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A Hint Frequency Based Approach to Enhancing the I/O Performance of Multilevel Cache Storage Systems

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Abstract With the enormous and increasing user demand, I/O performance is one of the primary considerations to build a data center. Several new technologies in data centers, such as tiered storage, prompt the widespread usage of multilevel cache techniques. In these storage systems, the upper level storage typically serves as a cache for the lower level, which forms a distributed multilevel cache system. However, although many excellent multilevel cache algorithms have been proposed to improve the I/O performance, they still have potential to be enhanced by investigating the history information of hints. To address this challenge, in this paper, we propose a novel hint frequency based approach (HFA), to improve the overall multilevel cache performance of storage systems. The main idea of HFA is using hint frequencies (the total number of demotions/promotions by employing demote/promote hints) to efficiently explore the valuable history information of data blocks among multiple levels. HFA can be applied with several popular multilevel cache algorithms, such as Demote, Promote and Hint-K. Simulation results show that, compared with original multilevel cache algorithms such as Demote, Promote and Hint-K, HFA can improve the I/O performance by up to 20% under different I/O workloads.

Keywords storage system, multilevel cache, hint, I/O performance

1 Introduction

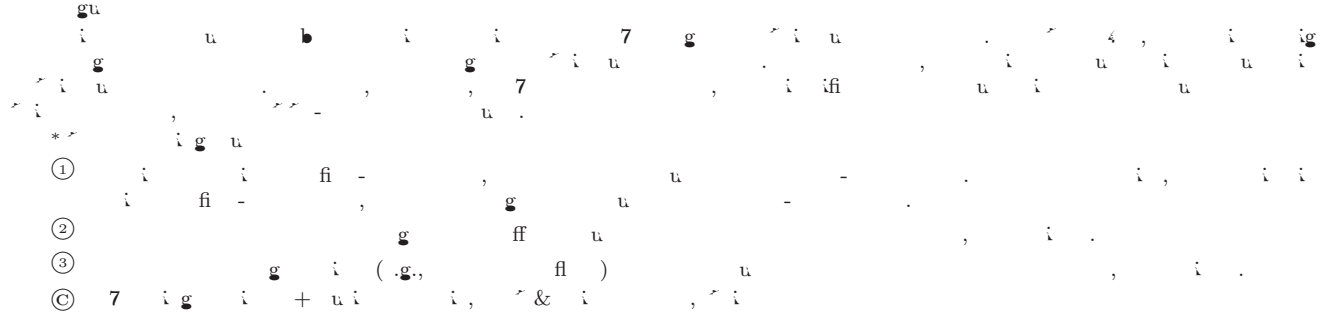
In big data era, I/O performance is still the bottleneck of data processing in many fields[1-10]. In large data centers, heterogeneous storage devices cooperate together to accelerate the I/O processing. Typically, the storage devices in the upper level serve as caches for the lower level, which forms a distributed multilevel cache system. In recent years, multilevel caches have received more attention due to the following reasons.

• *High I/O Performance.* By aggregating heterogeneous storage devices together, multilevel caches achieve higher I/O performance compared with using single level caches separately[11-13].

• *Low Monetary Cost.* Typically, multilevel cache policies can provide global management on all cache levels without any manual operations[14]. It can sharply decease the monetary cost.

• *High Flexibility.* Multilevel caches are widely used in many scenarios, such as in traditional client-sever model①[15-16], networked storage②[12-13] and hybrid storage③[17].

In the past two decades, many classic multilevel cache solutions were proposed to improve the I/O per-



formance of storage systems. One of the most effective approaches is making the cache exclusively among different hierarchies, where hints are well utilized to identify hot data blocks. These hints can provide a global view of a storage system, which can be optimized via general/specific replacement strategies.

According to the roles in different scenarios, hints can be divided into three categories, demote hints, promote hints and application hints. A demote hint[12] is a flag to mark a demotion operation, which occurs when a data block is evicted from an upper level to a lower level. Similarly, a promote hint[13] is used to identify a promotion, which is an opposite operation of demotion. Except for demote and promote hints, an application hint[18-19] is computed by well-defined formula(s) and is evaluated by the access patterns of I/O workloads. A hybrid hint is a flag containing information of a data block from multiple aspects such as demotion, promotion or application access patterns. In many previous literatures[20-22], hybrid hints are demonstrated to be an efficient way to enhance the performance significantly.

However, existing multilevel cache algorithms still have potential to be improved. Most multilevel cache algorithms[12-13,19] use hints to store the concentrated information of data blocks. The demote and promote hints based approaches only record the latest hint operations, thereby valuable history hint information is ignored. And the application hints are usually dependent on a specified application, which is not general to all scenarios. Some algorithms[22-23] keep the latest multiple steps hint information, but they are insufficient to describe the status of data blocks. The detailed illustration is given in Subsection 2.3.

To address the above problems, in this paper, we propose a novel hint frequency based approach, HFA, which is an efficient multilevel cache scheme to enhance the I/O performance. The main idea of HFA is using rich history hint information (e.g., hint frequencies) to efficiently identify hot data blocks.

Our contributions include the following aspects.

• We propose a novel hint frequency based approach, HFA, using history hint information of data blocks, which efficiently enhances the I/O performance of storage systems.

• HFA can cooperate with several famous multilevel algorithms, such as Demote, Promote and Hint-K.

• We implement HFA by combining with Demote, Promote and Hint-K algorithms. Simulation results demonstrate that HFA can enhance the cache performance under various I/O workloads.

The rest of this paper continues as follows. Section 2 briefly overviews related work and our motivation. In Section 3, we illustrate the design, model and replacement policies of HFA. Section 4 illustrates how HFA collaborates with other popular algorithms. In Section 5, we analyze the simulation results by using various multilevel cache approaches. Finally Section 6 concludes the paper.

2 Related Work and Our Motivation

Many classic cache schemes have been proposed to improve the I/O performance over the past several decades, which can be classified into two main categories: single level caches and multilevel caches. In this section, we briefly introduce the state-of-the-art algorithms and our motivation of this work.

2.1 Single Level Cache Algorithms

LRU[24] is widely used in buffer cache management. Since the 1990s, many LRU variants aim to improve the performance of single level caches. Due to page limit, here we only list some famous LRU-based algorithms: FBR[25], 2Q[26], LRU-K[27-28], UBM[29], LRFU[30], LIRS[31], ARC[32], CAR[33], SPCC[34], SARC[35], AMP[36], DULO[37], CLOCK-Pro[38], WOW[39], RACE[40], STOW[41].

2.2 Multilevel Cache Algorithms

Quite a few multilevel cache algorithms emerge to improve the aggregate I/O performance of distributed systems as summarized in Table 1. As introduced in Section 1, hints are widely used for cooperative cache for heterogeneous storage devices. Based on the usage of hints, we divide these cache algorithms into the following five classifications: multilevel algorithms without hints, those with demote hints, those with promote hints, those with application hints, and those with hybrid hints.

Without Hints. MQ[15] concentrates three properties for a good second-level buffer cache: minimal lifetime, frequency based priority, and temporal frequency to efficiently manage the second-level buffer cache.

With Demote Hints. The demote algorithm[12] first uses demote hints to describe evicted data information from the upper cache level, which makes caches exclusive. Through demote hints, the dynamic behavior of

evicted caching data is well captured, which increases the cache hit rate and decreases the average latency in different applications. From then on, demote hints have been extensively used in multilevel cache solutions. X-RAY[42] is another sample which uses demote hints in disk arrays. It gives the array cache the data information on the content through file-node operations and writes log updates. Other cache policies combine with demote hints and the analysis of access patterns to enhance the cache performance, such as EV[43], GL-MQ[16], uCache[44].

Table 1. iff i i g ig

	√	×	×	×	×
	×	√	×	×	×
	×	√	×	×	×
-	×	√	×	×	×
	×	√	×	√	√
-	×	√	×	×	×
u	×	√	×	×	×
	×	×	×	√	×
	×	√	√	×	√
	×	×	√	×	×
2	×	√	√	√	√
	×	×	×	√	×
- i	×	×	×	√	×
i -	×	√	√	×	√
	√	×	×	×	×
	×	√	√	×	√

i u i g i . i u i g i . u i g i i i . u i g b i i . i - i - .

With Promote Hints. The promote[13,45] algorithms are proposed when hot data needs to be promoted to the higher cache level. Different from demote hints, promotion may cross layers and is decided by more factors (like cache size and hint frequency). Promote policy achieves additional better performance when combined with the ARC algorithm[32].

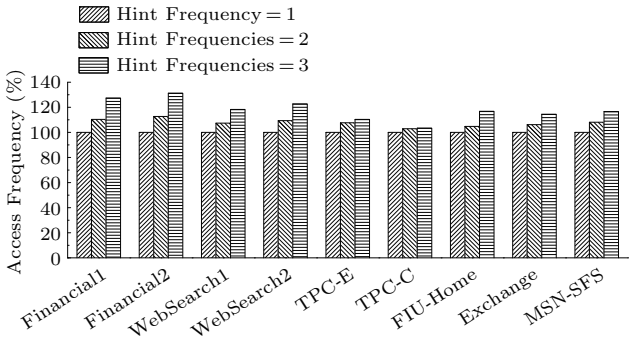
With Application Hints. TQ[18] is proposed to improve the efficiency of the second-level cache by using write hints. According to the access patterns in real database applications, three write hints (SYNCH, REPLACE and RECOV) are used. These hints provide strong indications to show the access patterns of current state and near future, which can manage the second cache level effectively. CLIC[19] uses dynamic application hints in various database applications to dramatically describe the hotness of data blocks, and has achieved good results. C-Hint[46] is a client-assisted cache management approach. It delivers sustainable high cache hit rate with limited cache capacity by analysing access history reports from clients.

With Hybrid Hints. Hybrid hints are appeared in ULC[47] algorithm. By combining with demote hints and application controlled hints (RETRIEVE), ULC effectively exploits hierarchical locality in multilevel cache. Karma[20] uses demote hints for exclusivity, and adds two additional operations (READ and READ-SAVE), which can be considered as promotions. Based on the Karma algorithm, MC^2[21] presents a solution for multiple clients with approximate application hints. A state-of-the-art implementation combining Karma and MC^2 is presented in [48]. Hint-K[22-23] uses the k-step hint history information of both demote and promote operations, which can efficiently describe the activeness of data blocks. In addition, with the development of tiered storage[49], unified single level cache algorithms (e.g., UARC[17]) are another way to provide a comprehensive solution for hybrid memory systems.

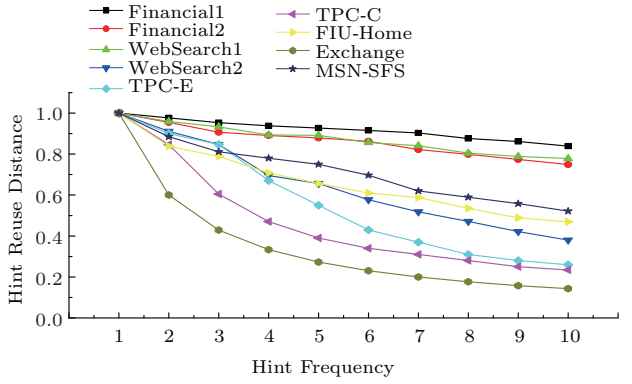
2.3 Our Motivation

Nowadays most commercial storage servers use a large storage cache to speed up I/O processing, where hint-based cache algorithms are primary solutions to smooth the gap among heterogenous storage devices[50-51]. Typically, a general purpose of these solutions is investigating history hint information to efficiently identify hot data blocks. They ignore some important history hint information, such as hint frequency and temporal locality, which motivates us to propose a new solution to enhance the I/O performance of storage systems.

We first study the effectiveness of hint frequency. Hint frequency is the total number of demotions/promotions (by employing demote/promote hints) in a period. The plots in Fig.1(a) show the number of block read hits of 200 pairs of sample blocks from nine traces. Each trace is simulated on a three-level cache with the cache space ratio of 1 : 2 : 4, and each kind of bar presents a hint frequency of three levels. The access frequencies of blocks with one demotion/promotion are normalized to 100%. We can see from Fig.1(a) that the blocks with higher hint frequency tend to be visited more frequently for all traces. It dedicates that the higher hint frequency has more important impacts on the access frequencies of data blocks.



(a)



(b)

ig. . i i g i u , u , i u i . i - . i i ' '4. g i [12-13] u i i . ( ) u iff . (b) i u i .

The temporal locality of buffer cache accesses describes the characteristics of traces, which is then used to design replace algorithms to manage buffer caches[52]. Similarly, we need to analyze the access patterns of demotions/promotions, and design a replacement algorithm based on those patterns. We use hint reuse distance to observe the temporal locality of the traces. Hint reuse distance is the number of distinct accesses between a demote operation and a read miss (or a promote) operation to the same block. For example, in a cache level L_i, if five distinct blocks are visited during the period between a demotion and later a promotion of a block x, then the hint reuse distance of block x is 5.

Fig.1(b) compares the temporal locality of nine traces on a cache that uses the same configuration with that in Fig.1(a). It shows the average hint reuse distance for the blocks grouped by the hint frequency from 1 to 10. The highest value of hint reuse distance for each trace is normalized to 100%. Obviously, for all nine traces, the blocks with higher hint frequency usually have a smaller hint reuse distance, despite that traces vary in terms of hint frequency sensitivity.

These two observations drive us to develop a practical approach to freeze or promote the blocks with higher hint frequencies in a certain cache level in order to improve the overall cache hit ratio.

3 Hint Frequency Based Approach (HFA)

In this section, we present the design and replacement policies of our hint frequency based approach, HFA. To facilitate the discussion, we summarize the symbols used in this paper in Table 2.

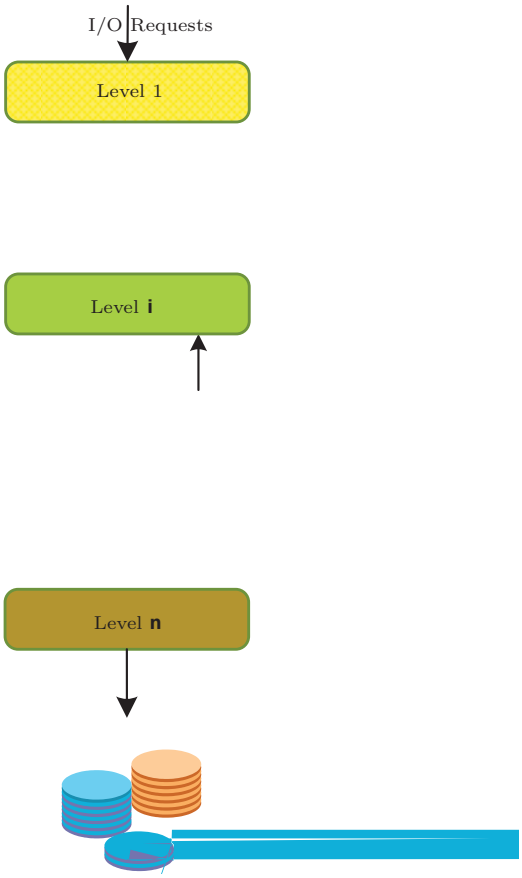
Table 2. i

	i i
n	u b
x	b i u i
L_i ($\leqslant i \leqslant n$)	i- (fi i L_1 i L_n)
D_i/P_i	i L_{i-1} L_i/ i L_{i+1} L_i
$D_i(x)/P_i(x)$	u b i / i b x i L_i
$hits(x)$	u b i b x i
T	i
t_1	gg g u i b i i b
t_2	u i b i i
k	b ' i - i i
δ	g i u
$F_i(x)$	i u i b x i L_i
$F_{\min}$	i u i i u u b i i
$H_i(x)$	u b x i L_i
S	i g b u u
N_C/N_H	u b / b i Q_1/Q_2
$t_C(x)/t_H(x)$	i u i / b i Q_1/Q_2

3.1 Overview

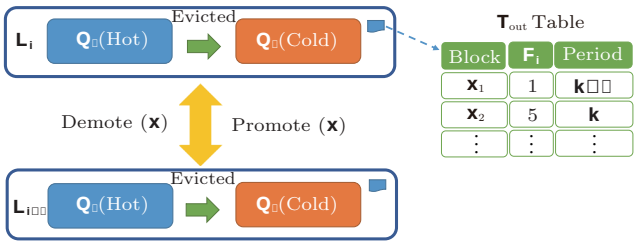
Our design is to improve I/O performance by investigating some potential history hint information of multilevel cache systems, such as hint frequencies. To achieve this goal, we propose a novel hint frequency based approach (HFA). As shown in Fig.2, the cache model of HFA consists of n cache levels ($L_1, L_2, ..., L_n$), excluding the first client level and the last storage de-

vice level. In this model, D_i delegates a demotion from L_{i-1} to L_i, and P_i stands for a promotion from L_{i+1} to L_i. $D_i(x)$ and $P_i(x)$ are used to represent the corresponding demotes/promotes for a data block x. In this model, hot blocks are encouraged to be promoted to the upper level, and cold blocks are evicted via demote operations.



hint frequency as we showed in the motivation to improve the cache performance, it calls a sophisticated design of the replacement policy.

As shown in Fig.3, there are two queues in HFA in each level. One is a queue (Q_1), which stores the data blocks with a high hotness value and sorts blocks by the hotness values. According to the observation from Fig.1(b), the blocks with a higher hint frequency value tend to be reused in a near future. Therefore, we set the other queue (Q_2), which saves the blocks with a low hotness value, but sorts the blocks by their hint frequencies. Q_1 has a higher priority than Q_2, that is, the evicted block from Q_1 will be inserted to Q_2, instead of erasing or demoting it to a lower level. As a result, blocks in Q_1 can resist in the cache longer.



ig. . u - u u u u .

Meanwhile, there are two types of blocks in Q_2 which can be promoted to Q_1. One is the blocks which are frequently visited. The other is the blocks whose hint frequency is higher than a threshold, because the increment on the value of hint frequency needs the movements of the block between cache levels. But the promoting process from Q_2 to Q_1 introduces the latency to the blocks with potential intensive accesses in the near future. To reduce the latency, the blocks in Q_2 will also be promoted to Q_1 after a hit.

The cache management of Q_2 can apply any proposed multilevel cache policy for single queue, such as Demote[12], Promote[13] and Hint-K[22]. Therefore, the management policy of Q_2 is not mentioned in the following paragraphs.

According to (2), hint frequencies are dynamic. To sort blocks by hint frequencies, in each level, HFA maintains a T_{out} table to record the hint frequency of the recent demoted/promoted blocks from a level (only cross cache level operations are considered; data blocks moving between Q_1 and Q_2 in a same cache level are not recorded in T_{out}). The detail usage of T_{out} is introduced in Subsection 3.2.3. The size of table T_{out} is fixed, which is set to 0.1% of the corresponding cache size in each level by default.

The table T_{out} organizes records in format $(x, F_i(x), k)$. It denotes that the hint frequency of block x in period from kT to $(k+1)T$ is $F_i(x)$. T_{out} retrieves entries to compute hotness value only when a block is inserted into a cache level. Simultaneously, it inserts or updates records only when a block is leaving a cache level. For example, block x_1 is evicted from a cache level at time t and $k_1T < t < (k_1+1)T$. Then a new record $(x_1, F_i(x_1), k_1)$ is inserted into T_{out}. If there has already existed a record $(x_1, F'(x_1), k_1)$ in T_{out}, the record will be replaced by $(x_1, F(x_1), k_1)$. The old records (resided longer than kT) in T_{out} are marked as invalid. When T_{out} is full, a cleanup process is called to remove all the invalid records. If T_{out} still has no space for the new record insertion after the cleanup process, a record with the lowest hint frequency in those oldest time intervals is evicted.

The HFA management policy is shown in Algorithm 1. Before kickoff, HFA sets a constant time interval T, a degradation ratio δ and creates two queues Q_1 and Q_2 on each cache level (line 1). For cache misses,

Algorithm 1. Pseudo-Code for HFA Cache Operations

Input: b x i
Initialize:
1 T δ, Q1 Q2
Cache miss:
2 **if** x b u i T_{out} **then**
3 u $F_i(x)$
4 **if** $F_i(x) > F_{\min}$ **then**
5 InsertQ1$(x, F_i(x))$
6 **else**
7 x i Q2
8 **end if**
9 **else**
10 x i Q2
11 **end if**

Cache hit in Q_1:
12 $Hit(x)++$
13 b x u i i fi b x' i
i fi $H(x') > H(x)$
14 x b i x'

Func InsertQ1$(x, F_i(x))$
Input: b x $F_i(x)$
15 $H_i(x) = F_i(x)$
16 **if** Q_1 i u **then**
17 i b x' i i i Q_1 Q_2
18 **end if**
19 x Q_1
20 **if** $hits(x') > hits_{\min}$ **then**
21 x' Q_2
22 **else**
23 Demote(x') x'
24 **end if**

HFA firstly checks whether corresponding records of a missing block x can be found in $T_{\rm out}$. If so, it reads $T_{\rm out}$ entries to calculate the hint frequency $F_i(x)$ and decides which queue the block x should reside (lines 2 and 3). If $F_i(x)$ is larger than $F_{\min}$, HFA calls a function $\mathsf{InsertQ_1}$ to insert x in Q_1. Otherwise, x is put in Q_2. $F_{\min}$ denotes a threshold value which is the minimal hint frequency that blocks need to meet to stay in Q_1 (lines 4∼8). In our implementation $F_{\min} = 1$ and $k = 6$. If x has no records in $T_{\rm out}$, HFA sends x to the head of Q_2 (line 10).

The function $\mathsf{InsertQ_1}$ takes a data block and its hint frequency value as inputs. If Q_1 is full, it evicts block x' with the minimal hotness from the queue, and then inserts x into Q_1 (lines 16∼19). The block x' is either demoted to a lower level or inserted into Q_2, by comparing $hits(x')$ with the lowest cache hits in Q_2, which is denoted by $hits_{\min}$. If $hits(x')$ is larger, then x' is sent to Q_2, otherwise, it calls function Demote to demote x' to a lower level (lines 20∼24). The demote policy will be introduced in Subsection 3.3. It is worth noting that HFA is an exclusive multilevel cache algorithm, and it never discards data blocks. The evicted block from one queue is either demoted or moved to another queue.

3.2.3 Lazy Update and Bubble Sort

The hint frequency of a block is a dynamic value, which is degrading along with time. Therefore, sorting blocks by their hotness values in Q_1 requires a real-time update which is costly and impractical for cache management. Therefore, we propose a lazy update and bubble sort to solve this problem.

Firstly, regarding the lazy update, we set a hotness expire duration (T) and a last update time for all blocks. We say the hotness of a block is expired if the duration from the last update time is longer than T. And we check $T_{\rm out}$ to update $H_i(x)$ when it is expired and x is called to use.

The demote and the promote processes of HFA work on the blocks with the minimal and the maximal hotness values, respectively. However, selecting those data blocks needs a sorting through all the blocks in a queue. To avoid this scenario, we introduce a bubble sort mechanism. The bubble sort increases $hits(x)$ by 1 if there is a cache hit on block x, and then it compares $H(x)$ with the blocks ahead sequentially until it finds block x' which satisfies $H(x') > H(x)$. Then, block x is allocated behind x' (lines 12∼14 in Algorithm 1). Instead of searching the block with the maximal and the minimal hotness values, the bubble sort only needs to retrieve the head and the tail blocks in a queue. Therefore, the bubble sort improves the sorting performance without correctness garranteed.

3.3 Demotion/Promotion Policies Among Multiple Levels

According to the cache policies in each level and history hint information, we adjust the original demotion/promotion policies for demote/promote-based cache algorithms, such as Demote[12], Promote[13], and Hint-K[22-23]. HFA uses hint frequency value as a hint. The hint is bundled with the corresponding data block and demoted or promoted to the other cache levels.

The demotions and promotions can happen on either Q_1 or Q_2. Since Q_2 is managed separately by a proposed multilevel cache policy, we only demonstrate the demotion and promotion process for Q_1. As shown in Algorithm 2, the demotion policy is implemented by function Demote, which takes a block x with the minimal hotness in Q_1 as an input. Before the demotion of x from cache level $i-1$, HFA updates $T_{\rm out}$ with $(x, F_i(x), k)$, and takes $F_i(x)$ as a hint. Then, $F_i(x)$ and block x are sent to level i. When cache level i receives x, HFA takes the hint and history records in $T_{\rm out}$ to calculate an initial hotness value $H_i(x)$ for the demoted block x by using (3). Then, $H_i(x)$ decides into which queue the block x should be inserted.

Algorithm 2 . Pseudo-Code for HFA Demotion and Promotion Processes

Func Demote(x)
Input: x Q_1
In cache level $i-$
$F_i(x)$ $T_{\rm out}$
$F_i(x)$ x i
x Q_1
In cache level i
$H_i(x)$
x
if x Q_1 **then**
Promote(x)
end if

Func Promote(x)
Input: x Q_1
In cache level i
x' Q_1
if $H_i(x') > H_i(x)$ **then**
$F(x')$ $T_{\rm out}$
$F(x')$ x' $i-$
x' Q_1
end if

Considering that the blocks with higher hint frequencies tend to be reused in a near future (shown in

Fig.1), HFA promotes hot blocks in Q_1 from a lower cache level i to a higher level $i-1$ to improve the cache response time on the hot blocks. The promotion process is awakened in a cache level i when Q_1 receives a demoted block x from $i-1$. Assuming that x' is a block with the maximal hotness in Q_1 of level i. HFA compares $H_i(x')$ with $H_i(x)$, and promotes x' to level $i-1$ if $H_i(x')$ is larger. After promotion, $F(x')$ is recorded in T_{out} and x' is evicted from Q_1.

3.4 Dynamic Partition

Dual-queue design in HFA prolongs the life of blocks with higher hint frequency in a cache level by managing the hot blocks in Q_1. The hot blocks in Q_1 are more likely to be visited again in a near future. However, an improper configuration on queue size impacts the cache performance negatively. A larger Q_1 could result in wasting the cache space for keeping cold blocks in Q_1, but replacing blocks in Q_2 more frequently. On the contrary, a smaller Q_1 losses the benefits gained from the hint frequency properties.

HFA uses a dynamic partition strategy in runtime to adjust the size ratio between Q_1 and Q_2. The basic idea of the dynamic partition is to enlarge Q_1 (shrink Q_2) if it contains a number of cold blocks ($H_i(x) = 0$ is considered as cold blocks in our configuration), but to shrink Q_1 (enlarge Q_2) if Q_2 contains too many hot blocks. The exchanged queue space between Q_1 and Q_2 is estimated by equation $S = N_{\text{C}} - N_{\text{H}}$, where N_{C} and N_{H} are the number of cold and hot blocks in Q_1 and Q_2 respectively.

In our implementation (see Algorithm 3), HFA repartitions the two queues over every T time in each cache level. Initially, the whole cache space is allocated to Q_1 and Q_2 evenly. Next, in run-time, HFA records the resident duration of cold blocks $t_{\text{C}}(x)$ in Q_1 and hot blocks $t_{\text{H}}(x)$ in Q_2 for every period T. And then it calculates S by using the average number of cold and hot blocks in Q_1 and Q_2 respectively.

$$S = \overline{N_{\text{C}}} - \overline{N_{\text{H}}},$$

where $\overline{N_{\text{C}}} = \frac{\sum_{x\in Q_1} t_{\text{C}}(x)}{T}$ and $\overline{N_{\text{H}}} = \frac{\sum_{x\in Q_2} t_{\text{H}}(x)}{T}$. The value will round down to the nearest integer. If S is a positive value, it indicates that the negative impact of cold blocks in Q_1 overweights that of hot blocks in Q_2. Thereby, HFA resizes the two queues by moving S space from Q_1 to Q_2. If Q_1 is full, S blocks are also reallocated to Q_2 from the tail of Q_1, vice versa. Note that the partitioning is logical, not physical, and the cache blocks are not actually moved in the cache during repartition.

Algorithm 3 . Dynamic Partition Process of HFA

```
Func Partition()
For each cache level
                          Q1      Q2
  for      T        do
           S
    if S >   then
             S              Q1    Q2
    end if
    if S <   then
             S              Q2    Q1
    end if
  end for
```

4 Case Study

HFA uses hint frequency information to improve the cache hit ratio in each cache level. Although the hint frequency predicts the cache access property in each level, it has two defects. Firstly, the hint frequency is a collection of history demotion and promotion operations, which usually has latency. For recency- and frequency-dominated applications, it may not catch the cache access pattern accurately. Secondly, the hint frequency improves the cache hit ratio of the blocks departure or arrival frequently in a period on each cache level. It does not catch the blocks that travel actively in different cache levels. For example, in a period T, a block x moves in and out level i for m times, where $m > F_{\min}$. It is considered as a hot block and will be kept longer in Q_1 in level i. Nevertheless, if x travels several different cache levels after it leaves level i, it will not be marked as a hot block. As proposed in [23], these blocks are considered as active blocks and have a potential to impact cache performance for many workloads.

The two-queue design of HFA makes it easy for cooperating with the other cache approaches to further improve the cache performance. In this section, we show how HFA integrates with algorithms like Demote, Promote and Hint-K to manage multilevel cache.

4.1 HFA Combined with Demote

Demote policy[12] introduces a DEMOTE operation to achieve exclusive caching. The blocks ejected from an upper cache are transferred to a lower level. Demote policy improves the cache system response time while the operation overhead is comparatively lower to the other multilevel cache approaches. Regarding

to the latency issue of HFA, HFA uses demote policy to manage Q_1 and sort blocks in Q_2 by hotness separately as shown in Algorithm 4. As a result, the MRU data blocks are marked as a hot block without waiting for any Demote/Promote operations. Thereby, Demote can reduce the latency for the recency-dominated applications.

Algorithm 4. Cache Management for HFA Combined with Demote Policy

For a cache read miss in cache level i:
1 ... x ... i
2 ... $F_i(x)$, ... x ... Q_2
3 ... Q_2 ... ,
4 $i+$
5 ... T_{out} ...

For a cache hit in Q_2 or Q_1:
6 ... Q_1
7 **if** Q_1 ...
8 ... $i+$, ... T_{out}
9 **end if**

4.2 HFA Combined with Promote

Promote approach[13] applies PROMOTE operation instead of DEMOTE. It achieves exclusive caching without demotions while the bandwidth cost and the cache aggregate response time are lower than those of DEMOTE. The principle of PROMOTE is to push the blocks that are most likely to be visited to the upper level. Combining HFA with PROMOTE can actively increase the hotness of those promoted blocks, which reduces the delay for hot blocks identification. To adapt PROMOTE, HFA assigns one bit hint for each block $hintP(x)$ to decide which cache should own the block. Computation of $hintP(x)$ in our implementation is the same with [13]. $hintP(x)$ is set to true when a cache hit or disk read is firstly formed and set to false when some cache decides to keep it. The management policy is shown in Algorithm 5.

4.3 HFA Combined with Hint-K

Hint-K approach explores the relationship between cache access and block activeness which is the degree of block movements between cache levels. Regarding to the second issue of HFA, Hint-K can gather the block history information from different cache levels which improves the hit ratio of HFA. Combining HFA and Hint-K needs some changes on the cache replacement policy (as shown in Algorithm 6). Instead of demotion and promotion with hint frequency, the combined algorithm uses K-step Hint Value (KHV)[23] as a hint. Q_2 is sort by LRU (Last Recent Use).

Algorithm 5. Cache Management for HFA Combined with Promote Policy

For a read request from upper level $i-$
if ... Q_2 **then**
... $i+$
else
... $hintP(x)$
if $hintP(x)$ ...
T_{out} ... x ... $i-$
end if
end if

For receiving a block x from the other levels
if $F_i(x) \leqslant F_{\min}$ **then**
if $hintP(x)$ ... **then**
T_{out} ... x ... $i-$
else
x ... Q_2
end if
else
x ... Q_1
end if

Algorithm 6. Cache Management for HFA Combined with Hint-K Policy

For Q_2 of level i,
receiving a block x:
if $x \in T_{\text{out}}$ **then**
x ... Q_1
else
x ... Q_2
end if

demoting a block:
Step 1. ... Q_2
Step 2. ...
Step 3. ...
$i+$
Step 4. ...

promoting a block at read miss:
Step 1. ... Q_2 ... $i-$
Step 2. x ... ,
x ...

Hint-K[22-23] is the closest approach to our work. Both approaches use a hybrid hint to improve the multi-level cache performance. However, there are two major differences between Hint-K and HFA. 1) The management policy of Hint-K in each cache level does not consider the period/sudden hot blocks, which means a block becomes a hotspot data in a short period. For example, for block x that was hopped between cache levels frequently in a transient time interval, Hint-K considers it as an active block and assigns x a high KHV to capture x in an upper level. If x is never used in the near future, we prefer to remove x from the queue im-

mediately. On the contrary, Hint-K resists x due to its high KHV, which reduces the cache hit ratio. This issue can get worse when those cold blocks are accumulated. Different from Hint-K, HFA considers this issue by degrading hint over time. A block can get cold and be demoted to a lower level when it receives no operation in a period. 2) Hint-K made an observation that hot blocks are usually active. In another word, a block is identified to be hot only after a number of inter-cache level movements of the block. Hence, there are always a latency and extra network traffic (typically, they are called warm-up cost of a data block[53]) to capture hot blocks in Hint-K. Instead, HFA reduces the warm-up response to hot blocks. We define a hot block by both hit and movement frequencies, which guarantees a quick detection on hot blocks and holds it in a higher priority queue.

5 Simulation Methodology and Analysis

To demonstrate the effectiveness of the HFA algorithm, we use a trace-driven simulation to evaluate HFA and other popular multilevel cache approaches under different I/O workloads.

5.1 Simulation Methodology

We use *fscachesim* as the simulator to evaluate various multilevel cache solutions, which appears in several previous literatures[12,22-23]. Nowadays most multilevel cache algorithms are based on demote and promote hints[12,16,22,42-44], thereby we select Demote[12], Promote[13] and Hint-K[22-23] algorithms in our comparison. HFA approach is collaborated with these algorithms, and we use D-HFA, P-HFA, H-HFA to delegate HFA combined with demote hints, promote hints and hybrid hints (both demote and promote hints), respectively. We select an ideal case on the knowledge of future hint information called Oracle HFA (Oracle for short), which is included in our comparison as well.

We use six I/O traces in our simulation as below. Statistics of the six traces are summarized in Table 3.

1) *WebSearch*: this I/O trace is collected from a popular search engine.

2) *FIU IODedup Homes* (*FIU*): the block traces are the collected downstream of an active page cache for three weeks from an NFS server that serves the home directories of SNIA research group.

3) *MSN Storage File System* (*MSN-SFS*): the traces are collected for MSN storage file server for a duration of 6 hours, which consists of 36 10-minute trace files; they trace the primarily disk I/O events at block level as well as file I/O events.

4) *Microsoft Exchange*: the Microsoft Exchange traces are collected from an Exchange 2007 SP1 server, which is a mail server for 5 000 corporate users.

5) *TPC-E*: the traces are collected at Microsoft running TPC-C benchmark.

6) *TPC-C*: the traces are collected at a server running TPC-C benchmark.

Table 3. u

		i	g ( ) / (× 6)
		( )	
b		4.	.7
		.	7.
-	7	.	4.
i	7	.	.
g			
-	7	.4	.7
-	7	7.	.

Unless otherwise mentioned, the following default parameters are used: two cache levels ($n = 2$) and the block size (4 KB). The ratio of cache size between an upper cache level and the next lower level is 1 : 4, and it is 1 : 2 for the Websearch and FIU traces. Aggregate cache size is the sum of all cache levels. Based on the default settings of *fscachesim*, the average access time of L_1 cache, L_2 cache and disks is 0.2 ms, 2 ms and 10 ms, respectively. We set the warm-up time to be long enough to make sure enough data blocks have been flooded to all cache levels.

In our simulation, we set proper values for several parameters in HFA. The size of T_{out} table is set to 0.1% of the cache size of each level, and δ is set to 0.5. T is set to the duration of 1 000 requests. We find that this group of setting gives the best performance in the experiment.

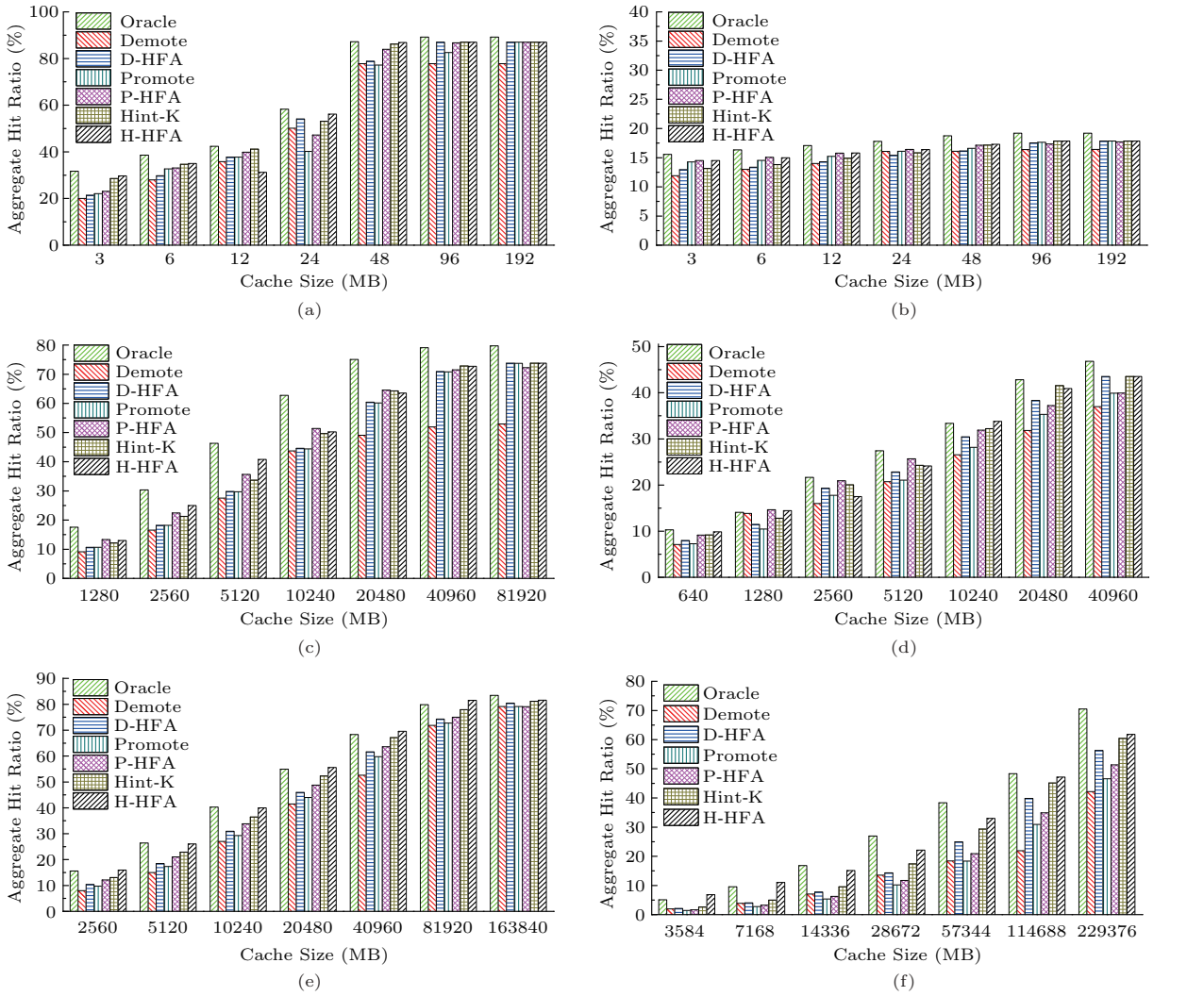
5.2 Simulation Results

In this subsection, we give the simulation results of different multilevel cache algorithms under various I/O workloads.

5.2.1 Cache Performance

First, we measure the cache performance under different workloads. In these simulations, we use two typical metrics, aggregate hit ratio and average response time, to evaluate the I/O performance.

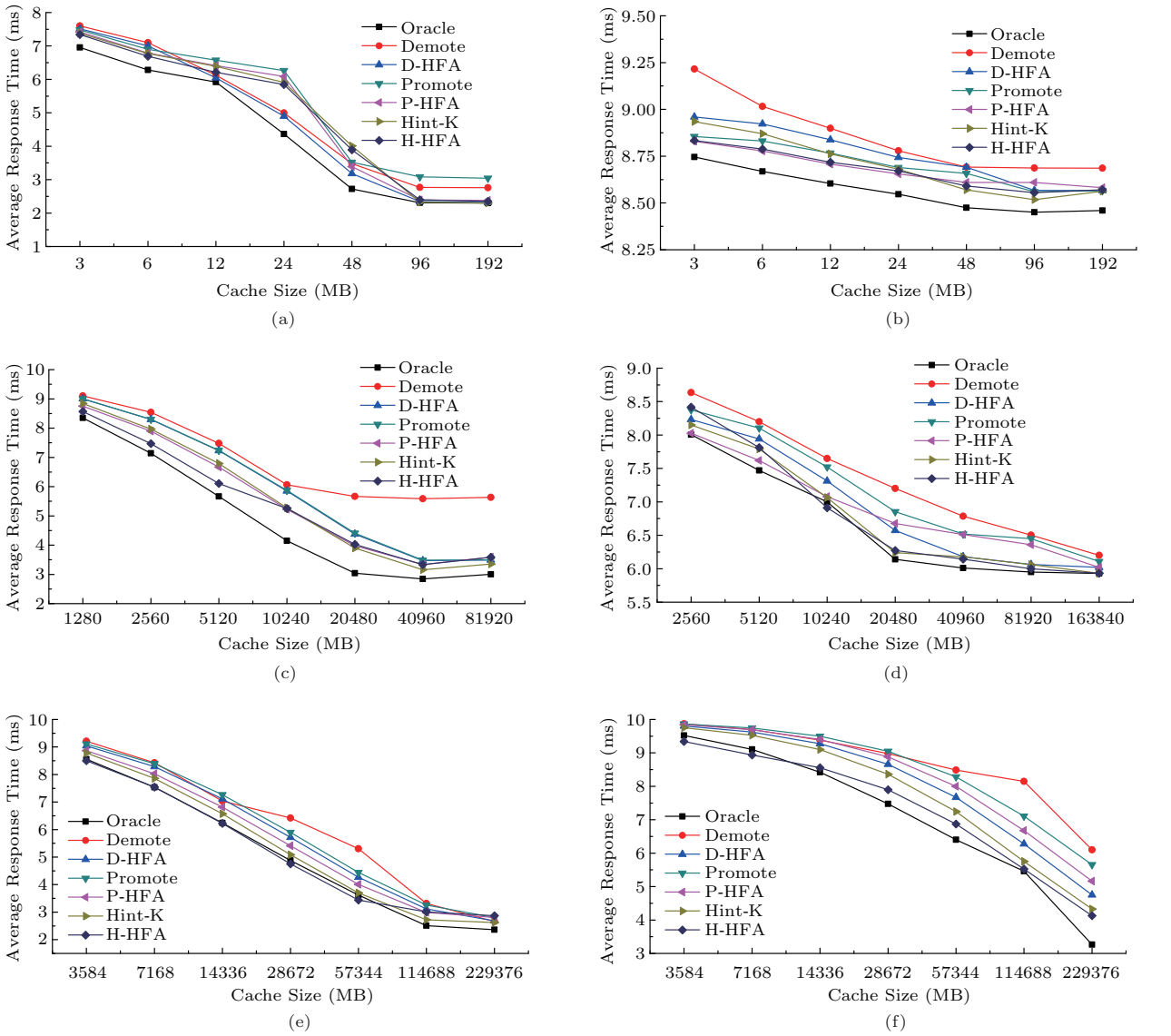
The results of aggregate hit ratio are presented in Fig.4. It is clear that compared with the corresponding original cache algorithms such as Demote, Promote



ig.4. gg g i i u i u i iff gg g i . - u - i i fi i i . - , i g - u - i i fi i i . ( ) b . (b) - . ( ) - . ( ) i g . ( ) - . ( ) -.

and Hint-K, HFA achieves performance gains by up to 19.1%, 7.1% and 6.5%, respectively. In most cases, it is easy to see that the gains from HFA are proportional to the cache size. This is because large cache size is suitable for HFA to allocate blocks to right queues. Further, increasing cache size beyond a value (such as 48 MB of WebSearch and 40 906 MB of MSN-SFS) does not seem to help hit ratio significantly. Moreover, compared with Hint-K, HFA presents a little improvement on Hint-K for various workloads, as shown in Figs.4(a)∼4(d). The reason is that those workloads show strong temporal locality. Then, in runtime, the size of Q_1 is much larger than the size of Q_2. As a result, the behaviour of H-HFA approaches to that of Hint-K.

The simulation results on response time under different workloads are shown in Fig.5. Compared with original Demote, Promote and Hint-K algorithms, HFA sharply decreases the average response time. For example, D-HFA reduces the average response time by up to 26% compared with Demote in Fig.5(c). P-HFA and H-HFA decrease the I/O latencies by up to 20.7% and 10.1%, respectively. Clearly, the latency improvement of HFA over Hint-K is comparatively smaller than that of D-HFA and P-HFA. It is because that both HFA and Hint-K are history hint based approaches. In Fig.5(b), we also notice a special case on cache size 96 MB that Promote responses faster than HFA. The reason is that, for trace FIU-HOMES, a large number of promoted blocks managed by HFA in the upper level are degraded



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as cold blocks and demoted quickly before the next visiting.

We summarize the previous results as shown in Table 4.

Table 4. i u i ˆ g i i gg g i i g i

g i	gg g i (%)	g i (%)
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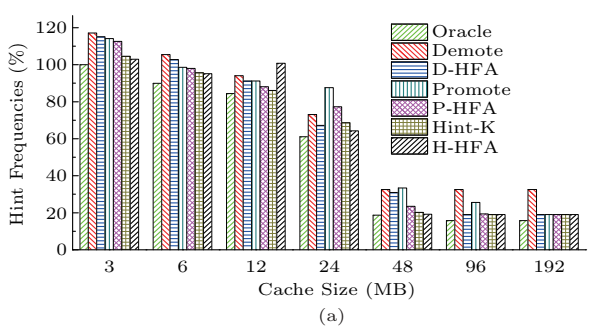
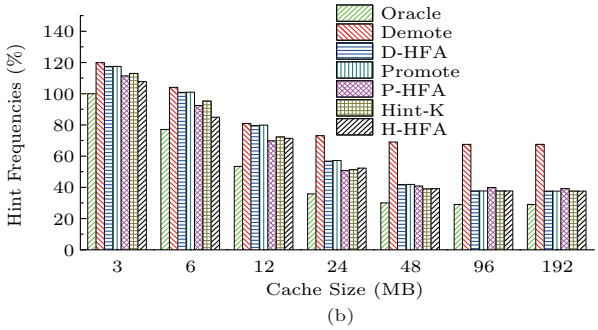
7.		.
i -	.	.

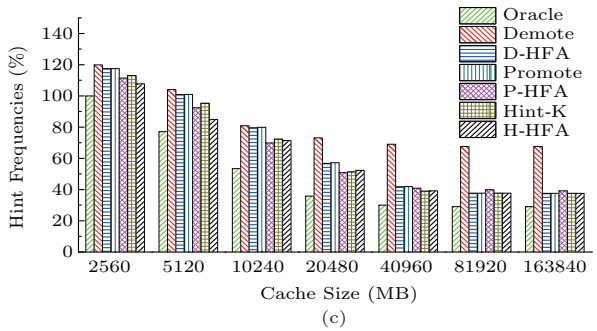
5.2.2 *Cache Overhead*

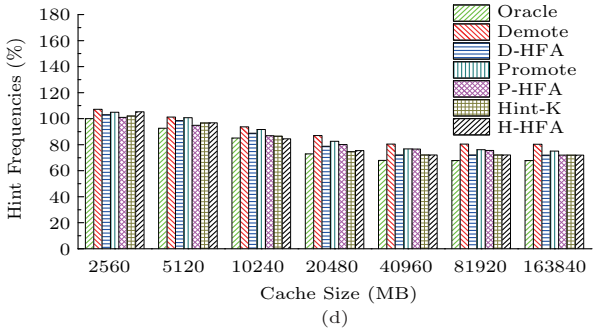
The first overhead in our evaluation is the consumption of inter-cache bandwidth of different algorithms, and the results are shown in Fig.6. The number of hint frequencies of all data blocks under different workloads is monitored. Obviously, HFA reduces hint frequencies by approximately 10% on average. It demonstrates that HFA is more efficient on keeping the hot data blocks at a proper level. We also notice that the enhancement becomes larger with the increased cache size.

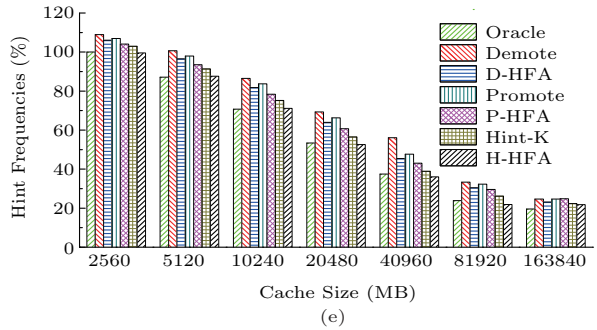
Regarding to the HFA scheme, the space overhead is decided by T_{out} and Q_1. In our simulation, the size of T_{out} is fixed to 0.1% of the corresponding cache size

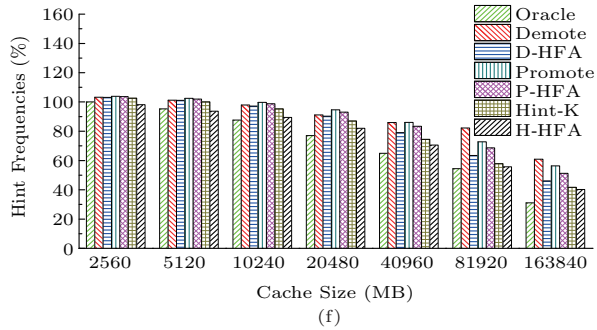








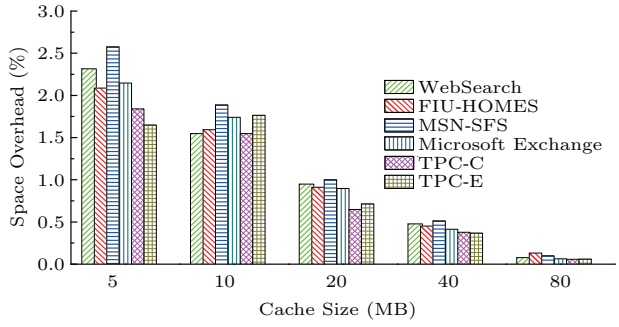




ig. . i u i b u iff / ( ) b . (b) - . ( ) - . ( ) i (i u i i i %). g . ( ) - . ( ) - .

in each level. Q_1 uses extra space (a few megabytes in typical) to record the history hint information of hot data blocks.

The space overhead is shown in Fig.7. It is clear that the space overhead of HFA is very low (less than 2.6%).



ig.7. u iff .

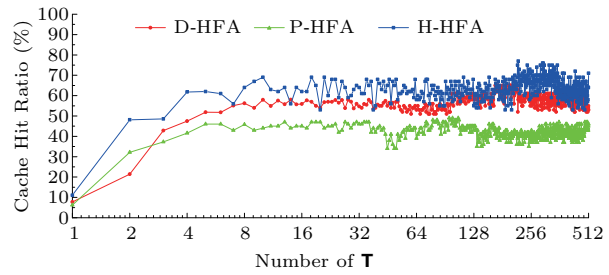
5.2.3 Stability

The stability of a cache system shows the changes on the system response speed in run time and how quick the system can reach a stable hit ratio in the first cache level after start-up. In this part we analyze the stability of HFA by choosing TPC-C as the benchmark, and implementing D-HFA, P-HFA and H-HFA on a three-level cache with the aggregate cache space of 114 GB. The cache space ratio of the three levels are $1:2:4$.

In Fig.8, the x-axis is the time that benchmarks run for 512 periods from the time when all the cache levels are warmed up. The y-axis of Fig.8(a) and Fig.8(b) is the cache hit ratio and the space proportion of $Q_1 : Q_2$, respectively. It is noted that the proportion in the first time period ($T = 1$) is $1 : 1$ for all three approaches.

Fig.8(a) shows the first level cache hit ratio for the three approaches along with the time. It is clear that

the hit ratio reaches a stable level at around 54, 39 and 62 after 8, 6 and 4 periods for D-HFA, P-HFA and H-HFA, respectively. The fluctuation of H-HFA (8.9% on average) is larger than the fluctuation of D-HFA (4.6%) and P-HFA (4.8%).

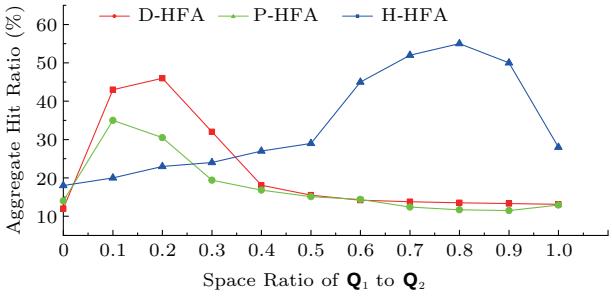


ig. . flu i i i b i i . ( ) i fi u iff . (b) i u u i u iff .

Fig.8(b) illustrates the results from the dynamic partition of changing of proportion between Q_1 and Q_2 along with the time. For D-HFA and P-HFA, Q_1 takes 13% and 9% of the whole cache space of the top level, respectively. On the contrary, Q_1 takes over 70% of the cache space in H-HFA. This is because that Hint-K assists to identify hot blocks from lower levels and aggregates them to the top level. Then the refresh frequency of blocks in the first cache level increases. Consequently, Q_1 requests more space to keep the hot blocks. Meanwhile, this is also the reason why the fluctuation of H-HFA is larger than that of the other approaches.

5.2.4 *Impact of Size Ratio of Two Queues*

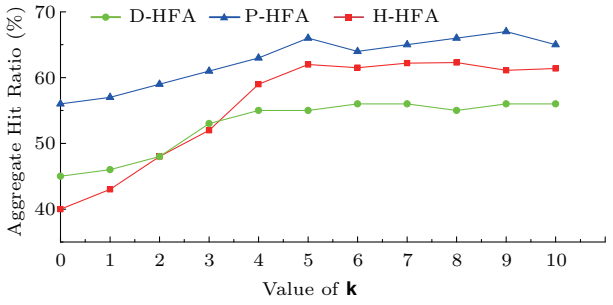
Fig.9 examines the impact of size ratio of Q_1 and Q_2 on the cache aggravate hit ratio. We use TPC-C as the benchmark in this evaluation. The aggregate cache size is 114 GB. The cache space ratio of the three levels is 1 : 2 : 4. Instead of dynamic partition, the space proportion of Q_1 : Q_2 is increased manually from 0% to 100% with an interval of 10%. From the figure, we notice that the aggregate hit ratio of D-HFA, P-HFA and H-HFA reaches a peak value of 46%, 35% and 55% at a space ratio of 2 : 8, 1 : 9, and 8 : 2, respectively, which is about 11% lower than the value that uses dynamic partition. It can be seen that P-HFA uses the smallest Q_1 space than the rest to reach the maximal aggregate hit ratio, because TPC-C has a weak temporal locality. Most of the blocks promoted from the lower level are stored in Q_2 and usually missed. This is another reason why D-HFA performs better on TPC-C. Moreover, it can be seen that Q_1 of H-HFA consumes over 80% of the whole cache space to meet the best hit ratio. As illustrated in Subsection 5.2.3, Hint-K increases the refresh frequency of blocks, which increases the hotness value of the block as well. As a result, it allocates more cache space to Q_1 to keep the hot blocks.



ig. . gg g i i - , - - i g i b Q1 Q2 - .

5.2.5 *Examination of Parameter k of HFA*

We now study the impact of parameter k. The trace and the cache configuration are the same with the previous evaluation. In Fig.10, we plot the parameter k versus the aggregate cache hit ratio. When k is zero, T_{out} is disabled, and the hotness of blocks is only related to the hit frequency which makes D-HFA, P-HFA and H-HFA behave close to original Demote, Promote and Hint-K respectively. It can be seen that the aggregate hit ratio increases to a peak value when k is 4 for P-HFA and 5 for both D-HFA and H-HFA, and then goes smoothly. The larger the value of k, the longer the operation history of blocks recorded in T_{out}, which calculates the hotness values more accurately. However, according to (3), the old history (large k) contributes much less to the hotness than new operations. Further, since T_{out}'s size is fixed, the old history could be removed by the clean-up process. As a result, after parameter k grows to a proper value, the aggregate hit ratio will not increase anymore. Therefore, in the configuration of HFA, we set k to a fixed value of 6 for all workloads.



ig. . k (i i)
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- - .
i i ' 4. gg g i 4 .

5.3 Analysis

From the results in Subsection 5.2, compared with the original Demote, Promote and Hint-K algorithms, it is clear that HFA approach has many advantages on cache performance. There are several reasons to achieve these gains. First, HFA is based on the analysis of the history hint information of data blocks, which is one of the most significant essences in multilevel cache systems. By effectively identifying the hint frequencies, hot data blocks are selected to have a long residence in upper-level cache, which increases the aggregate hit radio of data blocks and decreases the average response time. Second, HFA divides traditional queues into two dedicated queues, which keeps the hint information locally to reduce the usage of inter-cache bandwidth. Third, HFA reduces the overall hint frequencies (inter-cache demotions/promotions), which decreases the bandwidth consumption among different levels. Besides, the space cost of HFA approach is very low, which can help to provide high performance under various workloads. In addition, HFA exhibits a good stability from two aspects. On one hand, the turbulence on the cache hit ratio is low. On the other hand, it can reach a stable status in a short time.

6 Conclusions

In this paper, we proposed a novel multilevel cache approach called HFA, which explores hint frequencies of data blocks. HFA monitors the status of data blocks to keep hot data blocks with high hint frequencies resident in cache as long as possible. Mathematical definitions are given to effectively identify hot data blocks. And we discussed various types of hints combined with the HFA approach. The simulation results showed that, compared with original Demote, Promote and Hint-K algorithms, the corresponding algorithms combined with HFA approach achieve better performance under different I/O workloads.

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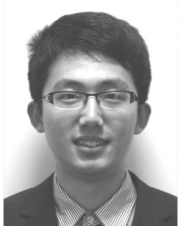

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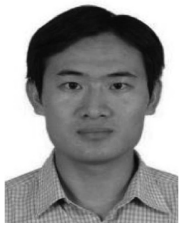

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