

Parallel sparse matrix-vector multiplication as a test case for hybrid MPI+OpenMP programming

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Abstract—We evaluate optimized parallel sparse matrix-vector operations for two representative application areas on widespread multicore-based cluster configurations. First the single-socket baseline performance is analyzed and modeled with respect to basic architectural properties of standard multicore chips. Going beyond the single node, parallel sparse matrix-vector operations often suffer from an unfavorable communication to computation ratio. Starting from the observation that nonblocking MPI is not able to hide communication cost using standard MPI implementations, we demonstrate that explicit overlap of communication and computation can be achieved by using a dedicated communication thread, which may run on a virtual core. We compare our approach to pure MPI and the widely used “vector-like” hybrid programming strategy.

Keywords—sparse matrix-vector multiply; hybrid parallelization; multicore

I. INTRODUCTION

Many problems in science and engineering involve the solution of large eigenvalue problems or extremely sparse systems of linear equations arising from, e.g., the discretization of partial differential equations. Sparse matrix-vector multiplication (spMVM) is the dominant operation in many of those solvers and may easily consume most of the total run time. A highly efficient scalable spMVM implementation is thus fundamental, and complements advancements and new development in the high-level algorithms.

For more than a decade there has been an intense debate about whether the hierarchical structure of current HPC systems needs to be considered in parallel programming, or if pure MPI is sufficient. Hybrid approaches based on MPI+OpenMP have been implemented in codes and kernels for various applications areas and compared with traditional MPI implementations. Most results are hardware-specific, and sometimes contradictory. In this paper we analyze hybrid MPI+OpenMP variants of a general parallel spMVM operation. Beyond the naive approach of using OpenMP for parallelization of kernel loops (“vector mode”) we also employ a hybrid “task mode” to overcome or mitigate a weakness of standard MPI implementations: the lack of truly asynchronous communication in nonblocking MPI calls. We test our implementation against pure MPI approaches for two application scenarios on an InfiniBand cluster as well as a Cray XE6 system.

A. Related work

In recent years the performance of various spMVM algorithms has been evaluated by several groups [1], [2], [3]. Covering different matrix storage formats and implementations on various types of hardware, they have reviewed a more or less large number of publicly available matrices and reported on the obtained performance. Scalable parallel spMVM implementations have also been proposed [4], [5], mostly based on an MPI-only strategy. Hybrid parallel spMVM approaches have already been devised before the emergence of multicore processors [6], [7]. Recently a “vector mode” approach could not compete with a scalable MPI implementation for a specific problem on a Cray system [4]. There is no up-to-date literature that systematically investigates novel features like multicore, ccNUMA node structure, and simultaneous multithreading (SMT) for hybrid parallel spMVM.

B. Sparse matrix-vector multiplication and node-level performance model

A possible definition of a “sparse” matrix is that the number of its nonzero entries grows only linearly with the matrix dimension; however, not all problems are easily scaled, so in general a sparse matrix may be defined to contain “mainly” zero entries. Since keeping such a matrix in computer memory with all zeros included is usually out of the question, an efficient format to store the nonzeros only is required. The most widely used variant is “Compressed Row Storage” (CRS) [8]. It does not exploit specific features that may emerge from the underlying physical problem like, e.g., block structures, symmetries, etc., but is broadly recognized as the most efficient format for general sparse matrices on cache-based microprocessors. All nonzeros are stored in one contiguous array `val`, row by row, and the starting offsets of all rows are contained in a separate array `row_ptr`. Array `col_idx` contains the original column index of each matrix entry. A matrix-vector multiplication with a right-hand-side (RHS) vector `B(:)` and a result vector `C(:)` can then be written as follows:

```

1 do i = 1, Nr
2   do j = row_ptr(i), row_ptr(i+1) - 1
3     C(i) = C(i) + val(j) * B(col_idx(j))
4   enddo

```

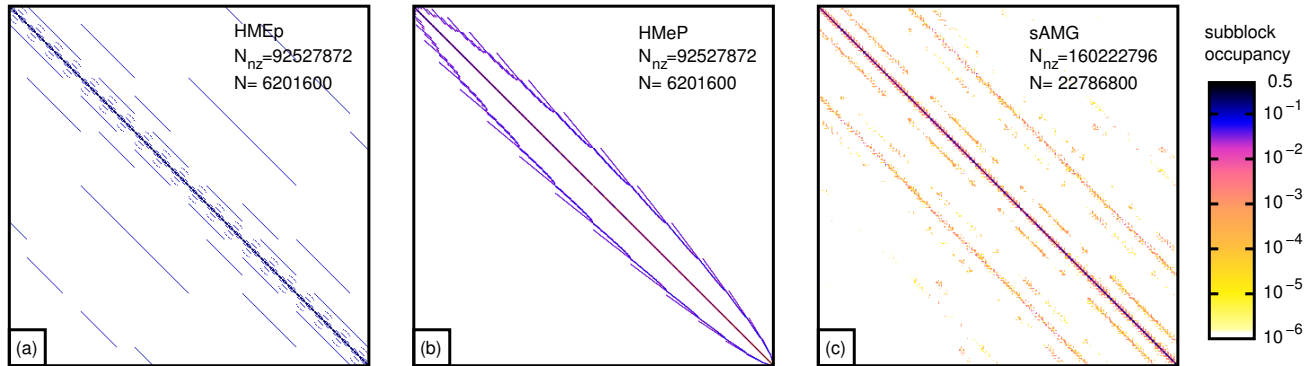


Fig. 1: Sparsity patterns of the Hamiltonian matrix described in the text with different numbering of the basis elements ((a) and (b)), and the sAMG matrix (c). Square subblocks have been aggregated and color-coded according to occupancy to improve visibility.

s enddo

Here N_r is the number of matrix rows. While arrays $C(:)$ and $val(:)$ are traversed contiguously, access to $B(:)$ is indexed and may potentially cause very low spatial and temporal locality in this data stream.

The performance of spMVM operations on a single compute node is often limited by main memory bandwidth. Code balance [9] is thus a good metric to establish a simple performance model. We assume the average length of the inner (j) loop to be $N_{nzt} = N_{nz}/N_r$, where N_{nz} is the total number of nonzero matrix entries. Then the contiguous data accesses in the CRS code generate $(8 + 4 + 16/N_{nzt})$ bytes of memory traffic for a single inner loop iteration, where the first two contributions come from the matrix $val(:)$ (8 bytes) and the index array $col_idx(:)$ (4 bytes), while the last term reflects the update of $C(i)$ (write allocate + evict). The indirect access pattern to $B(:)$ is determined by the sparsity structure of the matrix and can not be modeled in general. However, $B(:)$ needs to be loaded at least once from main memory, which adds another $8/N_{nzt}$ bytes per inner iteration. Limited cache size and nondiagonal access typically require loading at least parts of $B(:)$ multiple times in a single MVM. This is quantified by a machine- and problem-specific parameter κ : For each additional time that $B(:)$ is loaded from main memory, $\kappa = 8/N_{nzt}$ additional bytes are needed. Together with the computational intensity of 2 flops per j iteration the code balance is

$$B_{CRS} = \left(\frac{12 + 24/N_{nzt} + \kappa}{2} \right) \frac{\text{bytes}}{\text{flop}} = \left(6 + \frac{12}{N_{nzt}} + \frac{\kappa}{2} \right) \frac{\text{bytes}}{\text{flop}}. \quad (1)$$

On the node level B_{CRS} can be used to determine an upper performance limit by measuring the node memory bandwidth (e.g., using the STREAM benchmark) and assuming $\kappa = 0$. Moreover, κ can be determined experimentally from the sparse MVM floating point performance and the memory bandwidth drawn by the CRS code (see Sect. II). Since the matrices used here have $N_{nzt} \approx 7 \dots 15$, each additional access to $B(:)$ incurs a nonnegligible contribution to the data transfer.

Note that this simple model neglects performance-limiting aspects beyond bandwidth bottlenecks, like load imbalance, communication and/or synchronization overhead, and the adverse effects of nonlocal memory access across ccNUMA locality domains (LDs).

C. Experimental setting

1) *Test matrices*: Since the sparsity pattern may have substantial impact on the single node performance and parallel scalability, we have chosen two application areas known to generate extremely sparse matrices.

As a first test case we use a matrix from exact diagonalization of strongly correlated electron-phonon systems in solid state physics. Here generic microscopic models are used to treat both charge (electrons) and lattice (phonons) degrees of freedom in second quantization. Choosing a finite-dimensional basis set, which is the direct product of basis sets for both subsystems (electrons \otimes phonons), the generic model can be represented by a sparse Hamiltonian matrix. Iterative algorithms such as Lanczos or Jacobi-Davidson are used to compute low-lying eigenstates of the Hamilton matrices, and more recent methods based on polynomial expansion allow for computation of spectral properties [10] or time evolution of quantum states [11]. In all those algorithms, sparse MVM is the most time-consuming step.

In this paper we consider the Holstein-Hubbard model (cf. [12] and references therein) and choose six electrons (subspace dimension 400) on a six-site lattice coupled to 15 phonons (subspace dimension 1.55×10^4). The resulting matrix of dimension 6.2×10^6 is very sparse ($N_{nzt} \approx 15$) and can have two different sparsity patterns, depending on whether the phononic or the electronic basis elements are numbered contiguously (see Figs. 1 (a) and (b), respectively). We also applied the well-known ‘‘Reverse Cuthill-McKee (RCM)’’ algorithm [13] to the Hamilton matrix in order to improve spatial locality in the access to the right hand side vector, and to optimize interprocess communication patterns towards near-neighbor exchange. Since the RCM-optimized structure showed no performance advantage over the HMeP

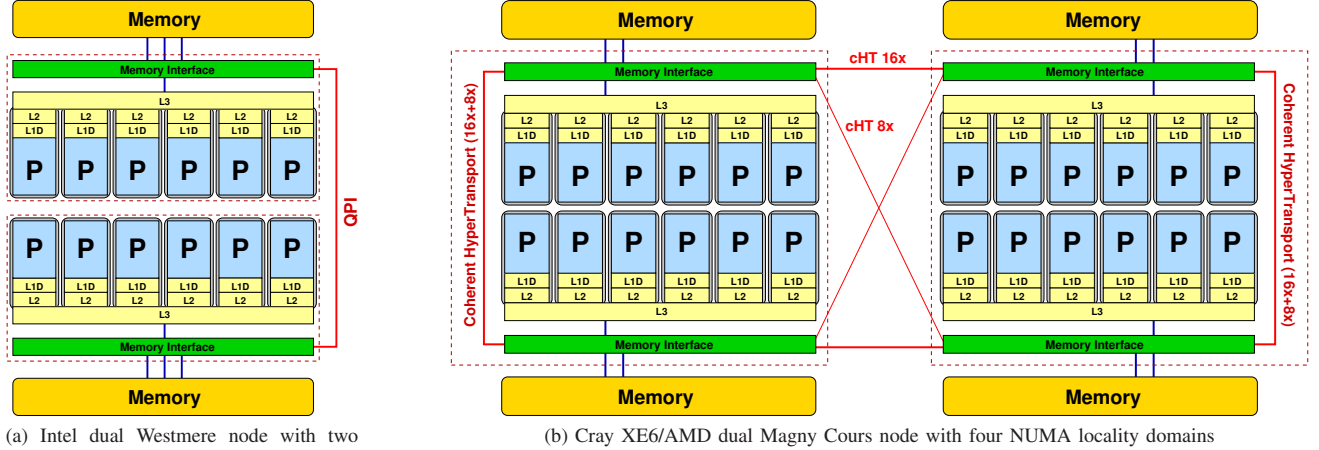


Fig. 2: Node topology of the benchmark systems. Dashed boxes indicate sockets.

variant (Fig. 1(b)) neither on the node nor on the highly parallel level, we will not consider RCM any further here.

The second matrix was generated by the adaptive multigrid code sAMG (see [14], [15], and references therein) for the irregular discretization of a Poisson problem on a car geometry. Its matrix dimension is 2.2×10^7 with an average of $N_{nz} \approx 7$ entries per row (see Fig. 1(c)).

For real-valued, symmetric matrices as considered here it is sufficient to store the upper triangular matrix elements and perform, e.g., a parallel symmetric CRS sparse MVM [4]. The data transfer volume is then reduced by almost a factor of two, allowing for a corresponding performance improvement. We do not use this optimization here for two major reasons. First, the discussion of the hybrid parallel vs. MPI-only implementation should not be restricted to the special case of explicitly symmetric matrices. Second, to our knowledge an efficient shared memory implementation of a symmetric CRS sparse MVM base routine has not yet been presented.

2) Test machines:

a) Intel Nehalem EP / Westmere EP: The two Intel platforms represent a “tick” step within Intel’s “tick-tock” product strategy. Both processors only differ in a few microarchitectural details; the most important difference is that Westmere, due to the 32 nm production process, accommodates six cores per socket instead of four while keeping the same L3 cache size per core (2 MB) as Nehalem. The processor chips (Xeon X5550 and X5650) used for the benchmarks run at 2.66 GHz base frequency with “Turbo Mode” and Simultaneous Multithreading (SMT) enabled. A single socket forms its own ccNUMA LD via three DDR3-1333 memory channels (see Fig. 2(a)), allowing for a peak bandwidth of 32 GB/s. We use standard dual-socket nodes that are connected via fully nonblocking QDR InfiniBand (IB) networks. The Intel compiler in version 11.1 and the Intel MPI library in version 4.0.1 were used throughout. Thread-core affinity was controlled with the LIKWID [16] toolkit.

b) Cray XE6 / AMD Magny Cours: The Cray XE6 system is based on dual-socket nodes with AMD Magny Cours 12-core processors (2.1 GHz Opteron 6172) and the latest Cray “Gemini” interconnect. The internode bandwidth of the 2D torus network is beyond the capability of QDR InfiniBand. The single node architecture depicted in Fig. 2(b) reveals a unique feature of the AMD Magny Cours chip series: The 12-core package comprises two 6-core chips with separate L3 caches and memory controllers, tightly bound by “1.5” HyperTransport (HT) 16x links. Each 6-core unit forms its own NUMA LD via two DDR3-1333 channels, i.e., a two-socket node comprises four NUMA locality domains. In total the AMD design uses eight memory channels, allowing for a theoretical main memory bandwidth advantage of 8/6 over a Westmere node. The Cray compiler in version 7.2.8 was used for the Cray/AMD measurements.

II. NODE-LEVEL PERFORMANCE ANALYSIS

The basis for each parallel program must be an efficient single core/node implementation. Assuming general sparse matrix structures the CRS format presented above is very suitable for modern cache-based multicore processors [17]. Even advanced machine-specific optimizations such as non-temporal prefetch instructions for Opteron processors provide only minor benefits [4] and are thus not considered here. A simple OpenMP parallelization of the outermost loop, together with an appropriate NUMA-aware data placement strategy has proven to provide best node-level performance. We choose the HMeP matrix as a reference problem. The results presented hold qualitatively for the other matrix structures as well. Differences will be discussed where relevant.

Intrasocket and intranode spMVM scalability should always be discussed together with effective STREAM triad numbers,

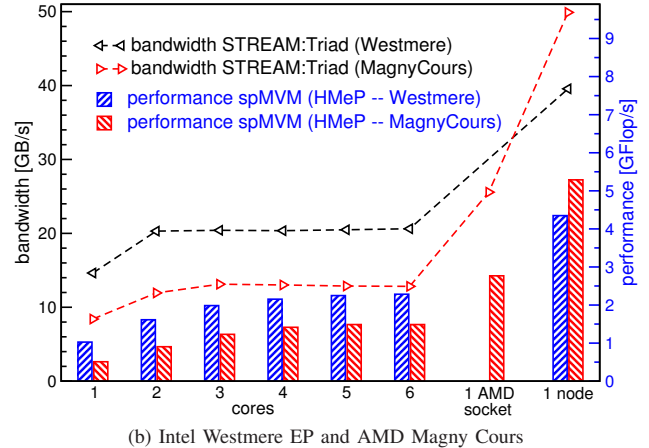
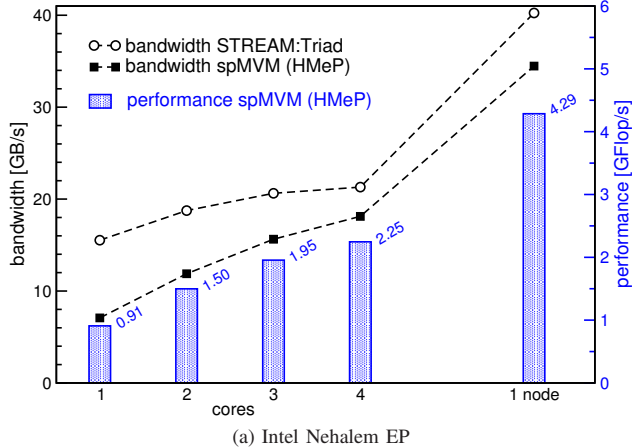


Fig. 3: Node-level performance for the test systems. Effective STREAM triads bandwidth¹, and performance for sparse MVM using the HMeP matrix (bars) is shown. In (a) we also report the measured memory bandwidth for the sparse MVM operation.

which form a practical upper bandwidth limit.¹ Figure 3(a) shows the memory bandwidth on the Nehalem EP platform drawn by the STREAM triad and the spMVM as measured with LIKWID [16]. While the STREAM bandwidth soon saturates within a socket, the spMVM bandwidth and the corresponding GFlop/s numbers still benefit from the use of all cores. This is a typical behavior for codes with (partially) irregular data access patterns. However, the fact that more than 85% of the STREAM bandwidth can be reached with spMVM indicates that our CRS implementation makes good use of the resources. The maximum spMVM performance can be estimated by dividing the memory bandwidth by the code balance (1), using $N_{nzt} = 15$ and $\kappa = 0$. For a single socket the spMVM draws 18.1 GB/s (STREAM triads: 21.2 GB/s), allowing for a maximum performance of 2.66 GFlop/s (3.12 GFlop/s). Combining the measured performance (2.25 GFlop/s) and bandwidth of the spMVM operation with $B_{CRS}(\kappa)$ we find $\kappa = 2.5$, i.e., 2.5 additional bytes of memory traffic on $B(\cdot)$ per inner loop iteration (37.3 bytes per row) are required due to limited cache capacity. Thus the complete vector $B(\cdot)$ is loaded six times from main memory to cache, but each element is used $N_{nzt} = 15$ times. This ratio gets worse if the matrix bandwidth increases. For the HMeP matrix we found $\kappa = 3.79$, which translates to a 50% increase in the additional data transfers for $B(\cdot)$. The code balance implies a performance drop of about 10%, which is consistent with our measurements.

In Fig. 3(b) we summarize the performance characteristics for Intel Westmere and AMD Magny Cours, which both comprise six cores per locality domain. While the AMD system is slower on a single LD, its node-level performance is about 25% higher than on Westmere due to its four LDs per node. Within the domains spMVM saturates at four cores on both architectures, leaving ample room to use the remaining

cores for other tasks, like communication (see Sect. III-C). In the following we will report results for the Westmere and Magny Cours platforms only.

III. DISTRIBUTED-MEMORY PARALLELIZATION

Strong scaling of MPI-parallel sparse MVM is inevitably limited by communication overhead. Hence, it is vital to find ways to hide communication costs as far as possible. A widely used approach is to employ nonblocking point-to-point MPI calls for overlapping communication with useful work. However, it has been known for a long time that most MPI implementations support progress, i.e., actual data transfer, only when MPI library code is executed by the user process, although the hardware even on standard InfiniBand-based clusters does not hinder truly asynchronous point-to-point communication.² Using the simple benchmark from [9] we have verified that this situation has not changed with current MPI versions (Intel 4.0.1, OpenMPI 1.5). In the following sections we will contrast the “naive” overlap applying non-blocking MPI with an approach that uses a dedicated OpenMP thread for explicitly asynchronous transfers. We adopt the nomenclature from [6] and [9] and distinguish between “vector mode” and “task mode.”

MPI parallelization of spMVM is generally done by distributing the nonzeros (or, alternatively, the matrix rows), the right hand side vector $B(\cdot)$, and the result vector $C(\cdot)$ evenly across MPI processes. Due to off-diagonal nonzeros, every process requires some parts of the RHS vector from other processes to complete its own chunk of the result, and must send parts of its own RHS chunk to others. Note that it is generally difficult to establish good load balancing for computation and communication at the same time. We use a balanced distribution of nonzeros across the MPI processes

¹Nontemporal stores have been suppressed in the STREAM measurements and the bandwidth numbers reported have been scaled appropriately ($\times 4/3$) to account for the write-allocate transfer.

²In fact, dedicated “offload” communication hardware was not unusual in historic supercomputer architectures, the Intel Paragon of the early 1990s being a typical example.

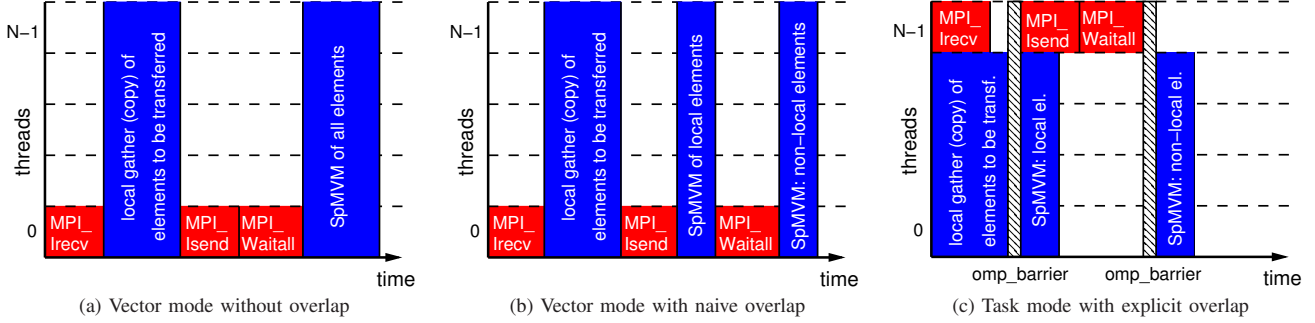


Fig. 4: Schematic timeline view of the implemented hybrid kernel versions. From left to right: no communication/calculation overlap, naive overlap using nonblocking MPI, and explicit overlap by a dedicated communication thread

here. At a given number of processes, the resulting communication pattern depends only on the sparsity structure, so the necessary bookkeeping needs to be done only once. The actual spMVM computations can be performed either by a single thread or, if threading is available, by multiple threads inside the MPI process.

A. Vector-like parallelization: Vector mode without overlap

Gathering the data to be sent by a process into a contiguous send buffer may be done after the receive has been initiated, potentially hiding the cost of copying (see Fig. 4 (a)). We call this naive approach “hybrid vector mode,” since it strongly resembles the programming model for vector-parallel computers [6]: The time-consuming (although probably parallel) computation step does not overlap with communication overhead. This is actually how “MPI+OpenMP hybrid programming” is still defined in most publications. The question whether and why using multiple threads per MPI process may improve performance compared to a pure MPI version on the same hardware is not easy to answer. Depending on the problem, different aspects come into play, and there is no general rule.

B. Vector-like parallelization: Vector mode with naive overlap

As an alternative one may consider hybrid vector mode with nonblocking MPI (see Fig. 4 (b)) to potentially overlap communication with the part of spMVM that can be completed using local RHS elements only. After the nonlocal elements have been received, the remaining spMVM operations can be performed. A disadvantage of splitting the spMVM in two parts is that the local result vector must be written twice, incurring additional memory traffic. The performance model (1) can be modified to account for an additional data transfer of $16/N_{\text{nzr}}$ bytes per inner loop iteration, leading to a modified code balance of

$$B_{\text{CRS}}^{\text{split}} = \left(6 + \frac{20}{N_{\text{nzr}}} + \frac{\kappa}{2} \right) \frac{\text{bytes}}{\text{flop}}. \quad (2)$$

For $N_{\text{nzr}} \approx 7 \dots 15$ and assuming $\kappa = 0$, one may expect a node-level performance penalty between 15% and 8%, and even less if $\kappa > 0$.

For simplicity we will also use the term “vector mode” for pure MPI versions with single-threaded computation.

C. Task mode with explicit overlap

A safe way to ensure overlap of communication with computation is to use a separate communication thread and leave the computational loops to the remaining threads. We call this “hybrid task mode,” because it establishes a functional decomposition of tasks (communication vs. computation) across the resources (see Fig. 4 (c)): One thread executes MPI calls only, while all others are used to copy data into send buffers, perform the spMVM with the local RHS elements, and finally (after all communication has finished) do the remaining spMVM parts. Since spMVM saturates at about 3–5 threads per locality domain (as shown in Fig. 3 (b)), at least one core per LD is available for communication without adversely affecting node-level performance. On architectures with SMT, like the Intel Westmere, there is also the option of using one compute thread per physical core and bind the communication thread to a logical core.

Apart from the additional memory traffic due to writing the result vector twice (see Sect. III-B), another drawback of hybrid task mode is that the standard OpenMP loop work-sharing directive cannot be used, since there is no concept of “subteams” in the current OpenMP standard. Work distribution is thus implemented explicitly, using one contiguous chunk of nonzeros per compute thread.

IV. INTERNODE PERFORMANCE RESULTS AND DISCUSSION

Figures 5 and 6 show strong scaling results for the two chosen matrices (HMeP and sAMG). We compare the hybrid kernel versions presented in Fig. 4 on the Westmere cluster and present the best result obtained on the Cray XE6 system for reference. For the considered matrix sizes and largest node counts, a single spMVM takes a couple of milliseconds.

A. Testcase HMeP (see Fig. 5)

At one MPI process per physical core (left panel), vector mode with naive overlap is always slower than the variant without overlap because the additional data transfer on the result vector cannot be compensated by overlapping communication with computation. Task mode was implemented here with one communication thread per MPI process, running on

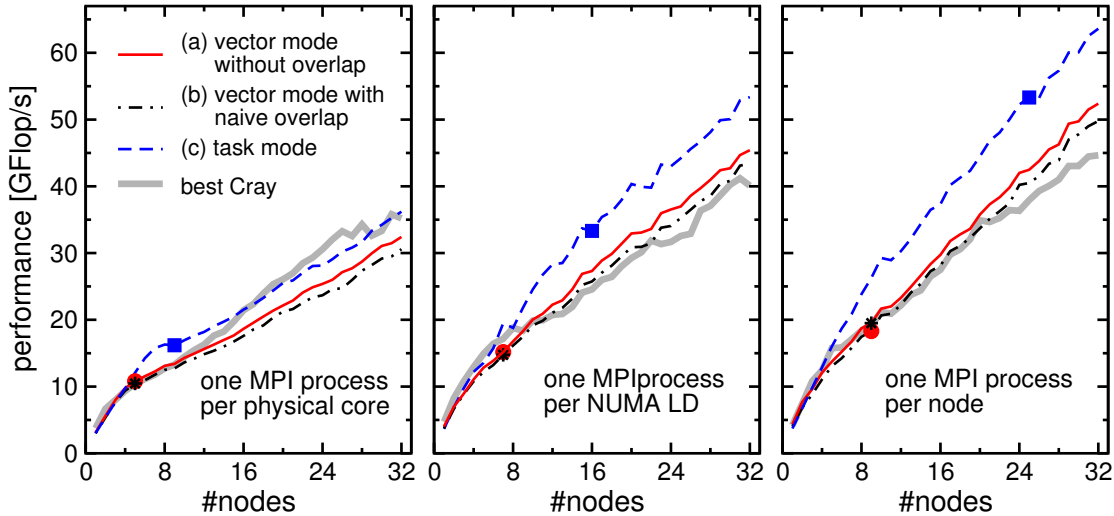


Fig. 5: Strong scaling performance data for spMVM with the HMeP matrix on the Intel Westmere cluster for different pure MPI and hybrid variants (kernel version (a) – (c)) as in Fig. 4). Symbols on each data set indicate the 50% parallel efficiency point with respect to the best single-node version. The best variant on the Cray XE6 system is shown for reference (see text for details).

the second virtual core. In this case, point-to-point transfers explicitly overlap with the local spMVM, leading to a noticeable performance boost. One may conclude that MPI libraries with support for progress threads could follow the same strategy and bind those threads to unused logical cores, thereby allowing overlap even with single-threaded user code.

With one MPI process per NUMA locality domain (middle panel) the advantage of task mode is even more pronounced. Since the memory bus of an LD is already saturated with four threads, it does not make a difference whether six worker threads are used with one communication thread on a virtual core, or whether a physical core is devoted to communication. The same is true with only one MPI process (12 threads) per node (right panel).

The symbols in Fig. 5 indicate the 50% parallel efficiency point (with respect to the best single-node performance as reported in Fig. 3 (b)) on each data set. In practice one would not go beyond this number of nodes because of bad resource utilization. For the matrix and the system under investigation it is clear that task mode allows strong scaling to much higher levels of parallelism with acceptable parallel efficiency than any variant of vector mode.

Contrary to expectations based on the single-node performance numbers (Fig. 3 (b)), the Cray XE6 can generally not match the performance of the Westmere cluster at larger node counts, with the exception of pure MPI where both are roughly on par (left panel, Cray results for vector mode with naive overlap). When using threaded MPI processes (middle and right panel), task mode performs best on the Cray system. The advantage over the other kernel variants is by far not as pronounced as on Westmere, however. We have observed a strong influence of job topology and machine load on the communication performance over the 2D torus network.

Since sparse MVM requires significant non-nearest-neighbor communication with growing process counts, the nonblocking fat tree network on the Westmere cluster seems to be better suited for this kind of problem. The presented results are best values obtained on a dedicated XE6 machine.

Interestingly, the hybrid vector mode variants with one MPI process per LD or per node already provide better scalability than pure MPI; we attribute this to the smaller number of messages in the hybrid case (message aggregation) and a generally improved load balancing. There is also a universal drop in scalability beyond about six nodes, which is largely independent of the particular hybrid mode. This can be ascribed to a strong decrease in overall internode communication volume when the number of nodes is small. The effect is somewhat less pronounced for pure MPI, since the overhead of intranode message passing cannot be neglected.

B. Testcase sAMG (see Fig. 6)

The sAMG matrix has much weaker communication requirements than HMeP, and the impact of load imbalance is very small. Hence, all variants and hybrid modes (pure MPI, one process per LD, and one process per node) show similar scaling behavior and there is no advantage of task mode over vector mode without overlap or pure MPI. This observation supports the general rule that it makes no sense to consider MPI+OpenMP hybrid programming if the pure MPI code already scales well and behaves in accordance with a single-node performance model.

On the Cray XE6, vector mode without overlap performs best across all hybrid modes, with a significant advantage when running one MPI process with six threads per LD. This aspect is still to be investigated.

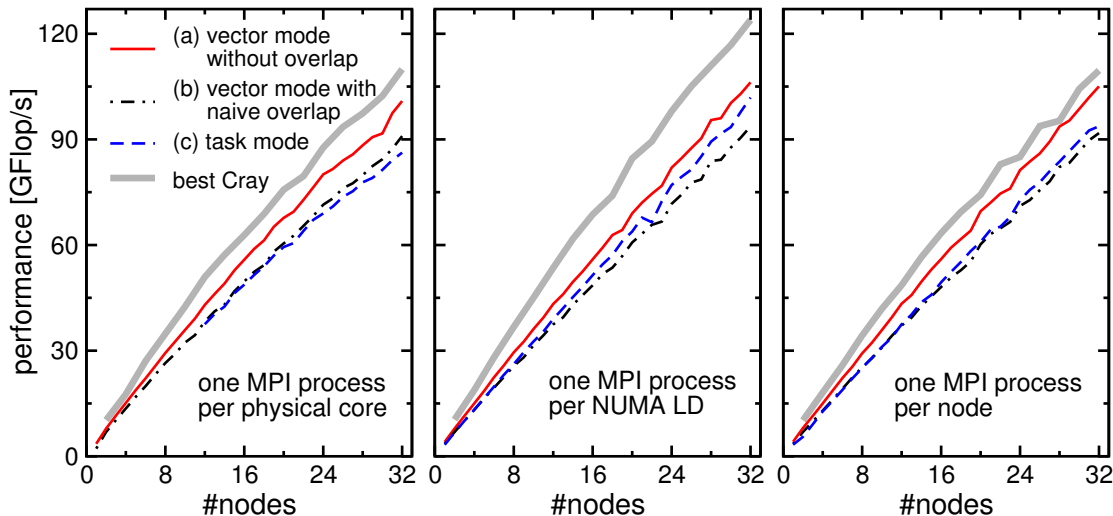


Fig. 6: Strong scaling performance data for spMVM with the sAMG matrix (same variants as in Fig. 5). Parallel efficiency is above 50% for all versions up to 32 nodes. The Cray system performed best in vector mode without overlap for all cases.

V. SUMMARY AND OUTLOOK

We have investigated the performance properties of different pure MPI and MPI+OpenMP hybrid variants of sparse matrix-vector multiplication on two current multicore-based parallel systems, using two matrices with significantly different sparsity patterns. The single-node performance model and analysis on Intel Westmere and AMD Magny Cours processors showed that memory-bound sparse MVM saturates the memory bus of a NUMA locality domain already at about four threads, leaving free resources for implementing explicit computation/communication overlap. Since most current standard MPI implementations do not support truly asynchronous point-to-point communication, explicit overlap enabled substantial performance gains in strong scaling scenarios for communication-bound problems, especially when running one process per NUMA domain or per node. Since the communication thread can run on a virtual core, MPI implementations could use the same strategy for internal “progress threads” and so enable asynchronous communication without changes in MPI-only user code.

Future work will cover a more complete investigation of load balancing effects, and a careful analysis of the performance properties of the Cray XE6 system. We will also employ development versions of MPI libraries that support asynchronous progress and compare with our hybrid task mode approach.

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