RACE: A Robust Adaptive Caching Strategy for Buffer Cache

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Abstract— **While many block replacement algorithms for buffer caches have been proposed to address the well-known drawbacks of the LRU algorithm, they are not robust and cannot maintain an consistent performance improvement over all workloads. This paper proposes a novel and simple replacement scheme, called RACE (Robust Adaptive buffer Cache management schemE), which differentiates the locality of I/O streams by actively detecting access patterns inherently exhibited in two correlated spaces: the discrete block space of program contexts from which I/O requests are issued and the continuous block space within files to which I/O requests are addressed. This scheme combines global I/O regularities of an application and local I/O regularities of individual files accessed in that application to accurately estimate the locality strength, which is crucial in deciding which blocks are to be replaced upon a cache miss. Through comprehensive simulations on eight real-application traces, RACE is shown to high hit ratios than LRU and all other state-of-the-art cache management schemes studied in this paper.**

Index Terms— **Operating systems, file systems management, memory management, replacement algorithms.**

I. Introduction

THIS paper presents a novel approach for buffer cache management, called RACE (Robust Adaptive Caching strategy for buffer cachE), that is motivated by the limitations of existing solutions and the need to further improve the buffer cache hit rate, a significant factor affecting the performance of the supported file system, given the relatively very high buffer cache miss penalties. RACE is shown to overall outperform all existing solutions significantly in most cases. In this section, we first describe the limitations of existing solutions, and then present the main motivations for this work, followed by an outline of the major contributions of the paper.

A. The Limitations of LRU and Recent Solutions, and Motivations

Designing an effective block replacement algorithm is an important issue in improving file system performance. In most real systems, the replacement algorithm is based on the Least-Recently-Used (LRU) scheme [1], [2] or its clock-based approximation [3]: upon a cache miss, the block whose last reference was the earliest among all cached blocks is replaced. LRU has the advantages of simple implementation and constant space and time complexity. While it has been theoretically verified that LRU can absorb the maximum number of I/O references under a spectrum of workloads that can be represented by the independent reference model [4], in reality LRU often suffers severely from two pathological cases.

- *Scan pollution*. After a long series of sequential accesses to one-time-use-only (cold) blocks, many frequently accessed blocks may be evicted out from the cache immediately, leaving all these cold blocks occupying the buffer cache for an unfavorable amount of time and thus resulting in a waste of the memory resources. A wise replacement strategy should consider the reference frequency of each block and hence can distinguish hot data from cold data.
- *Cyclic access to large working set*. A large number of applications, especially those in the scientific computation domain, exhibit a looping access pattern. When the total size of repeatedly accessed data is larger than the cache size, LRU always evicts the blocks that will be revisited in the nearest future, resulting in perpetual cache misses. For example, when repeatedly accessing a file that has 100 blocks, a LRU cache with 99 blocks always evicts the block that will be referenced next and leads to a zero hit ratio. A clever strategy would observe this access with long term locality and only generate cache misses for the references to the block that is least accessed.

To address the limitations of the LRU scheme, several novel and effective replacement algorithms [5]–[8] have been proposed to avoid the two pathological cases described above by using advanced knowledge of the unusual I/O requests. Specifically, they exploit the patterns exhibited in I/O workloads, such as sequential scan and periodic loops, and apply specific replacement polices that can best utilize the cache under that reference pattern.

According to the level at which the reference patterns are observed, these algorithms can be divided into three categories: 1) At the application level, DEAR [6] observes the patterns of references issued by a single application, assuming that the I/O patterns of each application are consistent; 2) At the file level, UBM [5], [9] examines the references to the same file, with an assumption that a file is likely to be accessed with the same pattern in the future. 3) At the program context level, PCC [7] and AMP [8] separate the I/O streams into substreams by program context and detect the patterns in each substream, assuming that a single program context tends to access files with the same pattern in the future.

To best exploit the access patterns, the design space centers around investigating an automatic pattern detection technique that should satisfy the following three requirements.

- **Accuracy** Applications often have certain I/O access patterns. An accurate detection of access patterns serves as the basis for quantitatively identifying the locality of accessed blocks and tuning caching policies accordingly. A misclassification of an access stream may increase the number of disk

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accesses by evicting useful blocks and taking up memory space. In addition, the detection algorithm should be able to detect not only reference patterns presented explicitly in the consecutive address space but also implicit patterns in a non-consecutive way. For example, a stream of references to blocks with a set of random addresses may belong to a sequential pattern category.

- **Responsiveness** Real applications within various phases of execution may exhibit different reference patterns. The cache replacement algorithm should adapt to different behaviors within one application and thus a good on-line detection algorithm is required to quickly reflect the transition of access patterns. A detection approach based on aggregate statistical measures of program behavior, as used by PCC and AMP, tends to have a large amount of inertia or reluctance and may not responsively detect local patterns, although it can correctly recognize global patterns.
- **Stability** A detection-based caching system applies different replacement policies for different reference patterns. To achieve this goal, a buffer cache is divided into multiple partitions and blocks from different patterns are stored in their corresponding partitions. An unstable detection scheme swings a block from different patterns and moves it repeatedly among cache partitions accordingly. In an asynchronous environment with multi-threads, moving a block between the links of different partitions relies on locks to ensure the consistency and correctness, which can be quite costly. A stable classification can eliminate the *lock contention* and reduce the overhead of cache maintenance.

The key in the design of an effective pattern detection scheme is to strike the optimal tradeoff among the above three requirements. A scheme with better stability may sacrifice its classification accuracy and responsiveness and vice versa. As strongly suggested by the results obtained from the extensive simulations conducted in this study, none of the currently existing schemes is able to maintain a good balance among the three requirements:

1) Application-level detection [6] has good stability but suffers in accuracy and responsiveness since many applications access multiple files and exhibit a mixture of access patterns, as shown in [5] and later in this paper.
2) File-level detection [5], [9] has a smaller observation granularity than the application-based approach but has two main drawbacks that limit its classification accuracy. First, a training process needs to be performed for each new file and thus is likely to cause a misclassification for the references targeted at new files. Second, to reduce the running overhead, the access patterns presented in small files are ignored. Nevertheless, this approach tends to have good responsiveness and stability due to the fact that most files tend to have stable access patterns, although large database files may show mixed access patterns.
3) Program-context-level detection [7], [8] trains only for each program context and has a relatively shorter learning period than the file-based one. While it can make correct classification for new files after training, it classifies the accesses to all files touched by a single program context into the same pattern category, and thus limits the detection accuracy. In addition, it has problems of responsiveness and stability. It bases its decision on aggregate statistical information and thus is not sensitive to pattern changes. The stability problem is caused by the fact that in real applications, as explained in Section III, multiple program contexts may access the same set of files but exhibit different patterns if observed from the program-context point of view.

B. Our Contributions

This paper makes the following three contributions. First, we collect the I/O traces for ten real applications and investigate I/O access patterns in two correlated spaces: the program context space from which I/O operations are issued, and the file space to which I/O requests are addressed. Second, our comprehensive pattern study in real applications reveals pathological behavior related to existing state-of-the-art cache replacement algorithms including a file-level detection method named UBM [5], [9] and two program context level detection methods named PCC [7] and AMP [8]. This observation motivates us to design a novel, robust and adaptive cache replacement scheme that is presented in this paper. Our new scheme, called RACE which has a time complexity of O(1), can accurately detect access patterns exhibited in both the discrete block space accessed by a program context and the continuous block space within a specific file, which leads to more accurate estimations and more efficient utilizations of the strength of data locality. We show that our design can effectively combine the advantages of both file-based and program context based caching schemes and best satisfy the requirements of accuracy, responsiveness and stability. Third, we conduct extensive trace-driven simulations by using eight different types of real life workloads and show that RACE substantially improves the absolute hit ratio of LRU by as much asas much as 56.9%, with an average of 15.5%. RACE outperforms UBM, PCC and AMP in absolute hit ratios by as much as 22.5%, 42.7% and 39.9%, with an average of 3.3%, 6.6% and 6.9%, respectively. These gains in absolute hit ratios by RACE are likely to have significant performance implications in applications' response times.

C. Outline of this Paper

The rest of this paper is organized as follows. Section II briefly reviews relevant studies in buffer cache management. Section III explains our RACE design in detail. Section IV presents the trace-driven evaluation method and Section V evaluates the performance of RACE and other algorithms and discusses the experimental results. Finally, Section VI concludes this paper.

II. Related Work on Buffer Cache Replacement Strategies

A large number of replacement algorithms have been proposed in the last few decades. These algorithms can be classified into three categories: 1) replacement algorithms that incorporate longer reference histories than LRU, 2) replacement algorithms that rely on application hints, and 3) replacement algorithms that actively detects the I/O access patterns. The following subsections describe the theoretically optimal replacement algorithm, followed by representative replacement algorithms in the above three categories.

A. Off-line Optimal Replacement

Off-line optimal policy [10], [11] replaces the block whose next reference is farthest in the future. This policy is not realizable in actual computer systems since it requires complete knowledge of future block references. However, it provides a useful upper bound on the achievable hit ratio of all practical cache replacement policies.

B. Deeper-history Based Replacement

To avoid the two pathological cases in LRU, described in the previous section, many cache replacement strategies are proposed to incorporate the "frequency" information when making a replacement decision. A common characteristic of such strategies is that all of them keep longer history information than LRU. A chronological list of these algorithms by date of publication includes LRU-K [12], 2Q [13], LRFU [14], EELRU [15], MQ [16], LIRS [17], and ARC [18]. A brief overview of each algorithm is given below.

For every block x, LRU-K [12] dynamically records the K^{th} backward distance, which is defined as the number of references during the time period from the last K^{th} reference to x to the most recent reference to x. A block with the maximum K^{th} backward distance is dropped to make space for missed blocks. LRU-2 is found to best distinguish infrequently accessed (cold) blocks from frequently accessed (hot) blocks. The time complexity of LRU-2 is $O(\log_2 n)$, where n is the number of blocks in the buffer.

2Q [13] is proposed to perform similarly to LRU-K but with considerably lower time complexity. It achieves quick removal of cold blocks from the buffer by using a FIFO queue $A1_{in}$, an LRU queue Am, and a "ghost" LRU queue $A1_{out}$ that holds no block contents except block identifiers. A missed block is initially placed in $A1_{in}$. When a block is evicted from $A1_{in}$, this block's identifier is added to $A1_{out}$. If a block in $A1_{out}$ or $A1_{in}$ is re-referenced, this block is promoted to Am.

LRFU (Least Recently/Frequently Used) [14], [19] endeavors to replace a block that is both least recently and least frequently used. A weight $C(x)$ is associated with every block x and a block with the minimum weight is replaced.

$$C(x) = \begin{cases} 1 + 2^{-\lambda}C(x) & \text{if } x \text{ is referenced at time } t; \\ 2^{-\lambda}C(x) & \text{otherwise.} \end{cases} \qquad (1)$$

where λ, $0 \leq \lambda \leq 1$, is a tunable parameter and initially $C(x) = 0$. LRFU reduces to LRU when $\lambda = 1$, and to LFU when $\lambda = 0$. By controlling λ, LRFU represents a continuous spectrum of replacement strategies that subsume LRU and LFU. The time complexity of this algorithm ranges between $O(1)$ and $O(\log n)$, depending on the value of λ.

EELRU (Early Eviction LRU) [15] builds a history queue that records the identifiers of recently evicted blocks and uses this queue to detect the recency of evicted blocks. Based on the recency distributions of referenced blocks, it dynamically changes its replacement strategies. Specifically, it performs LRU replacement by default but diverges from LRU and arbitrarily evicts some pages early to allow not-recently-touched blocks to remain longer when EELRU detects that many pages fetched recently have just been evicted.

MQ (Multi-Queue Replacement Algorithm) [16] uses $m + 1$ LRU queues (typically $m = 8$), $Q_0, Q_1, \ldots, Q_{m-1}$ and Q_{out}, where Q_i contains blocks that have been referenced at least 2^i times but no more than 2^{i+1} times recently, and Q_{out} contains the identifiers of blocks evicted from Q_0 in order to remember access frequencies. On a cache hit in Q_i, the frequency of the accessed block is incremented by 1 and this block is promoted to the most recently used position of the next level of queue if its frequency is equal to or larger than 2^{i+1}. MQ associates each block with a timer that is set to $currentTime + lifeTime$. $lifeTime$ is a tunable parameter that is dependent upon the buffer size and workload. It indicates the maximum amount of time a block can be kept in each queue without any access. If the timer of the head block in Q_i expires, this block is demoted into Q_{i-1}. The time complexity of MQ is $O(1)$.

LIRS (Low Inter-reference Recency Set) [17], [20] uses the distance between the last and second-to-the-last references to estimate the likelihood of the block being re-referenced. It categorizes a block with a large distance as a cold block and a block with a small distance as a hot block. A cold block is chosen to be replaced on a cache miss. LIRS uses two LRU queues with variable sizes to measure the distance and also provides a mechanism to allow a cold block to compete with hot blocks if the access pattern changes and this cold block is frequently accessed recently. The time complexity of LIRS is $O(1)$. Clock-pro [21] is an approximation of LIRS.

For a given cache size c, ARC (Adaptive Replacement Cache) [18], [22] uses two LRU lists L_1 and L_2, and they combinatorially contain c physical pages and c identifiers of recently evicted pages. While all blocks in L_1 have been referenced only once recently, those in L_2 have been accessed at least twice. The cache space is allocated to the L_1 and L_2 lists adaptively according to their recent miss ratios. More cache space is allocated to a list if there are more misses in this list. The time complexity of ARC is $O(1)$. CAR [23] is a variant of ARC based on clock algorithms.

All the above replacement algorithms base their cache replacement decisions on a combination of recency and reference frequency information of accessed blocks. However, they are not able to explicitly exploit the regularities exhibited in past behaviors or histories, such as looping or sequential references. Thus their performance is confined due to their limited knowledge of I/O reference regularities [7].

C. Application-controlled Replacement

Application-informed caching management schemes are proposed in ACFS [24] and TIP [25], and they rely on programmers to insert useful hints to inform operating systems of future access patterns. ACFS uses a two-level cache scheme, where a global cache management policy decides which application should give up a cache block upon a miss and the local policy decides intelligently which block of that application should be evicted by applying application-specific knowledge. TIP partitions the cache into three logical domains for hinted-prefetching blocks, hinted-caching blocks, and unhinted-caching blocks, respectively. Based on the estimated cost-benefits, TIP dynamically allocates file buffers among those three domains. To free the programmer from the onerous burden, Profet [26] exploits a compiler-based technique to automatically insert the crucial hints to facilitate I/O prefetching. However, this technique cannot achieve satisfactory performance level if the I/O access pattern is only known at runtime. Artificial intelligence tools [27] are proposed to learn these I/O patterns at execution time and thus obtain the hints dynamically.

D. Active Pattern-detection Based Replacement

Depending on the level at which patterns are detected, the pattern-detection based replacement can be classified into four categories: 1) block-level patterns, 2) application-level patterns, 3) file-level patterns, and 4) program-context-level patterns. An example of block level pattern detection policy is SEQ [28], which detects the long sequences of page cache misses and applies the Most-Recently-Used(MRU) [29] policy to such sequences to avoid scan pollution.

At the application level, DEAR (Detection Adaptive Replacement) [6] periodically classifies the reference patterns of each individual application into four categories: sequential, looping, temporally-clustered, and probabilistic. DEAR uses MRU as the replacement policy to manage the cache partitions for looping and sequential patterns, LRU for the partition of the temporally-clustered pattern, and LFU for the partition of the probabilistic pattern. The time complexity of DEAR is $O(n \log n)$ where n is the number of distinct blocks referenced in the detection period.

At the file level, the UBM (Unified Buffer Management) [5], [9] scheme separates the I/O references according to their target files and automatically classifies the access pattern of each individual file into one of three categories: *sequential references*, *looping references* and *other references*. It divides the buffer cache into three partitions, one for blocks belonging to each pattern category, and then uses different replacement policies on different partitions. For blocks in the sequentially-referenced partition, MRU replacement policy is used, since those blocks are never revisited. For blocks in the periodically referenced partition, a block with the longest period is first replaced and the MRU block replacement is used among blocks with the same period. For blocks that belong to neither the sequential partition nor the looping partition, a conventional algorithm, such as LRU, is used.

At the program context level, the Program Counter based Cache (PCC) [7] algorithm exploits virtual program counters exhibited in application's binary execution codes to classify the program signatures into the same three categories as UBM and then uses the same replacement policies for these categories respectively. While UMB classifies the I/O access patterns based on files, PCC classifies the patterns based on the virtual program counters of the I/O instructions in the program code. Adaptive Multi-Policy caching scheme (AMP) [8] inherits the design of PCC but proposes a new pattern detection algorithm. It defines an experiential mathematical expression to measure *recency* and classifies program counters according to the comparison between the average recency and a static threshold.

III. The Design of A Robust Adaptive Caching Replacement (RACE) Algorithm

This section presents the design of the RACE caching algorithm in detail. We first introduce the recently developed Program-Context-based technology in buffer caching and then analyze its limitations that in part motivate our RACE design, which is followed by the presentation of the details of our RACE algorithm.

A. PC-based Technology in Caching Replacement

Temporal locality of I/O references in all kinds of program executions has been extensively demonstrated and is a well known program behavior. Cache performance can be enhanced by taking full advantage of temporal locality. Based on this principle, many cache management algorithms, including PCC [7] and AMP [8], exploit temporal locality by using history information of program behavior to estimate the reuse distance of cache blocks. These studies successfully link the past I/O behavior to their future reoccurrences by borrowing a computer architectural concept: *program counters*, which indicates the location of the instructions in memory. It is found that a particular instruction, identified by its program counter, usually performs a very unique task and seldom changes its behavior. Thus these studies assume that there is a considerably high probability of the access pattern of a program counter remaining unchanged in the near future.

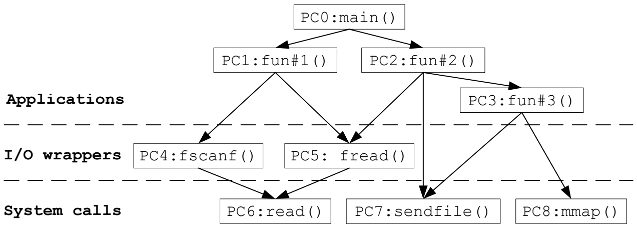


Fig. 1. An example call graph of some application.

Figure 1 presents a call graph to further illustrate the key idea behind the studies of PCC and AMP. A call graph represents the runtime calling relationships among a program's functions or procedures, in which a node corresponds to a function and an arc represents a call. An I/O instruction, issued by some function in the application layer, may be interpreted in the I/O wrapper layer that hides the I/O complexity and provides flexible interfaces, and eventually invokes system calls to access data. To uniquely identify the program context from which an I/O operation is invoked, a *program counter signature* is defined as the sum of the program counters of all functions along the I/O call path. Program counter signatures can be obtained by traversing the function stack frames backwards from the system calls *main()*. For simplicity, program signatures are denoted as PCs in the rest of this paper.

PCC and AMP separate the I/O references into sub-streams according to their PCs and then classify PCs into appropriate I/O reference pattern categories. A PC is assumed to exhibit the same I/O reference pattern in the future as it has been classified, and the target data blocks referenced by the current PC will be managed by the corresponding policy. Unfortunately, such an approach has three significant disadvantages.

1) The first iteration of each new PC in a global looping pattern will be misclassified as *sequential*. This is caused intrinsically by the inability of PC based schemes to detect the phenomenon of *pattern sharing* among multiple PCs. Pattern sharing in real applications is not rare. For example, it is highly likely that a subroutine is called by multiple parent subroutines but shares the same I/O access pattern. Recursive functions are another example since they generate a set of different program signatures but share the same reference patterns. Multi-threading can also lead to pattern sharing. Figure 2 and 3 show the traces of *gnu-*

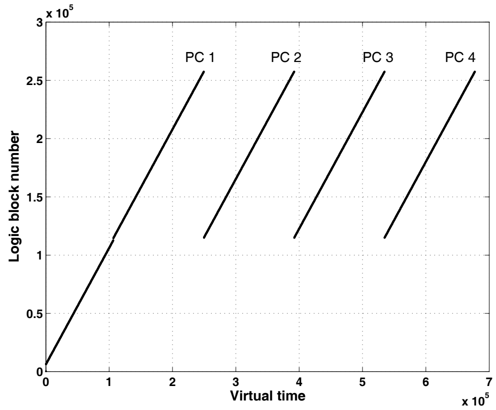


Fig. 2. Block references of gnuplot.

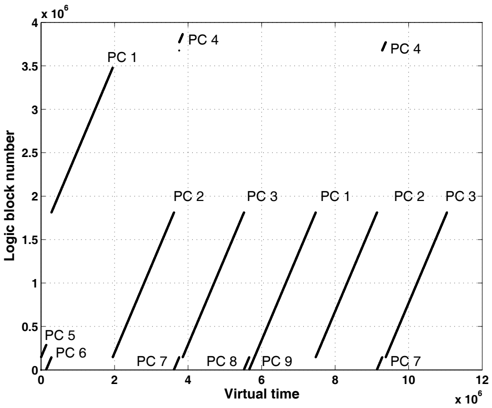


Fig. 3. Block references of BLAST.

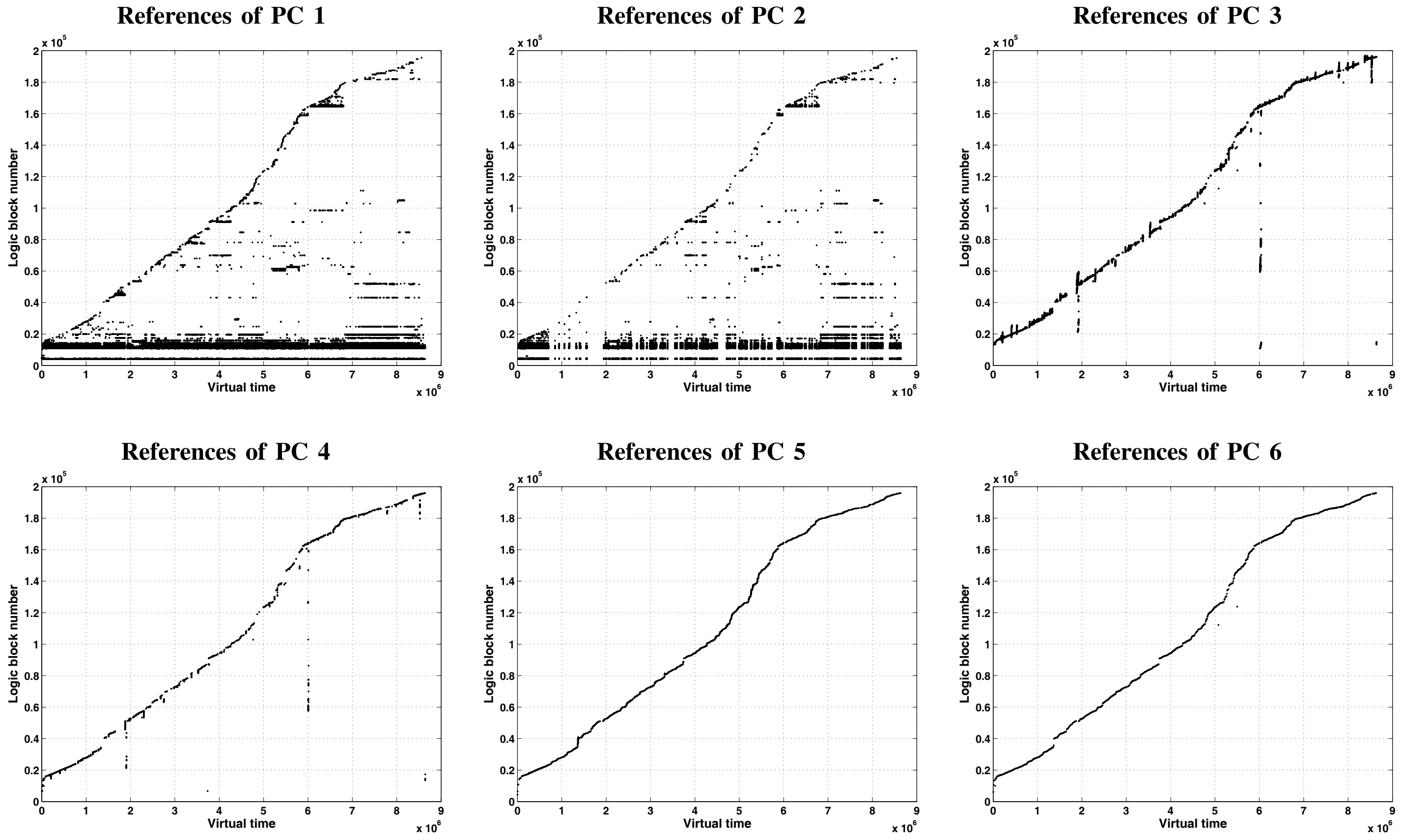


Fig. 4. Traces of 6 PCs with the highest numbers of references in gcc. The PCs, in order of decreasing numbers of references, are from 1 to 6.

plot and *BLAST* whose detailed descriptions are presented in Section IV. (Throughout this paper, the terms "block number" and "block address" are used interchangeably.) In the *gnuplot* trace, a sequence of plotting commands are issued in the order of *plot, plot, replot, plot3d, replot* to two large data files. While the two *replot* functions access a data file with the same pattern as their previous *plot* and *plot3d* functions, they follow a slightly different I/O path and thus have different PCs with each of the two *plots*. Although these plotting functions access the data repeatedly, a pure program counter based scheme, such as PCC or AMP, will erroneously classify these references as *sequential*. In the trace of *BLAST* (also described in Section IV), shown in Figure 3, the program forks three threads and searches through the database files simultaneously. While the database files are accessed repeatedly, program-counter based detectors will not be able to classify the patterns correctly due to their inability to retain the "global picture".

2) Pattern conflicts reduce detection accuracy and increase management overhead. Figure 4 presents traces of the top six PCs with the highest numbers of references, collected from the *gcc* trace described in Section IV. While PC1 and PC2 exhibit a looping pattern, PC5 and PC6 show a *sequential* pattern and PC3 and PC4 show a *sequential*

pattern with a small degree of repetition. Most referenced blocks thus are classified as *sequential* if they are initiated by PC3, PC4, PC5 and PC6, and as looping if by PC1 and PC2. Since the references of these PCs are interwoven with one another, blocks need to be continuously moved between the *sequential* partition and the *looping* partition. Such moves require *locks* to ensure consistency and correctness and can cause a significant maintenance overhead.

3) PC-based schemes cannot accurately distinguish *locality strengths*. Locality strength in the PC-based approach is used to determine which block is replaced. It is measured by the looping period, where a longer looping period represents a weaker locality. PCC uses a single period to measure the locality of all the blocks accessed by a particular PC on a cache miss, and evicts the block accessed by the PC that has the longest looping period. Although this period is averaged exponentially[1] by weighing recent periods more heavily than older ones, apparently a single looping period will not accurately measure the locality strength when a large amount of data is accessed. This can be easily observed from the traces of PC1 and PC2 in Figure 4. While PC1 and PC2 show a looping pattern, there is a significant portion of blocks whose actual looping periods are much longer than the average looping period.

B. The Design of RACE

Our RACE scheme is built upon the assumption that *future access patterns have a strong correlation with both the program context identified by program signatures and the past access behavior of current requested data.* While UBM only associates its prediction with the data's past access behavior, PCC and AMP only consider the relationship between future patterns and the program context in which the current I/O operation is generated. Our assumption is more appropriate for real workloads, as demonstrated by our comprehensive experimental study presented in Section V.

Our RACE scheme automatically detects an access pattern as belonging to one of the following three types:

- *Sequential references*: All blocks are referenced one after another and never revisited again;
- *Looping references*: All blocks are referenced repeatedly with a regular interval;
- *Other references*: All references that are not sequential or looping.

Figure 5 presents the overall structure of the RACE caching scheme. RACE uses two important data structures: a *file hash table* and a *PC hash table*. The *file hash table* records the sequences of consecutive block references and is updated for each block reference. The sequence is identified by the file description (*inode*), the starting and ending block numbers, the last access time of the first block, and their looping period. The *virtual access time* is defined on the reference sequence, where a reference represents a time unit. The looping period is exponentially averaged over the virtual time. The *PC hash table* records how many *unique* blocks each PC has accessed (*fresh*) and how many references (*reused*) each PC has issued to access blocks that have been visited previously. Although PCC also uses two counters, our RACE scheme is significantly different from PCC in that: 1) PCC's counters do not accurately reflect the statistical status of each PC process, resulting in misclassification of access patterns, as discussed later in this section, and 2) PCC only considers the correlations between the last PC and the current PC that accesses the same data block. In fact, many PCs exist in one application and it is likely more than two PCs access the same data blocks.

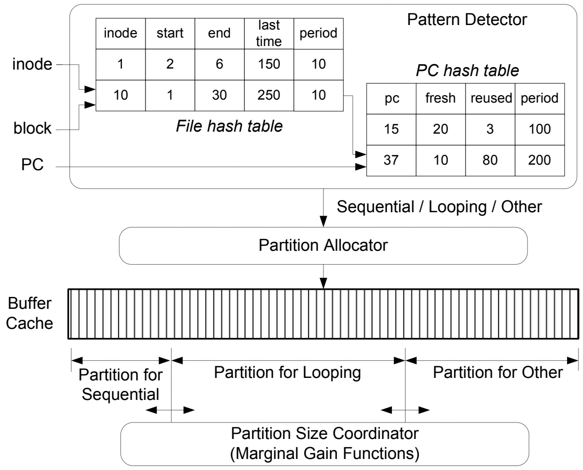


Fig. 5. The key structure of the RACE scheme. The Partition allocator and the Partition size coordinator take the results of pattern detector to adaptively fine-tune the size of each cache partition. If a sequence is found in the file hash table, then the period stored in the file hash table is used to update the period field in the PC hash table.

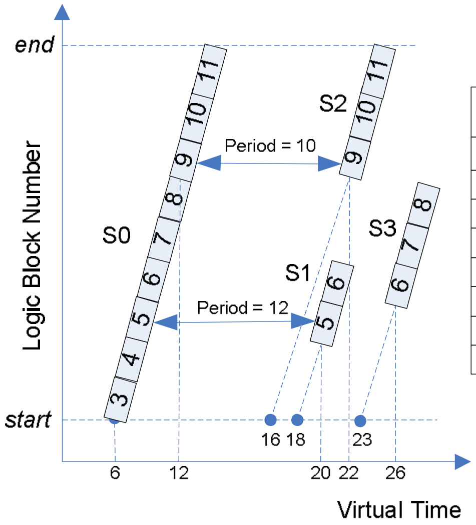
The detailed pattern detection algorithm is given in Algorithm 1. The main process can be divided into three steps. First, the file hash table is updated for each block reference. RACE checks whether the accessed block is contained in any sequence in the file hash table. If found, RACE updates both the last access time and the sequence's average access period. When a block is not included in any sequence of the file hash table, RACE then tries to extend an existing sequence if the current block address is the next block of that sequence or otherwise RACE assumes that the current request starts a new sequence. Second, RACE updates the PC hash table by changing the *fresh* and *reused* counters. For each revisited block, *fresh* and *reused* of the corresponding PC are decreased and increased, respectively. On the other hand, for a block that has not been visited recently, the *fresh* counter is incremented. The last step is to predict access patterns based on the searching results on the file and PC hash tables. If the file table reports that the currently requested block has been visited before, a "looping" pattern is returned. The looping period will identify how often this file have been accessed. If the file table cannot provide any history information of the current block, RACE relies on the PC hash table to make predictions. A PC with its *reused* counter larger than its *fresh* counter is considered to show a "looping" pattern. On the other hand, a PC is classified as "sequential" if the PC has referenced a certain amount of one-time-use-only blocks and as "others" if there are no strongly supportive evidence to make a prediction. By using the hashing data structure to index the file and PC tables, which is also used in LRU to facilitate the search of a block in the LRU stack, RACE can be implemented with a time complexity of $O(1)$.

How to efficiently calculate the average access time for each

[1] The exponential average S of a time series $u(t)$ is defined as $S(t+1) = \alpha \cdot S(t) + (1-\alpha) \cdot u(t+1)$ where $0 < \alpha < 1$.

Algorithm 1 Pseudocode for the RACE pattern detection algorithm.

```
RACE($inode$, $block$, $pc$, $curTime$)
{$\mathbb{F}$: File hash table; $\mathbb{P}$: PC hash table}
if $PC \notin \mathbb{P}$ then Insert ($pc$, 0, 0, $\infty$) into $\mathbb{P}$;
if $\exists f_1 \in \mathbb{F}$, $f_1.inode = inode$ and $f_1.start \leq block \leq f_1.end$ then
    $lastTime = curTime - (block - f_1.start)$; {infer "ghost" reference time of the $1^{st}$ block}
    $f_1.period = \alpha \cdot f_1.period + (1 - \alpha) \cdot (lastTime - f_1.lastTime)$; {exponential average}
    $\mathbb{P}[pc].reused$++; $\mathbb{P}[pc].fresh$--;
    $\mathbb{P}[pc].period = \beta \cdot f_1.period + (1 - \beta) \cdot \mathbb{P}[pc].period$; {exponential average}
    {update last reference time of the $1^{st}$ block}
    if access direction reversed then $f_1.lastTime = lastTime$;
    return("looping", $f.period$);
else if $\exists f_2 \in \mathbb{F}$, $f_2.inode = inode$ and $f_2.end = block - 1$; then
    $f_2.end = block$; {extend existing sequence}
    $\mathbb{P}[pc].fresh$++;
else
    $f.inode = inode$; $f.start = f.end = block$; $f.lastTime = curTime$; $f.period = \infty$;
    Insert $f$ into $\mathbb{F}$; {Insert a new sequence}
    $\mathbb{P}[pc].fresh$++;
end if
if $\mathbb{P}[pc].reused \geq \mathbb{P}[pc].fresh$ then return("looping", $\mathbb{P}[pc].period$);
if $\mathbb{P}[pc].fresh >$ threshold then return("sequential");
return("other");
```



Current Time	Current Blk Ref	Current Period	Last Access Time
20	5	18-6=12	6
21	6	18-6=12	6
22	9	16-6=10	6
23	10	16-6=10	6
24	11	16-6=10	6
26	6	23-18=5	18
27	7	23-18=5	18
28	8	23-18=5	18

Fig. 6. An example to illustrate the calculation of average access period.

access sequence is a challenging issue. It is not realistic to record the last access time of every accessed block due to prohibitively high overhead. We choose to only record the last access time of the very first block to reduce the overhead. The real implementation is slightly different than the abstract procedure given in Algorithm 1 and Figure 6 shows an example that illustrates the basic process. In a repeated I/O stream, such as $S1$, $S2$ and $S3$, the access time of each block reference is virtually projected back to the time of the *start* block. Then the current access period is the time difference between the projected time and the recorded last access time of the start block. The access period of a sequence is exponentially averaged over the access periods of all block references in that sequence. After the second reversing point (a decrement in access addresses), such as the time instant 16 in this example, the last access time recorded in the file hash table is then updated for all subsequent reversing points. Occasionally, the access periods may be erroneously calculated. For example, the access period of references to block 7 and 8 are incorrectly reported as 5. This approach, however, does not compromise the accuracy significantly, as indicated by our simulation results presented in Section V.

The number of repeatedly access blocks, rather than the number of repeatedly accessed files, is used to identify the loop patterns for each PC. This is because we want to make cold files, which are less frequently accessed, weight less in the classifying process. Previous studies have shown that a small fraction of files absorb most of the I/O activities in a file system [30]–[33]. We believe that this commonly existed file access locality justifies our choice. Otherwise, biased pattern predictions would be generated if we place the same weight on all files and do not consider how many

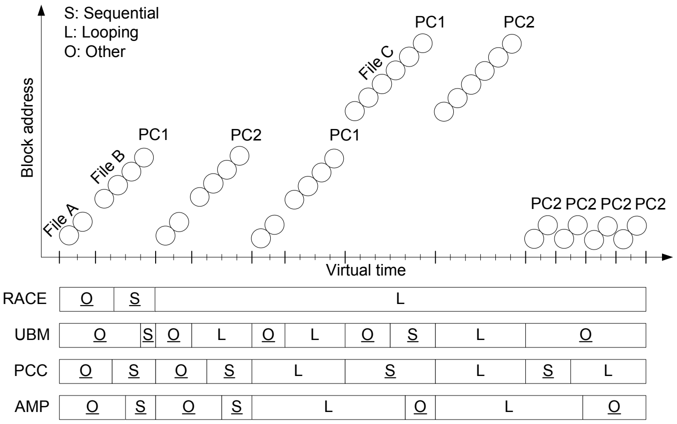


Fig. 7. An example of reference patterns. The sequentiality thresholds for UBM, PCC and RACE are 3. The sequentiality threshold, looping threshold and exponential average parameter for AMP are 0.4, 0.01, and 4 respectively. All incorrect classification results are underscored.

blocks have been accessed from individual files.

By observing the patterns both at the program context level and the file level and by exploiting the detection mechanism in both the continuous block address space within files and the discrete block address space in program contexts, RACE can more accurately detect access patterns. An example, shown in Figure 7, is used to illustrate and compare the classification results of RACE, UBM, PCC, and AMP, in which all false classification results are underscored.

RACE File A is initially classified as *other*. After File A is visited, the $fresh$ and $reused$ counters of PC1 are set to 2 and 0 respectively. After the first block of File B is accessed, the pattern of PC1 immediately changes to be *sequential* since the $fresh$ count becomes larger than the threshold. Thus during the first iteration of accesses to File A and B, RACE incorrectly classifies the first three blocks as *other* and then next three blocks as *sequential*. However, after the first iteration, RACE can correctly identify the access patterns. During the second and third iterations, the sequences for both File A and File B are observed in the file hash table and are correctly classified as *looping*. Although File C is visited for the first time, it is still correctly classified as *looping*. This is because the $fresh$ and $reused$ counters of PC1 are 0 and 6 respectively before File C is accessed. After that, all references are made by PC2 and they are classified as *looping* since the file hash table have access records of File B and C.

UBM Since the total number of blocks in File A is less than the threshold in UBM, all references to File A are incorrectly classified as *other*. The initial references to the first three blocks and the fourth block of File B are detected as *other* and *sequential*, respectively. After that all references to File B are classified as *looping*. Similar classification results are observed for references to File C.

PCC While the blocks of a sequential access detected by UBM has to be contiguous within a file, PCC considers sequential references as a set of distinct blocks that may belong to different files. The initial three blocks accessed by PC1 are classified as *other* and then PC1 is classified as *sequential*. Although PC2 is accessing the same set of blocks as PC1, it is still classified first as *other* and then as *sequential* when the threshold is reached. Before File C is accessed, the values of both *seq* and *loop* of PC1 are 6. Since *seq* of PC1 is increased and becomes larger than *loop*, accesses to File C made by PC1 are classified as *sequential*. Before File C is revisited by PC2, the values of both *seq* and *loop* of PC2 have changed to be 0 and 6 respectively through the references made by PC1, thus references to File C are detected as *looping*. After File C is accessed, the values of both *seq* and *loop* of PC2 are 6. References to File A made by PC2 are classified first as *sequential* and then as *looping*.

AMP The classification results are reported by the AMP simulator from its original author. To reduce the computation overhead, AMP uses a sampling method with some sacrifice to the detection accuracy. Since the sample trace used here is not large, the entire results are collected without using the sampling function in the AMP simulator. The initial *recency* of a PC, defined as the average ratios between the LRU stack positions and the stack length for all blocks accessed by the current PC, is set to be 0.4. Last references to File A made by PC2 are incorrectly detected as *other*, which indicates that AMP has a tendency to classify looping references as *other* in the long term. We can use a shorter and simpler reference stream to further explain it. Given a looping reference stream $L = \{1, 2, 3, 4, 3, 4, 3, 4\}$, the average recency of L is 0.67 that is higher than the threshold, 0.4. Accordingly, AMP falsely considers the pattern of L as *other*. In addition, AMP has another anomaly in which it has a tendency to erroneously classify a *sequential* stream as a *looping* one. For example, for a sequential reference stream $S = \{1, 2, 1, 2, 3, 4, 5, 6, 7, 8\}$, the average recency of S is 0 and AMP identifies this sequential pattern as *looping*. The first anomaly is more commonly observed in the workloads studies in this paper, which explains why the performance of AMP tends to be close to that of ARC in our experiments shown in Section V.

IV. Application Traces Used in the Simulation Study

The traces used in this paper are obtained by using a trace collection tool provided by [7]. This tool is built upon the Linux *strace* utility that intercepts and records all system calls and signals of traced applications. A PC signature is obtained by tracing backwards the function call stack in *strace*. The modified *strace* investigates all I/O-related activities and reports

TABLE I
TRACES USED AND THEIR STATISTICS

Trace	Request Num.	Data Size (MB)	File Num.	PC Num.
gcc	8765174	89.4	19875	69
gnuplot	677442	121.8	8	26
cscope	2131194	240	16613	40
glimpse	2810992	194	16526	7
BLAST	11042696	1789.6	13	20
tpch	13468995	1187	49	150850
tpcr	9415527	1087	49	150200

Trace	Concurrently Executed Applications	Request Num.	Data Size (MB)	File Num.	PC Num.
multi1	*glimpse + cscope*	4942186	434	33139	47
multi2	*gnuplot + BLAST*	11720138	1911	21	46
multi3	*cscope + BLAST + gcc*	21939064	2119	36501	129

the I/O triggering PC, file identifier(*inode*), I/O staring address and request size in bytes.

We use trace-driven simulations with various types of workloads to evaluate the RACE algorithm and compare it with other algorithms. These traces are considered typical and representative of applications in that most of them are routinely used in other caching algorithm studies. For example, the *cscope*, *glimpse* and *gcc* traces are used in [5], [7], [8], [17], [34], the *gnuplot* in [6], and tpch and tpcr in [35]. Table I summarizes the characteristics of these traces and more detailed description of each trace is presented below. The file and PC number represent the total number of unique files and pc signatures respectively.

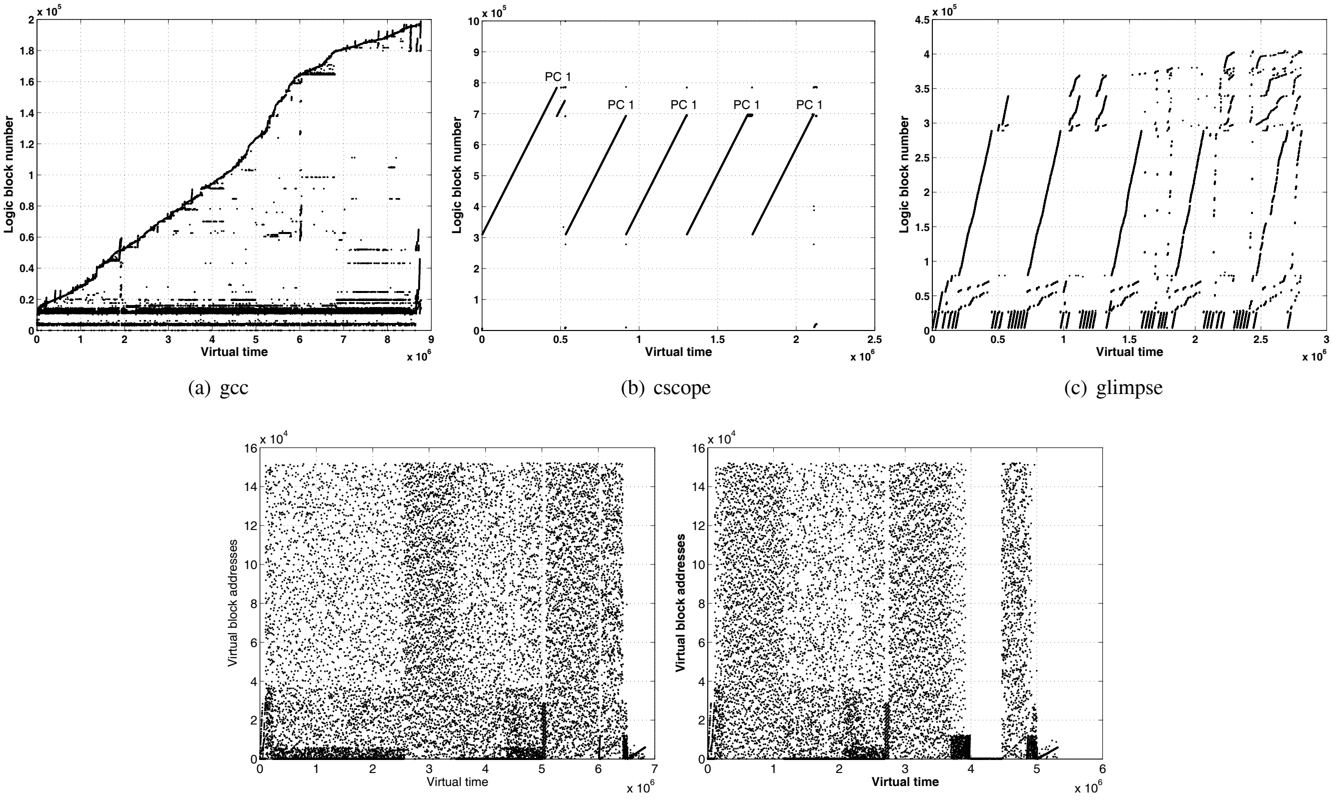
1) **gcc** is a GNU C compiler trace and it compiles and builds Linux kernel 2.6.10.
2) **cscope** [36] is an interactive utility that allows users to view and edit parts of the source code relevant to specified program items under the auxiliary of an index database. In *cscope*, an index database needs to be built first by scanning all examined source code. In our experiments, only the I/O operations during the searching phases are collected. The total size of the source code is 240MB and the index database is around 16MB.
3) **glimpse** [37] is a text information retrieval tool, searching for key words through large collections of text documents. It builds approximate indices for words and searches relatively fast with small index files. Similar to cscope, the I/O activities during the phase of index generation are not included in our collected trace. The total size of text is around 194MB and the glimpse index file is about 10MB.
4) **gnuplot** is a command-line driven interactive plotting program. Five figures are plotted by using four different plot functions that read data from two raw data files with sizes of 52MB and 70MB, respectively.
5) **BLAST** [38] is a widely used scientific application in computational biology. It is designed to find regions of local similarity between a query sequence and all sequences in a large gene database. In this study, a large database named *human EST* is used and it is roughly 1.8GB in size. Previous research has shown that the length of 90% of the query sequences used by biologists is within the range of 300-600 characters [39]. Thus, in this work, we choose to use a sequence of 568 characters extracted from the *ecoli.nt* database as the query sequence.
6) **tpch** and **tpcr** benchmarks [40] perform random access to a few large MySQL database files. The traces used in this study are obtained from Ref. [35]. Ref. [35] suggests that disk I/O prefetching should be disabled in both tpch and tpcr to prevent cache pollution. Thus we only use the traces without prefetching.
7) **multi1** is obtained by executing *glimpse* and *cscope* concurrently, which represents a text searching environment.
8) **multi2** is obtained by executing *gnuplot* and *BLAST* concurrently, which simulates an environment of database queries and scientific visualization.
9) **multi3** is obtained by concurrently executing three workloads, *cscope*, *BLAST*, and *gcc*, which provides a workload of database queries and code programming.

The traces of *gnuplot*, *BLAST*, *gcc cscope*, *glimpse*, *tpch*, and *tpcr* in Figure 2, Figure 3, and Figure 8, respectively, showing trace address as a function of the virtual time that is defined as the number of references issued so far and is incremented for each request. For the sake of visibility, the tpch and tpcr traces are shown with a sampling period of 400.

V. PERFORMANCE EVALUATION

This section presents the performance evaluation of RACE through a trace-driven simulation study with ten different but typical traces from real applications. We compare the performance of RACE with seven other replacement algorithms, including UBM [5], [9], PCC [7], AMP [8], LIRS [17], [20], ARC [18], LRU and the off-line optimal policy (OPT). Simulation results of UBM, LIRS and AMP were obtained using simulators from their original authors respectively. We implemented the ARC algorithm according to the detailed pseudocode provided in [22]. We also implemented the PCC simulator and our RACE simulator by modifying the UBM simulator code. The UBM's cache management scheme based on the notion of marginal gain is used in PCC and RACE without any modification, which allows an effective and fair comparison of the pattern detection accuracies of UBM, PCC, and RACE.

The measure of *hit ratio* is used as our primary metric in the performance comparison. Hit ratio is defined as the fraction of I/O requests that are successfully served by the cache without going off to the secondary disk storage. We believe that hit ratio is a



(a) gcc (b) cscope (c) glimpse

(d) tpch (e) tpcr

Fig. 8. Block references of *cscope*, *gcc*, *glimpse*, *tpch*, and *tpcr*

comprehensive metric to evaluate the accuracy, responsiveness, and stability of pattern-detection-based algorithms since these three factors can directly impact the hit ratios. More specifically, the accuracy of locality detection, in terms of access periods in this paper, directly influences the order of block eviction; Promptly adapting to patterns changes can avoid hit ratio degradation caused by obsolete information; Stability will guarantee consistently high hit ratios across different cache sizes and a wide spectrum of workloads.

A. Cache Management Scheme

PCC and RACE use the *marginal gain* in the original UBM [5], [9] simulator to manage the three partitions of the buffer cache. The marginal gain is defined as the expected extra hit ratios increased by adding one additional buffer [25], [41]. The marginal gain of the *sequential* partition is zero since no benefit can be obtained from caching one-time-use-only data. The marginal gain for the looping partition is $\frac{1}{p_{max}+1}$ where p_{max} is the maximum looping period of blocks in the looping partition. The marginal gain for the *other* partition is estimated according to Belay's life function [42]. UBM, PCC and RACE aim to maximize the expected hit ratios by dynamically allocating the cache space to the three partitions: *looping*, *sequential* and *other*. For the *sequential* partition, no more than one buffer is allocated, except when the buffers are not fully utilized, since its marginal gain is zero. The cache space is switched between the *looping* and the *other* partitions according to the comparison of their estimated marginal gains. It always frees a buffer in the partition with a smaller marginal gain and allocates it to the *other* partition until both marginal gains converge to the same value.

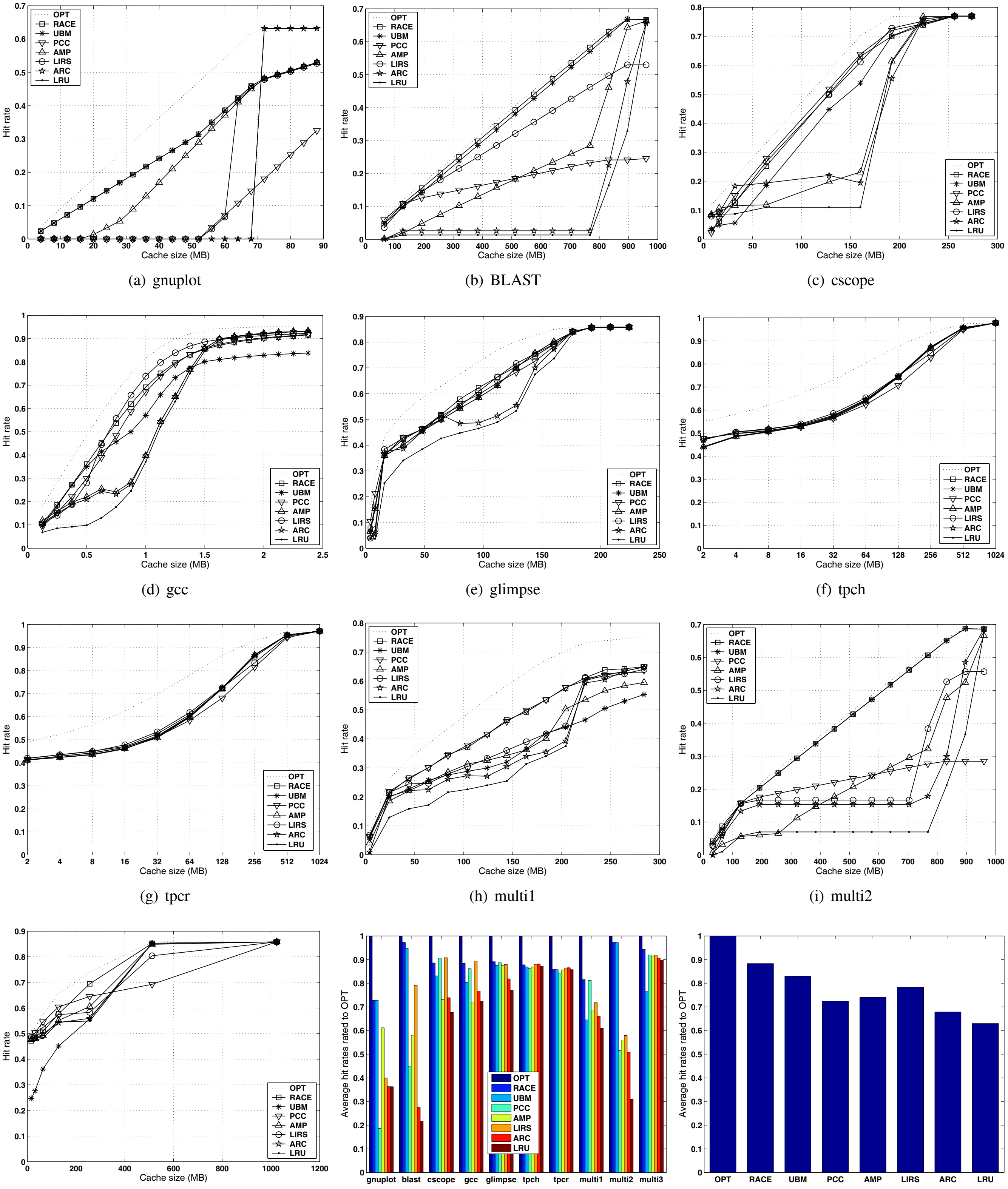
AMP proposes a randomized eviction policy to manage the cache partitions. Upon a cache miss, AMP randomly chooses a non-empty partition and frees the block at the MRU position of that partition. While this randomized eviction works well for their design that employs ARC [18] to manage cache replacement, this replacement algorithm does not work efficiently for UBM, PCC and RACE for the simple reason that UBM, PCC, and RACE only use LRU or MRU to manage cache in order to achieve a low overhead. While ARC itself can automatically adapt to the workload changes, LRU and MRU do not provide such adaptability.

B. Simulation Results

Based on access patterns, the ten traces used in the simulation study are divided into two main groups. Traces *gnuplot*, *BLAST*, *cscope* fit in the group in which looping patterns dominate. Traces *gcc*, *glimpse*, tpch, tpcr, *multi1*, *multi2* and *multi3* are in the group with mixed patterns. In what follows we report our simulation results in both groups and compare RACE with UBM, PCC, AMP, LIRS, ARC, LRU and OPT. The simulation parameters for these algorithms are given in Table II and all of them are suggested by their original authors in the literature except that the exponential average parameter α is not given in PCC [7].

1) Performance under Workloads with Looping Patterns:

- ***gnuplot*** Figure 9(a) shows the hit ratio comparisons for the workload *gnuplot* that has a looping pattern with long intervals. This workload generates a pathological case for



(a) gnuplot

(b) BLAST

(c) cscope

(d) gcc

(e) glimpse

(f) tpch

(g) tpcr

(h) multi1

(i) multi2

(j) multi3

(k) Average hit ratios (normalized to the average hit ratio of OPT)

(l) Average hit ratios for all traces (normalized to the average hit ratio of OPT)

Fig. 9. Comparison of hit ratios

TABLE II
PARAMETERS FOR CACHE REPLACEMENT POLICIES

Policy	Parameters
UBM	*max loop or sequential lists = 2000*, *threshold for detecting sequential access = 10*, *exponential average* $\alpha = 0.5$
PCC	*exponential average* α *= 0.5*, *no sampling*, *threshold for detecting sequential access = 100*
AMP	*threshold for detecting looping access = 0.4*, *exponential average* α *= 0.1*, *hit ratio threshold for detecting sequential = 0.001*
LIRS	*HIR =* 1% *of cache, LRU stact = 2* × *cache size*
ARC	*ghost cache = cache size*
RACE	*size of the file hash table = 2000*, *size of the PC hash table = 200*, $\alpha = 0.5$, $\beta = 0.1$ and *threshold for detecting sequential access = 100*

LRU when the size of accessed blocks in the loop is larger than the cache. Accordingly, LRU performs poorly and has the lowest hit ratios. Similar behavior is present in ARC as all blocks are accessed more than once and the frequency list is consequently managed by LRU. ARC achieves almost optimal hit rates when the cache is large since it can successfully evict out the least frequently used blocks. The benefit of LRU and ARC caching is only observed when the entire looping file set fits in the cache. Since the long sequential accesses are made by four PCs respectively as presented in Figure 2, PCC incorrectly classifies all references as *sequential* as expected and results in very low hit ratios. Both UBM and RACE, on the other hand, can correctly classify the references as *looping* after the first long sequence of sequential accesses, achieving much higher hit ratios. However, the cache management scheme employed in AMP is not efficient and thus resulting in lower performance than UBM and RACE. In sum, RACE achieves the same performance as UBM and a maximum of 52.3%, and 39.9% improvement in hit ratio over LRU and AMP respectively.

- ***BLAST*** The performance comparisons under the *BLAST* workload is presented in Figure 9(b). The accesses are dominated by three major PCs initiated by three concurrently running threads in the BLAST application. PCC cannot detect the access sharing among these three program counters and marks many blocks as *sequential*. This is the main reason why the hit ratios of PCC are 20.8%, 19.8% and 5.0% lower than those of RACE, UBM and AMP respectively on average. Since there are only 13 files accessed in this trace, the misclassification of the first iteration of accesses to new files does not significantly degrade the UBM performance under this workload. Thus UBM achieves comparable hit ratios with RACE. While RACE improves LRU by as much as 56.9%, for an average of 30.1%, ARC only improves LRU by 15.1% at the maximum, with an average of 2.3%. ARC is inherently capable of recording a reference history that is only twice the cache size. Under a workload with a large working set, such as *BLAST*, ARC fails to detect the looping patterns due to the lack of history information. Similarly, LIRS also suffers from limited history information that is stored in its two LRU stacks.
- ***cscope*** Figure 9(c) shows the hit ratio comparison for the *cscope* application. As explained in Section III, AMP tends to classify the looping references as *other* due to the fact that the average recency in AMP is highly sensitive to the stale history information as the center of working set shifts. As a result, the performance of AMP is close to that of ARC, which is used in AMP to manage the cache partition for the *other* pattern. PCC, LIRS and RACE achieves almost the same hit ratios and their hit ratios are 10.0% higher than that of UBM. Among the pattern-detection based algorithms, two main factors contribute to the inferior performance of UBM to RACE and PCC. First, with a total of 16613 files accessed in *cscope*, there are around 13.6% of files whose sizes are smaller than the threshold used in UBM. These small files form implicit looping patterns in a non-consecutive manner and thus are ignored in UBM. On the contrary, RACE and PCC can detect the implicit looping patterns in which a group of small files are repeatedly accessed. Secondly, there is around 5% of references that are issued to access files for the first time and UBM cannot make correct prediction for these references since UBM is intrinsically incapable of making accurate prediction when a file has not been accessed previously.

2) Performance under Workloads with Mixed Patterns:

- ***gcc*** Figure 9(d) shows the hit ratios under the workload of *gcc* that builds the newest version of the Linux kernel at the time of our experiments. Ref. [7] uses the trace collected only during pre-processing of an old Linux kernel (2.4.20). The trace does not reflect the whole I/O characteristics of building the kernel and it has only around 80000 read operations. We choose to use the trace that is collected during the whole building process of the newest Linux kernel 2.6.10 and it contains more than 9×10^6 read operations. We believe that this gives us a more comprehensive evaluation. In this trace, around 68% of the references are targeted at small files that are shorter than the threshold. When the cache size is smaller than 0.7MB, UBM and RACE perform the best. However, the hit rates of LIRS are the highest when the cache size is between 0.7MB and 1.5MB, although those of RACE come extremely close. Since the working set of *gcc* is not large, LIRS can better differentiate the locality strength of referenced blocks and is 2.4% and 0.7% better than PCC and RACE respectively. AMP cannot adapt to the shift of working set centers and falsely classifies almost all references as *others*, which explains why AMP and ARC share similarly poor performance.
- ***glimpse*** Figure 9(e) shows the hits ratio comparisons under the *glimpse* workload. The performance of RACE, UBM, AMP, PCC and LIRS are very close to one another and

perform much better than LRU. Specifically, RACE improves hit ratios of LRU by as much as 17.5%, with an average of 8.1%. Surprisingly, ARC clearly shows the Belady behavior where the hit ratio decreases while the cache size increases. This anomaly can be observed in the previous workloads as well. As introduced in Section II, ARC divides the cache of size c into two LRU lists L_1 and L_2, and they retain a total of c physical blocks and c identifiers of recently evicted blocks. While blocks in L_1 have been used only once, blocks in L_2 have been used twice or more. A hit in L_1 promotes the referenced block to L_2 so that it can stay in the cache for a longer time. ARC bases its replacement strategy on the following assumption: if the requested block identifier is in L_1 on a cache miss, then it is likely that the number of physical blocks in L_1 is too small; Similarly if the identifier of a missed block is in L_2, then the number of physical blocks in L_2 is conjectured to be too small. Thus ARC adaptively allocates more cache space to a list that has more misses. It achieves this goal by dynamically changing the number of physical blocks allocated to L_1 with a variable step size. Under the same I/O workload, the step size is continuously updated by its exponential average and is influenced by the size of cache. Thus the step size cannot truly distinguish the "cold" blocks from the "hot" ones and leads to the severe Belady anomaly.

- **tpch, tpcr** While the tpch and tpcr benchmarks repeatedly access a total of six large database files, only 3% references occur to immediately consecutive blocks [35] and over 80% stride distances between consecutive references are larger than 10 blocks. Figures 9(f) and 9(g) compare the hit ratio performance. The PCC performs slightly worse than LRU when the cache size is larger than 64MB. While the majority of references are absorbed by the six databases, there are over 15K program signatures and the mis-prediction of access periods degrades the performance in PCC. Compared with PCC, RACE not only correctly identifies more periodical accesses, but also provides more accurate access periods.
- ***multi1, multi2, multi3*** The hit ratio comparisons under the workloads of *multi1*, *multi2* and *multi3* are presented in Figures 9(h), 9(i) and 9(j) respectively. In sum, in *multi1*, RACE and PCC achieve the best hit ratios. In *multi2*, the hit ratios of RACE and UBM are the highest. RACE outperforms all other algorithms in *multi3*.

C. Average Hit Ratio Comparisons

Figure 9(k) shows the average hit ratios normalized to the average hit ratio of the OPT replacement algorithm for the eight workloads studied in this paper. Figure 10 compares the classification results between RACE, UBM, PCC, and AMP, which helps explain the reasons behind the superiority of RACE in terms of hit ratios. For *gnuplot*, *BLAST* and *multi2*, the PCC algorithm is pathological in that PCC cannot distinguish the pattern sharing among different PCs and falsely classifies many looping patterns as *sequential* patterns, as shown in Figure 10. For *cscope*, *gcc*, *glimpse*, *multi1*, and *multi3*, the UBM algorithm is pathological since it ignores the patterns clearly exhibited in small files and it is incapable of correctly detecting the access patterns for files that have not been referenced before. In almost all workloads, AMP erroneously identifies a larger fraction of accesses as the *other* pattern, as much as 74.9%, 19.7%, and 74.9% on average more than RACE, UBM, and PCC respectively, which dramatically lowers its hit ratios. RACE, on the contrary, exploits the detection mechanism in both the continuous block address space within files and the discrete block address space in program contexts, resulting in an average of 52.4%, 24.5%, and 70.8% more looping patterns being correctly detected than UBM, PCC and AMP respectively.

The experimental results on the ten workloads show that RACE is more robust than all other algorithms. Figure 9(l) presents the average values of hit ratios (normalized to the optimal hit ratios) presented in Figure 9(k). Compared with UBM, PCC, AMP, LIRS, ARC, LRU, the normalized hit ratio of RACE is higher by an average of 5.4%, 15.9%, 14.3%, 10.0%, 20.5%, and 25.4%, respectively. Table III shows the arithmetic average of absolute hit ratios of these algorithms with different sizes in each workload. RACE can successfully overcome the drawbacks of LRU and improve its absolute hit ratios by as much as 56.9%, with an average of 15.5%.

Compared with other state-of-the-art pattern-detection based schemes, RACE outperforms UBM, PCC and AMP by as much as 22.5%, 42.7% and 39.9%, with an average of 3.3%, 6.6% and 6.9%, respectively. In the *cscope* trace, RACE is 1.0% inferior to PCC on average due to the following fact: Although RACE correctly classifies files accessed at the end of first iteration as *looping*, these files are only accessed twice, as shown in Figure 8(b), and RACE wastes partial memory by caching them. Compared with the state-of-the-art recency/frequency based schemes, RACE consistently beats ARC in all workloads and outperforms LIRS in most workloads except *cscope* and *gcc*. In the *cscope* and *gcc* traces, RACE is on average 1.1% and 0.7% inferior to LIRS in absolute hit ratio. Since RACE improves the hit ratios of LIRS with an average of 6.0% over the eight workloads, we conclude that such slight performance degradation in *cscope* and *gcc* is not severe. The *gcc* workload is extremely LRU-friendly, in which 89.4 MB data is accessed and a LRU cache with a size of 1.5MB can achieve a hit ratio of 86%. It is our future work to avoid such slight performance degradation by improving our detection algorithm or by incorporating LIRS into RACE to manage the cache partitions. In sum, RACE improves the hit ratios of UBM, PCC, AMP, LIRS, ARC, and LRU relatively by 6.8%, 14.6%, 15.2%, 8.7%, 21.7.3% and 29.3% on average. This superiority indicates that our RACE scheme is more robust and adaptive than any of the other six caching schemes and also proves our assumption that the future access patterns are highly correlated with both program contexts and requested data.

D. Sensitivity Study on the Sampling Frequency

Our RACE algorithm needs to update both the file hash table and the PC hash table. The cache sizes are 1MB for *Linux*, 500MB for *mult1*, *mult2*, and *mult3*, and 50MB for the others. Figure 11 shows the sensitivity of the updating frequency. With a sampling frequency of less than 16 blocks, the hit ratios are barely adversely affected for most benchmarks except for *gcc* and *cscope*. In *gnuplot*, the performance of RACE reduces to LRU when the sampling frequency is large. From this analysis, we believe that the updating overhead and the memory requirement of the file hash tables and the PC tables can be traded off through appropriate sampling. A sampling period of 16 blocks provides a good tradeoff for the studied benchmarks.

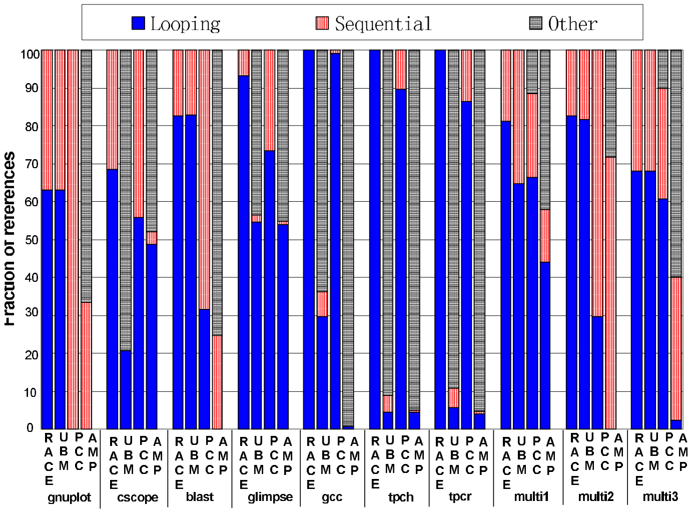


Fig. 10. Comparisons of classification results

TABLE III
HIT RATIOS UNDER THE 8 TRACES, AVERAGE OVER DIFFERENT CACHE SIZES

	OPT	RACE	UBM	PCC	AMP	LIRS	ARC	LRU
gnuplot	0.3961	**0.2884**	**0.2884**	0.0738	0.2423	0.1582	0.1437	0.1436
BLAST	0.3982	**0.3872**	0.3773	0.1789	0.2311	0.3149	0.1094	0.0860
cscope	0.5167	0.4577	0.4295	0.4681	0.3776	**0.4691**	0.3818	0.3496
gcc	0.7587	0.6704	0.6100	0.6536	0.5468	**0.6781**	0.5820	0.5492
glimpse	0.6681	**0.5954**	0.5849	0.5923	0.5849	0.5874	0.5469	0.5144
tpch	0.7724	0.6781	0.6711	0.6659	0.6709	0.6796	**0.6807**	0.6739
tpcr	0.7419	0.6378	0.6363	0.6257	0.6354	0.6413	**0.6423**	0.6364
multi1	0.5381	**0.4389**	0.3471	0.4371	0.3676	0.3863	0.3558	0.3280
multi2	0.4081	**0.3978**	0.3967	0.2104	0.2285	0.2363	0.2075	0.1263
multi3	0.6734	**0.6353**	0.5148	0.6190	0.6161	0.6187	0.6103	0.6047
overall	0.5872	**0.5187**	0.4856	0.4525	0.4501	0.4770	0.4261	0.4012

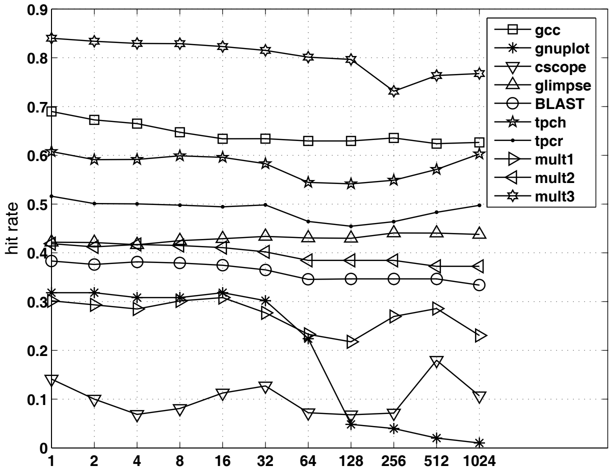


Fig. 11. Impacts of sampling frequency on hit ratios

VI. Conclusions

Cache replacement algorithms are crucial in bridging the increasing performance gap between processors and disk drives. Motivated by the limitations of existing state-of-the-art cache replacement algorithms, we propose a novel and simple block replacement algorithm called RACE. We make three main contributions: 1) We collected the I/O traces for eight real applications and investigate I/O access patterns in two correlated spaces: the program context space from which I/O operations are issued, and the file space to which I/O requests are addressed. 2) Our comprehensive application trace study revealed the pathological behavior in existing state-of-the-art cache replacement algorithms, including a file-level detection method (UBM) and two program context level detection methods (PCC and AMP). 3) Extensive simulation study conducted under these real-application workloads demonstrated that RACE, through its exploitation of the detection mechanism in both the continuous block address space within files and the discrete block address space in program contexts, is able to accurately detect reference patterns from both the file level and the program context level and thus significantly outperforms other state-of-the-art recency/frequency based algorithms and pattern-detection based algorithms. Due to the very high buffer cache miss penalties, which are typically 6 orders of magnitude higher than buffer cache hit times, we believe that the significant gains in hit ratios obtained by RACE over other algorithms will likely have significant performance implications in application response times.

Our study has two limitations. First, we have not implemented our design and evaluated it in real systems. Compared with recency/frequency based algorithms such as LRU, LIRS, and ARC, the program-context based algorithms, including RACE, PCC and AMP, need to pay the extra overhead of obtaining program counter signatures. Ref. [43] reports that it is inefficient to obtain program signatures through stack traversals in their quick-hack implementation. It is suggested that a library modification approach, which can read the PC directly from the calling program's stack and hence requires the least amount of overhead. Secondly, in order to achieve a direct comparison of pattern detection accuracy, RACE, as well as PCC, uses the marginal gain functions proposed in the UBM scheme to dynamically allocate the buffer cache. We believe that a more effective allocation scheme will be helpful to further improve the hit ratios. In the future, we will implement RACE into Linux systems and investigate other efficient allocation schemes.

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References

[1] M. J. Bach, *The design of the UNIX operating system*. Upper Saddle River, NJ, USA: Prentice-Hall, Inc., 1986.

[2] A. S. Tanenbaum and A. S.Woodhull, *Operating Systems Design and Implementation*. Upper Saddle River, NJ, USA: Prentice-Hall, Inc., 1987.

[3] R. W. Carr and J. L. Hennessy, "WSCLOCK - a simple and effective algorithm for virtual memory management," in *Proceedings of the eighth ACM symposium on Operating systems principles (SOSP)*. New York, NY, USA: ACM Press, 1981, pp. 87–95.

[4] A. J. Smith, "Analysis of the optimal, look-ahead demand paging algorithms," vol. 5, no. 4, pp. 743–757, Dec. 1976.

[5] J. M. Kim, J. Choi, J. Kim, S. H. Noh, S. L. Min, Y. Cho, and C. S. Kim, "A low-overhead, high-performance unified buffer management scheme that exploits sequential and looping references," in *4th Symposium on Operating System Design and Implementation (OSDI)*, Oct. 2000, pp. 119–134.

[6] J. Choi, S. H. Noh, S. L. Min, and Y. Cho, "An implementation study of a detection-based adaptive block replacement scheme," in *Proceedings of the 1999 USENIX Annual Technical Conference*, Jun. 1999, pp. 239–252.

[7] C. Gniady, A. R. Butt, and Y. C. Hu, "Program-counter-based pattern classification in buffer caching." in *Proceedings of 6th Symposium on Operating System Design and Implementation (OSDI)*, Dec. 2004, pp. 395–408.

[8] F. Zhou, R. von Behren, and E. Brewer, "AMP: Program context specific buffer caching," in *Proceedings of the USENIX Technical Conference*, Apr. 2005.

[9] J. Choi, S. H. Noh, S. L. Min, E.-Y. Ha, and Y. Cho, "Design, implementation, and performance evaluation of a detection-based adaptive block replacement scheme," *IEEE Trans. Comput.*, vol. 51, no. 7, pp. 793–800, 2002.

[10] L. A. Belady, "A study of replacement algorithms for a virtual-storage computer," *IBM Systems Journal*, vol. 5, no. 2, pp. 78–101, 1966.

[11] R. L. Mattson, J. Gecsei, D. R. Slutz, and I. L. Traiger, "Evaluation techniques for storage hierarchies." *IBM Systems Journal*, vol. 9, no. 2, pp. 78–117, 1970.

[12] E. J. O'Neil, P. E. O'Neil, and G. Weikum, "The lru-k page replacement algorithm for database disk buffering," in *Proceedings of the 1993 ACM SIGMOD international conference on Management of data*. New York, NY, USA: ACM Press, 1993, pp. 297–306.

[13] T. Johnson and D. Shasha, "2Q: A low overhead high performance buffer management replacement algorithm," in *Proceedings of the 20th International Conference on Very Large Data Bases (VLDB)*. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc., 1994, pp. 439–450.

[14] D. Lee, J. Choi, J.-H. Kim, S. H. Noh, S. L. Min, Y. Cho, and C. S. Kim, "On the existence of a spectrum of policies that subsumes the least recently used (LRU) and least frequently used (LFU) policies," in *Proceedings of the 1999 ACM SIGMETRICS International conference on Measurement and Modeling of Computer Systems*, 1999, pp. 134–143.

[15] Y. Smaragdakis, S. Kaplan, and P. Wilson, "EELRU: simple and effective adaptive page replacement," in *Proceedings of the 1999 ACM SIGMETRICS international conference on Measurement and modeling of computer systems*, New York, NY, USA, 1999, pp. 122–133.

[16] Y. Zhou, J. Philbin, and K. Li, "The multi-queue replacement algorithm for second level buffer caches," in *Proceedings of the General Track: 2002 USENIX Annual Technical Conference*. Berkeley, CA, USA: USENIX Association, 2001, pp. 91–104.

[17] S. Jiang and X. Zhang, "LIRS: An efficient low inter-reference recency set replacement policy to improve buffer cache performance," in *Proceedings of the ACM SIGMETRICS Conference on Measurement and Modeling of Computer Systems*, Jun. 2002, pp. 31–42.

[18] N. Megiddo and D. S. Modha, "ARC: A self-tuning, low overhead replacement cache," in *Proceedings of the 2nd USENIX Conference on File and Storage Technologies (FAST)*, Mar. 2003, pp. 115–130.

[19] D. Lee, J. Choi, J.-H. Kim, S. H. Noh, S. L. Min, Y. Cho, and C. S. Kim, "LRFU: A spectrum of policies that subsumes the least recently used and least frequently used policies," *IEEE Transactions on Computer*, vol. 50, no. 12, pp. 1352–1361, 2001.

[20] J. Song and Z. Xiaodong, "Making LRU friendly to weak locality workloads: A novel replacement algorithm to improve buffer cache performance," *IEEE Transactions on Computers*, vol. 54, no. 8, pp. 939–952, 2005.

[21] S. Jiang, F. Chen, and X. Zhang, "CLOCK-Pro: an effective improvement of the CLOCK replacement," in *Proceedings of 2005 USENIX Annual Technical Conference*, Apr. 2005.

[22] N. Megiddo and D. S. Modha, "One up on LRU," *;login: - The Magazine of the USENIX Association*, vol. 4, no. 18, pp. 7–11, 2003.

[23] S. Bansal and D. S. Modha, "CAR: Clock with adaptive replacement," pp. 187–200, Mar. 2004.

[24] P. Cao, E. W. Felten, A. R. Karlin, and K. Li, "Implementation and performance of integrated application-controlled file caching, prefetching, and disk scheduling," *ACM Transactions on Computer Systems*, vol. 14, no. 4, pp. 311–343, 1996.

[25] R. H. Patterson, G. A. Gibson, E. Ginting, D. Stodolsky, and J. Zelenka, "Informed prefetching and caching," in *Proceedings of the fifteenth ACM symposium on Operating systems principles (SOSP)*. New York, NY, USA: ACM Press, 1995, pp. 79–95.

[26] A. D. Brown, T. C. Mowry, and O. Krieger, "Compiler-based I/O prefetching for out-of-core applications," *ACM Transactions on Computer Systems*, vol. 19, no. 2, pp. 111–170, 2001.

[27] T. M. Madhyastha and D. A. Reed, "Learning to classify parallel input/output access patterns," *IEEE Trans. Parallel Distrib. Syst.*, vol. 13, no. 8, pp. 802–813, 2002.

[28] G. Glass and P. Cao, "Adaptive page replacement based on memory reference behavior," in *Proceedings of the ACM SIGMETRICS international conference on Measurement and Modeling of Computer Systems*. New York, NY, USA: ACM Press, 1997, pp. 115–126.

[29] K. So and R. N. Rechtschaffen, "Cache operations by MRU change." *IEEE Trans. Computers*, vol. 37, no. 6, pp. 700–709, 1988.

[30] R. Floyd, "Short-term file reference patterns in a UNIX environment," Computer Science Department, University of Rochester, Rochester, NY, Tech. Rep. TR-177, Mar. 1986.

[31] C. Staelin, "High performance file system design," Ph.D. dissertation, Department of Computer Science, Princeton University, Oct. 1991.

[32] V. Cate and T. Gross, "Combining the concepts of compression and caching for a two-level file system," in *Proceedings Architectural Support for Programming Languages and Operating Systems (ASPLOS)*, Santa Clara, CA, Apr. 1991, pp. 200–211.

[33] H. Tang and T. Yang, "An efficient data location protocol for self-organizing storage clusters," in *Proceedings of ACM/IEEE SuperComputing (SC)*, Phoenix, AZ, USA, Nov. 2003.

[34] P. Cao, E. W. Felten, and K. Li, "Application-controlled file caching policies," in *USENIX Summer Technical Conference*, Jun. 1994, pp. 171–182.

[35] A. R. Butt, C. Gniady, and Y. C. Hu, "The performance impact of kernel prefetching on buffer cache replacement algorithms," in *Proceedings*

of the International Conference on Measurements and Modeling of Computer Systems(SIGMETRICS). ACM, Jun. 2005, pp. 157–168.

[36] J. L. Steffen, “Interactive examination of a C program with Cscope,” in *Proceedings of Winter USENIX Technical Conference*, Jan. 1985.

[37] U. Manber and S. Wu, “GLIMPSE: A tool to search through entire file systems,” in *Proceedings of Winter USENIX Technical Conference*, San Francisco, CA, USA, 1994, pp. 23–32.

[38] S. F. Altschul, W. Gish, W. Miller, E. W. Myers, and D. J. Lipman, “Basic local alignment search tool.” *J Mol Biol*, vol. 215, no. 3, pp. 403–410, October 1990. [Online]. Available: http://dx.doi.org/10.1006/jmbi.1990.9999

[39] K. T. Pedretti, T. L. Casavant, R. C. Braun, T. E. Scheetz, C. L. Birkett, and C. A. Roberts, “Three complementary approaches to parallelization of local blast service on workstation clusters (invited paper),” in *Proceedings of the 5th International Conference on Parallel Computing Technologies (PACT)*. London, UK: Springer-Verlag, 1999, pp. 271–282.

[40] TPC, “Transaction Processing Council,” Website, http://www.tpc.org.

[41] D. Thiebaut, H. S. Stone, and J. L. Wolf, “Improving disk cache hit-ratios through cache partitioning,” *IEEE Transaction on Computer*, vol. 41, no. 6, pp. 665–676, 1992.

[42] J. R. Spirn, *Program Behavior: Models and Measurements*. New York, NY, USA: Elsevier Science Inc., 1977.

[43] C. Gniady, A. R. Butt, Y. C. Hu, and Y.-H. Lu, “Program counter-based prediction techniques for dynamic power management,” *IEEE Trans. Comput.*, vol. 55, no. 6, pp. 641–658, 2006.

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