Regular contribution

Exploiting transition locality in automatic verification of finite-state concurrent systems

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Published online: 6 July 2004 - © Springer-Verlag 2004

Abstract. In this paper we show that statistical properties of the transition graph of a system to be verified can be exploited to improve memory or time performances of verification algorithms.

We show experimentally that protocols exhibit transition locality. That is, with respect to levels of a breadthfirst state space exploration, state transitions tend to be between states belonging to close levels of the transition graph. We support our claim by measuring transition locality for the set of protocols included in the Mur φ verifier distribution.

We present a *cache-based verification algorithm* that exploits transition locality to decrease memory usage and a *disk-based verification algorithm* that exploits transition locality to decrease disk read accesses, thus reducing the time overhead due to disk usage. Both algorithms have been implemented within the Mur φ verifier.

Our experimental results show that our cache-based algorithm can typically save more than 40% of memory with an average time penalty of about 50% when using (Mur φ) bit compression and 100% when using bit compression and hash compaction, whereas our diskbased verification algorithm is typically more than ten times faster than a previously proposed disk-based verification algorithm and, even when using 10% of the memory needed to complete verification, it is only between 40 and 530% (300% on average) slower than (RAM) Mur φ with enough memory to complete the verification task at hand. Using just 300 MB of memory our disk-based $Mur\varphi$ was able to complete verification of a protocol with about 10^9 reachable states. This would require more than 5 GB of memory using standard $Mur\varphi$.

Keywords: Automatic verification – Model checking – Explicit state space exploration

1 Introduction

State space exploration (*reachability analysis*) is at the very heart of all algorithms for automatic verification of concurrent systems. In fact, checking that a *finite-state system* (FSS) satisfies a given property (e.g., a safety property) typically entails exploring (visiting) all reachable system states.

Unfortunately, reachability analysis is plagued by the well-known *state explosion* problem: that is, our computer runs out of memory because of the huge number of reachable states that have to be stored in memory.

Essentially there are two main techniques to perform state space exploration: *explicit* and *symbolic*. *Explicit* state space exploration uses a hash table to store the set of visited states, whereas *symbolic* state space exploration represents the set of visited states with its characteristic function which, in turn, is represented and manipulated using *ordered binary-decision diagrams* (OBDDs) [3, 4].

For protocol verification, *explicit* state space exploration often outperforms *symbolic* state space exploration [18]. Indeed, our results [26] show that explicit state space exploration can be quite useful also for automatic verification of *hybrid systems*. Since here we are mainly interested in protocol verification, we focus on explicit state space exploration: tools based on this technique are, e.g., SPIN [15, 32] and Mur φ [7, 23].

In our context, roughly speaking, two kinds of approaches have been studied to counteract (i.e., delay) state explosion: *memory saving* and *auxiliary storage*.

In a memory saving approach, essentially one tries to reduce the amount of memory needed to represent the

This research has been partially supported by MURST projects MEFISTO and SAHARA.

This paper is an extended version of the papers [27, 39].

set of visited states. Examples of the memory saving approach can be found in [16, 17, 19, 20, 28, 35, 36, 42].

In an auxiliary storage approach one tries to exploit disk storage as well as distributed processors (network storage) to enlarge the available memory (and CPU). Examples of this approach can be found in [29, 30, 33, 34, 38].

In this paper we study the possibility of exploiting a statistical property of protocol transition graphs, namely, the *transition locality*, to improve memory and time performances of state verification algorithms. This is quite similar to what is usually done when optimizing a CPU on the basis of program profiling [25]. Statistical properties of protocols have also been studied in the context of *probabilistic verification* [40].

We show experimentally (Sect. 3) that protocols exhibit *transition locality*. That is, transitions tend to be local with respect to levels of a breadth-first (BF) search. We support our claim by measuring transition locality for the set of protocols included in the Mur φ verifier distribution.

Finally, we present a *cache-based BF state space explo*ration algorithm (Sect. 4) that exploits transition locality to decrease memory usage and a *disk-based BF state space exploration* algorithm (Sect. 5) that exploits transition locality to save disk read accesses, thus reducing the time overhead with respect to a normal disk-based verification.

Both algorithms have been implemented within the Mur φ verifier [23] and are compatible with all the well-known state compression techniques (such as those in [16, 36]) and, in particular, with all state reduction techniques present in Mur φ .

By using Mur φ , we can take advantage of a fullfeatured verifier to test our algorithms together with all the other memory reduction techniques already implemented in Mur φ , and we have a large set of benchmark protocols to test. Of course, our algorithms can be included within any explicit verifier implementing a BF search (e.g., the latest SPIN version).

1.1 Cache-based BF state space exploration

In our *cache-based BF state space exploration* algorithm we essentially replace the hash table used in a memorybased BF state space exploration with a fixed-size *cache memory* (i.e., no collision detection is done), using auxiliary (disk) storage for the BF queue.

Therefore, we do not incur state explosion, but we may incur nontermination when our cache memory is *too small*: in fact, in this case we may visit the same set of states over and over. However, upon termination we are guaranteed that all reachable states have been visited. To the best of our knowledge this is the first time that such a fixed size memory state space exploration algorithm has been presented.

Note that our use of the cache memory differs from that in [42] (see also [8, 13, 14]). In fact [42] presents a state compression technique, and "no collision detection" in [42] refers to state signatures [34, 35], that is, a (signature) collision in [42] may lead to declare as visited a nonvisited state, whereas our algorithm simply forgets a visited state upon collision, thus possibly declaring as nonvisited a visited state.

The implementation of our cache-based algorithm within the Mur φ verifier (Sect. 4.2), named *CMurphi3.1*, can be downloaded from [5].

Experiments using our cache-based algorithm (Sect. 6.2) show that on average we can verify systems more than 40% larger than those that can be handled using a hash-table-based approach. Our time penalty is about 50% when using (Mur φ) bit compression and 100% when using bit compression and hash compaction.

1.2 Disk-based BF state space exploration

Our disk-based BF state space exploration algorithm is obtained from the one in [34] by using only a suitable subset of the visited states stored on disk to clean up the BF queue. By reducing disk read accesses we also reduce our time overhead with respect to a memory-based BF state space exploration.

Note that the SPIN verifier can use disk storage for the depth-first (DF) stack. However, visited states are still stored in a memory-based hash table, which is where state explosion typically occurs.

The implementation of our disk-based algorithm within the Mur φ verifier (Sect. 5), named *CMurphi4.1*, can be downloaded from [5].

Experimental results on using our disk-based algorithm (Sect. 6.4) show that, even when using 10% of the memory needed to complete verification, our diskbased Mur φ is only between 40 and 530% times slower (300% on average) than (memory-based) standard Mur φ with enough memory to complete the verification task at hand. Moreover, our disk-based algorithm is typically more than ten times faster than the disk-based algorithm presented in [34].

Using just 300 MB of memory our disk-based Mur φ was able to complete verification of a protocol with almost 10⁹ reachable states. Using standard Mur φ this protocol would require more than 5 GB of memory.

2 Background

In this section we give some basic information that will be useful in the subsequent discussion.

2.1 Finite-state systems

For our purposes, a protocol is represented as a *finite-state system*.

Definition 1. 1. A finite-state system (FSS) S is a 4tuple (S, I, A, R) where: S is a finite set (of states), $I \subseteq S$ is the set of initial states, A is a finite set (of transition labels), and R is a relation on $S \times A \times S$. R is usually called the transition relation of S.

- 2. Given states $s, s' \in S$ and $a \in A$, we say that there is a transition from s to s' labelled a if and only if R(s, a, s') holds. We say that there is a transition from s to s' (notation R(s, s')) if and only if there exists $a \in A$ so that R(s, a, s') holds. The set of successors of state s (notation next(s)) is the set of states s' so that R(s, s').
- The set of reachable states of S (notation Reach(S)) is the set of states of S reachable in 0 (zero) or more steps from I. Formally, Reach(S) is the smallest set so that 1. I ⊆ Reach(S),

2. For all $s \in \mathbf{Reach}(\mathcal{S})$, $\mathbf{next}(s) \subseteq \mathbf{Reach}(\mathcal{S})$.

In the following discussion we will always refer to a given system S = (S, I, A, R). Thus, for example, we will write **Reach** for **Reach**(S). Also, we may speak about the set of initial states I as well as about the transition relation R without explicitly mentioning S.

The core of all automatic verification tools is the *reachability analysis*, the computation of **Reach** given a definition of S in some language.

Since the transition relation R of a system defines a graph (*transition graph*), computing **Reach** means visiting (exploring) the transition graph starting with the initial states in I. This can be done, e.g., using a *depthfirst* (DF) search or a *breadth-first* (BF) search. For example, Mur φ [23] and (the latest version of) SPIN [32] may use a DF as well as a BF search.

In the following discussion we will focus on BF search. As is well known, a BF search defines *levels* on the transition graph. Initial states (i.e., states in I) are at level 0. The states in (next(I) - I) (states reachable in one step from I and not in I) are at level 1, etc.

Definition 2. Formally we define the set of states at level k (notation L(k)) as follows.

L(0) = I,

 $L(k+1) = \{s' | \text{ there exists } s \in L(k) \text{ so that } [R(s,s') \text{ and} s' \notin \bigcup_{i=0}^{i=k} L(i)] \}.$

Given a state $s \in \mathbf{Reach}$, we define $\operatorname{level}(s) = k$ if and only if $s \in L(k)$. That is, $\operatorname{level}(s)$ is the level of state s in a BF search of S.

The set Visited(k) of states visited (by a BF search) by level k is defined as follows. Visited(k) = $\bigcup_{i=0}^{i=k} L(i)$.

2.2 The Mur φ verifier

In this section we give a short overview of the Mur φ verifier. For further details we refer the reader to [7, 23].

From a conceptual point of view Mur φ takes as input a *finite-state system* S and checks whether a given invariant property φ for S is satisfied.

An *invariant property* can be seen as a map from (the states of) S to the set $\mathcal{B} = \{0, 1\}$ of boolean values. Thus

the verification goal is to check that, for each state s, reachable from an initial state of S, the given invariant φ holds (i.e., that $\varphi(s) = 1$). Of course, in general this check entails visiting all reachable system states.

Figure 1 shows the standard BF state space exploration algorithm. Essentially, this is the algorithm used by $Mur\varphi$ to visit the state space of a given system S. The algorithm makes use of two main memory data structures. A *queue*, where states are stored and retrieved (in FIFO order) during the search, and a *hash table* used to store all visited states. In Fig. 1 invariants for state s may be checked whenever function Enqueue(Q, s) is called.

Since S is a finite-state system, the algorithm in Fig. 1 always terminates since we never visit the same state more than once.

Note that $\operatorname{Mur}\varphi$ (like SPIN) represents states *explic*itly: each visited state is stored in memory (namely, in the hash table). There are model checkers that represent states *symbolically*. In symbolic model checking the set V of visited states is represented by its characteristic function f (i.e., $f(s) = \operatorname{if} s \in V \operatorname{then} 1 \operatorname{else} 0$) and suitable data structures (such as OBDDs, ordered binarydecision diagrams [3]) are used to represent f. Examples of symbolic model checkers are SMV [31], UPP-AAL [21, 41] (both based on OBDDs), and Hytech [1, 2, 12], which is based on polyedra in a multidimensional real space [6, 9–11].

Explicit model checkers (such as Mur φ and SPIN) typically perform better on *softwarelike* (asynchronous) systems [18], whereas *symbolic* model checkers (such as SMV) typically perform better on *hardwarelike* (synchronous) systems.

```
FIFO_Queue Q;
HashTable T;
bfs(init_states, next)
 /* load Q with initial states */
 foreach s in init_states Enqueue(Q, s);
 /* mark init states as visited */
 foreach s in init_states Insert(T, s);
 /* visit */
 while (Q is not empty)
 {
  s = Dequeue(Q);
  foreach s' in next(s)
   if (s' is not in T)
    Insert(T, s');
    Engueue(Q, s');
 }
}
```

Fig. 1. Explicit breadth-first search

Since explicitly storing each state can take a large amount of memory, $Mur\varphi$ offers several techniques to reduce the state size. In the development of our algorithms, two techniques are very important: bit compression [23] and hash compaction [34, 35].

When bit compression is enabled, $Mur\varphi$ saves memory by using every bit of the *state descriptor*, the memory structure maintaining the state variables. On the other hand, when bit compression is not used, state variables are aligned on byte boundaries of the state descriptor, thus wasting some space. Typically, bit compression saves on average 300% of memory; however, it slows down the verifier by approximately 25%.

When using hash compaction, compressed values (also called *state signatures*) are stored in the hash table instead of full state descriptors; however, there is a certain probability that some states will be omitted during verification, since different states may have the same signature. By default, $Mur\varphi$ compresses state descriptors up to 40 bits.

Hash compaction can be combined with bit compression: in this case, bit compression is applied on the state queue, whereas hash compaction is used on the hash table.

3 Transition locality for finite-state systems

In this section we define our notion of locality for transitions and show experimentally that, for protocols, most transitions are local. We do this by showing that, for all our benchmark protocols, most transitions are indeed local.

We used as benchmark protocols all those available in the Mur φ verifier distribution [23] plus the Kerberos protocol from [37]. Most of these protocols are scalable since they depend on a set of parameters. By modifying such parameters, the size of the protocol state space can be increased. To save time, in most of our experiments we set protocol parameters so as to obtain small-sized models. This is reasonable, since locality is a structural property of a protocol transition graph. That is, locality may or may not hold independently of the size of the transition graph.

The protocols tested cover a wide range of concurrent software typologies such as synchronization, authentication, cache coherence, distributed locks, etc. Thus we have a fairly representative benchmark set.

3.1 Transition locality

Informally, *transition locality* means that, for most transitions, source and target states will be in levels not too far apart.

Definition 3. Let S = (S, I, A, R) be an FSS. A transition in S from state s to state s' is said to be k-local if and only if $||evel(s') - |evel(s)| \le k$.

Transition R(s, a, s') is said to be a k-transition if and only if level(s') - level(s) = k. Note that for k-transitions, $k \leq 1$ and can be negative.

A 1-transition from state s is a forward transition, i.e., a transition leading to a new state [a state not in Visited(level(s))]. A k-transition with k < 0 is a backward transition, i.e., a transition leading to a visited state. A 0-transition from state s just leads to a state s' on the same level of s.

We are interested in the distribution of k-transitions in the transition graph. This motivates the following definition.

- **Definition 4.** 1. We denote by N(s, k) the number of k-transitions from s and by N(s) the number of transitions from s.
- 2. We define: $\delta(s,k) = N(s,k)/N(s)$. That is, $\delta(s,k)$ is the fraction of transitions from s that are k-transitions, which represents the probability of getting a ktransition when picking at random a transition from s. Of course, if s is on level λ , we have: $\sum_{k=-\lambda}^{k=1} \delta(s,k) =$ 1.
- 3. If we consider the experiment consisting of picking at random a state s in **Reach** and returning $\delta(s, k)$, then we get a random variable that we denote by $\Delta(k)$. The expected value $E\{\Delta(k)\}$ of $\Delta(k)$ is the average value of $\delta(s, k)$ on all reachable states. That is: $E\{\Delta(k)\} = \frac{1}{|\text{Reach}|} \sum_{s \in \text{Reach}} \delta(s, k)$.
- 4. As usual, we denote by $\sigma^2(k)$ the variance of $\Delta(k)$ and by $\sigma(k)$ its standard deviation [24].

Our choice of $\Delta(k)$ to measure locality stems from the fact that we also want to known how 1-local transitions are distributed in the transition graph. That is, we want to know if 1-local transitions are all concentrated on some part of the graph or if they are more or less uniformly distributed in the transition graph. This can be measured by computing the standard deviation of $\Delta(k)$.

3.2 Measuring locality

We measured locality using the Mur φ verifier [23]. This gives us a wide benchmark set for free since many protocols have already been defined using the Mur φ input language. We modified Mur φ so as to compute $E\{\Delta(k)\}$ and $\sigma(k)$ while carrying out state space exploration.

All the experiments were performed using bit compression (Mur φ option -b) and disabling deadlock detection (option -ndl). Mur φ stops the state exploration as soon as a deadlock or a bug is found; since our main interest here is in gathering information about the structure of the transition graph, deadlock detection has been disabled. This allows us to explore the whole reachable part of the transition graph also for protocols containing deadlocks (e.g., Kerberos kerb).

3.3 Experimental results about locality

We want to show experimentally that transitions in protocols tend to be *local* with respect to levels. We do this by showing that for the set of protocols shown in Table 1 most transitions are 1-local, that is, they are k-transitions with k = -1, 0, 1. In other words, for most transitions, R(s, a, s'), s' will be either on the same level as s (0transition) or on the next level (1-transition) or on the previous level (-1-transition). More information (e.g., number of reachable states, etc.) about the protocols in Table 1 are available in Sect. 6, Table 3.

The expected fraction of k-transitions is $E\{\Delta(k)\}$; thus the expected fraction of 1-local transitions is $SumAvg = E\{\Delta(-1)\} + E\{\Delta(0)\} + E\{\Delta(1)\}$. When this value is close to 1, almost all transitions in the protocol are 1-local, whereas when it is close to 0, there are almost no 1-local transitions in the protocol.

To get some understanding of how 1-local transitions are distributed in the transition graph, we compute the standard deviation $\sigma(k)$ of $\Delta(k)$. In fact, if $\sigma(k)$ is small compared to $E\{\Delta(k)\}$, then for most states $\delta(s,k)$ is close to $E\{\Delta(k)\}$.

The results of our experiments are shown in Table 1 where, for each protocol and for k = -1, 0, 1, we show $E\{\Delta(k)\}, \sigma(k)$ and SumAvg. Our measures depend neither on the used machine nor on the memory available as long as the visit is completed. Of course, we would have obtained the same results without bit compression. Note that the three protocols with superscript * in Table 1 contain bugs. In such cases, state space exploration stops as soon as a bug is found. We included such *buggy* protocols just for completeness. Our findings can be summarized as follows. **Experimental Fact 1.** From column SumAvg of Table 1 we observe that, in all protocols of our benchmark set, for most states more than 60% of the transitions are 1-local. Indeed, for most of these protocols, we have that for most states more than 85% of the transitions are 1-local. This shows that most transitions are 1-local.

Moreover, for many protocols, standard deviations $\sigma(-1)$, $\sigma(0)$, $\sigma(1)$ are *relatively small* compared to *SumAvg*. In such cases, *for most states* the fraction of 1-local transitions is close to *SumAvg*.

Since for most states most transitions are 1-local, we have that locality holds uniformly. Hence if we pick at random a state $s \in \mathbf{Reach}$, in most cases most transitions from s (say, about 85%) will be 1-local.

On the other hand, it is not difficult to define a simple example of a nonlocal system. Consider the system NLS defined in Fig. 2, whose transition graph is shown in Fig. 3. NLS is highly nonlocal: in fact, following the notation in Definition 4, we have that $E\{\Delta(i)\} = O\left(\frac{\log n}{n}\right), i = -1, 0, 1$; thus $E\{\Delta(-1)\} + E\{\Delta(0)\} + E\{\Delta(1)\} = O\left(\frac{\log n}{n}\right)$. Therefore, by choosing n large enough we can make the fraction of 1-local transitions in NLS as small as we like.

One may wonder why protocols exhibit locality. We conjecture that this is structural for *human-made* systems and, indeed, is a consequence of the techniques used (consciously or unconsciously) to master complexity in the design task.

Remark 1. A very interesting result would be to prove (or disprove) that almost all FSSs exhibit locality. Note, however, that, a priori, truthness or falsehood of such

Model	$E\{\mathbf{\Delta}(-1)\}$	$\sigma(-1)$	$E\{\mathbf{\Delta}(0)\}$	$\sigma(0)$	$E\{\mathbf{\Delta}(1)\}$	$\sigma(1)$	Sum Avg
cache3	0.0401213	0.178884	0.00476603	0.0558438	0.565482	0.381654	0.61036933
kerb	0	0	0.18417	0.385163	0.441651	0.494666	0.625821
ns-old	0.546833	0.497802	0	0	0.101695	0.302247	0.648528
ns	0.585714	0.492598	0	0	0.0969388	0.295874	0.6826528
ldash	0.0107259	0.0719168	0.0763593	0.138464	0.624139	0.191624	0.7112242
adash	0.0381775	0.122	0.00558149	0.0436066	0.723393	0.292406	0.76715199
newcache3	0.0360339	0.0991869	0.00912116	0.0533416	0.736229	0.227796	0.78138406
eadash	0.050598	0.0960145	0.015647	0.0562551	0.765236	0.178076	0.831481
$adashbug^*$	0.0376604	0.124403	0.00228899	0.0295028	0.793586	0.270018	0.83353539
sci	0.215646	0.238654	0.0108192	0.0617188	0.642466	0.265885	0.8689312
cache3multi	0.0389835	0.102299	0.00299148	0.0263492	0.831139	0.176004	0.87311398
list6	0.0183668	0.0710808	0.0246248	0.0815233	0.844018	0.189053	0.8870096
mcslock1	0.0128856	0.0675736	0	0	0.881379	0.162002	0.8942646
sym.cache3	0.041675	0.10478	0.00757049	0.0445772	0.876884	0.17786	0.92612949
mcslock2	0.0054652	0.0458147	0.00056426	0.0151108	0.921489	0.156949	0.92751846
$\texttt{arbiter}^*$	0.00848939	0.057543	0.0107366	0.0537135	0.92784	0.168859	0.94706599
n_peterson	0	0	0	0	0.958174	0.0877715	0.958174
list6too	0	0	0	0	0.988378	0.0621402	0.988378
newlist6	1.53327e-05	0.00175109	0	0	0.999586	0.00908985	0.9996

Table 1. Transition distribution table



Fig. 2. A simple nonlocal system



Fig. 3. Transition graph for the system in Fig. 2

a result would not imply anything about protocols in particular.

For example, for OBDDs we have already a similar situation (in *reverse mode*). In fact, in [22] it is proved that, for almost any boolean function f of n variables, the smallest OBDD for f has size exponential in n. Nevertheless, it is experimentally known that most of the boolean functions implemented by digital circuits have OBDDs of size polynomial (often about linear) in the number of variables.

4 Cache-based BF state space exploration

In this section we give an algorithm that takes advantage of the transition locality (Sect. 3) of protocols. Note that the correctness of our algorithm does not depend on the results in Sect. 3. However, such results help us to understand why the proposed algorithm is effective on protocol-like systems.

We modify the standard (hash-table-based) BF search to use a *cache memory* rather than a hash table. This means that we do not perform any collision check: when a state s' is hashed to an entry already holding a state s, we replace s with s', thus *forgetting* about s. In the following discussion, we shall call this algorithm CBFS (*cache-based breadth-first search*). Using a fixed-size cache rather than a hash table to store visited states is appealing since the cache size does not grow with the state space size. However, this approach faces two obvious obstacles:

Queue explosion. The queue size may get very large. In fact, since we forget visited states, at each level in our CBFS the *apparently* new states tend to be much more than those of a true (hash-table-based) BF search. This may quickly fill up our queue.

For this reason, unlike previous work on the use of auxiliary storage in state space exploration (e.g., in [34]), we use disk storage to hold the queue rather than the hash table. This is good news since keeping a queue on disk is much easier than keeping a hash table on disk and, since a queue has a high *locality* of reference (LOR) (whereas a hash table has a very poor LOR), the time overhead due to disk access is minimal. We point out that, working independently, Steven German at IBM [43] has also extended the queue implementation of the original Mur φ verifier so as to use disk storage for the queue.

Nontermination. Our state space exploration may not terminate. In fact, because of collisions, we forget visited states and thus we may visit again and again the same set of states.

Here is where *locality* helps us. Since most transitions are local, one can reasonably expect that, to avoid looping, it is enough to remember the *recently* visited states rather than *all* visited states. This is exactly what a *cache memory* is for.

Note that a cache memory implements the above discipline only in a *statistical sense*. That is, replaced (*forgotten*) states in the cache are *often* old states, but not always. Fortunately, this is enough for us. Of course, if the cache memory is *too small* with respect to the size of the state space, locality cannot help us.

Note that, whenever our CBFS terminates, it gives the correct answer. That is, *all* reachable states have been visited. However, when we stop our cache-based visit to prevent looping, we may or may not have visited all reachable states.

In the following discussion we sketch our algorithm and show how we integrated it into the $Mur\varphi$ verifier.

4.1 From BFS to CBFS

To take advantage of transition locality we modify the standard BF search of Fig. 1 as shown in Fig. 4.

We use a cache memory rather than a hash table and we guard the main search loop with a check on the collision rate (i.e., the ratio <number of collisions in cache> / <number of insertions in cache>) since, as was already stated, using a cache memory may lead to nontermination. Indeed, when the collision rate is close to 1, nearly every state stored in the cache overwrites another state, so we are forgetting too much to complete the search.

```
FIFO_Queue Q;
Cache T;
collision_rate = 0.0;
bfs(init_states, next)
{
 /* load Q with initial states */
 foreach s in init_states Enqueue(Q, s);
 /* mark init states as visited */
 foreach s in init_states Insert(T, s);
while ((Q is not empty) and
        (collision_rate <= 0.9))
 {
  s = Dequeue(Q);
  foreach s' in next(s)
  if (s' is not in T)
   {
    Insert(T, s');
    Enqueue(Q, s');
   }
 }
}
```

Fig. 4. Cache-based breadth-first search (CBFS)

Moreover, we implement our queue using auxiliary memory. In the present implementation we use a disk as auxiliary memory; thus, since disks are quite large, our disk queue approximates a potentially infinite queue. Note, however, that (the memory of) another workstation could have been used as well.

The implementation schema for the cache memory is quite standard. We reuse the open-addressed hash table and hash function implemented in $Mur\varphi$ to store the states. However, we limit the length of the collision chain so that if no free slot is found within MAX_HT_CHAIN_LENGTH steps, a random slot within the chain is selected and overwritten with the new state.

Figure 5 shows our implementation schema for the queue on disk. We split the queue **Q** into two segments: *head queue* and *tail queue*; both queues are in memory and each can hold ram_queue_size states.

States are *enqueued* in the tail queue and *dequeued* from the head queue. When the tail queue is full, its content is flushed on disk by appending it to swapout_file.

When the head queue is empty, it gets reloaded with states from swapin_file; if this file is also empty, we swap swapin_file and swapout_file and try to load states from swapin_file again; if it is still empty, we swap the head queue with the tail queue.

Note that, using pointers, swapping (for files and for queue segments) is immediate (just a few assignments).

4.2 Integrating CBFS within $Mur\varphi$

Rather than building a tool from scratch, we decided to integrate our algorithm into the $Mur\varphi$ verifier. This gives us at least two advantages. First, we have immediately

```
void Enqueue(state s)
if (tail queue is full) swap_out();
 /* tail_queue is not full */
 insert s into tail_queue;
 tail_queue_elements++;
}
/* hyp: Dequeue() always
 * called on non empty queue */
state Dequeue()
if (head queue is empty) swap in();
 /* head queue is not empty now */
head_queue_elements--;
return top of head_queue;
}
void swap_out()
{
 /* flush tail_queue on disk
 * and reset counter */
 append tail_queue to swapout_file;
 tail_queue_elements = 0;
}
void swap_in()
 /* load head_queue from disk */
 if (swapin_file is not empty)
 {
 load head_queue with
 at most ram_queue_size states
 from swapin_file;
 }
 else
  /* swapin_file is empty,
   * we use swapout_file */
  swap the swapin_file and swapout_file;
  if (swapin_file is not empty)
  {
   load head_queue
   with at most ram_queue_size states
   from swapin_file;
  }
  else
  {
   /* also swapout_file is empty,
    * we use tail_queue */
   swap the head_queue and tail_queue;
   if (head_queue is empty)
    /* underflow error */
    error("queue is empty");
   }
 }
 }
head_queue_elements =
 number of states in head_queue;
```

Fig. 5. Disk queue functions

available many benchmark systems for testing. Second, we can exploit other memory reduction techniques that have already been implemented. We call CMur φ (*Cached Mur\varphi*) [5] the resulting cache-based Mur φ verifier.

To be consistent with the *standard* (hash-table-based) Mur φ verifier, the value of **ram_queue_size** (Fig. 5) is such that the head queue and the tail queue together take the same amount of memory as the queue in standard Mur φ . That is, if M is the available memory for verification, then gPercentActive*M is the amount of RAM memory used for the queue in standard Mur φ as well as in our cache-based Mur φ (gPercentActive is in [0, 1] and is the Mur φ constant defining the fraction of memory Mused for the queue).

Integrating our algorithm into the Mur φ verifier requires some care and consideration. As far as we are concerned, Mur φ BF search can have two behaviors: one when hash compaction is not used and another when it is. All other Mur φ options have no impact on the hash table or the queue and thus are *transparent* to us.

When no hash compaction is used, to save memory, Mur φ stores states in the hash table and pointers to hash table slots (states) in the queue, whereas when hash compaction is used, it stores state signatures in the hash table and states in the queue.

Therefore, if we use a cache rather than a hash table, when hash compaction is not active and we overwrite a cache slot (collision), as a side effect we may also change the content of the queue, since that slot may be pointed to by the queue.

For this reason we modified the queue so that it holds states also when hash compaction is not used; all $Mur\varphi$ functions depending on this fact have been changed accordingly.

Of course, storing states rather than pointers (to states) takes more space: however, for the reasons explained above, we are going to use disk storage to implement our queue; thus having a large queue does not lead to any serious problem in our context.

Note that with our approach all optimization strategies implemented within the Mur φ verifier (bit compression, hash compaction, symmetry reduction, etc.) are also available to us. Moreover, the bound on the omission probability for the hash compaction computed "online" by Mur φ according to [36] is also (a fortiori) valid in our case: in fact, at each (BF) level we visit a superset of the states visited by a standard BF visit.

5 Disk-based BF state space exploration

Disk read/write times are much larger than memory read/write times. Thus, not surprisingly, the main drawback of DBFS (*disk-based breadth-first search*) with respect to RAM-BFS (*RAM-based breadth-first search*) is the time overhead due to disk usage. On the other hand, because of *state explosion*, memory is one of the main obstacles to automatic verification; thus using disks to increase the amount of memory available during verification is very appealing.

In [34] a DBFS algorithm has been proposed for the Mur φ verifier. Here we show how to improve that algorithm by exploiting *transition locality* (Sect. 3). In particular, disk accesses for reading can be reduced, leading to a reduction in the time overhead due to disk usage. In the following we call LDBFS our *locality*-based DBFS algorithm.

As in [34] we actually have two DBFS algorithms: one for the case in which *hash compaction* is enabled and one for the case in which it is not enabled. In the following discussion we only present the most interesting version that is compatible with the hash compaction option; the other version is simpler and easy to derive from the first.

We call $\mathrm{DMur}\varphi$ the resulting disk-based $\mathrm{Mur}\varphi$ verifier.

5.1 Data structures

The data structures used by LDBFS are in Fig. 6 and are essentially the same as the ones used in [34]. We have a table M to store signatures of *recently* visited states, a file D to store signatures of *all* visited states (*old states*), a *checked queue* Q_ck to store the states in the BFS level currently explored by the algorithm (BFS *front*), and an *unchecked queue* Q_unck to store pairs (s, h), where s is a state candidate to be on the next BFS level and h is the signature of state s.

State signatures in M do not necessarily represent *all* visited states. In M we just have *recently* visited states. Using the information in M we build the unchecked queue Q_{unck} that contains the set of state candidates to be in the next BFS level. Note that the states in Q_{unck} may be *old* (i.e., previously visited) since using M we can only avoid reinserting in Q_{unck} recently visited states. Indeed, we use disk file D to remove old state signatures from table M as well as to *check* Q_{unck} to get rid of old states. The result of this checking process is the checked queue Q_{ck} .

The main difference between our algorithm and the one in [34] is that in the checking process we only use

```
/* main memory table */
HashTable M;
/* disk table */
FILE D;
/* checked state queue */
FIFO_Queue Q_ck;
/* unchecked state queue */
FIFO_Queue Q_unck;
/* number of blocks to be read from D */
int disk_cloud_size;
```

Fig. 6. DMur φ global data structures

a subset of the state signatures in D. In fact, we divide D into blocks and then use only some of such blocks to clean up M and Q_{unck} . This decreases disk usage and thus speeds up verification; however, with this approach Q_{ck} may also contain some *old* state and, as a result, our algorithm may mark as new (unvisited) a state that indeed is old (visited).

This means that some state may be visited more than once and thus appended to file D more than once. However, thanks to *transition locality* (Sect. 3), this does not happen too often. It is exactly this statistical property of transition graphs that makes our approach effective.

The global variable disk_cloud_size holds the number of blocks of D we use to remove old state signatures from table M; our algorithm *dynamically* adjusts the value of disk_cloud_size during the search.

Table M is in memory, whereas file D is on disk; we use a disk also for the BFS queues Q_ck , Q_unck . Our lowlevel algorithm to handle disk queues Q_ck and Q_unck is exactly the same one we used in CMur φ (Sect. 4).

Note that all the data structures that grow with the state space size (namely, D, Q_ck, Q_unck) are on disk in LDBFS, whereas in [34] the state queues are in memory; since states in the BFS queue are not compressed [23], for large verification problems the BFS queue can be a limiting factor for [34].

5.2 The main LDBFS loop

The Search() function (Fig. 7) is a breadth-first search using the checked queue Q_ck as the current level state queue. It first loads the BFS queue (Q_ck) with the initial states and then begins dequeuing states from Q_ck; for each successor s' of each state dequeued, Search() calls Insert(s') to store potentially new states in M as well as in Q_unck.

Given a state s, Insert(s) (Fig. 8) computes the signature h of s and, if h is not in table M, it inserts the pair (s, h) in the unchecked queue Q_unck and signature h in table M.

When M is full, function Insert() calls function Checktable() to clean up M as well as the queues.

When Q_ck becomes empty, it means that all transitions from all states in the current BFS level have been explored; thus we have to move to the next BFS level. Function Search() does this by calling function Checktable(), which refills the checked queue Q_ck with fresh (nonvisited) states, if there are any, from the unchecked queue Q_unck. If, after calling Checktable(), Q_ck is still empty, it means that all reachable states have been visited and the BFS ends.

5.3 Exploiting locality in state filtering

The Checktable() function (Fig. 10), using disk file D, removes signatures of old (visited) states from table M.

```
Search()
 /* initialization */
M = \text{empty}; D = \text{empty};
 Q_ck = empty; Q_unck = empty;
 /* startstate generation */
 foreach s in init_states Insert(s);
 do
      /* search loop */
  while (Q_ck is not empty)
  {
   s = Dequeue(Q_ck);
   foreach s' in next(s)
    Insert(s');
  } /* while */
  Checktable();
 } while (Q_ck is not empty); /* do */
} /* Search()*/
```

Fig. 7. Search() function

```
Insert(state s)
{
  /* compute signature of state s */
  h = hash(s);
  if (h is not in M)
  {
    Insert h in M;
    Enqueue((s, h), Q_unck);
    if (M is full) Checktable();
  } /* if */
} /* Insert() */
```

Fig. 8. Insert() function

Then, using this cleaned M, it removes old states from the unchecked queue Q_{unck} . Finally, Checktable() moves the states that are in the (now cleaned) unchecked queue Q_{unck} to the checked queue Q_{ck} .

In [34], this function uses *all* the states' signatures in D, whereas exploiting locality (Sect. 3) here we are able to use only a fraction of these signatures: by reading fewer states from disk, we save, with respect to [34], some of the time overhead due to disk accesses.

The rationale of our approach stems from the following observations. First, we should note that state signatures are appended to the file D in the same order in which new states are discovered by the BFS; thus, as we move toward the *tail* of the file we find (signatures of) states whose BFS level is closer and closer to the *current* level reached by the BFS.

From Sect. 3 we know that most transitions are *local*, i.e., they lead to states that are on BFS levels close to the current one. This means that *most* of the old states in M can be detected and removed by only looking at the *tail* of file D.



Fig. 9. Probability curve for disk cloud block selection (used by GetDiskCloud())

We can take advantage of the above remarks by using the following approach. We divide the disk file D into *blocks*; then, rather than using the whole file D in the Checktable(), we only use a subset of the set of disk blocks, which we call *disk cloud*. The disk cloud is created by selecting at random several disk blocks; selection probability of disk blocks is not uniform; instead, to exploit locality, the selection probability increases as we approach the tail of D (Fig. 9).

Our experiments on $\text{CMur}\varphi$ (Sect. 6.2) show that locality allows us to save about 40% of the memory required to complete verification. This suggests that it is necessary to use, say, just 60% of the disk blocks; thus the size (number of blocks) of the disk cloud should be 60% of the number of disk blocks. This works fine; however, we can do more. Our experimental results show that, most of the time, we need much fewer than 60% of the disk blocks to carry out the cleanup implemented by function Checktable(). Thus we *dynamically* adjust the fraction of disk blocks used by function Checktable().

5.4 Disk cloud creation

The GetDiskCloud() function (Fig. 11) is called by the Checktable() function to create our disk cloud. The function selects disk_cloud_size disk blocks according to the probability curve shown in Fig. 9 and returns to Checktable() the indexes of the selected blocks.

We number disk blocks starting from 0 (oldest block); thus, the lower the disk block index, the older (closer to the head of file D) the disk block. On the *x*-axis of Fig. 9 we have the relative disk block index ρ , i.e., $\rho = <$ block index> / <number of blocks>. For instance, $\rho = 0$ is the (relative index of the) first (oldest) disk block inserted into disk D, whereas $\rho = 1$ is the last (newest) disk block inserted. On the *y*-axis of Fig. 9 we have the probability of selecting a disk block with a given ρ . The probability curve is split into three segments. States closer to the current one must have a high selection probability, whereas states that are not too far from the current one have a medium selection probability. Note that, defensively, the selection probability of old blocks (ρ close to 0) must always be greater than zero. This is because we want to have some old blocks to remove occasional far back states (i.e., states belonging to an old BFS level far from the current one) reached by occasional nonlocal transitions. This kind of selection probability curve ensures that the most recently created blocks (ρ close to 1) are selected with a higher probability than old blocks, thus exploiting transition locality.

Since our min and max values for the relative disk block indexes are, respectively, 0 and 1, in Fig. 9 we have $a_0 = 0$ and $a_3 = 1$. The value of b_3 is always 1/K, where Kis a normalization constant chosen so that the sum of the selection probabilities over all disk blocks is 1. The pairs $(a_1, b_1), (a_2, b_2)$ define our selection strategy.

We tested many sets of values for these parameters, and those that obtained the best results in our experiments are: $a_1 = 0.4$, $b_1 = 0.4/K$, $a_2 = 0.7$, $b_2 = 0.6/K$. Of course, these values can be further refined, or they can be dynamically adjusted together with the disk cloud size.

Two strategies are possible to partition disk D into state signature blocks. We can have either a variable number of fixed-size blocks or a fixed number of variable-size blocks.

Reading a block from disk D can be done with a sequential transfer, whereas moving disk heads from one block to another requires a disk *seek* operation. Since seeks take longer than sequential transfers, we decided to limit the number of seeks, so that the structure stored in disk D has a high *locality of reference*. This led us to use a fixed number of variable-size blocks.

Let N be the number of disk blocks we want to use and let S be the number of state signatures in file D, then each block (possibly with the exception of the last one that will be smaller) has $\lceil S/N \rceil$ state signatures. As a matter of fact, to avoid having too small blocks, we also impose a minimum value B for the number of state signatures in a block; thus we may have less than N blocks if S is too small.

In our experiments here we used N = 100 and $B = 10^4$; thus to have 100 disk blocks we need at least 10^6 reachable states.

5.5 Disk cloud size calibration

The Calibrate() function (Fig. 12) is called by the Checktable() function every time a calibration is needed for the disk cloud size.

Two parameters are passed to the Calibrate() function: the number of disk states deleted from M by Checktable() by only using disk blocks that are in the disk cloud (deleted_in_cloud) and the number of disk states deleted from M by only using disk blocks that are not in the disk cloud (deleted_not_in_cloud).

```
Checktable() /* old/new check for main memory table */
 /* Disk cloud defined in Sect. 5.3 */
 /* number of states deleted from M that are in disk cloud */
deleted_in_cloud = 0;
 /* number of states deleted from M
   that are in disk but not in disk cloud */
deleted_not_in_cloud = 0;
 /* Probabilistically choose indexes
   of disk blocks to read (disk cloud) */
DiskCloud = GetDiskCloud();
if (there exists a disk block not selected in DiskCloud) {
 something_not_in_cloud = true;
 } else {
 something_not_in_cloud = false;
Calibration_Required = QueryCalibration();
foreach Block in D {
 if (Block is in DiskCloud or Calibration_Required) {
  foreach state signature h in Block {
   if (h is in M) {
    remove h from M;
    if (Block is in DiskCloud) {
     deleted_in_cloud++;
    } else { /* Block is not in DiskCloud */
     deleted_not_in_cloud++;
    /* remove old states from unchecked states queue (Q_unck) and add new
   states to disk and checked states queue (Q_ck) */
while (Q_unck is not empty) {
 (s, h) = Dequeue(Q_unck);
 if (h is in M) {
  append h to D;
  remove h from M;
  Enqueue(Q_ck, s);
 } /* while (Q_unck is not empty) */
 /* clean up the hash table */
remove all entries from M;
 /* adjust disk cloud size, if requested */
if (Calibration_Required) {
 if (something_not_in_cloud and
    (deleted_in_cloud + deleted_not_in_cloud > 0)) {
  Calibrate(deleted_in_cloud, deleted_not_in_cloud);
 }
 if (disk access rate has been too long above a given critical limit)
  reset disk cloud size to its initial value
     with given probability P;
 }
} /* if Calibration_Required */
} /* Checktable() */
```

```
GetDiskCloud()
{
  Randomly select disk_cloud_size blocks
  from disk, according to the probability
  distribution shown in Fig. 9;
  Return the indexes of the selected blocks;
```

Fig. 11. GetDiskCloud() function

```
Calibrate(deleted_in_cloud,
          deleted_not_in_cloud)
deleted_states =
 deleted_in_cloud + deleted_not_in_cloud;
beta =
 deleted_not_in_cloud / deleted_states;
if (beta is close to 1)
  /* low disk cloud effectiveness:
   * increase disk access rate */
 {
  /* increase disk_cloud_size
   * by a given percentage */
 disk_cloud_size =
   (1 + speedup) * disk_cloud_size;
else if (beta is close to 0)
  /* high disk cloud effectiveness:
   * decrease disk access rate */
  /* decrease disk_cloud_size
  * by a given percentage */
 disk_cloud_size =
   (1 - slowdown) * disk cloud size;
}
}
```

Fig. 12. Calibrate() function

The function computes the ratio beta between the number of states deleted from M that are not in the disk cloud and the total number of states deleted from M (deleted_states). A value of beta close to 1 (low disk cloud effectiveness) means that the disk cloud has not been very effective in removing old states from table M. In this case, the variable disk_cloud_size is increased by (speedup*disk_cloud_size). A value of beta close to 0 (high disk cloud effectiveness) means that the disk cloud has been very effective in removing old states from table M. In this case, we decrease the value of disk_cloud_size by (slowdown*disk_cloud_size) in order to lower the disk access rate.

In our experiments we used perimetarrow speedup = 0.15 and proved slow down = 0.15.

5.6 Calibration frequency

The QueryCalibration() function tells Checktable() whether a calibration will be performed; that is, whether,

at the end of the Checktable() function, Calibrate() will be called (Fig. 10). If a calibration will be performed, the Checktable() function reads the *whole* file D rather than just the disk cloud.

The rationale behind the QueryCalibration() function is the following. Calling the Calibrate() function too often nullifies our efforts for reducing disk usage, since a calibration of the disk cloud size requires reading the whole file D. However, calling Calibrate() too sporadically may have the same effect: in fact, waiting too long for a calibration may lead to the use of an oversized disk cloud or an undersized one. An oversized disk cloud increases disk usage beyond needs; also, an undersized disk cloud increases disk usage, since many old states will not be removed from M and this will lead to revisiting many already visited states.

In our current implementation, the QueryCalibration() function enables a calibration every γ calls of the Checktable() function. We tried many different values for γ ; our experimental results suggest that 10 is a reasonable *calibration frequency*. A variable calibration frequency could make our algorithm more adaptive. However, the underlying heuristics should be chosen with extreme care. Indeed, our preliminary experiments showed that even a small change in the calibration frequency can produce a big degradation in the algorithm performances. This would be an interesting issue to investigate.

6 Experimental results

We report the experimental results we obtained using $CMur\varphi$ (Sect. 4) and $DMur\varphi$ (Sect. 5). We want to measure how much memory we can save by using our cachebased and disk-based approaches.

Our benchmark consists of some of the protocols in the Mur φ distribution [23] and the kerb protocol from [37]. For some of these protocols we used several different versions with different parameter sets.

To make the results from all protocols comparable and machine independent, we will first determine the best performance of standard Mur φ on each protocol and then give our experimental results as ratios with respect to the standard Mur φ results.

$6.1 Mur\varphi$ measures

First, for each protocol we determine the minimum amount of memory needed to complete verification using the $Mur\varphi$ verifier (namely, $Mur\varphi$ version 3.1 from [23]).

Let M be the amount of memory and g (in [0, 1]) the fraction of M used for the queue (g is gPercentActive using a Mur φ parlance). We say that the pair (M, g) is *suitable* for protocol p if and only if the verification of p can be completed with memory M and queue gM. For each protocol p we determine the least M so that for some

g, (M, g) is suitable for p. In the following discussion we denote by M(p) such an M.

Of course, M(p) depends on the compression options one uses. We determined M(p) when only bit compression is used (option -b) and when bit compression and hash compaction are used (option -b -c).

The results are shown in Tables 3 and 4. The meaning of the columns is shown in Table 2. Table 3 shows the original protocols from our benchmark, whereas Table 4 shows our results for some bigger protocols obtained from those in Table 3 by modifying some of their parameters. For such protocols, we only present results about experiments in which all compression options are enabled.

We may note that there are protocols requiring more than 512 MB of memory to complete. Thus we could not use standard Mur φ on our 512-MB PC. However, we were able to complete verification of such protocols using CMur φ (Sect. 4). In fact, when we give it enough memory, we get a very low *collision rate*, and from Sect. 6.2 we know that in this case the CPU time taken by CMur φ is essentially the same as that taken by standard Mur φ with enough memory to complete the verification task. Of course, these protocols will not be used in the CBFS experiments but only to test the LDBFS algorithm in Sect. 6.4.

6.2 Results for CBFS

To test CBFS performances, we run each protocol p using our cache-based Mur φ with the value of g (gPercentActive) chosen as in Table 3 and decreasing fractions of the minimal memory determined in Sect. 6.1. That is, we run p with memory limits $M(p), 0.9M(p), \ldots 0.1M(p)$.

This approach allows us to easily compare the experimental results obtained from different protocols. Note that, as in [18], our memory is not filled up. Thus OS buffers may reduce the time to access the queue. As a result, our measured time may be slightly smaller than that obtained with a filled up memory.

The results using bit compression (option -b) are in Table 5, whereas the results obtained using bit compression and hash compaction (options -b -c) are in Table 6. Note that the tables do not show the results for all the protocols in our benchmark set but only the most representative cases (including the best and worst cases).

In these tables, the memory fraction used for the experiment is shown as a real number α , with $\alpha = 1, 0.9, \ldots, 0.1$, on the top of each column; thus, e.g., column 0.5 gives information about the run of protocol p with memory 0.5M(p) (half of the minimal memory needed by standard Mur φ).

Attribute	Meaning
Model	Name of the model.
Parameters	If the model parameters have been changed, we report our parameter values in the same order in which they appear in the Const section of the model file. When this list is too long, we just list the modified assignments.
Bytes per state	Number of bytes needed to represent a state in the queue when bit compression is used. For model p we denote this number by StateBytes (p) . When bit compression and hash compaction are used, this number is always 5 bytes (signature size).
Reachable states	Number of reachable states for the model. For model p , we denote this number by $ \mathbf{Reach}(p) $.
Rules fired	Number of rules fired during state space exploration. Each rule represents a transition in the model transition graph. For model p , we denote this number by RulesFired (p) .
Max queue	Maximum queue size (i.e., number of states) attained during space state exploration. For model p we denote this number by $\mathbf{MaxQ}(p)$.
Diam	Diameter of the model transition graph.
Mem	Minimum amount of memory (in kilobytes) needed to complete state space exploration, denoted by $M(p)$. Let b_h be the number of bytes taken by a state in the hash table ($b_h = 5$ if hash compaction is used). From the Mur φ source code we can compute $M(p)$. We have: $M(p) = \mathbf{Reach}(p) (b_h + (\mathbf{MaxQ}(p)/ \mathbf{Reach}(p))\mathbf{StateBytes}(p)).$
g	Fraction of memory used for the queue. From the $Mur\varphi$ source code we can compute g . We have: $g = MaxQ(p)/ Reach(p) $.
Time	CPU time (in seconds) to complete state space exploration using the given parameters and Mur φ options. We denote this number by $T(p)$.

Table 2. Meaning of columns in Tables 3 and 4

Table 3. $Mur\varphi$ results on a Linux Pentium III 866-MHz PC with 256 MB RAM using bit compression and bit compression + 40-bit hash
compaction. All experiments have been carried out with deadlock detection disabled

						Bit compression			Bit Compression & Hash compaction		
Model	Bytes per state	Reachable states	Rules fired	Max queue	Diam	Mem	g	Time	Mem	g	Time
cache3	12	577	2440	102	16	10	0.4	0.15	4	0.4	0.15
list6too	20	1077	11622	64	36	26	0.2	15.55	6	0.1	16.83
arbiter	8	1103	2365	301	12	15	0.4	0.1	7	0.3	0.1
ns	24	980	2314	382	11	29	0.4	0.59	7	0.4	0.62
ns-old	24	1121	2578	424	11	33	0.4	0.69	8	0.4	0.69
adashbug	144	3742	39619	646	14	544	0.2	18.19	21	0.18125	17.60
newcache3	52	4357	20201	462	27	240	0.1125	8.01	24	0.15	7.93
adash	144	10466	137708	734	37	1516	0.075	60.57	55	0.075	62.98
newlist6	24	13044	53595	631	53	360	0.05	17.23	67	0.05	18.34
cache3multi	28	13738	65357	1229	29	435	0.1	34.16	73	0.1	35.11
sci	56	18193	60455	1175	62	1071	0.066	27.29	94	0.06875	28.17
list6	24	23410	99874	1095	53	645	0.05	13.73	119	0.05	14.90
mcslock1	12	23644	94576	928	69	373	0.04023	16.17	120	0.04375	16.76
sym.cache3	28	31433	264758	2877	32	994	0.1039	36.22	167	0.10625	36.03
kerb	80	109282	172111	20523	19	9046	0.191	291.49	615	0.190625	301.86
eadash	376	133491	1786047	9050	47	49571	0.06875	4102.33	688	0.06875	4114.71
n_peterson	16	163298	1143086	3775	145	3204	0.0233	269.13	813	0.0233	273.32
ldash	144	254986	2647358	14988	64	36930	0.075	4002.97	1307	0.062	3950.50
mcslock2	12	540219	1620657	15655	111	8503	0.0293	234.68	2693	0.02969	237.48

 $\label{eq:comparison} \begin{array}{l} \textbf{Table 4. } \operatorname{Mur}\varphi \mbox{ results on a 2-GHz INTEL Pentium IV Linux PC with 512 MB RAM using bit compression + 40-bit hash compaction.} \\ & \mbox{ All experiments have been carried out with deadlock detection disabled} \end{array}$

							Bit & Ha	Bit compression & Hash compaction		
Model	Parameters	Bytes per state	Reachable states	Rules fired	Max queue	Diam	Mem	g	Time	
n_peterson	9	20	2871372	25842348	46657	241	14932	0.02	764.27	
newlist6	7	32	3619556	21612905	140382	91	22060	0.04	1641.67	
sci	3,1,1,2,1	60	9299127	30037227	347299	94	65755	0.04	2852.03	
mcslock1	6	16	12783541	76701246	392757	111	68556	0.03	3279.45	
ldash	1,4,1,false	144	8939558	112808653	509751	72	115334	0.06	12352.93	
ns	1, 1, 3, 2, 10	96	2455257	8477970	1388415	12	142152	0.57	1211.02	
newlist6	8	40	81271421	563937480	2875471	110	509156	0.03	31114.87	
sci	3,1,1,5,1	64	75081011	254261319	2927550	95	549578	0.04	35904.86	
kerb	$\texttt{NumIntruders}{=}2$	148	7614392	9859187	4730277	15	720852	0.62	2830.83	
sci	$3,\!1,\!1,\!7,\!1$	68	126784943	447583731	4720612	143	932545	0.04	99904.47	

Rows **States**, **Rules**, and **Time** give the ratio between the visited states, the rules fired, and the time used to complete the state space exploration with $CMur\varphi$ using the given memory fraction and the same values obtained with standard $Mur\varphi$ with the same compression options, as determined in Sect. 6.1.

Row **Coll** gives the collision rate, that is, the ratio between the number of collisions and the number of states inserted in the cache. Since our state space exploration may not terminate, we stop our visit when the collision rate is greater than 0.9. We report also the information on these experiments to give an idea of the behavior of our approach when a visit is stopped prematurely.

In this case, we do not know a priori if all reachable states have been visited. However, in our experiments we have such information since all the protocols can actually fit in our memory. We mark with a * superscript the data obtained when the visit has been stopped because the collision rate exceeded 0.9 and all reachable states have been visited. We mark with a ∞ superscript the data obtained when the visit

Model	Memory fraction	1	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1
lrowh	atataa	1 001	1 001	1 002	1.007	1.015	1.025	1.049	1.007	1 000	1.107^{∞}
Kelp	rulos	1.001	1.001	1.005	1.007	1.010	1.025 1.057	1.040	1.097	1.220 1.285	1.107 1.019^{∞}
	time	0.082	0.986	0.987	0.004	1.058	1.057	1.092	1.101	1.200 1.221	1.012 0.828 $^{\infty}$
	coll	0.060	0.122	0.207	0.301	0.409	0.512	0.618	0.727	0.837	0.910^{∞}
ns	states	1.001	1.000	1.010	1.046	1.024	1.057	1.147	2.476	2.041^{*}	1.020^{∞}
	rules	1.032	1.000	1.066	1.140	1.047	1.128	1.284	2.998	1.974^{*}	0.891^{∞}
	time	1.085	1.068	1.102	1.169	1.119	1.169	1.305	2.864	1.746^{*}	0.746^{∞}
	coll	0.042	0.098	0.202	0.326	0.409	0.530	0.659	0.886	0.919^*	0.932^{∞}
sci	states	1.003	1.008	1.020	1.041	1.095	1.369	4.067^{*}	3.243^{∞}	2.089^{∞}	1.099^{∞}
	rules	1.003	1.009	1.022	1.045	1.102	1.382	3.975^{*}	2.919^{∞}	1.749^{∞}	0.850^{∞}
	time	1.017	1.016	1.025	1.048	1.104	1.392	3.970^{*}	2.912^{∞}	1.752^{∞}	0.858^{∞}
	coll	0.062	0.127	0.219	0.328	0.453	0.635	0.902^{*}	0.908^{∞}	0.906^{∞}	0.912^{∞}
mcslock2	states	1.009	1.017	1.032	1.063	1.178	2.751^{*}	4.008^{∞}	3.004^{∞}	2.269^{∞}	1.061^{∞}
	rules	1.009	1.017	1.032	1.063	1.178	2.749^{*}	3.742^{∞}	2.710^{∞}	1.986^{∞}	0.903^{∞}
	time	0.978	0.991	1.009	1.046	1.163	2.734^{*}	3.721^{∞}	2.692^{∞}	1.951^{∞}	0.879^{∞}
	coll	0.092	0.152	0.236	0.343	0.491	0.818^{*}	0.900^{∞}	0.900^{∞}	0.912^{∞}	0.906^{∞}
mcslock1	states	1.009	1.020	1.058	1.190	1.900	4.948^{*}	4.187^{∞}	3.299^{∞}	2.368^{∞}	1.100^{∞}
	rules	1.009	1.020	1.058	1.190	1.900	4.613^{*}	3.709^{∞}	2.818^{∞}	1.958^{∞}	0.895^{∞}
	time	1.015	1.030	1.074	1.198	1.890	4.547^{*}	3.605^{∞}	2.678^{∞}	1.799^{∞}	0.798^{∞}
	coll	0.069	0.140	0.248	0.412	0.685	0.900^{*}	0.904^{∞}	0.911^{∞}	0.917^{∞}	0.911^{∞}
newlist6	states	1.009	1.022	1.049	1.198	1.830	5.136^{*}	3.987^{∞}	3.527^{∞}	2.300^{∞}	1.227^{∞}
	rules	1.009	1.023	1.052	1.198	1.816	4.641^{*}	3.328^{∞}	2.783^{∞}	1.734^{∞}	0.888^{∞}
	time	1.005	1.020	1.052	1.198	1.810	4.656^{*}	3.320^{∞}	2.777^{∞}	1.725^{∞}	0.868^{∞}
	coll	0.066	0.134	0.239	0.415	0.671	0.903^{*}	0.900^{∞}	0.915^{∞}	0.914^{∞}	0.922^{∞}
adash	states	1.006	1.016	1.043	1.124	1.738	5.160^{*}	4.300^{∞}	3.631^{∞}	2.389^{∞}	1.147^{∞}
	rules	1.007	1.016	1.043	1.125	1.736	4.749^{*}	3.714^{∞}	2.937^{∞}	1.819^{∞}	0.782^{∞}
	time	1.001	1.010	1.039	1.124	1.747	4.824^{*}	3.792^{∞}	3.013^{∞}	1.889^{∞}	0.818^{∞}
	coll	0.063	0.132	0.236	0.377	0.655	0.904^{*}	0.907^{∞}	0.919^{∞}	0.916^{∞}	0.918^{∞}
newcache3	states	1.012	1.029	1.053	1.213	1.895	5.279^{*}	4.131^{∞}	2.984^{∞}	2.066^{∞}	1.148^{∞}
	rules	1.011	1.027	1.050	1.222	1.927	4.851*	3.446^{∞}	2.378^{∞}	1.551^{∞}	0.754^{∞}
	time	1.004	1.022	1.049	1.230	1.953	4.905*	3.487^{∞}	2.401^{∞}	1.577^{∞}	0.792^{∞}
	coll	0.069	0.141	0.242	0.423	0.683	0.907*	0.907∞	$0.902^{\circ\circ}$	0.911~	0.919~
cache3multi	states	1.009	1.030	1.098	1.291	2.422	5.387*	4.367^{∞}	3.203^{∞}	2.184^{∞}	0.946^{∞}
	rules	1.011	1.037	1.117	1.328	2.535	5.173*	3.902^{∞}	2.674^{∞}	1.725°	0.712^{∞}
	time	1.010	1.037	1.118	1.337	2.564	5.255°	3.974^{∞}	$2.730^{\circ\circ}$	1.759^{∞}	$0.728^{\circ\circ}$
	coll	0.062	0.141	0.272	0.458	0.752	0.908^{*}	$0.909^{\circ\circ}$	$0.908^{\circ\circ}$	0.911~	0.900∞
n_peterson	states	1.004	1.011	1.028	1.242	4.366^{*}	5.028^{*}	4.036^{*}	3.037^{∞}	2.039^{∞}	1.035^{∞}
	fired	1.004	1.011	1.028	1.242	4.364^{*}	4.994^{*}	3.997^{*}	2.992^{∞}	1.992^{∞}	0.993^{∞}
	time	0.972	0.981	1.004	1.201	4.222*	4.888*	3.914^{*}	2.959^{∞}	1.975^{∞}	1.017^{∞}
	coll	0.062	0.128	0.225	0.437	0.863^{*}	0.901*	0.901*	0.901^{∞}	0.902^{∞}	0.904^{∞}
ldash	states	1.019	1.058	1.295	7.495^{*}	6.114^{∞}	6.106^{∞}	4.067^{∞}	3.753^{∞}	2.361^{∞}	1.020^{∞}
	rules	1.018	1.056	1.287	6.698^{*}	5.084^{∞}	4.847^{∞}	3.086^{∞}	2.726^{∞}	1.633^{∞}	0.664^{∞}
	time	1.043	1.078	1.324	6.758*	5.112^{∞}	$4.984^{\circ\circ}$	3.177^{∞}	$2.828^{\circ\circ}$	1.703^{∞}	0.701^{∞}
	coll	0.069	0.161	0.382	0.907^{*}	0.902^{∞}	$0.918^{\circ\circ}$	0.902^{∞}	$0.920^{\circ\circ}$	$0.915^{\circ\circ}$	0.902^{∞}
Min	Time	0.972	0.981	0.987	0.994	1.004	1.015	1.041	1.090	1.221	//
Avg	Time	1.010	1.022	1.071	1.155	1.595	1.192	1.173	1.977	1.221	//
Max	Time	1.085	1.078	1.324	1.337	2.564	1.392	1.305	2.864	1.221	//

 $^{{\}bf Table \, 5.} \ {\rm Cache-based \ BF \ search \ with \ bit \ compression}$

Model	Memory fraction	1	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1
korb	statos	1.000	1.001	1.002	1.006	1.013	1.026	1.047	1.003	1 999	1.116^{∞}
Keib	rules	1.000	1.001	1.002	1.000	1.015	1.020	1.047	1.035 1 1/6	1.220 1.280	$1.110 \\ 1.020^{\infty}$
	time	0.983	0.990	1.000 1.002	1.010	1.004	1.000 1.054	1.050 1.078	1.140 1 135	1.200 1 274	0.891^{∞}
	coll	0.007	0.101	0.202	0.305	0.407	0.513	0.618	0.726	0.836	0.911^{∞}
sci	states	1 000	1 005	1.013	1 037	1 087	1 313	4 013*	3 <u>1</u> 33∞	2.309^{∞}	1.154^{∞}
501	rules	1.000	1.006	1.010	1.001	1.007	1.325	3.950^{*}	2.793^{∞}	1.916^{∞}	0.894^{∞}
	time	1.000 1.027	1.000 1.043	1.011	1 105	1.000	1.020	4.544^*	3.225^{∞}	2.226^{∞}	1.047^{∞}
	coll	0.005	0.108	0.210	0.331	0.450	0.618	0.902^{*}	0.906^{∞}	0.917^{∞}	0.920^{∞}
		1.000	1.000	1.005	1.100	1.505	5.010	1.401.00	0.001	0.011	0.020
adash	states	1.000	1.009	1.025	1.133	1.565	5.064*	4.491∞ a.oor∞	3.631°	2.293^{∞}	0.860°
	rules	1.000	1.009	1.025	1.133	1.568	4.684*	3.895∞	$2.931^{\circ\circ}$	1.763~	0.572^{∞}
	time	0.973	0.994	1.016	1.134	1.593	4.855^{+}	4.046°	3.081∞	1.863~	0.609°
	coll	0.002	0.103	0.207	0.380	0.611	0.902^{*}	0.911~	0.918∞	0.912^{∞}	$0.900^{\circ\circ}$
cache3multi	states	1.000	1.013	1.089	1.297	2.939	5.168^{*}	4.440^{∞}	3.421^{∞}	2.329^{∞}	0.946^{∞}
	rules	1.000	1.017	1.104	1.330	3.078	4.929^{*}	3.985^{∞}	2.862^{∞}	1.835^{∞}	0.713^{∞}
	time	0.978	1.005	1.107	1.363	3.344	5.418^{*}	4.399^{∞}	3.157^{∞}	2.026^{∞}	0.780^{∞}
	coll	0.003	0.114	0.264	0.457	0.798	0.905^{*}	0.911^{∞}	0.915^{∞}	0.918^{∞}	0.903^{∞}
newcache3	states	1.000	1.022	1.053	1.313	2.155	5.049^{*}	4.131^{∞}	3.213^{∞}	1.836^{∞}	1.148^{∞}
	rules	1.000	1.020	1.052	1.330	2.192	4.646^{*}	3.412^{∞}	2.564^{∞}	1.347^{∞}	0.742^{∞}
	time	1.032	1.061	1.111	1.450	2.483	5.462^{*}	4.026^{∞}	3.021^{∞}	1.604^{∞}	0.919^{∞}
	coll	0.003	0.136	0.239	0.488	0.725	0.903^{*}	0.908^{∞}	0.911^{∞}	0.909^{∞}	0.936^{∞}
newlist6	states	1.000	1.007	1.050	1.226	1.897	5.443^{*}	4.140^{∞}	3.373^{∞}	2.300^{∞}	1.073^{∞}
	rules	1.000	1.008	1.053	1.224	1.882	4.863^{*}	3.434^{∞}	2.674^{∞}	1.738^{∞}	0.776^{∞}
	time	1.046	1.066	1.140	1.360	2.192	6.009^{*}	4.263^{∞}	3.335^{∞}	2.155^{∞}	0.944^{∞}
	coll	0.002	0.100	0.237	0.434	0.682	0.909^{*}	0.905^{∞}	0.912^{∞}	0.917^{∞}	0.917^{∞}
mcslock1	states	1.000	1.010	1.046	1.163	1.848	5.160^{*}	4.145^{∞}	3.341^{∞}	2.326^{∞}	1.100^{∞}
	rules	1.000	1.010	1.046	1.163	1.848	4.817^*	3.680^{∞}	2.849^{∞}	1.926^{∞}	0.893^{∞}
	time	0.982	1.025	1.106	1.284	2.217	6.304^{*}	4.776^{∞}	3.652^{∞}	2.410^{∞}	1.085^{∞}
	coll	0.006	0.104	0.232	0.395	0.674	0.903^{*}	0.903^{∞}	0.911^{∞}	0.915^{∞}	0.910^{∞}
mcslock2	states	1.000	1.006	1.022	1.055	1.177	4.444^{*}	4.206^{∞}	3.038^{∞}	2.279^{∞}	1.063^{∞}
	rules	1.000	1.006	1.022	1.055	1.177	4.427^{*}	3.915^{∞}	2.734^{∞}	1.993^{∞}	0.905^{∞}
	time	1.023	1.092	1.181	1.301	1.538	6.956^{*}	6.202^{∞}	4.325^{∞}	3.043^{∞}	1.335^{∞}
	coll	0.009	0.105	0.217	0.337	0.490	0.888^{*}	0.905^{∞}	0.901^{∞}	0.912^{∞}	0.906^{∞}
n_peterson	states	1.000	1.005	1.024	1.225	4.262^{*}	5.021^{*}	4.036^{*}	2.988^{∞}	1.990^{∞}	0.998^{∞}
	rules	1.000	1.005	1.024	1.225	4.262^{*}	4.988^{*}	3.996^{*}	2.942^{∞}	1.944^{∞}	0.957^{∞}
	time	1.008	1.033	1.079	1.320	5.014^{*}	5.993^{*}	4.797^{*}	3.560^{∞}	2.374^{∞}	1.207^{∞}
	coll	0.006	0.104	0.219	0.428	0.859^{*}	0.901^{*}	0.901^{*}	0.900^{∞}	0.900^{∞}	0.900^{∞}
ldash	states	1.000	1.028	1.284	7.189^{*}	7.047^{∞}	5.953^{∞}	4.016^{∞}	3.722^{∞}	2.349^{∞}	1.016^{∞}
	rules	1.000	1.027	1.278	6.394^{*}	5.861^{∞}	4.719^{∞}	3.048^{∞}	2.705^{∞}	1.622^{∞}	0.062^{∞}
	time	1.013	1.075	1.346	6.851^{*}	6.177^{∞}	4.987^{∞}	3.278^{∞}	2.946^{∞}	1.762^{∞}	0.727^{∞}
	coll	0.007	0.125	0.377	0.903^{*}	0.915^{∞}	0.916^{∞}	0.901^{∞}	0.920^{∞}	0.915^{∞}	0.902^{∞}
Min	Time	0.973	0.990	1.002	1.011	1.026	1.054	1.078	1.135	1.274	//
Avg	Time	1.007	1.038	1.115	1.259	1.947	1.256	1.078	1.135	1.274	//
Max	Time	1.046	1.092	1.346	1.450	3.344	1.458	1.078	1.135	1.274	//

 ${\bf Table \, 6.} \ {\rm Cache-based \ BF \ search \ with \ bit \ compression \ and \ hash \ compaction}$

has been stopped because the collision rate exceeded 0.9 and there are reachable states that have not been visited.

The **Time** row shows the time overhead due to revisiting already visited states. Using only bit compres-

sion (Table 5) time penalty for column 0.6 (40% memory saving) ranges from 0 to 150% with an average value of about 50%. Using bit compression and hash compaction (Table 6) time penalty for column 0.6 ranges from 0 to 234% with an average value of about 100%.

Therefore, our experimental results show that our cache-based approach typically saves about 40% of memory with respect to a hash-table-based approach. This holds when using bit compression alone as well as when using bit compression and hash compaction.

The results of Table 6 are also plotted in Fig. 13, where we have the *Memory fraction* on the x-axis and *Time* on the y-axis.

Note that no memory saving may be possible for nonlocal protocols. For example, the state space exploration of the NLS system in Fig. 2 does not terminate unless we give the verifier enough memory to store all the reachable states.

6.3 A large protocol with CBFS

We also tested our cache-based approach with a large protocol that heavily loads our machine.

We used the ns protocol with parameters NumInitiators = 2, NumResponders = 1, NumIntruders = 2, NetworkSize = 2, MaxKnowledge = 10, giving to CMur φ 200, 150, and 130 MB of memory. The results are in Table 7. Columns **Cache memory** and **Cache size** give, respectively, the memory reserved for the cache and the max number of states that fit in that memory (each state takes 40 bits with hash compaction).

Columns **Queue memory** and **Queue size** give, respectively, the memory reserved for the queue and the max number of states that fit in that memory (each state takes 68 bytes in the queue).

Columns Max states queued and Max queue space used give, respectively, the max number of states actually contained in the BF queue (memory + disk) during the verification and the space they would require in memory. The other columns have their usual meaning.

When **Memory** = 200 (first row of Table 7), the collision rate is low; thus the number of visited states is about the number of reachable states. This means that completing verification for this protocol would require more than 1313 MB of memory using standard Mur φ (i.e., 200 MB for the hash table, 1113 MB for the queue). This is more than our machine can handle: however, using our cachebased Mur φ , we were able to complete verification using only 130 MB of memory (last row of Table 7).



Fig. 13. Time (time ratio) vs. Memory fraction from Table 6

Table 7. Cache-based BF search for protocol ns with parameters: NumInitiators = 2, NumResponders = 1, NumIntruders = 2, NetworkSize = 2, MaxKnowledge = 10. Results obtained on a Pentium III 866-MHz machine with 256 MB RAM using bit compression, 40-bit hash compaction, and no deadlock detection

Memory (Mb)	Cache size	Cache memory (Mb)	Queue size	Queue memory (Mb)	Visited states	Time	Collision rate	Max states queued	Max queue space used (Mb)
200	38836153	180	215756	20	44780625	19349.80	0.17024	16215144	1113.40
150	29127121	135	161817	15	46369727	19975.79	0.373777	16239606	1115
130	25243507	117	140241	13	48933778	21769.69	0.484372	16264901	1116.8

As shown in our experiments, there is a time-space tradeoff when using our cache-based approach. However, for verification tasks such a tradeoff is often acceptable and in any case better than being left with an **out of memory** message after hours of computation.

6.4 Results for LDBFS

In this section we report the experimental results we obtained by using DMur φ . Our experiments have two goals. First, we want to know if by exploiting locality there is indeed some gain with respect to the algorithm proposed in [34]. Second, we want to measure DMur φ

time overhead with respect to standard $\mathrm{Mur}\varphi$ performing a RAM–BFS.

We proceed using the same method used for CBFS in Sect. 6.2: we run each protocol p with our disk-based Mur φ , using decreasing fractions of the minimal memory determined in Sect. 6, i.e., we run protocol p with memory limits M(p), 0.5M(p) and 0.1M(p).

The results we obtained comparing our disk-based Mur φ with standard Mur φ are in Table 8. Column meanings are the same as those in Sect. 6.2. Note that, with the disk-based algorithm, the time to complete the verification is the time elapsed between the start and the end of the state space exploration process: that is, it in-

(using bit compression	and hash ee	inpaction	u)	
Model	Parameters	Memory fraction	1	0.5	0.1
n_peterson	9	States Rules Time	$1.178 \\ 1.178 \\ 2.148$	$1.124 \\ 1.124 \\ 2.056$	$1.199 \\ 1.199 \\ 2.783$
ns	1,1,3,2,10	States Rules Time	$1.348 \\ 1.487 \\ 1.734$	$1.405 \\ 2.011 \\ 2.144$	$1.373 \\ 1.645 \\ 1.953$
newlist6	7	States Rules Time	$1.366 \\ 1.365 \\ 1.703$	$1.335 \\ 1.334 \\ 1.765$	$1.384 \\ 1.382 \\ 2.791$
ldash	1,4,1,false	States Rules Time	$1.566 \\ 1.528 \\ 2.037$	$1.668 \\ 1.626 \\ 2.226$	$1.702 \\ 1.658 \\ 3.770$
sci	3,1,1,2,1	States Rules Time	$1.260 \\ 1.279 \\ 1.811$	$1.189 \\ 1.206 \\ 1.798$	$1.183 \\ 1.200 \\ 2.888$
mcslock1	6	States Rules Time	$1.346 \\ 1.346 \\ 1.915$	$1.550 \\ 1.550 \\ 2.477$	$1.703 \\ 1.703 \\ 5.259$
sci	3,1,1,5,1	States Rules Time		$1.169 \\ 1.195 \\ 1.828$	$1.143 \\ 1.167 \\ 2.553$
sci	3,1,1,7,1	States Rules Time		$1.130 \\ 1.152 \\ 1.421$	$1.097 \\ 1.115 \\ 1.743$
kerb	NumIntruders=2	States Rules Time		$1.282 \\ 1.060 \\ 1.234$	$1.279 \\ 1.080 \\ 1.438$
newlist6	8	States Rules Time	-	$1.416 \\ 1.412 \\ 2.612$	$1.406 \\ 1.405 \\ 4.436$
Min Avg Max		Time Time Time	1.703 1.891 2.148	1.234 1.954 2.612	1.438 2.961 5.259

Table 8. Comparing DMur φ with standard Mur φ (using bit compression and hash compaction)

cludes the CPU time as well as the time spent on disk accesses.

For the *biggest* models in our benchmark, requiring more than 512 MB of memory, we could not run the experiments with memory fraction $\alpha = 1$ on our machine with 512 MB of memory. However, the most interesting column for us is the one with $\alpha = 0.1$. Indeed, the experimental results show that, even when $\alpha = 0.1$, our diskbased approach is only between 1.4 and 5.3 (3 on average) times slower than a RAM–BFS with enough memory to complete the verification task.

The results of Table 8 are also plotted in Fig. 14, where we have the *Memory fraction* on the x-axis and *Time* (time fraction) on the y-axis.

$6.5 DMur\varphi vs. disk-based Mur\varphi$

To measure the time speedup we obtain by exploiting locality, we are also interested in comparing our localitybased disk algorithm $DMur\varphi$ with the disk-based $Mur\varphi$ presented in [34]. The latter algorithm is not available in the standard $Mur\varphi$ distribution, so we obtained it from $DMur\varphi$ by omitting the calibration step in the Checktable() function and always using all disk blocks to clean up the unchecked queue Q_unck and table M (Sect. 5.3). In the following discussion, we will refer to this algorithm as disk-based $Mur\varphi$.

Although we had to use our own implementation of the algorithm described in [34], we think that our comparison of it with our DMur φ is quite fair since our implementation of the algorithm in [34] shares all optimizations we implemented in DMur φ except the calibration step, which is what allows us to save disk accesses (and thus verification time) by exploiting transition locality.

For disk-based Mur φ , we repeated the same set of experiments we ran for DMur φ in Sect. 6.4. However, the *biggest* models of Table 4 took too long. Thus we did not include them in our set of experiments.

The results are in Table 9. Computations taking too much longer than the time in Table 4 were aborted. In such cases, we get a lower bound to the time overhead with respect to standard Mur φ . This is indicated with a > sign before the lower bound. For these aborted computations, the rows **States** and **Rules** are, of course, less than 1 and give us an idea of the fraction of the state space explored before the computation was terminated.

Finally, Table 10 compares performances of our DMur φ with those of the disk-based Mur φ .

Of course, the interesting cases for us are those with $\alpha = 0.1$, when there is not enough memory to complete verification using a RAM–BFS. For such cases, from the results in Table 10 we see that our algorithm is typically more than ten times faster than the one presented in [34].

6.6 A large protocol with LDBFS

We also tested our disk-based approach on a protocol out of reach for both standard Mur φ and CMur φ on our 512-MB machine.

We found that the protocol mcslock2 (with N = 4) suited our needs. Our results are in Table 11.

Columns Max states queued and Max queue space used give, respectively, the max number of states actually contained in the BF queue (memory + disk)



Fig. 14. Time (time ratio) vs. Memory fraction from Table 8

Model	Parameters	Memory fraction	Memory 1 0.5 fraction		0.1
n_peterson	9	States	1.000	1.000	0.527
		Rules	1.000	1.000	0.507
		Time	2.623	2.430	> 90.704
ns	$1,\!1,\!3,\!2,\!10$	States	1.000	1.000	0.747
		Rules	1.000	1.000	0.309
		Time	1.259	242.131	> 77.895
newlist6	7	States	1.000	1.000	0.253
		Rules	1.000	1.000	0.203
		Time	1.331	1.357	> 42.817
ldash	1,4,1,false	States	0.355	_	_
		Rules	0.245	_	_
		Time	> 50.660	—	_
sci	3,1,1,2,1	States	1.000	0.361	
		Rules	1.000	0.647	_
		Time	1.616	> 11.863	-
mcslock1	6	States	1.000	1.000	0.137
		Rules	1.000	1.000	0.115
		Time	1.821	1.691	> 11.605

Table 9. Comparing disk-based Mur φ with standard Mur φ (using bit compression and hash compaction)

Table 10. Comparing DMur φ with disk-based Mur φ (using bit compression and hash compaction)

Model	Parameters	Memory fraction	1	0.5	0.1
n_peterson ns newlist6 ldash sci mcslock1	9 1,1,3,2,10 7 1,4,1,false 3,1,1,2,1 6	Time Time Time Time Time Time	$\begin{array}{c} 1.221 \\ 0.726 \\ 0.781 \\ > 24 \\ 0.892 \\ 0.950 \end{array}$	$\begin{array}{c} 1.182 \\ 112.934 \\ 0.768 \\ > 24 \\ > 6 \\ 0.683 \end{array}$	> 32 > 39 > 15 > 24 > 6 > 2
Min Avg Max		Time Time Time	0.726 > 4.762 > 24	$0.683 > 24.261 \\ 112.934$	>2 > 19.667 > 39

during the verification and the space they would require in memory. Column **Hash table space used** gives the hash table size that would be needed if all reachable states were stored in a memory hash table. Column **Total space used** gives the memory (in kilobytes) needed to complete the verification task using a RAM–BFS with standard Mur φ (that is, **Max queue space used** + **Hash table space used**). The other columns have their usual meaning.

7 Conclusions

We showed experimentally (Sect. 3) that protocols exhibit *transition locality*. We supported our claim by meas-

uring transition locality for the set of protocols included in the $Mur\varphi$ verifier distribution.

We presented (Sect. 4) a (memory-based) BF explicit state space exploration algorithm to exploit transition locality and implemented it within the Mur φ verifier. Essentially our algorithm replaces the hash table used in a BF state exploration with a fixed-size cache (without collision detection) and uses disk storage for the BF queue. Our experimental results (Sect. 6.2) show that, with respect to a hash-table-based approach, our cachebased approach typically allows verification of systems more than 40% larger with a time overhead of about 100%.

We also presented (Sect. 5) a disk-based breadth-first explicit state space exploration algorithm as well as an

Memory (Mb)	Visited states	Rules fired	Diam	Time	Bytes per state	Hash table space used (Kb)	Max states queued	Max queue space used (Kb)	Total space used (Kb)
300	945950806	3783803224	153	406275	16	4729754	30091568	481465	5211219

 Table 11. Disk-based BF search for protocol mcslock2 with parameter N = 4. Results obtained on a 1-GHz Pentium IV PC with 512 MB RAM using bit compression, 40-bit hash compaction, and no deadlock detection

implementation of it within the Mur φ verifier. Our algorithm has been obtained from the one in [34] by exploiting transition locality to decrease disk usage (namely, disk read accesses). Our experimental results (Sect. 6.4) show that our algorithm is typically more than ten times faster than the disk-based algorithm proposed [34]. Moreover, even when using 1/10 of the memory needed to complete verification, our algorithm is only between 40 and 530% (300% on average) slower than RAM–BFS (namely, standard Mur φ) with enough memory to complete the verification task at hand.

Statistical properties of transition graphs (as transition locality is) have proven quite effective in improving state space exploration algorithms on a single-processor machine. Looking for new statistical properties and for ways to exploit such statistical properties when performing verification on distributed processors are natural further developments for our research.

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