

2-2018

## $H^2$ -Convergence of least-squares kernel collocation methods

Ka Chun Cheung

*Department of Mathematics, Hong Kong Baptist University, Hong Kong, kccheung@astri.org*

Leevan Ling

*Department of Mathematics, Hong Kong Baptist University, Hong Kong, lling@hkbu.edu.hk*

Robert Schaback

*Institut für Numerische und Angewandte Mathematik, Georg-August-Universität, Germany, schaback@math.uni-göttingen.de*

Follow this and additional works at: [https://repository.hkbu.edu.hk/hkbu\\_staff\\_publication](https://repository.hkbu.edu.hk/hkbu_staff_publication)



Part of the [Mathematics Commons](#)

This document is the authors' final version of the published article.

Link to published article: <http://dx.doi.org/10.1137/16M1072863>

---

### APA Citation

Cheung, K., Ling, L., & Schaback, R. (2018).  $H^2$ -Convergence of least-squares kernel collocation methods. *SIAM Journal on Numerical Analysis*, 56 (1), 614-633. <https://doi.org/10.1137/16M1072863>

This Journal Article is brought to you for free and open access by HKBU Institutional Repository. It has been accepted for inclusion in HKBU Staff Publication by an authorized administrator of HKBU Institutional Repository. For more information, please contact [repository@hkbu.edu.hk](mailto:repository@hkbu.edu.hk).

# $H^2$ -CONVERGENCE OF LEAST-SQUARES KERNEL COLLOCATION METHODS

KA CHUN CHEUNG\*, LEEVAN LING†, AND ROBERT SCHABACK‡

**Abstract.** The strong-form asymmetric kernel-based collocation method, commonly referred to as the Kansa method, is easy to implement and hence is widely used for solving engineering problems and partial differential equations despite the lack of theoretical support. The simple least-squares (LS) formulation, on the other hand, makes the study of its solvability and convergence rather non-trivial. In this paper, we focus on general second order linear elliptic differential equations in  $\Omega \subset \mathbb{R}^d$  under Dirichlet boundary conditions. With kernels that reproduce  $H^m(\Omega)$  and some smoothness assumptions on the solution, we provide conditions for a constrained least-squares method and a class of weighted least-squares algorithms to be convergent. Theoretically, for  $\max(2, \lceil (d+1)/2 \rceil) \leq \nu \leq m$ , we identify some  $H^\nu(\Omega)$  convergent LS formulations that have an optimal error behavior like  $h^{m-\nu}$ . For  $d \leq 3$ , the proposed methods are optimal in  $H^2(\Omega)$ . We demonstrate the effects of various collocation settings on the respective convergence rates.

**Key words.** Meshfree method, radial basis function, Kansa method, overdetermined collocation.

**AMS subject classifications.** 65D15, 65N35, 41A63.

**1. Introduction.** Mathematical models or differential equations are meaningful only if they can somehow mirror the overly complicated real world. Similarly, numerical methods are useful only if they can produce approximations guaranteed to converge to the outcome that the mathematical model predicts. It could take tens of years for some good numerical strategies to mature and become a well-established class of numerical methods with a complete and rigid theoretical framework. Take the finite element method as an example. It waited for a quarter of a century [5] to get its rigorous mathematical foundation. This paper aims to continue our theoretical contributions to the unsymmetric radial basis function (RBF) collocation method, which is also known as the Kansa method in the community and we shall use this name throughout this paper.

To quickly overview the development of the Kansa method and its connection to the radial basis function scattered data interpolation problem, let us look at some of its cornerstones [7, 8, 37]. An RBF is a smooth scalar function  $\phi : \mathbb{R}^d \rightarrow \mathbb{R}$ , which usually is induced from a kernel function  $\Phi : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{R}$  in today's applications, such that the interpolant of an interpolation problem is given as a linear combination

$$u = \sum_{j=1}^{n_Z} \lambda_j \phi(\|\cdot - z_j\|_2) = \sum_{j=1}^{n_Z} \lambda_j \Phi(\cdot, z_j), \quad (1.1)$$

of shifted RBFs in which the set  $Z = \{z_1, \dots, z_{n_Z}\}$  contains *trial centers* that specify the shifts of the kernel function in the expansion. Dealing with scaling has been another huge topic in Kansa methods [12, 18, 35] for a decade, but we will ignore this point for the sake of brevity.

---

\*Department of Mathematics, Hong Kong Baptist University, Kowloon Tong, Hong Kong & ASTRI Hong Kong Applied Science and Technology Research Institute Company Limited. (kccheung@astri.org)

†Department of Mathematics, Hong Kong Baptist University, Kowloon Tong, Hong Kong. (lling@hkbu.edu.hk)

‡Institut für Numerische und Angewandte Mathematik, Georg-August-Universität Göttingen, Germany. (schaback@math.uni-goettingen.de)

Impressed by the meshfree nature, simplicity to program, dimension independence, and arbitrarily high convergence rates in interpolations, E.J. Kansa [16, 17] proposed to modify the RBF interpolation method to solve partial differential equations (PDEs) in the early 90s. Using the same RBF expansion (1.1), Kansa imposed strong-form collocation conditions instead of interpolation conditions for identifying the unknown coefficients. Consider a PDE given by  $\mathcal{L}u = f$  in  $\Omega$  and  $\mathcal{B}u = g$  on  $\Gamma = \partial\Omega$ . The Kansa method collocates the PDE at the trial centers  $Z$  to yield exactly  $n_Z$  conditions:

$$\begin{aligned}\mathcal{L}u(z_i) &= \sum \lambda_j \mathcal{L}\phi(\|z_i - z_j\|), & \text{for } z_i \in Z \cap \Omega, \\ \mathcal{B}u(z_i) &= \sum \lambda_j \mathcal{B}\phi(\|z_i - z_j\|), & \text{for } z_i \in Z \cap \Gamma,\end{aligned}\tag{1.2}$$

for identifying the unknown  $\lambda_j$  or equivalently, a numerical approximation to  $u$  from the *trial space*

$$\mathcal{U}_Z = \mathcal{U}_{Z, \Omega, \Phi} := \text{span}\{\Phi(\cdot, z_j) : z_j \in Z\}.\tag{1.3}$$

This approach requires no re-formulation of the PDE and no triangularization. As long as one knows how to program for an interpolation problem, it only takes minutes to understand and code up something for the Kansa method. Since invented, the Kansa method has been widely used in vast numbers of applications in physics and engineering [3, 19, 22, 31].

Since the differential and boundary operators of a PDE are independently applied to yield different rows of the final linear system of equations, it is easy to see why any Kansa system matrix is unsymmetric. While this has some implications for the choice of linear solvers, the unsymmetric matrix places the Kansa method far away from the approximation theories from which RBFs interpolation theories were built. Though the technique introduced by Kansa is very successful in a large variety of applications in Engineerings and Science, there were no proven results about it for over 10 years. After many unsuccessful attempts to establish such a foundation, Hon and Schaback [14] showed in 2001 that there are extremely rare cases where the original approach can fail because the underlying linear system can be singular. This puts an end to all attempts to prove stability of the Kansa method in general. One workaround is to apply *symmetric collocation* [6, 9] that mimics scattered Hermite interpolation. While the Kansa trial space basis in (1.1) is independent of the collocation, the symmetric method takes a basis that is itself dependent on the collocation. This approach yields positive definite symmetric system matrices [39] at the expense of higher smoothness requirements and less stability. On the positive side, symmetric collocation can be proven [33] to be error-optimal, because it is a pointwise optimal recovery of the solution from discrete input data.

The lack of theory for the Kansa method remained the same until 2006, when we provided the first solvability results for an extended Kansa method. In order to ensure solvability, *overtesting* is applied. Keeping the trial space (1.3) based on a set  $Z$  of *trial centers*, the standard Kansa system (1.2) is modified by taking another, but usually larger discrete set  $X$  of collocation points that is sufficiently fine relative to the set  $Z$  of trial centers. Readers are referred to the original articles [26] and an extension [32] to the corresponding weak problems for details. In 2008, we had a partial answer to the convergence of an overdetermined Kansa formulation [27]. Our analysis was carried out based on the continuous and discrete maximum norms. We showed that the  $\ell_\infty$ -minimizer of a residual functional converges to the exact solution at the optimal speed, i.e. with the same convergence rate as the interpolant converges

to the exact solution. From then on, we attempted to extend the theories to the least-squares (LS) minimizer [20] and numerically verified in extended precision arithmetic that the LS-minimizer also converges at the optimal rate [21]. Recently, in [34], we gave an  $L^\infty$  convergence rate of  $m - 2 - d/2$  for an overdetermined Kansa method in  $H^m$  for  $m > 2 + d/2$ . In this study, we continue to work on the overdetermined Kansa method and concentrate on the popular LS solution. In Section 2, we will provide all the necessary assumptions and prove error estimates for a constrained least-squares (CLS) and a class of *weighted least-squares* (WLS) formulations. The convergence for the CLS formulation will then be given in Section 3. In Sections 4 and 5, the theory for WLS formulations in two trial spaces will be given. Lastly, we will numerically verify the accuracy and convergence rates of some proven convergent formulations in Section 6.

**2. Notations, assumptions and main theorems.** Throughout the paper, the notation  $C$  will be reserved for generic constants whose subscripts indicate the dependencies of the constant.

We consider a general second order elliptic differential equation in some bounded domain  $\Omega \subset \mathbb{R}^d$  subject to the Dirichlet boundary condition on  $\Gamma = \partial\Omega$ :

$$\mathcal{L}u = f \text{ in } \Omega \quad \text{and} \quad u = g \text{ on } \Gamma, \quad (2.1)$$

where

$$\begin{aligned} \mathcal{L}u(x) := & \sum_{i,j=1}^d \frac{\partial}{\partial x^j} \left( a^{ij}(x) \frac{\partial}{\partial x^i} u(x) \right) + \sum_{j=1}^d \frac{\partial}{\partial x^j} (b^j(x)u(x)) \\ & + \sum_{i=1}^d c^i(x) \frac{\partial}{\partial x^i} u(x) + d(x)u(x). \end{aligned} \quad (2.2)$$

The Sobolev regularity of the true solution will be denoted by  $m$ , and we will work in Hilbert spaces  $H^k(\Omega)$  and  $H^{k-1/2}(\Gamma)$  with standard Sobolev norms  $\|u\|_{k,\Omega}^2 = \sum_{|\alpha| \leq k} \|D^\alpha u\|_{L^2(\Omega)}^2$  and  $\|u\|_{k-1/2,\Gamma}$  defined via atlas [13] respectively, for  $k \leq m$ .

**ASSUMPTION 2.1** (Smoothness of domain). *We assume that the bounded domain  $\Omega$  has a piecewise  $C^m$ -boundary  $\Gamma$  so that  $\Omega$  is Lipschitz continuous and satisfies an interior cone condition.*  $\square$

Now the trace theorem [38] can be applied and we can define a trace operator:

$$\mathcal{T} : H^m(\Omega) \rightarrow H^{m-1/2}(\Gamma) \text{ such that } \mathcal{T}u = u|_\Gamma \text{ for all } u \in C^m(\bar{\Omega}),$$

for  $m > 1/2$ , with a continuous right-inverse linear extension operator  $\mathcal{E}$  such that

$$\mathcal{T} \circ \mathcal{E}g = g \text{ for all } g \in H^{m-1/2}(\Gamma).$$

The smoothness assumption also allows a partition of unity of the boundary [38], each part of which can be mapped to the unit ball in  $\mathbb{R}^{d-1}$  by a  $C^m$ -diffeomorphism. This allows us to define Sobolev norms on  $\Gamma$  and apply some Sobolev inequalities (i.e., kernel independent ones).

**ASSUMPTION 2.2** (Differential operator and solution). *Assume that  $\mathcal{L}$  as in (2.2) is a strongly elliptic operator with coefficients belonging to  $W_\infty^m(\Omega)$ . Also, we assume that the functions  $f$  and  $g$  are smooth enough to admit a classical solution*

$u^* \in H^m(\Omega)$ . □

By results in [11],  $\mathcal{L}$  is a bounded operator from  $H^m(\Omega)$  to  $H^{m-2}(\Omega)$  with

$$\|\mathcal{L}u\|_{m-k-2,\Omega} \leq C_{\Omega,\mathcal{L}} \|u\|_{m-k,\Omega}, \quad 0 \leq k \leq m-2, \quad k \in \mathbb{N}, \quad (2.3)$$

for all  $u \in H^m(\Omega)$ . Moreover, the following boundary regularity estimate [15] holds:

$$\|u\|_{k+2,\Omega} \leq C_{\Omega,\mathcal{L},k} (\|\mathcal{L}u\|_{k,\Omega} + \|u\|_{k+1+1/2,\Gamma}), \quad 0 \leq k \leq m-2, \quad (2.4)$$

for all  $u \in H^m(\Omega)$  with  $C_{\Omega,\mathcal{L},k}$  depending on  $\Omega$ , the ellipticity constant of  $\mathcal{L}$ , and  $k \geq 0$ .

**ASSUMPTION 2.3 (Kernel).** *Assume  $\Phi_m$  is a reproducing kernel of  $H^m(\Omega)$  for some integer  $m > \max(2, \lceil (d+1)/2 \rceil) + d/2$ . More precisely, we use a symmetric positive definite kernel  $\Phi_m$  on  $\mathbb{R}^d$  with smoothness  $m$  that satisfies*

$$c_{\Phi_m} (1 + \|\omega\|_2^2)^{-m} \leq \widehat{\Phi_m}(\omega) \leq C_{\Phi_m} (1 + \|\omega\|_2^2)^{-m} \quad \text{for all } \omega \in \mathbb{R}^d, \quad (2.5)$$

for two constants  $0 < c_{\Phi_m} \leq C_{\Phi_m}$ . □

For any  $m > d/2$ , its native space  $\mathcal{N}_{\Omega,\Phi_m}$  on  $\mathbb{R}^d$  [2, 37] is norm-equivalent to  $H^m(\mathbb{R}^d)$ . This includes the standard *Whittle-Matérn-Sobolev* kernel with exact Fourier transform  $(1 + \|\omega\|_2^2)^{-m}$  that takes the form

$$\Phi_m(x) := \|x\|_2^{m-d/2} \mathcal{K}_{m-d/2}(\|x\|_2) \quad \text{for all } x \in \mathbb{R}^d, \quad (2.6)$$

where  $\mathcal{K}_\nu$  is the Bessel functions of the second kind. The compactly supported piecewise polynomial Wendland functions [36] are another examples of kernels satisfying (2.5).

Let  $\mathcal{S}$  be any discrete set of  $n_{\mathcal{S}}$  points in  $\Omega$ . For describing the denseness of  $\mathcal{S} \subset \Omega$ , its *fill distance* for fixed  $\Omega$  and *separation distance* are defined as

$$h_{\mathcal{S}} := \sup_{\zeta \in \Omega} \min_{z \in \mathcal{S}} \|z - \zeta\|_{\ell_2(\mathbb{R}^d)} \quad \text{and} \quad q_{\mathcal{S}} := \frac{1}{2} \min_{\substack{z_i, z_j \in \mathcal{S} \\ z_i \neq z_j}} \|z_i - z_j\|_{\ell_2(\mathbb{R}^d)},$$

respectively, and the quantity  $h_{\mathcal{S}}/q_{\mathcal{S}} =: \rho_{\mathcal{S}}$  is commonly referred as its *mesh ratio*. For any  $u \in H^m(\Omega)$ , we define discrete norms on  $\mathcal{S}$  by  $\|u\|_{\mathcal{S}} = \|u\|_{0,\mathcal{S}} = \|u\|_{\ell_2(\mathcal{S})}$ , for  $0 \leq k < m - d/2$ . The same notations will also be used to denote discrete norms on boundary for any discrete set  $\mathcal{S} \subset \Gamma$ .

**ASSUMPTION 2.4 (Data points and trial space).** *Let  $Z = \{z_1, \dots, z_{n_Z}\}$  be a discrete set of trial centers in  $\Omega$ . Let  $X = \{x_1, \dots, x_{n_X}\}$  be a discrete set of PDE collocation points in  $\Omega$  and  $Y = \{y_1, \dots, y_{n_Y}\}$  be a set of boundary collocation points on  $\Gamma$ . We assume the set  $Z$  of trial centers is sufficiently dense with respect to  $\Omega$ ,  $\Phi$ , and  $\mathcal{L}$  but independent of the solution. In analogy to (1.3), but now with translation-invariance, we define the finite-dimensional trial space as*

$$\mathcal{U}_Z = \mathcal{U}_{Z,\Omega,\Phi_m} := \text{span}\{\Phi_m(\cdot - z_j) : z_j \in Z\} \subset \mathcal{N}_{\Omega,\Phi_m}.$$

For any  $u$  in the native space  $\mathcal{N}_{\Omega,\Phi_m}$  of  $\Phi_m$ , we denote  $I_Z u = I_{Z,\Phi_m} u$  to be the unique interpolant of  $u$  on  $Z$  from the trial space  $\mathcal{U}_Z$ . We assume all point sets are quasi-uniform and maintain linear ratios of oversampling as they were refined. That is, there exist constants  $\rho_{\mathcal{S}} \geq 1$  such that

$$q_{\mathcal{S}} \leq h_{\mathcal{S}} \leq \rho_{\mathcal{S}} q_{\mathcal{S}} \quad \text{for } \mathcal{S} \in \{X, Y, Z\} \quad (2.7)$$

and ratios of oversampling  $\gamma_S \geq 1$  such that

$$h_Z \leq \gamma_S h_S \quad \text{for } S \in \{X, Y\} \quad (2.8)$$

holds for all admissible sets of data points.  $\square$

Note that the sets  $X$  and  $Y$  of collocation points together have to be as dense as the trial centers in  $Z$  to ensure stability. This paper will provide rigid sufficient conditions for this.

Imposing strong testing on (2.1) at collocation points in  $X$  and  $Y$  yields  $n_X + n_Y > n_Z$  conditions, from which one can hopefully identify a numerical approximation from some trial spaces. The following theorems summarize our convergence results for three possible least-squares alternatives. The first concerns the case where we enlarge the set  $Z$  of trial points by adding the set  $Y$  of boundary collocation points to it. Then, we can keep the numerical solution to be exact on  $Y$ , and we add this as a constraint.

**THEOREM 2.5** (Constrained least squares (CLS)). *Suppose the Assumptions 2.1 to 2.4 hold. Let  $u^* \in H^m(\Omega)$  denote the exact solution of the elliptic PDE (2.1), and let an integer  $\nu$  with  $\max(2, \lceil (d+1)/2 \rceil) \leq \nu < m - d/2$  be given. In addition, suppose the sets  $X, Y$  and  $Z \cup Y$  satisfy conditions (2.8) with  $Z \cup Y$  instead of  $Z$  and (3.2). Let  $u_{X,Y}^{CLS} \in \mathcal{U}_{Z \cup Y}$  be the CLS solution defined as*

$$u_{X,Y}^{CLS} := \arg \inf_{u \in \mathcal{U}_{Z \cup Y}} \|\mathcal{L}u - f\|_X^2 \quad \text{subject to } u|_Y = g|_Y. \quad (2.9)$$

Then, the error estimates

$$\|u_{X,Y}^{CLS} - u^*\|_{\nu, \Omega} \leq C_{\Omega, \Phi_m, \mathcal{L}, \nu, \rho_X, \gamma_X} h_{Z \cup Y}^{m-d/2-\nu} \|u^*\|_{m, \Omega} \quad \text{for } m > \nu + \frac{d}{2},$$

and

$$\|u_{X,Y}^{CLS} - u^*\|_{\nu, \Omega} \leq C_{\Omega, \Phi_m, \mathcal{L}, \nu, \rho_X, \gamma_X} h_{Z \cup Y}^{m-\nu} \|u^*\|_{m, \Omega} \quad \text{for } m > \nu + 1 + \frac{d}{2},$$

hold for some constants that depend only on  $\Omega, \Phi_m, \mathcal{L}, \nu$ , mesh ratio  $\rho_X$  and ratio of oversampling  $\gamma_X$ .

The next case does not require exactness on  $Y$  but still keeps  $Z \cup Y$  as the set of trial centers.

**THEOREM 2.6** (Weighted least squares (WLS)). *Suppose all the assumptions in Theorem 2.5 hold. We further assume that  $h_X \leq h_Y < 1$ . For any  $\theta \geq 0$  and integer  $\nu$  with  $\max(2, \lceil (d+1)/2 \rceil) \leq \nu < m - d/2$ , let  $u_{X,Y,Z \cup Y}^{WLS, \theta} \in \mathcal{U}_{Z \cup Y}$  be the WLS solution defined as*

$$u_{X,Y,Z \cup Y}^{WLS, \theta} := \arg \inf_{u \in \mathcal{U}_{Z \cup Y}} \|\mathcal{L}u - f\|_X^2 + \left( \frac{h_Y}{h_X} \right)^{(d/2+2-\nu)\theta} h_Y^{-2\theta} \|u - g\|_Y^2. \quad (2.10)$$

Then, the error estimates

$$\|u_{X,Y,Z \cup Y}^{WLS, \theta} - u^*\|_{\nu, \Omega} \leq C_{\Omega, \Phi_m, \mathcal{L}, \nu, \rho_X, \gamma_X, \gamma_Y} h_{Z \cup Y}^{m-d/2-\nu-(2-\theta)_+} \|u^*\|_{m, \Omega} \quad \text{for } m > \nu + \frac{d}{2},$$

and

$$\|u_{X,Y,Z \cup Y}^{WLS, \theta} - u^*\|_{\nu, \Omega} \leq C_{\Omega, \Phi_m, \mathcal{L}, \nu, \rho_X, \gamma_X, \gamma_Y} h_{Z \cup Y}^{m-\nu-(2-\theta)_+} \|u^*\|_{m, \Omega} \quad \text{for } m > \nu + 1 + \frac{d}{2},$$

hold for some constants that depend only on  $\Omega$ ,  $\Phi_m$ ,  $\mathcal{L}$ ,  $\nu$ ,  $\rho_X$ , and ratios of oversampling  $\gamma_X$  and  $\gamma_Y$ .

Due to the presence of  $h_Y$  and  $q_{Z \cup Y}$ , condition (3.2) in Theorems 2.5 and 2.6 is satisfiable only when the generic constant there, which depends on the domain, differential operator, kernel and the value of  $\nu$ , is small. Since there is very little known about the magnitude of such a constant, it is not straightforward to verify if condition (3.2) is being met. If it is unsatisfied, the theoretical error bounds of both CLS and WLS will stagnate at a constant. In Section 6, we will numerically confirm that both formulations converge. To be more general, we go back to the case where  $Z$  is the set of trial nodes, independent of  $X$  and  $Y$ . Instead of (3.2), this allows us to use another condition (3.3), whose satisfiability is trivial by using sufficiently small  $h_X$  and  $h_Y$  with respect to  $q_Z$ .

**THEOREM 2.7** (WLS in a smaller trial space). *Suppose the Assumptions 2.1 to 2.4 hold. Moreover, the sets  $X$ ,  $Y$  and  $Z$  satisfy conditions (2.8) and (3.3). For any  $0 \leq \theta \leq 2$ , suppose the trial space of the weighted least-squares approximation (2.10) is restricted to  $u_{X,Y,Z}^{WLS,\theta} \in \mathcal{U}_Z$  instead of  $\mathcal{U}_{Z \cup Y}$ . Then, the error estimates in Theorem 2.6 with  $h_{Z \cup Y}$  replaced by  $h_Z$ , i.e.,*

$$\|u_{X,Y,Z}^{WLS,\theta} - u^*\|_{\nu,\Omega} \leq C_{\Omega,\Phi,\mathcal{L},\nu,\rho_X,\gamma_X,\gamma_Y} h_Z^{m-d/2-\nu-(2-\theta)_+} \|u^*\|_{m,\Omega} \quad \text{for } m > \nu + \frac{d}{2},$$

and

$$\|u_{X,Y,Z}^{WLS,\theta} - u^*\|_{\nu,\Omega} \leq C_{\Omega,\Phi,\mathcal{L},\nu,\rho_X,\rho_Y,\rho_Z,\gamma_X,\gamma_Y} h_Z^{m-\nu-(2-\theta)_+} \|u^*\|_{m,\Omega} \quad \text{for } m > \nu + 1 + \frac{d}{2},$$

hold for some constants that also depend on the mesh ratios  $\rho_Y$  and  $\rho_Z$ .

**3. Optimal convergence rates for CLS.** We first prove some necessary inequalities essential to our proofs.

**LEMMA 3.1** (Sampling Inequality of fractional order). *Suppose  $\Omega \subset \mathbb{R}^d$  is a bounded Lipschitz domain with a piecewise  $C^m$ -boundary. Then, there exists some constant that depends only on  $\Omega$ ,  $m$  and  $s$  such that the followings hold:*

$$\|u\|_{s,\Omega} \leq C_{\Omega,m,s} \left( h_X^{m-s} \|u\|_{m,\Omega} + h_X^{d/2-s} \|u\|_X \right) \quad \text{for } 0 \leq s \leq m,$$

and

$$\|u\|_{s-\frac{1}{2},\Gamma} \leq C_{\Omega,m,s} \left( h_Y^{m-s} \|u\|_{m,\Omega} + h_Y^{d/2-s} \|u\|_Y \right) \quad \text{for } \frac{1}{2} \leq s \leq m,$$

for any  $u \in H^m(\Omega)$  with  $m > d/2$  and any discrete sets  $X \subset \Omega$  and  $Y \subset \Gamma$  with sufficiently small mesh norm  $h_X$  and  $h_Y$ .

**PROOF.** The interior sampling inequality for  $X \subset \Omega$ , which only requires  $\Omega$  be a bounded Lipschitz domain, is a special case of a sampling inequality in [1]. Applying the interior sampling inequality to the union of unit balls in  $\mathbb{R}^{d-1}$ , which are images of the partition of unity of  $\Gamma$  under the  $C^m$ -diffeomorphism in Assumption 2.1, yields

$$\|u\|_{s-1/2,\Gamma} \leq C \left( h_Y^{(m-1/2)-(s-1/2)} \|u\|_{m-1/2,\Gamma} + h_Y^{(d-1)/2-(s-1/2)} \|u\|_Y \right),$$

for all  $1/2 \leq s \leq m$ . Finally, by applying the trace theorem, the desired boundary sampling inequality is obtained.  $\square$

LEMMA 3.2 (Inverse Inequality). *Let a kernel  $\Phi_m : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{R}$  satisfying (2.5) with smoothness  $m > d/2$  be given. Suppose  $\Omega \subset \mathbb{R}^d$  is a bounded Lipschitz domain satisfying an interior cone condition. Assume  $d/2 < \nu \leq m$ . Then there is a constant depending only on  $\Omega$ ,  $\Phi_m$ , and  $\nu$  such that*

$$\|u\|_{m,\Omega} \leq C_{\Omega,\Phi_m,\nu} q_Z^{-m+\nu} \|u\|_{\nu,\Omega} \quad \text{for all } u \in \mathcal{U}_Z \quad (3.1)$$

holds in the trial space of  $\Phi_m$  and all finite sets  $Z \subset \Omega$  with separation distance  $q_Z$ .

PROOF. Let  $u_\nu = I_{\Phi_\nu,Z} u_m$  be the interpolant of  $u_m \in \mathcal{U}_{Z,\Omega,\Phi_m}$  on  $Z$  in the trial space  $\mathcal{U}_{Z,\Omega,\Phi_\nu}$ . By [30, Cor.3.5], there exists a Paley-Wiener band-limited function

$$f_\sigma \in \mathcal{B}_\sigma = \{f \in L^2(\mathbb{R}^d) : \text{supp } \hat{f} \subseteq B(0, \sigma)\}$$

for some  $\sigma = C_{d,\nu} q_Z^{-1}$  such that  $f_\sigma|_Z = u_\nu|_Z = u_m|_Z$  and  $\|f_\sigma\|_{\nu,\mathbb{R}^d} \leq C_{\Omega,\nu} \|u_\nu\|_{\nu,\Omega}$ . Since  $f_\sigma$  is analytic, we have  $f_\sigma \in H^m(\mathbb{R}^d)$  and hence

$$\|u_m\|_{m,\Omega} \leq \|u_m - f_\sigma\|_{m,\Omega} + \|f_\sigma\|_{m,\Omega} \leq C_{\Phi_m,\Omega} \|f_\sigma\|_{m,\Omega} + \|f_\sigma\|_{m,\Omega}.$$

The last inequality is based on the fact that  $f_\sigma|_Z = u_m|_Z$  and therefore  $u_m = I_{\Phi_m,Z} f_\sigma$  is the unique interpolant in  $\mathcal{U}_{Z,\Omega,\Phi_m}$  of  $f_\sigma$ . By [37, Lem.10.24], we have

$$(I_{\Phi_m,Z} f_\sigma - f_\sigma, I_{\Phi_m,Z} f_\sigma)_{\mathcal{N}_{\Phi_m}(\Omega)} = 0,$$

which proves that the functions  $u_{m,f} - f_\sigma$  and  $u_{m,f}$  are mutually orthogonal:

$$\|u_{m,f} - f_\sigma\|_{\mathcal{N}_{\Phi_m}(\Omega)}^2 + \|u_{m,f}\|_{\mathcal{N}_{\Phi_m}(\Omega)}^2 = \|f_\sigma\|_{\mathcal{N}_{\Phi_m}(\Omega)}^2.$$

Hence,  $\|u_m - f_\sigma\|_{\mathcal{N}_{\Phi_m}(\Omega)} \leq \|f_\sigma\|_{\mathcal{N}_{\Phi_m}(\Omega)}$ . By the norm equivalence between  $\mathcal{N}_{\Phi_m}(\Omega)$  and  $H^m(\Omega)$ , we have

$$\|u_m - f_\sigma\|_{m,\Omega} \leq C_{\Phi_m,\Omega} \|f_\sigma\|_{m,\Omega}.$$

Using the Bernstein inequality for band-limited functions, e.g.,

$$\|D^\alpha f\|_{L^2(\mathbb{R}^d)} \leq \sigma^{|\alpha|} \|f\|_{L^2(\mathbb{R}^d)} \quad \text{for all } f \in \mathcal{B}_\sigma,$$

we obtain

$$\begin{aligned} \|u_m\|_{m,\Omega} &\leq (C_{\Phi_m,\Omega} + 1) \|f_\sigma\|_{m,\Omega} \\ &\leq (C_{\Phi_m,\Omega} + 1) \|f_\sigma\|_{m,\mathbb{R}^d} \\ &\leq (C_{\Phi_m,\Omega} + 1) C_{d,\nu} q_Z^{-m+\nu} \|f_\sigma\|_{\nu,\mathbb{R}^d} \\ &\leq (C_{\Phi_m,\Omega} + 1) C_{d,\nu} C_{\Omega,\nu} q_Z^{-m+\nu} \|u_\nu\|_{\nu,\Omega}. \end{aligned}$$

Finally,  $\|u_\nu\|_{\nu,\Omega} \leq C_{\Phi_\nu,\Omega} \|u_m\|_{\nu,\Omega}$  holds because  $u_\nu$  interpolates  $u_m$ .  $\square$

LEMMA 3.3 (Stability). *Let  $\nu$  be an integer  $\nu \geq 2$  and  $\nu > d/2$ . Let a kernel  $\Phi_m$  as in (2.5) with  $m \geq \nu$  be given. Suppose  $\Omega \subset \mathbb{R}^d$  is a bounded Lipschitz domain satisfying an interior cone condition. If the elliptic operator  $\mathcal{L}$  satisfies all assumptions to allow regularity (2.4), then there exists a constant depending only on  $\Omega$ ,  $\Phi_m$ ,  $\mathcal{L}$  and  $\nu$  such that*

$$\|u\|_{\nu,\Omega} \leq C_{\Omega,\Phi_m,\mathcal{L},\nu} \left( h_X^{d/2+2-\nu} \|\mathcal{L}u\|_X + h_Y^{d/2-\nu} \|u\|_Y \right)$$

holds in two circumstances:



- for all  $u \in \mathcal{U}_{Z \cup Y}$  under the condition

$$C_{\Omega, \Phi_m, \mathcal{L}, \nu} (h_X^{m-\nu} + h_Y^{m-\nu}) q_Z^{-m+\nu} < \frac{1}{2}, \quad (3.2)$$

- or for all  $u \in \mathcal{U}_Z$  under the condition

$$C_{\Omega, \Phi_m, \mathcal{L}, \nu} (h_X^{m-\nu} + h_Y^{m-\nu}) q_Z^{-m+\nu} < \frac{1}{2}, \quad (3.3)$$

for any finite sets  $X \subset \Omega$  and  $Y \subset \Gamma$ .

PROOF. For  $0 \leq k \leq m-2$ , we apply the first inequality of Lemma 3.1 (for  $u = \mathcal{L}u$ ,  $s = k$ ,  $m = m-2$ ) to get

$$\|\mathcal{L}u\|_{k, \Omega} \leq C_{\Omega, m-2, k} \left( h_X^{m-2-k} \|\mathcal{L}u\|_{m-2, \Omega} + h_X^{d/2-k} \|\mathcal{L}u\|_X \right) \quad \text{for all } u \in H^m(\Omega)$$

and, by (2.3),

$$\|\mathcal{L}u\|_{k, \Omega} \leq C_{\Omega, m-2, k} \left( h_X^{m-2-k} \|u\|_{m, \Omega} + h_X^{d/2-k} \|\mathcal{L}u\|_X \right) \quad \text{for all } u \in H^m(\Omega).$$

Using the second inequality of Lemma 3.1 (for  $s = k+2, m$ ), we get

$$\|u\|_{k+1+1/2, \Gamma} \leq C_{\Omega, m, 2} \left( h_Y^{m-2-k} \|u\|_{m, \Omega} + h_Y^{d/2-2-k} \|u\|_Y \right) \quad \text{for all } u \in H^m(\Omega)$$

and this combines with the boundary regularity estimate (2.4) into

$$\|u\|_{k+2, \Omega} \leq C_{\Omega, \mathcal{L}, m} \left( (h_X^{m-2-k} + h_Y^{m-2-k}) \|u\|_{m, \Omega} + h_X^{d/2-k} \|\mathcal{L}u\|_X + h_Y^{d/2-2-k} \|u\|_Y \right).$$

Up to here, we are still in full Sobolev space. Now we use the inverse inequality in Lemma 3.2, whatever the trial space is. If we only take  $Z$  nodes like in the lemma, then

$$\begin{aligned} \|u\|_{k+2, \Omega} &\leq C_{\Omega, \Phi, \mathcal{L}, \nu} \left( (h_X^{m-2-k} + h_Y^{m-2-k}) q_Z^{-m+\nu} \|u\|_{\nu, \Omega} \right. \\ &\quad \left. + h_X^{d/2-k} \|\mathcal{L}u\|_X + h_Y^{d/2-2-k} \|u\|_Y \right) \end{aligned}$$

for all  $u \in \mathcal{U}_Z$ . Setting  $k = \nu - 2$  with  $2 \leq \nu \leq m$ , the stability is

$$\|u\|_{\nu, \Omega} \leq C_{\Omega, \mathcal{L}, m, \nu} \left( h_X^{d/2+2-\nu} \|\mathcal{L}u\|_X + h_Y^{d/2-\nu} \|u\|_Y \right)$$

for all  $u \in \mathcal{U}_Z$  under the condition  $C_{\Omega, \Phi, \mathcal{L}, \nu} (h_X^{m-\nu} + h_Y^{m-\nu}) q_Z^{-m+\nu} < 1/2$ . If we now take  $Z \cup Y$  nodes, then the same stability holds for all  $u \in \mathcal{U}_{Z \cup Y}$  under the condition  $C_{\Omega, \Phi, \mathcal{L}, \nu} (h_X^{m-\nu} + h_Y^{m-\nu}) q_Z^{-m+\nu} < 1/2$ .  $\square$

LEMMA 3.4 (Consistency). *If the elliptic operator  $\mathcal{L}$  satisfies Assumption 2.2, the kernel  $\Phi_m$  as in (2.5) has smoothness order  $m > 2 + d/2$ , and  $X$  is quasi-uniform, then there exist some constants depending only on  $\Omega$ ,  $\Phi_m$ ,  $\mathcal{L}$  and  $\rho_X$  such that*

$$\min_{\substack{v \in \mathcal{U}_{Z \cup Y} \\ v|_Y = u^*|_Y}} \|\mathcal{L}v - \mathcal{L}u^*\|_X \leq C_{\Omega, \Phi_m, \mathcal{L}, \rho_X} h_X^{-d/2} h_{Z \cup Y}^{m-2-d/2} \|u^*\|_{m, \Omega} \quad \text{for } m > 2 + \frac{d}{2},$$

and  $\min_{\substack{v \in \mathcal{U}_{Z \cup Y} \\ v|_Y = u^*|_Y}} \|\mathcal{L}v - \mathcal{L}u^*\|_X \leq C_{\Omega, \Phi_m, \mathcal{L}, \rho_X} h_X^{-d/2} h_{Z \cup Y}^{m-2} \|u^*\|_{m, \Omega}$  for  $m > 3 + \frac{d}{2}$ ,  
 hold for any  $u^* \in H^m(\Omega)$ .

PROOF. By comparing the minimizer  $v^* \in \mathcal{U}_{Z \cup Y}$  of the optimization problem with the interpolant  $I_{Z \cup Y} u^* \in \mathcal{U}_{Z \cup Y}$  that also satisfies the constraints at  $Y$ , we turn the problem into an error estimate for radial basis function interpolation:

$$\|\mathcal{L}v^* - \mathcal{L}u^*\|_X \leq \|\mathcal{L}I_{Z \cup Y} u^* - \mathcal{L}u^*\|_X.$$

The first error estimate can be derived based on native space error estimates [37, Thm.11.9] and upper bounds of power functions [7, Sec.15.1.2]. For  $m > 2 + d/2$ , we have

$$\begin{aligned} \|\mathcal{L}I_{Z \cup Y} u^* - \mathcal{L}u^*\|_X &\leq n_X^{1/2} \|\mathcal{L}I_{Z \cup Y} u^* - \mathcal{L}u^*\|_{L^\infty(\Omega)} \\ &\leq C_{\Omega, \mathcal{L}} n_X^{1/2} \max_{|\alpha| \leq 2} |D^\alpha I_{Z \cup Y} u^* - D^\alpha u^*| \\ &\leq C_{\Omega, \mathcal{L}} n_X^{1/2} h_{Z \cup Y}^{m-d/2-2} \|u^*\|_{m, \Omega}. \end{aligned}$$

Noting that  $n_X \leq C_{\Omega} q_X^{-d} \leq C_{\Omega, \rho_X} h_X^{-d}$  yields the first estimate. If we employ kernels with a higher smoothness parameter  $m > 3 + d/2$ , we can use the estimates for functions with scattered zeros. Applying [29, Prop.3.3] to our Hilbert space setting and taking care of the definitions of discrete norms yield the desired error bound.  $\square$

To prove Theorem 2.5, suppose Assumptions 2.1–2.4 hold so that all lemmas in this section can be applied. Let  $u_{X, Y}^{CLS} \in \mathcal{U}_{Z \cup Y}$  be the CLS approximation of (2.1), defined as in (2.9). Moreover, let  $I_{Z \cup Y} u^*$  denote the unique interpolant of the exact solution  $u^* \in H^m(\Omega)$  from the trial space  $\mathcal{U}_{Z \cup Y} \subset \mathcal{N}_{\Omega, \Phi_m} = H^m(\Omega)$ . Assume the condition (3.2) holds; we shall show that the CLS solution converges to the interpolant in  $\mathcal{U}_{Z \cup Y}$ . Since the stability result in Lemma 3.3 only applies to functions in the trial space, the inequality

$$\|u_{X, Y}^{CLS} - u^*\|_{\nu, \Omega} \leq \|u_{X, Y}^{CLS} - I_{Z \cup Y} u^*\|_{\nu, \Omega} + \|I_{Z \cup Y} u^* - u^*\|_{\nu, \Omega},$$

suggests that we can focus on the difference  $u_{X, Y}^{CLS} - I_{Z \cup Y} u^* \in \mathcal{U}_{Z \cup Y}$ , which has zeros at nodes  $Y$ . Using Lemma 3.3, we have

$$\|u_{X, Y}^{CLS} - I_{Z \cup Y} u^*\|_{\nu, \Omega} \leq C_{\Omega, \Phi_m, \mathcal{L}, \nu} (h_X^{d/2+2-\nu} \|\mathcal{L}u_{X, Y}^{CLS} - \mathcal{L}I_{Z \cup Y} u^*\|_X + 0).$$

Applying Lemma 3.4 yields

$$\|u_{X, Y}^{CLS} - u^*\|_{\nu, \Omega} \leq C_{\Omega, \Phi_m, \mathcal{L}, \nu, \rho_X} (h_X^{2-\nu} + h_{Z \cup Y}^{2-\nu}) h_{Z \cup Y}^{m-2-d/2} \|u^*\|_{m, \Omega} \quad \text{for } m > \nu + d/2,$$

and

$$\|u_{X, Y}^{CLS} - u^*\|_{\nu, \Omega} \leq C_{\Omega, \Phi_m, \mathcal{L}, \nu, \rho_X} (h_X^{2-\nu} + h_{Z \cup Y}^{2-\nu}) h_{Z \cup Y}^{m-2} \|u^*\|_{m, \Omega} \quad \text{for } m > \nu + 1 + d/2.$$

For any  $\nu > 2$ , we use (2.8), i.e.,  $h_X^{2-\nu} \leq \gamma_X^{2-\nu} h_{Z \cup Y}^{2-\nu}$ , to complete the proof.

**4. Convergence for WLS.** Instead of a specific weight, we will consider a class of weighted least-squares formulations by a simple inequality.

LEMMA 4.1. *Let  $a, b > 0$ ,  $0 < \epsilon < 1$ , and  $0 \leq \theta \leq 2$ . Then the inequalities  $(\epsilon a + b)^2 \leq 2(\epsilon^\theta a^2 + b^2)$  holds.*

PROOF. Consider  $0 \leq \theta/2 \leq 1$ . From  $(\epsilon a + b)^2 \leq 2(\epsilon^2 a^2 + b^2)$  and  $\epsilon \leq \epsilon^{\theta/2}$ , we have  $(\epsilon a + b)^2 \leq 2(\epsilon^\theta a^2 + b^2)$ .  $\square$

LEMMA 4.2 (Stability). *Suppose the assumptions in Lemma 3.3 hold under the condition (3.2) and we further assume  $h_X \leq h_Y < 1$ . Let*

$$W_\theta := (h_Y/h_X)^{(d/2+2-\nu)\theta} h_Y^{-2\theta}.$$

*Then there exists a constant depending only on  $\Omega$ ,  $\Phi_m$ ,  $\mathcal{L}$  and  $\nu$  such that*

$$\|u\|_{\nu, \Omega} \leq C_{\Omega, \Phi_m, \mathcal{L}, \nu} h_Y^{d/2-\nu} W_\theta^{-\frac{1}{2}} \left( \|\mathcal{L}u\|_X^2 + W_\theta \|u\|_Y^2 \right)^{\frac{1}{2}} \quad \text{for all } 0 \leq \theta \leq 2, u \in \mathcal{U}_{Z \cup Y}$$

*holds for any finite sets  $X \subset \Omega$  and  $Y \subset \Gamma$ .*

PROOF. The CLS stability in Lemma 3.3 has to be further modified to suit the need of WLS. With the denseness requirement (3.2), let us start with

$$\|u\|_{\nu, \Omega} \leq C_{\Omega, \Phi_m, \mathcal{L}, \nu} (h_X^{d/2+2-\nu} \|\mathcal{L}u\|_X + h_Y^{d/2-\nu} \|u\|_Y) \quad (4.1)$$

for some  $\max(2, \lceil (d+1)/2 \rceil) \leq \nu < m - d/2$  and all  $u \in \mathcal{U}_{Z \cup Y}$ . We want to obtain a stability estimate with discrete sum of squares. Rewrite (4.1) as

$$\|u\|_{\nu, \Omega}^2 \leq C_{\Omega, \Phi_m, \mathcal{L}, \nu} h_Y^{d-2\nu} (\epsilon \|\mathcal{L}u\|_X + \|u\|_Y)^2 \quad \text{with } \epsilon = (h_X/h_Y)^{d/2+2-\nu} h_Y^2.$$

Note that having  $\epsilon < 1$  is a very mild requirement, for example  $h_X \leq h_Y < 1$ , and will not be an obstacle between theories and practice. By Lemma 4.1, we have

$$\begin{aligned} \|u\|_{\nu, \Omega} &\leq (C_{\Omega, \Phi_m, \mathcal{L}} h_Y^{d-2\nu} (\epsilon^\theta \|\mathcal{L}u\|_X^2 + \|u\|_Y^2))^{1/2} \\ &\leq C'_{\Omega, \Phi_m, \mathcal{L}} h_Y^{d/2-\nu} \epsilon^{\theta/2} (\|\mathcal{L}u\|_X^2 + \epsilon^{-\theta} \|u\|_Y^2)^{1/2}, \end{aligned}$$

for any  $0 \leq \theta \leq 2$ . Substituting  $\epsilon$  back yields and we obtain the desired WLS stability after simplification.  $\square$

LEMMA 4.3 (Consistency). *For any  $W > 0$ , define a functional  $J_W : H^m(\Omega) \rightarrow \mathbb{R}$  by  $J_W(u) := (\|\mathcal{L}u\|_X^2 + W\|u\|_Y^2)^{1/2}$ . Suppose the assumptions in Lemma 3.4 hold. Then, the error estimates in Lemma 3.4 also hold if the left-handed sides are replaced by  $\min_{v \in \mathcal{U}_{Z \cup Y}} J_W(v - u^*)$ .*

PROOF. Again, we compare the minimizer  $v^*$  with the interpolant  $I_{Z \cup Y} u^*$  in  $\mathcal{U}_{Z \cup Y}$ :

$$J_W^2(v^* - u^*) \leq J_W^2(I_{Z \cup Y} u^* - u^*) = \|\mathcal{L}I_{Z \cup Y} u^* - \mathcal{L}u^*\|_X^2 + W\|I_{Z \cup Y} u^* - u^*\|_Y^2,$$

where the last term vanishes due to the zeros of  $I_{Z \cup Y} u^* - u^*$  at  $Y$ .  $\square$

With both consistency and stability results, we can now prove the convergence of a class of WLS solutions defined by (2.10). By similar arguments used in Section 3,

we only need to show that the WLS solution converges to the interpolant  $I_{Z \cup Y} u^*$  of the exact solution  $u^*$  from the trial space  $\mathcal{U}_{Z \cup Y}$ . Consider the functional

$$J_{W_\theta}(u) := \left( \|\mathcal{L}u\|_X^2 + W_\theta \|u\|_Y^2 \right)^{1/2} \quad \text{for } 0 \leq \theta \leq 2, \quad (4.2)$$

where  $W_\theta$  is as defined in Lemma 4.2. Applying the results of Lemmas 4.2 and 4.3, we have the WLS solution convergence within the trial space; for simplicity, let  $\tau$  be  $d/2$  if  $m > \nu + d/2$  and zero if  $m > \nu + 1 + d/2$ . Then,

$$\begin{aligned} \|u_{X,Y,Z \cup Y}^{WLS,\theta} - I_{Z \cup Y} u^*\|_{\nu,\Omega} &\leq C_{\Omega,\Phi_m,\mathcal{L},\nu} h_Y^{d/2-\nu} W_\theta^{-1/2} J_{W_\theta} \left( u_{X,Y,Z \cup Y}^{WLS,\theta} - I_{Z \cup Y} u^* \right) \\ &\leq C_{\Omega,\Phi_m,\mathcal{L},\nu,\rho_X} h_X^{-(1-\theta/2)d/2-(\nu-2)\theta/2} h_Y^{-(1-\theta/2)(\nu-d/2)} h_{Z \cup Y}^{m-2-\tau} \|u^*\|_{m,\Omega} \\ &\leq C_{\Omega,\Phi_m,\mathcal{L},\nu,\rho_X} \max(\gamma_X, \gamma_Y)^{\theta-\nu} h_{Z \cup Y}^{m-\nu-(2-\theta)-\tau} \|u^*\|_{m,\Omega}. \end{aligned} \quad (4.3)$$

The last holds under the assumption (2.8) and  $\max(\gamma_X, \gamma_Y)^{\theta-\nu} \leq C_{\nu,\gamma_X,\gamma_Y}$  for all  $0 \leq \theta \leq 2$ . We can compare the difference between the WLS solution and the exact solution to obtain error estimates for any  $0 \leq \theta \leq 2$ . Now, we consider  $\theta = 2$

$$\|u_{X,Y,Z \cup Y}^{WLS,2} - u^*\|_{\nu,\Omega} \leq C_{\Omega,\Phi_m,\mathcal{L},\nu,\rho_X,\gamma_X,\gamma_Y} h_{Z \cup Y}^{m-\nu-\tau} \|u^*\|_{m,\Omega}.$$

The CLS and the above optimal WLS formulation share convergence estimates of the same form. They both match the convergence estimate of the interpolant exactly, that in turn confirms their optimality. To complete proving Theorem 2.6 for  $\theta > 2$ , we consider the stability for  $\theta = 2$  and Lemma 4.2 gives

$$\begin{aligned} \|u\|_{\nu,\Omega} &\leq C_{\Omega,\Phi_m,\mathcal{L}} h_X^{d/2+2-\nu} \left( \|\mathcal{L}u\|_X^2 + (h_Y/h_X)^{d+4-2\nu} h_Y^{-4} \|u\|_Y^2 \right)^{1/2} \\ &\leq C_{\Omega,\Phi_m,\mathcal{L}} h_X^{d/2+2-\nu} \left( \|\mathcal{L}u\|_X^2 + (h_Y/h_X)^{d+4-2\nu} h_Y^{-2\theta} \|u\|_Y^2 \right)^{1/2}, \end{aligned}$$

for any  $\theta \geq 2$  as long as  $h_Y < 1$ . We extend the definition of functional  $J_{W_\theta}$  in (4.2) to  $\theta \geq 2$  by  $W_\theta = (h_Y/h_X)^{d+4-2\nu} h_Y^{-2\theta}$ . Then, for any  $u \in H^m(\Omega)$ , we have

$$J_{\theta_1}(u) \leq J_{\theta_2}(u) \quad \text{for } 2 \leq \theta_1 \leq \theta_2 \leq \infty.$$

Since the CLS formulation is equivalent to the WLS with  $\theta = \infty$ , we have

$$\min_{v \in \mathcal{U}_{Z \cup Y}} J_{W_\theta}(v - u^*) \leq J_{W_\theta}(u_{X,Y}^{CLS} - u^*) \leq J_{W_\infty}(u_{X,Y}^{CLS} - u^*) \quad \text{for } \theta \geq 2,$$

where the last term is minimal by the definition of CLS solution. Theorem 2.6 can now be concluded based on Theorem 2.5. We have to take (3.2) into account in both theorems.

**5. WLS in a smaller trial space.** In this section, we will prove Theorem 2.7. To begin, let us return to the proof for WLS consistency (Lemma 4.3) but restrict the approximation in the smaller trial space  $\mathcal{U}_Z$ , within which the stability result in Lemma 4.2 remains valid. However, we can only compare the minimizer  $v^* \in \mathcal{U}_Z$  with the interpolant  $I_Z u^* \in \mathcal{U}_Z$  to the exact solution  $u^* \in H^m(\Omega)$ :

$$\min_{v \in \mathcal{U}_Z} J_{W_\theta}^2(v - u^*) \leq J_{W_\theta}^2(I_Z u^* - u^*) = \|\mathcal{L}I_Z u^* - \mathcal{L}u^*\|_X^2 + W_\theta \|I_Z u^* - u^*\|_Y^2.$$

The PDE residual on  $X$  is exactly the same as that in the previous section. Without  $Y$  in the trial centers to annihilate the boundary collocation, we simply need to identify

the extra terms associated to boundary error on  $Y$ . Following the ideas in the proof of Lemma 3.4, for  $m > \nu + d/2$ , we can bound the boundary term by

$$\begin{aligned} \|I_Z u^* - u^*\|_Y &\leq n_Y^{1/2} \|I_Z u^* - u^*\|_{L^\infty(\Gamma)} \leq n_Y^{1/2} \|I_Z u^* - u^*\|_{L^\infty(\Omega)} \\ &\leq C_{\Omega, \Phi_m, \mathcal{L}, \rho_Y} h_Y^{(d-1)/2} h_Z^{m-d/2} \|u^*\|_{m, \Omega}. \end{aligned}$$

Hence, the error estimate for WLS on  $\mathcal{U}_Z$  contains a non-dominating extra term

$$\begin{aligned} &h_Y^{d/2-2} W_\theta^{-1/2} \left( W_\theta^{1/2} C_{\Omega, \Phi_m, \mathcal{L}, \rho_Y} h_Y^{(d-1)/2} h_Z^{m-d/2} \|u^*\|_{m, \Omega} \right) \\ &\leq C_{\Omega, \Phi_m, \mathcal{L}, \rho_Y} h_Y^{d/2-2} h_Y^{-(d-1)/2} h_Z^{m-d/2} \|u^*\|_{m, \Omega} \\ &\leq C_{\Omega, \Phi_m, \mathcal{L}, \rho_Y, \gamma_Y} h_Z^{m-d/2-3/2} \|u^*\|_{m, \Omega}. \end{aligned} \quad (5.1)$$

For the other case when  $m > \nu + 1 + d/2$ , we want to bound the  $\ell_2(Y)$  norm on the boundary by some  $\ell_2(\tilde{Z} \cup Y)$  norm in the domain (like the trace theorem does). For any subset  $\tilde{Z} \subseteq Z$ , we have

$$\|I_Z u^* - u^*\|_Y = \|I_Z u^* - u^*\|_{\tilde{Z} \cup Y} \leq C_{\Omega, \Phi_m} n_{\tilde{Z} \cup Y}^{1/2} \rho_{\tilde{Z} \cup Y}^{d/2} h_Z^m \|u^*\|_{m, \Omega}.$$

We want to select  $\tilde{Z}$  so that  $\rho_{\tilde{Z} \cup Y}$  can be bounded by the denseness measures of  $Y$  and  $Z$ . We already assumed  $Y$  and  $Z$  are quasi-uniform in Assumption 2.4. We also assume  $Y$  is sufficiently dense with respect to  $\Omega$  so that  $q_{Y, \Gamma} < q_{Y, \Omega}$  (see [10, Thm.6]).

Consider the following subset that excludes all points in  $Z$  that are within distance  $h_Z$  to the boundary:  $\tilde{Z} := \left\{ z \in Z \cap \left\{ \zeta \in \Omega : \text{dist}(\zeta - \Gamma) > h_Z \right\} \right\} \subseteq Z$ . Then, we have

$$\begin{aligned} \min(q_Z, q_Y) &\leq q_{\tilde{Z} \cup Y} \leq h_{\tilde{Z} \cup Y} \leq \left( \sup_{\zeta \in \Omega_{h_Z}} + \sup_{\zeta \in \Omega \setminus \Omega_{h_Z}} \right) \min_{z \in \tilde{Z} \cup Y} \|z - \zeta\|_{\ell_2(\mathbb{R}^d)} \\ &\leq h_Z + (h_Z + h_Y). \end{aligned}$$

It is now clear that the set  $\tilde{Z} \cup Y$  is also quasi-uniform with respect to some parameter  $\rho_{\tilde{Z} \cup Y}$  that depends on  $\rho_Z$  and  $\rho_Y$ . Hence, we can bound  $\rho_{\tilde{Z} \cup Y}$  by some generic constant  $C_{\rho_Y, \rho_Z}$ . To control the term  $n_{\tilde{Z} \cup Y}$ , consider

$$n_{\tilde{Z} \cup Y} \leq n_Z + n_Y \leq C_{\Omega, \rho_Z} h_Z^{-d} + C_{\Omega, \rho_Y} h_Y^{-(d-1)} \leq C_{\Omega, \rho_Y, \rho_Z} (h_Y^{-d} + h_Y^{-d+1}).$$

Since we assumed  $h_Y < 1$ , we have  $n_{\tilde{Z} \cup Y} \leq C_{\Omega, \rho_Y, \rho_Z} h_Y^{-d}$ . Together, we have

$$\|I_Z u^* - u^*\|_Y \leq C_{\Omega, \Phi_m, \rho_Y, \rho_Z, \gamma_Y} h_Z^{-d/2} h_Z^m \|u^*\|_{m, \Omega}$$

and the extra term associated with boundary error on  $Y$  is

$$h_Y^{d/2-2} W_\theta^{-1/2} \left( W_\theta^{1/2} C_{\Omega, \Phi_m, \rho_Y, \rho_Z} h_Z^{-d/2} h_Z^m \|u^*\|_{m, \Omega} \right) \leq C_{\Omega, \Phi_m, \mathcal{L}, \rho_Y, \rho_Z, \gamma_Y} h_Z^{m-2} \|u^*\|_{m, \Omega}.$$

Boundary errors in both cases do not affect the convergence rates.

**6. Numerical demonstrations.** We test the proposed formulations in  $\Omega = [-1, 1]^2$ , Discretization is done by using regular  $Z$  with  $n_Z = 11^2, 16^2, \dots, 36^2$  and collocation points  $X$  are either regular or scattered, see Figure 6.1. For the regular cases, collocation points  $X$  (strictly in the interior) and  $Y$  are constructed similarly

with  $h_X = \gamma_X h_Z$  and  $h_Y = \gamma_Y h_Z$  with  $\gamma_X = 1, 1/2, 1/3$  and  $\gamma_Y = 1, 1/2$  such that  $Z \subseteq X$  and  $(Z \cap \Gamma) \subseteq Y$  respectively. All reported (absolute) errors are approximated by using a fixed set of  $100^2$  regular points, which is denser than the collocation  $X \cup Y$  sets in all tests.

In matrix form, collocation conditions for the PDE and boundary condition can be written as  $K_{\mathcal{L},X}\lambda = f|_X$  and  $K_{\mathcal{B},Y}\lambda = g|_Y$ , respectively, with entries  $[K_{\mathcal{L},X}]_{ij} = \mathcal{L}\Phi(x_i - z_j)$  and  $[K_{\mathcal{B},Y}]_{ij} = \Phi(y_i - z_j)$  for  $x_i \in X$  and  $y_i \in Y$ . Both resultant matrices have  $n_Z + n_Y$  (and  $n_Z$ ) columns for trial space  $\mathcal{U}_{Z \cup Y}$  (and  $\mathcal{U}_Z$ ) corresponding to each  $z_j$  from the trial space. In the CLS approach (2.9), the constraints at  $Y$  are enforced using the null space matrix of the boundary collocation matrix, denoted by  $\mathcal{N}_{\mathcal{B},Y} := \text{null}(K_{\mathcal{B},Y})$ , as in [25], so that the unknown coefficient is expressed in the form  $\lambda = \mathcal{N}_{\mathcal{B},Y}\tilde{\lambda} + K_{\mathcal{B},Y}^\dagger g|_Y$ , for some new unknown  $\tilde{\lambda}$ , which can be found by solving  $K_{\mathcal{L},X}\mathcal{N}_{\mathcal{B},Y}\tilde{\lambda} = f|_X - K_{\mathcal{L},X}K_{\mathcal{B},Y}^\dagger g|_Y$ .

In all WLS formulations, with weighting specified by  $W_\theta$  in Theorem 2.6, the unknown coefficient  $\lambda$  is obtained by solving the following overdetermined system

$$\begin{bmatrix} K_{\mathcal{L},X} \\ W_\theta K_{\mathcal{B},Y} \end{bmatrix} \lambda = \begin{bmatrix} f|_X \\ W_\theta g|_Y \end{bmatrix}$$

with the Matlab function `mldivide` in the least-squares sense. For all computations in this section, we did not employ any technique to deal with the problem of ill-conditioning. To deal with the numerical instability, readers are referred to our trial subspace selection techniques [23, 24, 28] that determine the trial set  $Z$  adaptively to circumvent the problem of ill-conditioning.

**EXAMPLE 6.1. How dense is dense?** First, we consider a Poisson problem with Dirichlet boundary conditions generated from three different exact solutions  $u^* = \sin(\pi x/2) \cos(\pi y/2)$ ,  $\text{peaks}(3x, 3y)$ , and  $\text{franke}(2x - 1, 2y - 1)$  by the corresponding functions in MATLAB. We cast the CLS formulation (2.9) using Whittle-Matérn-Sobolev kernels that reproduce  $H^m(\Omega)$  with  $m = 3, \dots, 6$ . Note that our proven  $H^2$ -convergence theories require  $m \geq 4$  for  $\Omega \subset \mathbb{R}^2$ . To see the effect of “oversampling”, all sets in this example are regular and we tested  $h_X = \{h_Z, h_Z/2, h_Z/3\}$  and  $h_Y = \{h_Z, h_Z/2\}$ . Figure 6.2 compactly shows all convergence profiles in  $H^2(\Omega)$  with respect to  $h_Z$  (instead of  $h_{Z \cup Y}$  for ease of comparison to the results in the next example).

To begin, let us focus on the  $H^2(\Omega)$  errors for  $u^* = \sin(\pi x/2) \cos(\pi y/2)$  in Figure 6.2. Generally speaking, all collocation settings demonstrate an  $m - 2$  convergence rate for all tested smoothness  $m$ ; this also includes the original Kansa formulation with  $Z = X \cup Y$ . It is obvious that the error profiles for each tested  $m$  are split into two groups. The least accurate groups (i.e., the group above) correspond to  $h_X = h_Z$ . Without over-testing the PDE, this setting would probably fail the denseness requirement (3.2) but yet allow convergence at the optimal rate. All errors reduce at a rather constant rate, except that we can see two unstable profiles in the cases of  $m = 6$ . These numerical instabilities correspond to the two cases with large numbers of boundary collocations;  $(h_X, h_Y) = (h_Z/2, h_Z/2)$  and  $(h_X, h_Y) = (h_Z/3, h_Z/2)$ . In comparison, the other two tested solutions,  $u^* = \text{peaks}(3x, 3y)$  and  $\text{franke}(2x - 1, 2y - 1)$ , are more oscillatory. We can see the CLS convergence rates slow down and approach an optimal  $m - 2$  order.

We omit the  $L^2(\Omega)$  error profiles, which show exactly two extra orders as one would expect and achieve an order- $m$  convergence before numerical instability kicks in.

$\mathcal{U}_{Z \cup Y}$		$\mathcal{U}_Z$	
$n_Y$	$\text{rank}(K_{\mathcal{B}, Y})$	$n_Y$	$\text{rank}(K_{\mathcal{B}, Y})$
80	80	80	80
160	104	160	96
244	108	244	96
328	100	328	96

TABLE 6.1

Numerical ranks of boundary collocation matrices resulting from different  $n_Y$ .

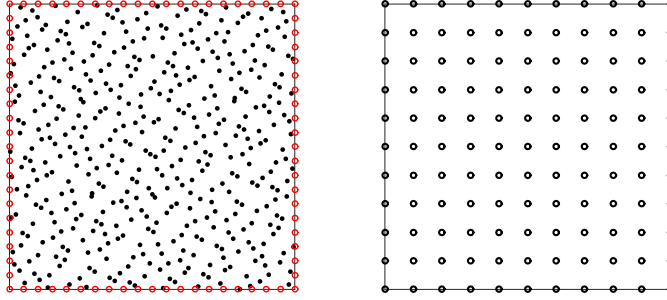


FIG. 6.1. Schematic point sets, collocations  $X$  and  $Y$  (left), and trial  $Z$  (right), used to solve various PDEs.

EXAMPLE 6.2. **CLS convergence in trial space  $\mathcal{U}_Z$ .** Putting the theoretical requirements aside, we are interested in the numerical performance of casting the CLS in the smaller and more practical trial spaces  $\mathcal{U}_Z$ . Elementary linear algebra says that if  $n_Z < n_Y$ , then we may not be able to find nontrivial functions from  $\mathcal{U}_Z$  with zeros at  $Y$ . However, one can observe numerically that the CLS formulation hardly runs into trouble when it is cast in this smaller trial space. Numerically, as  $h_Y \rightarrow 0$ , the rank of the boundary collocation matrix is bounded; for example, for  $n_Z = 21^2$  with finer and finer  $Y$ , we can see from Table 6.1 that the numerical ranks of the boundary matrices are bounded.

Figure 6.3 shows the  $H^2(\Omega)$  error profiles for the CLS performance in  $\mathcal{U}_Z$  with all other settings identical to those in Example 6.1. Comparing the CLS convergence rates in the two trial spaces, we observe that optimal convergence is also possible in  $\mathcal{U}_Z$  but only for small enough  $h_Z$ . The CLS accuracy can “catch up” when the numerical rank of  $K_{\mathcal{B}, Y}$  is relatively insignificant compared to  $n_Z$ . Therefore, the larger the  $\text{rank}(K_{\mathcal{B}, Y})$  the longer CLS takes to achieve optimal convergence. By using a smaller trial space, we not only gain computational efficiency but suffer less ill-conditioning. In all tested cases and parameters, we see no accuracy drop due to ill-conditioning.

EXAMPLE 6.3. **Numerically optimal weight for WLS.** Now we consider the WLS formulation in (2.10) with  $\theta \in \{\infty, 0, 0.5, 1, 2\}$ . We begin with the same set up as in Example 6.1 and set  $h_X = h_Y = h_Z/2$  to solve the Poisson problem in  $\Omega = [-1, 1]^2$ . The WLS weighting, as in (4.2), in this test are  $W_\theta \sim 1, n_Z, n_Z^2$  and  $n_Z^4$ , and using  $W_\infty$  is equivalent to the CLS. Figures 6.4–6.5 show the  $H^2(\Omega)$  error resulting from various  $W_\theta$  associated with  $u^* = \sin(\pi x/2, \pi y/2)$  and  $u^* = \text{peaks}(3x, 3y)$  respectively. The estimated convergence rates shown in the legends are obtained from least-squares fitting to all data; if the convergence profile is not “straight” enough, the corresponding estimate is not trustworthy.

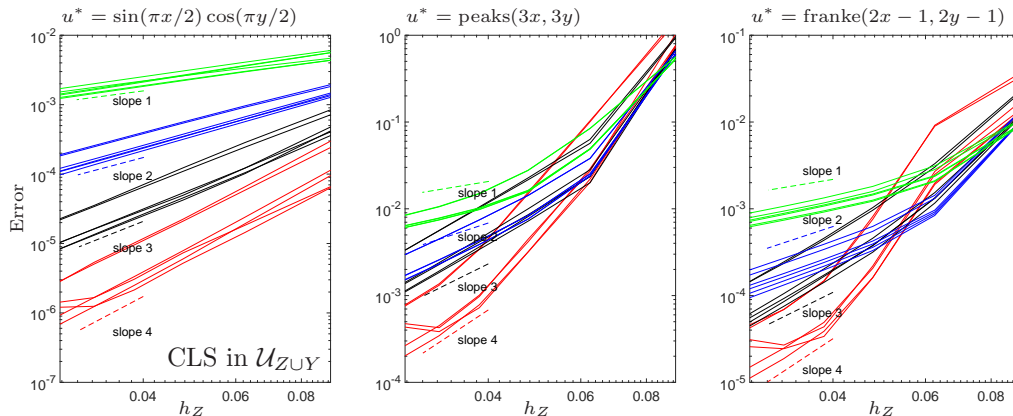


FIG. 6.2. Example 6.1:  $H^2(\Omega)$  error profiles for casting the CLS formulation in  $\mathcal{U}_{Z \cup Y}$  with Whittle-Matérn-Sobolev kernels of order  $m = 3, \dots, 6$  (colored green, blue, black, and red with the associated reference slopes  $1, \dots, 4$  respectively) to solve  $\Delta u = f$  with different exact solution  $u^*$ .

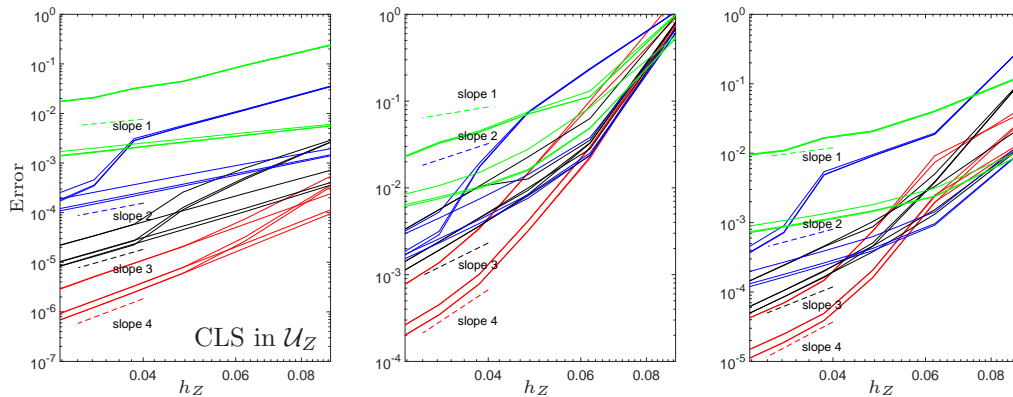


FIG. 6.3. Example 6.2:  $H^2(\Omega)$  error profiles for casting the CLS formulation in  $\mathcal{U}_Z$  to the same settings as in Figure 6.2.

From these figures, we immediately see that there is no benefit at all (in terms of both efficiency and accuracy) to go for the unweighted  $W_0$  formulation. Unlike the CLS in  $\mathcal{U}_Z$ , all tested  $W_\theta$  with  $\theta > 0$  do not have a lag in convergence rate but may suffer ill-conditioning for large  $\theta$ . By comparing all tested cases, we see that  $\theta = 1$  allows good accuracy and an optimal convergence rate in both trial spaces.

To further verify these observations, we now use sets of  $n_X$  scattered collocation points (generated by the Halton sequence; see Figure 6.1) to solve three different PDEs. Boundary collocation points remain regular with  $h_Y = h_Z/2$ . We present the numerical result for  $m = 4$  in Figure 6.6. All PDEs have

$$u^*(x, y) = \max(0, x)^4 - \max(0, y)^4,$$

whose biharmonic is discontinuous, as the exact solution. These results are compared to the results of  $m = 4$  in Figure 6.5 and the convergence patterns are very similar. More numerical examples in 3D can be found in [4].

**7. Conclusion.** We have proven some error estimates for a constraint least-squares and a class of weighted least-squares strong-form RBF collocation formula-



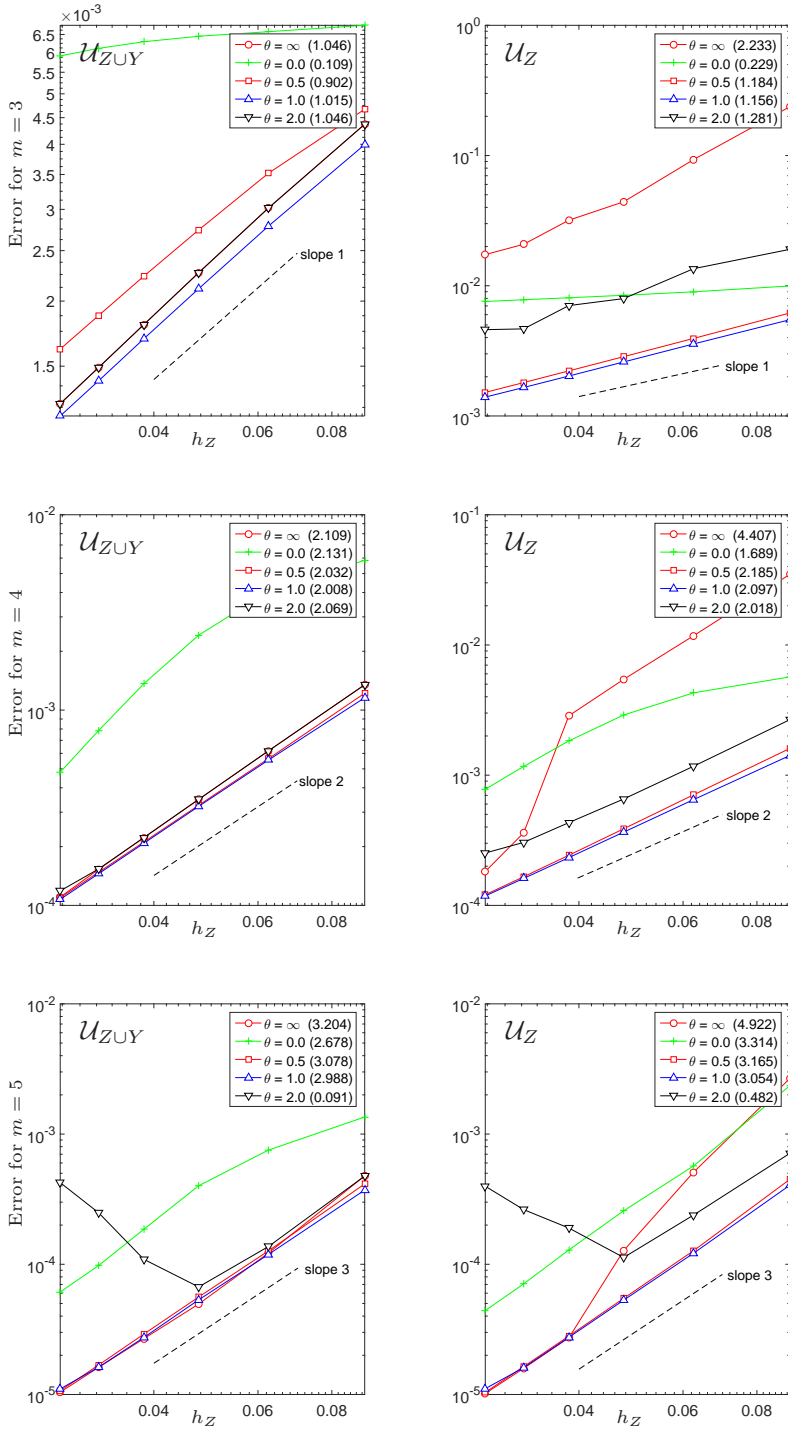


FIG. 6.4. Example 6.3:  $H^2(\Omega)$  error profiles and estimated convergence rates for casting the WLS formulation in  $U_{ZUY}$  and  $U_Z$  with Whittle-Matérn-Sobolev kernels of order  $m = 3, 4, 5$  (with estimated slopes in the legend) to solve  $\Delta u = f$  with exact solution  $u^* = \sin(\pi x/2, \pi y/2)$ .

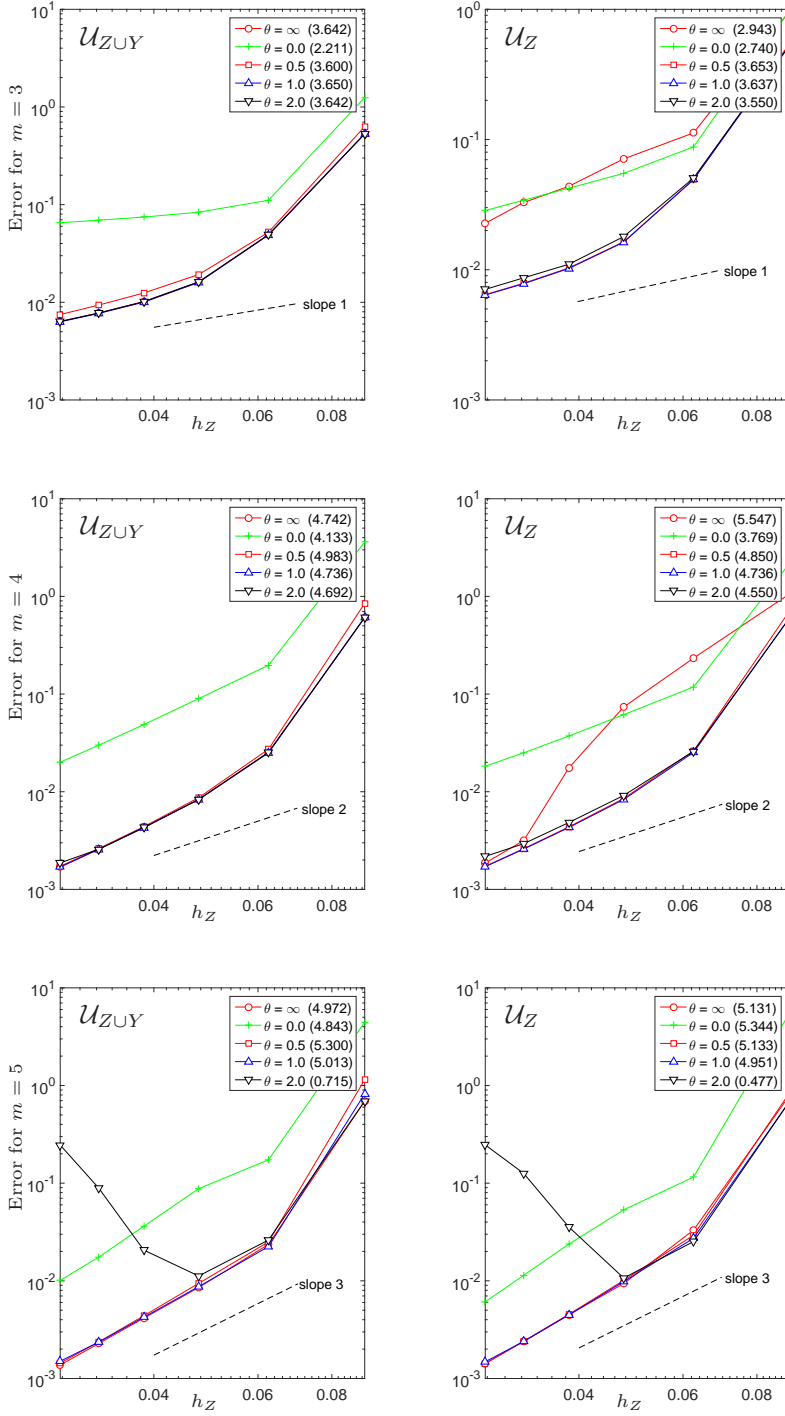


FIG. 6.5. Example 6.3:  $H^2(\Omega)$  error profiles and estimated convergence rates for casting the WLS formulation in  $\mathcal{U}_{ZUY}$  and  $\mathcal{U}_Z$  with Whittle-Matérn-Sobolev kernels of order  $m = 3, 4, 5$  (with estimated slopes in the legend) to solve  $\Delta u = f$  with exact solution  $u^* = \text{peaks}(3x, 3y)$ .

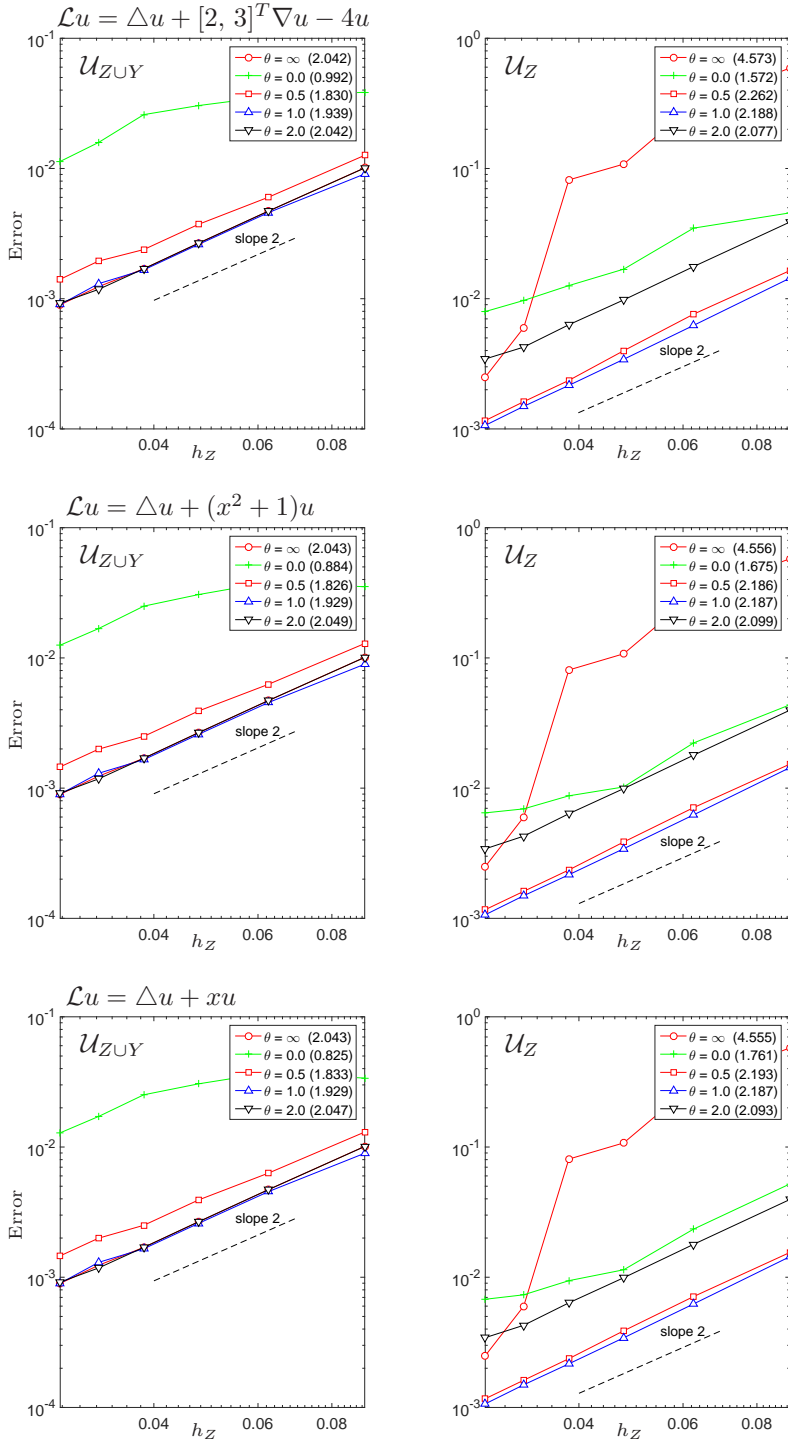


FIG. 6.6. Example 6.3:  $H^2(\Omega)$  error profiles and estimated convergence rates for casting the WLS formulation in  $U_{Z \cup Y}$  and  $U_Z$  with Whittle-Matérn-Sobolev kernels of order  $m = 4$  (with estimated slopes in the legend) to solve various PDEs with exact solution  $u^*(x, y) = \max(0, x)^4 - \max(0, y)^4$ .

tions for solving general second order elliptic problem with nonhomogenous Dirichlet boundary condition. All analysis is carried out in Hilbert spaces so that both PDE and RBF theories apply. We show that the CLS and WLS formulations using kernels, which reproduce  $H^m(\Omega)$ , with sufficient smoothness can converge at the optimal  $m - 2$  rate in  $H^2(\Omega)$  for  $d \leq 3$  with respect to the fill distance of the trial centers. Besides some standard smoothness assumptions for high order convergence, the convergence theories require some linear ratios of oversampling on both sets of PDE and boundary collocation points to hold. The mesh ratios of the collocation points will only affect the constant in the convergence estimates, which allows adaptive collocation when necessary. The techniques used in this paper cannot be further generalized to obtain optimal estimates in weaker norms. In particular, the consistency of PDE residuals measured in  $\ell_2(X)$  is capped at a rate of  $m - 2$ , which is a bottleneck for getting an optimal order- $m$  (or  $m - 1$ ) convergence estimates in  $L^2(\Omega)$  (or  $H^1(\Omega)$ ). We leave this problem open for further studies.

We verify by numerical examples that there are many convergent formulations for  $\Omega \subset \mathbb{R}^2$  that enjoy the optimal convergence rate. We thoroughly study the numerical performance of Whittle-Matérn-Sobolev kernels in two trial spaces. The larger space that includes all boundary collocation points as trial centers is more theoretically sound (in the sense of the range of optimal weighting), whereas the small one is computationally more efficient. Taking both accuracy and efficiency into consideration, casting WLS in the small trial space with a moderate weight consistently yields competitive accuracy and numerical stability.

**Acknowledgements.** This work was partially supported by a Hong Kong Research Grant Council GRF Grant, a Hong Kong Baptist University FRG Grant, and the National Natural Science Foundation of China (11528205).

#### REFERENCES

- [1] R. Arcangéli, M. C. L. de Silanes, and J. J. Torrens, *Extension of sampling inequalities to Sobolev semi-norms of fractional order and derivative data*, Numer. Math. **121** (2012), no. 3, 587–608.
- [2] M. D. Buhmann, *Radial basis functions: theory and implementations*, Cambridge Monographs on Applied and Computational Mathematics, vol. 12, Cambridge University Press, Cambridge, 2003. MR 1 997 878
- [3] C. S. Chen, C.-M. Fan, and P. Wen, *The method of approximate particular solutions for solving elliptic problems with variable coefficients*, Int. J. Comput. Methods **8** (2011), no. 3, 545–559.
- [4] K. C. Cheung and L. Ling, *Convergence studies for an adaptive meshless least-squares collocation method*, Int. J. Comp. Meth. and Exp. Meas. **5** (2017), no. 3, 377–386.
- [5] Inc. ESRD, *A brief history of FEA technology* (<http://www.esrd.com/Reliability/p-Version/HistoryofFEA.aspx>).
- [6] G. E. Fasshauer, *Solving differential equations with radial basis functions: multilevel methods and smoothing*, Adv. Comput. Math. **11** (1999), no. 2, 139–159.
- [7] ———, *Meshfree approximation methods with Matlab*, Interdisciplinary Mathematical Sciences 6. Hackensack, NJ: World Scientific., 2007.
- [8] G. E. Fasshauer and M. J. McCourt, *Kernel-based approximation methods using Matlab.*, Interdisciplinary Mathematical Sciences 19. Hackensack, NJ: World Scientific., 2015.
- [9] C. Franke and R. Schaback, *Solving partial differential equations by collocation using radial basis functions*, Appl. Math. Comput. **93** (1998), no. 1, 73–82.
- [10] E. J. Fuselier and G. B. Wright, *Scattered data interpolation on embedded submanifolds with restricted positive definite kernels: Sobolev error estimates*, SIAM J. Numer. Anal. **50** (2012), no. 3, 1753–1776.
- [11] P. Giesl and H. Wendland, *Meshless collocation: Error estimates with application to dynamical systems*, SIAM J. Numer. Anal. **45** (2007), no. 4, 1723–1741.

- [12] A. Golbabai, E. Mohebianfar, and H. Rabiei, *On the new variable shape parameter strategies for radial basis functions*, *Comput. Appl. Math.* **34** (2015), no. 2, 691–704.
- [13] N. Große and C. Schneider, *Sobolev spaces on Riemannian manifolds with bounded geometry: General coordinates and traces*, *Math. Nachrichten* **286** (2013), no. 16, 1586–1613.
- [14] Y. C. Hon and R. Schaback, *On unsymmetric collocation by radial basis functions*, *Appl. Math. Comput.* **119** (2001), no. 2-3, 177–186.
- [15] J. Jost, *Partial differential equations*, Graduate texts in mathematics, Springer, New York, 2007.
- [16] E. J. Kansa, *Multiquadrics—a scattered data approximation scheme with applications to computational fluid-dynamics. I. Surface approximations and partial derivative estimates*, *Comput. Math. Appl.* **19** (1990), no. 8-9, 127–145.
- [17] ———, *Multiquadrics—a scattered data approximation scheme with applications to computational fluid-dynamics. II. Solutions to parabolic, hyperbolic and elliptic partial differential equations*, *Comput. Math. Appl.* **19** (1990), no. 8-9, 147–161.
- [18] E. J. Kansa and R. E. Carlson, *Improved accuracy of multiquadric interpolation using variable shape parameters*, *Comput. Math. Appl.* **24** (1992), no. 12, 99 – 120.
- [19] E. J. Kansa and J. Geiser, *Numerical solution to time-dependent 4D inviscid Burgers’ equations*, *Eng. Anal. Bound. Elem.* **37** (2013), no. 3, 637–645.
- [20] T. O. Kwok and L. Ling, *On convergence of a least-squares Kansa’s method for the modified Helmholtz equations*, *Adv. Appl. Math. Mech.* **1** (2009), no. 3, 367–382.
- [21] C. F. Lee, L. Ling, and R. Schaback, *On convergent numerical algorithms for unsymmetric collocation*, *Adv. Comput. Math* **30** (2009), no. 4, 339–354.
- [22] W. Li, M. Li, C. S. Chen, and X. Liu, *Compactly supported radial basis functions for solving certain high order partial differential equations in 3D*, *Eng. Anal. Bound. Elem.* **55** (2015), no. SI, 2–9.
- [23] L. Ling, *An adaptive–hybrid meshfree approximation method*, *Int. J. Numer. Methods Eng.* **89** (2011), no. 5, 637–657.
- [24] ———, *A fast block-greedy algorithm for quasi-optimal meshless trial subspace selection*, *SIAM J. Sci. Comput.* **38** (2016), no. 2, A1224–A1250.
- [25] L. Ling and Y. C. Hon, *Improved numerical solver for Kansa’s method based on affine space decomposition*, *Eng. Anal. Bound. Elem.* **29** (2005), no. 12, 1077–1085.
- [26] L. Ling, R. Opfer, and R. Schaback, *Results on meshless collocation techniques*, *Eng. Anal. Bound. Elem.* **30** (2006), no. 4, 247–253.
- [27] L. Ling and R. Schaback, *Stable and convergent unsymmetric meshless collocation methods*, *SIAM J. Numer. Anal.* **46** (2008), no. 3, 1097–1115.
- [28] ———, *An improved subspace selection algorithm for meshless collocation methods*, *Int. J. Numer. Methods Eng.* **80** (2009), no. 13, 1623–1639.
- [29] F. J. Narcowich, J. D. Ward, and H. Wendland, *Sobolev bounds on functions with scattered zeros, with applications to radial basis function surface fitting*, *Math. Comput.* **74** (2005), no. 250, 743–763.
- [30] ———, *Sobolev error estimates and a Bernstein inequality for scattered data interpolation via radial basis functions*, *Constr. Approx.* **24** (2006), no. 2, 175–186.
- [31] G. Pang, W. Chen, and Z. Fu, *Space-fractional advection-dispersion equations by the Kansa method*, *J. Comput. Phys.* **293** (2015), no. SI, 280–296.
- [32] R. Schaback, *Convergence of unsymmetric kernel-based meshless collocation methods*, *SIAM J. Numer. Anal.* **45** (2007), no. 1, 333–351.
- [33] ———, *A computational tool for comparing all linear PDE solvers*, *Adv. Comput. Math* **41** (2015), no. 2, 333–355.
- [34] ———, *All well-posed problems have uniformly stable and convergent discretizations*, *Numer. Math.* **132** (2016), 597–630.
- [35] C. H. Tsai, J. Kolibal, and M. Li, *The golden section search algorithm for finding a good shape parameter for meshless collocation methods*, *Eng. Anal. Bound. Elem.* **34** (2010), no. 8, 738–746.
- [36] H. Wendland, *Error estimates for interpolation by compactly supported radial basis functions of minimal degree*, *J. Approx. Theory* **93** (1998), no. 2, 258–272. MR 99g:65015
- [37] ———, *Scattered data approximation*, Cambridge Monographs on Applied and Computational Mathematics, vol. 17, Cambridge University Press, Cambridge, 2005.
- [38] J. Wloka, *Partial differential equations*, Cambridge University Press, 1987.
- [39] Z. M. Wu, *Hermite-Birkhoff interpolation of scattered data by radial basis functions*, *Approx. Theory Appl.* **8** (1992), no. 2, 1–10. MR 93j:41007