

AN OBJECT-ORIENTED BSP LIBRARY FOR MULTICORE PROGRAMMING

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ABSTRACT. We show that the Bulk Synchronous Parallel (BSP) model, originally designed for distributed-memory systems, is also applicable for shared-memory multicore systems and, furthermore, that BSP libraries are useful in scientific computing on these systems. A proof-of-concept MulticoreBSP library has been implemented in Java, and is used to show that BSP algorithms can attain proper speedups on multicore architectures. This library is based on the BSPlib implementation, adapted to an object-oriented setting. In comparison, the number of function primitives is reduced, while the overall design simplicity is improved. We detail applying the BSP model and library on the sparse matrix–vector (SpMV) multiplication problem, and show by performing numerical experiments that the resulting BSP SpMV algorithm attains speedups, in one case reaching a speedup of 3.5 for 4 threads. While not described in detail in this paper, algorithms for the fast Fourier transform and the dense LU decomposition are also investigated; in one case attaining superlinear speedups of 5 for 4 threads. The predictability of BSP algorithms in the case of the sparse matrix–vector multiply is also investigated.

1. INTRODUCTION

Since multicore processors are now in widespread use, writing parallel programs is becoming highly relevant to a previously sequential world. For the parallel world, interest in shared-memory architectures, as opposed to classical distributed-memory architectures, is rekindled. A parallel programming model which is simple in design, yet able to cater to both memory models, can be of key importance.

For multicore systems, sharing memory is not for free. Usually main memory is accessible only via a cache hierarchy, which may or may not be shared amongst cores; threads may thus disrupt each other and slow down computation. An extension to the BSP model to take these caches explicitly into account has been proposed by Valiant [1]. Our BSP implementation, however, still follows the original BSP model [2]. This original model, as well as BSP communication libraries such as BSPlib [3] and PUB [4], were introduced to enable portable parallel programming, while attaining predictable performance. BSP being meant as a single program, multiple data (SPMD) model, a natural question is if it also performs well in a shared-memory setting. To this end, the *MulticoreBSP* proof-of-concept library has been implemented. This communications library is an object-oriented adaption of BSPlib, written in Java, and targeting only shared-memory systems.

The performance of this library is examined by re-implementing the educational BSPedupack [5] software package. This package contains parallel programs originally written in BSPlib for the following applications:

- vector inner-product calculation,
- dense LU decomposition,
- fast Fourier transform, and
- sparse matrix–vector (SpMV) multiplication.

We examine the performance of the MulticoreBSP library using these same applications. As a different system architecture is targeted, however, algorithms can differ to some extent from those originally presented in [5]. While experimental results are given for all these applications, the model and library are introduced by describing the inner-product calculation and SpMV multiplication only. The library and all applications are, however, freely available at www.multicorebsp.com.

Key words and phrases. Bulk Synchronous Parallel, BSP, parallel computing, sparse matrix–vector multiplication, multicore, shared-memory, fast Fourier transform, dense LU decomposition.

The choice of Java as our programming language underscores the portability goal of BSP. As an interpreted language, the library and applications built on it can be distributed to every machine for which a Java interpreter is available, without recompiling. Furthermore, using Java means that the BSP model is implemented in an object-oriented way, making the model easier to use while also reducing the number of BSP primitives from the already low number of 20 primitives. This is important since it enables easy learning, and helps with keeping the (idealised) parallel machine transparent.

Restricting the number of primitives also restricts the programmer, but this is preferable to simplicity without restriction. For example, with OpenMP [6], parallelism may be introduced in code by adding a parallel directive just before a for-loop. This is simple and nonrestrictive, but relies on programmer expertise to decide on the scope of variables. Variables defined before the directive is encountered are shared amongst threads, while those declared within the parallel block are considered local. The programmer must therefore be wary to avoid race conditions, and actively avoid the unintended sharing of variables. In contrast, the MulticoreBSP library adds robustness to algorithms by implicitly assuming all variables are local unless explicitly defined otherwise, while retaining programming simplicity. Also, by structuring computations in independent, sequential phases, separated by synchronisation barriers, another common trap in parallel programming is avoided: deadlocks. Usually these occur only rarely in parallel programs, making them hard to detect; while in BSP such deadlocks can only occur as a sequential error, not by misuse of communication primitives. In summary, we believe the BSP model has the following desirable properties:

- it is easy to learn by programmers and very transparent to them,
- it models both distributed-memory and shared-memory architectures,
- it predicts performance, and
- it is robust with respect to common parallel programming pitfalls.

This article has two aims: first, introduce the MulticoreBSP communications library, and second, demonstrate how to design shared-memory algorithms in BSP. In particular, we show that it is possible to exploit differences between distributed-memory and shared-memory architectures on the level of implementation. To this end, we introduce MulticoreBSP by implementing a shared-memory version of the sparse matrix–vector (SpMV) multiplication, and compare it to the original distributed-memory version from BSPedupack. Similar efforts have been made for dense LU decomposition and the Fast Fourier transform.

Our algorithm listings are close to the actual Java code, to demonstrate briefly but properly how the library operates in practice. Within our listings, all classes, member functions and variables defined in the library are printed in *italic*, while class and function names not defined therein are printed in **typewriter** font. Function code in listings is printed in plain roman, with the only further exception of reserved words, such as **for** and **return**, which are printed boldface.

The remainder of the article is structured as follows. The MulticoreBSP library is introduced in Section 2. Using this proof-of-concept Java library, Section 3 details the BSP SpMV algorithm for multicore systems, which is put to the test in Section 4. This section also reports on performance of the dense LU and FFT algorithms. Conclusions and future work follow in Section 5.

1.1. BSP model. The original BSP model targets distributed-memory systems and models them using four parameters: p, g, l , and r . The total number of parallel computing units (cores) of a BSP machine is given by p , while r measures the speed of each such core, in flops per second. Each core executes the same given program, usually working on different data; that is, BSP is a single program, multiple data (SPMD) model. The parallel program is broken down in *supersteps*, which are separated by *synchronisation barriers*. During a superstep, a process can execute any instruction, but it cannot communicate with other processes. It can, however, queue communication requests. When a process encounters a synchronisation barrier, execution halts until all processes encounter this barrier, upon which the next superstep is started concurrently. At synchronisation, all queued communication requests from the previous superstep are processed; the only communication thus occurs as part of synchronisation. The communication costs occurring this way are modelled in BSP by l , which models the time required to get past a synchronisation

barrier, and g , which models the *communication gap*, the time gap between two data words sent by a process during communication. Thus g corresponds to the inverse of the bandwidth, the speed at which data is communicated.

Suppose there are t supersteps, each superstep i contains $w^i(s)$ flops of work for process s , and each process receives $V_R^i(s)$ or sends $V_S^i(s)$ bytes of communication. Denote the maximum number of bytes communicated by $V^i(s) = \max\{V_R^i(s), V_S^i(s)\}$. Then the total running time (in seconds) on a BSP machine can be predicted as:

$$(1) \quad T = \sum_{i=0}^{t-1} \left(\frac{1}{r} \cdot \max_s w^i(s) + g \cdot \max_s V^i(s) + l \right).$$

This is the *BSP cost model*, as applicable to distributed-memory parallel computing, and enables performance prediction of BSP algorithms.

2. OBJECT-ORIENTED BULK SYNCHRONOUS PARALLEL LIBRARY

When communication occurs with object-oriented parallel programming on distributed-memory systems, entire *objects* need to be transferred. This is done by *marshalling* these objects in transferable code, a complex and time-consuming process: other objects that the object to transfer may depend on have to be identified and recursively marshalled as well. While this is less an issue on shared-memory systems, as in principle all objects are stored in shared-memory, MulticoreBSP demands that each communicable object can be *cloned* in memory; it must be possible for the library to copy an object and all its dependencies so that the resulting clone is completely independent of the original variable and its dependencies. Note that cloning differs from marshalling in that no transferable code is required.

Object-oriented BSP models have been researched before, for example in [7], targeting distributed-memory systems. Another parallel model is the Coarse Grained Model (CGM), by Dehne et al. [8]; its library CGMLib [9], by Chan and Dehne, also is object-oriented and targets distributed-memory systems by using an underlying communications library, such as MPI. Yelick et al. [10] introduced a Java dialect specifically for high performance computing and parallelism, using global memory space extended with advanced memory management based on programmer input. An object-oriented parallel model supporting both shared and distributed memory has been presented by Kaminsky [11]. Similarly, there also exists a BSP library for the Python programming language [12], usable on shared-memory multicore systems as well as on distributed-memory systems (by using a standard BSPLib implementation). A BSP model developed specifically for shared-memory systems has previously been researched by Tiskin [13], who introduced the Bulk Synchronous Parallel random access machine (BSPRAM). This model assumes that each parallel process can access two types of memory: local memory, on which it can execute local computations, and a shared memory accessible by all processes, facilitating inter-process communication. This model is more akin to OpenMP than to the pure BSP model used in this paper.

To introduce our object-oriented BSP library for multicore systems, we first recall some basic terminology from object-oriented languages. Programming code is grouped into classes, each class having its own (local) member variables as well as member functions. Multiple *instances* of a class can be created; much like there can be multiple data elements of the same type (e.g., integer). An instance is created by calling the *constructor* function of its class. Such a constructor may require specific parameters, so that an instance cannot be created without supplying those parameters. As an example, in Java, a new string can be created by writing “String str = new String();”. A class may be extended from a given superclass, meaning that it inherits all the members, including their visibility (see below), from its superclass. Such a subclass normally also defines new member variables or functions. Member variables or functions have one of the following *visibilities*:

- *private*, visible only to instances of the same class, but excluding subclasses;
- *protected*, visible only to instances of the same class, including subclasses;
- *public*, visible to all instances regardless of class.

purely virtual:

<i>main_part()</i>	will contain sequential code,
<i>parallel_part()</i>	will contain parallel code.

protected:

<i>bsp_begin(int)</i>	starts the parallel execution,
<i>bsp_nprocs()</i>	returns the number of threads executing this algorithm,
<i>bsp_pid()</i>	returns the current, unique thread identification number,
<i>bsp_sync()</i>	synchronises all threads,
<i>bsp_abort()</i>	aborts the parallel execution.

public:

<i>start()</i>	starts the program.
----------------	---------------------

TABLE 1. *BSP_PROGRAM* function list

Member functions may be defined, yet not implemented; in such a case the function is called *purely virtual*, and its corresponding class *abstract*. A normal virtual member function is already implemented, but can be redefined in subclasses.

A generic BSP program is defined to be a class, *BSP_PROGRAM*, having at least the functions in Table 1 defined. Any specific parallel algorithm is extended from this superclass, and must implement the following two protected, purely virtual, functions:

- *main_part()*: this code is only executed by a single process, and from the protected functions in Table 1 it can only call *bsp_begin(int)*,
- *parallel_part()*: this is the code run in parallel; once this function is reached, all BSP functions can be called, with the exception of *bsp_begin()*.

The sequential phase can be used to prepare data or determine algorithm parameters needed for the parallel phase. From within the sequential code, a call to *bsp_begin(int)* starts the parallel phase using the given number of processes. Each such process executes the exact same code, defined in the *parallel_part()* function. The number of concurrent processes can be queried by calling *bsp_nprocs()*, and a unique process ID can be retrieved by using *bsp_pid()*. Parallel execution can be terminated prematurely by calling *bsp_abort()*. The function *bsp_sync()* is a barrier that synchronises all processes; a process will halt execution when encountering this function, only to continue when all processes were halted.

Defining only this BSP program class, a simple parallel application can already be written; see the Hello World example, Algorithm 1. Since a program is in essence a class, to run it, an instance of it has to be created first: “Hello_World myInstance = new Hello_World();”. Creating an instance of a parallel job does not implicitly start it. To do that, the *start()* function is defined, and the job is executed by “myInstance.start();”. A short-hand way of doing this is shown in Algorithm 1. After starting, the program will print the following four lines, *in an undefined order*:

```
Thread 0 says: Hello World!
Thread 1 says: Hello World!
Thread 2 says: Hello World!
Thread 3 says: Hello World!
```

Every thread has its own instance of its parallel class; no variables are shared in any way. For most parallel jobs this is insufficient since data communication should be allowed to occur between threads, implying that variables should be shareable.

To facilitate this, we define an abstract BSP class *BSP_COMM*. Any shareable object type will have to implement (or extend) this class; in other words, all shared variables have *BSP_COMM* as superclass. No other objects can be communicated. Since a shared variable has no meaning if not connected to a parallel program, the constructor of every shared variable must take a *BSP_PROGRAM* as parameter, thus linking the shared variable and the parallel program it is used in. Communication always entails that some source data is transferred from a source process

Algorithm 1 Hello World example using the MulticoreBSP library

```

Class Hello_World extends BSP_PROGRAM {
protected function main_part():
  1: bsp_begin(4);
protected function parallel_part():
  1: print "Thread " + bsp_pid() + " says: Hello World!";
}
Start using:
  1: (new Hello_World()).start();

```

to a destination variable at a destination process. The MulticoreBSP library facilitates three communication methods to do this: one being to *put* data in the memory local to another thread, another being a method to *get* data from variables local to another thread, and, finally, a method to *send* messages to a variable local to another thread. In all cases, the destination variable must be shared, since by definition any non-shared variable is not visible to other threads. These *bsp_put(...)*, *bsp_get(...)*, and *bsp_send(...)* functions are therefore defined as public functions within *BSP_COMM*; that is, as functions of destination variables. Thus if “destination” is a shared variable, or rather, an instance of a class derived from *BSP_COMM*, then the following functions are defined:

- *destination.bsp_put*(source, destination_thread),
- *destination.bsp_get*(source, source_thread),
- *destination.bsp_send*(source, destination_thread).

In all cases, the source parameter is optional, by default referring to the destination variable at the current process. The source and destination threads are designated by referring to their thread IDs. All communication happens at synchronisation time; multiple puts or gets to the same location at the same process result in only one of them coming through at the destination. This is in contrast to the message-passing *bsp_send*, where communication is queued at the destination variable. Reading this queue is facilitated by *bsp_qsize*, which returns the number of messages still in queue, and *bsp_move*, which moves an item from the queue into its variable. A final function, *bsp_unregister*, is used to invalidate a shared variable, freeing up all memory it uses at all threads; this should never be called inside a superstep where the variable is still used.

The functions introduced so far have been available for distributed-memory systems as well, for example in BSPlib [3]. MulticoreBSP also introduces a new communication directive, *bsp_direct_get(...)*, so that it can take full advantage of the shared-memory architecture it is designed to work with. The syntax is the same as that for *bsp_get*, but semantics differ in that the communication is not queued: it is executed immediately, instead. A standard distributed-memory BSP algorithm can systematically be adapted to exploit shared-memory systems using this new primitive, as follows. When a superstep only communicates via get primitives while the data already is available at the remote process, these get primitives can be substituted for direct-gets and the next synchronisation barrier can be removed; the direct-get functionality thus can reduce the number of supersteps of a classical BSP algorithm on shared-memory architectures. Summarising, *BSP_COMM* defines the purely virtual functions used for communication shown in Table 2. Note that according to the BSP model, all communication is guaranteed to have been done after a synchronisation barrier is passed. Differences with the original BSPlib are that the *bsp_init()*, *bsp_push_reg()*, *bsp_pop_reg()*, and *bsp_end()* primitives no longer appear; *bsp_end()* is in effect assumed after the function *parallel_part* finishes, initialisation is moved to the program constructor, variable registration is moved to the variable constructor, and the *bsp_pop_reg* is replaced with the *bsp_unregister* function.

Regarding the BSP cost model, a difference is caused by the *bsp_direct_get* primitive, which is executed during a superstep. In determining the total communication cost, we assume the cost of a direct get is bounded by the cost of a normal get performed in synchronising. This way, when

public:

<i>bsp_put(source, destination_pid)</i>	puts source to this variable at destination_pid,
<i>bsp_get(source, source_pid)</i>	gets source from source_pid and stores it here,
<i>bsp_direct_get(source, source_pid)</i>	like <i>bsp_get</i> , but does not wait for sync,
<i>bsp_send(source, destination_pid)</i>	sends source to the queue of destination ID,
<i>bsp_qsize()</i>	gets the number of messages still in queue,
<i>bsp_move()</i>	moves an item from the queue to this variable,
<i>bsp_unregister()</i>	frees the local memory used by this variable.

TABLE 2. BSP_COMM virtual function list

determining the total running time, we can again take into account the maximum communication volume; the original BSP cost model shown in (1) is retained.

3. SPARSE MATRIX-VECTOR MULTIPLICATION IN MULTICOREBSP

We proceed with implementing the sparse matrix-vector (SpMV) multiplication using the library introduced in the previous section, but start with a simpler description of the parallel inner-product calculation, so that several standard communication variables can be introduced. The main implementation of a shared variable is *BSP_REGISTER<T>*, which stores a variable of type *T*, accessible using read and write methods. It extends *BSP_COMM*, and, as discussed earlier, *T* must support cloning. This class alone, although versatile, is not yet enough to attain efficient code.

3.1. Inner-product calculation. Given two real vectors $x, y \in \mathbb{R}^n$, we are interested in the parallel calculation of the inner product $(x, y) = \sum_{i=0}^{n-1} x_i y_i$. Assuming p threads are available, then an intuitive approach is to divide the vectors x and y into p blocks of (roughly) equal size, where each thread calculates the sum of the corresponding block. This is followed by communicating the partial results and summing them to obtain the final result. Assuming that this inner-product calculation is part of a larger parallel scheme, the vectors x and y already have been distributed in memory, and the only remaining task is to compute partial inner products and communicate the resulting partial sums. Each thread can define a shared array of variables storing double values, to which partial sums can be communicated. Such an array could be defined using a *BSP_REGISTER* and standard Java array constructs, as in “ArrayList<*BSP_REGISTER*<Double>> sums;”. The downside is that each register added to this array has to be individually constructed. Afterwards, putting a value x at index i at process s would be done by “sums.get(i).*bsp_put*(x, s);”. This has several disadvantages:

- low performance; a single entry must be accessed through multiple classes, and each register added to the array must be constructed separately,
- verbosity; a syntax-heavy approach to control a single element of the array,
- memory overhead; each vector element is registered separately.

Even worse is the syntax and overhead needed to put or get ranges of vectors, as, for example, required by the dense LU algorithm.

To improve this, we introduce the *BSP_COMM_ARR* subclass of *BSP_COMM*. The functions that *BSP_COMM_ARR* defines are in addition to those in Table 2, and are shown in Table 3. The put, get, and direct_get functions have been modified to copy a number of *length* elements of the array in a single communication request. If this number of elements is smaller than the array length, the use of *offsets* in either the source or destination array is convenient. For example, if x and y are arrays implementing the *BSP_COMM_ARR* class, the code “ y .*bsp_put*(x, x_o, s, y_o, l);” would replace y at process s by

$$(y_0, \dots, y_{y_o-1}, x_{x_o}, \dots, x_{x_o+l-1}, y_{y_o+l}, \dots).$$

The (direct) get function works in the expected similar fashion. The main implementation of *BSP_COMM_ARR* is *BSP_ARRAY<T>*, which makes available an array with elements of type *T*

public:

```

bsp_put      (source, s_offset, destination_pid, d_offset, length)
bsp_get      (source, source_pid, s_offset, d_offset, length)
bsp_direct_get(source, source_pid, s_offset, d_offset, length)

```

TABLE 3. BSP_COMM_ARR virtual function list, excluding those already defined by BSP_COMM

at each process. The type T must still support cloning. For efficiency¹, when T should be an `int` or `double` primitive type, we define the specialised `BSP_INT_ARRAY` and `BSP_DOUBLE_ARRAY` classes. Both of the specialised variants also define the `getData()` method, giving the programmer access to the underlying raw array. This reference is guaranteed constant with respect to the array object, from construction up until de-registration or end of the parallel phase. Algorithm 2 shows a MulticoreBSP inner-product algorithm, using the constructs introduced above.

Algorithm 2 Inner-product calculation for identically pre-distributed vectors x, y

Calculates the inner product $(x, y) = \sum_i x_i y_i$. Local subvectors \tilde{x} and \tilde{y} are assumed available, and distributed identically.

```

protected function bsp_ip() {
  1: sums = new BSP_DOUBLE_ARRAY(this, bsp_nprocs());
  2:  $\alpha = 0$ ;
  3: for  $i = 0$  to  $\tilde{x}.length - 1$  do
  4:    $\alpha = \alpha + \tilde{x}[i] \cdot \tilde{y}[i]$ ;
  5: for  $i = 0$  to  $bsp\_nprocs() - 1$  do
  6:   sums.bsp_put( $\alpha, 0, i, bsp\_pid(), 1$ );
  7: bsp_sync();
  8:  $\alpha = 0, a = \text{sums.getData}()$ ;
  9: for  $i = 0$  to  $bsp\_nprocs() - 1$  do
 10:    $\alpha = \alpha + a[i]$ ;
 11: return  $\alpha$ ;
}

```

3.2. Sparse matrix, dense vector distributions. To enable parallel computing of $y = Ax$, the matrix A and both vectors x and y must be distributed. If p processes are used, such distributions are given by the maps

$$(2) \quad \begin{aligned} \pi_A : [0, m - 1] \times [0, n - 1] &\rightarrow [0, p - 1], \\ \pi_x : [0, n - 1] &\rightarrow [0, p - 1], \\ \pi_y : [0, m - 1] &\rightarrow [0, p - 1]. \end{aligned}$$

Partitioners such as Mondriaan [14] or Zoltan [15] preprocess sparse matrices to find distributions optimised for parallel SpMV multiplication; this paper will not deal with partitioning methods, and simply assume the maps from (2) are available. Such maps, while containing in principle all necessary information, still need further preprocessing to make them directly suitable for parallel SpMV multiplication. The latest version of the Mondriaan package (version 3.11) can perform this step automatically, and gives us the following maps and local matrices. For each $s \in [0, p - 1]$, a local matrix A_s of size $m_s \times n_s$ is stored; this local matrix can be smaller than A itself since it stores only those entries $a_{ij} \in A$ for which $\pi_A(i, j) = s$, then removes empty rows and columns and renumbers nonempty rows and columns accordingly. A local input vector x^s is also stored, so that it contains the elements from x with index j for which $\pi_x(j) = s$, and similarly for y^s and π_y .

¹in Java, “Double” differs from “double”, the first being an object wrapping a raw double type. Accessing such a class incurs overhead, making `BSP_ARRAY<Double>` an inefficient construct.

Then, during local multiplication with elements from A_s , information is required at which process and index the corresponding element from the input vector x resides. and similarly for the output vector y . Thus the following maps are preferable to those in (2):

- $\pi_r^s : [0, m_s - 1] \rightarrow [0, p - 1]$, so that $\pi_r^s(i)$ is the process index for the element of the output vector corresponding to the i th row of A_s ,
- $\pi_c^s : [0, n_s - 1] \rightarrow [0, p - 1]$, so that $\pi_c^s(j)$ is the process index for the element of the input vector corresponding to the j th column of A_s ,
- $I_r^s : [0, m_s - 1] \rightarrow [0, \max_k m_k - 1]$, so that $I_r^s(i)$ is the index of the local output vector $y^{\pi_r^s(i)}$ corresponding to the i th row of A_s , and
- $I_c^s : [0, n_s - 1] \rightarrow [0, \max_k n_k - 1]$, so that $I_c^s(j)$ is the index of the local input vector $x^{\pi_c^s(j)}$ corresponding to the j th row of A_s .

3.3. Partially buffered multiplication. We assume that the local matrices A_s and vectors x^s, y^s as well as the appropriate mappings from the previous section are available, and examine the MulticoreBSP SpMV multiplication algorithm. During local multiplication, non-local elements from the input vector may be required. These values are buffered beforehand, by allocating an input vector buffer of size n_s , and copying local and non-local input vector elements into this buffer. This buffering of the input vector is called the *fan-out* step in [5, Chapter 4]; the only difference with the algorithm described there is that the shared-memory variant will make use of the direct-get primitive, which prevents the fan-out operation from having to be done in a separate superstep. This brings the parallel SpMV multiplication algorithm down from three supersteps, to only two.

After fan-out, upon entering the SpMV multiplication kernel, each process starts traversing the nonzeros in its local matrix A_s in a row-major order. For each encountered row, it looks up whether the corresponding output element from y is local or not. If so, products of nonzero values and elements from x are immediately added to the local y^s . If not, they are added to a local temporary double value, which, upon switching to the next row, is sent to the correct process using the *bsp_send* primitive. After local multiplication, all processes synchronise to prepare for the second and last superstep: the *fan-in*. In this step, incoming messages are processed. From each message, the target index and the remote contribution is read, and the contribution is added to the correct element of the local output vector.

An implementation detail regards the use of the send primitive in this setting; this directive on a shared array transmits objects of the same type, which are arrays. For the SpMV multiplication, however, we require instead sending only an index and a double value, so that a partial sum for y can be added at the correct position of the local vector at the target process. To this end, we define a Pair class, storing both an integer and a double value, and create a shared value of this class; on this type of variable, message passing with *bsp_send* will perform as required. Algorithm 3 clarifies this by showing the resulting implementation.

If we introduce the notation $|\{\pi_r^s = k\}|$ as the number of elements in π_r^s equal to k , the number of flops performed by process s can be expressed as:

$$2 \cdot \text{nz}(A_s) \quad \text{in superstep 1, and} \\ \sum_{i=0, i \neq s}^{p-1} |\{\pi_r^i = s\}| \quad \text{in superstep 2.}$$

Here, we count each nonzero as two flops, and the number of nonzeros of a matrix A is given by $\text{nz}(A)$. The communication volume sent $V_S(s)$ or received $V_R(s)$ by process s is:

$$\begin{aligned} V_S(s) &= |\{\pi_r^s \neq s\}| + \sum_{i=0, i \neq s}^{p-1} |\{\pi_c^i = s\}|, \\ V_R(s) &= |\{\pi_c^s \neq s\}| + \sum_{i=0, i \neq s}^{p-1} |\{\pi_r^i = s\}|, \text{ and} \\ (3) \quad V(s) &= \max\{V_S(s), V_R(s)\}. \end{aligned}$$

The time taken by this algorithm according to the BSP model then is:

$$(4) \quad T_{\text{SpMV}} = \frac{1}{r} \cdot \left(2 \cdot \max_s \text{nz}(A_s) + \max_s \sum_{i=0, i \neq s}^{p-1} |\{\pi_r^i = s\}| \right) + g \cdot \max_s V(s) + l.$$

Algorithm 3 Parallel sparse matrix–vector multiplication

Calculates $y = Ax$ in parallel. Based on buffering of input vector elements.

Input: local $m_s \times n_s$ submatrix A_s of A of process s ,
 local subvector x^s of x ,
 local subvector y^s of y ,
 mappings $\pi_r^s, \pi_c^s, I_r^s, I_c^s$.

```

class Pair() {
    int tag; double value;
    Pair( int _t, double _v ) {
        tag = _t; value = _v;
    }
}

protected function bsp_spmv() {
    1:  $s = \text{bsp\_pid}()$ ;
    2:  $\tilde{x} = \text{new BSP\_DOUBLE\_ARRAY}(\text{this}, n_s)$ ;
    3:  $\text{pairs} = \text{new BSP\_REGISTER}<\text{Pair}>(\text{this})$ ;
    4: for  $j = 0$  to  $n_s - 1$  do
    5:      $\tilde{x}.\text{bsp\_direct\_get}(x^s, \pi_c^s(j), I_c^s(j), j, 1)$ ;
    6: for  $i = 0$  to  $m_s - 1$  do
    7:     if  $\pi_r^s(i) = s$  then
    8:         for all  $a_{ij} \neq 0$  in the  $i$ th row of  $A_s$  do
    9:              $y_{I_r^s(i)}^s = y_{I_r^s(i)}^s + a_{ij} \cdot \tilde{x}_j$ ;
    10:    else
    11:         $\alpha = 0$ ;
    12:        for all  $a_{ij} \neq 0$  in the  $i$ th row of  $A_s$  do
    13:             $\alpha = \alpha + a_{ij} \cdot \tilde{x}_j$ ;
    14:         $\text{pairs}.\text{bsp\_send}(\text{new Pair}(I_r^s(i), \alpha), \pi_r^s(i))$ ;
    15:  $\text{bsp\_sync}()$ ;
    16: while  $\text{pairs}.\text{bsp\_qsize}() > 0$  do
    17:     $\text{pairs}.\text{bsp\_move}()$ ;
    18:     $y_{\text{pairs}.\text{read}().\text{tag}}^s = y_{\text{pairs}.\text{read}().\text{tag}}^s + \text{pairs}.\text{read}().\text{value}$ ;
}

```

4. EXPERIMENTS

SpMV experiments have been performed using the datasets presented in Table 4. These matrices are preprocessed using the Mondriaan software package², which partitions them for parallel SpMV and gives local versions of the input matrix, together with the final mappings introduced in Section 3.2. The preprocessing time required is reported in Table 4 as well. The BSP SpMV driver reads in the Mondriaan output, then performs 100 parallel SpMV multiplication as described in Algorithm 3, and reports the average time taken. This SpMV multiplication is part of a re-implementation of BSPedupack and is freely available³.

Experiments are run on three different architectures, namely:

²Available freely at: <http://www.math.uu.nl/people/bisselin/Mondriaan>

³See: <http://www.multicorebsp.com/BSPedupack>

Name	Rows	Columns	Nonzeroes	$p = 4$	$p = 64$
west0497	497	497	1721	1 sec.	1 sec.
fidap037	3565	3565	67591	1 sec.	2 sec.
s3rmt3m3	5357	5357	106526	1 sec.	5 sec.
memplus	17758	17758	126150	1 sec.	8 sec.
cavity17	4562	4562	138187	1 sec.	3 sec.
bcsstk17	10974	10974	219812	3 sec.	8 sec.
lhr34	35152	35152	764014	6 sec.	16 sec.
bcsstk32	44609	44609	1029655	15 sec.	31 sec.
nug30	52260	379350	1567800	43 sec.	4 min.
s3dkt3m2	90449	90449	1921955	39 sec.	1 min.
tbdlinux	112757	21067	2157675	3 min.	6 min.
stanford	281903	281903	2312497	5 min.	8 min.
stan-ber	683446	683446	7583376	13 min.	21 min.
cage14	1505785	1505785	27130349	16 min.	45 min.
wiki05	1634989	1634989	19753078	5.5 hr.	9 hr.
wiki06	2983494	2983494	37269096	19 hr.	23 hr.

TABLE 4. The matrices used in our experiments. The matrices are grouped into two sets by relative size, where the first set typically fits into the L2 cache, and the second does not. The last two columns show preprocessing times required for distributing the matrix over p processes, using the Mondriaan software package with the default strategy. This reordering was done on an AMD Opteron 2378.

- the AMD Phenom II 945e quad-core processor,
- the Intel Core 2 Q6600 quad-core processor, and
- the Sun Niagara2 processor.

The AMD and Intel systems both run a linux operating system, and use the 1.6.0_23 version of the Sun Java compiler and runtime environment; the Sun platform runs on the Solaris operating system, and uses the 1.5.0_27 version of Sun Java. These architectures follow very different design principles. The AMD processor has an L3 cache of 6MB, which is shared amongst all four cores, while each single core has its own 512kB L2 cache and 64kB L1 cache. This is in contrast to the Intel design: the Q6600 has no L3 cache, while the two available 4MB L2 caches available are each shared by two cores. Each core does have a local 64kB L1 cache. Thus with the AMD architecture, data transfer between cores is uniform, while in the Intel case, by connectivity of the L2 cache, a core has a faster transfer speed with one specific other core, while the other two cores must be accessed through the main memory. The BSP model used in this paper does not take this into account; this would require the Multi-BSP model [1], as well as an adaptation of the Mondriaan partitioner. The BSP algorithms presented here are expected to perform better on the AMD architecture, due to the more uniform access.

The Niagara2 architecture, being built specifically for multithreading applications, follows a completely different strategy. While typically operating at lower clock rates, there are 8 cores available on a single processor with each core supporting fast interleaved execution of 8 concurrent threads; a single processor thus can execute 64 threads. There are eight 4MB L2 caches, shared amongst all cores by means of a crossbar. Main memory is accessible through the L2 caches, and is divided over four different memory controllers, each directly linked to two of the L2 caches. The system I/O is connected via the crossbar. Each single core has its own 8kB L1 cache, but this cache is shared amongst 8 threads. Note that the Niagara2 shares a single memory controller amongst two cores, whereas the Intel processor shares an L2 cache; since the bandwidth to main memory is much lower than for a cache, the effects of sharing should be much less pronounced. Hence, overall, the Niagara2 system offers uniform access, especially when application data can be distributed over the L2 caches, thus avoiding communication to main memory. Hence we expect good scalability on this architecture, especially for smaller problems.

Intel Q6600				AMD 945e		
p	r (Mflop/s)	g (flops)	l (flops)	r (Mflop/s)	g (flops)	l (flops)
1	593.62	76.51	666	819.20	84.9	379
2	597.99	174.52	7764	890.43	357.7	31921
3	605.35	281.22	12342	851.23	1001.1	28748
4	600.17	323.79	28947	663.91	935.1	32950

Sun Niagara2			
p	r (Mflop/s)	g (flops)	l (flops)
1	47.08	50.19	228
2	47.98	74.78	3979
4	45.66	97.31	10579
8	44.66	119.17	24232
16	47.45	220.71	54409
32	34.43	577.39	76150
64	22.43	633.60	134631

TABLE 5. BSP benchmark data for an Intel Core 2 Q6600 Quad-core system, an AMD Phenom II 945e Quad-core system, and the Sun Niagara2 system consisting of eight cores with eight threads each.

For all BSP algorithms, we will report speedups for various problem instances, using a varying number of threads, as appropriate for the architecture experimented on. Speedups are relative to the parallel program run with $p = 1$, as comparable sequential algorithm in Java are not readily available; thus the reported values are optimistic speedups as parallel overheads are still present for one thread.

4.1. Benchmarking and prediction. The parameters r , g , and l are estimated via a benchmarking program, described in [5] and included in BSPedupack. In short, this benchmark sends messages of varying length to all processors, and measures the time it takes to send h messages and synchronise, a total of 1000 times. This measurement is conducted for $h = 1 \dots 128$. Afterwards, a least-squares fit is calculated to find the affine relation ($gh + l = t/1000$) between the message size h and the time t required to send 1000 messages. The speed of a single core is measured using dense vector operations. Results are shown in Table 5.

The Intel architecture shows a constant flops per second rate, while latency increases as the number of cores p is increased. As expected due to the sharing of the L2 caches, the communication gap and the latencies are much lower for $p = 2$ than for $p > 2$, where the communication gap is constant for $p = 3$ and $p = 4$. The AMD chip shows a more variable flop rate, and even shows a drop in performance for $p = 4$. When using more than one core the latency is constant, but slightly higher than that of the Intel processor. Like the Intel processor, the message gap increases for $p > 2$ but stabilises after $p = 3$, indicating that L3 cache sharing is faster for $p = 2$ than for higher p . The Sun machine behaves as expected for smaller p : r is constant, and g, l increase only slightly as more processes are used. This indicates that processes are first allocated to a single core, and spread over cores when more than eight processes are required. The large increase in g and l from $p = 8$ to $p = 16$ supports this, as using more than one core means communication has to go through the crossbar. This effect increases as more and more cores are utilised. An anomaly is the decrease in process speed for $p \geq 32$. A possible explanation is that for measuring the computing rate, regular data access to 4kB of data is required, per process. This means that all computation can be done locally for $p \leq 16$, when ideally distributed; for more processes, data movement by crossbar becomes increasingly necessary, in fact generating communication in-between supersteps. This can adversely affect the flop per second rate.

These values can be used to predict SpMV performance, as after benchmarking a BSP machine and partitioning an input matrix, all values in Equation (4) are known, so that the theoretical running time of the SpMV algorithm can be obtained. From these values the theoretical speedups

		Stanford			s3dkt3m2		
		$p = 2$	$p = 3$	$p = 4$	$p = 2$	$p = 3$	$p = 4$
Partitioner output	superstep 1	2418012	1667496	1237054	4120988	2719368	2056482
	superstep 2	225	600	607	609	603	0
	$\max_s V(s)$	225	601	608	609	1206	840
Intel prediction	time	4.1	3.1	2.4	7.1	5.1	3.9
	error factor	7.3	9.3	10.8	2.1	3.3	3.7
	speedup	1.9	2.6	3.2	1.8	2.5	3.2
	error factor	1.0	0.6	0.7	0.7	0.4	0.4
AMD prediction	time	2.8	2.7	2.8	4.9	4.6	4.3
	error factor	7.3	5.8	5.6	2.5	2.9	1.7
	speedup	2.0	2.1	2.0	1.9	2.0	2.1
	error factor	0.7	1.0	1.0	0.8	0.7	1.1
Sun prediction	time	50.8	-	28.6	86.9	-	47.1
	error factor	3.7	-	3.5	2.0	-	1.7
	speedup	1.9	-	3.4	1.8	-	3.4
	error factor	0.9	-	0.9	0.9	-	0.8

TABLE 6. Prediction of MulticoreBSP SpMV running time (in ms) and speedups with their error factors, defined as the measured value divided by the predicted value. Values are given for two test matrices. The BSP parameters r, g, l for the architectures tested are taken from Table 5.

		Stanford			s3dkt3m2		
		$p = 16$	$p = 32$	$p = 64$	$p = 16$	$p = 32$	$p = 64$
Partitioner output	superstep 1	317822	158942	79484	516096	258048	129024
	superstep 2	683	829	737	474	558	408
	$\max_s V(s)$	684	829	738	804	624	424
Sun prediction	time	11.1	20.8	30.4	15.8	20.2	23.7
	error factor	3.5	2.1	1.5	2.2	2.1	2.0
	speedup	8.9	4.7	3.2	10.1	7.9	6.7
	error factor	0.8	1.7	2.0	0.7	1.0	1.0

TABLE 7. As Table 6, but for a larger number of concurrent threads as supported by the Sun Niagara2.

can also be calculated. Using the actual running times reported in the following subsection, both predicted values can be compared to actual measurements. Dividing the measured values by the predicted values then gives the error factors; Tables 6 and 7 show the result of this experiment. Actual running time measurements are averaged over 100 SpMV multiplications.

Observed are errors of up to 11 times, compared to the actual measurements on the Intel platform. On the AMD platform slightly better error factors are obtained with a maximum of 8. Since these factors are not constant, the BSP model does not make very accurate predictions on the running time of the algorithm, when applied to the SpMV multiplication. The main cause is that the BSP benchmark measures process speed according to *dense* operations; sparse operations such as the SpMV multiply are known to perform at a fraction of peak performance, due to inefficient cache use [16, 17]. If inefficient cache use indeed is the cause, prediction should be more successful for smaller and for structured sparse matrices [16, 18]. Input and output vectors corresponding to the Stanford matrix do not fit entirely into the L2 caches of both architectures, and the matrix, representing a link matrix of the Stanford domain from 2002, inherently is unstructured. On the other hand, the s3dkt3m2 matrix is smaller so its vectors do fit into L2 cache, while additionally the matrix comes from a FEM application on a regular grid and thus is structured. On all architectures, the prediction errors indeed are smaller for the s3dkt3m2 matrix, especially on the Niagara2 with large p . Other causes for discrepancy may include overhead caused by the

Matrix	Intel Q6600			AMD 945e		
	$p = 2$	$p = 3$	$p = 4$	$p = 2$	$p = 3$	$p = 4$
west0497	0.61	0.69	0.59	0.97	1.08	0.54
fidap037	0.27	0.25	0.19	0.41	0.26	0.22
s3rmt3m3	0.28	0.23	0.34	0.44	0.32	0.29
memplus	0.96	0.35	0.32	0.95	0.48	0.37
cavity17	0.26	0.24	0.18	0.30	0.30	0.25
bcsstk17	0.96	0.41	1.18	1.20	0.45	0.78
lhr34	1.22	1.08	0.53	1.17	1.77	0.55
bcsstk32	0.73	0.89	0.87	1.04	0.99	1.20
nug30	0.69	0.64	0.46	0.74	0.75	0.59
s3dkt3m2	1.20	1.09	1.26	1.46	1.29	2.33
tbdlinux	1.20	0.96	0.87	1.52	1.23	1.46
stanford	1.72	1.79	1.98	1.46	1.92	1.93
stan-ber	1.22	1.25	1.26	1.51	1.79	1.82
cage14	0.85	0.93	0.78	1.14	1.46	1.34
wiki05	1.97	2.31	2.21	2.33	2.68	3.34
wiki06	1.83	2.06	2.17	1.38	2.17	2.00

TABLE 8. Measured speedup of MulticoreBSP sparse matrix–vector multiplication on the Intel Q6600 and AMD945e architectures. The speedup is calculated as the parallel time divided by the time taken for $p = 1$, and these timings are taken averaged over 100 SpMV runs. The best speedup for each architecture is shown in boldface.

MulticoreBSP library, which can depend on the parallel algorithm executed and can amplify the effects of cache misses. Hardware behaviour not taken into account with the BSP model (such as the case with the Intel Q6600), operating system jitter, or virtual machine jitter, can also be factors.

The speedups are predicted much more accurately than the running times, as the single-core and the multicore runs suffer in the same way from certain hardware peculiarities that are independent of the number of processes. It is possible to use the predicted speedup for instance to decide how many processes to allocate for a specific job, but otherwise it has limited practical applicability. Estimating speedups is more successful on the Stanford matrix and for the AMD architecture.

4.2. Sparse matrix–vector multiplication. The SpMV multiplication results for the Intel and AMD architectures are found in Table 8, and those for the Sun platform in Table 9. For the classical cache-based architectures, that is, the Intel and the AMD processors, speedups are only attained for larger matrices. This should come as no surprise, since for smaller matrices the input and output vectors both fit into L1 cache, which is not shared amongst cores. This differs for the Niagara2 architecture, where the L1 cache is much smaller and is shared amongst 8 threads simultaneously. For this machine, speedups are obtained even for the smaller matrices. The highest speedup obtained is 9.31 for the Stanford-Berkeley matrix using $p = 32$ processes. Still, speedups are mostly far from the optimal value of p . In general, better speedups are attained for the larger matrices, as the ratio of local work versus data movement due to communication is more favourable there. Increasing matrix size is not automatically beneficial for scalability, however; larger vectors may no longer fit into lower-level caches, and for higher-level caches the bandwidth is more limited, thus making minimisation of inter-core communication proportionally more important. In other words, for small matrices there is not enough work to attain efficient parallelisation, while for larger matrices communication costs may increase, as do the effects of inefficient cache use, especially when caches are shared. Such a situation occurs for the cage14 matrix, with a highest speedup of only 2.62 for 16 processes. This matrix is difficult to partition, causing a relatively large number of communications.

Matrix	$p = 2$	$p = 4$	$p = 8$	$p = 16$	$p = 32$	$p = 64$
west0497	1.20	0.94	0.81	0.62	0.39	0.24
fidap037	0.58	0.54	0.64	0.50	0.68	0.37
s3rmt3m3	0.91	1.42	1.47	1.63	0.93	0.68
memplus	1.50	1.18	1.01	0.86	0.78	0.44
cavity17	0.85	0.98	1.27	1.33	0.72	0.60
bcsstk17	1.79	2.95	2.57	2.96	2.20	1.36
lhr34	1.98	2.60	4.34	4.33	3.68	2.19
bcsstk32	1.59	2.71	4.68	6.40	7.02	4.43
nug30	1.24	1.41	1.21	1.03	0.79	0.55
s3dkt3m2	1.65	3.56	5.55	8.50	8.59	6.46
tbdlinux	1.89	3.01	3.97	4.19	2.75	1.51
stanford	1.64	3.05	5.03	6.80	8.02	6.42
stan-ber	1.64	2.95	5.00	7.31	9.31	9.27
cage14	1.31	2.04	2.43	2.62	1.98	1.63
wiki05	1.86	3.40	6.02	5.38	2.96	1.97
wiki06	1.82	3.38	6.12	2.50	1.98	2.56

TABLE 9. Measured speedup of MulticoreBSP sparse matrix–vector multiplication on a Sun Niagara2 machine, obtained in the same way as for Table 8.

4.3. The Fast Fourier transform. The fast Fourier transform (FFT) application from BSPedupack maps a complex-valued input vector of length n to its discrete Fourier transform, and does this in two supersteps, if $p \leq \sqrt{n}$. For algorithm details we refer to [5, Chapter 3]; what now follows is but a brief description. The input vector is assumed to be distributed cyclically over the p processors, and the algorithm starts with a parallel bit reversion, followed by a number of concurrent unordered sequential FFTs, and finally redistributes data and synchronises. The second and last superstep then proceeds with p concurrent unordered sequential generalised FFTs. If n is not large enough compared to the number of processors, more steps consisting of redistribution and concurrent unordered FFTs are required. Both the input vector size and the number of processors used by the algorithm are required to be powers of two. The advantage of this algorithm is that the sequential FFTs can be provided by external libraries like FFTW [19], or can even be recursively parallelised, for example when applied within a hierarchy of parallel machines.

Table 10 shows scalability results of this algorithm on our shared-memory architectures. It is immediately seen that speedups on the Intel and AMD platforms are only attained for large n ; this must be due to the smaller vectors fitting into the local caches, so that communicating between cores is more expensive than doing the entire computation on a single core. The AMD 945e computation starts to attain speedups for $n \geq 2^{18}$, which corresponds to 4MB of data; for $p = 1$, this is eight times the size of an L2 cache, for $p = 4$, this is twice the size. The Intel computation starts getting speedups for $p = 2$ at 16MB of data, and for $p = 4$ at 32MB. Note that the Intel processor does not have an L3 cache and will communicate through main memory for $n > 2^{18}$. The AMD does have an L3 cache, but its capacity is exceeded for the same n and communicates through main memory as well.

Starting at $n = 2^{22}$ (64MB) for the AMD processor, or $n = 2^{23}$ (128MB) for the Intel processor, speedups become superlinear. This is explained by better cache use due to data locality: the first superstep of the parallel FFT algorithm performs n/p unordered FFTs on contiguous blocks of size p , in parallel; that is, each processor performs n/p^2 unordered FFTs of small size, and thus performs extremely data-local computations. The second superstep performs p unordered generalised FFTs of size n/p ; these are less data-local and performance will drop if a vector of size n/p no longer fits into local cache. This drop is in comparison to the first superstep, however, and does not seem to negatively affect overall scalability⁴.

⁴See the results of $n \geq 2^{21}$ for the Intel architecture and $n \geq 2^{19}$ for the AMD; both exceed the L2 cache for the second superstep.

$\log_2 n$	Intel Q6600		AMD 945e	
	$p = 2$	$p = 4$	$p = 2$	$p = 4$
9	1.1	0.9	0.8	0.6
10	1.1	0.9	0.6	0.7
11	0.3	0.2	0.7	0.8
12	0.4	0.5	1.2	1.1
13	0.5	0.3	0.9	0.9
14	0.7	0.4	1.0	1.2
15	0.7	0.4	0.9	1.0
16	0.4	0.2	0.8	0.8
17	0.5	0.3	0.9	1.0
18	0.6	0.4	1.0	1.2
19	1.0	0.6	1.3	1.5
20	1.5	0.7	1.7	2.2
21	1.7	1.5	1.9	2.7
22	1.8	1.9	2.3	3.2
23	2.3	2.4	2.6	3.6
24	2.2	2.2	2.9	4.9
25	2.6	3.2	2.9	5.0

TABLE 10. Measured speedups of MulticoreBSP on two shared-memory architectures, the Intel Q6600 and the AMD 945e. The speedup is calculated as the parallel time divided by the time taken for $p = 1$, and these timings are taken averaged over 30 SpMV runs. The input vector size varies between 8kB (for $n = 2^9$) to 512MB (for $n = 2^{25}$).

Table 11 reports speedups attained on the Sun architecture. An input vector of size $n = 2^{13}$ is the smallest one that can be done in two supersteps with $p = 64$, hence we start the experiments at exactly that vector size. This does result in a slowdown of factor 0.8, however, which is the only reported slowdown for the FFT on the Niagara2. While for the AMD and Intel processors no speedups could be obtained for the shorter input vectors, the Sun platform starts at a speedup of 5.3, with the lowest maximum speedup being 2.9 for $n = 2^{15}$. As the problem size increases, the best speedups are attained for increasingly larger p . Superlinear speedups are attained as well, but, in contrast, only for $p < 16$ and sufficiently large n ; and in all cases a larger (but sublinear) speedup can be obtained by using a larger p .

4.4. Dense LU decomposition. The BSP LU algorithm performs a dense LU decomposition of an $n \times n$ dense matrix A . It is a straightforward parallelisation of the well-known LU decomposition algorithm with partial pivoting, for example presented in [20, Algorithm 3.4.1]. Note that this algorithm is not based on level-3 BLAS and that a better-performing algorithm may be obtained by using those; optimisation or parallelisation for high performance computing then typically requires hand-tuned [21] or auto-tuned [22] software. The parallel algorithm used is described in detail in [5, Chapter 2]; again we proceed with only a short description. We assume the matrix is cyclically distributed in two dimensions over $p = p_y p_x$ processes; that is, the i th row of A is local to a process with $s_i = i \bmod p_y$, and the j th column of A is local to a process with $s_j = j \bmod p_x$. Taking, e.g., the map $s = s_i p_x + s_j$, each combination of row and column properly corresponds to one unique process. For each stage k from 0 to $n - 1$, first a pivot element in the k th column is searched for, in parallel. When identified, the corresponding row is swapped with the k th row by using the get primitives. During this procedure, it is possible that $2p_x$ processes work and $(p_y - 2)p_x$ others idly stand by, thus negatively impacting the load balance. On the other hand, when the two swapped rows are local to the same processes, communication is local only, which may be preferable even if it causes load imbalance. These considerations do not contradict when p_y is taken to be 1; then there is no load imbalance and only local computations during pivoting. When swapping is complete, all local elements of the $(n - k) \times (n - k + 1)$ submatrix can be updated

$\log_2 n$	$p = 2$	$p = 4$	$p = 8$	$p = 16$	$p = 32$	$p = 64$
13	1.9	3.5	5.3	4.6	2.1	0.8
14	1.4	2.4	3.9	4.2	1.8	1.2
15	1.6	1.6	2.8	2.4	2.9	1.3
16	1.4	2.0	2.6	4.0	2.8	1.7
17	1.3	2.2	3.1	3.4	3.7	2.7
18	1.4	2.0	3.4	3.0	3.0	2.4
19	1.8	2.6	3.6	5.4	3.3	3.0
20	2.2	3.2	4.7	6.8	5.8	4.2
21	2.5	3.8	5.8	8.6	9.0	6.8
22	2.7	5.2	6.4	10.8	13.5	12.6
23	2.9	6.2	8.3	11.1	18.5	22.0
24	2.9	5.9	10.5	13.6	15.4	23.9
25	2.9	5.9	9.8	13.0	16.4	16.7

TABLE 11. Measured speedups of MulticoreBSP FFT on the Sun Niagara2, obtained in the same way as for Table 10. The input vector size varies between 128kB (for $n = 2^{13}$) to 512MB (for $n = 2^{25}$).

in parallel by caching (using direct-get primitives) the relevant ranges of the k th row and the k th column, including the pivot value. After updating, the algorithm increments k and continues with the next stage.

The LU algorithm differs from SpMV and FFT mainly in that the number of supersteps, as well as the amount of communication, are linearly related to n instead of being constant; the overhead of the algorithm is thus expected to be higher. Another difference is that local matrix entries are reused in the calculation, instead of only the components of input or output vectors; this makes it easier to attain good speedups. In our experiments, A is taken as a random matrix and 30 decompositions are timed, and the average time is reported. In our implementation, the matrix size must be divisible by both p_y and p_x ; we tested the sizes $n = 120, 600, 1200$.

For the smallest size tested, $n = 120$, no speedup was attained on the Intel and AMD architectures, while the Niagara2 architecture gained a maximum factor 1.4 for $p_y = 3$ and $p_x = 1$ and did not get slowdowns as long as $p_y p_x < 8$; these results are not included in tabular form. Speedups for $n = 600, 1200$ are reported in Table 12 and 13. For the Intel processor, no speedup is attained for $n = 600$. The AMD processor performs somewhat better with a factor 1.1 for $2 \cdot 1$ processors. As expected, the results improve for yet larger n ; both these architectures perform up to a factor 1.4 better, again by using $2 \cdot 1$ processors. The Sun platform performs somewhat better, reporting speedups up to 3.0 for $n = 600$ and 6.7 for $n = 1200$, using $2 \cdot 3$, respectively, $6 \cdot 2$ processors. Larger n will likely yield larger speedups using more processors, on this architecture. We observe that all architectures seem to prefer $p_y > p_x$; surprising, since this causes load-imbalance, as discussed earlier.

5. CONCLUSIONS

We have demonstrated that the Bulk Synchronous Parallel [2] programming paradigm can be efficiently used for shared-memory parallel programming. A proof-of-concept BSP library, MulticoreBSP, targeted towards shared-memory architectures, has been implemented and is freely available. It differs from prior work in that it exploits shared-memory architecture only through a *direct-get* method, otherwise assuming processes only have local memory and communicate only through distributed-memory primitives: the standard *get*, *put* and *send* methods. A sparse matrix–vector multiplication (SpMV) algorithm has been described and implemented using this library, similar to the algorithm introduced in [5], except that the number of supersteps has been reduced by use of the direct-get. Experiments on both the predictability and scalability of this algorithm have been performed. Predictions of the run time leave much to be desired; predictions of the speedup are more accurate.

600 × 600 :	Intel Q6600				AMD 945e			
	1	2	3	4	1	2	3	4
1	1.0	0.7	0.6	0.5	1.0	0.7	0.5	0.3
2	0.8	0.5	<i>0.3</i>	<i>0.3</i>	1.1	0.4	<i>0.2</i>	<i>0.2</i>
3	0.7	<i>0.4</i>	<i>0.3</i>	<i>0.2</i>	0.6	<i>0.3</i>	<i>0.2</i>	<i>0.2</i>
4	0.4	<i>0.3</i>	<i>0.2</i>	<i>0.2</i>	0.4	<i>0.2</i>	<i>0.2</i>	<i>0.2</i>

1200 × 1200 :	1	2	3	4	1	2	3	4
1	1.0	1.2	1.0	0.9	1.0	1.1	0.8	0.5
2	1.4	1.2	<i>0.9</i>	<i>0.8</i>	1.4	0.7	<i>0.4</i>	<i>0.4</i>
3	1.2	<i>1.0</i>	<i>0.8</i>	<i>0.6</i>	1.2	<i>0.5</i>	<i>0.4</i>	<i>0.3</i>
4	1.3	<i>0.9</i>	<i>0.7</i>	<i>0.6</i>	0.8	<i>0.5</i>	<i>0.3</i>	<i>0.3</i>

TABLE 12. Measured speedups for the MulticoreBSP LU algorithm on the Intel Q6600 and the AMD 945e processors. The algorithm has been run for square dense matrices of size 600 and 1200. The matrices are distributed over processes both rowwise and columnwise; the number of processes p_x used in the column direction are displayed horizontally in the four parts of the table, and the number of processes p_y used in the row direction are displayed vertically. The total number of processes $p = p_x p_y$ thus exceeds the available number of cores (4) in half the cases presented; those speedups are printed in italic. The largest speedup for each of the four parts is printed in boldface.

600 × 600:	1	2	3	4	5	6	8
1	1.0	1.8	2.3	2.6	2.8	2.2	2.1
2	1.8	2.8	3.0	2.9	2.6	2.0	1.8
3	2.4	3.0	2.9	2.4	2.2	1.6	1.4
4	2.7	2.9	2.4	2.0	1.8	1.4	1.2
5	2.9	2.6	2.2	1.9	1.6	1.2	1.0
6	3.0	2.4	2.0	1.7	1.4	1.0	0.8
8	2.9	2.2	1.6	1.3	1.0	0.8	0.7

1200 × 1200:	1	2	3	4	5	6	8
1	1.0	2.2	3.3	3.9	4.5	5.0	5.4
2	2.1	4.3	5.4	5.9	6.1	6.1	5.7
3	3.0	5.6	6.1	6.4	6.2	5.6	5.1
4	4.1	6.3	6.3	6.2	5.7	5.4	4.7
5	4.9	6.6	6.4	5.9	5.3	4.9	4.1
6	5.5	6.7	6.1	5.6	5.0	4.3	3.7
8	6.3	6.2	5.4	4.6	4.1	3.6	2.8

TABLE 13. Similar to Table 12, but for the Sun Niagara2 architecture.

Actual speedup measurements have been carried out on three different architectures, two quad-core machines (Intel and AMD) and one highly-threaded machine (Sun). Results of the SpMV multiplication show modest overall speedup, with the higher speedups reserved for the larger matrices, showing a speedup of 3.34 for the wikipedia-2005 matrix with $p = 4$, and superlinear speedup of 2.33 for $p = 2$ on the same matrix, both on the AMD architecture. Speedups for SpMV multiplication on the Sun Niagara2 processor are far from optimal. The largest measured speedup is 9.31 for $p = 32$ threads (out of 64 possible simultaneous threads on 8 cores), on the Stanford-Berkeley link matrix; which is puzzling, since of all link matrices, this one is the hardest to partition [16, 18]. For even larger matrices, the performance drops, gaining only good speedups for small p . We suspect the bottleneck lies in the highly irregular memory accesses as this is a well-known problem of SpMV multiplication, and our results testify to this.

Other example applications have been implemented and experimented with as well. They are the fast Fourier transform and dense LU decomposition. Both are easier to parallelise: most data

elements are used several times, instead of only once as is the case with SpMV multiplication. Good speedup, even superlinear speedup, is attained for the FFT: up to 6.2 for $p = 4$ on the Sun Niagara2, 5.0 for $p = 4$ on the AMD 945e, and 2.6 for $p = 2$ on the Intel Q6600. The maximum speedup for the Intel is 3.2 out of the maximum expected of 4, and that of the Niagara2 hovers around a factor 24, which is still far from the optimum, but both still seem to increase for larger n . The LU decomposition performs less well on the AMD and Intel architectures; we think this is due to the lack of optimisation of the algorithm. During each iteration of the algorithm, threads move along the pivot column unchecked while updating the local submatrices, which generally do not fit into local caches. This may yield much data movement for each thread in shared caches or main memory, while inside a computation superstep; this points to another large difference between distributed-memory and shared-memory BSP. Solutions lie within employing existing sequential optimisation techniques to limit unnecessary data movement, which should lead to speedups when using multiple threads, and not just in a constant factor gain. Supporting this, on the Niagara2, the speedups are much more pronounced, going up to a factor 6.7. Also for smaller problems, the Niagara2 attains a much better speedup than the more traditional Intel and AMD platforms. This is due to threads not having local caches, and the L1 cache closest to the CPU core being small and shared by 8 threads. The lack of a (large) local cache originally led us to believe data locality is of no priority on this architecture, but this is only partly supported by experiments as the expected speedups close to 64 are never observed.

In general, we have shown that the BSP model, library, and algorithms can be adapted for shared-memory architectures, and that these algorithms can work well, as tested on a variety of architectures. Similarities, but also some of the large differences have been discussed, leading to the observation that sequential optimisation is of increasing importance in shared-memory computing; gains in data movement result in less contention between memory accesses of many threads, resulting in better scalability. Nevertheless, such optimisations will benefit distributed-memory computing as well. Hence, the same efficient and scalable BSP algorithms can be employed, for both distributed-memory and shared-memory architectures.

5.1. Future work. While the MulticoreBSP library shows that the BSP model is valid for current shared-memory systems, the Java implementation is not viable for high-performance computing. While it attains modest speedups and is proper for concept testing and educational use, the algorithms are seen to perform slower than expected. Construction of a similar, more competitive library in, e.g., the C++ programming language should be worthwhile. Such a library can build forth on existing technologies such as POSIX threads, and may be augmented with the Message Passing Interface (MPI), or distributed-memory BSP; combining both can result in a BSP library which is able to switch as required between shared-memory and distributed-memory implementations. Moreover, by incorporating the Multi-BSP model [1] instead of the flat BSP model, such a library can automatically distribute a BSP algorithm over a hybrid distributed-memory and shared-memory system, thereby completely eliminating the need for explicit hybrid parallel programming.

While predictability here only has been investigated for the SpMV algorithm, we find, like many others, that processor speed is not always properly measured in flops per second. Instead, timings based on irregular data accesses may be of more importance, and may yield better predictions of BSP algorithms working on sparse problems. Such benchmarks may be integrated into the BSP benchmarking application, which would also benefit from an update to the Multi-BSP model; message size can be varied so that properties of the different levels of the memory hierarchy can be measured. Ideally, however, this also requires information on the exact memory size of each such memory level.

Regarding the SpMV multiplication specifically, interleaving the querying of π_r^s for locality of output vector elements results in a constant overhead during execution of the SpMV multiplication. An alternative is to buffer the remote elements locally, thus removing this overhead, which results in a more efficient kernel. After execution of this kernel, the local buffer is read out and non-local elements can again be sent out using the send primitive. The resulting *fully buffered* SpMV multiplication kernel enables the use of external multiplication code, which may perform additional

optimisation; see, e.g., [16, 18, 23, 24]. To attain better scalability, further optimisation surely is required. Applying partitioning to minimise communication between computing cores is not enough, as data access patterns of the input vector are not improved while bandwidth becomes more limited as more cores are involved in the computation. Future work should be directed towards combining communication minimisation with methods to enhance cache use, e.g., by permutation of the local input matrix representations [16, 18], by adapting the sparse matrix storage scheme [24, 25], or both.

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