Boundary element quadrature schemes for multi- and many-core architectures

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OP Research and Development for Innovation

- Boundary element method
- OpenMP threading
- OpenMP vectorization
- Adaptive cross approximation

2 Numerical experiments

- Full assembly
- ACA assembly

3 Conclusion

1 BEM4I

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- OpenMP vectorization
- Adaptive cross approximation
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 - Full assembly
 - ACA assembly

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BEM is an alternative to FEM for the solution of PDEs,

BEM4I - 3D boundary element library for

- Laplace equation (heat transfer),
- Helmholtz equation (wave scattering)
- Lamé equation (linear elasticity),
- time-dependent wave equation.

Specifications

- C++, interface to MKL or other BLAS, LAPACK,
- ACA for matrix sparsification.

Strategies

- SIMD vectorization for surface integrals (OpenMP, Vc library)
- OpenMP for local element contributions / individual ACA blocks,
- MPI for distributed matrices,
- BETI with the ESPRESO library,
- Intel MIC offload/native

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Boundary value problem for the Laplace equation

 $\begin{cases} -\Delta u = 0 & \text{in } \Omega, \\ u = f & \text{on } \Gamma_{\mathrm{D}}, \\ \frac{\partial u}{\partial n} = g & \text{on } \Gamma_{\mathrm{N}}. \end{cases}$

Representation formula for $oldsymbol{x} \in arOmega$

$$u(\boldsymbol{x}) = \frac{1}{4\pi} \int_{\partial\Omega} \frac{1}{\|\boldsymbol{x} - \boldsymbol{y}\|} \frac{\partial u}{\partial \boldsymbol{n}}(\boldsymbol{y}) \, \mathrm{d}\boldsymbol{s}_{\boldsymbol{y}} - \frac{1}{4\pi} \int_{\partial\Omega} \frac{\langle \boldsymbol{x} - \boldsymbol{y}, \boldsymbol{n}(\boldsymbol{y}) \rangle}{\|\boldsymbol{x} - \boldsymbol{y}\|^3} u(\boldsymbol{y}) \, \mathrm{d}\boldsymbol{s}_{\boldsymbol{y}}.$$

Boundary integral equations for $oldsymbol{x}\in\partial arOmega$

$$\frac{1}{4\pi} \int_{\partial\Omega} \frac{1}{\|\boldsymbol{x} - \boldsymbol{y}\|} \frac{\partial u}{\partial \boldsymbol{n}}(\boldsymbol{y}) \, \mathrm{d}\boldsymbol{s}_{\boldsymbol{y}} = \frac{1}{2} u(\boldsymbol{x}) + \frac{1}{4\pi} \int_{\partial\Omega} \frac{\langle \boldsymbol{x} - \boldsymbol{y}, \boldsymbol{n}(\boldsymbol{y}) \rangle}{\|\boldsymbol{x} - \boldsymbol{y}\|^{3}} u(\boldsymbol{y}) \, \mathrm{d}\boldsymbol{s}_{\boldsymbol{y}},$$
$$-\frac{\partial}{\partial \boldsymbol{n}_{\boldsymbol{x}}} \frac{1}{4\pi} \int_{\partial\Omega} \frac{\langle \boldsymbol{x} - \boldsymbol{y}, \boldsymbol{n}(\boldsymbol{y}) \rangle}{\|\boldsymbol{x} - \boldsymbol{y}\|^{3}} u(\boldsymbol{y}) \, \mathrm{d}\boldsymbol{s}_{\boldsymbol{y}} = \frac{1}{2} \frac{\partial u}{\partial \boldsymbol{n}}(\boldsymbol{x}) - \frac{1}{4\pi} \int_{\partial\Omega} \frac{\langle \boldsymbol{y} - \boldsymbol{x}, \boldsymbol{n}(\boldsymbol{x}) \rangle}{\|\boldsymbol{x} - \boldsymbol{y}\|^{3}} \frac{\partial u}{\partial \boldsymbol{n}}(\boldsymbol{y}) \, \mathrm{d}\boldsymbol{s}_{\boldsymbol{y}}.$$

Discretization leads to the systems

$$\mathsf{V}_h \boldsymbol{g} = \left(\frac{1}{2}\mathsf{M}_h + \mathsf{K}_h\right) \boldsymbol{f}, \qquad \mathsf{D}_h \boldsymbol{f} = \left(\frac{1}{2}\mathsf{M}_h - \mathsf{K}_h\right)^\top \boldsymbol{g}$$

with the matrices

$$\begin{split} \mathsf{V}_{h}[\ell,k] &:= \frac{1}{4\pi} \int_{\tau_{\ell}} \int_{\tau_{k}} \frac{1}{\|\boldsymbol{x} - \boldsymbol{y}\|} \, \mathrm{d}\boldsymbol{s}_{\boldsymbol{y}} \, \mathrm{d}\boldsymbol{s}_{\boldsymbol{x}} \\ \mathsf{K}_{h}[\ell,i] &:= \frac{1}{4\pi} \int_{\tau_{\ell}} \int_{\partial\Omega} \varphi_{i}(\boldsymbol{y}) \frac{\langle \boldsymbol{x} - \boldsymbol{y}, \boldsymbol{n}(\boldsymbol{y}) \rangle}{\|\boldsymbol{x} - \boldsymbol{y}\|^{3}} \, \mathrm{d}\boldsymbol{s}_{\boldsymbol{y}} \, \mathrm{d}\boldsymbol{s}_{\boldsymbol{x}} \\ \mathsf{D}_{h}[j,i] &:= \frac{1}{4\pi} \int_{\partial\Omega} \int_{\partial\Omega} \frac{\langle \mathbf{curl} \varphi_{i}(\boldsymbol{y}), \mathbf{curl} \varphi_{j}(\boldsymbol{x}) \rangle}{\|\boldsymbol{x} - \boldsymbol{y}\|} \, \mathrm{d}\boldsymbol{s}_{\boldsymbol{y}} \, \mathrm{d}\boldsymbol{s}_{\boldsymbol{x}} = \mathsf{T}_{h}^{\top} \, \mathrm{diag}(\mathsf{V}_{h}, \mathsf{V}_{h}, \mathsf{V}_{h}) \mathsf{T}_{h}, \\ \mathsf{M}_{h}[\ell,i] &:= \int_{\tau_{\ell}} \varphi_{i}(\boldsymbol{x}) \, \mathrm{d}\boldsymbol{s}_{\boldsymbol{x}}. \end{split}$$

• OpenMP threading for V_h

```
1 #pragma omp parallel for
2 for( int tau_k = 0; tau_k < E; ++tau_k ){ // columns
3 for( int tau_l = 0; tau_l < E; ++tau_l ){ // rows
4 SLIntegrator.getLocalMatrix( *tau_l, *tau_k, Vloc );
5 V.set( *tau_l, *tau_k, Vloc.get( 0, 0 ) );
6 } }
```

OpenMP threading for K_h

OpenMP threading for V_h

```
1 #pragma omp parallel for
2 for( int tau_k = 0; tau_k < E; ++tau_k ){ // columns
3 for( int tau_l = 0; tau_l < E; ++tau_l ){ // rows
4 SLIntegrator.getLocalMatrix( *tau_l, *tau_k, Vloc );
5 V.set( *tau_l, *tau_k, Vloc.get( 0, 0 ) );
6 }
```

OpenMP threading for K_h

```
1 #pragma omp parallel for
_{2} for(int tau k = 0: tau k < E: ++tau k){ // columns
  for( int tau_l = 0; tau_l < E; ++tau_l ){ // rows</pre>
3
    DLIntegrator.getLocalMatrix( *tau_l, *tau_k, Kloc );
4
5 #pragma omp atomic // (inside of add_atomic)
    K.add_atomic( *tau_l, tau_k->node[ 0 ], Kloc.get( 0, 0 ) );
6
7 #pragma omp atomic // (inside of add_atomic)
    K.add_atomic( *tau_l, tau_k->node[ 1 ], Kloc.get( 0, 1 ) );
8
9 #pragma omp atomic // (inside of add_atomic)
    K.add_atomic( *tau_l, tau_k->node[ 2 ], Kloc.get( 0, 2 ) );
10
   } }
11
```

OpenMP threading for V_h

```
1 #pragma omp parallel for
2 for( int tau_k = 0; tau_k < E; ++tau_k ){ // columns
3 for( int tau_l = 0; tau_l < E; ++tau_l ){ // rows
4 SLIntegrator.getLocalMatrix( *tau_l, *tau_k, Vloc );
5 V.set( *tau_l, *tau_k, Vloc.get( 0, 0 ) );
6 }
```

OpenMP threading for K_h

```
1 #pragma omp parallel for
2 \text{ for}(\text{ int tau } 1 = 0; \text{ tau } 1 < E; ++ \text{tau } 1) { // rows}
   for( int tau_k = 0; tau_k < E; ++tau_k ){ // columns</pre>
3
    DLIntegrator.getLocalMatrix( *tau_l, *tau_k, Kloc );
4
5
    K.add( *tau_1, tau_k->node[ 0 ], Kloc.get( 0, 0 ) );
6
7
    K.add( *tau_l, tau_k->node[ 1 ], Kloc.get( 0, 1 ) );
8
9
    K.add( *tau_l, tau_k->node[ 2 ], Kloc.get( 0, 2 ) );
10
   } }
11
```

Avoid #pragma omp critical, use #pragma omp atomic if applicable.

- Single Instruction Multiple Data (SIMD)
 - processing vector with a single operation,
 - provides data level parallelism,
 - elements are of the same type.



Vector length

- 256 bits for AVX-2 (Haswell), 4 DP operands,
- 512 bits for IMCI (KNC), AVX512 (KNL), 8 DP operands.
- Vectorization achieved by
 - compiler auto-vectorization (code refactoring can help),
 - OpenMP 4.0 pragmas (#pragma omp simd),
 - intrinsic functions,
 - wrapper library (Vc),
 - assembly.

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 - OpenMP 4.0 pragmas (#pragma omp simd),
 - intrinsic functions,
 - wrapper library (Vc),
 - assembly.

```
1 double * w = new double[S]:
2 w[0] = ... // init. weights
  // x^1_1, x^1_2, ..., x^S_1, x^S_2
3
  double x [ ] = { ... };
Δ
5
6
7
8
9
10
  for( int l = 0; l < S; ++1 ){</pre>
11
    result += w[1] * f( x[2 * 1], x[2 * 1 + 1]);
12
13
  }
14
  delete w;
15
```

```
1 double * w = new double[S]:
2 w[0] = ... // init. weights
3 // x<sup>1</sup>1, x<sup>1</sup>2, ..., x<sup>S</sup>1, x<sup>S</sup>2
  double x [ ] = { ... };
Д
5
6
7
8
9
  #pragma omp simd reduction( + : result )
10
11 for ( int l = 0; l < S; ++1 ) {
     result += w[1] * f( x[2 * 1], x[2 * 1 + 1]);
12
13 }
14
  delete w;
15
```

```
1 double * w = new double[S]:
2 w[0] = ... // init. weights
  // x^1_1, x^1_2, ..., x^S_1, x^S_2
3
  double x [ ] = { ... };
Д
5
6
7
8
9
  #pragma omp simd reduction( + : result )
10
  for( int 1 = 0; 1 < S; ++1 ){</pre>
11
    result += w[1] * f(x[2 * 1], x[2 * 1 + 1]);
12
13
  }
14
  delete w;
15
```



```
1 double * w = (double *) _mm_malloc( S * sizeof(double), 64 );
2 \mathbb{W} \begin{bmatrix} 0 \end{bmatrix} = \dots // \text{ init. weights}
3 // x<sup>1</sup> 1, ..., x<sup>S</sup> 1
4 double x1 [ ] __attribute__( ( aligned( 64 ) ) ) = { ... };
5 // x<sup>1</sup>_2, ..., x<sup>S</sup>_2
6 double x2 [ ] __attribute__( ( aligned( 64 ) ) ) = { ... };
7
8 __assume_aligned( w, 64 ); // tell compiler about alignment
9
  #pragma omp simd reduction( + : result )
10
11 for ( int l = 0; l < S; ++1 ) {
     result += w[l] * f( x1[l], x2[l]);
12
13 }
14
15 _mm_free( w );
```



Duffy substitution for $\tau_{\ell} \times \tau_k$,

$$\mathsf{V}_{h}[\ell,k] = \sum_{s} \int_{0}^{1} \int_{0}^{1} \int_{0}^{1} \int_{0}^{1} k(\mathbf{F}^{s}(\eta_{1},\eta_{2},\eta_{3},\xi)) \mathbf{S}^{s}(\eta_{1},\eta_{2},\eta_{3},\xi) \,\mathrm{d}\eta_{1} \,\mathrm{d}\eta_{2} \,\mathrm{d}\eta_{3} \,\mathrm{d}\xi$$

with $F^s \colon [0,1]^4 \to S \subset \tau_\ell \times \tau_k$,

 $\boldsymbol{F}^{s}(\eta_{1},\eta_{2},\eta_{3},\xi) = (\boldsymbol{x},\boldsymbol{y}), \qquad \boldsymbol{S}^{s}(\eta_{1},\eta_{2},\eta_{3},\xi) \,\mathrm{d}\eta_{1} \,\mathrm{d}\eta_{2} \,\mathrm{d}\eta_{3} \,\mathrm{d}\xi = \mathrm{d}\boldsymbol{s}_{\boldsymbol{x}} \mathrm{d}\boldsymbol{s}_{\boldsymbol{y}}.$

$$_{[0,1]^2} \times _{[0,1]^2} \rightarrow _{\tau} \times _{\tau} \rightarrow \overbrace{\tau_{\ell}} \times \overbrace{\tau_k}$$

Approximated by tensor Gauss quadrature

$$\mathsf{V}_{h}[\ell,k] \approx \sum_{s} \sum_{m} w_{m} \sum_{n} w_{n} \sum_{o} w_{o} \sum_{p} w_{p} k(\boldsymbol{F}^{s}(x_{m},x_{n},x_{o},x_{p}))\boldsymbol{S}^{s}(x_{m},x_{n},x_{o},x_{p}).$$

Collapsed integration loop in getLocalMatrix.

```
1 __assume_aligned( x1ss, 64 ); // all data aligned
  . . .
2
3
4 switch( type ){
  case( identicalElements ):
5
    for( int simplex = 0; simplex < 6; ++simplex ){</pre>
6
7
    refToTri( simplex, x1, ..., y3, x1ref, ..., y2ref, x1ss,
8
      ..., y3ss );
9
  #pragma omp simd reduction( + : entry )
10
     for ( c = 0; c < S1*S2*S3*S4; ++c ) { // collapsed</pre>
11
      kernel = weights_jacV[ c ]
12
        * evalSingleLayerKernel( x1ss[ c ], x2ss[ c ],
13
          x3ss[c], y1ss[c], y2ss[c], y3ss[c]);
14
     entry += kernel;
15
    } }
16
   break;
17
   ... // quadrature over other pairs of elements
18
19
```

SIMD evaluation of quadrature points in refToTri.

```
1 __assume_aligned( x1ss, 64 ); // all data aligned
2
  . . .
3
  #pragma omp simd
4
5 for( int c = 0; c < S1*S2*S3*S4; ++c ){</pre>
   x1ss[ c ] = x1[ 0 ]
6
   + ( x2[ 0 ] - x1[ 0 ] ) * x1ref[ simplex ][ c ]
7
   + ( x3[ 0 ] - x1[ 0 ] ) * x2ref[ simplex ][ c ];
8
    ... // compute x2ss, x3ss, y1ss, y2ss, y3ss
9
10 }
```

SIMD evaluation of the kernel in evalSingleLayerKernel.

```
#pragma omp declare simd
2 double evalSingleLayerKernel(
3 double x1, double x2, double x3,
4 double y1, double y2, double y3
5 ) const {
6
7 double d1 = x1 - y1, d2 = x2 - y2, d3 = x3 - y3;
8 double norm = sqrt( d1 * d1 + d2 * d2 + d3 * d3 );
9
9 return ( 1 / ( norm * 4.0 * M_PI ) );
1 }
```

SIMD evaluation of quadrature points in refToTri.

```
1 __assume_aligned( x1ss, 64 ); // all data aligned
2 ...
3
4 #pragma omp simd
5 for( int c = 0; c < S1*S2*S3*S4; ++c ){
6 x1ss[c] = x1[0]
7 + ( x2[0] - x1[0]) * x1ref[ simplex ][c];
8 + ( x3[0] - x1[0]) * x2ref[ simplex ][c];
9 ... // compute x2ss, x3ss, y1ss, y2ss, y3ss
10 }</pre>
```

SIMD evaluation of the kernel in evalSingleLayerKernel.

```
1 #pragma omp declare simd
2 double evalSingleLayerKernel(
  double x1, double x2, double x3,
3
  double v1, double v2, double v3
4
5) const {
6
   double d1 = x1 - y1, d2 = x2 - y2, d3 = x3 - y3;
7
   double norm = sqrt( d1 * d1 + d2 * d2 + d3 * d3 );
8
9
   return ( 1 / ( norm * 4.0 * M_PI ) );
10
11
  7
```

Intel Advisor

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worknow	worknow	😤 Summary 🛭 🛠 Survey Report 🧿 Refinement Reports		INTEL	AUVISUR 2017
OFF Batch mode	e	■ Function Call Sites and Loops ♦ Vector Issues Sett - Total Time Type Why No Vectorization?	vectorized Loops	B	Instructior
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analysis.	nns				
- There are no ma	rked loo	Source Top Down Code Analytics Assembly Recommendations Why No Vectorization?			
		File: BEIntegratorScalar.cpp:304 bemdi:BEIntegrator <int. bem4i:beintegratorlaplace<int.="" double="" double.="">>::computeElemMatrix1LaverSaul</int.>	terSchwabP0P0		
2.1 Check Depen	dencies	Line Source	Total Time %	Loop Time %	Traits
		298			
🕨 Collect 🖿 🔛		299 #if !defined(INTEL COMPTLER) INTEL COMPTLER >= 1600			
- Nothing to anal	VZP	300 #pragma omp simd linear(i : 1) reduction(+ : entry)			
		301 #elif defined(INTEL COMPILER) && INTEL COMPILER >= 1500			
2.2 Check Memor	ry Acce	302 #pragma simd linear(i : 1) reduction(+ : entry)			
		303 #endif			
Conecc .		304 ^{GB} for (i = 0; i < totalSize; ++i) {	7,001s	48,4145	
I Nothing to anal	lyze	<pre>305 entry += thisIntegrator->evalSingleLaverKernel(xlss[i], x2ss[i],</pre>	6.006s l		Division a
		306 x3ss[i], v1ss[i], v2ss[i], v3ss[i]) * w0[i] * w1[i] *	23.467s		
		307 w2[i]*w3[i]*jacobian[i]:	12,1465		
		308 }			
		39 }			
		310			
		311 SCVT innerArea =			
		<pre>312 this-sqetSpace()-sqetRightMesh()-sqetElemArea(innerElem);</pre>	0.053s [
		ata COT outories -			
		Selected (Total Time):	23,4075	and the second se	

Intel compiler reports

```
-qopt-report=5 -qopt-report-phase=vec
```

```
LOOP BEGIN at BEIntegratorScalar.cpp(304,5)
1
     remark 15340: pragma supersedes previous setting [
2
      BEIntegratorScalar.cpp(300,1) ]
     remark 15388: vectorization support: reference x1ss[i] has
3
      aligned access [ BEIntegratorScalar.cpp(305,55) ]
     ... // all data reported as aligned
4
     remark 15305: vectorization support: vector length 4
5
     remark 15309: vectorization support: normalized
6
      vectorization overhead 0.443
     remark 15301: OpenMP SIMD LOOP WAS VECTORIZED
7
     remark 15448: unmasked aligned unit stride loads: 16
8
     remark 15475: --- begin vector cost summary ---
9
     remark 15476: scalar cost: 97
10
     remark 15477: vector cost: 17,500
11
   remark 15478: estimated potential speedup: 5.510
12
     remark 15488: --- end vector cost summarv ---
13
  LOOP END
14
```

Adaptive cross approximation

- Complexity $\mathcal{O}(n^2) \to \mathcal{O}(n \log n)$,
- mesh divided into clusters,
- non-admissible clusters assembled in full,
- admissible clusters approximated as $C \approx UV^{\top}$,
- assembly of clusters distributed by OpenMP.



```
#pragma omp parallel for
2 for( int i = 0; i < n_nonadmissible_blocks; ++i ){
3 getNonadmissibleBlock( i, localBlock );
4 ACAMatrix.addNonadmissibleBlock( i, localBlock );
5 }
6
7 #pragma omp parallel for
8 for( int i = 0; i < n_admissible_blocks; ++i ){
9 getAdmissibleBlock( i, localBlock );
1 ACAMatrix.addAdmissibleBlock( i, localBlock );
1 }
```

Adaptive cross approximation

- Complexity $\mathcal{O}(n^2) \to \mathcal{O}(n \log n)$,
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#pragma omp parallel for
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    getNonadmissibleBlock( i, localBlock );
3
    ACAMatrix.addNonadmissibleBlock( i, localBlock );
4
  }
5
6
  #pragma omp parallel for
7
  for( int i = 0; i < n_admissible_blocks; ++i ){</pre>
8
    getAdmissibleBlock( i, localBlock );
9
    ACAMatrix.addAdmissibleBlock( i, localBlock );
10
11
  ł
```

- Boundary element method
- OpenMP threading
- OpenMP vectorization
- Adaptive cross approximation

2 Numerical experiments

- Full assembly
- ACA assembly

3 Conclusion

Experiment setting

- Full (ACA) assembly tested on a mesh with 20.480 (81.920) surface elements.
- 4 quadrature points in each dimension (256 per simplex) to utilize SIMD registers.
- ACA settings
 - maximal number of elements in clusters: 500,
 - preallocation: 10 %.

Assembly performed on single nodes

- Salomon 2 x Xeon 2680v3, AVX2, 2x12 cores, 2.5 GHz, 128 GB RAM,
- Salomon Xeon Phi 7120P, IMCI, 61 cores, 1.238 GHz, 16 GB RAM,
- Endeavor Xeon Phi 7210, AVX-512, 64 cores, 1.3 GHz, 16 + 96 GB RAM.

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OMP scalability, full assembly, 256 points per simplex



Xeon 2680v3										
matrix 2 4 8 16 24										
V_h	2.01	4.04	8.07	16.09	24.07					
K_h	1.99	3.98	7.97	15.83	23.68					

OMP scalability, full assembly, 256 points per simplex



Xeon Phi 7120P

matrix	2	4	8	16	32	61	122	183	244
V_h	2.01	3.98	8.06	15.96	32.14	60.23	78.33	85.90	84.29
K_h	2.02	4.06	8.28	16.42	32.72	61.38	88.54	102.71	107.53

OMP scalability, full assembly, 256 points per simplex



Xeon Phi 7210

matrix	2	4	8	16	32	64	128	192	256
V_h	1.99	3.99	7.90	15.93	31.48	62.26	62.89	54.22	57.65
K_h	2.00	4.07	8.07	16.20	31.89	62.76	73.64	67.76	73.64

SIMD scalability, full assembly, 256 points per simplex



architecture	threads	matrix	SSE4.2	AVX2	IMCI	AVX-512
Xeon E2680v3	24	V_h	1.92	2.23	—	—
	24	K_h	2.01	2.32		
Xeon Phi 7120P	244	V_h			3.77	
Xe011111111201	244	K_h			5.05	
Yoon Dhi 7210	100	\vee_h	2.45	4.95		9.94
	120	K_h	2.01	4.14		7.69

SIMD scalability, full assembly, 256 points per simplex



architecture	threads	matrix	SSE4.2	AVX2	IMCI	AVX-512
Voon E2690v2	24	V_h	1.92	2.23	_	_
A6011 E2000V3	24	K_h	2.01	2.32	—	
Yoon Dhi 7120D	244	V_h		—	3.77	
	244	K_h		—	5.05	
Yoon Dhi 7210	100	\vee_h	2.45	4.95		9.94
Xeon Fin 7210	128	K_h	2.01	4.14		7.69

SIMD scalability, full assembly, 256 points per simplex



architecture	threads	matrix	SSE4.2	AVX2	IMCI	AVX-512
Voon E2690v2	24	V_h	1.92	2.23	_	_
A6011 E2000V3	24	K_h	2.01	2.32	—	
Yoon Dhi 7120D	244	V_h	_	_	3.77	
	244	K_h	—	—	5.05	
Xeon Phi 7210	128	V_h	2.45	4.95	_	9.94
Acon Fill 7210	128	K_h	2.01	4.14	_	7.69

OMP scalability, ACA assembly, 256 points per simplex



Xeon 2680v3										
matrix 2 4 8 16 24										
V_h	2.00	3.97	7.89	15.74	23.13					
K_h	1.99	3.95	7.89	15.49	22.75					

OMP scalability, ACA assembly, 256 points per simplex



Xeon Phi 7120P

matrix	2	4	8	16	32	61	122	183	244
V _h	1.95	3.92	7.80	15.57	30.32	53.16	64.69	67.44	62.39
κ_h	1.95	3.88	1.67	15.10	28.49	52.17	67.20	72.94	70.66

OMP scalability, ACA assembly, 256 points per simplex



Xeon Phi 7210

matrix	2	4	8	16	32	64	128	192	256
V_h	1.97	3.93	7.80	15.57	30.36	57.92	57.08	50.57	49.34
K_h	2.01	3.95	1.18	15.03	28.34	49.17	55.92	51.02	47.30

SIMD scalability, ACA assembly, 256 points per simplex



architecture	threads	matrix	SSE4.2	AVX2	IMCI	AVX-512
X000 E2680v3	24	V_h	1.90	2.26	_	_
	24	K_h	1.98	2.27	_	
Yoon Dhi 7120D	244	V_h			2.94	
	244	K_h			3.47	
Yeen Dhi 7210	100	V_h	2.33	4.45		
Acon Fill 7210	120	K_h	1.96	3.71		5.43

SIMD scalability, ACA assembly, 256 points per simplex



architecture	threads	matrix	SSE4.2	AVX2	IMCI	AVX-512
Voon E2690u2	24	V_h	1.90	2.26	_	_
A6011 E2000V3	24	K_h	1.98	2.27		
V Dh: 7100	244	V_h	—	—	2.94	
	244	K_h		_	3.47	
Voon Dhi 7210	100	V_h	2.33	4.45		
	128	K_h	1.96	3.71		5.43

SIMD scalability, ACA assembly, 256 points per simplex



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Xeon Phi 7120P	244	V_h	—	—	2.94	
		K_h	—	—	3.47	
Xeon Phi 7210	128	V_h	2.33	4.45		8.06
		K_h	1.96	3.71	—	5.43

- Boundary element method
- OpenMP threading
- OpenMP vectorization
- Adaptive cross approximation

2 Numerical experiments

- Full assembly
- ACA assembly

3 Conclusion

Conclusion

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- KNL vs. HSW speedup
 - Full V_h 2.29, K_h 1.82,
 - ACA V_h 2.64, K_h 1.40.
 - What we learned
 - SIMD processing becoming more efficient with KNL,
 - multi-core code benefits from many-core optimizations.

Work in progress

- object-oriented offload to Xeon Phi (full, ACA).
- load balancing for offload mode (full, ACA),
- massively parallel BETI with ESPRESO library (MPI, OpenMP, SIMD, offload).

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References

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