YapOr: an Or-Parallel Prolog System based on Environment Copying

Ricardo Rocha

Fernando Silva

Vítor Santos Costa*

DCC-FC & LIACC, University of Porto, R. do Campo Alegre, 823 4150 Porto, Portugal {ricroc,fds,vsc}@ncc.up.pt

Abstract. YapOr is an or-parallel system that extends the Yap Prolog system to exploit implicit or-parallelism in Prolog programs. It is based on the environment copying model, as first implemented in Muse. The development of YapOr required solutions for some important issues, such as designing the data structures to support parallel processing, implementing incremental copying technique, developing a memory organization able to answer with efficiency to parallel processing and to incremental copying in particular, implementing the scheduler strategies, designing an interface between the scheduler and the engine, implementing the sharing work process, and implementing support to the cut builtin. An initial evaluation of YapOr performance showed that it achieves very good performance on a large set of benchmark programs. Indeed, YapOr compares favorably with a mature parallel Prolog system such as Muse, both in terms of base speed and in terms of speedups.

Keywords: Parallel Logic Programming, Scheduling, Performance.

1 Introduction

Prolog is arguably the most important logic programming language. It has been used for all kinds of symbolic applications, ranging from Artificial Intelligence to Database or Network Management. Traditional implementations of Prolog were designed for the common, general-purpose sequential computers. In fact, WAM [16] based Prolog compilers proved to be highly efficient for standard sequential architectures and have helped to make Prolog a popular programming language. The efficiency of sequential Prolog implementations and the declarativeness of the language have kindled interest on implementation for parallel architectures. In these systems, several processors work together to speedup the execution of a program [8]. Parallel implementations of Prolog should obtain better performance for current programs, whilst expanding the range of applications we can solve with this language.

Two main forms of implicit parallelism are present in logic programs [8]. And-Parallelism corresponds to the parallel evaluation of the various goals in

^{*} The first author is thankful to Praxis and Fundação para a Ciência e Tecnologia for their financial support. This work was partially funded by the Melodia (JNICT PBIC/C/TIT/2495/95) and Proloppe (PRAXIS/3/3.1/TIT/24/94) projects.

the body of a clause. This form of parallelism is usually further subdivided into *Independent And-Parallelism* in which the goals are independent, that is, they do not share variables, and *Dependent And-Parallelism* in which goals may share some variables with others. In contrast, *Or-Parallelism* corresponds to the parallel execution of alternative clauses for a given predicate goal.

Original research on the area resulted in several systems that successfully supported either and-parallelism or or-parallelism. These systems were shown to obtain good performance for classical shared-memory parallel machines, such as the Sequent Symmetry. Towards more flexible execution, recent research has investigated how to combine both and- and or-parallelism [6], and how to support extensions to logic programming such as constraints or tabling [12, 13].

Of the forms of parallelism available in logic programs, or-parallelism is arguably one of the most successful. Experience has shown that or-parallel systems can obtain very good speedups for a large range of applications, such those that require search. Designers of or-parallel systems must address two main problems, namely scheduling and variable binding representation. In or-parallel systems, available unexploited tasks arises irregularly and thus, careful scheduling is required. Several strategies have been proposed to this problem [5, 1, 4, 15, 14].

The binding representation problem is a fundamental problem that arises because the same variable may receive different bindings in different or-branches. A number of approaches [9] have been presented to tackle the problem. Two successful ones are environment copying, as used in Muse [2], and binding arrays, as used in Aurora [11]. In the copying approach, each worker maintains its own copy of the path in the search tree it is exploring. Whenever work needs to be shared, the worker that is moving down the tree copies the stacks from the worker that is giving the work. In this approach, data sharing between workers only happens through an auxiliary data structure associated with choice points.

In contrast, in the binding array approach work stacks are shared. To obtain efficient access, each worker maintains a private data structure, the binding array, where it stores its conditional bindings. To allow for quick access to the binding of a variable the binding array is implemented as an array, indexed by the number of variables that have been created in the current branch. The same number is also stored in the variable itself, thus giving constant-time access to private variable bindings.

Initial implementations of or-parallelism, such as Aurora or Muse, relied on detailed knowledge of a specific Prolog system, SICStus Prolog. Further, they were designed for the original shared memory machines, such as the Sequent Symmetry. Modern Prolog systems, even if emulator based, have made substantial improvements in sequential performance. These improvements largely result from the fact that though most Prolog systems are still based on the Warren Abstract Machine, they exploit several optimizations not found in the original SICStus Prolog. Moreover, the impressive improvements on CPU performance over the last years have not been followed by corresponding bus and memory performance. As a result, modern parallel machines show a much higher latency,

as measured by the number of CPU clock cycles, than original parallel architectures.

The question therefore arises of whether the good results previously obtained with Muse or Aurora in Sequent style machines are repeatable with other Prolog systems in modern parallel machines. In this work, we present YapOr, an or-parallel Prolog system, that is based on the high performance Yap Prolog compiler [7], and demonstrate that the low overheads and good parallel speedups are in fact repeatable for a new system in a very different architecture.

The implementation of or-parallelism in YapOr is largely based on the environment copying model as first introduced by Ali and Karlson in the Muse system [2, 1, 10]. We chose the environment copying model because of the simplicity and elegance of its design, which makes it simpler to adapt to a complex Prolog system such as Yap, and because of its efficiency as Muse has consistently demonstrated less overheads then competing or-parallel systems such as Aurora. However, in order to support other or-parallel models, the system has been designed such that it can easily be adaptable to alternative execution models.

The substantial differences between YapOr and Muse resulted in several contributions from our design. YapOr uses novel memory organization and locking mechanisms to ensure mutual exclusion. We introduce a different mechanism to handle backtracking, as an extension of WAM instructions, and not through a SICStus specific mechanism. As in the original Yap, YapOr uses just one stack for environments and choice points, in opposition to SICStus which uses two. This requires adjustments to the sharing and synchronization procedures when two workers share work. This also requires different formulas to calculate the portions of stacks that have to be copied when sharing work takes place. YapOr introduces a new protocol to handle the cut predicate and a new scheme to support the solutions that are being found by the system and that may correspond to speculative work.

Performance analysis showed that parallel performance was superior to that of the original Muse, and better than the latest Muse as available with the current commercial implementation of SICStus Prolog. A first YapOr implementation has integrated in the freely distributable YAP system.

The remainder of the paper is organized as follows. First we present the general concepts of the Environment Copying Model. Next, we introduce the major implementation issues in YapOr. We then give a detailed performance analysis for a standard set of benchmarks. Last, we present our conclusions and further work.

2 The Environment Copying Model

As previous systems, YapOr uses the multi-sequential approach [11]. In this approach, workers (or engines, or processors or processes) are expected to spend most of their time performing reductions, corresponding to useful work. When they have no more goals or branches to try, workers search for work from fellow

workers. Which workers they ask for work and which work they receive is a function of the *scheduler*.

Basic Execution Model

Parallel execution of a program is performed by a set of workers. Initially all workers but one are *idle*, that is, looking for their first work assignment. Only one worker, say P, starts executing the initial query as a normal Prolog engine. Whenever P executes a predicate that matches several execution alternatives, it creates a choice point (or node) in its local stack to save the state of the computation at predicate entry. This choice point marks the presence of potential work to be performed in parallel.

As soon an idle worker finds that there is work in the system, it will request that work directly from a busy worker. Consider, for example, that worker \mathbb{Q} requests work from worker \mathbb{P} . If \mathbb{P} has available work, it will share its local choice points with \mathbb{Q} . To do so, worker \mathbb{P} must turn its choice points public first. In the environment copying model this operation is implemented by allocating orframes in a shared space to synchronize access to the newly shared choice points. Next, worker \mathbb{P} will hand \mathbb{Q} a pointer to the bottom-most shared choice point.

The next step is taken by worker Q. In order for Q take a new task, it must copy the computation state from worker P up to the bottom-most shared choice point. After copying, worker Q must synchronize its status with the newly copied computation state. This is done by first simulating a failure to the bottom-most choice point and then by backtracking to the next available alternative within the branch and starting its execution as a normal sequential Prolog engine would.

At some point, a worker will fully explore its current sub-tree and become idle again. In this case, it will return into the scheduler loop and start looking for busy workers in order to request work from them. It thus enters the behavior just described for Q. Eventually the execution tree will be fully explored and execution will terminate with all workers idle.

Incremental Copying

The sharing work operation poses a major overhead to the system as it involves the copying of the executions stacks between workers. Hence, an incremental copying strategy [2] has been devised in order to minimize this source of overhead.

The main goal of sharing work is to position the workers involved in the operation in the same node of the search tree, leaving them with the same computational state. Incremental copying achieves this goal, making the receiving worker to keep the part of its state that is consistent with the giving worker, and only copying the differences between both.

This strategy can be better understood through Fig. 1. Suppose that worker Q does not find work in its branch, and that there is a worker P with available work. Q asks P for sharing, and backtracks to the first node that is common to P,

therefore becoming partially consistent with part of P. Consider that worker P decides to share its private nodes and $\mathbb Q$ copies the differences between P and $\mathbb Q$. These differences are calculated through the information stored in the common node found by $\mathbb Q$ and in the top registers of the local, heap and trail stacks of P. To fully synchronize the computational state between the two workers, worker $\mathbb Q$ needs to install from P the bindings trailed in the copied segments that refers to variables stored in the maintained segments.

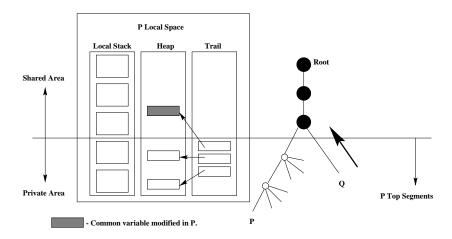


Fig. 1. Some aspects of incremental copying.

Scheduling Work

We can divide the execution time of a worker in two modes: scheduling mode and engine mode. A worker enters in scheduling mode whenever it runs out of work and starts searching for available work. As soon as it gets a new piece of work, it enters in engine mode. In this mode, a worker runs like a standard Prolog engine.

The scheduler is the system component that is responsible for distributing the available work between the various workers. The scheduler must arrange the workers in the search tree in such a way that the total time of a parallel execution will be the least possible. The scheduler must also maintain the correctness of Prolog sequential semantics and minimize the scheduling overheads present in operations such as sharing nodes, copying parts of the stacks, backtracking, restoring and undoing previous variable bindings.

To achieve these goals, the scheduler follows the following strategies:

- When a busy worker shares work, it must share all the private nodes it has in the moment. This will maximize the amount of shared work and possibly avoid that the requesting worker runs out of work too early.

- The scheduler selects the busy worker that simultaneously holds the highest work load and that is nearest to the idle worker. The work load is a measure of the amount of unexplored private alternatives. Being near corresponds to the closest position in the search tree. This strategy maximizes the amount of shared work and minimizes the stacks parts to be copied.
- To guarantee the correctness of a sharing operation, it is necessary that the idle worker is positioned in a node that belongs to the branch on which the busy worker is working. To minimize overheads, the idle worker backtracks to the bottom common node before requesting work. This reduces the time spended by the busy worker in the sharing operation.
- If at a certain time the scheduler does not find any available work in the system, it backtracks the idle worker to a better position, if available, in the search tree that should minimize the overheads of a future sharing operation.

We can resume the scheduler algorithm as follows: when a worker runs out of work it searches for the nearest unexplored alternative in its branch. If there is no such alternative, it selects a busy worker with excess of work load to share work according to the strategies above. If there is no such a worker, the idle worker tries to move to a better position in the search tree.

There are two alternatives to search for busy workers in the search tree: search below or search above the current node. Idle workers always start to search below the current node, and only if they do not find any busy worker there, they search above. The advantages of selecting a busy worker below instead of above are mainly two. The first is that the idle worker can request immediately the sharing operation, because its current node is already common to the busy worker. This avoids backtracking in the tree and undoing variable bindings. The other advantage is that the idle worker will maintain its relative position in the search tree, but restarting the execution in a bottom level. This corresponds to the environment copying model bottom-up scheduling strategy, that has proved to be more efficient than the top-down one [1].

As mentioned before, when the scheduler does not find unexplored alternatives and no busy workers below or above, it tries to move the idle worker to a better position in the search tree. An idle worker moves to a better position, if all workers below the current node are idle, or if there are busy workers above and no idle workers upper in its branch.

In the first situation, the idle worker backtracks until it reaches a node where there is at least one busy worker below. In the second one, it backtracks until it reaches the node that contains all the busy workers below. With this scheme, the scheduler tries to distribute the idle workers in such a way as that the probability of finding, as soon as possible, busy workers with excess of work below the corresponding idle workers' current nodes is substantially increased.

3 Extending Yap to support YapOr

We next discuss the main issues in extending the Yap Prolog system to support parallelism based on environment copying.

Memory Organization

Following the original WAM definition [16], the Yap Prolog system includes four main memory areas: code area, heap, local stack and trail. The local stack contains both environment frames and choice points. Yap also includes an auxiliary area used to support some internal operations.

The YapOr memory is divided into two big addressing spaces: the global space and a collection of local spaces (see Fig. 2). The *global space* is divided in two different areas and contains the global data structures necessary to support parallelism. The first area includes the code area inherited from Yap, and a global information area that supports the parallel execution. The second one, the *Frames Area*, is where the three types of parallel frames are allocated during execution. The *local space* represents one system worker. It contains a local information area with individual information about the worker, and the four WAM execution stacks inherited from Yap: heap, local, trail and auxiliary stack.

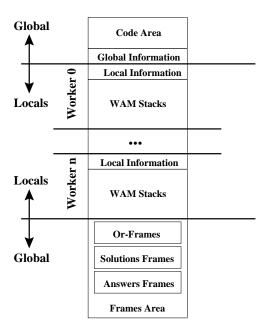


Fig. 2. Memory organization in YapOr.

In order to efficiently meet the requirements of incremental copy, we follow the principles used in Muse and implement the YapOr's memory organization with the *mmap* function. This function let us map a file on disk into a buffer in memory so that, when we fetch bytes from the buffer, the corresponding bytes of the file are read. When mapping, the memory buffers can be declared to be private or shared. Obviously, we are interested in shared memory buffers.

The starting worker, that is worker 0, uses mmap to ask for shared memory in the system's initialization phase. Afterwards, the remaining workers are created, through the use of the fork function, and inherit the addressing space previously mapped. Then, each new worker rotates all the local spaces, in such a way that all workers will see their own spaces at the same address.

This mapping scheme allows for efficient memory copying operations. To copy a stack segment between different workers, we simply copy directly from one worker given address to the relative address in the other worker's address space. Note that reallocation of address values in the copied segments is not necessary, because in all workers the stacks are located at the same addresses.

Choice Points and Or-Frames

In order to correctly execute the alternatives in a shared choice point, it is necessary to avoid possible duplicate alternative exploitation, as different workers can reference the choice point. Figure 3 represents the new structure of the choice points. The first six fields are inherited from Yap, while the last two were introduced in YapOr. The CP_PUA field contains the number of private unexplored alternatives in upper choice points, and is used to compute the worker's load. When a choice point is shared, the CP_OR-FR field saves a pointer to the corresponding or-frame associated with it. Otherwise, it not used.

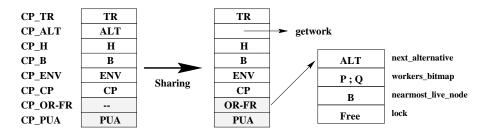


Fig. 3. Sharing a choice point.

A fundamental task when sharing work is to turn public the private choice points. Figure 3 illustrates the relation between the choice points before and after that operation, and the resulting connection with the correspondent orframe meanwhile created. The CP_ALT and CP_OR-FR choice point fields are updated to point respectively to the getwork pseudo-instruction (see next section) and to the newly created or-frame. The or-frame is initialized as follows: the next_alternative field stays with the ALT pointer, which was previously in the CP_ALT choice point field (i.e., the control of the untried alternatives goes into the or-frame); the workers involved in the sharing operation are marked in the workers_bitmap field; the nearmost_live_node field points to the parent choice point; and the lock field stays free to allow access to the structure.

New Pseudo-Instructions

YapOr introduced only two new instructions over Yap. One of them, is the already mentioned getwork, and the other is the getwork_first_time instruction. These two instructions are never generated by the compiler. They are introduced according to the progress of the parallel execution.

As mentioned earlier, a pointer to special code containing the <code>getwork</code> instruction is introduced in CP_ALT choice point field when the choice point is being turned public. This way, when a worker backtracks to a shared choice point, it executes the <code>getwork</code> instruction in place of the next untried alternative. The execution of this instruction allows for a synchronized access to untried alternatives among the workers sharing the correspondent or-frame.

Whenever the search tree for the top level goal is fully explored, all the workers, except worker 0, execute the getwork_first_time instruction. This instruction puts the workers in a delay state, waiting for a signal from worker 0, indicating the beginning of a new goal. On the other hand, worker 0 is responsible to give all the solutions encountered for the last exploited goal and to administrate the interface with the user until he makes a new query goal.

Worker's Load

Each worker holds a local register, load, as a measure of the number of private unexploited alternatives. The value in this register is used by the scheduler to select the best worker to share work with an idle worker. When a choice point is created, the field CP_PUA is initialized with the value of the private untried alternatives in the previous choice points. We do not include in this calculation values relative to the current choice point to avoid regular actualizations when backtracking occurs. The value of the load register is the sum of the previous value plus the number of untried alternatives in the created choice point.

A great number of Prolog programs contain predicates with relatively small tasks. To attain good performances in the system it is fundamental to avoid sharing such fine-gram work. In YapOr the update of the load register is delayed. It is only updated after a certain number of Call instructions are executed and whenever a sharing operation takes place, in which case it is reset to zero. A positive value in the load register indicates the scheduler that the worker has sharable work. By delaying the update of the load register, we want to encourage the workers to build up a reserve of local work and avoid over eager sharing.

Sharing Work

It is through the sharing process that parallel execution of goals becomes possible. This process takes place when an idle worker makes a sharing request to a busy worker and receives a positive answer. It can be divided in four main steps.

The *Initial step* is where the auxiliary variables are initialized and the stack segments to be copied are computed. The *Sharing step* is where the private choice points are turned into public ones. The *Copy step* is where the computed

segments are copied from the busy worker stacks to the idle worker ones. Finally, the *Installation step* is where the conditional variables in the maintained stacks of the idle worker are updated to the bindings present in the busy worker stacks.

To minimize the overheads in sharing, both workers cooperate in the execution of the four steps (see Fig. 4). The idea is as follows: after a common initial step, the worker P with excess of load starts the sharing step while the idle worker Q starts the copy one. Worker Q copies the stacks from P in the following order: trail, heap and local stack. The local stack can only be copied after P finishes its sharing step. After the sharing step, P can help Q in the copy step, if it was not yet concluded. It copies the stacks to Q but in a reverse order. This scheme has proved to be efficient because it avoids some useless variables checks and locks. Finally, worker P returns to its Prolog execution while worker Q executes the installation step and restarts a new task from the recently installed work. If meanwhile, worker P backtracks to a shared node, it has to wait until Q finishes its installation step in order to avoid possible undoing of variable bindings.

Worker P	Signals	Worker Q
Compute segments to copy	accept>	Waiting accept signal
Sharing step	2000po	Copy trail ? Copy heap ? Waiting sharing_ok signal
:	sharing_ok>	
Help Q in copy step?	ready>	
Waiting installation signal	<-installation-	
Back to Prolog execution	11115 04114 01011	Waiting ready signal
Backtrack to shared node ? Waiting ready signal		Installation step
•	<ready< td=""><td>. Back to Prolog execution</td></ready<>	. Back to Prolog execution
•		

Fig. 4. Synchronizations between $P \in Q$ during the sharing work process.

Implementation of Cut

Prolog programs use the cut builtin, !, to discard unnecessary alternatives. On the other hand, or-parallel execution means that workers may go ahead and execute work that will later be pruned by cut. One says in this case that the work is *speculative*.

YapOr currently implements a simple mechanism for cut. The worker executing cut, must go up in the tree until it reaches either the root cut choice

point or a choice point with workers executing left branches. While going up it may find workers in branches to the right. If so, it sends them a signal informing their branches have been pruned. When receiving such a signal, workers must backtrack to the shared part of the tree and become idle workers again.

Note that a worker may not be able to complete a cut if there are workers in left branches, as they can themselves prune the current cut. In these cases, one says the cut was left *pending*. In YapOr, pending cuts are only executed when all workers to the left finish their private work and backtrack into the public part of the tree. It will then be their responsibility to continue these cuts.

The existence of cuts and speculative work in the tree also affects scheduling. Muse implements a sophisticated strategy to avoid entering workers into scheduling work if there is non-speculative work available [3]. Further work is still necessary to make YapOr deal efficiently with this kind of work.

4 Performance Evaluation

The evaluation of YapOr was performed on a shared memory parallel machine, a Sun SparcCenter 2000 with 8 processors, 256 MBytes of main memory and a two level cache system. The system was running SunOS 5.6. The machine was otherwise idle while benchmarking.

A number of benchmark Prolog programs commonly used to assess other parallel Prolog systems were used to assess YapOr. All benchmarks find all the solutions for the problem. Multiple solutions are computed through "automatic backtracking on failure" after a solution has been found. We measured the timings and speedups for each benchmark, compared YapOr's performance with that of Muse, and analyzed the parallel activities to identify potential sources of overhead.

Timings and Speedups

To put the performance results in perspective we first compare YapOr's performance, configured with one worker, with the performance of Yap Prolog on the same machine. We would expect YapOr to be slower than Yap. YapOr must update the local work load register, check for sharing solicitations and for backtracking messages due to cut operations, and perform small tests to verify whether the bottom-most node is shared or private. It was found that Yap is on average 13% faster than YapOr.

Table 1 presents the performance of YapOr with multiple workers. The table presents the execution times in milliseconds, for the benchmark programs, with speedups relative to the 1 worker case given in parentheses. The execution times correspond to the best times obtained in a set of 10 runs.

The results show that YapOr is efficient in exploiting or-parallelism, giving effective speedups over execution with just one worker. The quality of the speedups achieved depends significantly on the amount of parallelism in the program being executed. The programs in the first group, puzzle, 9-queens, ham,

		Number of Workers					
Programs	1	2	4	6	7	8	
puzzle	10.042			1.550(6.48)			
9-queens	4.085	2.047(2.00)	1.026(3.98)	0.690(5.92)	0.596(6.85)	0.519(7.87)	
$_{ m ham}$	1.802	0.908(1.98)	0.474(3.80)	0.324(5.56)	0.281(6.41)	0.245(7.36)	
$5 \mathrm{cubes}$	1.029	0.516(1.99)	0.260(3.96)	0.181(5.69)	0.170(6.05)	0.145(7.10)	
8-queens 2	1.063	0.606(1.75)	0.288(3.69)	0.202(5.26)	0.159(6.69)	0.149(7.13)	
8-queens 1	0.450	0.225(2.00)	0.118(3.81)	0.080(5.63)	0.072(6.25)	0.067(6.72)	
nsort	2.089	1.191(1.75)	0.609(3.43)	0.411(5.08)	0.354(5.90)	0.315(6.63)	
sm*10	0.527	0.274(1.92)	0.158(3.34)	0.128(4.12)	0.118(4.47)	0.115(4.58)	
db5*10	0.167	0.099(1.69)	0.065(2.57)	0.068(2.46)	0.060(2.78)	0.061(2.74)	
db4*10	0.133	0.079(1.68)	0.056(2.38)	0.055(2.42)	0.052(2.56)	0.060(2.22)	
Σ	21.387	10.780(1.98)	5.370(3.98)	3.689(5.80)	3.201(6.68)	2.848(7.51)	
Average		(1.88)	(3.53)	(4.86)	(5.55)	(6.09)	

Table 1. YapOr execution times and speedups.

5cubes, 8-queens2 and 8-queens1, have rather large search spaces, and are therefore amenable to the execution of coarse-grained tasks. This group shows very good speedups up to 8 workers. The speedups are still reasonably good for the intermediate group, programs nsort and sm*10. For the last group, with programs db5*10 and db4*10, the speedups are rather poor and level off very quickly. The main reason for this to occur is the very low task granularities present in these programs.

It is interesting that in program puzzle, YapOr obtains super-linear speedups. This is probably due to lower miss rates, as the total cache size increases with the number of processors.

YapOr and Muse

Since YapOr is based on the same environment model as that used by the Muse system it is natural that we compare current YapOr's performance with that of Muse on a similar set of benchmark programs. We used the default compilation flags for Muse under SICStus, and also the default parallel execution parameters. The Muse version is the one available with SICStus Prolog release 3p6. Note that Muse under SICStus is a more mature system, and implements functionality that is still lacking in YapOr.

In table 2 we show the performance of Muse for the referred set of benchmark programs. YapOr benefits from the faster base performance of Yap, and manages to obtain about 20% better execution times on a single processor.

Surprisingly, the results also show that YapOr obtains better speedup ratios than Muse with the increase in the number of workers. This is the case even though YapOr has better base performance. We suppose this might a problem with the default parameters used in Muse.

	Number of Workers						
Programs	1	2	4	6	7	8	
puzzle	12.120					2.140(5.66)	
9-queens	3.890			0.690(5.64)			
$_{ m ham}$	2.550			0.520(4.90)			
$5 \mathrm{cubes}$	1.130	0.560(2.02)	0.280(4.04)	0.180(6.28)	0.160(7.06)	0.150(7.53)	
8-queens 2	1.350			0.270(5.00)			
8-queens 1	0.550	0.290(1.90)	0.160(3.44)	0.120(4.58)	0.110(5.00)	0.100(5.50)	
nsort	2.650	1.450(1.83)	0.810(3.27)	0.550(4.82)	0.510(5.20)	0.450(5.89)	
sm*10	0.670	0.360(1.86)	0.220(3.05)	0.170(3.94)	0.160(4.19)	0.150(4.47)	
db5*10	0.190	0.110(1.73)	0.080(2.38)	0.070(2.72)	0.070(2.72)	0.070(2.72)	
db4*10	0.160	0.090(1.78)	0.060(2.67)	0.070(2.29)	0.060(2.67)	0.070(2.29)	
Σ	25.260	13.720(1.84)	7.650(3.30)	5.310(4.76)	4.690(5.39)	4.370(5.78)	
Average		(1.85)	(3.22)	(4.47)	(4.90)	(5.27)	

Table 2. Muse execution times and speedups.

Parallel Execution Overheads

In this section we examine the various activities that take place during YapOr's parallel execution. In particular we timed the various activities a worker may be involved during execution in order to help determine which of those activities are causing a decrease in performance. The main activities traced are:

Prolog: time spent in Prolog execution, in verifying work-sharing requests and in keeping the work-load register updated.

Search: time spent searching for a busy worker.

Sharing: time spent in the four phases of the work-sharing process.

Get-Work: time spent in obtaining a new alternative from a shared node. It includes backtracking to that node and locking to ensure mutual exclusion.

Cut: includes the time spent in the execution of a cut in the shared region and the time to move to another node whenever a cut operation takes place.

Table 3 shows the percentage of the execution time spent in each activity for two benchmark programs, one in the high-parallelism class and the other in the medium-parallelism class. The percentages were taken for a number of workers ranging between 1 and 8 workers.

The results show that when the number of workers increases the percentage of the execution time spent on the *Search* and *Sharing* activities have the biggest increase. This happens because of the increased competition for finding work which makes workers get smaller tasks and consequently increase the frequency by which they have to search for new work. The increased competition also makes for unexploited alternatives to be situated more and more in the shared part of the tree which increases the *Get-Work* activity.

The percentage of the execution time spent executing the cut predicate is minimal, indicating minimal overheads when executed in parallel.

	Number of Workers						
Activity	1	2	4	6	7	8	
puzzle							
Prolog	100.00	99.95	99.56	99.20	99.02	98.68	
Search	0.00	0.02	0.16	0.32	0.41	0.60	
Sharing	0.00	0.02	0.17	0.32	0.38	0.50	
Get-Work	0.00	0.01	0.10	0.17	0.19	0.23	
Cut	0.00	0.00	0.00	0.00	0.00	0.00	
sm							
Prolog	100.00	97.68	86.71	74.56	69.08	63.29	
Search	0.00	0.81	5.02	11.50	13.85	16.87	
Sharing	0.00	0.86	5.64	10.17	13.14	15.76	
Get-Work	0.00	0.61	2.51	3.52	3.61	3.88	
Cut	0.00	0.04	0.13	0.25	0.32	0.20	

Table 3. Workers activities during execution.

One possible explanation for the decrease on the amount of parallelism is shown in table 4. This table shows the average number of tasks executed by one worker and the average size of a task. The size of a task may be defined as the average number of goals (that is *Call* instructions) executed within that task.

	Number of Workers						
	1	2	4	6	7	8	
puzzle							
Tasks	1	213	1780	2763	3095	3813	
Calls per task	171024	803	96	62	55	45	
sm							
Tasks	1	53	188	267	308	362	
Calls per task	7965	150	42	30	26	22	

Table 4. Average number of tasks and call instructions per task.

The table clearly shows that increasing the number of workers decreases the granularity of the available parallelism. The consequence of this is that workers run out of work more quickly and therefore the activities related to work search, work sharing and getting work will become more important in the execution, causing overheads to increase. It is therefore no surprise that the performance for benchmark programs such as *salt-mustard* degrades significantly for larger numbers of workers.

5 Conclusions

We have presented YapOr, an or-parallel Prolog system based on the environment copying model. The system has good sequential and parallel performance

on a large set of benchmark programs. It was able to achieve excellent speedups for applications with coarse-grained parallelism and it performs better than Muse for the applications with medium parallelism. The good performance was also explained by the fact that for most benchmarks YapOr spends its time mainly executing reductions and not managing parallelism.

Recently, we have extended Yap to execute tabled logic programs. We are now working on adjusting the YapOr system to support parallel execution of such tabled logic programs [12, 13].

References

- 1. K. A. M. Ali and R. Karlsson. Full Prolog and Scheduling OR-Parallelism in Muse. *International Journal of Parallel Programming*, 19(6):445–475, Dec. 1990.
- 2. K. A. M. Ali and R. Karlsson. The Muse Approach to OR-Parallel Prolog. *International Journal of Parallel Programming*, 19(2):129–162, Apr. 1990.
- 3. K. A. M. Ali and R. Karlsson. Scheduling Speculative Work in Muse and Performance Results. *International Journal of Parallel Programming*, 21(6), Dec. 1992.
- 4. A. Beaumont, S. M. Raman, and P. Szeredi. Scheduling Or-Parallelism in Aurora with the Bristol Scheduler. In *PARLE'91*, LNCS. Springer-Verlag, Apr. 1991.
- 5. A. Calderwood and P. Szeredi. Scheduling Or-parallelism in Aurora the Manchester Scheduler. In *ICLP'89*, pages 419–435, Lisbon, June 1989. The MIT Press.
- 6. M. Correia, F. Silva, and V. S. Costa. The SBA: Exploiting Orthogonality in AND-OR Parallel Systems. In *ILPS'97*, Port Jefferson, Oct. 1997. The MIT Press.
- L. Damas, V. S. Costa, R. Reis, and R. Azevedo. YAP User's Guide and Reference Manual. Centro de Informática da Universidade do Porto, 1989.
- 8. G. Gupta, K. A. M. Ali, M. Carlsson, and M. Hermenegildo. Parallel Execution of Prolog Programs: A Survey. Mar. 1996. Preliminary Version.
- 9. G. Gupta and B. Jayaraman. Analysis of Or-parallel Execution Models. *ACM Transactions on Programming Languages*, 15(4):659-680, Sep. 1993.
- Roland Karlsson. A High Performance OR-parallel Prolog System. PhD thesis, The Royal Institute of Technology, Stockholm, Mar. 1992.
- 11. E. Lusk and et. all. The Aurora Or-parallel Prolog System. In FGCS'88, pages 819–830. ICOT, Tokyo, Nov. 1988.
- R. Rocha, F. Silva, and V. S. Costa. On Applying Or-Parallelism to Tabled Evaluations. In TLP'97, Leuven, Belgium, July 1997.
- R. Rocha, F. Silva, and V. S. Costa. Or-Parallelism within Tabling. In PADL'99, number 1551 in LNCS, pages 137–151. Springer-Verlag, 1998.
- Fernando M. A. Silva. An Implementation of Or-Parallel Prolog on a Distributed Shared Memory Architecture. PhD thesis, Dept. of Computer Science, Univ. of Manchester, Sep. 1993.
- R. Sindaha. The Dharma Scheduler Definitive Scheduling in Aurora on Multiprocessor Architecture. Tech. Report, Dept. of Computer Science, Univ. of Bristol, Nov. 1991.
- 16. David H. D. Warren. An Abstract Prolog Instruction Set. Technical Note 309, SRI International, Sep. 1983.