\|_{H^{1/2}(\Gamma)} \leq \frac{\epsilon}{2} + \frac{\epsilon}{2} \leq \epsilon.$$

This concludes the proof.

3.2.3 Inverse estimates

Next, we present some inverse estimates which stem from [AFF⁺15, Theorem 3.1], [FGHP16b, Proposition 4.1] and [FGP].

Theorem 3.3 Let $[\mathcal{T}_{\star}] \in [\mathbb{T}]$. Then, there exists a constant $C_{inv} > 0$ such that

$$\|h_{\star}^{1/2}(1/2 - K')\psi\|_{L^{2}(\Gamma)} \leq C_{\mathrm{inv}}(\|\psi\|_{H^{-1/2}(\Gamma)} + \|h_{\star}^{1/2}\psi\|_{L^{2}(\Gamma)}) \quad \text{for all } \psi \in L^{2}(\Gamma)$$
(3.18)

and

$$\|h_{\star}^{1/2}Wv\|_{L^{2}(\Gamma)} \leq C_{\mathrm{inv}}(\|v\|_{H^{1/2}(\Gamma)} + \|h_{\star}^{1/2}\nabla v\|_{L^{2}(\Gamma)}) \quad \text{for all } v \in H^{1}(\Gamma).$$
(3.19)

The constant $C_{inv} > 0$ depends only on $\check{\kappa}_{max}$ and γ . Moreover, there exists a constant $\widetilde{C}_{inv} > 0$ such that

$$\|h_{\star}^{1/2}\Psi_{\star}\|_{L^{2}(\Gamma)} + \|h_{\star}^{1/2}(1/2 - K')\Psi_{\star}\|_{L^{2}(\Gamma)} \leq \widetilde{C}_{\mathrm{inv}}\|\Psi_{\star}\|_{H^{-1/2}(\Gamma)} \quad \text{for all } \Psi_{\star} \in \mathcal{P}^{p}(\mathcal{T}_{\star})$$
(3.20)

as well as,

$$\|h_{\star}^{1/2}\nabla V_{\star}\|_{L^{2}(\Gamma)} + \|h_{\star}^{1/2}WV_{\star}\|_{L^{2}(\Gamma)} \leq \widetilde{C}_{\mathrm{inv}}\|V_{\star}\|_{H^{1/2}(\Gamma)} \quad \text{for all } V_{\star} \in \mathcal{X}_{\star}.$$
(3.21)

The constant $\widetilde{C}_{inv} > 0$ depends only on $\check{\kappa}_{max}, p, w_{min}, w_{max}$, and γ .

Proof. The proof of (3.18) and (3.19) is found in [AFF⁺15, Theorem 3.1] with $w_h := h_{\star}^{1/2}$. To see (3.20), one can directly use (3.18) in combination with the inverse estimate from [FGHP16b, Proposition 4.1]. Estimate (3.21) is considered in [FGP] and follows by standard interpolation techniques together with the fact that J_{\star} is L^2 - and H^1 -stable.

3.2.4 Approximation property of Π_{\star}

Due to numerical reasons, we have to approximate the Neumann data ϕ , which leads to an additional consistency error. The following lemma helps to control this error. We follow the ideas of [CP06, Theorem 4.1].

Lemma 3.4 Let $\Pi_{\star}: L^2(\Gamma) \to \mathcal{P}^p(\mathcal{T}_{\star})$ be the L²-orthogonal projection onto $\mathcal{P}^p(\mathcal{T}_{\star})$. Then, there exists a constant $C_{apx} > 0$ such that

$$\|\psi - \Pi_{\star}\psi\|_{H^{-1/2}(\Gamma)} \le C_{\mathrm{apx}} \|h_{\star}^{1/2}(\psi - \Pi_{\star}\psi)\|_{L^{2}(\Gamma)} \quad \text{for all } \psi \in L^{2}(\Gamma).$$
(3.22)

The constant $C_{apx} > 0$ depends only on the boundary Γ .

Proof. For $\Pi_0: L^2(\Gamma) \to \mathcal{P}^0(\mathcal{T}_*)$ being the L^2 -orthogonal projection onto $\mathcal{P}^0(\mathcal{T}_*)$ and each $T \in \mathcal{T}_*$, it holds for all $\phi \in L^2(T)$ that

$$\|\psi - \Pi_{\star}\phi\|_{L^{2}(T)} = \inf_{\phi_{h} \in \mathcal{P}^{p}(\mathcal{T}_{\star})} \|\phi - \phi_{h}\|_{L^{2}(T)}$$

$$\leq \inf_{\phi_{h} \in \mathcal{P}^{0}(\mathcal{T}_{\star})} \|\phi - \phi_{h}\|_{L^{2}(T)} = \|\phi - \Pi_{0}\phi\|_{L^{2}(T)}.$$
(3.23)

Next, we use [Fae00, Lemma 2.5], which leads to

$$\|\phi - \Pi_0 \phi\|_{L^2(T)} \lesssim \underbrace{|T|^{1/2}}_{=h_{\star,T}^{1/2}} \underbrace{|\phi - \Pi_0 \phi|_{H^{1/2}(T)}}_{\stackrel{\text{def.}}{=} |\phi|_{H^{1/2}(T)}} \le h_{\star,T}^{1/2} \|\phi\|_{H^{1/2}(T)} \quad \text{for all } \phi \in H^{1/2}(T).$$
(3.24)

Now, let $\psi \in L^2(\Gamma)$ and $\phi \in H^{1/2}(\Gamma)$. Since the orthogonal projection is self-adjoint, it holds that

$$\langle (1 - \Pi_{\star})\psi;\phi\rangle_{\Gamma} = \langle \psi; (1 - \Pi_{\star})\phi\rangle_{\Gamma} \le \sum_{T \in \mathcal{T}_{\star}} \|\psi\|_{L^{2}(T)} \|\phi - \Pi_{\star}\phi\|_{L^{2}(T)}.$$
(3.25)

Combining (3.23) - (3.25), we get

$$\langle (1 - \Pi_{\star})\psi;\phi\rangle_{\Gamma} \leq \sum_{T \in \mathcal{T}_{\star}} \|\psi\|_{L^{2}(T)} \|\phi - \Pi_{\star}\phi\|_{L^{2}(T)} \overset{(3.24)}{\lesssim} \sum_{T \in \mathcal{T}_{\star}} \|h_{\star}^{1/2}\psi\|_{L^{2}(T)} \|\phi\|_{H^{1/2}(T)} \\ \leq \|h_{\star}^{1/2}\psi\|_{L^{2}(\Gamma)} \|\phi\|_{H^{1/2}(\Gamma)}.$$

Replacing ψ by $\psi - \Pi_{\star}\psi$ and using the idempotency of the orthogonal projection, it follows that

$$\begin{aligned} \|\psi - \Pi_{\star}\psi\|_{H^{-1/2}(\Gamma)} &= \|(1 - \Pi_{\star})(\psi - \Pi_{\star}\psi)\|_{H^{-1/2}(\Gamma)} \\ &= \sup_{\substack{\phi \in H^{1/2}(\Gamma) \\ \phi \neq 0}} \frac{\langle (1 - \Pi_{\star})(\psi - \Pi_{\star}\psi); \phi \rangle_{\Gamma}}{\|\phi\|_{H^{1/2}(\Gamma)}} \le C_{\mathrm{apx}} \|h_{\star}^{1/2}(\psi - \Pi_{\star}\psi)\|_{L^{2}(\Gamma)}. \end{aligned}$$

This concludes the proof.

3.3 Data approximation error $\widetilde{\text{osc}}_{\star}$

We first look at the oscillation term of the error estimator ρ_{\star} . For $[\mathcal{T}_{\star}] \in [\mathbb{T}]$ and $\phi \in L^2(\Gamma)$, we define

$$\widetilde{\text{osc}}_{\star}([T]) := \|\widetilde{h}_{\star}^{1/2}(\phi - \phi_{\star})\|_{L^{2}(T)},$$
(3.26)

as well as

$$\widetilde{\operatorname{osc}}_{\star} := \widetilde{\operatorname{osc}}_{\star}([\mathcal{T}_{\star}]) \quad \text{with } \widetilde{\operatorname{osc}}_{\star}([\mathcal{E}_{\star}])^{2} := \sum_{[T] \in [\mathcal{E}_{\star}]} \widetilde{\operatorname{osc}}_{\star}([T])^{2} \quad \text{for all } [\mathcal{E}_{\star}] \subseteq [\mathcal{T}_{\star}].$$
(3.27)

Proposition 3.5 Let $[\mathcal{T}_+] \in \operatorname{ref}([\mathcal{T}_\star])$ with $[\mathcal{T}_\star] \in [\mathbb{T}]$. For the data oscillation terms $\widetilde{\operatorname{osc}}_+$ and $\widetilde{\operatorname{osc}}_\star$, the following properties (i)–(iii) hold:

(i) Stability on non-contracting part: There holds that

$$\widetilde{\operatorname{osc}}_{+}([\mathcal{T}_{+}] \setminus [\omega_{+}]([\mathcal{T}_{+}] \setminus [\mathcal{T}_{\star}])) = \widetilde{\operatorname{osc}}_{\star}([\mathcal{T}_{\star}] \setminus [\omega_{\star}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}])).$$
(3.28)

(ii) Reduction on contracting part: With the constant $q_{\rm ctr}$ from (2.20), there holds that

$$\widetilde{\operatorname{osc}}_{+}([\omega_{+}]([\mathcal{T}_{+}] \setminus [\mathcal{T}_{\star}]))^{2} \leq q_{\operatorname{ctr}} \widetilde{\operatorname{osc}}_{\star}([\omega_{\star}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]))^{2}.$$
(3.29)

(iii) Discrete reliability: There exists a constant $C_{\widetilde{osc}} > 0$ such that

$$\|\phi_{+} - \phi_{\star}\|_{H^{-1/2}(\Gamma)} \le C_{\widetilde{\operatorname{osc}}} \widetilde{\operatorname{osc}}_{\star}([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]).$$
(3.30)

The constant $C_{\widetilde{\text{osc}}} > 0$ depends only on $\check{\kappa}_{\max}$, p and γ .

Proof. We only consider $\phi_{\star} := \Pi_{\star} \phi$, since the other case is trivial. The proof works analogously as in [FFK⁺15, Proposition 3.7].

Since Π_{\star} is the L^2 -orthogonal projection onto $\mathcal{P}^p(\mathcal{T}_{\star})$, we know that it is the \mathcal{T}_{\star} -elementwise best approximation. Hence, it holds that $\phi_{\star} = \phi_+$ on the non-contracting part $\Gamma \setminus \omega_{\star}([\mathcal{T}_{\star}] \setminus [\mathcal{T}_+]) \subseteq \bigcup([\mathcal{T}_{\star}] \cap [\mathcal{T}_+])$, and (2.21) proves (3.28).

Note that $\|\phi - \phi_+\|_{L^2(T)} \leq \|\phi - \phi_\star\|_{L^2(T)}$ for all $T \in \mathcal{T}_+$. This and $\tilde{h}_+ \leq q_{\text{ctr}} \tilde{h}_\star$ on the contracting part $\omega_\star([\mathcal{T}_\star] \setminus [\mathcal{T}_+]) = \omega_+([\mathcal{T}_+] \setminus [\mathcal{T}_+])$, which follows directly from the definition of \tilde{h} in Proposition 2.3, imply

$$\widetilde{\operatorname{osc}}_{+}([\omega_{+}]([\mathcal{T}_{+}] \setminus [\mathcal{T}_{\star}])) = \|\widetilde{h}_{+}^{1/2}(\phi - \phi_{+})\|_{L^{2}(\omega_{+}([\mathcal{T}_{+}] \setminus [\mathcal{T}_{\star}]))} \leq q_{\operatorname{ctr}}^{1/2} \|\widetilde{h}_{\star}^{1/2}(\phi - \phi_{\star})\|_{L^{2}(\omega_{+}([\mathcal{T}_{+}] \setminus [\mathcal{T}_{\star}]))} = q_{\operatorname{ctr}}^{1/2} \widetilde{\operatorname{osc}}_{\star}([\omega_{\star}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}])),$$

which concludes the proof of (3.29).

For (3.30), we need the following elementwise identities, which we get by the fact that Π_+ as well as Π_* are orthogonal projections and that $\mathcal{X}_* \subseteq \mathcal{X}_+$,

$$\Pi_{+}(1 - \Pi_{\star}) = \Pi_{+} - \Pi_{\star} = (1 - \Pi_{\star})\Pi_{+}$$

For $\phi \in L^2(\Gamma)$, this reads as follows

$$\Pi_{+}(\phi - \phi_{\star}) = \phi_{+} - \phi_{\star} = \phi_{+} - \Pi_{\star}\phi_{+}.$$

Now, we use (3.22), $\phi_{\star} = \phi_+$ in $\bigcup([\mathcal{T}_{\star}] \cap [\mathcal{T}_+])$, $\tilde{h}_{\star} \simeq h_{\star}$ and $\|\Pi_+\psi\|_{L^2(T)} \leq \|\psi\|_{L^2(T)}$ for $\psi \in L^2(\Gamma)$ and $T \in \mathcal{T}_{\star}$, to see

$$\begin{split} \|\phi_{+} - \phi_{\star}\|_{H^{-1/2}(\Gamma)} &= \|\phi_{+} - \Pi_{\star}\phi_{+}\|_{H^{-1/2}(\Gamma)} \overset{(3.22)}{\lesssim} \|\widetilde{h}_{\star}^{1/2}(\phi_{+} - \Pi_{\star}\phi_{+})\|_{L^{2}(\Gamma)} \\ &= \|\widetilde{h}_{\star}^{1/2}(\phi_{+} - \phi_{\star})\|_{L^{2}(\bigcup([\mathcal{T}_{\star}]\setminus[\mathcal{T}_{+}]))} = \|\widetilde{h}_{\star}^{1/2}\Pi_{+}(\phi - \phi_{\star})\|_{L^{2}(\bigcup([\mathcal{T}_{\star}]\setminus[\mathcal{T}_{+}]))} \\ &\leq \|\widetilde{h}_{\star}^{1/2}(\phi - \phi_{\star})\|_{L^{2}(\bigcup([\mathcal{T}_{\star}]\setminus[\mathcal{T}_{+}]))} \\ &= \widetilde{\operatorname{osc}}_{\star}([\mathcal{T}_{\star}]\setminus[\mathcal{T}_{+}]). \end{split}$$

We see that the hidden constant $C_{\widetilde{\text{osc}}} > 0$ depends only on C_{apx} from (3.22) and the equivalence constant C_{wt} from (2.18).

3.4 Error estimator $\tilde{\rho}_{\star}$

The following theorem states some basic properties of $\tilde{\rho}_{\star}$. A similar version was already proved in [FFK⁺15, Theorem 3.8].

Theorem 3.6 Let $[\mathcal{T}_+] \in \operatorname{ref}([\mathcal{T}_*])$ and U_* resp. U_+ be the corresponding Galerkin solutions to (3.2). The error estimators $\tilde{\rho}_*$ resp. $\tilde{\rho}_+$ satisfy the following properties (i)–(iii):

(i) Stability on non-contracting part: There exists a constant $C_{\text{stab}} > 0$ such that

$$\begin{split} \left| \widetilde{\rho}_{+} \left([\mathcal{T}_{+}] \setminus [\omega_{+}]([\mathcal{T}_{+}] \setminus [\mathcal{T}_{\star}]) \right) &- \widetilde{\rho}_{\star} \left([\mathcal{T}_{\star}] \setminus [\omega_{\star}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]) \right) \right| \\ &\leq C_{\mathrm{stab}} \left(\|U_{+} - U_{\star}\|_{H^{1/2}(\Gamma)} + \|\phi_{+} - \phi_{\star}\|_{H^{-1/2}(\Gamma)} \right). \end{split}$$
(3.31)

(ii) Reduction on contracting part: There exist constants $0 < q_{red} < 1$ and $C_{red} > 0$ such that

$$\widetilde{\rho}_{+}([\omega_{+}]([\mathcal{T}_{+}] \setminus [\mathcal{T}_{\star}]))^{2} \leq q_{\mathrm{red}} \, \widetilde{\rho}_{\star}([\omega_{\star}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]))^{2} + C_{\mathrm{red}}(\|U_{+} - U_{\star}\|_{H^{1/2}(\Gamma)}^{2} + \|\phi_{+} - \phi_{\star}\|_{H^{-1/2}(\Gamma)}^{2}).$$

$$(3.32)$$

(iii) Discrete reliability: There exist constants $C_{drl}, C_{ref} > 0$ such that

$$|U_{+} - U_{\star}||_{H^{1/2}(\Gamma)} + ||\phi_{+} - \phi_{\star}||_{H^{-1/2}(\Gamma)} \le C_{\mathrm{drl}} \widetilde{\rho}_{\star} ([\omega_{\star}^{2p}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}])).$$
(3.33)

Obviously,

$$\left| \left[\omega_{\star}^{2p} \right] ([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]) \right| \le C_{\mathrm{ref}} \left| [\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}] \right|.$$

$$(3.34)$$

The constants $C_{\text{stab}}, C_{\text{red}}, C_{\text{drl}}, C_{\text{ref}} > 0$ and $0 < q_{\text{red}} < 1$ depend only on $\check{\kappa}_{\max}, p, w_{\min}, w_{\max}$ and γ .

Proof. We prove the three points for $\phi_{\star} := \phi$ as well as $\phi_{\star} := \Pi_{\star} \phi$. Note that in the case $\phi_{\star} = \phi$ some argumentations become trivial.

(i) Stability on non-contracting part (3.31): We recall that $\tilde{h}_+ = \tilde{h}_*$ on $\Gamma \setminus \omega_*([\mathcal{T}_*] \setminus [\mathcal{T}_+]) = \Gamma \setminus \omega_+([\mathcal{T}_+] \setminus [\mathcal{T}_*]) \subseteq \bigcup([\mathcal{T}_*] \cap [\mathcal{T}_+])$. We use the stability (3.28) of the data oscillations, the mesh-size

equivalence (2.21), and the reverse triangle inequality to see

$$\begin{split} \left| \tilde{\rho}_{+} \left([\mathcal{T}_{+}] \setminus [\omega_{+}]([\mathcal{T}_{+}] \setminus [\mathcal{T}_{\star}]) \right) &- \tilde{\rho}_{\star} \left([\mathcal{T}_{\star}] \setminus [\omega_{\star}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]) \right) \right| \\ &= \left| \left(\sum_{[T] \in [\mathcal{T}_{+}] \setminus [\omega_{+}]([\mathcal{T}_{+}] \setminus [\mathcal{T}_{\star}])} \tilde{\rho}_{+}(T)^{2} \right)^{1/2} - \left(\sum_{[T] \in [\mathcal{T}_{\star}] \setminus [\omega_{\star}]([\mathcal{T}_{+}] \setminus [\mathcal{T}_{+}])} \tilde{\rho}_{\star}(T)^{2} \right)^{1/2} \right| \\ &\leq \left(\sum_{[T] \in [\mathcal{T}_{+}] \setminus [\omega_{+}]([\mathcal{T}_{+}] \setminus [\mathcal{T}_{\star}])} \left\| \tilde{h}_{+}^{1/2} \left((1/2 - K')\phi_{+} - WU_{+} \right) \|_{L^{2}(T)} \right)^{2} \right)^{1/2} \\ &\leq \left(\sum_{[T] \in [\mathcal{T}_{+}] \setminus [\omega_{+}]([\mathcal{T}_{+}] \setminus [\mathcal{T}_{\star}])} \| \tilde{h}_{+}^{1/2} \left((1/2 - K')\phi_{+} - WU_{+} \right) - \tilde{h}_{+}^{1/2} \left((1/2 - K')\phi_{\star} - WU_{\star} \right) \|_{L^{2}(T)} \right)^{1/2} \\ &= \| \tilde{h}_{+}^{1/2} \left((1/2 - K')\phi_{+} - WU_{+} \right) - \tilde{h}_{+}^{1/2} \left((1/2 - K')\phi_{\star} - WU_{\star} \right) \|_{L^{2}(\Gamma \setminus \omega_{+}([\mathcal{T}_{+}] \setminus [\mathcal{T}_{\star}]))} \\ &\leq \| \tilde{h}_{+}^{1/2} W(U_{+} - U_{\star}) \|_{L^{2}(\Gamma)} + \| \tilde{h}_{+}^{1/2} (1/2 - K')(\phi_{+} - \phi_{\star}) \|_{L^{2}(\Gamma)}. \end{split}$$

The inverse estimates (3.20) and (3.21) lead to

$$\lesssim \|U_{+} - U_{\star}\|_{H^{1/2}(\Gamma)} + \|\phi_{+} - \phi_{\star}\|_{H^{-1/2}(\Gamma)},$$

which concludes the proof of (i).

(ii) Reduction on contracting part (3.32): By definition, the error estimator satisfies

$$\begin{split} \widetilde{\rho}_{+}([\omega_{+}]([\mathcal{T}_{+}] \setminus [\mathcal{T}_{\star}]))^{2} \\ &= \sum_{[T] \in [\omega_{+}]([\mathcal{T}_{+}] \setminus [\mathcal{T}_{\star}])} \left(\|\widetilde{h}_{+}^{1/2} ((1/2 - K')\phi_{+} - WU_{+})\|_{L^{2}(T)} + \|\widetilde{h}_{+}^{1/2}(\phi - \phi_{+})\|_{L^{2}(T)} \right)^{2} \\ &= \sum_{[T] \in [\omega_{+}]([\mathcal{T}_{+}] \setminus [\mathcal{T}_{\star}])} \left(\|\widetilde{h}_{+}^{1/2} ((1/2 - K')(\phi_{+} - \phi_{\star} + \phi_{\star}) - W(U_{+} - U_{\star} + U_{\star}))\|_{L^{2}(T)} \\ &+ \|\widetilde{h}_{+}^{1/2}(\phi - \phi_{+})\|_{L^{2}(T)} \right)^{2}. \end{split}$$

It holds $\tilde{h}_+ \leq q_{\text{ctr}}\tilde{h}_{\star}$ on $\omega_+([\mathcal{T}_+] \setminus [\mathcal{T}_{\star}]) = \omega_{\star}([\mathcal{T}_{\star}] \setminus [\mathcal{T}_+])$. Hence, with Young's inequality for $\delta > 0$ and, for the case $\phi_+ := \Pi_+ \phi$, the fact that Π_+ is the \mathcal{T}_+ -elementwise L^2 -best approximation, we have with a constant $C_{\delta} > 0$ which depends only on δ and the inverse estimates (3.20)–(3.21), that

$$\begin{split} \widetilde{\rho}_{+}([\omega_{+}]([\mathcal{T}_{+}]\setminus[\mathcal{T}_{\star}]))^{2} \\ &\leq \sum_{[T]\in[\omega_{+}]([\mathcal{T}_{+}]\setminus[\mathcal{T}_{\star}])} \left((1+\delta)q_{\mathrm{ctr}} \left(\|\widetilde{h}_{\star}^{1/2}((1/2-K')\phi_{\star}-WU_{\star})\|_{L^{2}(T)} + \|\widetilde{h}_{\star}^{1/2}(\phi-\phi_{\star})\|_{L^{2}(T)} \right)^{2} \\ &\quad + 2(1+\delta^{-1})\|\widetilde{h}_{+}^{1/2}(1/2-K')(\phi_{+}-\phi_{\star})\|_{L^{2}(T)}^{2} \\ &\quad + 2(1+\delta^{-1})\|\widetilde{h}_{+}^{1/2}W(U_{+}-U_{\star})\|_{L^{2}(T)}^{2} \right) \\ &\leq (1+\delta)q_{\mathrm{ctr}}\,\widetilde{\rho}_{\star}([\omega_{\star}]([\mathcal{T}_{\star}]\setminus[\mathcal{T}_{+}]))^{2} + C_{\delta}(\|U_{+}-U_{\star}\|_{H^{1/2}(\Gamma)}^{2} + \|\phi_{+}-\phi_{\star}\|_{H^{-1/2}(\Gamma)}^{2}). \end{split}$$

We choose $\delta > 0$ sufficiently small and set $q_{\text{red}} := (1 + \delta)q_{\text{ctr}}$.

(iii) Discrete reliability (3.33): We split the proof into seven steps. **Step 1:** Let $U_{\star,+} \in \mathcal{X}_+$ denote the unique Galerkin solution to

$$\langle\!\langle U_{\star,+}; V_+ \rangle\!\rangle_{W+S} = \langle (1/2 - K')\phi_{\star}; V_+ \rangle_{\Gamma} \text{ for all } V_+ \in \mathcal{X}_+.$$

Both $U_{\star,+} \in \mathcal{X}_+$ as well as $U_{\star} \in \mathcal{X}_{\star}$ are Galerkin solutions to the same right-hand side $f = (1/2 - K')\phi_{\star}$.

Step 2: In this step, we show that $||U_{\star,+} - U_{\star}||^2_{H^{1/2}(\Gamma)} \simeq \langle f - WU_{\star}; (1 - J_{\star})(U_{\star,+} - U_{\star}) \rangle_{\Gamma}$: From Section 1.2 we know, that $|| \cdot ||_{H^{1/2}(\Gamma)}$ and $||| \cdot ||_{W+S}$ are equivalent norms, whence we get with the Galerkin orthogonality

$$\begin{split} \|U_{\star,+} - U_{\star}\|_{H^{1/2}(\Gamma)}^{2} &\simeq \|\|U_{\star,+} - U_{\star}\|_{W+S}^{2} = \langle\!\langle U_{\star,+} - U_{\star}; U_{\star,+} - U_{\star}\rangle\!\rangle_{W+S} \\ &= \langle\!\langle U_{\star,+} - U_{\star}; (1 - J_{\star})(U_{\star,+} - U_{\star})\rangle\!\rangle_{W+S} \\ &= \langle W(U_{\star,+} - U_{\star}); (1 - J_{\star})(U_{\star,+} - U_{\star})\rangle_{\Gamma} \\ &+ \langle 1; U_{\star,+} - U_{\star}\rangle_{\Gamma} \langle 1; (1 - J_{\star})(U_{\star,+} - U_{\star})\rangle_{\Gamma} \end{split}$$

The second summand is zero, due to

$$0 = \langle\!\langle U_{\star,+} - U_{\star}; 1 \rangle\!\rangle_{W+S} = \underbrace{\langle W(U_{\star,+} - U_{\star}); 1 \rangle_{\Gamma}}_{= \langle U_{\star,+} - U_{\star}; W1 \rangle_{\Gamma} = 0} + \langle 1; U_{\star,+} - U_{\star} \rangle_{\Gamma} \underbrace{\langle 1; 1 \rangle_{\Gamma}}_{= |\Gamma|}$$

This implies

$$\|U_{\star,+} - U_{\star}\|_{H^{1/2}(\Gamma)}^{2} \simeq \langle f - WU_{\star}; (1 - J_{\star})(U_{\star,+} - U_{\star}) \rangle_{\Gamma}.$$
(3.35)

Step 3: We apply Lemma 3.1 (i) to $U_{\star,+} - U_{\star}$: Let $T \in \mathcal{T}_{\star}$ with $T \subseteq \Gamma \setminus \omega_{\star}^{2p}([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}])$ up to finitely many points. It holds $\omega_{\star}^{2p}(T) \subseteq \bigcup([\mathcal{T}_{\star}] \cap [\mathcal{T}_{+}])$, wherefore $(U_{\star,+} - U_{\star})|_{\omega_{\star}^{p}(T)} \in \mathcal{X}_{\star}|_{\omega_{\star}^{p}(T)}$. Hence, we can use Lemma 3.1 (i), to see

$$J_{\star}(U_{\star,+} - U_{\star})|_{T} = (U_{\star,+} - U_{\star})|_{T}$$

Step 4: We use Step 1, Step 2, and the Cauchy-Schwarz inequality to get

$$\begin{split} \|U_{\star,+} - U_{\star}\|_{H^{1/2}(\Gamma)}^{2} \\ &\lesssim \langle f - WU_{\star}; (1 - J_{\star})(U_{\star,+} - U_{\star}) \rangle_{\Gamma} \\ &= \langle f - WU_{\star}; (1 - J_{\star})(U_{\star,+} - U_{\star}) \rangle_{\omega_{\star}^{2p}([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}])} \\ &\stackrel{\text{C.S.}}{\leq} \|\widetilde{h}_{\star}^{1/2}(f - WU_{\star})\|_{L^{2}(\omega_{\star}^{2p}([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}])} \|\widetilde{h}_{\star}^{-1/2}(1 - J_{\star})(U_{\star,+} - U_{\star})\|_{L^{2}(\omega_{\star}^{2p}([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}])} \end{split}$$

With the approximation property (3.12) of J_{\star} , it follows directly

$$\|U_{\star,+} - U_{\star}\|_{H^{1/2}(\Gamma)}^{2} \stackrel{(3.12)}{\lesssim} \widetilde{\rho}_{\star}([\omega_{\star}^{2p}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]))\|U_{\star,+} - U_{\star}\|_{H^{1/2}(\Gamma)}.$$

Hence, we end up with

$$\|U_{\star,+} - U_{\star}\|_{H^{1/2}(\Gamma)} \lesssim \widetilde{\rho}_{\star}([\omega_{\star}^{2p}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}])).$$
(3.36)

We note that, in the case $\phi_{\star} := \phi$, this step already concludes the proof of discrete reliability, since $U_{\star,+} = U_+$.

Step 5: Next, the equivalence of $\|\cdot\|_{H^{1/2}(\Gamma)}$ and $\|\cdot\|_{W+S}$ on $H^{1/2}(\Gamma)$, the definition of U_+ and $U_{\star,+}$, as well as the continuity of K' lead to

$$\begin{split} \|U_{+} - U_{\star,+}\|_{H^{1/2}(\Gamma)}^{2} \lesssim \| U_{+} - U_{\star,+} \|_{W+S}^{2} &= \langle (U_{+} - U_{\star,+}; U_{+} - U_{\star,+}) \rangle_{W+S} \\ &= \langle (1/2 - K')\phi_{+} - (1/2 - K')\phi_{\star}; U_{+} - U_{\star,+} \rangle_{\Gamma} \\ &\lesssim \|(1/2 - K')\phi_{+} - (1/2 - K')\phi_{\star}\|_{H^{-1/2}(\Gamma)} \|U_{+} - U_{\star,+}\|_{H^{1/2}(\Gamma)} \\ &\lesssim \|\phi_{+} - \phi_{\star}\|_{H^{-1/2}(\Gamma)} \|U_{+} - U_{\star,+}\|_{H^{1/2}(\Gamma)}, \end{split}$$

which is equivalent to

$$\|U_{+} - U_{\star,+}\|_{H^{1/2}(\Gamma)} \lesssim \|\phi_{+} - \phi_{\star}\|_{H^{-1/2}(\Gamma)}.$$
(3.37)

Step 6: We know from the discrete reliability (3.30) of the data oscillations that

$$\|\phi_{+} - \phi_{\star}\|_{H^{-1/2}(\Gamma)} \lesssim \widetilde{\operatorname{osc}}_{\star}([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]) \le \widetilde{\rho}_{\star}([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]).$$
(3.38)

Step 7: Finally, we combine (3.36)–(3.38) to get

$$\begin{split} \|U_{+} - U_{\star}\|_{H^{1/2}(\Gamma)} + \|\phi_{+} - \phi_{\star}\|_{H^{-1/2}(\Gamma)} \\ &\leq \|U_{+} - U_{\star,+}\|_{H^{1/2}(\Gamma)} + \|U_{\star,+} - U_{\star}\|_{H^{1/2}(\Gamma)} + \|\phi_{+} - \phi_{\star}\|_{H^{-1/2}(\Gamma)} \\ &\lesssim \widetilde{\rho}_{\star}([\omega_{\star}^{2p}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}])), \end{split}$$

which concludes the proof.

From the aforegoing basic properties, we can deduce the following corollary.

Corollary 3.7 Let $[\mathcal{T}_+] \in \operatorname{ref}([\mathcal{T}_*])$ for some $[\mathcal{T}_*] \in [\mathbb{T}]$ and U_* resp. U_+ be the corresponding Galerkin solutions to (3.2) and u the solution to (3.1). The error estimators $\tilde{\rho}_*$ resp. $\tilde{\rho}_+$ satisfy the following properties:

(i) Quasi-monotonicity: There exists a constant $C_{\text{mon}} > 0$ such that

$$\widetilde{\rho}_{+} \le C_{\rm mon}\,\widetilde{\rho}_{\star}.\tag{3.39}$$

(ii) Reliability: With the constant C_{drl} from (3.33), it holds

$$\|u - U_\star\|_{H^{1/2}(\Gamma)} \le C_{\mathrm{drl}}\,\widetilde{\rho}_\star.\tag{3.40}$$

(iii) Estimator reduction: For $0 < \theta \le 1$, there exist constants $C_{est} > 0$ and $0 < q_{est} \le 1$ such that the following implication holds

$$\theta \widetilde{\rho}_{\star}^{2} \leq \widetilde{\rho}_{\star} ([\omega_{\star}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]))^{2} \implies \widetilde{\rho}_{+}^{2} \leq q_{\text{est}} \widetilde{\rho}_{\star}^{2} + C_{\text{est}} (\|U_{+} - U_{\star}\|_{H^{1/2}(\Gamma)}^{2} + \|\phi_{+} - \phi_{\star}\|_{H^{-1/2}(\Gamma)}^{2})$$

$$(3.41)$$

The constant $C_{\text{mon}} > 0$ depends only on $\check{\kappa}_{\text{max}}, p, w_{\min}, w_{\max}$, and γ . The constants $C_{\text{est}} > 0$ and $0 < q_{\text{est}} \leq 1$ depend additionally on θ .

Proof. As before, the proof holds for $\phi_{\star} := \phi$ as well as $\phi_{\star} := \prod_{\star} \phi$.

(i) Quasi-monotonicity (3.39): It holds that

$$\widetilde{\rho}_{+}^{2} = \widetilde{\rho}_{+}([\omega_{+}]([\mathcal{T}_{+}] \setminus [\mathcal{T}_{\star}]))^{2} + \widetilde{\rho}_{+}([\mathcal{T}_{+}] \setminus [\omega_{+}]([\mathcal{T}_{+}] \cap [\mathcal{T}_{\star}]))^{2}.$$

The reduction property (3.32) yields

$$\widetilde{\rho}_+([\omega_+]([\mathcal{T}_+]\setminus[\mathcal{T}_\star]))^2 \lesssim \widetilde{\rho}_\star([\omega_\star]([\mathcal{T}_\star]\setminus[\mathcal{T}_+]))^2 + \|U_+ - U_\star\|^2_{H^{1/2}(\Gamma)} + \|\phi_+ - \phi_\star\|^2_{H^{-1/2}(\Gamma)}.$$

The stability (3.31) implies

$$\begin{split} \widetilde{\rho}_+([\mathcal{T}_+] \setminus [\omega_+]([\mathcal{T}_+] \setminus [\mathcal{T}_\star]))^2 \\ \lesssim \widetilde{\rho}_\star([\mathcal{T}_\star] \setminus [\omega_\star]([\mathcal{T}_\star] \setminus [\mathcal{T}_+]))^2 + \|U_+ - U_\star\|^2_{H^{1/2}(\Gamma)} + \|\phi_+ - \phi_\star\|^2_{H^{-1/2}(\Gamma)})^2 \end{split}$$

Together with the discrete reliability (3.33), these two estimates yield

 $\widetilde{\rho}_+^2 \lesssim \widetilde{\rho}_\star^2.$

This concludes the proof.

(ii) Reliability (3.40): Due to Lemma 3.2, there exists for all $\epsilon > 0$ a mesh $[\mathcal{T}_{\bullet}] \in \operatorname{ref}([\mathcal{T}_{\star}])$ such that $\|u - U_{\phi,\bullet}\|_{H^{1/2}(\Gamma)} \leq \epsilon$, where $U_{\phi,\bullet}$ is the unique solution to

 $\langle\!\langle U_{\phi,\bullet}; V_{\bullet} \rangle\!\rangle_{W+S} = \langle (1/2 - K')\phi; V_{\bullet} \rangle_{\Gamma} \text{ for all } V_{\bullet} \in \mathcal{X}_{\bullet}.$

We define $U_{\phi,\star} \in \mathcal{X}_{\star}$ analogously, and apply the discrete reliability (3.33) to see

$$\begin{aligned} \|u - U_{\star}\|_{H^{1/2}(\Gamma)} &\leq \|u - U_{\phi,\bullet}\|_{H^{1/2}(\Gamma)} + \|U_{\phi,\bullet} - U_{\phi,\star}\|_{H^{1/2}(\Gamma)} + \|U_{\phi,\star} - U_{\star}\|_{H^{1/2}(\Gamma)} \\ &\leq \epsilon + C_{drl}^{1/2} \|\widetilde{h}_{\star}^{1/2} \left((1/2 - K')\phi - WU_{\phi,\star} \right) \|_{L^{2}(\omega_{\star}^{2p}([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{\bullet}]))} \\ &\quad + \|U_{\phi,\star} - U_{\star}\|_{H^{1/2}(\Gamma)}. \end{aligned}$$
(3.42)

In the case $\phi_{\star} := \phi$, this already concludes the proof of reliability, since $U_{\phi,\star} = U_{\star}$ and $\epsilon > 0$ is arbitrary.

For the square of the last summand, we obtain via norm equivalence, the continuity of the adjoint double-layer operator K', (3.22), and (2.21) that

$$\|U_{\phi,\star} - U_{\star}\|_{H^{1/2}(\Gamma)}^{2} \simeq \|\|U_{\phi,\star} - U_{\star}\|_{W+S}^{2} = \langle (U_{\phi,\star} - U_{\star}; U_{\phi,\star} - U_{\star}) \rangle_{W+S}$$

$$= \langle (1/2 - K')\phi - (1/2 - K')\phi_{\star}; U_{\phi,\star} - U_{\star} \rangle_{\Gamma}$$

$$\leq \|(1/2 - K')(\phi - \phi_{\star})\|_{H^{-1/2}(\Gamma)} \|U_{\phi,\star} - U_{\star}\|_{H^{1/2}(\Gamma)}$$

$$\lesssim \|\phi - \phi_{\star}\|_{H^{-1/2}(\Gamma)} \|U_{\phi,\star} - U_{\star}\|_{H^{1/2}(\Gamma)}$$

$$\lesssim \|\widetilde{h}_{\star}^{1/2}(\phi - \phi_{\star})\|_{L^{2}(\Gamma)} \|U_{\phi,\star} - U_{\star}\|_{H^{1/2}(\Gamma)}.$$
(3.43)

To get an estimate for the second summand of (3.42) we use the auxiliary results (3.18), (3.21), (3.22) as well as (3.43) to see

Altogether, we have

 $\|u - U_\star\|_{H^{1/2}(\Gamma)} \lesssim \epsilon + \widetilde{\rho}_\star.$

Since $\epsilon > 0$ was arbitrary, this concludes the proof.

(iii) Estimator reduction (3.41): Obviously,

$$\widetilde{\rho}_{+}^{2} = \widetilde{\rho}_{+}([\mathcal{T}_{+}] \setminus [\omega_{+}]([\mathcal{T}_{+}] \setminus [\mathcal{T}_{\star}]))^{2} + \widetilde{\rho}_{+}([\omega_{+}]([\mathcal{T}_{+}] \setminus [\mathcal{T}_{\star}]))^{2}.$$

We use the stability (3.31) to see

$$\widetilde{\rho}_{+}([\mathcal{T}_{+}] \setminus [\omega_{+}]([\mathcal{T}_{+}] \setminus [\mathcal{T}_{\star}]))^{2} \leq (1+\delta) \, \widetilde{\rho}_{\star}([\mathcal{T}_{\star}] \setminus [\omega_{\star}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}])^{2} \\ + 2(1+\delta^{-1}) \, C_{\mathrm{stab}}^{2} \left(\|U_{+}-U_{\star}\|_{H^{1/2}(\Gamma)}^{2} + \|\phi_{+}-\phi_{\star}\|_{H^{-1/2}(\Gamma)}^{2} \right)$$

For the remaining part, the reduction property (3.32) yields

$$\begin{aligned} \widetilde{\rho}_{+}([\omega_{+}]([\mathcal{T}_{+}] \setminus [\mathcal{T}_{\star}]))^{2} \\ &\leq q_{\mathrm{red}} \, \widetilde{\rho}_{\star}([\omega_{\star}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]))^{2} + C_{\mathrm{red}} \big(\|U_{+} - U_{\star}\|_{H^{1/2}(\Gamma)}^{2} + \|\phi_{+} - \phi_{\star}\|_{H^{-1/2}(\Gamma)}^{2} \big) \end{aligned}$$

We define $C_{\text{est}} := 2(1 + \delta^{-1}) C_{\text{stab}}^2 + C_{\text{red}}$ and end up with

$$\begin{split} \widetilde{\rho}_{+}^{2} &\leq (1+\delta)\widetilde{\rho}_{\star}([\mathcal{T}_{\star}] \setminus [\omega_{\star}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]))^{2} + q_{\mathrm{red}} \, \widetilde{\rho}_{\star}([\omega_{\star}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]))^{2} \\ &+ C_{\mathrm{est}}\big(\|U_{+} - U_{\star}\|_{H^{1/2}(\Gamma)}^{2} + \|\phi_{+} - \phi_{\star}\|_{H^{-1/2}(\Gamma)}^{2} \big). \end{split}$$

The assumption $\theta \tilde{\rho}_{\star}^2 \leq \tilde{\rho}_{\star}([\omega_{\star}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]))^2$ implies

$$(1+\delta)\widetilde{\rho}_{\star}([\mathcal{T}_{\star}] \setminus [\omega_{\star}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]))^{2} + q_{\mathrm{red}}\widetilde{\rho}_{\star}([\omega_{\star}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]))^{2}$$
$$= (1+\delta)\widetilde{\rho}_{\star}^{2} - (1+\delta - q_{\mathrm{red}})\widetilde{\rho}_{\star}([\omega_{\star}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]))^{2}$$
$$\leq (1+\delta - \theta(1+\delta - q_{\mathrm{red}}))\widetilde{\rho}_{\star}^{2}.$$

For sufficiently small $\delta > 0$, this proves the estimator reduction with $q_{\text{est}} := 1 + \delta - \theta(1 + \delta - q_{\text{red}})$. \Box

3.5 Adaptive algorithm

We consider the following adaptive algorithm:

INPUT: adaptivity parameter $0 < \theta \leq 1$, polynomial order $p \in \mathbb{N}$, initial mesh $[\mathcal{T}_0]$, initial weights \mathcal{W}_0 , $\ell := 0$.

- (i) Compute discrete approximation ϕ_{ℓ} .
- (ii) Compute the Galerkin solution $U_{\ell} \in \mathcal{X}_{\ell}$ of (3.2).
- (iii) Compute refinement indicators $\mu_{\ell}(z)$ for all $z \in \mathcal{N}_{\ell}$.
- (iv) Determine an up to the multiplicative constant $C_{\text{mark}} > 0$ minimal set of nodes $\mathcal{M}_{\ell} \subseteq \mathcal{N}_{\ell}$ such that

$$\theta \mu_{\ell}^2 \le \sum_{z \in \mathcal{M}_{\ell}} \mu_{\ell}(z)^2.$$
(3.44)

- (v) Generate the refined mesh $[\mathcal{T}_{\ell+1}] := \operatorname{ref}([\mathcal{T}_{\ell}], \mathcal{M}_{\ell}).$
- (vi) Increment $\ell \leftarrow \ell + 1$ and go to (i).

OUTPUT: Galerkin solutions U_{ℓ} and error estimators μ_{ℓ} for all $\ell \in \mathbb{N}_0$.

4 Linear convergence of adaptive IGABEM

The following theorem and corollary are the analogons to [FFK⁺15, Theorem 4.2] resp. [FFK⁺15, Corollary 4.3].

Theorem 4.1 Let $[\mathcal{T}_+] \in \operatorname{ref}([\mathcal{T}_\star])$ for some $[\mathcal{T}_\star] \in [\mathbb{T}]$ and $U_\star \in \mathcal{X}_\star$ resp. $U_+ \in \mathcal{X}_+$ the corresponding Galerkin solutions to (3.2). By $u_\star, u_+ \in H^{1/2}(\Gamma)$, we denote the unique solutions to

$$\langle\!\langle u_{\star}; v \rangle\!\rangle_{W+S} = \langle (1/2 - K')\phi_{\star}; v \rangle_{\Gamma} \qquad \text{for all } v \in H^{1/2}(\Gamma),$$

$$\langle\!\langle u_{+}; v \rangle\!\rangle_{W+S} = \langle (1/2 - K')\phi_{+}; v \rangle_{\Gamma} \qquad \text{for all } v \in H^{1/2}(\Gamma).$$

Suppose that the set $[\omega_{\star}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}])$ satisfies the Dörfler marking

$$\theta \, \widetilde{\rho}_{\star}^2 \le \widetilde{\rho}_{\star}([\omega_{\star}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]))^2 \tag{4.1}$$

for some $0 < \theta \leq 1$. Then, there are constants $\alpha, \beta > 0$ and $0 < q_{\text{lin}} < 1$ such that the quasi-errors

$$\begin{split} \Delta_{\star} &:= \| \| u_{\star} - U_{\star} \| \|_{W+S}^2 + \alpha \widetilde{\rho}_{\star}^2 + \beta \widetilde{\operatorname{osc}}_{\star}^2, \\ \Delta_{+} &:= \| \| u_{+} - U_{+} \| \|_{W+S}^2 + \alpha \widetilde{\rho}_{+}^2 + \beta \widetilde{\operatorname{osc}}_{+}^2 \end{split}$$

satisfy the contraction property

$$\Delta_+ \le q_{\rm lin} \,\Delta_\star. \tag{4.2}$$

The constants $\alpha, \beta > 0$ and $0 < q_{\text{lin}} < 1$ depend only on C_{drl} from (3.33), C_{est} and q_{est} from (3.41), as well as on Γ .

Proof. We split the proof into six steps:

Step 1: First, we recall the norm equivalence $\|\cdot\|_{W+S} \simeq \|\cdot\|_{H^{1/2}(\Gamma)}$, i.e.,

$$C_1^{-1} \|v\|_{H^{1/2}(\Gamma)} \le \|v\|_{W+S} \le C_1 \|v\|_{H^{1/2}(\Gamma)} \quad \text{for all } v \in H^{1/2}(\Gamma),$$

$$(4.3)$$

where $C_1 > 0$ depends only on Γ . Step 2: We show that

$$||| u_+ - u_\star |||_{W+S}^2 \lesssim \widetilde{\operatorname{osc}}_\star ([\mathcal{T}_\star] \setminus [\mathcal{T}_+])^2.$$

It holds that

$$\begin{split} \|u_{+} - u_{\star}\|_{H^{1/2}(\Gamma)}^{2} &\simeq \|\|u_{+} - u_{\star}\|\|_{W+S}^{2} = \langle \langle u_{+} - u_{\star}; u_{+} - u_{\star} \rangle \rangle_{W+S} \\ &= \langle (1/2 - K')\phi_{+} - (1/2 - K')\phi_{\star}; u_{+} - u_{\star} \rangle_{\Gamma} \\ &\lesssim \|(1/2 - K')\phi_{+} - (1/2 - K')\phi_{\star}\|_{H^{-1/2}(\Gamma)} \|u_{+} - u_{\star}\|_{H^{1/2}(\Gamma)} \\ &\lesssim \|\phi_{+} - \phi_{\star}\|_{H^{-1/2}(\Gamma)} \|u_{+} - u_{\star}\|_{H^{1/2}(\Gamma)}, \end{split}$$

which is equivalent to

 $\|u_{+} - u_{\star}\|_{H^{1/2}(\Gamma)}^{2} \lesssim \|\phi_{+} - \phi_{\star}\|_{H^{-1/2}(\Gamma)}^{2}.$

Together with the norm equivalence and the discrete reliability (3.30) of the data oscillation, we have with a constant $C_2 > 0$

$$||| u_{+} - u_{\star} ||_{W+S}^{2} \leq C_{2} || \phi_{+} - \phi_{\star} ||_{H^{-1/2}(\Gamma)}^{2} \leq C_{2} C_{\widetilde{\text{osc}}}^{2} \widetilde{\text{osc}}_{\star} ([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}])^{2},$$

$$(4.4)$$

where $C_2 > 0$ depends only on Γ .

Step 3: The next step is to derive an estimation for $||| u_+ - U_+ |||_{W+S}^2$. We recall the Galerkin orthogonality,

$$\langle\!\langle u_+ - U_+; V_+ \rangle\!\rangle_{W+S} = 0 \quad \text{for all } V_+ \in \mathcal{X}_+,$$

which yields the Pythagorean identity

$$||| u_{+} - U_{+} |||_{W+S}^{2} = ||| u_{+} - U_{\star} |||_{W+S}^{2} - ||| U_{+} - U_{\star} |||_{W+S}^{2}.$$

$$(4.5)$$

For $\epsilon > 0$, the triangle inequality and Young's inequality yield

$$\| u_{+} - U_{\star} \|_{W+S}^{2} \leq \left(\| u_{+} - u_{\star} \|_{W+S} + \| u_{\star} - U_{\star} \|_{W+S} \right)^{2} \\ \leq (1+\epsilon) \| u_{\star} - U_{\star} \|_{W+S}^{2} + (1+\epsilon^{-1}) \| u_{+} - u_{\star} \|_{W+S}^{2}.$$

$$(4.6)$$

Next, we combine (4.4), (4.5) and (4.6), which leads to

$$\| u_{+} - U_{+} \|_{W+S}^{2} \leq (1+\epsilon) \| u_{\star} - U_{\star} \|_{W+S}^{2} - \| U_{+} - U_{\star} \|_{W+S}^{2} + (1+\epsilon^{-1})C_{2}C_{\widetilde{\text{osc}}}^{2} \widetilde{\text{osc}}_{\star}([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}])^{2}.$$

$$(4.7)$$

Step 4: Now, we use Step 3 to get a first estimation for Δ_+ . To this end, we define $C_3 := (1 + \epsilon^{-1}) C_2 C_{\tilde{osc}}^2 + \alpha C_{est} C_{\tilde{osc}}^2$ and use the estimator reduction (3.41), (4.7), the norm equivalence (4.3), and (4.4) to see

$$\begin{aligned} \Delta_{+} &\leq (1+\epsilon) \| u_{\star} - U_{\star} \|_{W+S}^{2} - \| U_{+} - U_{\star} \|_{W+S}^{2} + (1+\epsilon^{-1})C_{2}C_{\widetilde{osc}}^{2} \widetilde{osc}_{\star}([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}])^{2} \\ &+ \alpha q_{\text{est}} \widetilde{\rho}_{\star}^{2} + \alpha C_{\text{est}} \left(\| U_{+} - U_{\star} \|_{H^{1/2}(\Gamma)}^{2} + \| \phi_{+} - \phi_{\star} \|_{H^{-1/2}(\Gamma)}^{2} \right) + \beta \widetilde{osc}_{+}^{2} \\ &\leq (1+\epsilon) \| u_{\star} - U_{\star} \|_{W+S}^{2} + \alpha q_{\text{est}} \widetilde{\rho}_{\star}^{2} + C_{3} \widetilde{osc}_{\star}([\omega_{\star}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]))^{2} + \beta \widetilde{osc}_{+}^{2} \\ &+ (\alpha C_{\text{est}} C_{1}^{2} - 1) \| U_{+} - U_{\star} \|_{W+S}^{2}. \end{aligned}$$

$$(4.8)$$

Step 5: In this step, we fix the free parameters $\alpha, \beta > 0$. Let $\alpha := C_{\text{est}}^{-1}C_1^{-2}$, wherefore the last term in (4.8) vanishes.

We recall that $\tilde{h}_+ \leq q_{\text{ctr}}\tilde{h}_{\star}$ on $\omega_+([\mathcal{T}_+] \setminus [\mathcal{T}_{\star}]) = \omega_{\star}([\mathcal{T}_{\star}] \setminus [\mathcal{T}_+])$, while $\tilde{h}_+ = \tilde{h}_{\star}$ on $\Gamma \setminus \omega_+([\mathcal{T}_+] \setminus [\mathcal{T}_{\star}])$, see Proposition 2.3. Let $\chi_{\omega_+([\mathcal{T}_+] \setminus [\mathcal{T}_{\star}])}$ be the characteristic function on $\omega_+([\mathcal{T}_+] \setminus [\mathcal{T}_{\star}])$. Hence, it holds

$$(1-q_{\rm ctr})\widetilde{h}_{\star}\chi_{\omega+([\mathcal{T}_{+}]\setminus[\mathcal{T}_{\star}])} \leq \widetilde{h}_{\star} - \widetilde{h}_{+} \quad \text{pointwise a.e. on } \Gamma.$$

Together with the best approximation property of Π_+ , this yields

$$(1 - q_{\rm ctr})\widetilde{\operatorname{osc}}_{\star}([\omega_{\star}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]))^{2} = \sum_{[T] \in [\omega_{\star}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}])} \|(1 - q_{\rm ctr})^{1/2} \widetilde{h}_{\star}^{1/2} (\phi - \phi_{\star})\|_{L^{2}(T)}^{2}$$

$$\leq \sum_{[T] \in [\mathcal{T}_{\star}]} \|(\widetilde{h}_{\star} - \widetilde{h}_{+})^{1/2} (\phi - \phi_{\star})\|_{L^{2}(T)}^{2}$$

$$\leq \|\widetilde{h}_{\star}^{1/2} (\phi - \phi_{\star})\|_{L^{2}(\Gamma)}^{2} - \|\widetilde{h}_{+}^{1/2} (\phi - \phi_{+})\|_{L^{2}(\Gamma)}^{2}$$

$$= \widetilde{\operatorname{osc}}_{\star}^{2} - \widetilde{\operatorname{osc}}_{+}^{2}$$

Step 4 shows

$$\begin{split} \Delta_+ &\leq (1+\epsilon) \| \, u_\star - U_\star \, \|_{W+S}^2 + \alpha \, q_{\text{est}} \, \widetilde{\rho}_\star^2 + C_3 \, \widetilde{\text{osc}}_\star ([\omega_\star]([\mathcal{T}_\star] \setminus [\mathcal{T}_+]))^2 + \beta \, \widetilde{\text{osc}}_+^2 \\ &\leq (1+\epsilon) \| \, u_\star - U_\star \, \|_{W+S}^2 + \alpha \, q_{\text{est}} \, \widetilde{\rho}_\star^2 + C_3 (1-q_{\text{ctr}})^{-1} (\widetilde{\text{osc}}_\star^2 - \widetilde{\text{osc}}_+^2) + \beta \, \widetilde{\text{osc}}_+^2 \end{split}$$

We set $\beta := C_3 (1 - q_{ctr})^{-1}$ and end up with

$$\Delta_{+} \leq (1+\epsilon) \| u_{\star} - U_{\star} \|_{W+S}^{2} + \alpha q_{\text{est}} \widetilde{\rho}_{\star}^{2} + \beta \widetilde{\text{osc}}_{\star}^{2}.$$

$$\tag{4.9}$$

Step 6: Since u_{\star} and U_{\star} are determined by the same right-hand side $f = (1/2 - K')\Pi_{\star}\phi$, norm equivalence (4.3) together with reliability (3.40) yields

$$C_4 ||\!| u_{\star} - U_{\star} ||\!|_{W+S}^2 \le \widetilde{\rho}_{\star}^2,$$

where $C_4 := C_1^{-2} C_{\text{drl}}^{-2}$. Obviously, $\widetilde{\operatorname{osc}}_{\star}^2 \leq \widetilde{\rho}_{\star}^2$. Hence, we get from (4.9) for $\delta > 0$ that

$$\Delta_{+} \leq (1 + \epsilon - \alpha \,\delta \,C_{4}) \| u_{\star} - U_{\star} \| _{W+S}^{2} + \alpha \,(q_{\text{est}} + 2\delta) \widetilde{\rho}_{\star}^{2} + (\beta - \alpha \,\delta) \widetilde{\text{osc}}_{\star}^{2} \leq q_{\text{lin}} \Delta_{\star},$$
where

$$q_{\text{lin}} := \max\{1 + \epsilon - \alpha \,\delta \,C_4, q_{\text{est}} + 2\delta, (\beta - \alpha \,\delta)/\beta\}.$$

The choice $\delta < (1 - q_{\text{est}})/2$ and $\epsilon < \alpha \, \delta \, C_4$ finally concludes the proof with $0 < q_{\text{lin}} < 1$.

As a direct consequence, we get the following corollary, which states the linear convergence of the nodebased error estimator μ_{\star} .

Corollary 4.2 Suppose that (M1) from Assumption 2.2 is satisfied for the mesh-refinement. Then for each $0 < \theta \leq 1$, Algorithm 3.5 guarantees linear convergence of the error estimator sequence, i.e., there exist constants $0 < q_{\text{lin}} < 1$ and $C_{\text{lin}} > 0$ such that

$$\mu_{\ell+k} \le C_{\ln q} k_{\ln \mu_{\ell}} \quad \text{for all } k, \ell \in \mathbb{N}_0. \tag{4.10}$$

The constants q_{lin} and C_{lin} depend only on $p, w_{\min}, w_{\max}, \gamma, \theta$, and $\check{\kappa}_{\max}$.

Proof. Local equivalence of $\tilde{\rho}_{\ell}$ and μ_{ℓ} , the Dörfler marking (3.44) and $\mathcal{M}_{\ell} \subseteq \omega_{\ell}([\mathcal{T}_{\ell}] \setminus [\mathcal{T}_{\ell+1}])$ imply

$$\theta \widetilde{\rho}_{\ell}^2 \simeq \theta \mu_{\ell}^2 \leq \sum_{z \in \mathcal{M}_{\ell}} \mu_{\ell}(z)^2 \simeq \sum_{\substack{[T] \in [\mathcal{T}_{\ell}] \\ T \subseteq \omega_{\ell}(\mathcal{M}_{\ell})}} \widetilde{\rho}_{\ell}([T])^2 \leq \sum_{[T] \in [\omega_{\ell}] \setminus [\mathcal{T}_{\ell+1}])} \widetilde{\rho}_{\ell}([T])^2 = \widetilde{\rho}_{\ell}([\omega_{\ell}]([\mathcal{T}_{\ell}] \setminus [\mathcal{T}_{\ell+1}]))^2$$

where the hidden constants depend only on $\check{\kappa}_{\max}$, p, and γ . Hence, $\tilde{\rho}_{\ell}$ satisfies the Dörfler marking with some parameter $0 < \tilde{\theta} < 1$, and Theorem 4.1 applies. Inductively, the contraction property (4.2) leads to

 $\Delta_{\ell+k} \le q_{\rm lin}^k \,\Delta_\ell \quad \text{for all } \ell, k \in \mathbb{N}_0,$

and the norm equivalence $\|\cdot\|_{W+S} \simeq \|\cdot\|_{H^{1/2}(\Gamma)}$ combined with the reliability (3.40) provides

$$\widetilde{
ho}_{\ell}^2 \lesssim \Delta_{\ell} \lesssim \widetilde{
ho}_{\ell}^2.$$

From this, we infer

$$\mu_{\ell+k} \simeq \widetilde{\rho}_{\ell+k}^2 \simeq \Delta_{\ell+k} \le q_{\lim}^k \Delta_\ell \simeq q_{\lim}^k \widetilde{\rho}_\ell^2 \simeq q_{\lim}^k \mu_\ell^2 \quad \text{for all } \ell, k \in \mathbb{N}_0$$

and hence conclude the proof.

5 Optimal convergence of adaptive IGABEM

In this section, we want to show that the proposed Algorithm 3.5 converges even with the optimal algebraic rate in the following sense: Following [FGHP16b, Chapter 3] and [FFK⁺15, Chapter 5], let

$$[\mathbb{T}_N] := \{ [\mathcal{T}_\star] \in [\mathbb{T}] : |\mathcal{K}_\star| - |\mathcal{K}_0| \le N \}$$

$$(5.1)$$

be the finite set of all refinements having at most N knots more than $[\mathcal{T}_0]$. For s > 0, we define

$$\mathbb{A}_s := \left\{ u \in H^{1/2}(\Gamma) : \|u\|_{\mathbb{A}_s} < \infty \right\}$$
(5.2)

with

$$\|u\|_{\mathbb{A}_s} := \sup_{N \in \mathbb{N}_0} \left((N+1)^s \min_{[\mathcal{T}_\star] \in [\mathbb{T}_N]} \mu_\star \right).$$
(5.3)

This means, that the error estimator μ can provide an algebraic convergence rate of $\mathcal{O}(N^{-s})$, if the optimal meshes are chosen, which are not necessarily nested. The main result states that the sequence of estimators μ_{ℓ} generated by Algorithm 3.5 also decays asymptotically with any rate s > 0, if $\|u\|_{\mathbb{A}_s} < \infty$.

Up to now, the assumption (M1) of Assumption 2.2 was enough. For the optimality, we also need the assumptions (M2)-(M3) on the mesh-refinement.

The proof of the next lemma follows the the ideas of [FFK⁺15, Lemma 5.2].

Lemma 5.1 (Optimality of Dörfler marking) With the constants C_{stab} from (3.31) and C_{drl} from (3.33), we set

$$\widetilde{\theta}_{\text{opt}} := (1 + C_{\text{stab}}^2 C_{\text{drl}}^2)^{-1}.$$
(5.4)

For all $0 < \tilde{\theta} < \tilde{\theta}_{opt}$, there exists $0 < q_{opt} < 1$ such that for any $[\mathcal{T}_{\star}] \in [\mathbb{T}]$ and $[\mathcal{T}_{+}] \in ref([\mathcal{T}_{\star}])$ the following implication is satisfied:

$$\widetilde{\rho}_{+}^{2} \leq q_{\text{opt}} \, \widetilde{\rho}_{\star}^{2} \quad \Longrightarrow \quad \widetilde{\theta} \, \widetilde{\rho}_{\star}^{2} \leq \widetilde{\rho}_{\star} \left([\omega_{\star}^{2p}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]) \right)^{2}. \tag{5.5}$$

The constant $0 < q_{\text{opt}} < 1$ depends only on $\tilde{\theta}$, C_{stab} , and C_{drl} .

Proof. From the stability property (3.31) of the error estimator and Young's inequality, we get for $\delta > 0$

$$\begin{split} \widetilde{\rho}_{\star}^{2} &= \widetilde{\rho}_{\star} \left([\mathcal{T}_{\star}] \setminus [\omega_{\star}] ([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]) \right)^{2} + \widetilde{\rho}_{\star} \left([\omega_{\star}] ([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]) \right)^{2} \\ &\leq (1+\delta) \widetilde{\rho}_{+} \left([\mathcal{T}_{+}] \setminus [\omega_{+}] ([\mathcal{T}_{+}] \setminus [\mathcal{T}_{\star}]) \right)^{2} + \widetilde{\rho}_{\star} \left([\omega_{\star}] ([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]) \right)^{2} \\ &+ (1+\delta^{-1}) C_{\mathrm{stab}}^{2} \left(\|U_{+} - U_{\star}\|_{H^{1/2}(\Gamma)} + \|\phi_{+} - \phi_{\star}\|_{H^{-1/2}(\Gamma)} \right)^{2}. \end{split}$$

Now, we take the assumption $\tilde{\rho}_{+}^2 \leq q_{\text{opt}} \tilde{\rho}_{\star}^2$ into account, where q_{opt} is fixed later on. Together with the discrete reliability (3.33) and the last inequality, we end up with

$$\widetilde{\rho}_{\star}^2 \leq (1+\delta)q_{\text{opt}}\,\widetilde{\rho}_{\star}^2 + (1+(1+\delta^{-1})\,C_{\text{stab}}^2\,C_{\text{drl}}^2)\widetilde{\rho}_{\star}\left([\omega_{\star}^{2p}]([\mathcal{T}_{\star}]\setminus[\mathcal{T}_{+}])\right)^2.$$

Hence, this yields

$$\widetilde{\theta} \, \widetilde{\rho}_{\star}^2 \leq \widetilde{\rho}_{\star} \left([\omega_{\star}^{2p}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]) \right)^2 \quad \text{for all } 0 < \widetilde{\theta} \leq \frac{1 - (1 + \delta)q_{\text{opt}}}{1 + (1 + \delta^{-1})C_{\text{stab}}^2 \, C_{\text{drl}}^2}.$$

For each $0 < \tilde{\theta} < \tilde{\theta}_{opt}$, there exist $\delta > 0$ and $0 < q_{opt} < 1$ such that $\tilde{\theta} < \frac{1 - (1 + \delta)q_{opt}}{1 + (1 + \delta^{-1})C_{stab}^2 C_{drl}^2}$, which concludes the proof.

The crucial part of the proof of the main result is the following lemma. It is the analogous version of [FGHP16b, Lemma 5.6] and its proof is more or less verbatim the same.

Lemma 5.2 Let s > 0, $u \in \mathbb{A}_s$ and $0 < \tilde{\theta} < \tilde{\theta}_{opt}$. Then, there exist constants $C_5, C_6 > 0$ such that for all $[\mathcal{T}_{\star}] \in [\mathbb{T}]$ there is a refinement $[\mathcal{T}_{+}] \in ref([\mathcal{T}_{\star}])$ with

$$\left| \left[\omega_{\star}^{2p} \right] \left(\left[\mathcal{T}_{\star} \right] \setminus \left[\mathcal{T}_{+} \right] \right) \right| \le C_5 \, C_6^{1/s} \, \|u\|_{\mathbb{A}_s}^{1/s} \, \widetilde{\rho}_{\star}^{-1/s}, \tag{5.6}$$

and

$$\widetilde{\theta}\,\widetilde{\rho}_{\star}^{2} \leq \widetilde{\rho}_{\star}\left([\omega_{\star}^{2p}]([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}])\right)^{2}.\tag{5.7}$$

The constants C_5 and C_6 depend only on C_{drl} from (3.33), C_{mon} from (3.39), q_{opt} from (5.5), and p.

Proof. Define $\zeta := C_{\text{mon}}^{-2} q_{\text{opt}}$ and $\delta^2 := \zeta \tilde{\rho}_{\star}^2$. We split the proof into three steps: **Step 1:** There exists a mesh $[\mathcal{T}_{\delta}] \in [\mathbb{T}]$ such that

 $\widetilde{\rho}_{\delta} \leq \delta \quad \text{and} \quad |\mathcal{K}_{\delta}| - |\mathcal{K}_{0}| \leq \|u\|_{\mathbb{A}_{s}}^{1/s} \, \delta^{-1/s}.$

Let $N \in \mathbb{N}_0$ be minimal with $||u||_{\mathbb{A}_s} \leq (N+1)^s \delta$. If N = 0, we can set $[\mathcal{T}_{\delta}] = [\mathcal{T}_0]$ due to $\tilde{\rho}_0 \leq ||u||_{\mathbb{A}_s} \leq \delta$. If N > 0, minimality of N yields $||u||_{\mathbb{A}_s}^{1/s} \delta^{-1/s} > N$. Now, we choose $[\mathcal{T}_{\delta}] \in [\mathbb{T}]$ such that

$$\widetilde{\rho}_{\delta} = \min_{[\mathcal{T}_{\bullet}] \in [\mathbb{T}_N]} \widetilde{\rho}_{\bullet}$$

By definition of $\|\cdot\|_{\mathbb{A}_s}$, it follows that

$$\widetilde{\rho}_{\delta} \le (N+1)^{-s} \|u\|_{\mathbb{A}_s} \le \delta$$

By definition of $[\mathbb{T}_N]$, we get

$$|\mathcal{K}_{\delta}| - |\mathcal{K}_{0}| \le N < ||u||_{\mathbb{A}_{\alpha}}^{1/s} \delta^{-1/s}.$$

Step 2: We take the common refinement $[\mathcal{T}_+] := [\mathcal{T}_* \oplus \mathcal{T}_\delta]$ of (M2). Now, the assumptions on the refinement come into play. The overlay estimate (M2) and Step 1 imply

$$|\mathcal{K}_{+}| - |\mathcal{K}_{\star}| \le \left(|K_{\delta}| + |\mathcal{K}_{\star}| - |\mathcal{K}_{0}|\right) - |\mathcal{K}_{\star}| = |\mathcal{K}_{\delta}| - |\mathcal{K}_{0}| < ||u||_{\mathbb{A}_{s}}^{1/s} \delta^{-1/s}.$$

With estimate (2.14), we see

$$\left[\omega_{\star}^{2p}\right]\left(\left[\mathcal{T}_{\star}\right]\setminus\left[\mathcal{T}_{+}\right]\right)\right|\lesssim\left|\left[\mathcal{T}_{\star}\right]\setminus\left[\mathcal{T}_{+}\right]\right|\leq 2\left(\left|\mathcal{K}_{+}\right|-\left|\mathcal{K}_{\star}\right|\right).$$

Combining the last two estimates, we get

$$\left| \left[\omega_{\star}^{2p} \right] ([\mathcal{T}_{\star}] \setminus [\mathcal{T}_{+}]) \right| \lesssim \| u \|_{\mathbb{A}_{s}}^{1/s} \zeta^{-1/(2s)} \widetilde{\rho}_{\star}^{-1/s}$$

which proves (5.6).

Step 3: The quasi-monotonicity (3.39) yields

$$\tilde{\rho}_+^2 \le C_{\mathrm{mon}}^2 \, \tilde{\rho}_\delta^2 \le C_{\mathrm{mon}}^2 \, \delta^2 = q_{\mathrm{opt}} \, \tilde{\rho}_\star^2.$$

Finally, we apply Lemma 5.1 to see (5.7).

Finally, we state our main result, cf. [FGHP16b, Theorem 3.2] resp. [FFK⁺15, Theorem 5.1].

Theorem 5.3 Under Assumption 2.2 on the mesh-refinement strategy, there exists a constant $0 < \theta_{opt} < 1$ such that for all $0 < \theta < \theta_{opt}$, there exists a constant $C_{opt} > 0$ such that, for all s > 0 the following implication holds:

$$u \in \mathbb{A}_s \implies \mu_{\ell} \le \frac{C_{\text{opt}}^{1+s}}{(1-q_{\text{lin}}^{1/s})^s} \|u\|_{\mathbb{A}_s} \left(|\mathcal{K}_{\ell}| - |\mathcal{K}_0|\right)^{-s} \quad \text{for all } \ell \in \mathbb{N}_0$$
(5.8)

with the constant q_{lin} from (4.10). The constant θ_{opt} depends only on θ_{opt} from (5.4) and C_{loc} from (3.8). Moreover, C_{opt} depends only on C_{mesh} from (2.17), C_{loc} from (3.8), C_{mark} from (3.44), C_{lin} from (4.10), and C_5 , C_6 from (5.6).

Proof. Let $C_{\text{loc}} > 0$ be the constant from (3.8). Define $\theta_{\text{opt}} := \tilde{\theta}_{\text{opt}}/C_{\text{loc}}^2$ and $\tilde{\theta} := C_{\text{loc}}^2 \theta$. In addition, assume that θ is sufficiently small, i.e., $\theta < \theta_{\text{opt}}$. Hence, $\tilde{\theta} < \tilde{\theta}_{\text{opt}}$. We let $\ell \in \mathbb{N}_0$, $j \leq \ell$ and choose a refinement $[\mathcal{T}_+] \in \text{ref}([\mathcal{T}_j])$ according to Lemma 5.2. With (3.8), we get

$$\begin{aligned} \theta \,\mu_j^2 &\leq C_{\mathrm{loc}}^{-1} \,\widetilde{\theta} \,\widetilde{\rho}_j^2 \leq C_{\mathrm{loc}}^{-1} \,\widetilde{\rho}_j([\omega_j^{2p}]([\mathcal{T}_j] \setminus [\mathcal{T}_+])))^2 \\ &= C_{\mathrm{loc}}^{-1} \, \sum_{[T] \in [\omega_j^{2p}]([\mathcal{T}_j] \setminus [\mathcal{T}_+])} \widetilde{\rho}_j([T])^2 \leq \sum_{z \in \mathcal{N}_j \cap \omega_j^{2p}([\mathcal{T}_j] \setminus [\mathcal{T}_+])} \mu_j(z)^2. \end{aligned}$$

We see, that $\mathcal{N}_j \cap \omega_j^{2p}([T_j] \setminus [\mathcal{T}_+])$ satisfies the Dörfler marking of Algorithm 3.5. Moreover, the chosen set \mathcal{M}_j of Algorithm 3.5 has minimal cardinality. Hence, we derive with (5.6) and the constant $C_{\text{mark}} > 0$ of Algorithm 3.5 that

$$|\mathcal{M}_j| \le C_{\text{mark}} \left| \mathcal{N}_j \cap \omega_j^{2p}([T_j] \setminus [\mathcal{T}_+]) \right| \le 2 C_{\text{mark}} \left| [\omega_j^{2p}]([T_j] \setminus [\mathcal{T}_+]) \right| \le 2 C_{\text{mark}} C_5 C_6^{1/s} \|u\|_{\mathbb{A}_s}^{1/s} \widetilde{\rho}_j^{-1/s}.$$

Next, we use the mesh-closure estimate (M3) and end up with

$$\begin{aligned} |\mathcal{K}_{\ell}| - |\mathcal{K}_{0}| &\leq C_{\text{mesh}} \sum_{j=0}^{\ell-1} |\mathcal{M}_{j}| \leq 2 C_{\text{mark}} C_{\text{mesh}} C_{5} C_{6}^{1/s} \|u\|_{\mathbb{A}_{s}}^{1/s} \sum_{j=0}^{\ell-1} \widetilde{\rho_{j}}^{-1/s} \\ &\leq 2 C_{\text{mark}} C_{\text{mesh}} C_{5} C_{6}^{1/s} C_{\text{loc}}^{1/s} \|u\|_{\mathbb{A}_{s}}^{1/s} \sum_{j=0}^{\ell-1} \mu_{j}^{-1/s}. \end{aligned}$$

With the linear convergence (4.10), we see

 $\mu_{\ell} \leq C_{\ln} q_{\ln}^{\ell-j} \mu_j \quad \text{for all } j = 0, \dots, \ell.$

Hence, with the help of the geometric series, this finally yields

$$\begin{aligned} |\mathcal{K}_{\ell}| - |\mathcal{K}_{0}| &\leq 2 \, C_{\text{mark}} \, C_{\text{mesh}} \, C_{5} \, C_{6}^{1/s} \, C_{\text{loc}}^{1/s} \, \|u\|_{\mathbb{A}_{s}}^{1/s} \sum_{j=0}^{\ell-1} \mu_{j}^{-1/s} \\ &\leq 2 \, C_{\text{mark}} \, C_{\text{mesh}} \, C_{5} \, (C_{6} \, C_{\text{lin}} \, C_{\text{loc}})^{1/s} \|u\|_{\mathbb{A}_{s}}^{1/s} \, \mu_{\ell}^{-1/s} \sum_{j=0}^{\ell-1} (q_{\text{lin}}^{1/s})^{\ell-j} \\ &\leq (C_{6} \, C_{\text{lin}} \, C_{\text{loc}})^{1/s} \frac{2 \, C_{\text{mark}} \, C_{\text{mesh}} \, C_{5}}{1 - q_{\text{lin}}^{1/s}} \|u\|_{\mathbb{A}_{s}}^{1/s} \, \mu_{\ell}^{-1/s}. \end{aligned}$$

The latter is equivalent to

$$\mu_{\ell} \leq \frac{C_6 C_{\mathrm{lin}} C_{\mathrm{loc}} \left(2 C_{\mathrm{mark}} C_{\mathrm{mesh}} C_5\right)^s}{(1 - q_{\mathrm{lin}}^{1/s})^s} \|u\|_{\mathbb{A}_s} \left(|\mathcal{K}_{\ell}| - |\mathcal{K}_0|\right)^{-s},$$

which concludes the proof.

6 Numerical approximation

This section is closely related to [Gan14, Section 5], where the numerical solution of Symm's integral equation is discussed. However, most of the appearing integrals are of the same type and therefore, they are treated in a similar way.

Let γ be the parametrization of the boundary of the open set $\Omega \subset \mathbb{R}^2$ of Section 1. For $a = \check{z}_0^{\gamma} < \cdots < \check{z}_{n_{\gamma}}^{\gamma} = b$, we assume, that $\gamma|_{[\check{z}_{j-1}^{\gamma},\check{z}_{j}^{\gamma}]}$ is even two times continuously differentiable for $j = 1, \ldots, n_{\gamma}$, and, additionally, that γ is positively orientated. The latter means, that the outer normal vector ν at any point $x = \gamma(t) = \binom{\gamma_1(t)}{\gamma_2(t)} \in \Gamma \setminus \{\gamma(\check{z}_1^{\gamma}), \ldots, \gamma(\check{z}_{n_{\gamma}}^{\gamma})\}$ satisfies $\nu(x) = \frac{1}{\gamma_2(t)} \left(\frac{\gamma'_2(t)}{\gamma'_2(t)} \right)$

$$\nu(x) = \frac{1}{|\gamma'(t)|} \begin{pmatrix} \gamma'_2(t) \\ -\gamma'_1(t) \end{pmatrix}.$$

We consider the equivalent variational formulation (1.11) of the hyper-singular integral equation

$$\langle\!\langle u; v \rangle\!\rangle_{W+S} = \langle (1/2 - K')\phi; v \rangle_{\Gamma} \text{ for all } v \in H^{1/2}(\Gamma),$$

and its boundary element discretization via the finite dimensional subspace $\mathcal{X}_h \subset H^{1/2}(\Gamma)$ with $\phi_h := \phi$ or $\phi_h = \prod_h \phi$, where $\prod_h : L^2(\Gamma) \to \mathcal{P}^p(\mathcal{T}_h)$ is the L^2 -orthogonal projection onto $\mathcal{P}^p(\mathcal{T}_h)$. The discrete solution $U_h \in \mathcal{X}_h$ then solves

$$\langle\!\langle U_h; V_h \rangle\!\rangle_{W+S} = \langle (1/2 - K')\phi_h; V_h \rangle_{\Gamma} \quad \text{for all } V_h \in \mathcal{X}_h.$$

$$(6.1)$$

To calculate $\Pi_h \phi$, we solve the linear system

$$\langle \Pi_h \phi; \Psi_h \rangle_{\Gamma} = \langle \phi; \Psi_h \rangle_{\Gamma} \quad \text{for all } \Psi_h \in \mathcal{P}^p(\mathcal{T}_h).$$

We use the notation of Section 2.5 and abbreviate

$$\widehat{B}_{i,p} := B_{i,p}^{\mathcal{K}_{h,p+1}}|_{[a,b)} \circ \gamma|_{[a,b)}^{-1} \quad \text{for } i = 1 - p, \dots, N_{p+1} - p.$$

Now, we use the ansatz $\Pi_h \phi = \sum_{i=1-p}^{N_{p+1}-p} x_{h,i} \widehat{B}_{i,p}$. Hence, we have for $j = 1 - p, \ldots, N_{p+1} - p$

$$\sum_{i=1-p}^{N_{p+1}-p} x_{h,i} \langle \widehat{B}_{i,p}; \widehat{B}_{j,p} \rangle_{\Gamma} = \langle \phi; \widehat{B}_{j,p} \rangle_{\Gamma},$$

which is a uniquely solvable system of linear equations. Now, we recall the basis of \mathcal{X}_h , which we mentioned in Section 2.5

$$\left\{R_{i,p}|_{[a,b)} \circ \gamma|_{[a,b)}^{-1} : i = 2 - p, \dots, N - p - 1\right\} \cup \left\{\left(R_{1-p,p}|_{[a,b)} + R_{N-p,p}|_{[a,b)}\right) \circ \gamma|_{[a,b)}^{-1}\right\}.$$

We introduce the following notation:

$$\overline{R}_{1-p} := (R_{1-p,p}|_{[a,b)} + R_{N-p,p}|_{[a,b)}) \circ \gamma|_{[a,b)}^{-1}$$

$$\overline{R}_i := R_{i,p}|_{[a,b)} \circ \gamma_{[a,b)}^{-1} \quad \text{for } i = 2-p, \dots, N-p-1.$$

Let $U_h \in \mathcal{X}_h$ be the solution to (6.1). Then, there exists a unique coefficient vector $c_h := (c_{h,1-p}, \ldots, c_{h,N-p-1})^T$ with $U_h = \sum_{i=1-p}^{N-p-1} c_{h,i} \overline{R}_i$. Therefore, it holds for $j = 1 - p, \ldots, N - p - 1$ that

$$\sum_{i=1-p}^{N-p-1} c_{h,i} \langle\!\langle \overline{R}_i; \overline{R}_j \rangle\!\rangle_{W+S} = \langle (1/2 - K')\phi; \overline{R}_j \rangle_{\Gamma}$$

or explicitly,

$$\sum_{i=1-p}^{N-p-1} c_{h,i} \Big(\langle W\overline{R}_i; \overline{R}_j \rangle_{\Gamma} + \langle \overline{R}_i; 1 \rangle_{\Gamma} \langle \overline{R}_j; 1 \rangle_{\Gamma} \Big) = \langle (1/2 - K')\phi; \overline{R}_j \rangle_{\Gamma}.$$

With the real, symmetric, and positive definite matrix

$$W_h + S_h := \left(\underbrace{\langle W\overline{R}_i; \overline{R}_j \rangle_{\Gamma}}_{=:W_h} + \underbrace{\langle \overline{R}_i; 1 \rangle_{\Gamma} \langle \overline{R}_j; 1 \rangle_{\Gamma}}_{=:S_h} \right)_{i,j=1-p}^{N-p-1}$$

and the right-hand side vector

$$F_h := \left(\langle (1/2 - K')\phi_h; \overline{R}_j \rangle_{\Gamma} \right)_{j=1-p}^{N-p-1},$$

it holds that

$$(W_h + S_h)c_h = F_h.$$

Therefore, we have to solve this system of linear equations, to compute the solution U_h . Only for very special geometries, the arising integrals and/or double integrals can be computed analytically. To approximate these integrals numerically, we want to use a tensorial Gauss quadrature. For a continuous function $f \in C([0, 1]^2)$ and weight functions $\theta_1, \theta_2 \in L^1([0, 1])$, we set

$$I(f) := \int_{[0,1]} \int_{[0,1]} f(s,t)\theta_1(s)\theta_2(t) \, dt \, ds.$$

We define the tensorial Gauss quadrature of order $n := (n_1, n_2)$ for the nodes ξ_{1,q_1}, ξ_{2,q_2} and weights $\omega_{1,q_1}, \omega_{2,q_2}$ of the Gaussian quadrature on [0, 1] by

$$Q^{n} \colon C([0,1]^{2}) \to \mathbb{R}$$
$$f \mapsto \sum_{q_{1}=1}^{n_{1}} \sum_{q_{2}=1}^{n_{2}} f(\xi_{1,q_{1}},\xi_{2,q_{2}})\omega_{1,q_{1}}\omega_{2,q_{2}},$$

and the quadrature error by

$$E^n := I - Q^n$$
.

We denote for $g \in C([0, 1])$

$$I_{\ell}g := \int_{[0,1]} g(r)\theta_{\ell}(r) \, dr,$$
$$Q_{\ell}^{n_{\ell}}g := \sum_{q_{\ell}=1}^{n_{\ell}} g(\xi_{\ell,q_{\ell}})\omega_{\ell,q_{\ell}},$$
$$E_{\ell}^{n_{\ell}} := I_{\ell} - Q_{\ell}^{n_{\ell}} \quad \text{for } \ell = 1, 2.$$

The following theorem is important for the convergence of the quadrature error.

Theorem 6.1 For arbitrary $f \in C([0,1]^2)$, there holds the error estimate

$$|E^{n}f| \leq \|\theta_{1}\|_{L^{1}([0,1])} \max_{t \in [0,1]} |E_{2}^{n_{2}}f(\cdot,t)| + \|\theta_{2}\|_{L^{1}([0,1])} \max_{s \in [0,1]} |E_{1}^{n_{1}}f(s,\cdot)|,$$

where the right-hand side converges to zero for $n_1 \to \infty$ and $n_2 \to \infty$.

Proof. As the proof of the inequality is shown in [SS11, Theorem 5.3.15], we will only prove the convergence of the right-hand side. We only consider the first summand, since the second works analogously. The aim is to show, that each subsequence of a given sequence has a subsequence itself, which converges to zero. As a consequence, the full sequence itself converges to zero. Let $(t_{n_2})_{n_2 \in \mathbb{N}}$ be a sequence in [0, 1] such that

$$|E_2^{n_2}f(\cdot,t_{n_2})| = \max_{t \in [0,1]} |E_2^{n_2}f(\cdot,t)|,$$

and $|E_2^{n_2(k)}f(\cdot, t_{n_2(k)})|$ the according subsequence. The sequence $t_{n_2(k)}$ takes values in the compact interval [0, 1]. Therefore, there exists some $t_{\infty} \in [0, 1]$ and a subsequence $t_{n_2(k(j))}$ such that $t_{n_2(k(j))}$ converges to t_{∞} as $j \to \infty$. We get the following estimate

$$|E_2^{n_2(k(j))}f(\cdot,t_{n_2(k(j))})| \le |E_2^{n_2(k(j))}f(\cdot,t_{n_2(k(j))}) - E_2^{n_2(k(j))}f(\cdot,t_{\infty})| + |E_2^{n_2(k(j))}f(\cdot,t_{\infty})|$$

The last summand of the right-hand side is just the quadrature error of a standard Gauss quadrature on [0, 1] with the weight function θ_2 , which converges to 0, compare e.g. [Pra06, Chapter 6.3]. So the only remaining factor is the first term,

$$\begin{split} |E_2^{n_2(k(j))}f(\cdot,t_{n_2(k(j))}) - E_2^{n_2(k(j))}f(\cdot,t_{\infty})| \\ &\leq |I_2f(\cdot,t_{n_2(k(j))}) - I_2f(\cdot,t_{\infty})| + |Q_2^{n_2(k(j))}f(\cdot,t_{n_2(k(j))}) - Q_2^{n_2(k(j))}f(\cdot,t_{\infty})| \\ &\leq 2\|\theta_2\|_{L^1([0,1])}\|f(\cdot,t_{n_2(k(j))}) - f(\cdot,t_{\infty})\|_{L^{\infty}([0,1])} \end{split}$$

The mapping $t \to f(\cdot, t)$ from [0, 1] to C([0, 1]) is continuous. This yields the convergence to zero of the last term. This concludes our prove.

Remark 6.2 The previous lemma hints, why we consider the two different choices of ϕ_h , namely, $\phi_h := \phi$ or $\phi_h := \Pi_h \phi$. To get convergence of the quadrature error, we need certain smoothness of ϕ , see also Lemma 6.5–6.7. In practice, for the interesting cases, where adaptive refinement leads to a higher convergence order than uniform refinement, this smoothness is not given. This leads to numerical problems for the computation of the right-hand side F_h as well as the pointwise evaluation of $K'\phi(\cdot)$. Hence, we use the approximation $\Pi_h \phi$ instead. However, as a consequence, we have to take care of the additional data oscillations. As we have seen, the convergence theory therefore gets more complicated.

6.1 Approximation of W_h

In this section, we follow the ideas of [Gan14, Section 5.1].

For $t \in [a, b]$ and $x = \gamma(t) \in \Gamma$, we use the following abbreviations

$$\Gamma_{\ell} := \gamma([t_{\ell-1}t_{\ell}]),$$

$$\begin{pmatrix}\nu_{1}(x)\\\nu_{2}(x)\end{pmatrix} := \nu(x) = \frac{1}{|\gamma'(t)|} \begin{pmatrix}\gamma'_{2}(t)\\-\gamma'_{1}(t)\end{pmatrix},$$

$$H_{\ell} := t_{\ell} - t_{\ell-1},$$

$$\gamma_{\ell}(t) := \gamma(t_{\ell-1} + (t_{\ell} - t_{\ell-1})t),$$

$$\operatorname{curl}_{\Gamma}\overline{R}_{\ell}(x) := \nu_{1}(x)\frac{\partial}{\partial x_{2}}\overline{R}_{\ell}(x) - \nu_{2}(x)\frac{\partial}{\partial x_{1}}\overline{R}_{\ell}(x),$$

where \overline{R}_{ℓ} on the right hand side of $\operatorname{curl}_{\Gamma} \overline{R}_{\ell}$ is an appropriate extension to a neighbourhood, compare [Ste08, Section 6.5] for more details.

For $i, j = 2 - p, \ldots, N - p - 1$, it holds due to [Ste08, Theorem 6.15]

$$\langle W\overline{R}_i; \overline{R}_j \rangle_{\Gamma} = -\frac{1}{2\pi} \int_{\Gamma} \operatorname{curl}_{\Gamma} \overline{R}_j(x) \int_{\Gamma} \log|x-y| \operatorname{curl}_{\Gamma} \overline{R}_i(y) \, ds_y \, ds_x = -\frac{1}{2\pi} \sum_{k=1}^N \sum_{m=1}^N \int_{\Gamma_k} \operatorname{curl}_{\Gamma} \overline{R}_j(x) \int_{\Gamma_m} \log|x-y| \operatorname{curl}_{\Gamma} \overline{R}_i(y) \, ds_y \, ds_x.$$

If we insert the definition of the curl operator and the parametrization, we get

$$\begin{split} &= -\frac{1}{2\pi} \sum_{k=1}^{N} \sum_{m=1}^{N} \int_{\Gamma_{k}} [\nu_{1}(x) \frac{\partial}{\partial x_{2}} \overline{R}_{j}(x) - \nu_{2}(x) \frac{\partial}{\partial x_{1}} \overline{R}_{j}(x)] \\ &\int_{\Gamma_{m}} \log |x - y| [\nu_{1}(y) \frac{\partial}{\partial y_{2}} \overline{R}_{i}(y) - \nu_{2}(y) \frac{\partial}{\partial y_{1}} \overline{R}_{i}(y)] \, ds_{y} \, ds_{x} \\ &= -\frac{1}{2\pi} \sum_{k=1}^{N} \sum_{m=1}^{N} \int_{[t_{k-1}, t_{k}]} [\nu_{1}(\gamma(t)) \frac{\partial}{\partial x_{2}} \overline{R}_{j}(\gamma(t)) - \nu_{2}(\gamma(t)) \frac{\partial}{\partial x_{1}} \overline{R}_{j}(\gamma(t))] \cdot |\gamma'(t)| \\ &\int_{[t_{m-1}, t_{m}]} \log |\gamma(t) - \gamma(s)| [\nu_{1}(\gamma(s)) \frac{\partial}{\partial y_{2}} \overline{R}_{i}(\gamma(s)) - \nu_{2}(\gamma(s)) \frac{\partial}{\partial y_{1}} \overline{R}_{i}(\gamma(s))] \cdot |\gamma'(s)| \, ds \, dt. \end{split}$$

The characterization of ν and some further simplifications provide

$$\begin{split} &= -\frac{1}{2\pi} \sum_{k=1}^{N} \sum_{m=1}^{N} \int_{[t_{k-1},t_k]} [\gamma'_2(t) \frac{\partial}{\partial x_2} \overline{R}_j(\gamma(t)) + \gamma'_1(t) \frac{\partial}{\partial x_1} \overline{R}_j(\gamma(t))] \\ &\int_{[t_{m-1},t_m]} \log |\gamma(t) - \gamma(s)| [\gamma'_2(s) \frac{\partial}{\partial y_2} \overline{R}_i(\gamma(s)) + \gamma'_1(s) \frac{\partial}{\partial y_1} \overline{R}_i(\gamma(s))] \, ds \, dt \\ &= -\frac{1}{2\pi} \sum_{k=1}^{N} \sum_{m=1}^{N} \int_{[t_{k-1},t_k]} \frac{\partial}{\partial t} \overline{R}_j(\gamma(t)) \int_{[t_{m-1},t_m]} \log |\gamma(t) - \gamma(s)| \frac{\partial}{\partial s} \overline{R}_i(\gamma(s)) \, ds \, dt \\ &= -\frac{1}{2\pi} \sum_{k=1}^{N} \sum_{m=1}^{N} \int_{[t_{k-1},t_k]} R'_j(t) \int_{[t_{m-1},t_m]} \log |\gamma(t) - \gamma(s)| R'_i(s) \, ds \, dt \\ &= -\frac{1}{2\pi} \sum_{k=\max(j,1)}^{N} \sum_{m=\max(i,1)}^{N} \int_{[t_{k-1},t_k]} \int_{[t_{m-1},t_m]} \log |\gamma(t) - \gamma(s)| R'_i(s) \, ds \, dt \end{split}$$

We use the transformations $t \mapsto t_{k-1} + (t_k - t_{k-1})t$ and $s \mapsto t_{m-1} + (t_m - t_{m-1})s$

$$= -\frac{1}{2\pi} \sum_{k=\max(j,1)}^{\min(j+p,N)} \sum_{m=\max(i,1)}^{\min(i+p,N)} H_k H_m \int_{[0,1]} \int_{[0,1]} \log |\gamma_k(t) - \gamma_m(s)| R'_{j,k}(t) R'_{i,m}(s) \, ds \, dt.$$

We now have to distinguish between different cases, where the summands are unequal to zero, i.e., $H_k, H_m \neq 0$. These cases are treated in a similar way to [Gan14, Section 5]

1. Case: $\gamma([t_{k-1}, t_k]) \cap \gamma([t_{m-1}, t_m]) = \emptyset$: In this case, the integrand has no singularities. Therefore, we can use a tensorial Gauss quadrature with weight function 1 to approximate the integral and Theorem 6.1 is applicable.

2. Case: $\gamma([t_{k-1}, t_k]) = \gamma([t_{m-1}, t_m])$: This implies, that k = m. As a result we get

$$\int_{[0,1]} \int_{[0,1]} \log |\gamma_k(t) - \gamma_m(s)| R'_{j,k}(t) R'_{i,m}(s) \, ds \, dt$$

=
$$\int_{[0,1]} \int_{[0,1]} \log |\gamma_k(t) - \gamma_k(s)| R'_{j,k}(t) R'_{i,k}(s) \, ds \, dt.$$

The transformation $s \mapsto t - s$ and splitting the integral yield

$$= \int_{[0,1]} \int_{[t-1,t]} \log |\gamma_k(t) - \gamma_k(t-s)| R'_{j,k}(t) R'_{i,k}(t-s) \, ds \, dt$$

$$= \int_{[0,1]} \int_{[t-1,0]} \log |\gamma_k(t) - \gamma_k(t-s)| R'_{j,k}(t) R'_{i,k}(t-s) \, ds \, dt$$

$$+ \int_{[0,1]} \int_{[0,t]} \log |\gamma_k(t) - \gamma_k(t-s)| R'_{j,k}(t) R'_{i,k}(t-s) \, ds \, dt$$
(6.2)

Take a look at the first integral of (6.2). We use the transformations $t \mapsto 1 - t$ and $s \mapsto -s$ to get

$$\begin{split} &\int_{[0,1]} \int_{[t-1,0]} \log |\gamma_k(t) - \gamma_k(t-s)| R'_{j,k}(t) R'_{i,k}(t-s) \, ds \, dt \\ &= \int_{[0,1]} \int_{[-t,0]} \log |\gamma_k(1-t) - \gamma_k(1-t-s)| R'_{j,k}(1-t) R'_{i,k}(1-t-s) \, ds \, dt \\ &= \int_{[0,1]} \int_{[0,t]} \log |\gamma_k(1-t) - \gamma_k(1-t+s)| R'_{j,k}(1-t) R'_{i,k}(1-t+s) \, ds \, dt. \end{split}$$

Now we use the transformation $(s,t) \mapsto (st,t)$ such that the singularities are either at s = 0 or t = 0. Afterwards, we apply basic logarithmic identities

$$= \int_{[0,1]} \int_{[0,1]} \log |\gamma_k(1-t) - \gamma_k(1-t+st)| R'_{j,i}(1-t) R'_{i,k}(1-t+st) t \, ds \, dt$$

$$= \int_{[0,1]} \int_{[0,1]} \log \left| \frac{\gamma_k(1-t) - \gamma_k(1-t+st)}{st} \right| R'_{j,k}(1-t) R'_{i,k}(1-t+st) t \, ds$$

$$+ \int_{[0,1]} \int_{[0,1]} \log(s) R'_{j,k}(1-t) R'_{i,k}(1-t+st) t \, ds \, dt$$

$$+ \int_{[0,1]} \int_{[0,1]} \log(t) R'_{j,k}(1-t) R'_{i,k}(1-t+st) t \, ds \, dt.$$
(6.3)

Consider the second integral in (6.2). We use again the transformation $(s,t) \mapsto (st,t)$, followed by basic logarithmic identities, to see

$$\begin{split} &\int_{[0,1]} \int_{[0,1]} \log |\gamma_k(t) - \gamma_k(t-s)| R'_{j,k}(t) R'_{i,k}(t-s) \, ds \, dt \\ &= \int_{[0,1]} \int_{[0,1]} \log |\gamma_k(t) - \gamma_k(t-st)| R'_{j,k}(t) R'_{i,k}(t-st) \, t \, ds \, dt \\ &= \int_{[0,1]} \int_{[0,1]} \log \left| \frac{\gamma_k(t) - \gamma_k(t-st)}{st} \right| R'_{j,k}(t) R'_{i,k}(t-st) \, t \, ds \, dt \\ &+ \int_{[0,1]} \int_{[0,1]} \log(s) R'_{j,k}(t) R'_{i,k}(t-st) \, t \, ds \, dt \\ &+ \int_{[0,1]} \int_{[0,1]} \log(t) R'_{j,k}(t) R'_{i,k}(t-st) \, t \, ds \, dt \end{split}$$
(6.4)

To approximate the integrals in (6.3) respectively (6.4), we use a tensorial Gauss quadrature with weight functions 1 and $\log(\cdot)$ accordingly. This is justifiable due to the following lemma, which allows us to apply Theorem 6.1.

Lemma 6.3 Let the parametrization γ be $q \geq 2$ times continuously differentiable on all $[\check{z}_{\ell-1}^{\gamma}, \check{z}_{\ell}^{\gamma}]$ with $\ell \in \{1, \ldots, n_{\gamma}\}$, where $\{\check{z}_{j}^{\gamma} : j = 1, \ldots, n_{\gamma}\}$ is the set of all nodes. Then the integrands in (6.3) and (6.4) are, up to $\log(s)$ resp. $\log(t), q-1$ times continuously partially differentiable on $[0, 1] \times [0, 1]$.

Proof. We just consider the integrals in (6.3), since the ones in (6.4) can be treated analogously. Obviously, the statement of the lemma holds for the second and third summand. Consider the singular part of the integrand of the first summand and let $s, t \in (0, 1]$,

$$\frac{\gamma(t_{k-1} + H_k(1-t)) - \gamma(t_{k-1} + H_k(1-t+st))}{st} = \frac{\int_{[t_{k-1} + H_k(1-t+st), t_{k-1} + H_k(1-t)]} \gamma'(\tau) d\tau}{st}$$
$$= \frac{(t_{k-1} + H_k(1-t) - t_{k-1} - H_k(1-t+st)) \int_{[0,1]} \gamma'(t_{k-1} + H_k(1-t+st) - H_kst\tau) d\tau}{st}$$
$$= -H_k \int_{[0,1]} \gamma'(t_{k-1} + H_k(1-t+st) - H_kst\tau) d\tau$$

This term can be continuously extended for s = 0 or t = 0 by $-H_k \gamma|'_{[t_{k-1},t_k]}(t_{k-1} + H_k(1-t))$. Due to the smoothness of the integrand, the term is q - 1 times continuously partially differentiable. Since γ is injective and γ' vanishes nowhere, the modulus is strictly positive for all $s, t \in [0, 1]$. Therefore, we can apply $\log(|\cdot|)$, which has no influence on the differentiability. This concludes the proof, since the remaining parts of the integrand fullfill the needed differentiability. \Box

3. Case: $\gamma([t_{k-1}, t_k]) \cap \gamma([t_{m-1}, t_m]) = \{z\}$ for some $z \in \Gamma$: In this case, there exists a singularity of the integrand at either t = 0 and s = 1, or at t = 1 and s = 0. Without loss of generality, we consider the case t = 0 and s = 1. The other case can be treated analogously.

Obviously, $t_{k-1} = t_m$, or $t_m = b$ and $t_{k-1} = a$. Therefore, after the transformation $s \mapsto 1 - s$ and splitting the inner integral, we get

$$\int_{[0,1]} \int_{[0,1]} \log |\gamma_k(t) - \gamma_m(s)| R'_{j,k}(t) R'_{i,m}(s) \, ds \, dt
= \int_{[0,1]} \int_{[0,t]} \log |\gamma_k(t) - \gamma_m(1-s)| R'_{j,k}(t) R'_{i,m}(1-s) \, ds \, dt
+ \int_{[0,1]} \int_{[t,1]} \log |\gamma_k(t) - \gamma_m(1-s)| R'_{j,k}(t) R'_{i,m}(1-s) \, ds \, dt$$
(6.5)

Consider the first integral in (6.5). We use the Duffy transformation $(s, t) \mapsto (st, t)$, which transforms the singularity to t = 0. With basic logarithmic identities, it follows

$$\begin{split} &\int_{[0,1]} \int_{[0,1]} \log |\gamma_k(t) - \gamma_m(1-s)| R'_{j,k}(t) R'_{i,m}(1-s) \, ds \, dt \\ &= \int_{[0,1]} \int_{[0,1]} \log |\gamma_k(t) - \gamma_m(1-st)| R'_{j,k}(t) R'_{i,m}(1-st) \, t \, ds \, dt \\ &= \int_{[0,1]} \int_{[0,1]} \log \left| \frac{\gamma_k(t) - \gamma_m(1-st)}{t} \right| R'_{j,k}(t) R'_{i,m}(1-st) \, t \, ds \, dt \\ &- \int_{[0,1]} \int_{[0,1]} \log(t) R'_{j,k}(t) R'_{i,m}(1-st) \, t \, ds \, dt \end{split}$$
(6.6)

For the second integral in (6.5), we use Fubini's Theorem, followed by the transformation $(s,t) \mapsto (s,st)$ and basic logarithmic identities. This gives

$$\begin{split} &\int_{[0,1]} \int_{[t,1]} \log |\gamma_k(t) - \gamma_m(1-s)| R'_{j,k}(t) R'_{i,m}(1-s) \, ds \, dt \\ &= \int_{[0,1]} \int_{[0,s]} \log |\gamma_k(t) - \gamma_m(1-s)| R'_{j,k}(t) R'_{i,m}(1-s) \, dt \, ds \\ &= \int_{[0,1]} \int_{[0,1]} \log |\gamma_k(st) - \gamma_m(1-s)| R'_{j,k}(st) R'_{i,m}(1-s) \, s \, dt \, ds \\ &= \int_{[0,1]} \int_{[0,1]} \log \left| \frac{\gamma_k(st) - \gamma_m(1-s)}{s} \right| R'_{j,k}(st) R'_{i,m}(1-s) \, s \, dt \, ds \\ &- \int_{[0,1]} \int_{[0,1]} \log(s) R'_{j,k}(st) R'_{i,m}(1-s) \, s \, dt \, ds \end{split}$$
(6.7)

For the final integrals in (6.6) and (6.7), we can use a tensorial Gauss quadrature with weight functions 1, $\log(t)$, and $\log(s)$ accordingly. Again, Theorem 6.1 can be applied, because of the following lemma.

Lemma 6.4 Let the parametrization γ be $q \geq 2$ times continuously differentiable on all $[\check{z}_{\ell-1}^{\gamma}, \check{z}_{\ell}^{\gamma}]$ with $\ell \in \{1, \ldots, n_{\gamma}\}$. Then the integrands in (6.6) and (6.7) are, up to $\log(s)$ resp. $\log(t)$, q-1 times continuously partially differentiable on $[0, 1] \times [0, 1]$.

Proof. We just consider the integrals in (6.6), since the ones in (6.7) can be treated analogously. Since $R'_{j,k}(t)R'_{i,m}(1-st)t$ is smooth, the statement of the lemma holds for the second summand. Consider the singular part of the integrand of the first summand $\log \left|\frac{\gamma_k(t)-\gamma_m(1-st)}{t}\right|$. Without loss of generality, assume $t_{k-1} = t_m$. Let $t \in (0, 1], s \in [0, 1]$. Then,

$$\frac{\gamma(t_{k-1} + (t_k - t_{k-1})t) - \gamma(t_{m-1} + (t_m - t_{m-1})(1 - st))}{t} = \frac{\int_{[t_m - H_m st, t_m + H_k t]} \gamma'(\tau) d\tau}{t} = \int_{[-H_m s, H_k]} \gamma'(t_m + t\tau) d\tau$$

We can extend this term for t = 0 continuously by $H_m s \gamma'^{\ell}(t_m) + H_k \gamma'^{r}(t_m)$. The integrand is smooth on $[-H_m s, 0]$ resp. $[0, H_k]$. Hence, the term is q - 1 times continuously partially differentiable. Due to (1.1) the modulus of it is strictly positive, and we can apply $\log(|\cdot|)$ without affecting the differentiability. The smoothness of the remaining factors in (6.6) is obvious. The case $t_m = b$ and $t_{k-1} = a$ can be treated analogously.

Up to this point, we assumed i, j = 2 - p, ..., N - p - 1 for $\langle W\overline{R}_i; \overline{R}_j \rangle_{\Gamma}$. However, the remaining cases, i.e., i = j = 1 - p, $i \neq j = 1 - p$ and $1 - p = i \neq j$, can be treated similarly by splitting \overline{R}_{1-p} into its two summands.

6.2 Approximation of S_h

We use the following abbreviations for $t \in [a, b]$:

$$\Gamma_{\ell} := \gamma([t_{\ell-1}, t_{\ell}]), \\
H_{\ell} := t_{\ell} - t_{\ell-1}, \\
R_{k,\ell} := R_k(t_{\ell-1} + (t_{\ell} - t_{\ell-1})t) \\
\gamma_{\ell}(t) := \gamma(t_{\ell-1} + (t_{\ell} - t_{\ell-1})t).$$

Let $i, j \neq 1 - p$. Then,

$$\begin{split} \langle \overline{R}_i; 1 \rangle_{\Gamma} \langle \overline{R}_j; 1 \rangle_{\Gamma} &= \int_{\Gamma} \int_{\Gamma} \overline{R}_i(x) \overline{R}_j(y) \, ds_y \, ds_x \\ &= \sum_{k=1}^N \sum_{m=1}^N \int_{\Gamma_k} \int_{\Gamma_m} \overline{R}_i(x) \overline{R}_j(y) \, ds_y \, ds_x \\ &= \sum_{k=1}^N \sum_{m=1}^N \int_{[t_{k-1}, t_k]} \int_{[t_{m-1}, t_m]} \overline{R}_i(\gamma(t)) \overline{R}_j(\gamma(s)) |\gamma'(t)| |\gamma'(s)| \, ds \, dt \\ &= \sum_{k=1}^N \sum_{m=1}^N \int_{[t_{k-1}, t_k]} \int_{[t_{m-1}, t_m]} R_i(t) R_j(s) |\gamma'(t)| |\gamma'(s)| \, ds \, dt \\ &= \sum_{k=1}^{\min(i+p, N)} \sum_{m=\max(j, 1)}^N H_k H_m \int_{[0, 1]} \int_{[0, 1]} R_{i,k}(t) R_{j,m}(s) |\gamma'_k(t)| |\gamma'_m(s)| \, ds \, dt \end{split}$$

As the integrand is smooth, we can use Gauss quadrature with weight function 1 and apply Theorem 6.1. The other cases for i, j can be treated as above by splitting \overline{R}_{1-p} into its two summands.

6.3 Approximation of F_h

This section is the analogon of [Gan14, Section 5.2].

We use the following abbreviations:

$$\Gamma_{\ell} := \gamma([t_{\ell-1}, t_{\ell}]), \\
H_{\ell} := t_{\ell} - t_{\ell-1}, \\
R_{k,\ell} := R_k(t_{\ell-1} + (t_{\ell} - t_{\ell-1})t), \\
\gamma_{\ell}(t) := \gamma(t_{\ell-1} + (t_{\ell} - t_{\ell-1})t).$$

For $j \neq 1 - p$, it holds that

$$\langle (1/2 - K')\phi_h; \overline{R}_j \rangle_{\Gamma} = \langle \phi_h; (1/2 - K)\overline{R}_j \rangle_{\Gamma} = \langle \phi_h; 1/2\overline{R}_j \rangle_{\Gamma} - \langle \phi_h; K\overline{R}_j \rangle_{\Gamma}.$$

We consider the first summand,

$$\begin{split} \langle \phi_h; 1/2\overline{R}_j \rangle_{\Gamma} &= \frac{1}{2} \int_{\Gamma} \phi_h(x) \overline{R}_j(x) \, ds_x = \frac{1}{2} \sum_{k=1}^N \int_{\Gamma_k} \phi_h(x) \overline{R}_j(x) \, ds_x \\ &= \frac{1}{2} \sum_{k=\max(j,1)}^{\min(j+p,N)} \int_{[t_{k-1},t_k]} \phi_h(\gamma(t)) R_j(t) |\gamma'(t)| \, dt \\ &= \frac{1}{2} \sum_{k=\max(j,1)}^{\min(j+p,N)} H_k \int_{[0,1]} \phi_h(\gamma_k(t)) R_{j,k}(t) |\gamma'_k(t)| \, dt. \end{split}$$

We use Gauss quadrature with weight function 1. Theorem 6.1 is applicable if ϕ_h is at least piecewise continuous.

The second summand is more difficult,

$$\begin{split} \langle \phi_h; K\overline{R}_j \rangle_{\Gamma} &= \int_{\Gamma} \int_{\Gamma} \phi_h(x) \partial_{n_y} G(x, y) \overline{R}_j(y) \, ds_y \, ds_x \\ &= \sum_{k=1}^N \sum_{m=1}^N \int_{\Gamma_k} \int_{\Gamma_m} \phi_h(x) \partial_{n_y} G(x, y) \overline{R}_j(y) \, ds_y \, ds_x \\ &= \sum_{k=1}^N \sum_{m=1}^N \int_{[t_{k-1}, t_k]} \int_{[t_{m-1}, t_m]} \phi_h(\gamma(t)) \partial_{n_{\gamma(s)}} G(\gamma(t), \gamma(s)) \overline{R}_j(\gamma(s)) |\gamma'(t)| |\gamma'(s)| \, ds \, dt \\ &= \sum_{k=1}^N \sum_{m=\max(j, 1)}^{\min(j+p, N)} H_k H_m \int_{[0, 1]} \int_{[0, 1]} \phi_h(\gamma_k(t)) \partial_{n_{\gamma(s)}} G(\gamma_k(t), \gamma_m(s)) R_{j,m}(s) |\gamma'_k(t)| |\gamma'_m(s)| \, ds \, dt. \end{split}$$

Again, we have to consider 3 cases.

1. Case: $\gamma([t_{k-1}, t_k]) \cap \gamma([t_{m-1}, t_m]) = \emptyset$: As before, the integrand does not have any singularity in this case. Therefore, we can use Gauss quadrature with weight function 1.

2. Case: $\gamma([t_{k-1}, t_k]) = \gamma([t_{m-1}, t_m])$: It holds m = k, and we can simplify the integral as follows:

$$\int_{[0,1]} \int_{[0,1]} \phi_h(\gamma_k(t)) \partial_{n_y} G(\gamma_k(t), \gamma_m(s)) R_{j,m}(s) |\gamma'_k(t)| |\gamma'_m(s)| \, ds \, dt$$

=
$$\int_{[0,1]} \int_{[0,1]} \phi_h(\gamma_k(t)) \partial_{n_y} G(\gamma_k(t), \gamma_k(s)) R_{j,k}(s) |\gamma'_k(t)| |\gamma'_k(s)| \, ds \, dt.$$

We use the transformation $s \mapsto t - s$ and split the integral

$$= \int_{[0,1]} \int_{[t-1,t]} \phi_h(\gamma_k(t)) \partial_{n_y} G(\gamma_k(t), \gamma_k(t-s)) R_{j,k}(t-s) |\gamma'_k(t)| |\gamma'_k(t-s)| \, ds \, dt$$

$$= \int_{[0,1]} \int_{[0,1]} \phi_h(\gamma_k(t)) \partial_{n_y} G(\gamma_k(t), \gamma_k(t-s)) R_{j,k}(t-s) |\gamma'_k(t)| |\gamma'_k(t-s)| \, ds \, dt$$

$$+ \int_{[0,1]} \int_{[t-1,0]} \phi_h(\gamma_k(t)) \partial_{n_y} G(\gamma_k(t), \gamma_k(t-s)) R_{j,k}(t-s) |\gamma'_k(t)| |\gamma'_k(t-s)| \, ds \, dt$$
(6.8)

Consider the first summand in (6.8). Using the transformation $(s,t) \mapsto (st,t)$, we get

$$\int_{[0,1]} \int_{[0,1]} \phi_h(\gamma_k(t)) \partial_{n_y} G(\gamma_k(t), \gamma_k(t-s)) R_{j,k}(t-s) |\gamma'_k(t)| |\gamma'_k(t-s)| \, ds \, dt$$

$$= \int_{[0,1]} \int_{[0,1]} \phi_h(\gamma_k(t)) \partial_{n_y} G(\gamma_k(t), \gamma_k(t-st)) R_{j,k}(t-st) |\gamma'_k(t)| |\gamma'_k(t-st)| \, t \, ds \, dt \tag{6.9}$$

For the second summand in (6.8), we use the transformations $t \mapsto 1 - t$, $s \mapsto -s$ and $(s, t) \mapsto (st, t)$,

$$\begin{split} \int_{[0,1]} \int_{[t-1,0]} \phi_h(\gamma_k(t)) \partial_{n_y} G(\gamma_k(t), \gamma_k(t-s)) R_{j,k}(t-s) |\gamma'_k(t)| |\gamma'_k(t-s)| \, ds \, dt \\ &= \int_{[0,1]} \int_{[-t,0]} \phi_h(\gamma_k(1-t)) \partial_{n_y} G(\gamma_k(1-t), \gamma_k(1-t-s)) \\ &\qquad R_{j,k}(1-t-s) |\gamma'_k(1-t)| |\gamma'_k(1-t-s)| \, ds \, dt \\ &= \int_{[0,1]} \int_{[0,1]} \phi_h(\gamma_k(1-t)) \partial_{n_y} G(\gamma_k(1-t), \gamma_k(1-t+s)) \\ &\qquad R_{j,k}(1-t+s) |\gamma'_k(1-t)| |\gamma'_k(1-t+s)| \, ds \, dt \\ &= \int_{[0,1]} \int_{[0,1]} \phi_h(\gamma_k(1-t)) \partial_{n_y} G(\gamma_k(1-t), \gamma_k(1-t+st)) \\ &\qquad R_{j,k}(1-t+st) |\gamma'_k(1-t)| |\gamma'_k(1-t+st)| \, t \, ds \, dt \end{split}$$
(6.10)

Now we can again use a tensorial Gauss quadrature with weight function 1 for the resulting two integrals, due to the following lemma and Theorem 6.1.

Lemma 6.5 Let the parametrization γ be $q \geq 2$ times and let $\phi_h \circ \gamma$ be q - 2 times continuously differentiable on all $[\check{z}_{\ell-1}, \check{z}_{\ell}]$ with $\ell \in \{1, \ldots, n\}$. Then the integrands in (6.9) and (6.10) are q - 2 times continuously partially differentiable on $[0, 1] \times [0, 1]$.

Proof. We will only consider the integral (6.9), as (6.10) can be treated analogously. To simplify the inegrand $\partial_{n_y} G(\gamma_k(t), \gamma_k(t-st))$, we firstly notice that

$$\partial_{n_y} G(\gamma_k(t), \gamma_k(t-st)) = \frac{1}{2\pi} \frac{\langle \gamma_k(t) - \gamma_k(t-st); \nu(\gamma_k(t-st)) \rangle}{|\gamma_k(t) - \gamma_k(t-st)|^2}.$$

Additionally, we expand $\gamma(\cdot)$ into its Taylor series,

$$\gamma_k(t) = \gamma_k(t - st) + \gamma'_k(t - st)H_kt(1 - (1 - s)) + \int_{[t_{k-1} + H_k(t - st), t_{k-1} + H_kt]} \gamma''(\tau)(t_{k-1} + H_kt - \tau) d\tau$$

Combining these two equations, we get for $s, t \in (0, 1]$

$$\begin{split} \partial_{n_y} G(\gamma_k(t), \gamma_k(t-st)) \\ &= \frac{1}{2\pi} \frac{\langle \gamma'_k(t-st) H_k t(1-(1-s)); \nu(\gamma_k(t-st)) \rangle}{|\gamma_k(t) - \gamma_k(t-st)|^2} \\ &+ \frac{1}{2\pi} \frac{\langle \int_{[t_{k-1}+H_k(t-st), t_{k-1}+H_kt]} \gamma''(\tau)(t_{k-1}+H_kt-\tau) \, d\tau; \nu(\gamma_k(t-st)) \rangle}{|\gamma_k(t) - \gamma_k(t-st)|^2} \\ &= \left\langle \int_{[0,1]} \gamma''(t_{k-1}+H_k(t-st) + H_kt(1-(1-s))\tau)(1-\tau) \, d\tau; \nu(\gamma_k(t-st)) \right\rangle \\ &\quad \frac{1}{2\pi} \frac{H_k^2 |t(1-(1-s))|^2}{|\gamma_k(t) - \gamma_k(t-st)|^2}. \end{split}$$

For t = 0 or s = 0, we can extend the first factor continuously by

$$\frac{1}{2} \langle \gamma |_{[t_{k-1},t_k]}''(t_{k-1} + H_k t; \nu(\gamma_k|_{[t_{k-1},t_k]}(t-st))) \rangle_{\Gamma}.$$

The integrand is obviously q - 2 times continuously partially differentiable. So we have to deal with the second factor,

$$\begin{split} \frac{1}{2\pi} \frac{H_k^2 |t(1-(1-s))|^2}{|\gamma_k(t) - \gamma_k(t-st)|^2} &= \frac{1}{2\pi} \frac{H_k^2 |t(1-(1-s))|^2}{|\gamma(t_{k-1} + H_k t) - \gamma(t_{k-1} + H_k (t-st)|^2)} \\ &= \frac{1}{2\pi} \frac{H_k^2 |ts|^2}{|\int_{[t_{k-1} + H_k (t-st), t_{k-1} + H_k t]} \gamma'(\tau) \, d\tau|^2} \\ &= \frac{1}{2\pi} \frac{H_k^2 |ts|^2}{H_k^2 |st|^2 |\int_{[0,1]} \gamma'(t_{k-1} + H_k (t-st) + H_k st\tau) \, d\tau|^2}. \end{split}$$

This final term can be continuously extended at t = 0 or s = 0 by $1/(2\pi|\gamma|'_{[t_{k-1},t_k]}(t_{k-1}+H_kt)|^2)$. The integrand is q-1 times continuously partially differentiable, and $(s,t) \mapsto \partial_{n_y} G(\gamma_k(t), \gamma_k(t-st))$ is q-2 times continuously partially differentiable on $[0,1] \times [0,1]$. This proves the lemma, as the remaining factors are obviously sufficiently smooth.

3. Case: $\gamma([t_{k-1}, t_k]) \cap \gamma([t_{m-1}, t_m]) = \{z\}$ for some $z \in \Gamma$: As before, there is either a singularity at t = 0 and s = 1, or at t = 1 and s = 0. Without loss of generality, let the singularity occur at t = 0 and s = 1. The other case can be treated analogously. It follows that either $t_{k-1} = t_m$, or $t_m = b$ and $t_{k-1} = a$. First, we split the integral as follows

$$\int_{[0,1]} \int_{[0,1]} \phi_h(\gamma_k(t)) \partial_{n_y} G(\gamma_k(t), \gamma_m(s)) R_{j,m}(s) |\gamma'_k(t)| |\gamma'_m(s)| \, ds \, dt \\
= \int_{[0,1]} \int_{[0,1]} \phi_h(\gamma_k(t)) \partial_{n_y} G(\gamma_k(t), \gamma_m(s)) R_{j,m}(s) |\gamma'_k(t)| |\gamma'_m(s)| \, ds \, dt \\
+ \int_{[0,1]} \int_{[t,1]} \phi_h(\gamma_k(t)) \partial_{n_y} G(\gamma_k(t), \gamma_m(s)) R_{j,m}(s) |\gamma'_k(t)| |\gamma'_m(s)| \, ds \, dt.$$
(6.11)

Considering the first summand in (6.11), we use the transformation $(s, t) \mapsto (1 - st, t)$ to transform the singularity to t = 0,

$$\int_{[0,1]} \int_{[0,1]} \phi_h(\gamma_k(t)) \partial_{n_y} G(\gamma_k(t), \gamma_m(s)) R_{j,m}(s) |\gamma'_k(t)| |\gamma'_m(s)| \, ds \, dt$$

$$= \int_{[0,1]} \int_{[0,1]} \phi_h(\gamma_k(t)) \partial_{n_y} G(\gamma_k(t), \gamma_m(1-st)) R_{j,m}(1-st) |\gamma'_k(t)| |\gamma'_m(1-st)| \, t \, ds \, dt.$$
(6.12)

For the second summand in (6.11), we use Fubini's Theorem and the transformation $(s,t) \mapsto (1-s,st)$

to transform the singularity to s = 0,

$$\int_{[0,1]} \int_{[t,1]} \phi_h(\gamma_k(t)) \partial_{n_y} G(\gamma_k(t), \gamma_m(s)) R_{j,m}(s) |\gamma'_k(t)| |\gamma'_m(s)| \, ds \, dt \\
= \int_{[0,1]} \int_{[0,s]} \phi_h(\gamma_k(t)) \partial_{n_y} G(\gamma_k(t), \gamma_m(s)) R_{j,m}(s) |\gamma'_k(t)| |\gamma'_m(s)| \, dt \, ds \\
= \int_{[0,1]} \int_{[0,1]} \phi_h(\gamma_k(st) \partial_{n_y} G(\gamma_k(st), \gamma_m(1-s)) R_{j,m}(1-s) |\gamma'_k(st)| |\gamma'_m(1-s)| \, s \, ds \, dt.$$
(6.13)

To approximate the integrals (6.12) and (6.13), we can use a tensorial Gauss quadrature with weight function 1. Theorem 6.1 can be applied due to the following lemma.

Lemma 6.6 Let the parametrization γ be $q \geq 2$ times and let $\phi_h \circ \gamma$ be q-1 times continuously differentiable on all $[\tilde{z}_{\ell-1}, \tilde{z}_{\ell}]$ with $\ell \in \{1, \ldots, n\}$. Then the integrands in (6.12) and (6.13) are q-1 times continuously partially differentiable on $[0, 1] \times [0, 1]$.

Proof. As (6.13) can be treated analogously, we will only consider equation (6.12). To this end, let first $t_{k-1} = t_m$. For $t \in (0, 1]$ and $s \in [0, 1]$, it holds

$$\partial_{n_y} G(\gamma_k(t), \gamma_m(1-st)) \cdot t = \frac{1}{2\pi} \frac{\langle \gamma_k(t) - \gamma_m(1-st); \nu(\gamma_m(1-st)) \rangle}{|\gamma_k(t) - \gamma_m(1-st)|^2} \cdot t$$

Take a deeper look at

$$\begin{split} &\frac{\gamma_k(t) - \gamma_m(1 - st)}{|\gamma_k(t) - \gamma_m(1 - st)|^2} \cdot t \\ &= \frac{t^2}{|\gamma(t_{k-1} + H_k t) - \gamma(t_{m-1} + H_m(1 - st))|^2} \cdot \frac{\gamma(t_{k-1} + H_k t) - \gamma(t_{m-1} + H_m(1 - st))}{t} \\ &= \frac{t^2}{|\int_{[t_{k-1} - H_m st, t_{k-1} + H_k t]} \gamma'(\tau) \, d\tau|^2} \cdot \frac{\int_{[t_{k-1} - H_m st, t_{k-1} + H_k t]} \gamma'(\tau) \, d\tau}{t} \\ &= \frac{\int_{[-H_m s, H_k]} \gamma'(t_{k-1} + t\tau) \, d\tau}{|\int_{[-H_m s, H_k]} \gamma'(t_{k-1} + t\tau) \, d\tau|^2}. \end{split}$$

Since $\gamma'^{\ell}(t_{k-1})$ is no negative multiple of $\gamma'^{r}(t_{k-1})$, we can extend this term at t=0 continuously by

$$\frac{H_m s \gamma^{\prime_\ell}(t_{k-1}) + H_k \gamma^{\prime_r}(t_{k-1})}{|H_m s \gamma^{\prime_\ell}(t_{k-1}) + H_k \gamma^{\prime_r}(t_{k-1})|^2}.$$

Additionally, it is even q-1 continuously partially differentiable, which proves the demanded differentiability of $(s,t) \mapsto \partial_{n_y} G(\gamma_k(t), \gamma_m(1-st)) \cdot t$ on $[0,1] \times [0,1]$. As the remaining factors in (6.12) have the same smoothness, and the case $t_m = b$ and $t_{k-1} = a$ works analogously, the lemma is proved.

The case $\langle (1/2 - K')\phi_h; \overline{R}_{1-p} \rangle_{\Gamma}$ can be treated analogously by splitting \overline{R}_{1-p} into its two summands.

6.4 Numerical evaluation of $K'\phi_h$

Let $x = \gamma(s)$ with $s \in [a, b] \setminus \{t_0, \ldots, t_n\}$ and $k_s \in \{1, \ldots, n\}$ with $s \in [t_{k_s-1}, t_{k_s}]$. We use the following abbreviations:

$$\begin{split} &\Gamma_{\ell} := \gamma([t_{\ell-1}, t_{\ell}]), \\ &H_{\ell} := t_{\ell} - t_{\ell-1}, \\ &\gamma_{\ell}(t) := \gamma(t_{\ell-1} + (t_{\ell} - t_{\ell-1})t), \end{split}$$

and $B(x,\epsilon) := \{y \in \mathbb{R}^2 : |x-y| < \epsilon\}$ for the open ball centered at x with radius ϵ .

It holds that

$$K'\phi_{h}(x) = \lim_{\epsilon \to 0} \int_{\Gamma \setminus B(x,\epsilon)} \partial_{n_{x}} G(x,y)\phi_{h}(y) \, ds_{y}$$
$$= \sum_{\substack{k=1\\k \neq k_{s}}}^{N} \int_{\Gamma_{k}} \partial_{n_{x}} G(x,y)\phi_{h}(y) \, ds_{y} + \lim_{\epsilon \to 0} \int_{\Gamma_{k_{s}} \setminus B(x,\epsilon)} \partial_{n_{x}} G(x,y)\phi_{h}(y) \, ds_{y}.$$
(6.14)

With the help of the mean value theorem, it follows that $|\partial_{n_x} G(x, y)| \leq C$ for all $x, y \in \Gamma_{k_s}$ with C > 0. Hence, [Pra07, Lemma 4.23] yields the existence of the improper integral (6.14) and it follows

$$\begin{split} K'\phi_{h}(x) &= \sum_{\substack{k=1\\k\neq k_{s}}}^{N} \int_{[t_{k-1},t_{k}]} \partial_{n_{x}} G(\gamma(s),\gamma(t))\phi_{h}(\gamma(t))|\gamma'(t)| \, dt \\ &+ \int_{[t_{k_{s}-1},s]} \partial_{n_{x}} G(\gamma(s),\gamma(t))\phi_{h}(\gamma(t))|\gamma'(t)| \, dt \\ &+ \int_{[s,t_{k_{s}}]} \partial_{n_{x}} G(\gamma(s),\gamma(t))\phi_{h}(\gamma(t))|\gamma'(t)| \, dt \\ &= \sum_{\substack{k=1\\k\neq k_{s}}}^{N} H_{k} \int_{[0,1]} \partial_{n_{x}} G(\gamma(s),\gamma_{k}(t))\phi_{h}(\gamma_{k}(t))|\gamma'_{k}(t)| \, dt \\ &+ (s-t_{k_{s}-1}) \int_{[0,1]} \partial_{n_{x}} G(\gamma(s),\gamma(s-(s-t_{k_{s}-1})t)) \\ &\cdot \phi_{h}(\gamma(s-(s-t_{k_{s}}-s)t))|\gamma'(s-(s-t_{k_{s}-1})t)| \, dt \\ &+ (t_{k_{s}}-s) \int_{[0,1]} \partial_{n_{x}} G(\gamma(s),\gamma(s+(t_{k_{s}}-s)t)) \\ &\cdot \phi_{h}(\gamma(s+(t_{k_{s}}-s)t))|\gamma'(s+(t_{k_{s}}-s)t)| \, dt. \end{split}$$
(6.15)

We approximate these final integrals in (6.15) by Gauss quadrature with weight function 1, which is justified by the following lemma.

Lemma 6.7 Let the parametrization γ be $q \geq 2$ times and let $\phi_h \circ \gamma$ be q - 2 times continuously differentiable on $[\check{z}_{\ell-1}, \check{z}_{\ell}]$ for $\ell \in \{1, \ldots, n\}$. Then, the integrands in (6.15) are q - 2 times continuously differentiable on [0, 1].

Proof. The integrand $\partial_{n_x} G(\gamma(s), \gamma_k(t)) \phi_h(\gamma_k(t)) |\gamma'_k(t)|$ of the first integral in (6.15), is smooth since $\gamma(s) \neq \gamma_k(t)$ for all $k \neq k_s$. Hence, it is sufficient to consider only the second and third summand in (6.15). For $t \in (0, 1]$, it holds that

$$\partial_{n_x} G(\gamma(s), \gamma(s - (s - t_{k_s - 1})t)) = -\frac{1}{2\pi} \frac{\langle \gamma(s) - \gamma(s - (s - t_{k_s - 1})t); \nu(\gamma(s)) \rangle}{|\gamma(s) - \gamma(s - (s - t_{k_s - 1})t)|^2}.$$

The Taylor expansion yields

$$\gamma(s - (s - t_{k_s-1})t) = \gamma(s) - \gamma'(s)(s - t_{k_s-1})t + \int_{[s,s-(s-t_{k_s-1})t]} \gamma''(\tau)(s - (s - (t_{k_s-1})t - \tau) d\tau) d\tau$$
$$= \gamma(s) - \gamma'(s)(s - t_{k_s-1})t + ((s - t_{k_s-1})t)^2 \int_{[0,1]} \gamma''(s - (s - t_{k_s-1})t\tau)(1 - \tau) d\tau$$

Altogether, we end up with

$$\begin{split} \partial_{n_x} G(\gamma(s), \gamma(s - (s - t_{k_s-1})t)) \\ &= -\frac{1}{2\pi} \frac{\langle \gamma'(s)(s - t_{k_s-1})t; \nu(\gamma(s)) \rangle_{\Gamma}}{|\gamma(s) - \gamma(s - (s - t_{k_s-1})t)|^2} \\ &+ \frac{1}{2\pi} \frac{((s - t_{k_s-1})t)^2}{|\gamma(s) - \gamma(s - (s - t_{k_s-1})t)|^2} \Big\langle \int_{[0,1]} \gamma''(s - (s - t_{k_s-1})t\tau)(1 - \tau) \, d\tau; \nu(\gamma(s)) \Big\rangle \\ &= \frac{1}{2\pi} \frac{((s - t_{k_s-1})t)^2}{|\gamma(s) - \gamma(s - (s - t_{k_s-1})t)|^2} \Big\langle \int_{[0,1]} \gamma''(s - (s - t_{k_s-1})t\tau)(1 - \tau) \, d\tau; \nu(\gamma(s)) \Big\rangle \\ &= \frac{1}{2\pi} \frac{((s - t_{k_s-1})t)^2}{|\int_{[\gamma(s - (s - t_{k_s-1})t), \gamma(s)]} \gamma'(\tau) \, d\tau|^2} \Big\langle \int_{[0,1]} \gamma''(s - (s - t_{k_s-1})t\tau)(1 - \tau) \, d\tau; \nu(\gamma(s)) \Big\rangle \\ &= \frac{1}{2\pi} \frac{((s - t_{k_s-1})t)^2}{((s - t_{k_s-1})t)^2 |\int_{[0,1]} \gamma'(s - (s - t_{k_s-1})t + (s - t_{k_s-1})t\tau) \, d\tau|^2} \\ &\quad \cdot \Big\langle \int_{[0,1]} \gamma''(s - (s - t_{k_s-1})t\tau)(1 - \tau) \, d\tau; \nu(\gamma(s)) \Big\rangle \end{split}$$

which can be continuously extended at t = 0 by

$$\frac{1}{2\pi} \frac{\langle \gamma''(s); \nu(\gamma(s)) \rangle_{\Gamma}}{2|\gamma'(s)|^2}.$$

The continuous extension is even q - 2 times countinuously differentiable for $s \in [0, 1]$. Hence, the integrand in the second summand of (6.15) is q - 2 times continuously differentiable as well. The third summand is treated analogously.

6.5 Numerical evaluation of WU_h

For the implementation, we used the so called NURBS-BEM package from A. Bantle, M. Bantle, and S. Funken, developed at the Institute for Numerical Mathematics at the University of Ulm. This package provides a stable black box implementation of the numerical evaluation of WU_h .

7 Numerical experiment

In this section, we consider different geometries and compare uniform refinement to the adaptive Algorithm 3.5 for various problems.

The parametrization γ of the boundary Γ is of the form

$$\gamma(t) = \sum_{i \in \mathbb{Z}} C_i R_{i,p}(t) \text{ for all } t \in [a, b],$$

where $p \in \mathbb{N}$ is the polynomial degree, $\{R_{i,p} : i \in \mathbb{Z}\}$ are the NURBS from (2.4), and $(C_i)_{i \in \mathbb{Z}}$ are control points in \mathbb{R}^2 . Curves represented in this way are called NURBS curves.

The main idea of isogeometric analysis is to use NURBS for both the geometry and the ansatz spaces to avoid possible data approximation errors of the boundary. Therefore, we use the polynomial degree as well as knots and weights of the geometry for the initial ansatz space \mathcal{X}_0 .

7.1 Slit problem

Although we assumed $\Gamma := \partial \Omega$ for the whole theory in the previous sections, it is also possible to prove everything for a connected $\Gamma_0 \subsetneq \partial \Omega$ with just some minor changes in the proofs. However, we have to adjust the ansatz and test space of the variational formulation. Instead of $H^{1/2}(\Gamma)$, we take the space $\widetilde{H}^{1/2}(\Gamma_0) := \{ \widehat{v} |_{\Gamma_0} : \widehat{v} \in H^{1/2}(\Gamma), \operatorname{supp} \widehat{v} \subseteq \overline{\Gamma}_0 \}$, where $\overline{\Gamma}_0$ denotes the closure of Γ_0 .

Let $\Gamma_0 := (-1, 1) \times \{0\} \subseteq \mathbb{R}^2$. We consider the hyper-singular integral equation

$$\langle\!\langle u; v \rangle\!\rangle_W = \langle \phi; v \rangle_{\Gamma} \quad \text{for all } v \in H^{1/2}(\Gamma_0), \tag{7.1}$$

with the right-hand side $\phi = 1$ and the exact solution $u(x, 0) = 2\sqrt{1-x^2}$. In this case, no stabilization term is necessary. The discrete variational formulation reads

$$\langle\!\langle U_{\ell}; V_{\ell} \rangle\!\rangle_W = \langle \Pi_{\ell} \phi; V_{\ell} \rangle_{\Gamma} \quad \text{for all } V_{\ell} \in \mathcal{X}_{\ell,0},$$

$$(7.2)$$

where $\mathcal{X}_{\ell,0} := \mathcal{X}_{\ell} \cap \widetilde{H}^{1/2}(\Gamma_0).$

Since Π_{ℓ} is the piecewise L^2 -best approximation, it holds $\Pi_{\ell}\phi = \phi$. Hence, the oscillation term of the node-based error estimator μ_{ℓ} , which steers Algorithm 3.5, vanishes and μ_{ℓ} simplifies to

$$\mu_{\ell}(z) = \|h_{\ell}^{1/2}(\phi - WU_{\ell})\|_{L^{2}(\omega_{*}(z))} \text{ for all } z \in \mathcal{N}_{\ell}$$

As a consequence, we can use the Galerkin orthogonality to compute the error in the energy norm by

$$||| u - U_{\ell} |||_{W}^{2} = ||| u |||_{W}^{2} - ||| U_{\ell} |||_{W}^{2} = \pi - ||| U_{\ell} |||_{W}^{2} =: \operatorname{err}_{\ell}^{2}.$$

The energy norm $||| u |||_W^2 = \pi$ is computed analytically, whereas $||| U_\ell ||_W^2$ can be easily computed via $||| U_\ell ||_W^2 = c_{h_\ell} \cdot W_{h_\ell} c_{h_\ell}$. Here, W_{h_ℓ} is the stiffness matrix and c_{h_ℓ} is the coefficient vector corresponding to U_ℓ as in Section 6.

The slit is paramatrized on [0, 1] for a fixed $p \in \mathbb{N}$ by the NURBS curve induced by

$$p_{\gamma} = p,$$

$$\tilde{\mathcal{K}}^{\gamma} = \left(\underbrace{0, \dots, 0}_{p+1 \text{ times}}, \frac{1}{5}, \frac{2}{5}, \frac{3}{5}, \frac{4}{5}, \underbrace{1, \dots, 1}_{p+1 \text{ times}}\right),$$

$$\mathcal{W}^{\gamma} = (\underbrace{1, \dots, 1}_{2p+6 \text{ times}}),$$

$$(C_{i})_{i=1}^{N_{\gamma}} = \left(\binom{-1}{0}, \binom{-1+2/(p+4)}{0}, \binom{-1+4/(p+4)}{0}, \dots, \binom{1-2/(p+4)}{0}, \binom{1}{0}\right).$$

The first and the last knot have the demanded multiplicity p + 1 for $p \in \mathbb{N}$. Hence, we can directly use the knot resp. weight vector for the corresponding initial ansatz space \mathcal{X}_0 .

Figure 7.1 shows the slit for p = 1. The images $\{\gamma(t_{\ell}) : \ell \in \{0, \dots, N_{\gamma}\}\}$ of the initial nodes are also plotted.



Figure 7.1: Slit geometry with initial nodes for p = 1.

In Figure 7.2, we compare the exact solution u of (7.1) and the discrete solution U_{ℓ} of (7.2) for p = 1. Here, the different meshes are generated by the adaptive Algorithm 3.5 with $\theta = 0.5$.



Figure 7.2: The solution u of (7.1) resp. the discrete solution U_{ℓ} of (7.2) are plotted for the starting mesh $[\mathcal{T}_0]$ and the refinements $[\mathcal{T}_1]$, $[\mathcal{T}_5]$ and $[\mathcal{T}_{15}]$ over the parameter domain [0, 1].

First, we look at Algorithm 3.5 for $\theta = 1$, i.e., uniform refinement and choose $p \in \{1, \ldots, 5\}$. The optimal order of convergence is given by $\mathcal{O}(h^{1/2+p}) = \mathcal{O}(N^{-1/2-p})$, cf. [SS11, Theorem 4.1.51]. Figure 7.3 shows in a double logarithmic plot that uniform refinement only leads to the suboptimal rate $\mathcal{O}(N^{-1/2})$, independently of the chosen p. This is due to limited regularity $u \in H^{1-\epsilon}(\Gamma) \setminus H^1(\Gamma)$ of the exact solution for all $\epsilon > 0$.



Figure 7.3: Uniform refinement leads to suboptimal order of convergence $\mathcal{O}(N^{-1/2})$ of the energy error $\operatorname{err}_{\ell}$ as well as the error estimator μ_{ℓ} .

Contrary to uniform refinement, we see in Figure 7.4 that the adaptive Algorithm 3.5 with $\theta = 0.5$ regains the optimal order of convergence $\mathcal{O}(N^{-1/2-p})$ for both $\operatorname{err}_{\ell}$ and μ_{ℓ} .

The histogram in Figure 7.5 shows the knot distribution of the last refinement step of the adaptive Algorithm 3.5 with $\theta = 0.5$ and p = 1. Clearly, the algorithm refines mainly at t = 0 and t = 1, as one would expect.

The question arises, which marking parameter θ one should choose for the adaptive Algorithm 3.5. Figure 7.6 shows that the adaptive Algorithm 3.5 converges with the optimal order of convergence $\mathcal{O}(N^{-3/2})$ for all $\theta \in \{0.1, \ldots, 0.9\}$. In Figure 7.7, we consider the cumulative number of knots

$$N_{\rm cum} := \sum_{j=0}^{\ell} |\mathcal{K}_j|,\tag{7.3}$$

which are necessary to reach the prescribed accuracy $\mu_{\ell} < 10^{-3}$. Note that an adaptively generated mesh and thus the computational effort depend on the full history of preceeding meshes. Hence, the cumulative sum $N_{\rm cum}$ provides a good measure of comparison. We see that independently of the chosen p a marking parameter $\theta \approx 0.75$ is a good choice for the adaptive Algorithm 3.5 and that $\theta < 0.5$ results in higher computational effort compared to $0.5 \leq \theta$.



Figure 7.4: Adaptive refinement with $\theta = 0.5$ regains the optimal order of convergence $\mathcal{O}(N^{-1/2-p})$ of the energy error $\operatorname{err}_{\ell}$ as well as the error estimator μ_{ℓ} .



Figure 7.5: Histogram of the knot distribution of the last refinement step $[\mathcal{T}_{26}]$ with $|\mathcal{K}_{26}| = 521$ for the adaptive Algorithm 3.5 with $\theta = 0.5$ and p = 1 for the slit problem (7.1).



Figure 7.6: Comparison of different marking parameters θ for the adaptive Algorithm 3.5 for the slit problem with p = 1.



Figure 7.7: Comparison of the slit problem with p = 1, ..., 5 in terms of the cumulative number of knots $N_{\text{cum}} := \sum_{j=0}^{\ell} |\mathcal{K}_j|$ necessary to reach the prescribed accuracy $\mu_{\ell} < 10^{-3}$.

7.2 Indirect BEM

Let Γ be the boundary of the L-shaped domain $\Omega = (-1, 1)^2 \setminus [0, 1]^2$. We consider the hyper-singular integral equation

$$Wu = f \quad \text{on } \Gamma, \tag{7.4}$$

where f(x,y) = x - c. The constant c = -1/8 is chosen such that the integral mean $\int_{\Gamma} f \, ds = 0$ vanishes. In this case, we do not have any data oscillation terms.

The L-shape shown in Figure 7.8 is parametrized on [0, 6] by the NURBS curve induced by

$$p_{\gamma} = 1,$$

$$\tilde{\mathcal{K}}^{\gamma} = (0, 0, 1, 2, 3, 4, 5, 6, 6),$$

$$\mathcal{W}^{\gamma} = (1, 1, 1, 1, 1, 1, 1, 1, 1),$$

$$(C_{i})_{i=1}^{N_{\gamma}} = \left(\begin{pmatrix} -1 \\ -1 \end{pmatrix}, \begin{pmatrix} 1 \\ -1 \end{pmatrix}, \begin{pmatrix} 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \end{pmatrix}, \begin{pmatrix} -1 \\ 1 \end{pmatrix}, \begin{pmatrix} -1 \\ -1 \end{pmatrix} \right).$$

$$\begin{pmatrix} 1.5 \\ \gamma(5) \\ \gamma(5) \\ \gamma(4) \\ \gamma(3) \\ \gamma(3) \\ \gamma(3) \\ \gamma(2) \\ \gamma(3) \\ \gamma(2) \\ \gamma(3) \\ \gamma(2) \\ \gamma(3) \\ \gamma(3) \\ \gamma(2) \\ \gamma(3) \\ \gamma(2) \\ \gamma(3) \\ \gamma(3) \\ \gamma(3) \\ \gamma(2) \\ \gamma(3) \\ \gamma(3) \\ \gamma(2) \\ \gamma(3) \\ \gamma(3) \\ \gamma(3) \\ \gamma(2) \\ \gamma(3) \\ \gamma(3)$$

Figure 7.8: L-shape $(-1, 1)^2 \setminus [0, 1]^2$ with initial nodes.

Again, we compare uniform refinement of the mesh to adaptive refinement for the adaptive Algorithm 3.5 steered by the node-based error estimator μ_{ℓ} with $\theta = 0.5$. Since the exact solution u of (7.4) is unknown, we use the extrapolated value $||| u |||_{W+S}^2 = 12.952418804$ to compute the absolute error $||| u - U_{\ell} ||_{W+S}$. In Figure 7.9, we see that uniform refinement leads to the order of convergence $\mathcal{O}(N^{-2/3})$, whereas the adaptive strategy regains the optimal order $\mathcal{O}(N^{-3/2})$.

The histogram in Figure 7.10 indicates that the adaptive Algorithm 3.5 refines especially at the corners $\gamma(0), \ldots, \gamma(6)$.

In Figure 7.11, the error estimator μ_{ℓ} is plotted for different choices of the marking parameter θ of the adaptive Algorithm 3.5. For all $\theta \in \{0.1, \ldots, 0.9\}$, the estimator decays at optimal order of convergence. Figure 7.12 shows the cumulative sum N_{cum} , cf. Definition (7.3), which is necessary to reach an accuracy of $\mu_{\ell} < 10^{-3}$, plotted over θ . We observe that the optimal marking parameter seems to be at $\theta \approx 0.8$.



Figure 7.9: Comparison of uniform and adaptive refinement on the L-shaped domain $(-1,1)^2 \setminus [0,1]^2$.



Figure 7.10: Histogram of the knot distribution of the last refinement step $[\mathcal{T}_{35}]$ with $|\mathcal{K}_{35}| = 3185$ for the adaptive Algorithm 3.5 with $\theta = 0.5$ for the problem (7.4).



Figure 7.11: Comparison of different marking parameters θ for the adaptive Algorithm 3.5 on the L-shaped domain $(-1, 1)^2 \setminus [0, 1]^2$.



Figure 7.12: Comparison of the marking parameter θ in terms of the cumulative number of knots $N_{\text{cum}} := \sum_{j=0}^{\ell} |\mathcal{K}_j|$ necessary to reach the prescribed accuracy $\mu_{\ell} < 10^{-3}$.

7.3 Neumann problem with singular right-hand side ϕ

We consider the Neumann problem

$$Wu = (1/2 - K')\phi \quad \text{on } \Gamma, \tag{7.5}$$

where Γ is the boundary of the L-shaped domain Ω shown in Figure 7.13 and ϕ is given by the normal derivative of the function

$$P(x,y) = r^{\tau} \cos(\tau \alpha).$$

Here, (r, α) denotes the polar coordinates of $(x, y) \in \mathbb{R}^2$ and $\tau = 2/3$. The normal derivative of P reads

$$\phi(x,y) = \begin{pmatrix} \cos(\alpha)\cos(\tau\alpha) + \sin(\alpha)\sin(\tau\alpha)\\ \sin(\alpha)\cos(\tau\alpha) - \cos(\alpha)\sin(\tau\alpha) \end{pmatrix} \cdot \nu(x,y) \cdot \tau \cdot r^{\tau-1}$$

and has a generic singularity at the origin.



Figure 7.13: Rotated L-shape with initial nodes.

Let $\beta = \pi/12$. The rotated L-shape is parametrized on [0, 6] by the NURBS curve induced by

$$p_{\gamma} = 1,$$

$$\check{\mathcal{K}}^{\gamma} = (0, 0, 1, 2, 3, 4, 5, 6, 6),$$

$$\mathcal{W}^{\gamma} = (1, 1, 1, 1, 1, 1, 1, 1, 1),$$

$$(C_{i})_{i=1}^{N_{\gamma}} = \frac{1}{4} \cdot \begin{pmatrix} \cos(\beta) & \sin(\beta) \\ -\sin(\beta) & \cos(\beta) \end{pmatrix} \cdot \begin{pmatrix} \begin{pmatrix} -1 \\ -1 \end{pmatrix}, \begin{pmatrix} 1 \\ -1 \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \end{pmatrix}, \begin{pmatrix} -1 \\ 1 \end{pmatrix}, \begin{pmatrix} -1 \\ -1 \end{pmatrix} \end{pmatrix}$$

In Figure 7.14, the solution u of (7.5) as well as the corresponding discrete solution are plotted for different refinements. The meshes are obtained by the adaptive Algorithm 3.5 with $\theta = 0.5$. One can see, that even after 20 adaptive steps, the number of knots is rather small. We know that the right-hand side ϕ is singular at the origin. Hence, we expect that the adaptive Algorithm 3.5 refines mainly at the origin. This is underpinned by the histogram in Figure 7.15.



Figure 7.14: The solution u of (7.5) resp. the discrete solution U_{ℓ} of the according variational formulation are plotted for the initial mesh $[\mathcal{T}_0]$ and the refinements $[\mathcal{T}_5]$, $[\mathcal{T}_{12}]$, and $[\mathcal{T}_{20}]$ over the parameter domain [0, 6].

Since the solution $u := P|_{\Gamma}$ is smooth, one would expect that the estimator decays at a rate $\mathcal{O}(N^{-3/2})$. First, we implemented the adaptive Algorithm 3.5 without any approximation of the right-hand side ϕ . We observed that neither uniform nor adaptive refinement regained this order of convergence. The problem was, that the right-hand side of the discrete variational formulation was not integrated numerically well enough. In order to solve this problem, we replaced ϕ by the L^2 -projection $\Pi_*\phi$ and incorporated the arising data oscillation terms into the overall adaptive scheme and its analysis.

We look at a uniform refinement strategy in comparison to the adaptive Algorithm 3.5 with $\theta = 0.5$. In Figure 7.16, the node-based error estimator μ_{ℓ} is plotted over the number of knots for both uniform and adaptive refinement. Since the function ϕ misses regularity at the origin, uniform refinement only leads to an order of convergence $\mathcal{O}(N^{-2/3})$. The adaptive strategy, on the other hand, regains the optimal order of convergence $\mathcal{O}(N^{-3/2})$. Figure 7.17 shows that this optimal order of convergence is independent of the chosen marking parameter $\theta \in \{0.1, \ldots, 0.9\}$.

We prescribe an accuracy of 10^{-4} for the error estimator μ_{ℓ} . Figure 7.18 shows the cumuluative sum $N_{\rm cum}$, cf. Definition (7.3), plotted over the marking parameter θ . We see that $\theta \approx 0.8$ is a good choice for θ .



Figure 7.15: Histogram of the knot distribution of the last refinement step $[\mathcal{T}_{48}]$ with $|\mathcal{K}_{48}| = 3517$ for the adaptive Algorithm 3.5 with $\theta = 0.5$ for the Neumann problem (7.5) with singular right-hand side ϕ .



Figure 7.16: Comparison of uniform and adaptive refinement on the rotated L-shape for the Neumann problem (7.5).



Figure 7.17: Comparison of different marking parameters θ for the adaptive Algorithm 3.5 on rotated L-shape for the Neumann problem (7.5).



Figure 7.18: Comparison of the marking parameter θ in terms of the cumulative number of knots $N_{\text{cum}} := \sum_{j=0}^{\ell} |\mathcal{K}_j|$ necessary to reach the prescribed accuracy $\mu_{\ell} < 10^{-4}$.

A Implementation

This section is dedicated to the implementation of the adaptive Algorithm 3.5. All the main files needed are given below.

For better performance, most parts are coded in C. However, they can all be used in MATLAB via MEX files. One example of such a MEX file is also given.

The algorithms used are mostly based on the approaches discussed in Section 6 and [de 86].

A.1 Functions.h

In this file, some basic functions and examples for the Neumann boundary conditions ϕ are defined, cf. [Gan14, Appendix B].

```
1
    #ifndef _Functions_h
    #define _Functions_h
2
3
   #include <stdio.h>
4
\mathbf{5}
    #include <stdlib.h>
   #include <math.h>
6
   #define EPS 1e-14
7
8
   inline int mod(int x, int y){
9
10
         // returns \boldsymbol{x} \mbox{ mod } \boldsymbol{y} for integer \boldsymbol{x} and positive integer \boldsymbol{y}
         int z=x%y;
^{11}
         if (z<0) {z=z+y;}</pre>
12
^{13}
         return z;
^{14}
   }
15
16
   inline int floordiv(int x, int y) {
17
         // returns floor(((double)x)/((double)y)) for int x and pos. int y
18
         if (x \ge 0) {return x/y;}else{return (x-y+1)/y;}
^{19}
    }
20
^{21}
22
   inline double min(double x, double y) {
23
^{24}
         if (x<=y){return x;}else{return y;}</pre>
   }
25
26
27
   inline double max(double x, double y){
28
29
         if (x<=y){return y;}else{return x;};</pre>
    }
30
31
32
    inline int nearly_equal(double x, double y) {
33
         if (x==0){
34
              if(fabs(y)<=EPS)</pre>
35
                  return 1;
36
37
              else
                  return 0;
38
         }
39
40
         if (y==0) {
             if(fabs(x)<=EPS)</pre>
^{41}
42
                  return 1;
^{43}
              else
                  return 0;
44
^{45}
         if (fabs(x-y) \leq EPS \star max(fabs(x), fabs(y)))
46
             return 1;
47
^{48}
         }else{
49
              return 0;
         }
50
51
    }
52
53
54
   inline int nearly_leq(double x, double y) {
```

```
if (nearly_equal(x,y) || (x<y)){
55
            return 1;
56
        }else{
57
            return 0:
58
59
        }
   }
60
61
62
   inline double norm(double* vector){
63
        return sqrt(vector[0]*vector[0]+vector[1]*vector[1]);
64
    }
65
66
67
   inline void mvm(double* output, double* A, int n, double* x) {
68
69
        int i:
70
        int j;
71
^{72}
        for (i=0; i<n; i=i+1) {</pre>
            output[i] = 0;
73
            for (j=0; j<n; j=j+1) {
74
75
                 output[i] = output[i] + A[i+j*n]*x[j];
            }
76
77
        }
    }
78
79
80
   inline double phi(double* x){
81
        // returns phi(x) for x in Gamma for various geometries
82
83
        // L-shape
84
        // singular right-hand side:
85
         double tau=2.0/3.0;
86
         double r=norm(x);
87
88
         double alpha=atan2(x[1],x[0]);
         if (nearly_leq(0, x[0]) \& arrly_leq(x[1], 0))
89
             return (tau*pow(r,tau-1)*(cos(alpha-tau*alpha)
90
                              -sin(alpha-tau*alpha)))/sqrt(2);
91
         else if (nearly_leq(0,x[0]))
^{92}
93
             return (tau*pow(r,tau-1)*(cos(alpha-tau*alpha)
^{94}
                              +sin(alpha-tau*alpha)))/sqrt(2);
         else if (nearly_leq(0.25,x[1]))
95
96
             return (tau*pow(r,tau-1)*(-cos(alpha-tau*alpha)
97
                              +sin(alpha-tau*alpha)))/sqrt(2);
         else if (nearly_leq(0,x[1]))
98
             return (tau*pow(r,tau-1)*(-cos(alpha-tau*alpha)
99
                              -sin(alpha-tau*alpha)))/sqrt(2);
100
         else if (nearly_leq(-0.25,x[1]))
101
             return (tau*pow(r,tau-1)*(-cos(alpha-tau*alpha)
102
                              +sin(alpha-tau*alpha)))/sqrt(2);
103
104
         else if (nearly_leq(x[1], -0.25))
             return (tau*pow(r,tau-1)*(-cos(alpha-tau*alpha)
105
                              -sin(alpha-tau*alpha)))/sqrt(2);
106
107
   }
108
109
    #endif
110
```

A.2 Structures.h

In this file, the main structures NURBSData and QuadData are defined. They are used to store NURBS and quadrature data, cf. [Gan14, Appendix B].

```
1 #ifndef _Structures_h_
2 #define _Structures_h_
3 #include <stdio.h>
4 #include <stdlib.h>
5
```

```
6
   // NURBSData
7
   typedef struct _NURBSData_{
8
        double a; // left point of real interval [a,b]
9
        double* knots; // non-decreasing points in (a,b],
10
        //t_1=knots[0],...,t_N=knots[N-1]=b with #t_i<=p+1</pre>
11
        int N; // number of t_i in (a,b]
12
13
        double* weights; // positive weights correspoding to knots
        int p; // polynomial degree
14
        double* nodes; // unique(knots)
15
        int n; // number of nodes
16
        int is_rational; // 0 if all weights are one, 1 else
17
   }NURBSData;
18
19
20
   NURBSData* new_NURBSData(double a, double* knots, int N, double* weights, int p,
^{21}
                              double* nodes, int n, int is_rational) {
22
        NURBSData* Data = malloc(sizeof(NURBSData));
^{23}
^{24}
       Data \rightarrow a = a;
25
26
        Data->knots = knots;
        Data \rightarrow N = N;
27
28
       Data->weights = weights;
        Data->p = p;
29
        Data->nodes=nodes;
30
31
        Data->n=n;
32
        Data->is_rational=is_rational;
33
        return Data;
34
35 }
36
37
  NURBSData* del_NURBSData(NURBSData* Data) {
38
        if (Data != NULL) {
39
            free(Data);
40
41
        }
^{42}
        return NULL;
43 }
44
45
46 // get NURBSData
47 inline double get_NURBSData_a (NURBSData* Data) {return Data->a;}
48 inline double* get_NURBSData_knots(NURBSData* Data) {return Data->knots;}
49 inline int get_NURBSData_N (NURBSData * Data) {return Data->N; }
50 inline double* get_NURBSData_weights(NURBSData* Data) {return Data->weights;}
51 inline int get_NURBSData_p(NURBSData* Data) {return Data->p;}
52 inline double* get_NURBSData_nodes(NURBSData* Data){return Data->nodes;}
53 inline int get_NURBSData_n (NURBSData* Data) {return Data->n;}
54 inline int get_NURBSData_is_rational (NURBSData* Data)
55 {return Data->is_rational;}
56
57
58
59
60
   // OuadData
   typedef struct _QuadData_{
61
        double* nodes; // nodes of Gauss guadrature in [0,1]
62
        double* weights; // weights of Gauss quadrature in [0,1]
63
        int n; // number of nodes resp. weights
64
   }QuadData;
65
66
67
   QuadData* new_QuadData(double* nodes, double* weights, int n) {
68
        QuadData* Data = malloc(sizeof(QuadData));
69
70
71
        Data->nodes = nodes;
72
        Data->weights = weights;
       Data \rightarrow n = n;
73
^{74}
       return Data;
75
```

```
76 }
77
78
   QuadData* del_QuadData (QuadData* Data) {
79
       if (Data != NULL) {
80
           free(Data);
81
       }
82
83
       return NULL;
   }
84
85
86
  // get OuadData
87
  inline double* get_QuadData_nodes (QuadData* Data) {return Data->nodes;}
88
  inline double* get_QuadData_weights(QuadData* Data) {return Data->weights;}
89
90
  inline int get_QuadData_n (QuadData* Data) {return Data->n;}
91
  #endif
92
```

A.3 Spline.h and Spline.c

These two files contain the functions needed to evaluate and derive NURBS, cf. [Gan14, Appendix B].

```
1 #ifndef _Spline_h
2 #define _Spline_h
3
4 #include "Structures.h"
   #include "Functions.h"
\mathbf{5}
6
7 /* parameters:
    Data...NURBSData*, see Structures.h
8
   i...arbitrary unfixed integer
9
   t...arbitrary unfixed evaluation point in [a,b)
10
    wcpoints1...first component of weighted control points w_l*C_l
11
    for geometry corresponding to knots
12
   wcpoints2...second component of weighted control points w_l*C_l
13
    for geometry corresponding to knots
14
15
    */
16
17
  inline double knotseq(NURBSData* Data, int i);
18
  // returns t_i, (knots (b-a)-periodic extended)
19
20
^{21}
   int find_Span(NURBSData* Data, double t);
22 // returns integer index between 0 and N-1 with t in [t_index,t_{index+1})
23 // using binary search
^{24}
25 int find_Span_nodes(NURBSData* Data, double t);
  // returns integer index between 0 and n-1 with t in [t_index,t_{index+1})
26
27
   // using binary search
28
  double deBoor_help(NURBSData* Data, int i, double* coeffdata, int coefftype,
29
                       int l,double t);
30
31 // help function for function deBoor which returns
  // a_i^{[1]}(t) = (1-beta_{i,p-l+1}(t)) * a_{i-1}^{[l-1]}(t)
32
33 // +\beta-{i,p-l+1}(t) *a_i^[l-1](t), where a_i^[0]=c_{i+1}
   // (see B-Spline Basics: Algorithm 9 with k=p+1 and a_i=c_{i+1}),
34
  // for parameter description see function deBoor
35
36
37
38 double deBoorDeriv_help(NURBSData* Data, int i, double* coeffdata,
                            int coefftype,int l,double t);
39
  // help function for function deBoorDeriv which returns
40
41 // (not derivative of function a_i^[1])
42 // a.i'^[l](t)=(1-\beta_{i,p-l}) *a_{i-1}'^[l-1]+\beta_{i,p-l}*a_i'^[l-1] with
  // a_i'^[0]=a_i'=p*(a_i-a_{i-1})/(t_{i+p}-t_i)
^{43}
44 // (see B-Spline Basics: Algorithm 9 and Algorithm 10 with k=p+1 and
  // a_i=c_{i+1}), for parameter description see function deBoorDeriv
45
```
```
46
47
48 double deBoor(NURBSData* Data, double* coeffdata, int coefftype, double t);
49 // returns sum_{i in Zc_i*B_{i,p}(t) using deBoor algorithm, where:
  // if coefftype=0: coeffdata[i+p-1]=c_i for i=(1-p)...(N-#b+1)
50
51 // if coefftype=1: coeffdata[i-1]=c.i for i=1...N, c.i N-periodic extended
52 // if coefftype=2: coeffdata[0] is unique integer i where c_i!=0, it is c_i=1
53
54 double deBoorDeriv(NURBSData* Data,double* coeffdata,int coefftype,double t);
  // returns sum-{i in Z}c_i*D^r(B_{i,p})(t) using deBoor algorithm and formula
55
  // for derivative coefficients c_i', where:
56
57 // if coefftype=0: coeffdata[i+p-1]=c_i for i=(1-p)...(N-#b+1)
  // if coefftype=1: coeffdata[i-1]=c.i for i=1...N, c.i N-periodic extended
58
  // if coefftype=2: coeffdata[0] is unique integer i where c_i!=0, it is c_i=1
59
60
  double eval_NURBS(NURBSData* Data, int i, double t);
61
  // returns R_{i,p}(t)
62
63
64
65 double eval_NURBSDeriv(NURBSData* Data, int i, double t);
66
   // returns D^r(R_{i,p})(t) by using quotient rule
67
68
  void eval_NURBSCurve(double* output, NURBSData* Data, double* wcpoints1,
69
                       double* wcpoints2, double t);
70
  // turns output[0] resp. output[1] into first resp. second coordinate of
71
  // sum_{l in Z} C_l*R_{l,p}(t)
72
  // =(sum_{l in Z} w_l*C_l*B_{l,p}(t))/(sum_{l in Z} w_l*B_{l,p}(t))
73
74
// turns output[0] resp. output[1] into first resp. second coordinate of
77
78 // right derivative of
   // sum_{l in Z} C_l*R_{l,p}(t)
79
  // =(sum_{l in Z} w_l*C_l*B_{l,p}(t))/(sum_{l in Z} w_l*B_{l,p}(t))
80
81 // using quotient rule
82
83 double eval_NURBSComb(NURBSData* Data, double* wcoeffs, double t);
  // returns sum.{l in Z} c_l*R_{1,p}(t), where wcoeffs[l+p-1]=w_l*c_l
84
85
   // for l=(1-p),...,(N-#b+1)
86
  double eval_NURBSCombDeriv(NURBSData* Data,double* wcoeffs, double t);
87
   // returns sum_{l in Z} c_l*R_{l,p}'(t), where wcoeffs[l+p-1]=w_l*c_l
88
   // for l=(1-p), \ldots, (N-\#b+1)
89
90
91
92 #endif
```

```
1 #include "Spline.h"
2
3
4 inline double knotseq(NURBSData* Data, int i) {
5
       double a= get_NURBSData_a(Data);
6
       double* knots=get_NURBSData_knots(Data);
7
       int N=get_NURBSData_N(Data);
8
       double b=knots[N-1];
9
10
       // t_i=t_{i mod N}+(b-a)*floor(i/N)
11
       if (mod(i,N)!=0) {
12
            return knots[mod(i,N)-1]+(b-a)*floordiv(i,N);
13
       } else {
14
            return a+(b-a)*floordiv(i,N); // a=t_0
15
16
       }
17
   }
18
19
  int find_Span(NURBSData* Data, double t){
20
```

```
21
^{22}
        int N=get_NURBSData_N(Data);
        int low=0, high=N+1; // t in [t_low,t_high)
23
        int index=(low+high)/2;
24
        double t_index=knotseq(Data,index); // t_index
^{25}
        double t_indexp1=knotseq(Data,index+1); // t_{index+1}
26
27
^{28}
        while (t<t_index || t_indexp1<=t) {</pre>
            if (t<0){
29
30
                 return 0;
            }
31
32
            if (t<t_index) {</pre>
33
                high=index;
34
35
            } else {
                 low=index;
36
            }
37
38
            index=(low+high)/2;
            t_index=knotseq(Data, index);
39
            t_indexp1=knotseq(Data, index+1);
40
^{41}
        }
42
43
        return index;
   }
44
45
46
\mathbf{47}
48
   int find_Span_nodes(NURBSData* Data, double t) {
^{49}
50
        int n=get_NURBSData_n(Data);
51
        double* nodes=get_NURBSData_nodes(Data);
52
        double a=get_NURBSData_a(Data);
53
54
        if (a<=t && t<nodes[0]){</pre>
55
            return 0;
56
57
        }
58
        int low=0, high=n-1; // t in [t_low,t_high)
59
60
        int index=(low+high)/2;
61
        while (t<nodes[index] || nodes[index+1]<=t) {</pre>
62
            if (t<nodes[index]) {</pre>
63
                 high=index;
64
            } else {
65
                 low=index;
66
            J
67
            index=(low+high)/2;
68
69
        }
70
        return index+1;
   }
71
72
73
74
75
   double deBoor_help(NURBSData* Data,int i, double* coeffdata,int coefftype,
76
                         int l, double t) {
77
78
        int N=get_NURBSData_N(Data);
79
        int p=get_NURBSData_p(Data);
80
        int k,m;
81
        double beta; // beta_{k,p-m+1}
82
        double t_k,t_kppmmp1; // t_k, t_{k+p-m+1}
83
        double A[l+1]; // help vector
84
85
        // calculation of a_k^[0]=a_k=c_{k+1}=A[k+1-i]
86
87
        for (k=(i-l);k<=i;k=k+1){</pre>
            switch(coefftype){
88
89
                 case 0:
                     A[k+l-i]=coeffdata[k+p]; break;
90
```

```
case 1:
 91
 ^{92}
                      if (mod(k+1,N)!=0) {
                          A[k+1-i] = coeffdata[mod(k+1,N)-1];
 93
                      } else {
 94
                           A[k+l-i]=coeffdata[N-1];
 95
                      } break;
 96
 97
                  case 2:
 ^{98}
                      // c_{k+1}=delta_{k+1, coeffdata[0]}
                      if ( ((int) coeffdata[0]) == (k+1) ) {
 99
100
                           A[k+l-i]=1;
                       } else {
101
                          A[k+1-i]=0;
102
                      }break;
103
             }
104
         }
105
106
         // calculation of a_k^{m} = A[k+1-i-m]
107
108
         for (m=1;m<=1;m=m+1) {</pre>
             for (k=(i-l+m); k<=i; k=k+1) {</pre>
109
                  t_k=knotseq(Data,k);
110
111
                  t_kppmmp1=knotseq(Data,k+p-m+1);
                     beta_{k,p-m+1}
112
113
                  if (!(nearly_equal(t_k,t_kppmmp1))) {
                      beta=(t-t_k)/(t_kppmmpl-t_k);
114
                  } else {
115
116
                      beta=0;
117
                  }
                  // a_k^{[m]=(1-beta_{k,p-m+1}) * a_{k-1}^{[m-1]}
118
                  // + \beta_{k,p-m+1}*a_k^[m-1]
119
                  A[k+1-i-m] = (1-beta) * A[k+1-i-m] + beta * A[k+1-i-m+1];
120
             }
121
         }
122
123
         return A[0];
124
    }
125
126
127
128
    double deBoorDeriv_help(NURBSData* Data, int i, double* coeffdata,
                               int coefftype,int l,double t){
129
130
         int N=get_NURBSData_N(Data);
131
132
         int p=get_NURBSData_p(Data);
133
         int k,m;
         double beta; // beta_{k,p-m}
134
         double t_k,t_kppmm,t_kpp; // t_k, t_{k+p-m}, t_{k+p}
135
         double tmp1,tmp2;
136
         double A_prime[l+1]; // help vector A'
137
138
139
         // calculation of a_k'^[0]=a_k'=c_{k+1}'=A'[k+1-i]
140
         for (k=(i-l); k<=i; k=k+1) {</pre>
141
             t_k=knotseq(Data,k);
142
143
             t_kpp=knotseq(Data,k+p);
             switch(coefftype){
144
145
                  case 0:
146
                      if (nearly_equal(t_kpp,t_k)){
                           A_{prime[k+1-i]} = 0;
147
148
                      }else{
                           A_prime[k+l-i]=p*(coeffdata[k+p]-coeffdata[k+p-1])
149
                           /(t_kpp-t_k);
150
151
                      } break;
                  case 1:
152
                      if (mod(k,N)!=0) {
153
                           tmpl=coeffdata[mod(k,N)-1]; // c_k
154
                      } else {
155
156
                           tmpl=coeffdata[N-1]; // c_k
157
                      }
                      if (mod(k+1,N)!=0) {
158
159
                           tmp2=coeffdata[mod(k+1,N)-1]; // c_{k+1}
                      } else {
160
```

tmp2=coeffdata[N-1]; // c_{k+1} 161 162} if (nearly_equal(t_kpp,t_k)){ 163 A_prime[k+l-i] = 0; 164 } else { 165 $A_{prime[k+l-i]=p*(tmp2-tmp1)/(t_{kpp-t_k);}$ 166 } break; 167 168 case 2: // c_{k+1}=delta_{k+1, coeffdata[0]} 169 170 if (((int) coeffdata[0]) == (k+1))if (nearly_equal(t_kpp,t_k)){ 171 $A_prime[k+1-i]=0;$ 172 }else{ 173 A_prime[k+l-i]=p/(t_kpp-t_k); 174} 175 } else { 176if (((int) coeffdata[0]) == k)177 178if (nearly_equal(t_kpp,t_k)){ 179 A_prime[k+1-i] = 0; }else{ 180 181 A-prime[k+l-i] = -p/(t_kpp-t_k); } 182 183 } else { $A_prime[k+1-i]=0;$ 184} 185 186 } break; 187 } } 188 189 // calculation of a_k'^[m]=A'[k+l-i-m] 190 for (m=1;m<=l;m=m+1) {</pre> 191 for (k=(i-l+m); k<=i; k=k+1) {</pre> 192t_k=knotseq(Data,k); 193 194 t_kppmm=knotseq(Data,k+p-m); $beta_{k,p-m}$ 195 if (!(nearly_equal(t_k,t_kppmm))) { 196 197 $beta=(t-t_k)/(t_kppmm-t_k);$ } else { 198 beta=0; 199 200 } // a_k'^[m]=(1-\beta_{k,p-m}) *a_{k-1}'^[m-1] // +\beta_{k,p-m}*a_k'^[m-1] 201 202 $A_{prime}[k+1-i-m] = (1-beta) * A_{prime}[k+1-i-m]$ 203 + beta*A_prime[k+l-i-m+1]; 204205 } } 206 207 return A_prime[0]; 208 } 209 210 211double deBoor(NURBSData* Data, double* coeffdata, int coefftype, double t) { 212 213int p=get_NURBSData_p(Data); 214215 double index=find_Span(Data,t); 216return deBoor_help(Data, index, coeffdata, coefftype, p, t); 217 218 } 219220 221double deBoorDeriv(NURBSData* Data,double* coeffdata,int coefftype,double t) { 222 int p=get_NURBSData_p(Data); 223 224double index=find_Span(Data,t); 225return deBoorDeriv_help(Data,index,coeffdata,coefftype,p-1,t); 226227 } 228 229 double eval_NURBS(NURBSData* Data, int i, double t){ 230

```
231
232
         int N=get_NURBSData_N(Data);
         double* weights=get_NURBSData_weights(Data);
233
         int is_rational=get_NURBSData_is_rational(Data);
234
         double weight, nominator, denominator;
235
         double coeffdata[1]={(double)i};
236
237
238
         if (is_rational==0) {
239
             return deBoor(Data, coeffdata, 2, t);
         }else{
240
                (mod(i,N)!=0) {
241
             if
                 weight=weights[mod(i,N)-1]; // w_i
242
             } else {
243
                 weight=weights[N-1]; // w_i
244
             }
245
             nominator=weight*deBoor(Data,coeffdata,2,t);
246
             denominator=deBoor(Data,weights,1,t);
247
248
             return nominator/denominator;
         }
249
    }
250
251
252
253
    double eval_NURBSDeriv(NURBSData* Data, int i, double t) {
254
         int N=get_NURBSData_N(Data);
255
256
         double* weights=get_NURBSData_weights(Data);
         int is_rational=get_NURBSData_is_rational(Data);
257
         double weight, nominator, nominator_prime, denominator, denominator_prime;
258
         double coeffdata[1]={(double)i};
259
260
         if (is_rational==0) {
261
             return deBoorDeriv(Data, coeffdata, 2, t);
262
         }else{
263
264
             if
                 (mod(i,N)!=0) {
                 weight=weights[mod(i,N)-1]; // w_i
265
266
             } else {
                 weight=weights[N-1]; // w_i
267
             }
268
269
             nominator=weight*deBoor(Data,coeffdata,2,t);
270
             nominator_prime=weight*deBoorDeriv(Data,coeffdata,2,t);
             denominator=deBoor(Data,weights,1,t);
271
272
             denominator_prime=deBoorDeriv(Data,weights,1,t);
273
             return (nominator_prime*denominator-nominator*denominator_prime)
             /(denominator*denominator);
274
         }
275
    }
276
277
278
    void eval_NURBSCurve(double* output, NURBSData* Data, double* wcpoints1,
279
280
                           double* wcpoints2, double t){
281
         int N=get_NURBSData_N(Data);
282
283
         double* weights=get_NURBSData_weights(Data);
         int is_rational=get_NURBSData_is_rational(Data);
284
285
         double nominator1, nominator2, denominator;
286
         if (is_rational==0) {
287
288
             output[0]=deBoor(Data,wcpoints1,1,t);
             output[1]=deBoor(Data,wcpoints2,1,t);
289
         }else{
290
             nominator1=deBoor(Data,wcpoints1,1,t);
291
             nominator2=deBoor(Data,wcpoints2,1,t);
292
             denominator=deBoor(Data,weights,1,t);
293
294
             output[0]=nominator1/denominator;
295
296
             output[1]=nominator2/denominator;
297
         }
    }
298
299
300
```

```
77
```

```
301
    void eval_NURBSCurveDeriv(double* output, NURBSData* Data, double* wcpoints1,
                                double* wcpoints2, double t){
302
303
        int N=get_NURBSData_N(Data);
304
        double* weights=get_NURBSData_weights(Data);
305
        int is_rational=get_NURBSData_is_rational(Data);
306
307
        double nominator1, nominator2, denominator;
308
        double nominator1_prime, nominator2_prime, denominator_prime;
309
        if (is_rational==0) {
310
             output[0]=deBoorDeriv(Data,wcpoints1,1,t);
311
             output[1]=deBoorDeriv(Data,wcpoints2,1,t);
312
313
        }else{
            nominator1=deBoor(Data,wcpoints1,1,t);
314
315
             nominator2=deBoor(Data,wcpoints2,1,t);
316
             denominator=deBoor(Data,weights,1,t);
             nominator1_prime=deBoorDeriv(Data,wcpoints1,1,t);
317
             nominator2_prime=deBoorDeriv(Data,wcpoints2,1,t);
318
             denominator_prime=deBoorDeriv(Data, weights, 1, t);
319
320
321
             output[0]=(nominator1-prime*denominator-nominator1*denominator-prime)
             /(denominator*denominator);
322
323
             output[1]=(nominator2_prime*denominator-nominator2*denominator_prime)
324
             /(denominator*denominator);
        }
325
    }
326
327
328
    double eval_NURBSComb(NURBSData* Data, double* wcoeffs, double t) {
329
330
        double* knots=get_NURBSData_knots(Data);
331
        int N=get_NURBSData_N(Data);
332
        double* weights=get_NURBSData_weights(Data);
333
334
        int p=get_NURBSData_p(Data);
        int is_rational=get_NURBSData_is_rational(Data);
335
        double b=knots[N-1];
336
        int multb=0; // #b
337
        while (nearly_equal(knots[N-multb-1],b)) {multb=multb+1;}
338
339
        double weight, nominator, denominator;
340
        if (is_rational==0){
341
             return deBoor(Data,wcoeffs,0,t);
342
         }else{
343
            nominator=deBoor(Data,wcoeffs,0,t);
344
             denominator=deBoor(Data,weights,1,t);
345
             return nominator/denominator;
346
        }
347
    }
348
349
350
    double eval_NURBSCombDeriv(NURBSData* Data, double* wcoeffs, double t) {
351
352
353
        double* knots=get_NURBSData_knots(Data);
        int N=get_NURBSData_N(Data);
354
355
        double* weights=get_NURBSData_weights(Data);
        int p=get_NURBSData_p(Data);
356
        int is_rational=get_NURBSData_is_rational(Data);
357
        double b=knots[N-1];
358
359
        int multb=0; // #b
        while (nearly_equal(knots[N-multb-1],b)) {multb=multb+1;}
360
        double weight, nominator, denominator;
361
362
        if (is_rational==0) {
363
            return deBoorDeriv(Data,wcoeffs,0,t);
364
        }else{
365
366
             nominator=deBoor(Data,weights,1,t)*deBoorDeriv(Data,wcoeffs,0,t)
367
                         -deBoor(Data,wcoeffs,0,t) *deBoorDeriv(Data,weights,1,t);
             denominator=deBoor(Data,weights,1,t) *deBoor(Data,weights,1,t);
368
369
             return nominator/denominator;
370
```

A.4 phi_approx.h and phi_approx.c

These two files provide the functions to compute the approximation $\Pi_h \phi$ of the given Neumann boundary condition ϕ .

```
#ifndef _phiapprox_
1
   #define _phiapprox_
2
3
  #include <math.h>
4
   #include <stdio.h>
\mathbf{5}
6 #include "Spline.h"
7
8
   void build_phi_approx(double* output, int p, NURBSData* Data_Gamma,
                double* wcpoints1_gam, double* wcpoints2_gam,
9
                NURBSData* Data_Basis, QuadData* Data_Gauss);
10
^{11}
12
^{13}
   #endif
```

```
1
   #include "phi_approx.h"
2
3
^{4}
   // build_phi_approx
\mathbf{5}
6
   void build_phi_approx(double* output, int p, NURBSData* Data_Gamma,
7
                 double* wcpoints1_gam, double* wcpoints2_gam,
8
                 NURBSData* Data_Basis,QuadData* Data_Gauss) {
9
10
        double* nodes_gauss=get_QuadData_nodes(Data_Gauss);
11
        double* weights_gauss=get_QuadData_weights(Data_Gauss);
12
        int n_gauss=get_QuadData_n(Data_Gauss);
13
^{14}
        int N=get_NURBSData_N(Data_Basis);
15
        int n=get_NURBSData_n (Data_Basis);
16
17
        int j_tmp=0;
18
19
        int counter=0;
^{20}
        int k1=0;
        int i=0;
^{21}
22
        int j=0;
        int k=0;
^{23}
        int q1=0;
24
^{25}
        double t_k1m1=0;
26
        double t_k1=0;
27
        double H_k1=0;
^{28}
29
30
        double intpoint1=0;
31
        double tmp[2];
32
33
        double tmp2[2];
        double y[p+1];
34
35
        double x[p+1];
        double lhs[n][p+1][p+1];
36
        double rhs[n][p+1];
37
38
39
        double L[p+1][p+1];
        double U[p+1][p+1];
40
^{41}
^{42}
        double knots_tmp[p+1];
^{43}
```

```
for (i=0;i<p+1;++i) {</pre>
44
^{45}
             knots_tmp[i]=1;
        }
46
        double weights_tmp[p+1];
47
        for (i=0;i<p+1;++i) {</pre>
^{48}
             weights_tmp[i]=1;
49
50
        }
51
        double nodes_tmp[1];
52
        nodes_tmp[0]=1;
        int is_rational_tmp=0;
53
        NURBSData * Basis_tmp=new_NURBSData(0,knots_tmp,p+1,weights_tmp,p,nodes_tmp,1,0);
54
55
56
57
        double sum=0;
58
59
         for (i=0;i<n*(p+1);++i) {</pre>
60
61
             output[i]=0;
         }
62
63
64
         //build left hand side
        for (k1=1;k1<=N;++k1) {</pre>
65
66
             t_k1m1=knotseq(Data_Basis,k1-1);
             t_k1=knotseq(Data_Basis,k1);
67
             H_k1=t_k1-t_k1m1;
68
69
             if (0<H_k1) {
70
71
                  for (j_tmp=0; j_tmp<p+1;++j_tmp){</pre>
72
                      knots_tmp[j_tmp]=t_k1;
73
                  }
74
                  nodes_tmp[0]=t_k1;
75
                  Basis_tmp=del_NURBSData(Basis_tmp);
76
77
                  Basis_tmp=new_NURBSData(t_k1m1,knots_tmp,p+1,weights_tmp,p,nodes_tmp,1,0);
78
                  for (i=0;i<=p;++i) {</pre>
79
                      for (j=0;j<=p;++j) {</pre>
80
                           lhs[counter][i][j]=0;
81
82
83
                           for (q1=0;q1<n_gauss;++q1) {</pre>
                                intpoint1=t_k1m1+H_k1*nodes_gauss[q1];
84
85
                               eval_NURBSCurveDeriv(tmp,Data_Gamma,wcpoints1_gam,
                                                           wcpoints2_gam, intpoint1);
86
87
                               lhs[counter][i][j] += weights_gauss[q1]
88
                                             *eval_NURBS(Basis_tmp,i-p+1,intpoint1)
89
                                             *eval_NURBS(Basis_tmp,j-p+1,intpoint1)
90
                                             *norm(tmp);
91
92
                           lhs[counter][i][j] *= H_k1;
93
                      }
^{94}
                  }
95
96
                  ++counter;
             }
97
98
        }
99
        counter=0;
100
101
         //build right hand side
         for (k1=1;k1<=N;++k1) {</pre>
102
             t_k1m1=knotseq(Data_Basis,k1-1);
103
104
             t_k1=knotseq(Data_Basis,k1);
             H_k1=t_k1-t_k1m1;
105
106
             if (0<H_k1) {
107
108
                  for (j_tmp=0; j_tmp<p+1;++j_tmp){</pre>
109
110
                      knots_tmp[j_tmp]=t_k1;
                  }
111
112
                  nodes_tmp[0]=t_k1;
                  Basis_tmp=del_NURBSData(Basis_tmp);
```

```
80
```

113

```
114
                   Basis_tmp=new_NURBSData(t_k1m1,knots_tmp,p+1,weights_tmp,p,nodes_tmp,1,0);
115
116
117
118
                   for (i=0;i<=p;++i) {</pre>
119
                       rhs[counter][i]=0;
120
121
122
                        for (q1=0;q1<n_gauss;++q1) {</pre>
123
                            intpoint1=t_k1m1+H_k1*nodes_gauss[q1];
                            eval_NURBSCurveDeriv(tmp,Data_Gamma,wcpoints1_gam,
124
                                                             wcpoints2_gam, intpoint1);
125
                            eval_NURBSCurve(tmp2,Data_Gamma,wcpoints1_gam,
126
                                                        wcpoints2_gam, intpoint1);
127
128
                            rhs[counter][i] += weights_gauss[q1]
129
                                               *eval_NURBS(Basis_tmp,i-p+1,intpoint1)
130
131
                                               *norm(tmp)*phi(tmp2);
                        }
132
                        rhs[counter][i] *= H_k1;
133
134
                   }
                   ++counter;
135
136
              }
137
         }
138
139
         counter=0;
140
         //solve system for each element via LU-decomposition
141
142
         for (k1=1;k1<=N;++k1) {</pre>
              t_k1m1=knotseq(Data_Basis,k1-1);
143
              t_k1=knotseq(Data_Basis,k1);
144
              H_k1=t_k1-t_k1m1;
145
              if (0<H_k1){
146
147
                   //compute L and U
                   for (i=0;i<=p;++i) {</pre>
148
149
                        L[i][i]=1;
150
                        for (k=i;k<=p;++k) {</pre>
                            if (k>=i) {
151
                                 sum=0;
152
153
                                 for (j=0; j<i;++j) {</pre>
                                      sum += L[i][j]*U[j][k];
154
155
                                 }
                                 U[i][k]=lhs[counter][i][k]-sum;
156
                            }
157
                            if (k>i) {
158
                                 sum=0;
159
                                 for (j=0; j<i;++j) {</pre>
160
                                      sum += L[k][j]*U[j][i];
161
162
                                 L[k][i]=(lhs[counter][k][i]-sum)/U[i][i];
163
                            }
164
                       }
165
166
                   }
167
                   //solve lhs*x=LU*x=L*y=rhs
168
169
                   for (j=0; j<=p;++j) {</pre>
                       sum=0;
170
171
                        for(k=0;k<j;++k){</pre>
                            sum += L[j][k]*y[k];
172
                        }
173
174
                        y[j]=rhs[counter][j]-sum;
                   }
175
176
                   //solve U*x=y
177
                   for (j=p; j>=0;---j) {
178
179
                        sum=0;
180
                        for (k=p;k>j;---k) {
                            sum += U[j][k]*x[k];
181
182
                        }
                       x[j]=(y[j]-sum)/U[j][j];
183
```

```
}
184
185
186
                    for (i=0;i<=p;++i) {</pre>
187
                         output[(counter) * (p+1) +i] =x[i];
188
                    }
189
190
                    ++counter;
191
               }
          }
192
          Basis_tmp=del_NURBSData(Basis_tmp);
193
    }
194
```

A.5 WMatrix.h and WMatrix.c

These two files contain everything to compute the mass matrix W_h from Section 6.

```
1
   #ifndef _WMatrix_
2 #define _WMatrix_
3
4 #include <math.h>
  #include <stdio.h>
5
  #include "Spline.h"
6
7
  double W_h1_integrand_smooth(NURBSData* Data_Gamma, double* wcpoints1_gam,
8
               double* wcpoints2_gam, NURBSData* Data_Basis, double s,
9
10
               double t, int i, int k, double denominator, double Jdet);
11
12 double W_h1_integrand_log(NURBSData* Data_Basis, double s,double t,int i,
13
               int j, double Jdet);
14
  double W_h1_integral_identical(NURBSData* Data_Gamma, double* wcpoints1_gam,
15
               double* wcpoints2_gam, NURBSData* Data_Basis,
16
               QuadData* Data_Gauss, QuadData* Data_LogGauss,
17
               int i, int j, int k);
18
19
  double W_h1_integral_adjacent (NURBSData* Data_Gamma, double* wcpoints1_gam,
20
               double* wcpoints2_gam, NURBSData* Data_Basis,
21
               QuadData* Data_Gauss,QuadData* Data_LogGauss,
22
               int i, int j, int k1, int k2);
23
^{24}
  void build_W_h1(double* output, NURBSData* Data_Gamma, double* wcpoints1_gam,
25
26
               double* wcpoints2_gam, NURBSData* Data_Basis,
27
               QuadData* Data_Gauss, QuadData* Data_LogGauss);
^{28}
29
  void build_W_h2 (double* output, NURBSData* Data_Gamma, double* wcpoints1_gam,
               double* wcpoints2_gam, NURBSData* Data_Basis,
30
               QuadData* Data_Gauss,QuadData* Data_LogGauss);
31
32
33
  void build_W(double* output, NURBSData* Data_Gamma, double* wcpoints1_gam,
               double* wcpoints2_gam, NURBSData* Data_Basis,
34
               QuadData* Data_Gauss, QuadData* Data_LogGauss);
35
36
  #endif
37
```

```
#include "WMatrix.h"
1
2
3
4
5 // W_h1_integrand_smooth
   //-
6
7
8
   double W_h1_integrand_smooth(NURBSData* Data_Gamma, double* wcpoints1_gam,
9
               double* wcpoints2_gam, NURBSData* Data_Basis, double t,
10
^{11}
               double s, int i, int j, double denominator, double Jdet){
```

```
12
     double tmp1[2];
13
     double tmp2[2];
14
     double diff_gam[2];
15
     double R_st_j=0; // R_j^\prime(s)
16
     double R_st_i=0; // R_i^\prime(t)
17
18
19
     //gamma(s)
     eval_NURBSCurve(tmp1, Data_Gamma, wcpoints1_gam, wcpoints2_gam,t);
20
^{21}
22
     //gamma(t)
     eval_NURBSCurve(tmp2, Data_Gamma, wcpoints1_gam, wcpoints2_gam,s);
23
^{24}
     //gamma(s)-gamma(t)
25
     diff_gam[0]=tmp1[0]-tmp2[0];
26
     diff_gam[1]=tmp1[1]-tmp2[1];
^{27}
28
^{29}
     //R'_j(t)
     R_st_j=eval_NURBSDeriv(Data_Basis, j, t);
30
31
32
     //R'_i(s)
     R_st_i=eval_NURBSDeriv(Data_Basis, i, s);
33
34
     return -log(norm(diff_gam)/fabs(denominator))/(2*M_PI)*R_st_j*R_st_i*Jdet;
35
36 }
37
38
39
  // W_h1_integrand_log
40
41
42
^{43}
  double W_h1_integrand_log(NURBSData* Data_Basis, double t, double s, int i,
44
^{45}
                int j, double Jdet){
46
       double R_st_i=0; // R_i^\prime(s)
47
       double R_st_j=0; // R_j^\prime(t)
48
49
       R_st_j = eval_NURBSDeriv(Data_Basis, j, t);
50
51
       R_st_i = eval_NURBSDeriv(Data_Basis, i, s);
52
       return R_st_j *R_st_i*Jdet/(2*M_PI);
53
54 }
55
56
57
   // W_h1_integral_identical
58
59
60
61
   double W_h1_integral_identical(NURBSData* Data_Gamma, double* wcpoints1_gam,
62
                double* wcpoints2_gam, NURBSData* Data_Basis,
63
64
                QuadData* Data_Gauss, QuadData* Data_LogGauss,
               int i, int j, int k){
65
66
       double* nodes_gauss=get_QuadData_nodes(Data_Gauss);
67
       double* weights_gauss=get_QuadData_weights(Data_Gauss);
68
69
       int n_gauss=get_QuadData_n(Data_Gauss);
70
       double* nodes_loggauss=get_QuadData_nodes(Data_LogGauss);
71
       double* weights_loggauss=get_QuadData_weights(Data_LogGauss);
72
       int n_loggauss=get_QuadData_n(Data_LogGauss);
73
74
       int q1=0;
75
       int q2=0;
76
77
       double t_km1=knotseq(Data_Basis,k-1); // t_{k-1}
78
       double t_k=knotseq(Data_Basis,k); // t_k
79
80
       double H_k=t_k-t_km1; // H_k
81
```

```
82
        double squareint=0;
        double intpoint1=0;
 83
        double intpoint2=0;
 84
 85
        double denominator;
 86
        double Jdet;
 87
 88
 89
         //smooth integrals
 90
         for (q1=0; q1<n_gauss; q1++) {</pre>
             for (q2=0; q2<n_gauss; q2++) {</pre>
 91
                  intpoint1=t_km1+H_k*(1-nodes_gauss[q1]);
 92
                  intpoint2=t_km1+H_k*(1-nodes_gauss[q1]
93
                               +nodes_gauss[q1]*nodes_gauss[q2]);
 94
                  denominator=nodes_gauss[q1]*nodes_gauss[q2];
 95
 96
                 Jdet=nodes_gauss[q1];
 97
                  squareint += weights_gauss[q1]*weights_gauss[q2]
 98
 99
                               *W_h1_integrand_smooth(Data_Gamma, wcpoints1_gam,
                                        wcpoints2_gam, Data_Basis, intpoint1,
100
                                        intpoint2, i, j, denominator, Jdet);
101
102
                  intpoint1=t_km1+H_k *nodes_gauss[q1];
103
104
                  intpoint2=t_kml+H_k*(nodes_gauss[q1]
                               -nodes_gauss[q1]*nodes_gauss[q2]);
105
                  denominator=nodes_gauss[q1]*nodes_gauss[q2];
106
                 Jdet=nodes_gauss[q1];
107
108
                  squareint += weights_gauss[q1] *weights_gauss[q2]
109
                               *W_h1_integrand_smooth(Data_Gamma, wcpoints1_gam,
110
                                        wcpoints2_gam, Data_Basis, intpoint1,
intpoint2, i, j, denominator, Jdet);
111
112
113
             }
        }
114
115
         //integrals with t-logarithmic singularity
116
         for (q1=0;q1<n_loggauss;q1++) {</pre>
117
             for (q2=0;q2<n_gauss;q2++) {</pre>
118
                  intpoint1=t_km1+H_k*(1-nodes_gauss[q2]);
119
                  intpoint2=t_km1+H_k*(1-nodes_gauss[q2]
120
121
                               +nodes_loggauss[q1]*nodes_gauss[q2]);
                  Jdet=nodes_gauss[g2];
122
123
                  squareint += weights_loggauss[q1] *weights_gauss[q2]
124
                               *W_h1_integrand_log(Data_Basis, intpoint1,
125
                                        intpoint2, i, j, Jdet);
126
127
                  intpoint1=t_km1+H_k*(nodes_gauss[q2]);
128
                  intpoint2=t_km1+H_k * (nodes_gauss[q2]
129
                               -nodes_loggauss[q1]*nodes_gauss[q2]);
130
131
                 Jdet=nodes_gauss[q2];
132
                 squareint += weights_loggauss[q1] *weights_gauss[q2]
133
134
                               *W_h1_integrand_log(Data_Basis, intpoint1,
                                        intpoint2, i, j, Jdet);
135
136
             }
         }
137
138
         // integrals with s-logarithmic singularity
139
         for (q1=0;q1<n_gauss;q1++) {</pre>
140
             for (q2=0;q2<n_loggauss;q2++) {</pre>
141
                  intpoint1=t_km1+H_k*(1-nodes_loggauss[q2]);
142
                  intpoint2=t_km1+H_k*(1-nodes_loggauss[q2]
143
                               +nodes_gauss[q1]*nodes_loggauss[q2]);
144
                 Jdet=nodes_loggauss[q2];
145
146
                  squareint += weights_gauss[q1] *weights_loggauss[q2]
147
148
                               *W_h1_integrand_log(Data_Basis, intpoint1,
                                        intpoint2, i, j, Jdet);
149
150
                  intpoint1=t_km1+H_k *nodes_loggauss[q2];
151
```

```
152
                  intpoint2=t_km1+H_k * (nodes_loggauss[q2]
                               -nodes_gauss[q1]*nodes_loggauss[q2]);
153
                  Jdet=nodes_loggauss[q2];
154
155
                  squareint += weights_gauss[q1]*weights_loggauss[q2]
156
                               *W_h1_integrand_log(Data_Basis, intpoint1,
157
158
                                       intpoint2, i, j, Jdet);
159
             }
         }
160
         return squareint;
161
    }
162
163
164
165
    // W_h1_integral_adjacent
166
167
168
169
    double W_h1_integral_adjacent(NURBSData* Data_Gamma, double* wcpoints1_gam,
170
                  double* wcpoints2_gam, NURBSData* Data_Basis,
171
172
                 QuadData* Data_Gauss, QuadData* Data_LogGauss,
                 int i, int j, int k1, int k2){
173
174
         double* nodes_gauss=get_QuadData_nodes(Data_Gauss);
175
         double* weights_gauss=get_QuadData_weights(Data_Gauss);
176
         int n_gauss=get_QuadData_n(Data_Gauss);
177
178
         double* nodes_loggauss=get_QuadData_nodes(Data_LogGauss);
179
         double* weights_loggauss=get_QuadData_weights(Data_LogGauss);
180
         int n_loggauss=get_QuadData_n (Data_LogGauss);
181
182
         int q1=0;
183
         int q2=0;
184
185
         double t_k1m1=knotseq(Data_Basis,k1-1); // t_{k_1-1} == t_{k-1}
186
         double t_k1=knotseq(Data_Basis,k1); // t_{k_1} == t_k
187
         double H_k1=t_k1-t_k1m1; // H_{k_1} == H_k
188
189
         double t_k2m1=knotseq(Data_Basis,k2-1); // t_{k_2-1} == t_{m-1}
190
191
         double t_k2=knotseq(Data_Basis,k2); // t_{k_2} == t_m
         double H_k2=t_k2-t_k2m1; // H_{k_2} == H_m
192
193
         double squareint=0; // integral over square
194
         double intpoint1=0; // first and second integration point
195
         double intpoint2=0;
196
         double denominator;
197
         double Jdet; // Jacobi determinant of Duffy transformation
198
199
200
         // smooth integrals
201
         for (q1=0;q1<n_gauss;q1++) {</pre>
             for (q2=0;q2<n_gauss;q2++) {</pre>
202
                 intpoint1=t_k1m1+H_k1*nodes_gauss[q1];
203
204
                  intpoint2=t_k2m1 + H_k2*(1-nodes_gauss[q1]*nodes_gauss[q2]);
                 denominator=nodes_gauss[q1];
205
206
                 Jdet=nodes_gauss[q1];
207
                 squareint += weights_gauss[q1] *weights_gauss[q2]
208
209
                               *W_h1_integrand_smooth(Data_Gamma, wcpoints1_gam,
210
                                        wcpoints2_gam, Data_Basis, intpoint1,
                                       intpoint2, i, j, denominator,Jdet);
211
212
                  intpoint1 = t_k1m1+H_k1*nodes_gauss[q1]*nodes_gauss[q2];
213
                 intpoint2 = t_k2m1+H_k2*(1-nodes_gauss[q2]);
214
                 denominator = nodes_gauss[q2];
215
                 Jdet = nodes_gauss[q2];
216
217
218
                 squareint += weights_gauss[q1] *weights_gauss[q2]
                              *W_hl_integrand_smooth(Data_Gamma, wcpoints1_gam,
wcpoints2_gam, Data_Basis, intpoint1,
219
220
                                        intpoint2, i, j, denominator, Jdet);
221
```

```
}
222
223
         }
224
         // integral with t-logarithmic singularity
225
         for (q1=0;q1<n_loggauss;q1++) {</pre>
226
             for (q2=0;q2<n_gauss;q2++) {</pre>
227
                  intpoint1 = t_k1m1+H_k1*nodes_loggauss[q1];
228
229
                  intpoint2 = t_k2m1+H_k2*(1-nodes_loggauss[q1]*nodes_gauss[q2]);
230
                  Jdet = nodes_loggauss[q1];
231
                  squareint += weights_loggauss[q1] *weights_gauss[q2]
232
                               *W_h1_integrand_log(Data_Basis, intpoint1,
233
                                       intpoint2, i, j, Jdet);
234
             }
235
         }
236
237
         // integral with t-logarithmic singularity
238
239
         for (q1=0;q1<n_gauss;q1++) {</pre>
             for (q2=0;q2<n_loggauss;q2++) {</pre>
240
                  intpoint1 = t_k1m1+H_k1*nodes_gauss[q1]*nodes_loggauss[q2];
241
                  intpoint2 = t_k2m1+H_k2*(1-nodes_loggauss[q2]);
242
                  Jdet = nodes_loggauss[q2];
243
244
                  squareint += weights_gauss[q1] *weights_loggauss[q2]
245
                               *W_h1_integrand_log(Data_Basis, intpoint1,
246
247
                                       intpoint2, i, j, Jdet);
             }
248
         }
249
250
         return squareint;
251
    }
252
253
254
255
    // build_W_h1
256
257
258
259
    void build_W_h1(double* output, NURBSData* Data_Gamma, double* wcpoints1_gam,
260
261
             double* wcpoints2_gam, NURBSData* Data_Basis, QuadData* Data_Gauss,
             QuadData* Data_LogGauss) {
262
263
         double* nodes_gauss=get_QuadData_nodes(Data_Gauss);
264
         double* weights_gauss=get_QuadData_weights(Data_Gauss);
265
         int n_gauss=get_QuadData_n(Data_Gauss);
266
267
         int N=get_NURBSData_N(Data_Basis);
268
         int p=get_NURBSData_p(Data_Basis);
269
270
271
         double tmp[2];
272
         int i=0;
273
274
         int j=0;
         int k1=0;
275
276
         int k2=0;
         int q1=0;
277
         int q2=0;
278
279
         int multb=1+p; // #b
280
281
282
         double R_st [N][p+1][n_gauss];
         // R_st [i-1+p][k1-i][q1] = R_{i,k1}^\prime(nodes_gauss[q1])
283
284
         double gamma1[N][n_gauss];
285
         // gammal[k1-1][q1] is first component of
286
         // gamma(t_{k1-1}+H_k1*nodes_gauss[q1])
287
288
         double gamma2[N][n_gauss];
289
         // gamma2[l1-1][q1] is second component of
290
         // gamma(t_{11-1}+H_11*nodes_gauss[q1])
291
```

```
292
293
         double squareint=0; // integral over square
         double t_k1m1=0;
294
         double t_k1=0:
295
         double H_k1=0;
296
         double t_k2m1;
297
298
         double t_k2=0;
299
         double H_k2=0;
300
         // t_{k1-1},t_k1,H_k1,t_{k2-1},t_k2,H_k2
301
         double intpoint; // integration point
302
303
304
         // calculation of R_st
305
         // R_i_st
306
         for (i=1-p;i<=(N-p);i++) {</pre>
307
             for (k1=max(i,1);k1<=min(i+p,N);k1++){</pre>
308
309
             // elements with nonemty intersection with support of R_i
310
                  // quadrature points
                  for (q1=0;q1<n_gauss;q1++) {</pre>
311
312
                      t_k1m1 = knotseq(Data_Basis, k1-1);
                      t_k1 = knotseq(Data_Basis,k1);
313
314
                      H_k1 = t_k1-t_k1m1;
                      intpoint = t_k1m1+H_k1*nodes_gauss[q1];
315
316
317
                      R_st[i-1+p][k1-i][q1] = eval_NURBSDeriv(Data_Basis, i, intpoint);
318
                  }
319
             }
320
         }
321
322
         // calculation of gamma1, gamma2
323
         for (k1=1;k1<=N;k1++) {</pre>
324
325
             for (q1=0;q1<n_gauss;q1++) {</pre>
                  t_k1m1 = knotseq(Data_Basis, k1-1);
326
                  t_k1 = knotseq(Data_Basis,k1);
327
                  H_k1 = t_k1 - t_k1m1;
328
329
                  intpoint=t_k1m1+H_k1*nodes_gauss[q1];
330
331
                  eval_NURBSCurve(tmp, Data_Gamma, wcpoints1_gam, wcpoints2_gam,
                                    intpoint);
332
333
                  gamma1[k1-1][q1] = tmp[0];
                  gamma2[k1-1][q1] = tmp[1];
334
             }
335
         }
336
337
338
         // calculation of W_h1_matrix
339
         // R_i
340
         for (i=1-p;i<=(N-p);i++) {</pre>
341
              // R_j
342
             for (j=1-p;j<=i;j++) {</pre>
343
344
                  output[i+p-1+(j+p-1)*(N)]=0;
                  // elements with nonemty intersection with support of R_j
345
346
                  for (k1=max(j,1);k1<=min(j+p,N);k1++) {</pre>
                       // elements with nonemty intersection with support of R_i
347
                      for (k2=max(i,1);k2<=min(i+p,N);k2++) {</pre>
348
349
                           t_k1m1 = knotseq(Data_Basis,k1-1);
                           t_k1 = knotseq(Data_Basis,k1);
350
                           t_k2m1 = knotseq(Data_Basis,k2-1);
351
352
                           t_k2 = knotseq(Data_Basis,k2);
                           H_k1 = t_k1 - t_k1m1;
353
                           H_k2 = t_k2 - t_k2m1;
354
                           // quadrature
355
                           if (0<min(H_k1,H_k2)){
356
357
                                // elements with no intersection
358
                               squareint=0;
                               if ((!nearly_equal(t_k1m1,t_k2m1))
359
360
                                    && (!nearly_equal(t_k1m1,t_k2))
                                    && (!nearly_equal(t_k1,t_k2m1))
361
```



```
432
433
         double* nodes_gauss=get_QuadData_nodes(Data_Gauss);
         double* weights_gauss=get_QuadData_weights(Data_Gauss);
434
         int n_gauss=get_QuadData_n(Data_Gauss);
435
436
         //double* knots=get_NURBSData_knots(Data_Basis);
437
         int N=get_NURBSData_N(Data_Basis);
438
439
         int p=get_NURBSData_p(Data_Basis);
         double tmp[2];
440
441
         int i,j,k1,k2,q1,q2;
442
         //double b=knots[N-1];
443
         int multb=p+1; // #b
444
445
         double R_til[N_multb+1+p][p+1][n_gauss];
446
         // R_til[i-1+p][k1-i][q1]=\tilde{R}_{i,k1} (nodes_gauss[q1])
447
448
449
         double squareint; // integral over square
         double t_k1m1,t_k1,H_k1,t_k2m1,t_k2,H_k2;
450
         // t_{ll-1},t_ll,H_ll,t_{l2-1},t_l2,H_l2
451
452
         double intpoint; // integration point
453
454
         // calculation of R_til
455
         // R_i
456
457
         for (i=1-p;i<=(N-p);i++) {</pre>
              // elements with nonemty intersection with support of R_i
458
             for (k1=max(i,1);k1<=min(i+p,N);k1++) {</pre>
459
                  // quadrature points
460
                  for (q1=0;q1<n_gauss;q1++) {</pre>
461
                      t_k1m1=knotseq(Data_Basis,k1-1);
462
                      t_k1=knotseq(Data_Basis,k1);
463
                      H_k1=t_k1-t_k1m1:
464
465
                      intpoint=t_k1m1+H_k1*nodes_gauss[q1];
                      eval_NURBSCurveDeriv(tmp,Data_Gamma,wcpoints1_gam,
466
                                              wcpoints2_gam, intpoint);
467
                      R_til[i-1+p][k1-i][q1]=eval_NURBS(Data_Basis, i,intpoint)
468
469
                      *norm(tmp);
                  }
470
471
             }
         }
472
473
         // calculation of W_h2_matrix
474
         // R_i
475
         for (i=1-p;i<=(N-multb+1);i++) {</pre>
476
             // R_j
477
             for (j=1-p;j<=i;j++) {</pre>
478
                  // elements with nonemty intersection with support of \ensuremath{\mathtt{R}}\xspace\_i
479
                  if (i==N-p || j==N-p){
480
                      output[i+p-1+(j+p-1)*N]=0;
481
                  }
482
                  for (k1=max(i,1);k1<=min(i+p,N);k1++) {</pre>
483
484
                       // elements with nonemty intersection with support of R_{\rm -}j
                      for (k2=max(j,1);k2<=min(j+p,N);k2++) {</pre>
485
486
                           t_k1m1 = knotseq(Data_Basis,k1-1);
                           t_k1 = knotseq(Data_Basis,k1);
487
                           t_k2m1 = knotseg(Data_Basis,k2-1);
488
                           t_k2 = knotseq(Data_Basis,k2);
489
                           H_k1 = t_k1 - t_k1m1;
490
                           H_k2 = t_k2 - t_k2m1;
491
492
                           // quadrature
                           if (0<min(H_k1,H_k2)){
493
                                // elements with no intersection
494
                                squareint=0;
495
                                for (q1=0;q1<n_gauss;q1++) {</pre>
496
                                    for (q2=0;q2<n_gauss;q2++) {</pre>
497
498
                                         squareint += weights_gauss[q1] *weights_gauss[q2]
                                                           *R_til[i-1+p][k1-i][q1]
499
500
                                                           *R_til[j-1+p][k2-j][q2];
                                    }
501
```

```
}
502
503
                          }
504
                          output[i+p-1+(j+p-1)*(N-multb+1+p)] += H_k1*H_k2
505
                                                                        *squareint;
506
                      }
507
                 }
508
509
                  if (i!=j) {
510
511
                      // W_h2 symmetric
                      output[j+p-1+(i+p-1)*(N-multb+1+p)] = output[i+p-1+(j+p-1)]
512
                                                                   *(N-multb+1+p)];
513
514
                 }
             }
515
        }
516
        output[0] += 2 * output[N-1] + output[N*N-1];
517
518
519
         for(i=2-p;i<=N-p-1;i++){</pre>
             output[i+p-1] += output[i+p-1+(N-1)*N];
520
             output[(i+p-1)*N] += output[N-1+(i+p-1)*N];
521
522
         }
    }
523
524
525
526
527
    // build_W_h
528
529
530
    void build_W(double* output, NURBSData* Data_Gamma, double* wcpoints1_gam,
531
532
                 double* wcpoints2_gam, NURBSData* Data_Basis,
                 QuadData* Data_Gauss,QuadData* Data_LogGauss) {
533
534
535
        build_W_h1 (output, Data_Gamma, wcpoints1_gam, wcpoints2_gam,
                 Data_Basis, Data_Gauss, Data_LogGauss);
536
        build_W_h2(output, Data_Gamma, wcpoints1_gam, wcpoints2_gam,
537
                 Data_Basis, Data_Gauss, Data_LogGauss);
538
539
    }
```

A.6 FVector.h and FVector.c

These two files are used to compute the right-hand side vector F_h from Section 6.

```
1 #ifndef _Fvector_h
2
  #define _Fvector_h
3
4 #include <math.h>
5
  #include <stdio.h>
6
   #include "Spline.h"
   #include "phi_approx.h"
7
8
   double F_integrand_K (NURBSData* Data_Gamma, double* wcpoints1_gam,
9
               double* wcpoints2_gam,NURBSData* Data_Basis,NURBSData* Basis_tmp,
10
                int j,double t,double s,double Jdet,int p-phi-approx,double* coeff);
11
12
13
   double F_integral_K_identical (NURBSData* Data_Gamma, double* wcpoints1_gam,
14
                double* wcpoints2_gam,NURBSData* Data_Basis,NURBSData* Basis_tmp,
15
16
                QuadData* Data_Gauss, double* coeff,
               int j, int k, int p_phi_approx);
17
18
19
  double F_integral_K_Adjacent(NURBSData* Data_Gamma, double* wcpoints1_gam,
20
21
                double* wcpoints2_gam,NURBSData* Data_Basis,NURBSData* Basis_tmp,
                QuadData* Data_Gauss, double* coeff,
^{22}
                int j,int k1,int k2,int singtype,int p_phi_approx);
23
^{24}
```

```
void build-Fvector(double* output,NURBSData* Data_Gamma,double* wcpoints1_gam,
double* wcpoints2_gam,NURBSData* Data_Basis,
QuadData* Data_Gauss,QuadData* Data_Gauss_small,
QuadData* Data_Gauss_phi_approx,
int with_K,int p_phi_approx, double* coeff);
and
if #endif
```

```
#include "Fvector.h"
1
2
3
4
   // F_integrand_K
\mathbf{5}
6
7
8
   double F_integrand_K(NURBSData* Data_Gamma, double* wcpoints1_gam,
9
            double* wcpoints2_gam, NURBSData* Data_Basis, NURBSData* Basis_tmp,
10
11
            int j, double t, double s, double Jdet, int p_phi_approx, double* coeff){
12
13
        double a=get_NURBSData_a(Data_Basis);
        int n=get_NURBSData_n (Data_Basis);
^{14}
        double* nodes=get_NURBSData_nodes(Data_Basis);
15
        double nodesa[n+1];
16
17
        nodesa[0]=a;
18
        int j_tmp=0;
19
20
        for (j_tmp=1; j_tmp<=n; ++ j_tmp) {</pre>
21
            nodesa[j_tmp]=nodes[j_tmp-1];
^{22}
        }
23
^{24}
        double sum=0;
^{25}
        int index=0;
26
27
        index=find_Span_nodes(Data_Basis,t);
^{28}
29
30
        double knots_tmp[p_phi_approx+1];
        double nodes_tmp[1];
31
32
        double weights_tmp[p_phi_approx+1];
33
34
        for (j_tmp=0;j_tmp<p_phi_approx+1;j_tmp++) {</pre>
35
            knots_tmp[j_tmp]=nodesa[index+1];
36
37
            weights_tmp[j_tmp]=1;
38
        }
        nodes_tmp[0]=nodesa[index+1];
39
40
        NURBSData* Data_Basis_tmp=new_NURBSData(nodesa[index], knots_tmp,
^{41}
                     p_phi_approx+1, weights_tmp, p_phi_approx, nodes_tmp, 1, 0);
42
^{43}
44
45
        double tmp1[2];
46
        double tmp2[2];
47
        double diff_gam[2]; // gamma(t)-gamma(s)
48
        double phi_til,R_nu1,R_nu2;
49
50
        eval_NURBSCurve(tmp1,Data_Gamma,wcpoints1_gam,wcpoints2_gam,t);
51
        // gamma(t)
52
        eval_NURBSCurve(tmp2,Data_Gamma,wcpoints1_gam,wcpoints2_gam,s);
53
        // gamma(s)
54
        sum=0;
55
56
        for (j_tmp=0; j_tmp<=p_phi_approx;++j_tmp) {</pre>
            sum+=coeff[index*(p_phi_approx+1)+j_tmp]
57
                                  *eval_NURBS(Data_Basis_tmp,j_tmp-p_phi_approx+1,t);
58
59
        }
60
```

```
61
        phi_til=sum;
 62
        diff_gam[0] = tmp1[0] - tmp2[0];
 63
        diff_gam[1] = tmp1[1] - tmp2[1];
 64
 65
        R_nu1 = eval_NURBS(Data_Basis, j, s);
 66
 67
        R_nu2 = eval_NURBS(Data_Basis, j, s);
 68
        eval_NURBSCurveDeriv(tmp1,Data_Gamma,wcpoints1_gam,wcpoints2_gam,t);
 69
        // gamma'(t)
 70
        eval_NURBSCurveDeriv(tmp2,Data_Gamma,wcpoints1_gam,wcpoints2_gam,s);
 71
        // gamma'(s)
 72
 73
        phi_til *= norm(tmp1);
 74
        R_nu1 *= tmp2[1];
 75
        R_nu2 *= -tmp2[0];
 76
 77
        Data_Basis_tmp=del_NURBSData(Data_Basis_tmp);
 78
 79
        return ((diff_gam[0]*R_nu1 + diff_gam[1]*R_nu2)
 80
 81
                          / (2*M_PI*norm(diff_gam)))*(Jdet/norm(diff_gam)) * phi_til;
    }
 82
 83
 84
 85
    // F_integral_K_identical
 86
 87
 88
 89
    double F_integral_K_identical(NURBSData* Data_Gamma, double* wcpoints1_gam,
 90
                 double* wcpoints2_gam, NURBSData* Data_Basis, NURBSData* Basis_tmp,
 91
                 QuadData* Data_Gauss,double* coeff, int j, int k, int p_phi_approx){
 ^{92}
 93
 94
        double* nodes_gauss=get_QuadData_nodes(Data_Gauss);
        double* weights_gauss=get_QuadData_weights(Data_Gauss);
 95
        int n_gauss=get_QuadData_n (Data_Gauss);
 96
        int q1,q2;
 97
 98
        double t_km1=knotseq(Data_Basis,k-1); // t_{k-1}
 99
100
        double t_k=knotseq(Data_Basis,k); // t_{k}
        double H_k=t_k-t_km1; // H_k
101
102
        double squareint=0; // integral over square
        double intpoint1, intpoint2; // first and second integration point
103
        double Jdet; // Jacobi determinant for Duffy transformation
104
105
        for (q1=0;q1<n_gauss;q1++) {</pre>
106
             for (q2=0;q2<n_gauss;q2++) {</pre>
107
                 intpoint1=t_km1+H_k *nodes_gauss[q1];
108
                 intpoint2=t_km1+H_k *nodes_gauss[q1]*(1-nodes_gauss[q2]);
109
110
                 Jdet=nodes_gauss[q1];
111
                 squareint+=weights_gauss[q1] *weights_gauss[q2]
112
113
                              *F_integrand_K(Data_Gamma, wcpoints1_gam, wcpoints2_gam,
                                           Data_Basis, Basis_tmp, j, intpoint1,
114
115
                                           intpoint2, Jdet, p_phi_approx, coeff);
116
                 intpoint1=t_km1+H_k*(1-nodes_gauss[g1]);
117
118
                 intpoint2=t_km1+H_k*(1-nodes_gauss[q1]+nodes_gauss[q1]*nodes_gauss[q2]);
                 Jdet=nodes_gauss[q1];
119
120
                 squareint+=weights_gauss[q1] *weights_gauss[q2]
121
                              *F_integrand_K(Data_Gamma, wcpoints1_gam, wcpoints2_gam,
122
                                           Data_Basis, Basis_tmp, j, intpoint1,
123
                                           intpoint2, Jdet, p_phi_approx, coeff);
124
             }
125
126
        }
127
        return squareint;
    }
128
129
130
```

```
131
    // F_integral_K_Adjacent
132
133
134
135
    double F_integral_K_Adjacent(NURBSData* Data_Gamma, double* wcpoints1_gam,
136
137
                 double* wcpoints2_gam, NURBSData* Data_Basis, NURBSData* Basis_tmp,
                 QuadData* Data_Gauss, double* coeff, int j, int k1,
138
139
                 int k2, int singtype, int p_phi_approx) {
140
        double* nodes_gauss=get_QuadData_nodes(Data_Gauss);
141
        double* weights_gauss=get_OuadData_weights(Data_Gauss);
142
        int n_qauss=get_QuadData_n(Data_Gauss);
143
        int q1,q2;
144
        double t_k1m1=knotseq(Data_Basis,k1-1); // t_{1-1-1}
145
146
        double t_k1=knotseq(Data_Basis,k1); // t_{1_1}
        double H_k1=t_k1-t_k1m1; // H_{1_1}
147
        double t_k2m1=knotseq(Data_Basis,k2-1); // t_{1.2-1}
148
        double t_k2=knotseq(Data_Basis,k2); // t_{l_2}
149
        double H_k2=t_k2-t_k2m1; // H_{1_1}
150
151
        double squareint=0; // integral over square
        double intpoint1, intpoint2; // first and second integration point
152
153
        double Jdet; // Jacobi determinant of Duffy transformation
154
        if (singtype==0){
155
             for (q1=0;q1<n_gauss;q1++) {</pre>
156
                 for (q2=0;q2<n_gauss;q2++) {</pre>
157
                     // first double integral
158
                     intpoint1=t_k1m1+H_k1*nodes_gauss[q1];
159
                     intpoint2=t_k2m1+H_k2*(1-nodes_gauss[q1]*nodes_gauss[q2]);
160
161
                     Jdet=nodes_gauss[q1];
                     squareint+=weights_gauss[q1] *weights_gauss[q2]
162
                                  *F_integrand_K(Data_Gamma, wcpoints1_gam, wcpoints2_gam,
163
164
                                          Data_Basis, Basis_tmp, j, intpoint1,
                                          intpoint2, Jdet, p_phi_approx, coeff);
165
166
                      // second double integral
167
                     intpoint1=t_k1m1+H_k1*nodes_gauss[q1]*nodes_gauss[q2];
168
169
                     intpoint2=t_k2m1+H_k2*(1-nodes_gauss[q2]);
170
                     Jdet=nodes_gauss[q2];
                     squareint+=weights_gauss[q1] *weights_gauss[q2]
171
172
                                  *F_integrand_K(Data_Gamma, wcpoints1_gam,
173
                                           wcpoints2_gam, Data_Basis, Basis_tmp,
                                           j, intpoint1, intpoint2, Jdet,
174
                                           p_phi_approx, coeff);
175
                 }
176
             }
177
        } else {
178
             for (q1=0;q1<n_gauss;q1++) {</pre>
179
                 for (q2=0;q2<n_gauss;q2++) {</pre>
180
                      // first double integral
181
                     intpoint1=t_k1m1+H_k1*(1-nodes_gauss[q1]*nodes_gauss[q2]);
182
                     intpoint2=t_k2m1+H_k2*nodes_gauss[q2];
183
                     Jdet=nodes_gauss[g2];
184
185
                     squareint+=weights_gauss[q1]*weights_gauss[q2]
                                  *F_integrand_K(Data_Gamma, wcpoints1_gam, wcpoints2_gam,
186
                                           Data_Basis, Basis_tmp, j, intpoint1,
187
188
                                           intpoint2, Jdet, p_phi_approx, coeff);
189
                     // second double integral
190
                     intpoint1=t_k1m1+H_k1*(1-nodes_gauss[q1]);
191
                      intpoint2=t_k2m1+H_k2*nodes_gauss[q1]*nodes_gauss[q2];
192
193
                     Jdet=nodes_gauss[g1];
                      squareint+=weights_gauss[q1] *weights_gauss[q2]
194
                                  *F_integrand_K(Data_Gamma, wcpoints1_gam, wcpoints2_gam,
195
196
                                           Data_Basis, Basis_tmp, j, intpoint1,
197
                                           intpoint2, Jdet, p_phi_approx, coeff);
                 }
198
             }
199
        }
200
```

```
201
         return squareint;
202
    }
203
204
205
    // build_Fvector
206
207
    //-
208
209
    void build_Fvector(double* output, NURBSData* Data_Gamma, double* wcpoints1_gam,
210
                  double* wcpoints2_gam, NURBSData* Data_Basis, QuadData* Data_Gauss,
211
                 QuadData* Data_Gauss_small, QuadData* Data_Gauss_phi_approx,
212
                  int with_K, int p_phi_approx, double* coeff) {
213
214
215
         double* nodes_gauss=get_QuadData_nodes(Data_Gauss);
         double* weights_gauss=get_QuadData_weights(Data_Gauss);
216
         int n_gauss=get_QuadData_n(Data_Gauss);
217
218
         double* knots_gam=get_NURBSData_knots(Data_Gamma);
219
         int N_gam=get_NURBSData_N(Data_Gamma);
220
221
         int N=get_NURBSData_N(Data_Basis);
222
223
         int p=get_NURBSData_p(Data_Basis);
224
         double tmp[2];
225
         int j,k1,k2,q1,q2;
226
227
         int multb=p+1; // #b
228
229
         double R_til[N_multb+1+p][p+1][n_gauss];
230
         // R_til[i-1+p][k1-i][q1]=tilde{R}_{i,k1}(nodes_gauss[q1])
231
232
         double gamma1[N][n_gauss];
233
234
         // gamma1[k1-1][q1] is first component of
         // gamma(t_{k1-1}+H_k1*nodes_gauss[q1])
235
236
         double gamma2[N][n_gauss];
237
         // gamma2[k1-1][q1] is second component of
238
         // gamma(t_{k1-1}+H_k1*nodes_gauss[q1])
239
240
         double phi_til[N][n_gauss];
241
242
         //phi[k1-1][q1] is \phi(\gamma(t_{k-1}+
         //H_k * nodes_gauss[q1])) * \\ gamma'(t_{k-1}+H_k * nodes_gauss[q1]) |
^{243}
244
         double R_nu1[N][p+1][n_gauss];
^{245}
         // R_nu1[j+p-1][k2-j][q2] is first component of
// {{0,1}, {-1,0}}*gamma'(t_{k2-1}+H_k2*nodes_gauss[q2])
246
247
         // *R_j(t_{k2-1}+H_k2*nodes_gauss[q2])
248
249
250
         double R_nu2[N][p+1][n_gauss];
         // R_nu2[j+p-1][k2-j][q2] is second component of
251
         // {{0,1}, {-1,0}}*gamma'(t_{k2-1}+H_k2*nodes_gauss[q2])
252
253
         // *R_j(t_{k2-1}+H_k2*nodes_gauss[q2])
254
         double squareint; // integral over square
255
256
         //double Jdet; // Jacobi determinant of Duffy transformation
257
258
         //double diff_gam[2];
259
260
         double t_k1m1,t_k1,H_k1,t_k2m1,t_k2,H_k2;
261
         // t_{k1-1},t_k1,H_k1,t_{k2-1},t_k2,H_k2
262
263
         double intpoint1, intpoint2; // first and second integration point
264
         int index; // help index
265
266
267
         int i=0;
268
         double knots_tmp[p_phi_approx+1];
269
         for (i=0;i<p_phi_approx+1;++i) {</pre>
270
```

```
271
             knots_tmp[i]=1;
272
         }
         double weights_tmp[p_phi_approx+1];
273
         for (i=0;i<p_phi_approx+1;++i) {</pre>
274
             weights_tmp[i]=1;
275
         }
276
277
         double nodes_tmp[1];
278
         nodes_tmp[0]=1;
279
         int is_rational_tmp=0;
280
         NURBSData* Basis_tmp=new_NURBSData(0, knots_tmp, p_phi_approx+1,
                                        weights_tmp, p_phi_approx, nodes_tmp, 1, 0);
281
282
         int n=get_NURBSData_n (Data_Basis);
283
         double* nodes=get_NURBSData_nodes(Data_Basis);
284
         double sum=0;
285
         int j_tmp=0;
286
         int index2=0;
287
288
289
         // calculation of R.til, R.nu1, R.nu2
         // R_i
290
291
         for (j=1-p; j<=(N-multb+1); j++) {</pre>
             // elements with nonemty intersection with support of R_i
292
293
             for (k2=max(j,1);k2<=min(j+p,N);k2++) {</pre>
                  // quadrature points
294
                  for (q2=0;q2<n_gauss;q2++) {</pre>
295
296
                      t_k2m1=knotseq(Data_Basis,k2-1);
                      t_k2=knotseq(Data_Basis, k2);
297
                      H_k2=t_k2-t_k2m1;
298
                      intpoint2=t_k2m1+H_k2*nodes_gauss[q2];
299
300
                      R_nu1[j-1+p][k2-j][q2] = eval_NURBS(Data_Basis, j, intpoint2);
301
                      R_nu2[j-1+p][k2-j][q2] = eval_NURBS(Data_Basis, j, intpoint2);
302
303
304
                      eval_NURBSCurveDeriv(tmp, Data_Gamma, wcpoints1_gam,
                                        wcpoints2_gam, intpoint2);
305
306
                      R_nu1[j-1+p][k2-j][q2] *= tmp[1];
307
                      R_nu2[j-1+p][k2-j][q2] *= -tmp[0];
308
                      R_til[j-1+p][k2-j][q2] = eval_NURBS(Data_Basis, j, intpoint2)
309
310
                                                          *norm(tmp);
                  }
311
312
             }
313
         }
314
         if (with_K==1) {
315
316
             // calculation of gamma1, gamma2, phi_til
317
             for (k1=1;k1<=N;k1++) {</pre>
318
319
                  t_k1m1=knotseq(Data_Basis,k1-1);
320
                  t_k1=knotseq(Data_Basis,k1);
321
                  H_k1=t_k1-t_k1m1;
322
323
                  if(0<H_k1){
324
325
                      index2=find_Span_nodes(Data_Basis,t_k1m1);
326
327
328
                      for (j_tmp=0; j_tmp<p_phi_approx+1;++j_tmp) {</pre>
                           knots_tmp[j_tmp]=t_k1;
329
                      }
330
331
                      nodes_tmp[0]=t_k1;
                      Basis_tmp=del_NURBSData(Basis_tmp);
332
                      Basis_tmp=new_NURBSData(t_k1m1, knots_tmp, p_phi_approx+1,
333
                                            weights_tmp, p_phi_approx, nodes_tmp, 1, 0);
334
335
336
                      for (q1=0;q1<n_gauss;q1++) {</pre>
337
338
339
                           intpoint1=t_k1m1+H_k1*nodes_gauss[q1];
340
```

```
341
                            eval_NURBSCurve(tmp,Data_Gamma,wcpoints1_gam,
342
                                                   wcpoints2_gam, intpoint1);
                            gamma1[k1-1][q1]=tmp[0];
343
                            gamma2[k1-1][q1]=tmp[1];
344
345
                            sum=0;
346
                            for (j_tmp=0;j_tmp<=p_phi_approx;++j_tmp) {</pre>
347
348
                                 sum+=coeff[index2*(p_phi_approx+1)+j_tmp]
                                               *eval_NURBS(Basis_tmp,j_tmp-p_phi_approx+1,
349
350
                                                             intpoint1);
351
                            phi_til[k1-1][q1]=sum;
352
                            eval_NURBSCurveDeriv(tmp,Data_Gamma, wcpoints1_gam,
353
                                               wcpoints2_gam, intpoint1);
354
                            phi_til[k1-1][q1] *= norm(tmp);
355
                       }
356
                  }
357
              }
358
359
360
361
              // calculation of <phi,K\hat{R}_j>_{L_2(Gamma)}
              // R_j
362
363
              for (j=1-p; j<=(N-multb+1); j++) {</pre>
364
                  output[j+p-1]=0;
                  // elements with nonemty intersection with support of \ensuremath{\mathtt{R}}\xspace j
365
366
                   for (k1=1;k1<=N;k1++) {</pre>
367
                       // all elements
                       for (k2=max(j,1);k2<=min(j+p,N);k2++) {</pre>
368
                            t_k1m1=knotseq(Data_Basis,k1-1);
369
                            t_k1=knotseq(Data_Basis,k1);
370
371
                            t_k2m1=knotseq(Data_Basis,k2-1);
                            t_k2=knotseq(Data_Basis,k2);
372
                            H_k1=t_k1-t_k1m1;
373
374
                            H_k2=t_k2-t_k2m1;
375
                            // quadrature
                            if (0<min(H_k1,H_k2)){
376
377
                                 squareint=0;
378
                                 // elements with no intersection
                                 if ((!nearly_equal(t_k1m1,t_k2m1))
379
380
                                     && (!nearly_equal(t_k1m1,t_k2))
                                     && (!nearly_equal(t_k1,t_k2m1))
381
382
                                     && (!nearly_equal(t_k1,t_k2))
                                      \begin{array}{c} \&\& & ((k1!=(N-multb+1)) || & (k2!=1)) \\ \&\& & ((k2!=(N-multb+1)) || & (k1!=1))) \end{array} 
383
384
                                     for (q1=0;q1<n_gauss;q1++) {</pre>
385
                                          for (q2=0;q2<n_gauss;q2++) {</pre>
386
                                               tmp[0] = gamma1[k1-1][q1] - gamma1[k2-1][q2];
387
                                               tmp[1] = gamma2[k1-1][q1] - gamma2[k2-1][q2];
388
                                               squareint += (weights_gauss[q1] *weights_gauss[q2]
389
390
                                                             *(tmp[0]*R_nu1[j-1+p][k2-j][q2]
                                                             +tmp[1] *R_nu2[j-1+p][k2-j][q2])
391
                                                             /norm(tmp))/norm(tmp)
392
393
                                                             *phi_til[k1-1][q1]/(2*M_PI);
                                          }
394
                                     }
395
                                 }
396
                                 // elements with intersection
397
398
                                else {
                                        identical elements
399
                                     if (k1==k2){
400
401
                                          squareint=F_integral_K_identical(Data_Gamma,
                                                             wcpoints1_gam, wcpoints2_gam,
402
                                                             Data_Basis, Basis_tmp,
403
                                                             Data_Gauss_small, coeff,
404
                                                             j, k1, p_phi_approx);
405
406
                                     }
407
                                     // elements with point intersection
                                     else{
408
                                          // singularity at s=0,t=1
409
                                          if (nearly_equal(t_k1m1,t_k2)
410
```

```
|| ((k2==(N-multb+1)) && (k1==1))) {
411
412
                                            index=1;
413
                                            while(!nearly_equal(t_k2, knots_gam[index-1])){
                                                 index=index+1;
414
415
                                                 if (index==(N_gam+1)) {break;}
416
                                            }
                                             // t_k2 no knot of Gamma
417
418
                                            if (index==(N_gam+1)){
                                                 squareint=F_integral_K_Adjacent(Data_Gamma,
419
420
                                                              wcpoints1_gam, wcpoints2_gam,
                                                              Data_Basis, Basis_tmp,
421
                                                              Data_Gauss_small, coeff,
422
                                                              j, k1, k2, 0, p_phi_approx);
423
                                            }
// t_k2 knot of Gamma
424
425
                                            else {
426
                                                 squareint=F_integral_K_Adjacent(Data_Gamma,
427
428
                                                              wcpoints1_gam, wcpoints2_gam,
                                                              Data_Basis, Basis_tmp,
429
                                                              Data_Gauss, coeff, j,
430
                                                              k1, k2, 0, p_phi_approx);
431
                                            }
432
433
                                        }
434
                                        // singularity at s=1,t=0
                                        else{
435
436
                                            index=1;
437
                                            while(!nearly_equal(t_k1, knots_gam[index-1])){
                                                 index=index+1;
438
439
                                                 if (index==(N_gam+1)){break;}
440
                                            }
                                             // t_k1 no knot of Gamma
441
                                             if (index==(N_gam+1)){
442
                                                 squareint=F_integral_K_Adjacent(Data_Gamma,
443
444
                                                              wcpoints1_gam, wcpoints2_gam,
                                                              Data_Basis, Basis_tmp,
445
                                                              Data_Gauss_small, coeff,
446
447
                                                              j, k1, k2, 1, p_phi_approx);
448
                                            }
                                             // t_kl knot of Gamma
449
450
                                            else {
                                                 squareint=F_integral_K_Adjacent (Data_Gamma,
451
452
                                                              wcpoints1_gam, wcpoints2_gam,
                                                              Data_Basis, Basis_tmp,
453
                                                              Data_Gauss, coeff, j,
454
455
                                                              k1, k2, 1, p_phi_approx);
                                            }
456
                                        }
457
                                   }
458
                               }
459
                               output[j+p-1] += H_k1 * H_k2 * squareint;
460
                          }
461
                      }
462
463
                  }
                 output[j+p-1] = -output[j+p-1];
464
465
             }
466
         }
467
468
         // calculation of <phi,R_hat_j/2-K R_hat_j>_{L_2(Gamma)}
469
         // R_j
470
471
         for (j=1-p;j<=(N-multb+1);j++) {</pre>
             if (with_K==0) {
472
                 output[j+p-1]=0;
473
             }
474
             // elements with nonemty intersection with support of R_j
475
             for (k1=max(j,1);k1<=min(j+p,N);k1++) {</pre>
476
477
                 t_k1m1=knotseq(Data_Basis,k1-1); // t_{11-1}
                 t_k1=knotseq(Data_Basis,k1); // t_l1
478
                 H_k1=t_k1-t_k1m1;
479
                 // quadrature
480
```

```
if (0<H_k1){
481
482
                      index2=find_Span_nodes(Data_Basis,t_k1m1);
483
                      for (j_tmp=0; j_tmp<p_phi_approx+1;++j_tmp) {</pre>
484
                          knots_tmp[j_tmp]=t_k1;
485
                      }
486
487
                      nodes_tmp[0]=t_k1;
488
                      Basis_tmp=del_NURBSData(Basis_tmp);
                      Basis_tmp=new_NURBSData(t_k1m1,knots_tmp,p_phi_approx
489
490
                                        +1,weights_tmp,p_phi_approx,nodes_tmp,1,0);
491
                      for (q1=0;q1<n_gauss;q1++) {</pre>
492
                          eval_NURBSCurve(tmp,Data_Gamma,wcpoints1_gam,wcpoints2_gam,
493
                                            t_k1m1+H_k1*nodes_gauss[q1]);
494
495
496
                          sum=0;
497
498
                          for (j_tmp=0; j_tmp<=p_phi_approx;++j_tmp) {</pre>
                               sum+=coeff[index2*(p_phi_approx+1)+j_tmp]
499
                                        *eval_NURBS(Basis_tmp, j_tmp-p_phi_approx+1,
500
501
                                        t_k1m1+H_k1*nodes_gauss[q1]);
                          }
502
503
                          output[j+p-1] += H_k1*weights_gauss[q1]*sum
                                            /2*R_til[j-1+p][k1-j][q1];
504
                      }
505
                 }
506
507
             }
        }
508
        output[0] += output[N-1];
509
        Basis_tmp=del_NURBSData(Basis_tmp);
510
511
    }
```

A.7 res_RHS.h and res_RHS.c

These two files are used to evaluate the right-hand side $(1/2 - K')\phi_h(x)$ for $x \in \Gamma \setminus \{z_1, \ldots, z_n\}$.

```
1 #ifndef _eval_RHS_h
2 #define _eval_RHS_h
3
4 #include <math.h>
5 #include <stdio.h>
6 #include "Spline.h"
   #include "phi_approx.h"
7
8
9
  double Integrand_K_pr(NURBSData* Data_Gamma, double* wcpoints1_gam,
10
               double* wcpoints2_gam,double s,double t, NURBSData* Data_Basis,
11
12
               int p_phi_approx, double* coeff);
13
  double eval_RHS(NURBSData* Data_Gamma, double* wcpoints1_gam,
14
               double* wcpoints2_gam,NURBSData* Data_Basis,
15
               QuadData* Data_Gauss, double s, int with_K, int p_phi_approx, double* coeff);
16
17
18
19 #endif
```

```
double* wcpoints2_gam, double s, double t, NURBSData* Data_Basis,
10
            int p_phi_approx, double* coeff){
11
12
       double a=get_NURBSData_a(Data_Basis);
13
       int n=get_NURBSData_n(Data_Basis);
14
       double* nodes=get_NURBSData_nodes(Data_Basis);
15
16
       double nodesa[n+1];
17
       nodesa[0]=a;
18
       int j_tmp=0;
19
       for (j_tmp=1; j_tmp<=n;++j_tmp) {</pre>
20
            nodesa[j_tmp]=nodes[j_tmp-1];
21
^{22}
       double sum=0;
^{23}
       int index=find_Span_nodes(Data_Basis,t);
24
       double knots_tmp[p_phi_approx+1];
25
       double nodes_tmp[1];
26
27
       double weights_tmp[p_phi_approx+1];
^{28}
       for (j_tmp=0;j_tmp<p_phi_approx+1;j_tmp++) {</pre>
29
30
            knots_tmp[j_tmp]=nodesa[index+1];
            weights_tmp[j_tmp]=1;
31
32
       }
       nodes_tmp[0]=nodesa[index+1];
33
       NURBSData* Data_Basis_tmp=new_NURBSData(nodesa[index],knots_tmp,
34
35
                                           p_phi_approx+1, weights_tmp, p_phi_approx,
                                           nodes_tmp,1,0);
36
       sum=0;
37
       for (j_tmp=0;j_tmp<=p_phi_approx;++j_tmp){</pre>
38
            sum+=coeff[index*(p_phi_approx+1)+j_tmp]
39
40
                              *eval_NURBS(Data_Basis_tmp,j_tmp-p_phi_approx+1,t);
41
        }
42
       double phi_nu[2];
^{43}
       double s_hat[2];
44
45
       double t_hat[2];
       double tmp[2];
46
       double tmp2[2];
47
48
       double tmp3[2];
49
       eval_NURBSCurve(s_hat,Data_Gamma,wcpoints1_gam,wcpoints2_gam,s);
       eval_NURBSCurve(t_hat,Data_Gamma,wcpoints1_gam,wcpoints2_gam,t);
50
51
       eval_NURBSCurveDeriv(tmp,Data_Gamma,wcpoints1_gam,wcpoints2_gam,s);
52
       // \gamma'(s)
53
       eval_NURBSCurveDeriv(tmp2,Data_Gamma,wcpoints1_gam,wcpoints2_gam,t);
54
        // \gamma'(t)
55
       phi_nu[0] = sum * tmp[1];
56
       phi_nu[1] = -sum * tmp[0];
57
       tmp3[0] = s_hat[0] - t_hat[0]; // \gamma(s)-\gamma(t)
tmp3[1] = s_hat[1] - t_hat[1];
58
59
60
       Data_Basis_tmp=del_NURBSData(Data_Basis_tmp);
61
62
        return -(tmp3[0]*phi_nu[0] + tmp3[1]*phi_nu[1])*norm(tmp2)/norm(tmp)
63
64
                                                    / (2*M_PI*pow(norm(tmp3),2));
   }
65
66
67
68
   // eval_RHS
69
70
71
72
   double eval_RHS(NURBSData* Data_Gamma, double* wcpoints1_gam,
73
            double* wcpoints2_gam,NURBSData* Data_Basis,
74
75
            QuadData* Data_Gauss, double s, int with_K,
            int p_phi_approx, double* coeff){
76
77
       double a=get_NURBSData_a(Data_Gamma);
78
       double* nodes=get_NURBSData_nodes(Data_Basis);
79
```

```
80
         int n=get_NURBSData_n(Data_Basis);
         double* nodes_gauss=get_QuadData_nodes(Data_Gauss);
 81
         double* weights_gauss=get_QuadData_weights(Data_Gauss);
 82
         int n_gauss=get_QuadData_n (Data_Gauss);
 83
         int j,q;
 84
         double output=0;
 85
 86
         double x_ch_jm1, x_ch_j, h_j;
 87
 88
         double intpoint;
         double s_hat[2];
 89
         eval_NURBSCurve(s_hat,Data_Gamma,wcpoints1_gam,wcpoints2_gam,s);
 90
 91
 92
         double nodesa[n+1];
 93
 94
         nodesa[0]=a;
 95
         int j_tmp=0;
         for (j_tmp=1; j_tmp<=n; ++ j_tmp) {</pre>
 96
 97
              nodesa[j_tmp]=nodes[j_tmp-1];
         }
 98
         double sum=0;
 99
100
         int index=find_Span_nodes(Data_Basis,s);
         double knots_tmp[p_phi_approx+1];
101
102
         double nodes_tmp[1];
         double weights_tmp[p_phi_approx+1];
103
104
105
         for (j_tmp=0; j_tmp<p_phi_approx+1; j_tmp++) {</pre>
              knots_tmp[j_tmp]=nodesa[index+1];
106
              weights_tmp[j_tmp]=1;
107
108
         }
         nodes_tmp[0]=nodesa[index+1];
109
         NURBSData* Data_Basis_tmp=new_NURBSData(nodesa[index],knots_tmp,
110
111
                                                       p_phi_approx+1, weights_tmp,
                                                       p_phi_approx,nodes_tmp,1,0);
112
113
         sum=0;
         for (j_tmp=0; j_tmp<=p_phi_approx;++j_tmp) {</pre>
114
              sum+=coeff[index*(p_phi_approx+1)+j_tmp]
115
                                *eval_NURBS(Data_Basis_tmp,j_tmp-p_phi_approx+1,s);
116
         }
117
118
119
120
121
         if (with_K==1) {
122
              // calculation of K'phi(\gamma(s))
123
              for (j=1; j<=n; j=j+1) {</pre>
124
                  if (j==1) {x_ch_jm1=a;} else {x_ch_jm1=nodes[j-2];}
125
                  x_ch_j=nodes[j-1];
126
                  h_j=x_ch_j-x_ch_jm1;
127
128
                 if ((!nearly_leq(x_ch_jm1,s)) || (!nearly_leq(s,x_ch_j))){
129
                       for (q=0;q<n_gauss;q=q+1) {</pre>
130
                           intpoint = x_ch_jm1 + h_j * nodes_gauss[q];
131
132
                           output += h_j * weights_gauss[q] * Integrand_K_pr(Data_Gamma,
                                                                wcpoints1_gam, wcpoints2_gam, s,
133
134
                                                                intpoint, Data_Basis,
                                                                p_phi_approx, coeff);
135
                       }
136
                  }else{
137
138
                          first integral
                       if (!nearly_equal(s,x_ch_jm1)){
139
                           for (q=0;q<n_gauss;q=q+1) {</pre>
140
                                intpoint = s - (s - x_ch_jm1) * nodes_gauss[q];
output += (s - x_ch_jm1) * weights_gauss[q]
141
142
                                              * Integrand_K_pr(Data_Gamma,wcpoints1_gam,
143
                                                       wcpoints2_gam, s, intpoint,
144
145
                                                       Data_Basis,p_phi_approx,coeff);
                           }
146
                       }
147
                       //second integral
148
                       if (!nearly_equal(s,x_ch_j)){
149
```

```
150
                              for (q=0;q<n_gauss;q=q+1) {</pre>
                                   intpoint = s + (x_ch_j - s) * nodes_gauss[q];
output += (x_ch_j - s) * weights_gauss[q]
151
152
                                                  * Integrand_K_pr(Data_Gamma,wcpoints1_gam,
153
                                                             wcpoints2_gam, s, intpoint,
154
                                                            Data_Basis,p_phi_approx,coeff);
155
                  }
                             }
156
157
158
               }
159
          }
160
161
          Data_Basis_tmp=del_NURBSData(Data_Basis_tmp);
162
          return sum*0.5-output;
163
164
    }
```

A.8 mark.m

This file uses Doerfler marking to mark nodes resp. elements, cf. [Gan14, Appendix B].

```
function [marked_nodes,marked_elements]=mark(indicators,theta,a,knots,p,is_open_gam,href)
1
2
   % input:
   2
       indicators...column vector of error indicators
3
^{4}
   8
       theta...constant for Doerfler marking
   Ŷ
       a...left interval boundary of [a,b]
\mathbf{5}
6
   8
       knots...column vector of knots in (a,b] with mult<=p+1 \ensuremath{\mathsf{mult}}
7
   8
       p...polynomial degree
       is_open_gam...1 if Gamma is open, 0 else
   ÷
8
       href...1 for pure h-refinement, 0 for new proposed algorithm
9
   2
10
   % output:
      marked_nodes...column vector of indices of (finally) marked nodes
   8
11
  8
       marked_elements...column vector of indices of (finally) marked elements
12
13
14
  % Doerfler marking for nodes
15
   if theta<1
16
        [indicators_tmp,tmp] = sort(indicators,'descend');
17
       sum_indicatorssq = cumsum(indicators_tmp.^2);
18
       index = find(sum_indicatorssq >= (sum_indicatorssq(end)*theta),1);
19
20
       marked_nodes = sort(tmp(1:index))-is_open_gam;
  else
^{21}
22
       marked_nodes=(1:length(indicators))'-is_open_gam;
^{23}
   end
^{24}
25
   % my modulo
26
   if is_open_gam==0
       my_mod=@(x, y) \mod (x, y) + y \star (mod(x, y) == 0);
27
28
  else
^{29}
       my_mod=@(x,y) \min(x,y);
  end
30
31
   % resulting marked nodes and elements
32
33 nodes0=[a;unique(knots)];
n=length(nodes0)-1;
35 marked_elements=[];
36
   del_nodes=[];
   % h-refinement of elements whose nodes are marked
37
38
  for i=1:(length(marked_nodes)-is_open_gam)
        if marked_nodes(my_mod(i+1,length(marked_nodes))) == my_mod(marked_nodes(i)+1,n)
39
           marked_elements=[marked_elements;my_mod(marked_nodes(i)+1,n)];
40
            del_nodes=[del_nodes;marked_nodes(i);my_mod(marked_nodes(i)+1,n)];
41
^{42}
       end
43 end
44 marked_nodes=setdiff(marked_nodes,del_nodes);
   del_nodes=[];
45
   \ensuremath{\$} h-refinement for elements with marked intersection node and (full multiplicity
46
  % or href==1)
47
```

```
48
   for i=1:length(marked_nodes)
       if (sum(knots==nodes0(marked_nodes(i)+1))==(p)..
49
                    sum(knots==nodes0(marked_nodes(i)+1)) == (p+1)...
50
                    || marked_nodes(i)==0 || href==1)
51
           marked_elements=...
52
                [marked_elements; max(1, marked_nodes(i)); my_mod(marked_nodes(i)+1, n)];
53
54
           del_nodes=[del_nodes;marked_nodes(i)];
55
       end
56
  end
  marked_nodes=setdiff(marked_nodes,del_nodes);
57
  marked_elements=unique(marked_elements);
58
```

A.9 insert_cpoint.m, increase_Mult and refine_BoundaryMesh

The file insert_cpoint.m computes the new control points of a NURBS curve, if one knot is added, such that the curve does not change. The file increase_Mult computes the new knot resp. weight vector and the new control points, if the multiplicity of a given set of nodes is increased by one. The file refine_BoundaryMesh refines a given boundary mesh.

```
1
   function [ cpoints_new ] = insert_cpoint(a,knots,weights,cpoints,p,knot_added)
2
  knots_a=[a*ones(p+1,1);knots];
3
  weights=[weights(end-p+1:end);weights(1:end-p)];
4
\mathbf{5}
  cpoints=[cpoints(:,end-p+1:end),cpoints(:,1:end-p)];
6
   ind=find(knots_a<=knot_added,1,'last');</pre>
7
8
9 cpoints_added=[];
10 alpha=[];
11 P=[];
12 Q=[];
13
  for k=0:p
14
15
       P=[[cpoints(:,ind-k).*weights(ind-k);weights(ind-k)],P];
  end
16
17
   for k=0:p-1
18
       alpha=[(knot_added-knots_a(ind-k))/(knots_a(ind-k+p)-knots_a(ind-k)), alpha];
19
^{20}
  end
^{21}
   for k=0:p-1
22
       Q=[P(:,p-k).*(1-alpha(p-k))+P(:,p-k+1).*alpha(p-k),Q];
23
  end
24
25
   for k=1:p
26
       cpoints_added=[cpoints_added,Q(1:2,k)./Q(3,k)];
27
^{28}
   end
29
  cpoints_new=[cpoints(:,1:(ind-p)),cpoints_added,cpoints(:,ind:end)];
30
31
32 cpoints_new=[cpoints_new(:,p+1:end),cpoints_new(:,1:p)];
33 end
```

```
function [knots_fine,weights_fine,cpoints_fine]=increase_Mult_cpoints(a,...
1
       knots,weights,cpoints,p,marked)
2
3 % input:
       a...left interval boundary of [a,b]
4
   2
  8
      knots...column vector of knots in (a,b] with mult<=p+1 and mult=p+1 of b
5
6
  8
      weights...column vector of positive weights corresponding to knots
   8
      marked...column vector with indices of marked nodes
7
   % output:
8
  2
     knots_fine...column vector of refined knots (via knot insertion),
9
   8
      weights_fine...column vector of new weights corresponding to knots_fine
10
11
  % comments:
12 % we assume that
```

```
13 % -) number of knots N>=p+1
   2
       -) number of nodes n>=4
14
15
16 b=knots(end):
17
18 % start data
19 weights_current=weights;
20 knots_current=knots;
21
22 weights_current_tmp=weights;
23 cpoints_current=cpoints;
24
25 N_current=length(knots_current);
26 nodes=unique(knots);
27 marked_current=marked; % marked nodes of current mesh
28
   % loop, in each step one insertion
while ~isempty(marked_current)
29
30
       incr=marked_current(1); % node whose mult is increased
31
       tmp=find(knots_current==nodes(incr));
32
33
       l=tmp(1);
       mult=length(tmp);
34
35
       % marked node = t_l
       t_l=knotseq(a, knots_current, l);
36
37
       % insert knot
38
       t_pr=t_l; % t'
39
       weights_tmp=zeros(N_current+1,1); % w'''
40
       weights_tmp(1:(l-p+mult))=weights_current(1:(l-p+mult));
41
       for i=max(1,(l-p+mult+1)):1
42
43
            t_iml=knotseq(a, knots_current, i-1);
            t_imlpp=knotseq(a,knots_current,i-1+p);
44
            if t_im1<t_im1pp
45
46
                beta=(t_pr-t_im1)/(t_im1pp-t_im1);
            else
47
48
                beta=0;
            end
^{49}
            weights_tmp(i) = (1-beta) *weights_current(i-1+N_current*(i==1))...
50
51
                +beta*weights_current(i);
52
       end
       weights_tmp((l+1):(N_current+1))=weights_current(l:N_current);
53
       weights_current(1:min(N_current+1, l+N_current+1+mult-p))=...
54
            weights_tmp(1:min(N_current+1, l+N_current+1+mult-p));
55
        for i=(l+N_current+mult+2-p):(N_current+1)
56
            t_im2=knotseq(a, knots_current, i-2);
57
            t_im2pp=knotseq(a,knots_current,i-2+p);
58
            if t_im2<t_im2pp</pre>
59
                beta=(t_pr+b-a-t_im2)/(t_im2pp-t_im2);
60
61
            else
62
                beta=0;
            end
63
            weights_current(i) = (1-beta) * weights_tmp(i-1)...
64
65
                +beta*weights_tmp(i);
       end
66
67
       % update data
68
       cpoints_current=insert_cpoint (a, knots_current, weights_current_tmp,...
69
70
                                                            cpoints_current,p,t_pr);
71
       weights_current_tmp=weights_current;
72
       knots_current=[knots_current(1:(l-1));t_pr;knots_current(l:end)];
73
       N_current=N_current+1;
74
       marked_current=marked_current(2:end);
75
76 end
77
78 cpoints_fine=cpoints_current;
79
  knots_fine=knots_current;
80
81 weights_fine=weights_current;
82 end
```

```
103
```

```
83
84 function output=knotseq(a,knots,i)
85 % returns t_i
86 b=knots(end);
87 N=length(knots);
88 if (mod(i,N)~=0)
89 output=knots(mod(i,N))+(b-a)*floor(i/N);
90 else
91 output=a+(b-a)*floor(i/N);
92 end
93 end
```

```
1 function [knots_fine, knots_added, weights_fine, cpoints_fine]=refine_BoundaryMesh_cpoints(...
       a, knots, weights, cpoints, p, marked, kappa_max, is_open_gam)
2
   % input:
3
^{4}
   2
       a...left interval boundary of [a,b]
   8
       knots...column vector of knots in (a,b] with mult<=p+1
5
           where kappa(\check{\mathcal{T}}) <= kappa_max
   S
6
7
   8
       weights...column vector of positive weights corresponding to knots
   8
       p...polynomial degree
8
9
   2
       marked...column vector with indices of marked elements
       kappa_max...maximal allowed mesh constant
10
   8
   2
       is_open_gam...1 if Gamma is open, 0 else
11
12 % output:
   e
       knots_fine...column vector of refined knots (via knot insertion),
13
           where kappa(\check{\mathcal{T}}_fine)<=kappa_max, at least all
  응
14
  ÷
           marked elements are
15
           refined, no element is refined more than one time
   8
16
       knots_added...column vector of all added knots
17
   2
       weights_fine...column vector of new weights corresponding to knots_fine
18
  8
   % comments:
19
20
   % we assume that
      -) number of knots N>=p+1
21 %
       -) number of nodes n \ge 4
22 %
^{23}
24 b=knots(end);
25
26
  % start data
27 weights_current=weights;
28 knots_current=knots;
29
30 weights_current_tmp=weights;
31 cpoints_current=cpoints;
32
33 knots_added=[];
34 N_current=length(knots_current);
35 nodes_current=unique(knots_current);
36 n_current=length(nodes_current);
37 nodes0_current=[a;nodes_current];
38 marked_current=marked; % marked elements of current mesh
39
  % loop, in each step one refinement
while ~isempty(marked_current)
40
41
       refine=marked_current(1); % element to be refined
42
       l=find(knots_current==nodes_current(refine),1);
43
44
       % marked element = [t_{1-1}, t_1]
45
       t_lm1=knotseq(a, knots_current, l-1);
       t_l=knotseq(a, knots_current, l);
46
47
       % length of first marked element and its neighbours
^{48}
       if (refine~=1)
49
           h_ch_left=nodes0_current (refine) - nodes0_current (refine-1);
50
51
       else
52
           if is_open_gam==0
               h_ch_left=b-nodes0_current(n_current);
53
           end
54
55
       end
       h_ch=nodes0_current (refine+1) -nodes0_current (refine);
56
```

```
57
        if (refine = n_current)
             h_ch_right=nodes0_current (refine+2)-nodes0_current (refine+1);
 58
        else
 59
             if is_open_gam==0
 60
                 h_ch_right=nodes0_current(2)-a;
 61
             end
 62
 63
        end
 64
         if is_open_gam==1
             if refine==1
 65
                 h_ch_left=h_ch;
 66
             elseif refine==n_current
 67
                 h_ch_right=h_ch;
 68
 69
             end
        end
 70
         % mark neighbours of first marked element if necessary
 71
         % to guarantee kappa<=kappa_max (+1e-3)
 72
         if max((h_ch/2)/h_ch_left,h_ch_left/(h_ch/2))>(kappa_max+1e-3)
 73
 74
             marked_current=unique([refine-1+n_current*(refine==1);...
                 marked_current]);
 75
        end
 76
 77
         if max((h_ch/2)/h_ch_right, h_ch_right/(h_ch/2))>(kappa_max+1e-3)
             marked_current=unique([marked_current;...
 78
 79
                 refine+1-n_current*(refine==n_current)]);
 80
        end
 81
        % refine element
 82
        t_pr=(t_lm1+t_l)/2; % t'
 83
        weights_tmp=zeros(N_current+1,1); % w'''
 84
        weights_tmp(1:(l-p))=weights_current(1:(l-p));
 85
        for i=max(1,(l+1-p)):1
 86
 87
             t_iml=knotseq(a, knots_current, i-1);
             t_imlpp=knotseq(a,knots_current,i-1+p);
 88
             if t_im1<t_im1pp
 89
 90
                 beta=(t_pr-t_im1)/(t_im1pp-t_im1);
             else
 91
 92
                 beta=0;
             end
 93
             weights_tmp(i) = (1-beta) *weights_current(i-1+N_current*(i==1))...
 ^{94}
 95
                 +beta*weights_current(i);
 96
        end
        weights_tmp((l+1):(N_current+1))=weights_current(l:N_current);
 97
        weights_current(1:min(N_current+1, l+N_current+1-p))=...
 98
             weights_tmp(1:min(N_current+1, l+N_current+1-p));
 99
         for i=(l+N_current+2-p):(N_current+1)
100
             t_im2=knotseq(a, knots_current, i-2);
101
             t_im2pp=knotseq(a,knots_current,i-2+p);
102
103
             if t_im2<t_im2pp
                 beta=(t_pr+b-a-t_im2)/(t_im2pp-t_im2);
104
105
             else
106
                 beta=0;
             end
107
             weights_current(i)=(1-beta) *weights_tmp(i-1)...
108
109
                 +beta*weights_tmp(i);
        end
110
111
         % update data
112
        cpoints_current=insert_cpoint (a, knots_current, weights_current_tmp,...
113
114
                                                            cpoints_current,p,t_pr);
115
        weights_current_tmp=weights_current;
116
        knots_current=[knots_current(1:(l-1));t_pr;knots_current(l:end)];
117
        knots_added=[knots_added;t_pr];
118
119
120
        N_current=N_current+1;
121
122
        nodes_current=unique(knots_current);
123
        n_current=length(nodes_current);
        nodes0_current=[a;nodes_current];
124
125
        marked_current=[marked_current(marked_current<refine);...</pre>
             1+marked_current (marked_current>refine)];
126
```

```
127
128
    end
129
    cpoints_fine=cpoints_current;
130
131
132 knots_fine=knots_current;
133 knots_added=sort(knots_added);
134
    weights_fine=weights_current;
135
   end
136
    function output=knotseq(a,knots,i)
137
138
    % returns t i
   b=knots(end);
139
   N=length(knots);
140
    if (mod(i,N)~=0)
141
        output=knots(mod(i,N))+(b-a)*floor(i/N);
142
143
   else
144
        output=a+(b-a) *floor(i/N);
   end
145
146
    end
```

A.10 MEX file

The following example of a MEX file can be used to compute the Matrix W from Section 6.

```
#include "mex.h"
1
   #include "Spline.c"
2
   #include "WMatrix.c"
3
4
   void mexFunction(int nlhs, mxArray* plhs[], int nrhs, const mxArray* prhs[]) {
\mathbf{5}
       double a=*mxGetPr(prhs[0]);
6
       double* knots_gam=mxGetPr(prhs[1]);
7
       double* weights_gam=mxGetPr(prhs[2]);
8
       int p_gam=(int)*mxGetPr(prhs[3]);
9
       double* nodes_gam=mxGetPr(prhs[4]);
10
       int is_rational_gam=(int) *mxGetPr(prhs[5]);
11
12
       double* cpoints_gam=mxGetPr(prhs[6]);
       double* knots=mxGetPr(prhs[7]);
13
       double* weights=mxGetPr(prhs[8]);
14
15
       int p=(int) *mxGetPr(prhs[9]);
       double* nodes=mxGetPr(prhs[10]);
16
17
       int is_rational=(int) *mxGetPr(prhs[11]);
18
       double* nodes_gauss=mxGetPr(prhs[12]);
       double* weights_gauss=mxGetPr(prhs[13]);
19
       double* nodes_loggauss=mxGetPr(prhs[14]);
20
       double* weights_loggauss=mxGetPr(prhs[15]);
21
       double* output;
22
23
       int l;
^{24}
       int N_gam=mxGetM(prhs[1]);
25
       int n_gam=mxGetM(prhs[4]);
26
       int N=mxGetM(prhs[7]);
27
       int n=mxGetM(prhs[10]);
^{28}
       int n_gauss=mxGetM(prhs[12]);
29
       int n_loggauss=mxGetM(prhs[14]);
30
31
       double b;
       int multb=0; // #b
32
       NURBSData* Data_Basis;
33
       NURBSData* Data_Gamma;
34
       QuadData* Data_Gauss;
35
36
       QuadData* Data_LogGauss;
       double wcpoints1_gam[N_gam];
37
       double wcpoints2_gam[N_gam];
38
39
40
       b=knots[N-1];
       while (nearly_equal(knots[N-multb-1],b)) {
41
            multb=multb+1;
42
```

```
if (multb==N) {break;}
^{43}
^{44}
       }
       plhs[0]=mxCreateDoubleMatrix(N-multb+1+p,N-multb+1+p,mxREAL);
^{45}
       output=mxGetPr(plhs[0]);
46
47
       if (is_rational_gam==0) {
^{48}
            for (l=0; l<N_gam; l=l+1) {</pre>
49
50
                wcpoints1_gam[1]=cpoints_gam[0+2*1];
                wcpoints2_gam[l]=cpoints_gam[1+2*l];
51
52
            }
       }else{
53
            for (l=0;l<N_gam;l=l+1) {</pre>
54
                wcpoints1_gam[1]=weights_gam[1]*cpoints_gam[0+2*1];
55
                wcpoints2_gam[l]=weights_gam[l]*cpoints_gam[1+2*1];
56
            }
57
       }
58
59
60
       Data_Basis=new_NURBSData(a, knots, N, weights, p, nodes, n, is_rational);
       Data_Gamma=new_NURBSData(a,knots_gam,N_gam,weights_gam,p_gam,nodes_gam,
61
                                  n_gam, is_rational_gam);
62
63
       Data_Gauss=new_QuadData(nodes_gauss,weights_gauss,n_gauss);
       Data_LogGauss=new_QuadData(nodes_loggauss,weights_loggauss,n_loggauss);
64
65
       build_W(output,Data_Gamma,wcpoints1_gam,wcpoints2_gam,Data_Basis,
66
                       Data_Gauss,Data_LogGauss);
67
68
69
       Data_Basis=del_NURBSData(Data_Basis);
       Data_Gamma=del_NURBSData(Data_Gamma);
70
71
       Data_Gauss=del_QuadData(Data_Gauss);
       Data_LogGauss=del_QuadData(Data_LogGauss);
72
   }
73
```
References

- [AFF⁺13] M. Aurada, M. Feischl, T. Führer, M. Karkulik, and D. Praetorius. Efficiency and optimality of some weighted-residual error estimator for adaptive 2D boundary element methods. *Comput. Methods Appl. Math.*, 13(3):305–332, 2013.
- [AFF⁺15] M. Aurada, M. Feischl, T. Führer, M. Karkulik, J. M. Melenk, and D. Praetorius. Local inverse estimates for non-local boundary integral operators. *arXiv:1504.04394*, April 2015.
- [BdVBSV14] L. Beirão da Veiga, A. Buffa, G. Sangalli, and R. Vázquez. Mathematical analysis of variational isogeometric methods. Acta Numer., 23:157–287, 2014.
- [Car97] C. Carstensen. An a posteriori error estimate for a first-kind integral equation. *Math. Comp.*, 66(217):139–155, 1997.
- [CHB09] J. Cottrell, T. Hughes, and Y. Bazilevs. *Isogeometric analysis: toward integration of CAD and FEA*. John Wiley & Sons, 2009.
- [CP06] C. Carstensen and D. Praetorius. Averaging techniques for the effective numerical solution of Symm's integral equation of the first kind. *SIAM J. Sci. Comput.*, 27(4):1226–1260, 2006.
- [CS95] C. Carstensen and E. P. Stephan. A posteriori error estimates for boundary element methods. *Math. Comp.*, 64(210):483–500, 1995.
- [de 86] C. de Boor. *B(asic)-spline basics*. Mathematics Research Center, University of Wisconsin-Madison, 1986.
- [Fae00] B. Faermann. Localization of the Aronszajn-Slobodeckij norm and application to adaptive boundary element methods. I: The two-dimensional case. IMA J. Numer. Anal., 20(2):203– 234, 2000.
- [FFK⁺15] M. Feischl, T. Führer, M. Karkulik, J. M. Melenk, and D. Praetorius. Quasi-optimal convergence rates for adaptive boundary element methods with data approximation. Part II: Hyper-singular integral equation. *Electron. Trans. Numer. Anal.*, 44:153–176, 2015.
- [FGHP16a] M. Feischl, G. Gantner, A. Haberl, and D. Praetorius. Adaptive 2D IGA boundary element methods. Eng. Anal. Bound. Elem., 62:141–153, 2016.
- [FGHP16b] M. Feischl, G. Gantner, A. Haberl, and D. Praetorius. Optimal convergence for adaptive IGA boundary element methods for weakly-singular integral equations. *Numer. Math.*, pages 1–36, 2016.
- [FGP] T. Führer, G. Gantner, and D. Praetorius. Optimal convergence for adaptive IGA boundary element methods with knot multiplicity decrease. Unpublished.
- [FGP15] M. Feischl, G. Gantner, and D. Praetorius. Reliable and efficient a posteriori error estimation for adaptive IGA boundary element methods for weakly-singular integral equations. *Comput. Methods Appl. Mech. Engrg.*, 290:362–386, 2015.
- [Gan14] G. Gantner. Adaptive isogeometric BEM. Master's thesis, Institute for Analysis and Scientific Computing, TU Wien, Wien, 2014.
- [HCB05] T. Hughes, J. Cottrell, and Y. Bazilevs. Isogeometric analysis: CAD, finite elements, NURBS, exact geometry and mesh refinement. Comput. Methods Appl. Mech. Engrg., 194(39):4135–4195, 2005.
- [PGK⁺09] C. Politis, A. Ginnis, P. Kaklis, K. Belibassakis, and C. Feurer. An isogeometric BEM for exterior potential-flow problems in the plane. In 2009 SIAM/ACM Joint Conference on Geometric and Physical Modeling, pages 349–354. ACM, 2009.

- [Pra06] D. Praetorius. *Numerische Mathematik*. Lecture Notes, Institute for Analysis and Scientific Computing, TU Wien, Wien, 2006.
- [Pra07] D. Praetorius. *Boundary Element Method*. Lecture Notes, Institute for Analysis and Scientific Computing, TU Wien, Wien, 2007.
- [SS11] S. A. Sauter and C. Schwab. *Boundary element methods*. Springer, Berlin, 2011.
- [SSE⁺13] M. Scott, R. Simpson, J. Evans, S. Lipton, S. Bordas, T. Hughes, and T. Sederberg. Isogeometric boundary element analysis using unstructured t-splines. *Comput. Methods Appl. Mech. Engrg.*, 254:197–221, 2013.
- [Ste08] O. Steinbach. Numerical approximation methods for elliptic boundary value problems. Springer, New York, 2008.