A WAVELET-GALERKIN BOUNDARY ELEMENT METHOD
ON POLYHEDRAL SURFACES IN $\mathbb{R}^3$ 1

Christian Lage and Christoph Schwab
Seminar für Angewandte Mathematik
ETH-Zürich
Rämistrasse 101
CH-8092 Zürich, Switzerland

SUMMARY

The implementation of a wavelet-based Galerkin discretization of the double layer potential operator on polyhedral surfaces $\Gamma \subset \mathbb{R}^3$ is described. The algorithm generates an approximate stiffness matrix with $O(N(\log N)^2)$ entries in $O(N(\log N)^3)$ operations where $N$ is the number of degrees of freedom on the boundary. The condition number of the compressed stiffness matrix is bounded uniformly with respect to $N$. A C++ realization of the data structure containing the compressed stiffness matrix is described. It can be set up in $O(N(\log N)^2)$ operations and requires $O(N(\log N)^3)$ memory. Numerical experiments show the asymptotic complexity estimates and convergence rates to be accurate already for moderate $N$. Problems with $N > 10^5$ were computed in core on a workstation.

PROBLEM FORMULATION

Let $\Omega \subset \mathbb{R}^3$ be a bounded polyhedron with Lipschitz boundary $\Gamma = \partial \Omega$ and let $n(y)$ denote the exterior unit normal vector at $y \in \Gamma$. We consider the Dirichlet Problem

$$\Delta U = 0 \text{ in } \Omega, \quad U|_{\Gamma} = f.$$  \hspace{1cm} (1)

By $L^2(\Gamma)$ we denote the space of functions $u : \Gamma \to \mathbb{R}$ that are square integrable with respect to the surface measure $d\sigma_x$.

We equip $L^2(\Gamma)$ with the inner product

$$\langle u, v \rangle = \int_{\Gamma} uv d\sigma_x.$$  \hspace{1cm} (2)

The double layer ansatz
\[ U(x) = \langle K(x, \cdot), u \rangle \]  \tag{3}
where the double layer kernel \( K \) is given by
\[ K(x, y) = \frac{n(y) \cdot (x - y)}{4\pi |x - y|^3} \]
leads with the jump relations to the second kind boundary integral equation
\[ u \in L^2(\Gamma) : \quad \langle v, Au \rangle = \langle v, f \rangle \quad \forall v \in L^2(\Gamma) \]  \tag{4}
for the unknown density \( u : \Gamma \to \mathbb{R} \). Here \( A \) is the classical double layer potential operator which is defined almost everywhere on \( \Gamma \) by
\[ (Au)(x) = -\frac{1}{2}u(x) + \int_{\Gamma} K(x, y)u(y)ds_y, \quad x \in \Gamma. \]  \tag{5}

It is well-known that under our assumptions the operator \( A : L^2(\Gamma) \to L^2(\Gamma) \) is bounded, thus the Galerkin equations (4) make sense. Moreover, in the pointwise definition (5), the fraction 1/2 is to be modified when \( x \) is on an edge or a vertex; this, however, does not affect the weak formulation (4).

MULTIWAVELET DISCRETIZATION

We present now a fully discrete wavelet Galerkin discretization of (4) together with its properties. Full proofs for all assertions can be found in \([PSS],[PS],[LS],[R]\). \([R]\) analyzes also a fully discrete wavelet algorithm for boundary integral equations of the type \( Au = f \); there, however, collocation and tensor product wavelets are discussed.

GALERKIN DISCRETIZATION

The boundary \( \Gamma \) is partitioned into \( N_0 \) planar, open pieces \( \Gamma_j \) which are affine images of the triangle \( \mathcal{U}^0 = \{(x_1, x_2) \mid 0 < x_1 < 1, 0 < x_2 < x_1 \} \) in \( \mathbb{R}^2 \), i.e. there exist bijective, linear maps \( \chi_j \) such that \( \Gamma_j = \chi_j(\mathcal{U}^0) \). The partition \( \{\Gamma_j\}_{j=1}^{N_0} \) is assumed to be regular, i.e. for \( i \neq j \) the set \( \Gamma_i \cap \Gamma_j \) is either empty, a vertex, or an entire edge.

An inner product \( \langle \cdot, \cdot \rangle \) equivalent to \( \langle \cdot, \cdot \rangle \) in \( L^2(\Gamma) \) can be defined by
\[ (u, v) = \sum_{j=1}^{M} \int_{\mathcal{U}_j^{\Gamma}} (u|_{\Gamma_j} \circ \chi_j) (v|_{\Gamma_j} \circ \chi_j) \, dx_2 \, dx_1 \]  \tag{6}
For \( s > 0 \), we consider also the Sobolev spaces \( H^s(\Gamma_j) \) of functions with pullback in \( H^s(\mathcal{U}^0) \) endowed with the norm \( \| \cdot \|_s \). The space of functions \( u \in L^2(\Gamma) \) with \( u|_{\Gamma_j} \in H^s(\Gamma_j) \) for
\( s > 0 \) is \( \prod_{j=1}^{N_0} H^4(\Gamma_j) \), equipped with the norm

\[
\|u\|_s := \left( \sum_{j=1}^{N_0} \|u\|_{H^s(\Gamma_j)}^2 \right)^{1/2}.
\] (7)

We define a dense subspace sequence \( V^l \subset L^2(\Gamma) \), \( l = 0, 1, 2, \ldots \) as follows: divide \( U^0 \) into \( 4^l \) congruent subdomains \( \{U^l_k\} \) by successively halving the sides \( l \) times. Then define spaces

\[
V^l = \{ u \in L^2(\Gamma) \mid (u|_{\Gamma_j} \circ \chi_j)|_{U^l_k} = \text{const}, \quad j = 1, \ldots, N_0, \quad k = 1, \ldots, 4^l \}.
\]

of piecewise constant (with respect to \( \chi_j \)), discontinuous functions. Obviously, the spaces \( V^l \) form a hierarchy, i.e.,

\[
V^0 \subset V^1 \subset \cdots \subset V^l \subset V^{l+1} \subset \cdots,
\] (8)

\( N_l = \dim(V^l) = N_0 4^l \) and the \( V^l \) are dense in \( L^2(\Gamma) \).

The Galerkin approximation \( u^L \) of \( u \) is given by

\[
u^L \in V^L \quad \langle v, Au^L \rangle = \langle v, f \rangle \quad \forall v \in V^L.
\] (9)

We make the fundamental assumption that the Galerkin scheme (9) is stable in the following sense: For \( L_0 \) sufficiently large, there exists \( C > 0 \) such that

\[
\forall L \geq L_0 : \quad \inf_{0 \neq u^L \in V^L} \sup_{0 \neq u^L \in V^L} \frac{\langle v^L, Au^L \rangle}{\|u^L\|_0 \|v^L\|_0} \geq c > 0
\] (10)

where \( P_L \) denotes the \( L^2 \)-projection

\[
P_L : L^2(\Gamma) \to V^L, \quad ((v - P_L v), \varphi) = 0 \quad \forall \varphi \in V^L.
\] (11)

The stability (10) implies that for sufficiently large \( L \), the Galerkin solutions \( u^L \) of (9) exist and are quasi-optimal, i.e.

\[
\|u - u^L\|_0 \leq C \inf_{v \in V^L} \|u - v\|_0.
\] (12)

Remark 1 The stability (10) of the Galerkin discretization (9) follows, for example, from a Gårding inequality in \( L^2(\Gamma) \) of the operator \( A \). However, on polyhedral boundaries \( \Gamma \), such an inequality generally is not valid. Nevertheless, stability of (9) has been shown, at least for certain polyhedra, in [El] provided that \( V^L \) is constrained to be zero in an \( O(h) \) vicinity of the edges of \( \Gamma \). It has been observed in numerous numerical experiments, however, that on polyhedra (10) apparently holds even without the zero constraint, although a proof does not seem to be available. We assume (10) in our analysis.
MULTIWAVELET BASIS

We denote by $\Gamma := \chi_{I}(U_{l}^{k})$, $I \in \mathcal{I}_{l}$, $l = 0, \ldots, L$ the images of $U_{l}^{k}$ under respective coordinate transformations where the index sets $\mathcal{I}_{l}$ are defined by

$$\mathcal{I}_{l} := \{(j, l, k) : 1 \leq j \leq N_{0}, 1 \leq k \leq 4^{l}\}.$$  

A basis for $V^{L}$ is given by $\{\varphi_{I} : I \in \mathcal{I}_{L}\}$ with

$$\varphi_{I}|_{V_{l}} := \begin{cases} 2^{l} & \text{if } I = I', \\ 0 & \text{otherwise}, \end{cases} \quad I, I' \in \mathcal{I}_{l}, \ l = 0, \ldots, L.$$  

Then

$$(\varphi_{I}, \varphi_{I'}) = \delta_{II'} \quad I, I' \in \mathcal{I}_{L}$$

and (4) is equivalent to a linear system of equations with a dense stiffness matrix, i.e. it requires $O(N^{2})$ memory.

The multiscale Galerkin method is also given by (4), but a multiwavelet basis is used for the representation of the solution and the stiffness matrix of (4). To describe this wavelet discretization, we define a sequence $W^{l}$ of subspaces as orthogonal complement with respect to $(\cdot, \cdot)$ of $V^{l-1}$ in $V^{l}$:

$$W^{l} := \{\psi \in V^{l} \mid (\varphi, \psi) = 0 \ \forall \varphi \in V^{l-1}\}, \ l \geq 1. \quad (13)$$

Then $V^{l+1} = V^{l} \oplus W^{l+1}$ and we obtain the multilevel splitting

$$V^{L} := W^{0} \oplus W^{1} \oplus \cdots \oplus W^{L} \quad (14)$$

where $W^{0} := V^{0}$. Hence every function $u^{L} \in V^{L}$ admits a unique decomposition

$$u^{L} = w^{0} + w^{1} + \cdots + w^{L}, \quad w^{l} \in W^{l}, \ l = 0, \ldots, L. \quad (15)$$

Let $P_{-1} = 0$. Then $u^{l} = (P_{l} - P_{l-1})u^{L}$ in (15).

To obtain an orthonormal basis for $W^{l}$ we proceed as follows: consider the space $W^{1}$ of piecewise constant functions on the four subdomains $U_{l}^{k} \subset U^{0}$, $k = 1, \ldots, 4$ which have vanishing mean. We denote by $\tilde{\psi}_{1}, \tilde{\psi}_{2}, \tilde{\psi}_{3}$ an orthogonal basis of $W^{1}$ with $\|\tilde{\psi}_{i}\|_{L^{2}(U^{0})} = 1$. These multiwavelets are the analogs of the Haar-wavelet in one dimension. For $l \geq 1$ we define the basis functions $\psi_{J}: \Gamma \to \mathbb{R}$ of $W^{l}$ as usual by means of the mother wavelets $\tilde{\psi}_{\nu}$:

$$\psi_{(I, \nu)}|_{V_{l}} := \begin{cases} 2^{l-1}\tilde{\psi}_{\nu} \circ \chi_{I}^{-1} & \text{if } I = I', \\ 0 & \text{otherwise}, \end{cases} \quad I, I' \in \mathcal{I}_{l-1}, \ \nu = 1, \ldots, 3. \quad (16)$$

For $l = 0$ we use the basis functions

$$\psi_{(I,0)} := \varphi_{I}, \ I \in \mathcal{I}_{0} \quad (17)$$

Then for $l \in \mathbb{N}_{0}$ an orthonormal basis of $W^{l}$ is given by the functions $\{\psi_{J} \mid J \in \mathcal{J}_{l}\}$ with the index sets $\mathcal{J}_{l}$ defined by

$$\mathcal{J}_{l} := \begin{cases} \{(I, \nu) \mid I \in \mathcal{I}_{l-1}, 1 \leq \nu \leq 3\} & \text{for } l \geq 1, \\ \{(I, 0) \mid I \in \mathcal{I}_{0}\} & \text{for } l = 0. \quad (18)$$

By (14) an orthonormal basis of $V^{l}$ for $l \in \mathbb{N}_{0}$ is then given by

$$\{\psi_{J} \mid J \in \mathcal{J}_{0} \cup \ldots \cup \mathcal{J}_{l}\}.$$  

Accordingly, $\|u\|_{L^{2}(\Gamma)}$ can be characterized by the multiwavelet expansion coefficients.
Proposition 2 For every $u \in L^2(\Gamma)$, there holds
\[
\|u\|_{L^2(\Gamma)}^2 \sim \sum_{l=0}^{\infty} \sum_{J \in \mathcal{J}_l} |(u, \psi_J)|^2
\]
where $\sim$ denotes the equivalence of norms.

We use the multiwavelet basis (17), (16) in the Galerkin equations (4). To this end, we write $u^L$ in its wavelet representation
\[
u^L = \sum_{l=0}^{L} \sum_{J \in \mathcal{J}_l} u^L_J \psi_J, \quad u^L_J = \langle u^L, \psi_J \rangle
\]
and denote by $\tilde{u} = (u^L_J)_{J \in \mathcal{J}_0 \cup \ldots \cup \mathcal{J}_L}$ the vector of wavelet coefficients of $u^L$. It is determined by the linear system
\[
\sum_{\nu'=0}^{L} \sum_{J' \in \mathcal{J}_{\nu'}} \langle \psi_J, A_{J,J'} \psi_{J'} \rangle u^L_{J'} = \langle \psi_J, f \rangle, \quad J \in \mathcal{J}_l; \ l = 0, \ldots, L.
\]

We denote the $N_L \times N_L$ stiffness matrix in the wavelet basis by $A^L$, i.e.,
\[
A^L_{J,J'} := \langle \psi_J, A_{J,J'} \psi_{J'} \rangle, \quad J \in \mathcal{J}_l, \ J' \in \mathcal{J}_{\nu'}, \ l, \nu' = 0, \ldots, L.
\]

Then we can write (21) as
\[
A^L \tilde{u} = \tilde{f}
\]
where $\tilde{f} = (\langle \psi_J, f \rangle)_{J \in \mathcal{J}_0 \cup \ldots \cup \mathcal{J}_L}$. Note that $A^L$ is not symmetric in general. It follows from the stability (10) and the norm equivalence (19) that the condition numbers of the sequence $\{A^L\}$ of matrices are bounded: There exists $\kappa^* \in \mathbb{R}$ such that for all $L$
\[
\text{cond}_2(A^L) \leq \kappa^*.
\]

COMPRESSION

The wavelet basis $\{\psi_J\}$ defined in (17), (16) has vanishing mean in local coordinates which implies that many of the entries $A^L_{J,J'}$ are smaller than in the standard Galerkin basis (see Lemma 6.1 of [PSS] or [Sch] for details). This allows to neglect most elements $A^L_{J,J'}$ without essentially compromising the asymptotic convergence rate of the scheme.

Theorem 3 Let $s, \tilde{s} \in [0,1]$ and assume that
\[
1 \geq \alpha \geq \frac{s+1}{2}, \quad 1 \geq \tilde{\alpha} \geq \frac{\tilde{s}+1}{2}.
\]

With $a \geq 1$ a parameter to be selected define truncation parameters
\[
\delta_{\nu} = \max\{a2^{-\nu}2^{\alpha(L-\nu)}2^{\tilde{\alpha}(L-\nu)}, 2^{-L}, 2^{-\nu}\}
\]
and the corresponding compressed stiffness matrix $\tilde{A}^L$ by

$$\tilde{A}_{J,J'} := \begin{cases} A_{J,J'} & \text{if } d_{J,J'} \leq \delta \nu, \\ 0 & \text{otherwise} \end{cases}$$  \hspace{1cm} (27)$$

where $J = (I, \nu)$, $J' = (I', \nu')$ and $d_{J,J'} := \text{dist}(\Gamma_I, \Gamma_I')$ the Euclidean distance of $\Gamma_I$ and $\Gamma_I'$. Solve

$$\tilde{A}^L \tilde{u} = \tilde{f}.$$  \hspace{1cm} (28)

and denote by

$$\tilde{u}^L = \sum_{l=0}^L \sum_{J \in J_l} \tilde{u}^L_J \psi_J \in V^L$$

the corresponding approximate solution. Then the following holds:

1. Denote by $N(\tilde{A}^L)$ the number of nonzero entries in $\tilde{A}^L$. Then

$$N(\tilde{A}^L) = \begin{cases} O(N_L (\log N_L)^2) & \text{if } \alpha = \bar{\alpha} = 1, \\ O(N_L \log N_L) & \text{otherwise}. \end{cases}$$  \hspace{1cm} (29)$$

2. There exists a level $L_0$ such that for a sufficiently large in (26) the compressed Galerkin scheme is stable, i.e. for $L \geq L_0$ the $\tilde{A}^L$ are nonsingular and uniformly bounded, i.e.

$$\forall L \geq L_0 : \text{cond}(\tilde{A}^L) \leq \kappa.$$  \hspace{1cm} (30)$$

3. Assume that we have for some $0 \leq s \leq 1$ the regularity

$$f \in H^s(\Gamma) \implies u \in H^s(\Gamma)$$  \hspace{1cm} (31)$$

Then, for sufficiently large $a$ and $L_0$ in (26) and (30), respectively, we have

$$\|u - \tilde{u}^L\|_0 \leq C (\log N_L)^\nu N_L^{-s/2} \|u\|_s = Ch^s \|\log h\| \|u\|_s$$  \hspace{1cm} (32)$$

where $\nu = 0$ if $0 \leq s < 1$ and $\nu = 3/2$ if $s = 1$.

4. Let $x \in \Omega$ and denote by $\varphi$ the solution of the adjoint problem $A^* \varphi = K(x, \cdot)$. Assume the regularity $\varphi \in H^2(\Gamma)$ for some $0 \leq \bar{s} \leq 1$ and, as before, that $u \in H^s(\Gamma)$. Compute an approximate solution $\tilde{U}^L(x)$ to the Dirichlet problem (1) by inserting the approximate density $\tilde{u}^L$ into (3).

Then, for sufficiently large $a$ and $L_0$ and $\alpha, \bar{\alpha}$ as in (25) there holds the error estimate

$$\left| U(x) - \tilde{U}^L(x) \right| \leq C x a^{-2} (\log N_L)^3 N_L^{-\left(\bar{s} + \bar{\alpha} + \bar{\alpha}ight)/2} \|u\|_s \|\varphi\|_{\bar{s}}$$

$$= C' x a^{-2} h^{s + \bar{s}} \|\log h\|^2 \|u\|_s \|\varphi\|_{\bar{s}}.$$  \hspace{1cm} (33)$$

This theorem is a special case of [PS] (see also [DPS], [Sch] and [PSS]). Even with the space $V^L$ of piecewise constants, we have essentially the maximal asymptotic convergence rate $O(h^2)$ (this rate will usually not be achieved, however, due to edge- and vertex singularities of $u$).
NUMERICAL QUADRATURE

Theorem 3 still assumed that the entries
\[ \tilde{A}_{J,J'} = -\frac{1}{2} \int_{\Gamma} \psi_J(x) \psi_{J'}(x) dx + \int_{\Gamma} \int_{\Gamma} K(x,y) \psi_J(x) \psi_{J'}(y) dy dx, \]
for \( J, J' \in J_0 \cup \ldots \cup J_L \) of the compressed stiffness matrix \( \tilde{A}^L \) were evaluated exactly. This is not possible, in general, and approximations \( \tilde{A}_{J,J'} = Q K \psi_J \psi_{J'} \) must be used, where \( Q_{J,J'} \) is a family of quadrature rules to be specified. In our implementation we used the quadrature scheme that was proposed and analyzed in [PS]. We now describe it briefly and present its principal properties (for the sake of brevity, we discuss only the quadruple integral in (34)).

Since each multiwavelet \( \psi_J \) is piecewise constant in local coordinates, the integral (34) with \( J = (I, \nu), J' = (I', \nu') \) may be assembled from 16 “elementary” integrals over pairs \( \Gamma_{I_c} \times \Gamma_{I'}, (I_c, I'_c) \in \text{child}(I) \times \text{child}(I') \) where the set
\[ \text{child}(I) := \{ I_c \in \mathcal{I}_{I+1} : \Gamma_{I_c} \subset \Gamma_I \}, \quad I \in \mathcal{I} \]
specifies the indices of the four subdomains of \( \Gamma_I \). We consider therefore now only the fourfold integrals over such pairs. We distinguish two types of integrals to be evaluated: a) non-singular case \( d_{IJ} > 0 \), b) singular case \( d_{IJ} = 0 \). Since \( K(x,y) \) is analytic for \( x \neq y \) and the multiwavelets piecewise constant in local coordinates, in case a) the integrands are analytic on \( \Gamma_I \times \Gamma_{I'} \). For analytic integrands Gaussian quadrature formulas converge, as it is well-known, exponentially with the rate depending on the size of the integrand’s domain of analyticity. The only difficulty that arises is that for \( d_{IJ} < \max \{ \text{diam}(\Gamma_I), \text{diam}(\Gamma_{I'}) \} \) the integrand’s domain of analyticity and consequently the rate of exponential convergence of Gaussian quadrature may be very small. This can be prevented by subdivision of the larger panel (see [S], [PS]).

**Lemma 4** Let \( \gamma > 0 \) be a parameter that depends only on the boundary \( \Gamma \) and its parametrization. Assume \( \text{diam}(\Gamma_{I'}) \geq \text{diam}(\Gamma_I) \) and \( d_{IJ} > 0 \). Then there exists a binary partition \( \{ \Gamma_I : \Gamma_{I'} \in \mathcal{A}(I, I') \} \) of \( \Gamma_I \) such that \( d_{IJ} \geq \gamma^{-1} 2^{-l-1} \) for all \( I \in \mathcal{A}(I, I') \). Moreover, the number of subelements \( \Gamma_{I'} \subset \Gamma_I \) is bounded by
\[ |\mathcal{A}(I, I')| \leq C(\gamma)(l - l' + 1). \]
A recursive partition with a stronger subdivision ratio would yield better errors [S], but the binary partition in Lemma 4 is natural in our multiscale context (the data structures for discretization and quadrature coincide).

Next, we apply Gaussian quadrature to each pair \( (\Gamma_I, \Gamma_{I'}) \). For that, the triangular elements are transformed to \((-1,1)^2\) via the degenerate mapping
\[ \Phi(\xi) = \begin{pmatrix} \xi_1 \\ \xi_1 \xi_2 \end{pmatrix} \]
yielding the transformed kernel
\[ K_{IJ}(\xi, \xi') := 4 |\Gamma_I| |\Gamma_{I'}| \xi_1 \xi'_1 K(\chi_J \circ (\kappa_I^{-1}) \circ \Phi(\xi), \chi_{J'} \circ (\kappa_{I'}^{-1}) \circ \Phi(\xi')). \]
In summary, we formulate a variable order, composite quadrature rule (see [S]) for the approximation of \( A_{J,J'} \):
**Lemma 5** Let \( J = (I, \nu) \in \mathcal{J}_L \) and \( J' = (I', \nu') \in \mathcal{J}_L \) with \( l \geq l' \) and \( d_{J'J} > 0 \). Compute approximations \( \hat{A}_{J,J'} \) to the corresponding nonzero entries \( \hat{A}_{J,J'} \) of \( \hat{A}^L \) by the variable order, composite quadrature rule

\[
\hat{A}_{J,J'} = \sum_{l \in \Lambda(I,I')} \sum_{l_c \in \text{child}(I)} \sum_{l_c \in \text{child}(I)} \psi_J|_{l_c} \psi_{J'}|_{l_c} G_{\xi}^{n_1} G_{\xi'}^{n_2} K_{l_c,l_c}(\xi,\xi')
\]

where the orders of the Gaussian quadrature rules \( G_{\xi}^{n_1} \) and \( G_{\xi'}^{n_2} \) satisfy

\[
n_i(I, \bar{I}, I') = \frac{1}{2} + \frac{2\log_2 \gamma + \log_2(l - l' + 1) + 2(2L - l - l') + l' - l + 2}{\log_2 \rho_i}
\]

with \( \rho_1 := 1 + \gamma 2^{l+1} d_{JJ} \), \( \rho_2 := 1 + \gamma 2^{l+1} d_{JJ} \)

Let the singular integrals be computed exactly. Then the total quadrature work is bounded by \( O(N_L(\log N_L)^3) \) kernel evaluations and all assertions of Theorem 3 still hold for the numerically integrated, compressed stiffness matrix.

The singular case \( d_{J'J} = 0 \) is, after possible subdivision of the larger element, reduced to the above case plus a singular integral over two panels of equal size. Here special variable transformations are applied ([HSS], [PS]) which render the integrand analytic, yielding also here a consistent quadrature approximation in \( O(N_L(\log N_L)^3) \) work (see [PS] and note that integrals over panel pairs on the same side of \( \Gamma \) do not contribute). In summary, we have

**Theorem 6** For the quadrature approximation \( \hat{A}^L \) of the compressed stiffness matrix according to Lemma 5, all results of Theorem 3 still hold. The total cost of the fully discrete method is not greater than \( O(N_L(\log N_L)^3) \) kernel evaluations.

**IMPLEMENTATION**

For the implementation of our method we used the object oriented framework for boundary element methods described in [L1] and [L2]. This framework provides the mathematical concepts of boundary elements such as subspaces, dualforms, operators or functions, in terms of classes. Two major extensions of the framework are necessary to cover the demands of our wavelet discretization: a specialization of the base class **DualForm** endowed with the variable order, composite quadrature rule of the previous Section and a specialization of the base class **Operator** to assemble and store the compressed stiffness matrix.

For the sake of brevity, we only discuss the algorithmic aspects of the underlying classes and omit their precise definition.

**QUADRATURE ALGORITHM**

The assembly of the stiffness matrix imposes the evaluation of the element matrices
integrate($I, \bar{I}, I'$) {
    if dist($I_c, \bar{I}_c$) $\geq \gamma^{-1} 2^{-i-1}$ {
        for ($I_c, \bar{I}_c$) $\in$ child($I$) $\times$ child($\bar{I}$) {
            calculate $(E'_{II})_{I_c, \bar{I}_c} := 2^{l+1} 2^{l+2} G_{\xi}^{n_1(I, I', I')} G_{\xi'}^{n_2(I, I', I')} K_{I_c, \bar{I}_c} (\xi, \xi')$
            calculate $(E'_{II})_{I_c, \bar{I}_c} := 2^{l+1} 2^{l+2} G_{\xi}^{n_1(I, I', I')} G_{\xi'}^{n_2(I, I', I')} K_{I_c, \bar{I}_c} (\xi, \xi')$
        }
    } else {
        for $\bar{I}_c$ $\in$ child($\bar{I}$) $(E'_{I'I}, E''_{I'I}) \leftarrow$ integrate($I$, $\bar{I}_c$, $I'$)
        evaluate $E'_{II}$, $E''_{II}$ using $E'_{I'I}$, $E''_{I'I}$, with $\bar{I}_c \in$ child($\bar{I}$)
    }
    return $(E'_{II}, E''_{II})$
}

Algorithm 1: Composite quadrature rule, $l \geq \bar{l} \geq l'$.

$\left( E_{II'} \right)_{\nu \nu'} := \left( A_{(I, I') \nu \nu'} \right)_{\nu \nu'}$, $\nu, \nu' = \begin{cases} 0, \ldots, 3 & \text{if } I, I' \in \mathcal{I}_0, \\ 1, \ldots, 3 & \text{otherwise} \end{cases}$

for $I, I' \in \mathcal{I}_0 \cup \ldots \cup \mathcal{I}_L$. We manage this task by calculating the corresponding element matrices related to the standard basis functions $\varphi_I$ using the variable order, composite quadrature rule (39):

$\left( E'_{I'\bar{I}} \right)_{I_c, \bar{I}_c} := Q_{I'I} K_{\varphi_{I_c} \varphi_{\bar{I}_c}}$, $I_c \in$ child($I$), $I'_c \in$ child($I'$).

Afterwards, a transformation $E'_{I'I} \mapsto E_{I'I}$ is applied. Algorithm 1 illustrates the recursive implementation of the subdivision. The initial call integrate($I', I'$) evaluates the matrix $E'_{II}$, as well as its symmetric counterpart $E'_{II}$ simultaneously. In this way the construction of the subdivision which is identical in both cases is fully exploited. In the interests of efficiency temporary matrices generated during the subdivision on higher levels are cached, such that subsequent calls can profit. It turns out that a cache size of $O(N_{\mathcal{L}})$ together with special calling sequence is sufficient to guarantee an optimal usage of data. Moreover, the size of the cache could be reduced to $O(\log N_{\mathcal{L}})$ still yielding the same performance as before. But, from the object oriented point of view, this approach weakens the important encapsulation between assembly and quadrature.

**ASSEMBLY AND COMPRESSION**

According to Theorem 3, the truncation criterion (27) yields a compressed stiffness matrix with $O(N_{\mathcal{L}} (\log N_{\mathcal{L}})^2)$ nonzero entries. For a practical implementation it is essential,
assemble($I$, $I'$) {
    if dist$(\Gamma_I, \Gamma_i) \leq \delta_W$ {
        if $l = l'$ and $(j, k) < (j', k')$ return
        $(E_{IP}, E_{1IP}) \leftarrow (E'_{IP}, E'_{1IP}) \leftarrow \text{integrate}(I, I', I')$
        store $E_{IP}, E_{1IP}$ in $A^L$ in compressed form
        if $l > l'$
            for $I_c \in \text{child}(I')$ assemble$(I, I'_c)$
        }
    return
}

Algorithm 2: Assembly and compression.

However, that the nonzero entries in the compressed stiffness matrix can be localized also
in essentially $O(N_L)$ operations, i.e. without scanning the whole $N_L^2$ entries of the full
matrix. This objective is easily achieved if one exploits the tree structure of the index set
$\mathcal{I}_0 \cup \ldots \cup \mathcal{I}_L$ implied by the sets child$(I)$ as it is done in the function assemble() sketched
in Algorithm 2. With this function the compressed stiffness matrix is generated by:

$$
\text{for } I \in \mathcal{I}_0 \cup \ldots \cup \mathcal{I}_L \\
\text{for } I' \in \mathcal{I}_0 \text{ assemble}(I, I')
$$

Except the generation of element matrices, each task of the recursive function assemble() is of order $O(1)$. Hence, the complexity of determining the nonzero entries is proportional
to the number of calls of the function which again is proportional to the number of nonzero
entries, i.e. $O(N_L(\log N_L)^2)$. This is borne out by our numerical experiments below.

For our compression technique we borrow from the well known encoding algorithm of
Ziv, Lempel and Welch described for example in [Wo] which encodes repeated substrings
more efficiently. In our case we only encode sequences of zero entries in the stiffness matrix
by their length. In order to achieve high compression rates long sequences of zero and
nonzero entries, respectively, are desired. Therefore, we arrange the wavelets $\psi_f$ according
to the preorder depth first traversal of the domains $\Gamma_I$ (cf. Algorithm 2) which takes the
local relations of the domains into account. Note that the symmetry $\delta_{lF} = \delta_{lI}$ of the
threshold values is transmitted to the pattern of zero and nonzero entries of the stiffness
matrix, such that the simultaneous evaluation of the element matrix $E_{1IP}$ and its dual in
Algorithm 1 is justified. Moreover, the same pattern of compression can be applied to
rows and columns of the stiffness matrix. For a detailed discussion of this topic see [LS].

NUMERICAL EXPERIMENTS

Here we present some preliminary numerical experiments obtained with the described
implementation of the multiscale scheme. We solved (4) on several polyhedral domains with quite similar performance. For all considered domains one can verify that Theorem 3 holds with $s = s = 1$ [LS]. We report here only those from the prism $\Omega = T \times (0, 1)$ where $T$ is an equilateral triangle with sides of length 1. The initial triangulation was the coarsest possible one to cover $\Gamma$ and contained $N_0 = 8$ triangles. For the right hand side $f$ of (4) we chose the harmonic function \( \frac{1}{2} \sin\left(\frac{\pi}{2} x\right) \cos(\pi y) \sinh\left(\frac{\sqrt{2} \pi}{2} z\right) \).

![Figure 1: Number of nonzero elements in the compressed stiffness matrix.](image)

In Figure 1, we show the number of nonzero entries in the compressed stiffness matrix – we clearly see the predicted $O(N(\log N)^2)$ behaviour. This, however, is not worth much if the memory overhead used to administer the sparse data structure is excessive. Therefore, in Figure 2 we show total memory used to store the compressed stiffness matrix $\tilde{A}^L$ (i.e. memory used for the nonzero entries of $A^L$ as well as for the supporting data structure). We see also here the predicted $O(N(\log N)^2)$ behaviour. Next, in Figure 3, we show the CPU time used to generate the sparse stiffness matrix $\tilde{A}^L$; this includes the time to locate the nonzero entries as well as the set-up of the sparse data structure. We see here a $O(N(\log N)^2)$ behaviour rendering the estimates of Theorem 6 (numerical quadrature) overly pessimistic. We also note that the total memory required to store the compressed matrix at $L = 7$ and $N_L = 131072$ unknowns amounts to 421MB which just fits in the core of our workstation. At this level, the compression rate is, inclusive the overhead for administering the sparse data structure, $3 \cdot 10^{-3}$. The CPU-time for the iterative solution (GMRes) is shown in Figure 4. Its behaviour consonant to the number of iterations

<table>
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<tr>
<th>level</th>
<th>1</th>
<th>2</th>
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<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>iterations</td>
<td>15</td>
<td>19</td>
<td>20</td>
<td>21</td>
<td>22</td>
<td>22</td>
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validates the bounded condition numbers of the compressed stiffness matrices $\tilde{A}^l$ (see item 2 of Theorem 3).
We point out that the CPU-time for the solution accounts only for about 15 per cent of the total CPU-time. Therefore, with the present method the BEM-paradigm that most of the work is spent for quadrature is still valid and a speed up similar to the one for dense matrices can be achieved with the parallelization of the matrix assembly. In Figure 5 the error at interior points is depicted. The dashed lines shown illustrate the bounds $O(N^{-1})$ and $O(N^{-1}(\log N)^3)$, respectively (cf. (33)). It can be observed that the expected convergence of essentially $O(h^2)$ is preserved by the compression. The same is true for the convergence of the $L^2$-norm of the discrete density $u^t$ (Figure 6) showing the behaviour $\|u^t\|_0 - \|u\|_0 \leq Ch^\kappa$ with $\kappa \sim 1.3$.

CONCLUSION

We close the present paper with some remarks. We have realized an $O(N(\log N)^3)$ implementation of a fully discrete Galerkin boundary element method for potential problems in general polyhedral domains. For the problems considered the method as well as the implementation converge at interior points of the domain with essentially $O(h^2)$. The implementation is sufficiently general so that other partial differential equations of mathematical physics, such as Stokes, elasticity or Helmholtz (for moderate wavenumber) can be easily accommodated [LS]. Problems with $N > 10^5$ DOF can be computed in core on a serial workstation in less than half an hour (see Figure 3).

For a simplistic complexity comparison with a FEM in $\Omega$, we assume uniform mesh as for the BEM, and linear continuous elements. The number of unknowns in the FEM would then grow like $O(h^{-3})$, but the rate of convergence, using the $H^2$-regularity in a
convex polyhedron, would also be essentially $O(h^2)$. Using an optimal $O(N) = O(h^{-3})$ multigrid solver, we would therefore achieve convergence at an interior point of order $O(W^{-2/3})$ in terms of the work measure $W$ whereas our wavelet BEM gives interior point convergence of order $O(W^{-1})$, i.e. the lower dimension of the domain to be discretized pays off if the solution is only desired in a few points.

We finally emphasize that the quadrature- and compression strategies described here apply verbatim also to curved surfaces with analytic parametrizations $\chi_j$ (see [PS]). Apart from earlier work on collocation schemes (see [Sch], [R]), the present work appears to be the first realization of a wavelet-Galerkin boundary element method for general surfaces and second kind equations.

REFERENCES


Figure 4: CPU-time for the solution of the linear system.


Figure 5: Error at interior points versus $N$ with bounds $O(N^{-1})$ and $O(N^{-1}(\log N)^3)$.

Figure 6: $\|u^f\|_0 - \|u\|_0$ versus $N$ with bound $O(N^{-\frac{1}{3}})$. 