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Distributed futures for efficient data transfer between parallel processes

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ABSTRACT
This paper defines distributed futures, a construct that provides at the same time a data container similar to a distributed vector, and a single synchronization entity that behaves similarly to a standard future. This simple construct makes it easy to program a composition, in a task-parallel way, of several massively data-parallel tasks. The approach is implemented and evaluated in the context of a bulk synchronous parallel (BSP) active object framework.

CCS CONCEPTS
• Software and its engineering → Parallel programming languages: Concurrent programming structures.

KEYWORDS
Parallel and distributed programming. Futures

1 CONTEXT AND INTRODUCTION
Two of the most common parallel abstractions are task-parallelism, which decomposes work into different parts that can be executed in parallel and can be functionally different, and data-parallelism, which splits the work by distributing the data. Because task parallelism and data parallelism are convenient to parallelize different parts of an application, it is valuable to mix them into one programming framework. In data-parallel models, synchronization and data exchanges between the tasks are quite restricted while task parallelism is generally very flexible on these aspects. This is why several interaction patterns exist in task parallel models, we focus here on futures, a programming construct that both serves to synchronize tasks and to exchange data. While futures are convenient for task-parallel models, they are not very well integrated in data-parallel models. To enable a better interaction of these two programming models, this article designs and shows how to implement distributed futures.

A future is a placeholder for a value being computed by a task. While the task is not finished, the future is unresolved, automatically, the future gets filled by the value computed by the task when it finishes (the future is fulfilled). Futures can also be accessed by trying to get their value, synchronizing the current task with the resolution of the future. Several mechanisms exist for accessing futures, either blocking on the result or registering a continuation to be executed when the future is resolved. All these mechanisms provide a convenient and safe way to write parallel and distributed applications, with a behavior close to a sequential program.

Here, we choose actors as the task-parallel model, and BSP (Bulk Synchronous Parallel [13]) as the data-parallel programming framework. The Actor [1] model is a task-parallel paradigm. Actors prevent data-races by enforcing that asynchronous message passing is the only interaction between processes: actors communicate with each other by putting messages in their mailboxes. In this article we use active objects [4], which are objects that are at the same time actors. In active objects, a method call to an active object creates a message that reaches its mailbox and a future is used to represent the result returned by such an asynchronous method invocation. Data-parallel programming abstractions like BSP are better suited to parallel computations on large amounts of data. BSP algorithms are defined as a sequence of supersteps, each made up of three phases: computation, communication, and synchronization. BSP is limited in terms of application elasticity or loose coupling of computing components as it relies on the strong synchronization of all computing entities.

The scope of our contribution is broader than the strict context of BSP and active objects. As soon as one wants to compose task-parallel and data-parallel programming models, the question of the interaction between the synchronization mechanisms arises. In this article, we focus on futures, which are synchronization artefacts frequently used in task-parallel applications. However, because a future encapsulates a single piece of data on which synchronization is possible, it is not suited to the context of data-parallelism that requires data to be spread over different processes. This is why we design, implement, and evaluate distributed futures: futures representing data distributed over multiple processes.

1.1 Futures in programming languages
Many languages use futures because they provide a high-level synchronization paradigm. Futures are used in actors [14], active objects [4], Synchronous languages [6], but also many mainstream...
languages like C++ or Java. Basic future usages include synchroniza-
tion of a process on the availability of the future’s referred data (i.e.
the resolution of the future) and asynchronous reaction to the reso-
lution of a future, i.e. registration of a continuation to be executed
upon future resolution. The synchronization primitive is generally
called get and waits for a future to be resolved while blocking the
current thread of execution. Some languages like Akka [14] favour
asynchronous chaining of the form f. onSuccess( . . . ) that does not
execute the consequence of the future resolution immediately,
but registers what is to be executed when f becomes available.

1.2 A data-parallel and task-parallel
framework: BSP Active Objects

As highlighted above, data-parallelism and task-parallelism should
benefit from each other and both are often integrated in the same
application. A few frameworks for coupling different parallel codes
support the design of these applications.

In particular, we rely on BSP Active Objects[9], a C++ library that
allows the coordination of several data-parallel tasks imple-
mented in BSP by using an actor-based task-parallel interaction
with basic (non distributed) futures. It runs on top of MPI and uses
the BSPPonMPI v0.2 implementation of the BSPlib specification.

A BSP active object is running on several processes, one of them
is called the head process; this process handles the active object
requests sequentially, it is able to run a parallel function by giving
it as parameter of a bsp_run primitive. This parallel function is exe-
cuted on all the processes of the active object, which communicate
in a BSP manner. A class can be declared as an active object class,
tagging some of the methods as “active object methods”. Each BSP
process has two threads. The first one is a worker thread that exe-
cutes the user’s code. The other one is called a management thread:
it ensures responsiveness of the active object as it is available when
the processes are inside a BSP computation. We will use this per
BSP process thread to perform tasks dedicated to our distributed
future management. The use of BSP active objects is illustrated
in [9].

2 DISTRIBUTED FUTURES

2.1 Principle

To incorporate data-parallelism inside a task-parallel framework,
the most efficient solution is to use multiple processes for each
entity that handles a parallel task. This means that one needs to
gather all the parts of the computed result into a single place in order
to return back a result as a future even if it was distributed among
processes. This gathering raises a performance issue whenever the
result array is large, especially when passed to another task that
scatters it again to do data-parallel processing. Consequently, it is
more efficient that every data-parallel process keeps its part of the
result, and transmits it directly where it is needed. The data-parallel
processes thus only need to send a description of the part of the
result it holds. We call this description a distributed future because
it represents a distributed vector being computed in the same way a
future represents a value being computed. A distributed future is
a future on which synchronization is possible, but its content is the
description of a distributed vector. Provided the distributed future
is way smaller than the distributed vector, a distributed future is
cheaper to pass around between tasks. Using a distributed future,
any process in a data-parallel task can obtain the distributed vector
parts it needs, directly from the processes that hold them. The
programmer does not have to know where each part is located and
on how many processes each part is distributed.

Resolving a distributed future means waiting to get the metadata,
which is returned from an active object producing a distributed vec-
tor. However the meta-data is only produced after the distributed
vector is produced. This means resolving a distributed future waits for
the full distributed vector be produced, but only transfer its metadata.
Every process only receives the data it is interested in, and directly
from process(es) that computed these data. A synchronization on
a distributed future consists in retrieving metadata necessary to
access the content of the distributed future value, then the differ-
ent part(s) of the effective data collection. Our design is such that
requesting the value of a distributed future and making use of it
to trigger effective data transfer is similar to using a lazy synchro-
nization strategy with classical futures: the data is only transmitted
upon need. Indeed, because data parallelism is often bandwidth-
bound, we need precise control of the communication when large
amounts of data may be communicated over multiple processes.

A more declarative strategy can also be envisioned: the program-
mer could declare a distribution policy inside each actor and this
policy could be used by the different data-parallel processes hosted
in this actor to pre-fetch the data before the computation is started.
Such a pre-fetching strategy is outside the scope of this paper.

2.2 Implementation

Our implementation of distributed futures is based on the BSP active
object library, described in Section 1.2 above. To implement the
concept of distributed futures, two aspects have to be implemented:
the future resolution and the future access. We review our solution
for both of them below. We start by defining a data structure to
represent a distributed vector, this data structure is stored in the
distributed future when it is resolved.

When a distributed future is resolved, we assign it a collection of
(pid, local_id, size, offset) quadruplets. Each quadruplet describes a
part of a distributed vector. pid is the process which owns this part;
local_id is the part identifier that is unique within the owner; size is
the part size; offset is the index in the distributed vector. Fields offset
and size are specified in bytes. For example, a part with offset 1 and
size 1 is the second byte of a distributed vector. This structure allows
storing different types of contiguous elements, including structs.
The simplest data distribution is the block distribution, which stores
one contiguous range per process, in this case the distributed future
is made of one quadruplet per process. For example, if we have a
block-distributed vector of 40 elements computed by 4 processes
numbered 1, 2, 3 and 4, then the distributed future value is the list
((1, 1, 10, 0), (2, 12, 10, 10), (3, 41, 10, 20), (4, 33, 10, 30)). Processes
own consecutive parts of size 10 each.

We provide 4 main high-level primitives for manipulating
vector_distribution, shown in Figure 1. Their following descrip-
tion can be followed along figure 2.

The register_result function stores a distributed vector part
of size size at local address data into the management thread’s
memory of the current process; offset is the position of this
part within the distributed vector. This step creates a quadruplet as defined in Section 2.2. After all parts are registered, a call to
\texttt{gather\_vd\_parts} by the head process assembles the quadruplet list as a \texttt{vector\_distribution} structure, which, when given as
return value, becomes a distributed future. Resolving this future with
an usual get returns this \texttt{vector\_distribution}, after the associ-
ated distributed vector was produced. The \texttt{broadcast\_vd} primitive
allows a head process to send it to its other active object processes.
The \texttt{get\_part} primitive then enables any of these processes to
request any subpart of the distributed vector, where its distribution
is transparently deduced from the \texttt{vector\_distribution} given as
parameter. In Figure 2, the second process of \texttt{objectB} requests
the second half of the distributed vector, which is deduced to be on \texttt{P1}
and \texttt{P2} of \texttt{objectA}.

3 EXPERIMENTS

In this section, we demonstrate the performance gain of distributed
futures when used between parallel actors. To do so, we create a
pipeline of three such actors, and we focus on the middle one that
receives a distributed future, work with it, and produces another.
This actor is a parallel image compressor, of which the performance
vary with the number of assigned processes. We configure other
actors so that the compressor is the bottleneck in the pipeline. The
pipeline is set-up from a coordinator process, which executes a
code similar to figure 3.

3.1 Experimental setting

For these experiments, we are using seven Huawei RH2288v2
servers, each with two Intel Xeon E5-2690v2 CPUs that have ten
cores each. We use the Intel C++ compiler version 18.0.1. Because
each BSP active object process uses two threads, we put a maximum
of ten processes on each of these servers. When an active
object is assigned more than ten processes, it means it is distributed
over multiple nodes. For example twenty processes are distributed
over two. We dedicate one of our servers to the main coordinator
process, so that all active objects are on remote nodes.

3.2 Results

We choose large image sizes: 36 Mega-pixel images of resolution
4912 x 7360. Each of these images amounts to about 108 MB uncom-
pressed in pure bitmap format. We execute our pipeline for 1000 of
these images, measure its performance while varying the number of
compressor processes, as shown in figure 4. Because the compressor
is the bottleneck in the pipeline, the whole pipeline performance
improves with the compressor performance. Here the performance
stops improving at sixteen processes with distributed futures and
four processes with normal futures. This experiment clearly shows
the advantages of distributed futures, showing the gain brought by
parallel data transfers instead of gathers and scatters.

4 RELATED WORKS

Several works focus on the efficient use of futures in concurrent
and distributed settings [2, 7, 12], sometimes synchronizing a group
of tasks, but none of them use a single future as the abstraction
of a large set of data. In the domain of parallel and distributed
computing, such an abstraction is generally provided by distributed
arrays. To the best of our knowledge we are the first to define
futures of distributed data in the form of distributed vectors.

ParT [8] in the Encore language, provides the notion of arrays
of futures that distributes data as different futures, but does not
allow to synchronize parts of data as a single future. It can be used
to implement speculative parallelism or barriers gathering a set of
results. The set of futures is not viewed as a distributed array but
rather as an array of futures. Also, the implementation is local to
a single machine and there is no support for distributing a ParT
over multiple machines or the possibility to transparently allocate a range of data to a process.

The notion of streaming futures was defined in the context of ABS in [2]. This approach provides a solution for tailoring futures to large amounts of data and in particular data streams. Streaming futures can be accessed multiple times to obtain different data, which departs from the traditional future concept. The advantage is that such futures can create a streaming channel, and the communication pattern can then be optimized using existing streaming techniques. Our distributed futures are geared more toward high-performance computing than to data-streaming applications, because a single synchronization waits for completion of all data.

Distributed arrays, have been used as basic data structures for data parallel algorithms since the early days of parallel computing. In particular, they solve a scalability issue. On distributed memory systems, where memory is partitioned, an array that could not be stored on a single node can be stored on a distributed memory. In the context of (direct mode) BSP programming, distributed arrays are a natural way of dealing with integer-indexed data, because the programming model assumes distributed memory. For that reason, many BSP programming languages and frameworks support distributed arrays, sometimes implicitly like registered memory in BSPlib [10], and other times more explicitly like the parallel vectors in BSML [3] and coarrays in Bulk [5]. OSL [11] too is a library of data parallel algorithmic skeletons which follow the BSP model. OSL arrays are distributed but are manipulated as normal arrays by the programmer, passing them as parameter to functions such as parallel map or zip which return a new distributed array as result, that can further be passed as parameter. OSL proposes to avoid the creation of intermediate distributed arrays within a sequence of supersteps. On the contrary, our distributed futures allow a vector to be passed around to any method call without the need to delimit a sequence of calls. The use of futures triggers a synchronization but the data transfer is decoupled. Moreover, contrary to OSL where arrays must be block-distributed, we can define an unbalanced distribution of the future.

Distributed arrays require redistribution usually when two parallel programs exchange data, because, for example, the number of processes doesn’t match, or the problem domain favors a different distribution. E.g. in MPI, programs can use intercommunicators to transfer data between producer and consumer tasks. However, both must know exactly how data is redistributed, something that must be specified on both ends by the programmer. In frameworks with shared-memory like OpenMP, all offset and address calculations and the synchronization can be done by the consumer task itself. Still, the programmer must know exactly which process owns what data on the producer task. Contrarily to the MPI-like approaches, our distributed futures offer a better abstraction of distribution than classical distributed arrays. The distribution information is stored with the future as meta-data, obtained upon synchronization, and the programmer doesn’t need to know its content or to ask individual processes for subparts.

5 CONCLUSION

We presented the concept of distributed futures, an unification of futures and distributed arrays where a distributed future represents a distributed array. It provides synchronization capacities on the entire array and enables optimized communications by allowing processes to fetch directly the parts they need from the processes that computed them. Distributed futures as a programming abstraction makes programming easier, in particular synchronization and data transfer; it also makes the communication between data-parallel entities more efficient than with standard futures. We implemented this notion in the context of BSP active objects that allows several BSP entities to interact in a task parallel and asynchronous manner. We showed the practical benefits of this approach.

As future work, pre-fetching strategies would allow an active object to trigger transfer between BSP processes earlier. Instead of pulling data when the BSP computation starts, by invocation of a get_part primitive, the idea is to push the data on the BSP processes while the request is in the input (FIFO) queue of the active object, i.e. between the moment the request is sent to the active object and the moment the request is handled by the active object.

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Pierre Leca, Ludovic Henrio, Françoise Baude, and Wijnand Suijlen