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Programming BSP and MULTI-BSP algorithms in ML

Victor Allombert · Frédéric Gava

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Abstract The BSML and MULTI-ML languages have been designed for programming in ML algorithms of the respectively BSP and MULTI-BSP bridging models. MULTI-BSP is an extension of the well-know BSP model by taking into account the different levels of networks and memories of modern hierarchical architectures. This is a new model, as well as MULTI-ML, while BSP and BSML have been used for a long time in many different domains. But designing and programming MULTI-BSP algorithms is intuitively more complex than with BSP. One can ask if it is beneficial to rewrite BSP algorithms using the MULTI-BSP model? In this paper, we thus investigate the *pro and cons* of the aforementioned models and languages by experimenting with them on different typical applications. We use a methodology to measure the level of difficulty of writing code and we also benchmark them in order to show if writing MULTI-ML code is worth the effort.

Keywords BSP, MULTI-BSP, ML, hierarchical, performance, algorithms

1 Introduction

Context. Our previous work aimed at designing a parallel *functional* language based on the **B**ulk **S**ynchronous **P**arallelism (BSP) *bridging model* called BSML [13]. BSP is a model of parallelism which offers a high level of abstraction and takes into account real communication and synchronisation cost [22]. BSP has been used successfully for a broad variety of applications: scientific computation [6], artificial intelligence, big-data and graph frameworks (such as PREGEL [18]), *etc.* To be compliant to a *bridging model* eases the way of writing

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code and ensures *efficiency* and *portability* from one architecture to another. Thanks to a cost model it is also possible to reason on the algorithmic *costs*.

As modern HPC (High Performance Computing) architectures are *hierarchical* and have multiple layers of parallelism, communication between distant nodes cannot be as fast as among the cores of a given processor. BSP was designed for *flat* architectures, we now consider the MULTI-BSP model [23], an extension of BSP which is dedicated to hierarchical architectures. MULTI-ML [3] is extension of OCAML (<http://ocaml.org/>) for programming MULTI-BSP algorithms. MULTI-ML uses a small set of primitives similarly to BSML for BSP algorithms.

Comparing languages. Since we now have two programming languages, we ask ourselves whether they differ in terms of performances and written code. Both have structured models of execution. Both have an MPI implementation. However, BSML has been designed for flat parallelism whereas MULTI-ML is designed for controlled nested parallelism. To compare them, we have chosen three different cases that are in the field of symbolic, numerical and big-data computations.

We want to *compare* the two languages for both *performance* and the *ease* of writing code. For the performance, we have chosen *speedup* and/or timing for some data-sets. We also change the target architecture by modifying the number of cores, processors and nodes of the machines. For the code, we have choose some traditional *metrics* which are the *Halstead difficulty* and the *McCabe cyclomatic complexity*. These metrics mainly count the number of operands and programming structures such as conditionals, loops, *etc.* We have adapted them to take into account the number of *parallel operators*. These metrics are not perfect but are easy to use. Finally, we have used one interesting ability of both BSML and MULTI-ML: programming parallel algorithms in an *incremental* manner from sequential codes, which simplifies the development of parallel code. As explained later, this is due to the fact that both BSML and MULTI-ML provide a global view of programs, *i.e.* their programs can be seen as sequential programs working on parallel data structures (“seq of par”) while in many HPC libraries such as MPI, programs are written in the SPMD style and are understood as a parallel composition of communicating sequential programs (“par of seq”).

Outline. The rest of this paper is structured as follows: first, section 2 briefly presents the two aforementioned languages. Subsection 3.1 defines our methodology of comparison of the languages. We apply it to different *use cases* (subsections 3.2 to 3.4), hoping they are general enough to stand for a representative sample of HPC applications. For all of them, we give some *benchmarks* in terms of both performance and difficulty of writing the code. In section 4 we discuss related work and section 5 concludes the paper by giving a brief outlook of future work.

2 BSML and Multi-ML: similar but different languages

2.1 Programming BSP algorithms in ML

2.1.1 The BSP bridging model

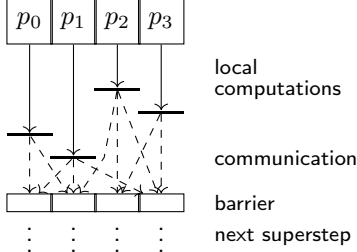


Fig. 1 A BSP superstep.

In the BSP model, a computer is a set of p *uniform* pairs of processor-memory components with a communication network. A BSP program is executed as a *sequence* of *supersteps* (Fig. 1), each one divided into three successive disjoint phases: (1) each processor only uses its local data to perform sequential computations and to request data transfers to other nodes; (2) the network delivers the requested data; (3) a *global synchronisation barrier* occurs, making the transferred data available for the next superstep.

The *performance* of the BSP computer is characterised by 4 *parameters* (that we do not detail in this article). To reliably *estimate* the execution time of a BSP program, these parameters could be easily benchmarked [6]. The execution time (cost) of a superstep is the maximal of the sum of the local processing time, the data delivery and the global synchronisation times. The total cost of a BSP program is the sum of its supersteps's costs.

2.1.2 The BSML language

BSML [13] uses a *small set of primitives* and is currently implemented as a library (<http://tracinfo.univ-orleans.fr/bsml/>) for the ML programming language OCAML. An important feature of BSML is its *confluent* semantics: whatever the order of execution of the processors is, the final value will be the same. Confluence is convenient for *debugging* since it allows to get an *interactive loop* (toplevel). It also simplifies programming since the parallelisation can be done *incrementally* from an OCAML program.

A BSML program is built as a ML one but using a specific data structure called *parallel vector*. Its ML type is 'a *par*'. A vector expresses that each of the p processors *embeds* a value of any type 'a'. Fig 2 summarises the BSML primitives. Informally, they work as follows: let $\ll e \gg$ be the vector holding e everywhere (on each processor), the $\ll \gg$ indicates that we enter into the scope of a (parallel) vector. Within a vector, the syntax $\$x\$$ can be used to read the vector x and get the local value it contains. The *ids* can be accessed with the predefined vector **pid**.

The **proj** primitive is the only way to *extract* local values from a vector. Given a vector, it returns a function such that, applied to the *pid* of a processor, returns the value of the vector at this processor. **proj** performs communication to make local results available globally and ends the current superstep.

Primitive	Type	Informal semantics
$\langle\langle e \rangle\rangle$	'a par (if e:'a)	$\langle e, \dots, e \rangle$, a vector of size p the number of processors
pid	int par	A predefined vector: i on processor i
$\$v\$$	'a (if v: 'a par)	v_i on processor i , assumes $v \equiv \langle v_0, \dots, v_{p-1} \rangle$
proj	'a par \rightarrow (int \rightarrow 'a)	$\langle x_0, \dots, x_{p-1} \rangle \mapsto (\text{fun } i \rightarrow x_i)$
put	(int \rightarrow 'a) par \rightarrow (int \rightarrow 'a) par	$\langle f_0, \dots, f_{p-1} \rangle \mapsto \langle (\text{fun } i \rightarrow f_i \ 0), \dots, (\text{fun } i \rightarrow f_i \ (p-1)) \rangle$

Fig. 2 Summary of the BSML primitives.

The **put** primitive is another communication primitive. It allows any local value to be *transferred* to any other processor. It is also synchronous, and ends the current superstep. The parameter of **put** is a vector that, at each processor, holds a function returning the data to be sent to processor j when applied to j . The result of **put** is another vector of functions: at a processor j the function, when applied to i , yields the value *received from* processor i by processor j .

2.2 Programming Multi-BSP algorithms in ML

2.2.1 The Multi-BSP bridging model

MULTI-BSP is a *model* [23] which is adapted to hierarchical architectures, mainly *clusters* of *multi-cores*. There exist other hierarchical models [16] but MULTI-BSP describes them in a simpler way. The structure and abstraction brought by MULTI-BSP allows to have portable programs with *scalable* performance predictions, without dealing with low-level details of the architectures. This model brings a *tree*-based view of nested components (*sub-machines* or *siblings*) of hierarchical architectures where the lowest stages (*leaves*) are processors and every other stage (*node*) contains memory. Fig. 3 illustrates the difference between the BSP and MULTI-BSP models for a multi-core.

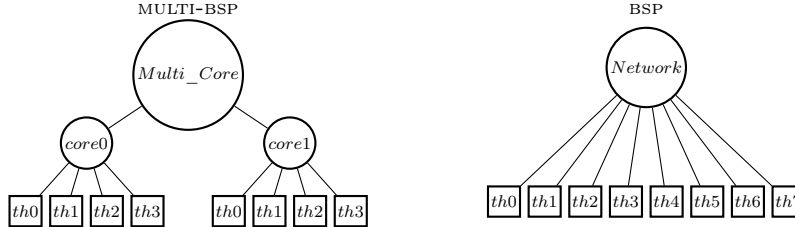


Fig. 3 The difference between the MULTI-BSP and BSP models for a multi-core architecture.

Every component can execute code but they have to synchronise in favour of data exchange. Thus, MULTI-BSP does not allow subgroup synchronisation of any group of processors: at a stage i there is only a synchronisation of the sub-components, a synchronisation of each of the computational units that manage the stage $i - 1$. So, a node executes some code on its nested

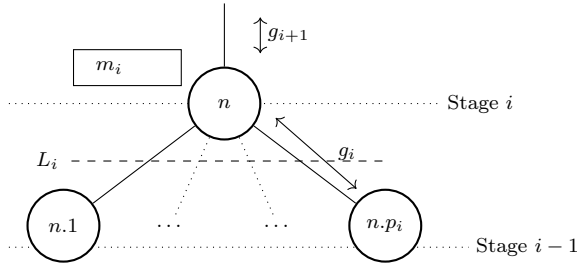


Fig. 4 The Multi-BSP parameters.

components (*aka* “*children*”), then waits for results, does the communication and synchronises the sub-machine. A MULTI-BSP algorithm is thus composed of several supersteps, each step is synchronised for each sub-machine.

Mainly, an instance of MULTI-BSP is defined by \mathbf{d} , the fixed depth of the (balanced and homogeneous) tree architecture, and by the 4 BSP performance parameters (plus the memory size) for each *stage* i of the tree. Thus, we have (p_i, g_i, L_i, m_i) where p_i is the number of sub-components inside the $i - 1$ stage; g_i is the bandwidth between stages i and $i - 1$; the ratio of the number of operations to the number of words that can be transmitted in a second; L_i is the synchronisation cost of all sub-components of a component of $i - 1$ stage; m_i is the amount of memory available at stage i for each component of this stage. The Fig 4 describes the the MULTI-BSP parameters.

The cost of a MULTI-BSP algorithm is the sum of the costs of the supersteps of the root node, where the cost of each of these supersteps is the maximal cost of the supersteps of the sub-components (plus communication and synchronisation); And so on.

2.2.2 The Multi-ML language

MULTI-ML [2,3] (<https://git.lacl.fr/vallombert/Multi-ML>) is based on the idea of executing BSML-like codes on every stage of a MULTI-BSP architecture. This approach facilitates *incremental* development from BSML codes to MULTI-ML ones. MULTI-ML follows the MULTI-BSP approach where the hierarchical architecture is composed of *nodes* and *leaves*. On nodes, it is possible to build parallel vectors, as in BSML. This parallel data structure aims to manage values that are stored on the sub-nodes: at stage i , the code **let** $\mathbf{v} = \langle\langle \mathbf{e} \rangle\rangle$ evaluates the expression \mathbf{e} on each $i - 1$ stages. Inside a parallel vector, we note $\#x\#$ to copy the value x stored at stage i to the memory $i - 1$.

We also introduce the concept of *multi-function* to recursively go through a MULTI-BSP architecture. A *multi-function* is a particular recursive function, defined by the keyword **let multi**, which is composed of two codes: the node and the leaf codes. The *recursion* is initiated by calling the multi-function (recursively) inside the scope of a parallel vector, that is to say, on the sub-nodes. The evaluation of a multi-function starts (and ends) on the root node.

The code of Fig. 5 shows how a multi-function is defined. After the definition of the multi-function `mf` on line 1 where `[args]` symbolises a set of arguments, we define the node code (from line 2 to 6). The recursive call of the multi-function is done on line 5, within the scope of a parallel vector. The node code ends with a value `v`, which is available as a result of the recursive call from the upper node. The leaf code, from lines 7 to 9 consists of sequential computations.

```

1 let multi mf [args]=
2   where node =
3     (* BSML code*)
4     ...
5     <<mf [args]>>
6     ... in v
7   where leaf =
8     (* OCaml code *)
9     ... in v

```

Fig. 5 A multi-function code.

As expected, the synchronous communication primitives of BSML are also available to communicate values from/to parallel vectors. We also propose another parallel data structure called *tree*. A tree is a distributed structure where a value is stored in every node and leave memories. A tree can be built using a multi-tree-function, using the **let multi tree** keyword. We propose three primitives to handle such a parallel data structure: (1) To easily construct a tree with a simple expression,

mktree `e` can be used; It aims to execute the expression `e` on each component of the architecture, resulting in a tree; (2) The function **at** can be used to access the value of a tree within a component; (3) The *global identifier* **gid** is shaped as a tree of identifiers, and is useful, for example, to distribute data depending on the position in the architecture.

3 Application cases

We now compare BSML and MULTI-ML. To do so, we have selected three typical cases of various domains: state space calculation (basis of model-checking); implementation of the FFT using algorithmic skeletons; and finally a classical big-data problem that is computing the similarity of millions of pairs. We first describe our methodology for the comparison and apply it to each case.

In this paper we present non optimal implementations that cannot be compared to cutting-edge implementations: we neither use specific data-structures nor domain specific tricks. For example, in the state-space algorithms, our sets of states do not use shared possibilities of the states as modern model-checkers do [9]. We use the standard OCAML's sets and a naive representation of the states. Here, our objective is to compare the languages and their performances. Programming the most optimised implementations is not the purpose of this work.

3.1 Methodology

BSML and MULTI-ML have been designed to program parallel algorithms incrementally: from a sequential OCAML code to a BSP code in BSML and finally to

a MULTI-BSP code in MULTI-ML. We presume that the programs will be, unfortunately, more and more complex. But we can expect better performance.

To measure the difficulty we have used: (a) The **Halstead Effort** (HE) which depends on both the length and complexity of the code; The **Halstead Difficulty** (HD) considers the amount of different operators used; (b) The **McCabe Cyclomatic Complexity** (CC) that is the number of linearly independent paths through the source; (c) The **Maintainability Index** (MI) which depends on HE and CC.

To do so we have adapted the OCAML metrics tool (<http://forge.ocamlcore.org/projects/ocaml-metrics/>) to BSML and MULTI-ML. We now count, as an operand, each parallel primitive; And, as a new path, each multi function and vector.

Benchmarks were performed on two architectures: (MIREV2) 8 nodes with 2 quad-cores (AMD 2376 at 2.3Ghz) with 16GB of memory per node and a 1Gbit/s network; (MIREV3) 4 nodes with 2 octo-cores with 2 hyper-threads (INTEL XEON E5 – 2650 at 2.6Ghz) with 64GB of memory per node and a 10Gbit/s network. We measure the *speedup* for different sizes of data and different configurations of our architectures with a variation of the number of nodes \times processors \times cores \times threads used. The configurations were chosen arbitrarily, in order to compare performances with a growing number of components with both distributed and shared memories. All the sources and data are available in the MULTI-ML's GIT repository. We note ∞ when the program fails.

Thus, we aim to compare both the *code difficulty* and the difference, in terms of performances, between BSML and MULTI-ML codes.

3.2 First case: symbolic computation

Our first experiment is about **Model-Checking** (MC) which is a formal method often used to verify *safety-critical systems* [9]. Before verifying a *logical formula*, one must first compute the *state-space* of the systems. The parallelisation of this construction is a frequently used method in the industry [11].

```

1 let algo_seq succ s0 =
2   let known=HashSet.empty
3   and todo=HashSet.empty in
4   HashSet.add s0 todo;
5   while not(todo = ∅) do
6     let t=RandChoose todo in
7     HashSet.remove t todo;
8     HashSet.add known t;
9     update todo known (succ t);
10  done

```

Fig. 6 The OCAML code for MC.

ML where a set called **known** contains all the states that have been processed and would finally contain the state-space. It also involves a set **todo** that is

The finite *state-space construction* problem consists of exploring all the states *accessible via a successor function succ* (returning a set of states) from an *initial state* s_0 . This problem is computing and data intensive because realistic systems have a tremendous amount of scenarios. Usually, during this operation, all the explored states must be kept in memory in order to avoid multiple explorations of a same state. Fig. 6 shows the usual sequential algorithm in

used to hold all the states whose successors have not yet been constructed; each state t from **todo** is processed in turn (lines 5 to 10) and added to **known** (line 8) while its successors are added to **todo** unless they are already known —line 9.

```

1 let algo_bsp succ s0 =
2   let finish=ref false in
3   let known=<<HashSet.empty>> in
4   let todo=<<HashSet.empty>> in
5   <<$todo$:=HashSet.add s0 $todo$>> ;
6   while not(!finish) do
7     let tosend=<<local_successors succ
8       $this$ $known$ $todo$>>
9     in exchange finish todo known tosend
10  done

```

Fig. 7 The BSML code for MC.

processor and thus provide only a partial view of the ongoing computations (lines 3–4). Initially, only state s_0 is known and only its owner puts it in its **todo** set (line 5). Once again, processors enlarge their own local sets of states by applying the successor function on the received states; recursively to their descendants until no new states are computed (line 7). Then, a synchronous communication primitive computes and performs, for each processor, the set of received states that are not yet locally known (line 9). To ensure termination, we use the additional variable **finish** in which we test if some states have been exchanged or not by the processors. If not, there is no need to continue the computation (line 6).

The standard parallelisation of this problem is based on the idea that each process only computes the successors for its own states. The MC code written with BSML is given in Fig. 7. To do this incremental parallelisation, a *partition* function (hashing) returns, for each state, a processor id; *i.e.* $\text{hash}(s)$ returns the owner of s . Sets **known** and **todo** are still used but become local to each

```

1 let algo_multi succ s0 =
2   let known=mktree HashSet.empty
3   and todo =mktree HashSet.empty in
4   let multi space toPerform =
5     where node =
6       let sendBrothers=[| Map.empty ... Map.empty |] in
7       let sendUp=[| Map.empty ... Map.empty |] in
8       if (isEmpty toPerform) then (sendUp,sendBrothers)
9       else
10        let finish = ref false in
11        let scatt = (scatterDown toPerform mygid nbChildren) in
12        while not(!finish) do
13          let up = exchange finish <<space #scatt#>> scatt in
14          gatherUp up sendUp sendBrothers mygid nbChildren;
15          done;
16          (sendUp,sendBrothers)
17        where leaf =
18          local_successors succ (at gid) nbSiblings (at known) toPerform.(at gid)
19    in space [| ...hash(HashSet.single(s0)) ... |]

```

Fig. 8 The MULTI-ML code for MC.

The main difference between the BSP and MULTI-BSP codes is that the MULTI-BSP algorithm uses a hashing function to distribute the states on the sub-trees. Fig. 8 summarises the MULTI-ML code. Each sub-tree of the MULTI-BSP architecture is in charge of keeping the states it owns. Moreover, on two different sub-trees, there could be different numbers of supersteps depending of the verifying system: the synchronous communication primitive is performed on different sub-trees leading to implicit sub-group synchronisations. Due to a random strategy of walk (hashing) in the set of states, the load-balancing is mainly preserved —with specific industrial systems, different kinds of load-balancing strategies would be necessary for an industrial development. There is not only communication between the *siblings* but also between parents and children. Indeed, some states might not be in their right sub-trees. Thus, each leaf only computes its own states, like in the BSP algorithm (line 18). Each node manages the sub-trees of its children by performing exchanges between siblings as in the BSP algorithm (line 13) but also gathers the states that are not in the right sub-trees (line 14); It also distributes the states between the sub-trees of its children (line 11). To perform the communications, the code uses two arrays of sets, each of the size of the number of siblings of each level of the MULTI-BSP architecture. The reader can notice that the MULTI-ML code is again an incremental update of the BSML one, using the hierarchical ability of the MULTI-BSP model: “same” main loop and local computations.

For our experiments, we compute the state-space of the well-known cryptographic Needham-Schroeder Public-Key protocol with a standard universal Dolev-Yao intruder residing in the network. Note that during the computation, most of the scenarios can be detected as faulty at their very beginning using a specialised MC; But this is not the subject of this article.

Fig. 9 summarises the benchmarks. To measure the code difficulty, we take into account the algorithm part only and not the reading of the data. We recall that: The **Halstead Effort** (HE) which depends on both the length and complexity of the code; The **Halstead Difficulty** (HD) considers the amount of different operators used; The **McCabe Cyclomatic Complexity** (CC) that is the number of linearly independent paths through the source; The **Maintainability Index** (MI) which depends on HE and CC. As intended, the MULTI-ML code is the more complex: by a factor of 2 compared to BSML, which is also 2 times more complex than the OCAML code.

To measure the code performance we use the version 4.02.1 of OCAML and MPICH 3.1. We execute the codes on MIREV2 and MIREV3 by using different configurations. For example, $2 \times 2 \times 8 \times 2$ means that the code is executed on an architecture made by 2 nodes with 2 multi-cores using 8 cores with 2 threads; thus, we use 64 computing units. Using the hierarchical capacities is not beneficial for small architectures. But when the number of cores increases too much on nodes, for both MIREV2 and MIREV3, MULTI-ML exceeds BSML. This is not surprising since more communications append between cores without communicating through the network at every step of the algorithm. The BSP algorithm saturates the network with a large amount of communications and thus, this congestion drastically decreases the performances. On

Measures Languages	HE	HD	CC	MI
OCAML	2k	25	6	208
BSML	17k	56	15	420
MULTI-ML	110k	346	78	845

OCAML	$\begin{cases} \text{MIREV2} \rightarrow 22m49s \\ \text{MIREV3} \rightarrow 12m14s \end{cases}$	BSML	MULTI-ML
MIREV2	$2 \times 2 \times 2$	3.2	3
MIREV2	$4 \times 2 \times 1$	4.3	5.3
MIREV2	$8 \times 2 \times 1$	5.8	12.5
MIREV2	$8 \times 2 \times 4$	7	14.7
MIREV3	$2 \times 2 \times 2 \times 1$	4	4.9
MIREV3	$2 \times 2 \times 4 \times 1$	5.4	8
MIREV3	$2 \times 2 \times 8 \times 1$	1.2	6.5
MIREV3	$2 \times 2 \times 8 \times 2$	0.9	6.7

Fig. 9 Benchmarks (measures and speedup) of the MC of a security protocol.

the contrary, the MULTI-ML program focuses on communications through local memories and communicates through the network only when necessary. Thus, the network is less saturated and the performance is better. On a configuration with many cores and physical threads but for a small number of machines, the performance is disappointing. This is due to too much caches-misses and RAM congestion. Indeed, our current algorithms take into account the different network capacities but *not* the memory sizes.

We have notice a strange behaviour when using OCAML + MPI. Indeed, the OCAML's runtime slows down by a factor of $\simeq 2$ when it massively allocates memory. We suspect an overhead (or incompatibility) between the OCAML garbage collector and the MPI's memory allocation system.

3.3 Second case: algorithmic skeletons and a numerical application

We can observe that many parallel algorithms can be characterised and classified by their adherence to a small number of generic *patterns* of computation. Skeletal programming proposes that such patterns can be *abstracted* and provided as a programmer's toolkit with specifications. Thus, they can transcend architectural variations with implementations which enhance performance [10].

A disadvantage of skeleton languages is that the only admitted parallelism is, usually, the skeleton one, while many applications cannot be easily expressed as instances of known skeletons. Skeleton languages must be constructed to allow the integration of skeletal and *ad-hoc* parallelism [10]. In this way, having skeletons in a more general language would combine the expression power of collective communication patterns with the clarity of the skeleton approach.

In this work we consider the implementation of well-known data-parallel skeletons as they are simpler to use than task-parallel ones and because they encode many scientific computation problems and scale naturally. Even if this

implementation is surely less efficient compared to a dedicated skeleton language, the programmer can compose skeletons when it is natural for him to do so and use a BSML or MULTI-ML programming style when new patterns are needed.

The functional semantics of the considered set of data-parallel skeletons in described in [4, 10]. It can also be seen as a naive sequential implementation using lists. The skeletons work as follows: skeleton **repl** creates a new list containing n times element x . The **map** and **mapidx** skeletons are equivalent to the classical *Single-Program-Multiple-Data* (SPMD) style of parallel programming, where a single program f is applied to different data, in parallel. The **scan** skeleton, like the collective operation **MPI_Scan**, computes the partial (prefix) sums for all list elements. A more complex data-parallel skeleton, the **Distributable Homomorphism (dh)** presented in [4], is used to express divide-and-conquer algorithms. $dh \oplus \otimes l$ transforms a list $l = [x_1, \dots, x_n]$ of size $n = 2^m$ into a result list $r = [y_1, \dots, y_n]$ of the same size, whose elements are recursively computed as follows:

$$y_i = \begin{cases} u_i \oplus v_i & \text{if } i \leq \frac{n}{2} \\ u_{i-\frac{n}{2}} \otimes v_{i-\frac{n}{2}} & \text{otherwise} \end{cases}$$

where $u = \mathbf{dh} \oplus \otimes [x_1, \dots, x_{\frac{n}{2}}]$, *i.e.* **dh** applied to the left half of the input list l and $v = \mathbf{dh} \oplus \otimes [x_{\frac{n}{2}+1}, \dots, x_n]$, *i.e.* **dh** applied to the right half of l . The **dh** skeleton provides the well-known butterfly pattern of computation which can be used to implement many computations.

With appropriate \oplus and \otimes operators, we can get different applications [4]. We choose the **Fast Fourier Transform (FFT)** where a list $x = [x_0, \dots, x_{n-1}]$ of length $n = 2^m$ yields a list where the i th element is defined as: $(FFT x)_i = \sum_{k=0}^{n-1} x_k \omega_n^{ki}$ where ω_n denotes the n th complex root of unity $e^{2\pi\sqrt{-1}/n}$. The skeletal code is:

$$\begin{aligned} (\text{FFT } l) \quad \equiv \quad & \text{let } \Omega = \mathbf{scan} + 1 (\mathbf{repl} (\omega_n) \frac{n}{2}) \\ & \text{in map } \pi_1 (\mathbf{dh} \oplus_{\Omega} \otimes_{\Omega} (\mathbf{mapidx triple } l)) \end{aligned}$$

The code for asynchronous skeletons such as **map** is trivial. Using BSML:

```
1 let map f fl = <<(Lisp.map f) fl>>
```

Each processor owns a sub-part of the list. The scan code for both BSML and MULTI-ML can be found in [3]: we use a logarithmic parallel reducing algorithm for BSML and a divide-and-conquer one for MULTI-ML.

The code for **dh** in BSML looks like a reducing. The one for MULTI-ML is in Fig. 10 and works as follows. We recursively split the list (lines 4 – 5) from the root node to the leaf where **local_dh** computes, locally, the **dh** skeleton. Then we gather the temporary results and perform a **local_dh** on the data (line 7). Note that these skeletons do not change the size of the “lists” so they can be implemented using vector of arrays, that is one array per processor. It is still a divide-and-conquer strategy and, in this case, the codes for BSML and

Measures Languages	HE	HD	CC	MI
OCAML	46	62	11	304
BSML	118k	158	29	149
MULTI-ML	81k	139	17	607

	BSML		MULTI-ML	
	19	21	19	21
MIREV2 $2 \times 2 \times 2$	4.3	3.7	2.5	2.7
MIREV2 $4 \times 2 \times 1$	3.6	4.2	3.1	3.2
MIREV2 $8 \times 2 \times 1$	4.2	5	4	3.8
MIREV2 $8 \times 2 \times 4$	3.8	3.9	2.6	2.8
MIREV3 $2 \times 2 \times 2 \times 1$	3.5	4.5	3.4	3.3
MIREV3 $2 \times 2 \times 4 \times 1$	3.6	4.3	3.7	3.8
MIREV3 $2 \times 2 \times 8 \times 1$	3.5	4.5	2.6	2.5
MIREV3 $4 \times 2 \times 8 \times 1$	2.6	3.9	3.8	4.5

	m=	19	21
For OCAML:	MIREV2	16s	74s
	MIREV3	10s	41s

Fig. 11 Benchmarks (measures and speedup) of FFT using skeletons.

MULTI-ML really differ. This is mainly due to the fact that there is no subgroup synchronisation using BSML whereas it is natural using MULTI-ML.

```

1 let dh op1 op2 arr =
2   let multi dh_call arr =
3     where node =
4       let v=mkpar (fun i →
5         split arr nbChildren i) in
6       let res=gather <<dh_call $ v $>>
7       in local_dh op1 op2 res; res
8   where leaf=local_dh op1 op2 arr; arr
9 in dh_call arr

```

Fig. 10 The MULTI-ML code for **dh**.

to the fact that the MULTI-ML **dh** implementation needs to transfer the data between each memory level of the architecture. This issue was an expected drawback of the MULTI-ML algorithm. In this algorithm, the sub-synchronisation mechanism on MULTI-ML is under-exploited. As the architecture grows in terms of both machines and cores, MULTI-ML takes a small advantage on MIREV3 as BSML floods the network. However, the complexity of the code is in favour of MULTI-ML. So there is ultimately no problem using it. The overall performance of both implementations are disappointing but it is the best we can hope for such a *toy* implementation of the FFT.

We have tested our two implementations of the **dh** skeleton. To measure the difficulty, we use the implementation of the skeletons only. We test the FFT for two values of m , 19 and 21, leading to 2^m elements as input. We can notice an overhead with MULTI-ML on small architecture with a small input; and thus a speedup in favour of BSML. This is mainly due

3.4 Third case: big-data application

Given a collection of objects, the **All Pairs Similarity Search** problem (APSS) involves discovering all the pairs of objects whose similarity is above a given threshold. It may be used to detect redundant documents, similar users in social networks, *etc.* Due the huge number of objects present in real-life systems and its quadratic complexity, similarity scores are usually computed off-line.

Assuming a set of n documents of terms $D = \{d_1, d_2, \dots, d_n\}$. Each document d is represented as a sparse vector containing at most m terms. $d[i]$ denotes the number of occurrences of the i th term in the document d . The problem is to find all pairs (x, y) of documents and their exact value of similarity $\text{sim}(x, y) = \sum_i x[i] * y[i]$ if the similarity is greater than a certain threshold σ .

Different parallel algorithms have been proposed to APSS [1] and some of them deal with approximation techniques. Our work focuses on exact solutions only and we use inverted indexes as it is now the most common technique [5] (our OCAML code is an implementation of this kind of algorithm). For BSP-like computing two algorithms [1] are mainly used. The first algorithm is based on a systolic-like loop. We assume that each processor i holds a subset of documents D_i . Initially, each processor i computes the similarity $\text{sim}(D_i, D_i)$ of D_i 's documents with each other documents of D_i . Then each subset is passed around from processor to processor in a sequence of $\mathbf{p}/2$ supersteps (exploiting the symmetric similarity of two subsets): each processor receives a subset D_j and calculates $\text{sim}(D_i, D_j)$ and then it sends D_j to its right-hand neighbour, while at the same time receiving the documents from its left-hand neighbour. If \mathbf{p} is odd, half of the processors perform an additional exchange.

```

1 let algoMapReduce vectors =
2   (* indexing *)
3   let map1=<<merge $vectors$>> in
4   shuffle map1;
5   (* Similarity *)
6   let map2=<<allPairs $map1$>> in
7   shuffle map2;
8   <<reduce $map2$>>

```

Fig. 12 The BSML code for APPS.

The second algorithm is based on two simple MAPREDUCE [20] phases as illustrated in Fig 12: (1) Indexing; for each term in the document, each processor merges the term as key, and a pair $(d, d[t])$ consisting of document id d and weight of the term as the value (line 3). Then the algorithm handles the grouping by key of these pairs (the shuffle, line 4); (2)

Similarity; each processor emits pairs of document ids that are in the same group G as keys (line 6). There will be $m \times (m - 1)/2$ exchange pairs where $m = |G|$ for the shuffle (line 7); Then they associate to each pair the product of the corresponding term weights. Finally they reduce the sums of all the partial similarity scores for a pair to generate the final similarity scores (line 8).

The MULTI-BSP algorithm is again an incremental improvement of the two above BSP algorithms. It is based on the following idea (Fig 13): Initially, on leaves, we perform a systolic-like loop to initiating the index lists and the similarities. Then, each node selects some documents (on the sub-nodes, line 4) that already have a similarity: these documents are thus a greater opportunity

Measures Languages	HE	HD	CC	MI
OCAML	47k	38	10	203
BSML(MAPREDUCE-like)	148k	104	26	863
BSML(systolic loop)	128k	68	19	424
MULTI-ML (hybrid)	250k	224	33	1100

In seconds	BSML		MULTI-ML	
	10M	17M	10M	17M
MIREV2 $2 \times 2 \times 2$	∞	∞	∞	∞
MIREV2 $4 \times 2 \times 1$	201	∞	190	∞
MIREV2 $8 \times 2 \times 1$	91	155	87	143
MIREV2 $8 \times 2 \times 4$	38	269	31	253
MIREV3 $2 \times 2 \times 2 \times 1$	∞	∞	∞	∞
MIREV3 $2 \times 2 \times 4 \times 1$	∞	∞	785	∞
MIREV3 $2 \times 2 \times 8 \times 1$	64	96	57	90
MIREV3 $2 \times 2 \times 8 \times 2$	41	87	39	72

Fig. 14 Benchmarks of the all pairs similarity search problem (APPS).

to be similar with other documents. These documents are passed around from sibling to sibling (line 5) and are passed down to leaves as pairs as in the MAPREDUCE method. Now all the leaves update their similarity scores (line 7). And so on until no more documents are sending around siblings.

```

1 let multi apps docs =
2   where node =
3     while not(newDoc) do
4       let down=proj <<apps (select docs)>> in
5       systolic <<apps (#down# (at gid))>>
6     done
7   where leaf = update (at indexList) docs

```

Fig. 13 The MULTI-ML code for APPS.

with approximately 1.5 billion of followings) available at <http://an.kaist.ac.kr/traces/WWW2010.html> as data-set. For our experiments, we take sub-parts of the original file. A pair corresponds to the same kind of following. We do not use any disk to store temporary results. There are 600M (resp. 1.5G) of pairs for 10M (resp. 17M) followings. The sequential code fails on these too large data-sets (not enough memory) so we give the execution times only. We do not use the common pruning of documents [5]: that reduces the overall computing time by reducing the number of documents to be compared and communicated but that is “independent” of using parallel algorithms. Our threshold is very low (even if it’s not realistic), thus many pairs are computed. The number of pairs quadratically increases to the size of the data-set. The fails (∞) corresponds to “out of memory” or MPI fails when too much data is exchanged (*i.e.* when less nodes take part in the computation or there are too many cores in use on a single node).

As before, to measure the performances and the difficulty of writing the programs, we take into account the algorithm part only and not the reading of the data. We use the Twitter’s follower graph (July 2009, 24GB file

As already seen in [1], for BSP computing, the systolic method is faster than the MAPREDUCE one by an important order of magnitude. This is mainly due to a quadratic number of sending pairs. Thus, we do not give these timings.

The performances of the programs are not impressive because we use the generic data structures of OCAML which are not optimised for pairs and thus consumes too much memory. The losses are mainly due to a large use of the RAM. As intended, the MULTI-BSP code is more complex but gives better performance. The gain is not spectacular: using a BSP systolic algorithm, only one core sends data to another core of a machine. So there are few data exchanged in the network and there is thus not a congestion as in the MC example. This also explains why the performances are better using MIREV2 than MIREV3: there are too many memory accesses in the RAM. However when using the MULTI-BSP algorithm, even if the computations and the memory uses are of the same order of magnitude as in the BSP algorithm, there is a massive use of synchronisation of sub-machines which allow a better load-balancing. Even if there is more (local) supersteps, each performs less computation leading to less congestion when accessing to the RAM.

We can conclude that to have efficient MULTI-BSP algorithms, we need to massively exchange data between the fastest memories. Indeed, on standard INTEL or AMD architectures, memories close to the physical threads (L1, L2 and L3 memories) are very fast. As a counter part, they are so small that it is a challenge to maximise their usage. As expected, we must concentrate on maximising data exchanges between computation units of the same memory locality.

4 Related work

Hierarchical programming and Multi-BSP libraries. There are many papers about the gains of mixing shared and distributed memories, *e.g.* MPI and OPEN-MP [7]. As intended, the programmer must manage the distribution of the data for these two different models. For example, with the MC case, the algorithm of [19] handles a specific data-structure (with locks) shared by the threads on cores and distributes the states across the nodes using the hash technique. We can also cite the work of [14] in which a BSP extension of C++ runs the same code on both a cluster and on multi-cores. But it is the responsibility of the programmer to avoid harmful nested parallelism. This is thus not a dedicated language working for hierarchical architectures. We can also highlight the work of NESTSTEP [15] which is a C/JAVA library for BSP computing, which authorises nested computations in case of a cluster of multi-cores — but without any safety.

Distributed functional languages. Except in [17], there is a lack of comparisons between parallel functional languages. It is difficult to compare them since many parameters have to be taken into account: efficiency, scalability, expressiveness, *etc.* A data-parallel extension of HASKELL call NEPAL has been done in [8], an abstract machine is responsible for the distribution

of the data over the available processors. MULTIMLTON [21] is a multi-core aware runtime for standard ML, which is an extension of the MLTON compiler. It manages composable and asynchronous events using, in particular, *safe-futures*. A description of other bridging models for hierarchical architectures and other parallel languages can be found in [2]. Currently, we are not aware of any safe and efficient functional parallel language dedicated to hierarchical architectures.

5 Conclusion and future work

5.1 Conclusion

We have benchmarked different distributed applications using a flat bridging model (BSP) and its hierarchical extension (MULTI-BSP). We used two ML-like languages for both. We tried to compare both speedup and difficulty to write code using different methodologies. Currently, we are not aware of similar works in the literature. Regarding the proposed case study, the hierarchical programs are more efficient, in general, but they are more difficult to write as a counterpart. As expected, there are also some cases where designing and programming a hierarchical algorithm does not yield much. Intuitively, to get a performance gain, you have to maximise the locality (in the lowest memories of your machine) of calculations as well as the synchronisations/communications.

Thanks to our approach, the BSP programs have been written incrementally from the sequential ones, as well as the MULTI-BSP programs extend the BSP ones. This seems to be an interesting point for software HPC development engineering: in a project, it is possible to work by successive additions of codes and it is not necessary to rewrite the code from scratch. However, it is still less flexible than the skeleton approach where only the patterns need to be efficiently implemented. Nevertheless, regarding an efficient MULTI-BSP algorithm, it is simpler to implement it using MULTI-ML code rather than in a skeleton framework.

5.2 Future work

The next phase will be to work on the optimisation of the previous programs. For example, how the states are kept in the memories is not optimised at all and induces many cache-misses. Using the last parameter of the MULTI-BSP model, that is the size of the memories, should lead to better algorithms. That should also reduce the execution time for exact APSS by using a cache-conscious data layout. Our methodology also suffers from the fact that we make the hypothesis that the algorithms are known. However, designing an efficient BSP algorithm is harder than a sequential one. The effort is even harder for MULTI-BSP even though we perform an incremental development.

In the continuity of this work, we see two interesting points: (1) Doing programming experiments of our languages with students or users; This will

allow to test if coding MULTI-BSP algorithms using MULTI-ML is really more difficult than coding BSP algorithms with BSML and/or sequential algorithms with OCAML; We think that designing the algorithms themselves is clearly the most difficult part; (2) Comparing the experimental timings with the expected cost formulae. The second author has already done this work in the context of BSP and BSML [12]. The conclusion is that the main difficulty is finding these cost formulae.

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