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R -Tree for Phase Change Memory

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Abstract. Nowadays, many applications use spatial data for instance-location information, so storing spatial data is important. We suggest using R -Tree over PCM. Our objective is to design a PCM-sensitive R -Tree that can store spatial data as well as improve the endurance problem. Initially, we examine how R -Tree causes endurance problems in PCM, and we then optimize it for PCM. We propose doubling the leaf node size, writing a split node to a blank node, updating parent nodes only once and not merging the nodes after deletion when the minimum fill factor requirement does not meet. Based on our experimental results while using benchmark dataset, the number of write operations to PCM in average decreased by 56 times by using the proposed R -Tree. Moreover, the proposed R -Tree scheme improves the performance in terms of processing time in average 23% compared to R -Tree.

Keywords: spatial database, spatial data, PCM, R -Tree, spatial tree, endurance, indexing algorithm.

1. Introduction

Nowadays, most enterprises use DRAM for in-memory databases for fast decision support. DRAM needs periodic backup to prevent data loss, because it is a volatile memory. Phase change memory (PCM) is a byte-addressable storage system that is two to four times denser than DRAM and has better read latency than NAND Flash memory [2, 6]. While PCM's endurance is 10 times better than NAND Flash memory, unlike DRAM, it is still limited to 10^6 times per PCM cell.

In this paper, we propose a new R -Tree scheme using PCM for the spatial data because of its outstanding properties, except for the endurance problem, which we are going to improve in this paper. Many wear-leveling methods have been proposed for NAND Flash memory; however, they are not appropriate for PCM. The foremost reason is that PCM is byte-addressable, but NAND Flash memory is page addressable. Thus, the key goal of this paper is to reduce the number of write operations, through which we will keep PCM cells alive as long as possible, improve the endurance problem and also improve the performance in terms of processing time.

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B+ -Tree - the most used index structure algorithm - has already been optimized for PCM [3–5]. At present, it is used more frequently than before in smartphones, Google Earth, T-map, global positioning systems (GPSs), etc. However, location information cannot be handled well by B+ Tree. R -Tree is similar to B+ -Tree in the k dimension, capable of storing "spatial" information, such as geographic coordinates and multi-dimensional objects. So, we propose using R -Tree on PCM in order to improve the endurance problem, as well as to give it the ability to store multi-dimensional data for in-memory databases.

R -Tree groups nearby objects and represents them with minimum bounding rectangles (MBRs) in the next higher level of the tree. R -Tree consumes a lot of writes during insertion and deletion and in maintaining the consistency of the tree. This paper designs a PCM-aware R -Tree that is efficient at storing spatial data.

Primarily, we find out whether R -Tree causes endurance problems by inserting a synthetically developed three-million-piece dataset, as well as measuring the performance in terms of processing time for insertion, search, and deletion. The experiment results show that the number of writes to some PCM cells are much higher than to others, meaning those cells will expire earlier. In this project, we make the following contributions.

- Our analysis shows that the number of writes rises when elements within a node are sorted for a split. Sorting the elements within a node is needed to find the proper split point. Moreover, this process has a negative effect on the performance of the system. We propose to increase the leaf node size, compared to intermediate nodes, which will postpone the Split operation. This will decrease the number of writes, as well as improve performance.
- The number of writes increases when the elements within the node are sorted for split, and the nodes that frequently split have much higher number of writes than others. Reducing the number of writes among all PCM cells is essential to increasing lifetime of PCM. We propose replacing the split node with a blank node when the node splits, and rewriting elements from the split node to a newly created node. The blank node will be the one with the minimum number of writes. Although this technique requires one extra write, in practice, it equally distributes the number of writes to memory cells.
- Moreover, updating a parent node to maintain the consistency of the tree structure downgrades endurance. We discovered that R -Tree updates parent nodes by comparing each child with parent nodes one by one, and if necessary, updates the parent nodes sequentially. So, we propose writing to the parent nodes only once, after comparing all child-node MBRs, which will significantly reduce the number of writes.
- It may be very early to merge nodes if the node is just less than half full. In proposed scheme the nodes do not merge if the minimum fill factor requirement does not meet after deletion.
- We propose a novel PCM-aware R -Tree algorithm by applying the techniques presented above.
- Our evaluation results verify that the proposed R -Tree scheme decreases the number of writes by at least five times, and improves performance in terms of processing time.

To the best of our knowledge, we are the first to show that R -Tree causes endurance problems in PCM and propose solution to this problem. According to our experimental results, by using both synthetic and benchmark datasets, the proposed R -Tree deals significantly with this endurance problem by reducing the number of PCM writes, and in addition, improves performance.

The rest of this paper is organized as follows. In Section 2, we present background for PCM and R -Tree variants and related works. In Section 3, we explain our PCM-aware R -Tree. In the subsequent section, we show the results of our performance evaluation. Finally, we end the paper with a conclusion that suggests future work.

2. Background and Related Work

2.1. PCM

Various non-volatile memories exist, such as MRAM, ReRAM, STT-RAM, etc. MRAM and STT-RAM do not have endurance limitations, and the endurance of ReRAM is much higher than that of PCM. Because of the low endurance of PCM, R -Tree could not be directly implemented on PCM as an alternative to DRAM. Table 1 presents a list of parameters, such as type, minimum access unit, read and write latencies, endurance and energy consumption for read and write operations, and density for DRAM, PCM, NAND Flash memory, and HDD. The technical parameters of PCM are better than NAND Flash memory and HDD (except that HDD, like DRAM, has unlimited endurance). The main disadvantage of NAND Flash memory is that its minimum access unit is the page, so to update a few bytes, a whole page must be rewritten. This is an enormous weakness for a storage system with a limited number of writes. Additionally, the endurance of NAND Flash memory is 10 times weaker than PCM.

Table 1. Parameters of DRAM, PCM, NAND Flash Memory, and HDD .Table contents are based on [8, 11, 13]

Parameters	DRAM	PCM	NAND Flash.	HDD
Type	volatile	non-volatile	non-volatile	non-volatile
Minimum Access Unit	Byte	Byte	Page	Sector
Read Latency	1.25 ns	1.25 ns	25 µ	12.7 ms
Write Latency	1.25 ns	15.6 ns	200 µ	12.7 ms
Endurance	∞	10^6	10^5	∞
Read Energy	0.8 J/GB	1 J/GB	1.5 J/GB	65 J/GB
Write Energy	1.2 J/GB	6 J/GB	17.5 J/GB	65 J/GB
Density	1x	2-4x	4x	N/A

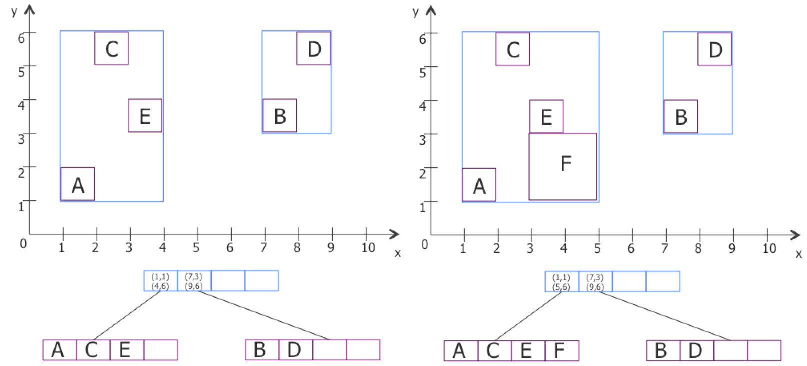
The key advantage of DRAM over PCM is its faster write latency and endurance. Furthermore, being volatile memory, DRAM's energy consumption is much less than other memory types for both reads and writes. The energy consumption for PCM read operations is very similar to the energy consumption of DRAM, but even though the energy consumption of PCM write operation is much less than HDD and NAND Flash memory, it is still higher than DRAM energy consumption. By decreasing the number of PCM writes, in practice, we will get memory with similar parameters, such as DRAM. Furthermore, PCM can be used as main memory as well as storage memory, or combined main and storage memory, due to its non-volatile characteristic.

2.2. R -Tree

Antonin Guttman proposed R -Tree [7] in 1984 to efficiently handle spatial data. R -Tree, which is similar to B+ -Tree [1], consists of an intermediate node to store grouping rectangles, and a leaf node to store data objects. R -Tree is a height-balanced tree similar to B+ -Tree, with index records in its leaf nodes that contain pointers to data objects. In other words, all data objects in R -Tree are stored in leaf nodes. In R -Tree, both data objects and grouping rectangles are in the form of minimum bounding rectangles: (1,2)(3,4) exemplify an MBR; (1,2) are the lower left point coordinates and (3,4) are the upper right point coordinates. We can determine the locations of given rectangles by checking the lower left and upper right points. In R -Tree, each node consists of records; the number of records is defined as the "fill factor". The number of elements within a node should be in a range between a given minimum and maximum fill factor. R -Tree shrinks the area and makes structures more quadratic in order to use less space. R -Tree must satisfy several requirements:

- The root must have at least two children (unless it is a leaf).
- Every node must have children between the minimum and maximum fill factors.
- All leaf nodes should appear on the same level.

Figure 1 depicts an example of R -Tree where the minimum fill factor is 2 and the maximum fill factor is 4. In Figure 1 (a), data objects A, C, E, B, and D are grouped into two nodes and have the same parent node. When data F is inserted into R -Tree, it first decides which rectangle it should be attached to, and then changes its coordinates, as depicted in Figure 1 (b). Furthermore, the MBR of the parent node is also updated.



(a) R -Tree (b) Inserting data F to R -Tree

Fig. 1. Example of R -Tree.

There are several algorithms that need to be mentioned. The Insert operation is used to add new data to one of the leaf nodes. The ChooseSubtree function descends from the root of the tree until it reaches the leaf node, and it finds the most proper sub-tree to provide the data objects being inserted. The proper sub-tree represents the least area enlargement.

Consequently, the data that are chosen by the ChooseSubtree function are inserted into the leaf node, and if it is necessary, parent MBRs are updated. The Split function is used if the number of objects in the node exceeds the maximum fill factor value. The parent node might also need to split after the child node splits.

There are several split algorithms for R -Tree, such as exponential, quadratic, and linear split. Because the search performance of a quadratic split is better (according to [9]) than the alternatives, we decided to use the quadratic split for our evaluation. In the quadratic split, the Pick Seeds function calculates waste area x, and returns the pair with the largest waste area x for each pair of elements in a node. For instance, we are given pair a and b, and the MBR is c. In this case, the waste area will be calculated as follows:

$$WasteArea = Area(c) - Area(a) - Area(b) \tag{1}$$

After calculating the waste area based on Equation 1, the element of the pair with the largest waste area becomes a separate node. The rest of the elements from the initial node are inserted into the newly created node that has the least area increase. In this case, the Pick Next function is again used to find the entry with the best area-goodness-value for each case.

The Search operation is used to retrieve the data. This operation functions from the root of the tree and continues till the searched data of the leaf node are within the MBR of the intermediate node elements.

To remove the data, the Delete function is used. In order to remove the data, first we have to know their location by using the Search function, and then we can delete the data. If the minimum fill factor requirement is not fulfilled after deletion, then the remaining elements in a given node should be removed and inserted again.

2.3. Related Works

Chi et al. [4] proposed a PCM-efficient B+ -Tree where unsorted leaf versions of B+ -Tree proposed by Chen et al. [3] were optimized. Split operations of unsorted leaf versions of B+ -Tree require sorting the leaf node before a split, which lowers the performance and causes endurance problems. Chi et al. proposed a sub-balanced unsorted node scheme where, instead of sorting, a pivot key is selected assigning elements into two nodes. A pivot key is the average of the highest and lowest elements within the split node. They also proposed an overflow node scheme where leaf nodes should not be on the same level. This scheme has an overflow factor: the maximum difference between minimum and maximum tree heights. Furthermore, a merging factor scheme was proposed where nodes' filling degrees can be adjusted. In B+ -Tree, at least half of the nodes must be populated for a node to exist; otherwise, the elements of the node must be merged with other nodes, which create an endurance problem. In order to handle this issue, Chi et al. proposed a merging factor scheme where the node could exist even if less than half its size is populated.

PB+ -Tree [5] is also an extension of B+ -Tree where the nodes are divided into two parts: Area 1 and Area 2. Newly inserted elements are initially attached to Area 2. The Area 2 part is not sorted; however, the Area 1 part is sorted. Once Area 2 is completely occupied, the elements in Area 2 move to Area 1. During retrieval, Area 1 is searched first, and if the data are not found, Area 2 is searched.

Tousidou et al. [12] has been used S -tree in order to improve performance and they proposed parallel S -tree. S -tree is a dynamic height-balanced tree similar in structure to B+ -Tree and designed for storing signatures. In this work, methods for designing multi-disk B -Trees are adopted to S -Tree and novel method of parallelizing S -Trees are developed that achieves better performance by accessing several disks simultaneously.

The above mentioned techniques optimize B+ -Tree like structures for PCM. As our goal is to store spatial data in memory, they cannot be efficiently stored using B+ -Tree or S -tree.

R -Tree is commonly used for storing spatial data. Work most similar to ours has been done [9, 10, 14], where a redesigned version of R -Tree was applied to SSD and Flash memory. Wu [14] aimed to efficiently handle fine-grained updates caused by R -Tree index access to spatial data over Flash memory. Wu proposed using a reservation buffer and a node translation table to reduce the number of unnecessary and frequent updates of information in Flash memory storage systems. Under this approach, newly generated objects would be temporarily held in a reservation buffer. Since reservation buffers can only store a limited number of objects, these objects should be flushed to Flash memory in a timely fashion. This technique slightly reduces the number of writes in NAND Flash memory, as it is page addressable.

Lv et al. [9] proposed a tree index structure named Log Compacted R -Tree. They combined newly arrived logs with origin logs on the same node, which rendered a great decrement in random writes and, at most, one additional read for each node access. In other words, a new log of a node is compacted with its former ones; if possible, the logs of different nodes are compacted into one page. As a result, the number of random write operations decreases without a huge increment in reads. This strikes a balance between read and write performance.

Other researchers [10] separated R -Tree metadata and aggregated data into different sectors of Flash memory.

However, the above-mentioned versions of R -Tree [9, 10, 14] cannot be applied to PCM due to the technical characteristics of PCM. Different from PCM, which is byte-addressable, NAND Flash memory is page-addressable. The above-mentioned techniques do not require updating the whole page for every single write, but simply delaying updates to NAND Flash memory results in the number of writes decreasing. However, those approaches are not suitable for PCM, as we only need to update the bytes that have been modified. Even by applying the techniques presented [9, 10, 14], we do not get any improvement over PCM.

Table 2. Summary of Related Works.

Research	Problems
[3–5, 12]	Could not handle spatial data efficiently
[9, 10, 14]	Designed for page addressable NAND Flash memory

3. Proposed R -Tree

At first, it is essential to check whether R -Tree causes an endurance problem. So, we added a counting system to the R -Tree implementation, which calculates the number of writes per node, as well as per record. We inserted a synthetically generated dataset that consists of three million data objects, and simulated our experiments with 32, 64, 128, 256, and 512 maximum fill factor values, where the minimum fill factor value is half of the maximum fill factor value.

3.1. Motivation

Simulation Environment. Table 3 describes the key specifications of the server we used for the experiments throughout this paper. Two datasets were used: a synthetically developed dataset containing three million data objects, and a benchmark dataset that contains 76,999 objects. We have created the synthetic dataset by using the uniform distribution. The benchmark dataset was downloaded from an R-tree portal, which is a geographic spatial dataset of Germany in 2D space[4].

Table 3. Test-Bed Configuration.

CPU	Intel Xeon E3-1220 v3 3.10GHz
L2 Cache Size	8192 KB
Main Memory	8GB
HDD	1TB
OS	Linux 3.19.0

Simulation Results. Figure 2 shows the plotted graphs for 64 and 256 maximum fill factor values collected by inserting the synthetic dataset into R -Tree. We also observed similar results using 32, 128, and 512 maximum fill factor values. Due to space limitations, we omit the other results. Table 5 shows the standard deviation of the number of writes to leaf and internal nodes when maximum fill factor values are 64 and 256 (for the results illustrated in Figure 2). Experiment results shows that the numbers of writes to internal nodes are higher than the number of writes to the leaf nodes. In R -Tree the internal nodes are updated only when there is a change in leaf nodes (updating parent nodes in order to keep the consistency of the tree) or when node splits. The Split operation causes many writes, because when a node needs to split, it must be sorted to find an appropriate split point. The entire parent node must be updated if there is any change in leaf nodes.

3.2. Proposed Scheme

Our approach consists of four straightforward steps that are comparably simple, yet effective.

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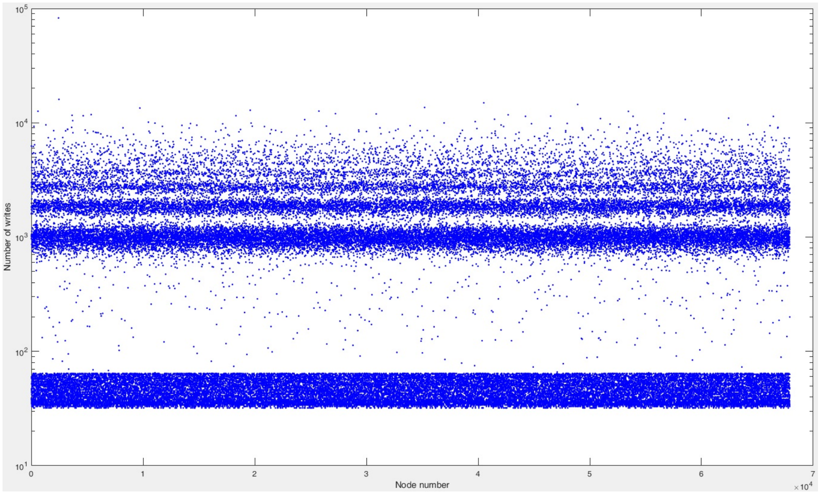
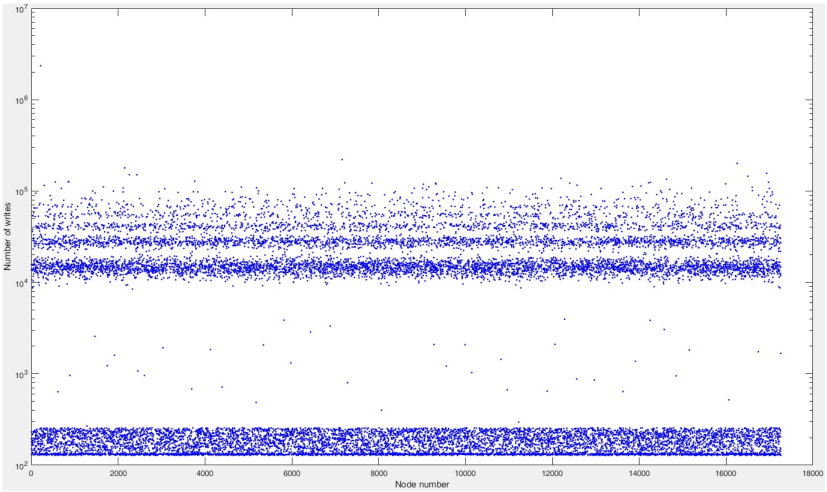
[4] http://chorochronos.datastories.org/?q=node/54.



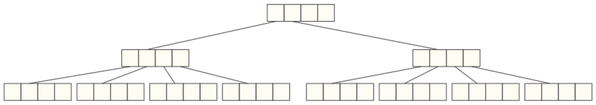
(a) per node with 64 maximum fill factor value



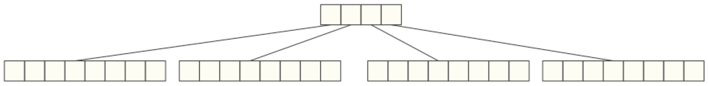
(b) per node with 256 maximum fill factor value

Fig. 2. The number of write operations per node when inserting three million objects with 64 and 256 maximum fill factor value into the R -Tree. Logarithmic scale graph (base 10).

Increased leaf node size. In R -Tree, a split always starts from a leaf node when it exceeds the maximum fill factor value, and if necessary, parent nodes are also split. By postponing the Split operation, we will decrease the number of writes to PCM cells. So, we propose to increase the leaf node size to postpone the Split operation. In R -Tree overflows mostly happen in leaf nodes that cause high number of writes. The larger the leaf node size is less overflows will happen. However, if the size of both leaf and internal nodes will be doubled the performance for insert, search and delete will go lower as larger nodes takes more time to insert, search and delete. However, if we increase only the size of leaf nodes that would not much affect the performance, which is shown in performance evaluation part. From Figure 3, we can see that by doubling the leaf node size, the tree structure becomes more compact as fewer intermediate nodes are required. Thus, doubling leaf node size will postpone splitting the leaf nodes, which will decrease the number of writes, and improve performance. Moreover, as the height of the tree decreases by doubling the leaf node size, the number of writes for updating parent nodes also decreases. In performance evaluation section we will compare two leaf node size such as increasing the leaf node size two (2X) and four (4X) times compared to intermediate nodes.



(a) Original R -Tree max fill factor = 4



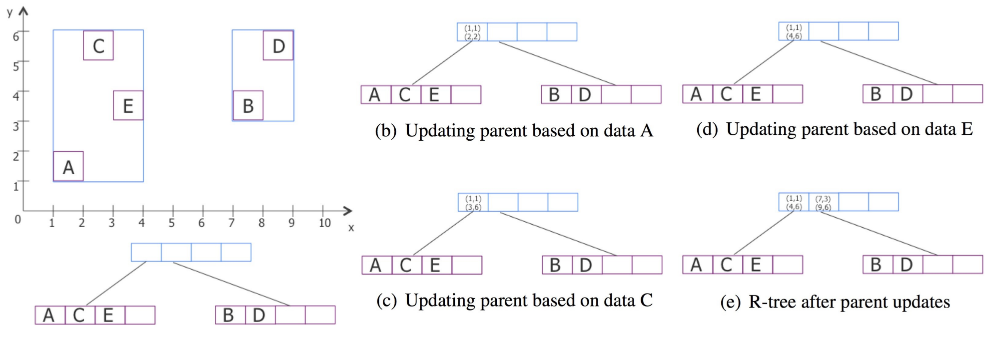
(b) Proposed R -Tree (leaf max fill factor = 8, non-leaf max fill factor = 4)

Fig. 3. Example of original and proposed R -Tree that stores 32 data elements.

Replace the split node with a blank one. When the node is full and needs to split, it is necessary to find an appropriate split point. Even though sorting the elements within a node is an expensive operation for PCM, it is essential for determining a proper split point. We propose exchanging a split node that has a high number of writes with an empty one that has a minimum number of writes. In more detail, once the node splits, we generate a new node and then copy the contents of the split node (where all re-arrangement has been handled) to this newly created node. Lastly, we exchange the split node for the newly created node. A new node is an empty node with a minimum number of writes. Even though this approach increases the number of writes by one time per updated cell, it lets us distribute the number of writes among all PCM nodes, and keeps all PCM cells usable as long as possible.

Single Parent Update. In order to maintain consistency in R -Tree, it is essential to update all the parent nodes if there is any change in the leaf nodes. It is clear that each update decreases the endurance. Figure 4 illustrates how R -Tree updates the parent node, where the root node should be updated in Figure 4 (a). The updating parent node algorithms of the original R -Tree will write to the parent node five times, based on the given example. First, it writes the MBR of data object A, which is (1,1)(2,2), to its parent, as shown in Figure 4 (b). Next, the MBR of data object C should be compared with its parents' MBR and updated again to (1,1)(3,6), as shown in Figure 4 (c). Then the MBR of data object E should be compared with its parents' MBR and must be updated again to (1,1)(4,6), as depicted in Figure 4 (d). The above process continues till the parent node is compared and updated with all the elements of the child node. So, there will be another two writes while updating the neighboring leaf node. As the maximum fill factor was not large in the example, the root node has been updated already five times. Conversely, for large maximum fill factor values, the number of updates is much higher. Also, the number of updates increases as the tree becomes higher.

We propose comparing the value of MBRs of child node elements to figure out the MBR value for the parent node. Next, we write the computed value to the parent node. Compared to the original R -Tree update parent node function, which updates the example depicted in Figure 4 five times, the proposed version of the update parent node function will update the root node only twice.



(a) R-tree

(b) Updating parent based on data A

(c) Updating parent based on data C

(d) Updating parent based on data E

(e) R-tree after parent updates

Fig. 4. Example of updating parent node in R -Tree.

No minimum fill factor requirement In order to satisfy the minimum fill factor requirements of R -Tree, if the node contains less elements than minimum fill factor value after deletion, the elements of that node should merge with other nodes. However it may be very early to merge nodes when they just become less than half full as the merge operation waste the endurance of PCM and degrades the performance. Merge operation wastes the endurance and lowers the performance because the node that does not meet the minimum fill factor requirement should be deleted and the data objects of that deleted node should be re-inserted to tree again. So in the proposed scheme we disable the minimum fill factor requirement for delete operation. In performance evaluation sections we will compare the standard deviation of the number of writes of the proposed R -Tree with and without merge, as well as performance in terms of processing time.

3.3. Space Consumption

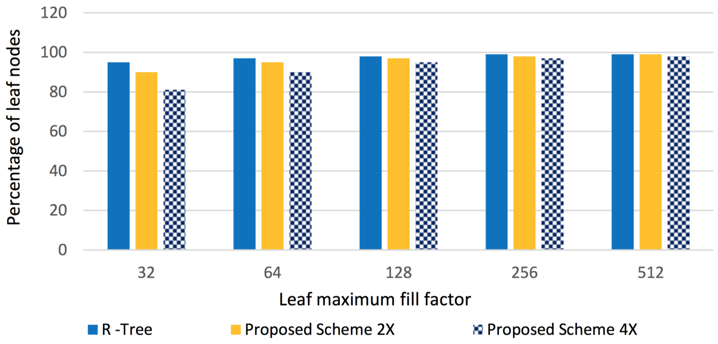


Fig. 5. Percentage of leaf and non-leaf nodes when benchmark dataset is inserted. Logarithmic scale graph (base 10).

After increasing the size of leaf nodes in the proposed R -Tree, it was challenging to decide whether the maximum fill factor value of the tree is based on leaf nodes or non-leaf nodes. This question is significant for the objective evaluation of the proposed R -Tree against the original R -Tree. As a solution to this question, we calculated the percentage of leaf nodes in the proposed R -Tree by inserting a benchmark dataset presented in Section 3.1. According to the results (Figure 5), the quantity of leaf nodes is much higher than the quantity of non-leaf nodes. Based on the results, as the maximum fill factor value increases, the percentage of leaf nodes increases as well. In the worst case scenario, only 19% of nodes are non-leaf nodes (Proposed Scheme 4X, leaf node maximum fill factor value = 32), and in the best case scenario, 1% of nodes are non-leaf. According to experiment results of the proposed scheme, in average 6% of nodes are non-leaf nodes and remaining 94% of nodes are leaf nodes. Therefore, we decide the maximum fill factor value for the proposed R -Tree based on its leaf node size.

However, the difference in node size would also affect the space consumption of the tree. Equations 2 and 3, respectively, show how space consumption has been calculated for R -Tree and the proposed R -Tree, where num_{leaf} leaf is the number of leaf nodes, $\text{num}_{\text{nonleaf}}$ is the number of non-leaf nodes, ff is the maximum fill factor value, ff_{leaf} is the maximum fill factor for leaf nodes and $\text{ff}_{\text{nonleaf}}$ is the maximum fill factor value for non-leaf nodes. Furthermore, each record takes 32 bytes of memory.

$$SpaceConsumption_{R-Tree} = (num_{leaf} + num_{nonleaf}) * ff * 32 \tag{2}$$

$$SpaceConsumption_{proposedR-Tree} = ((num_{leaf} * ff_{leaf}) + (num_{nonleaf} * ff_{nonleaf})) * 32 \tag{3}$$

Figure 6 shows the space consumption (the final space used by R -Tree) when the benchmark dataset is inserted. Moreover, the newly created node has also been taken into consideration. According to Figure 6, the proposed R -Tree consumes slightly more

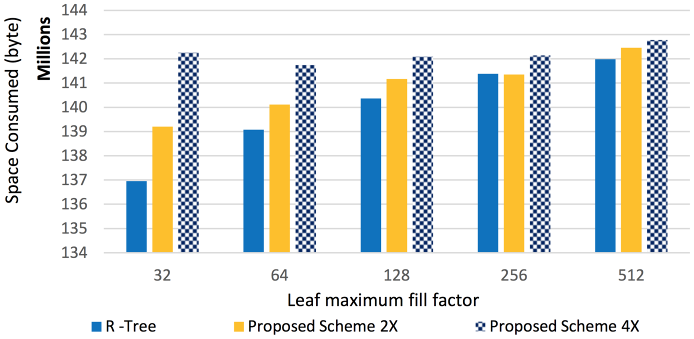


Fig. 6. Space consumption when the benchmark dataset is inserted. Shown in bytes.

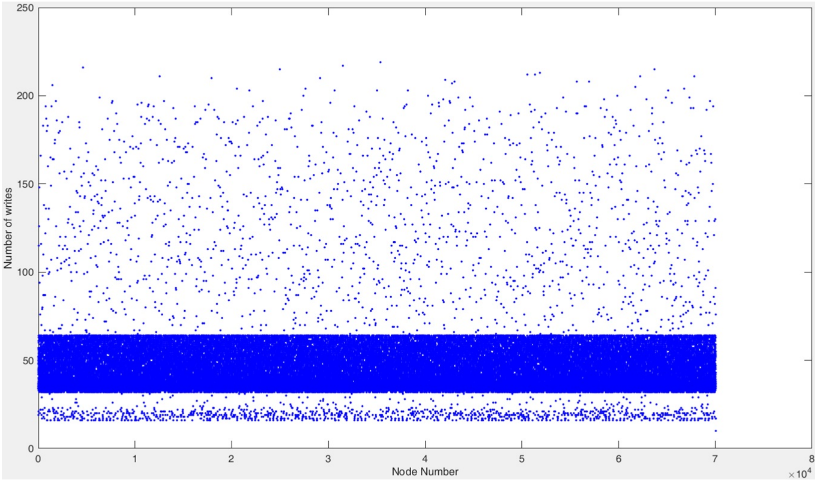
storage space when the maximum fill factor value is low. However when the maximum fill factor value increases, its space consumption gets closer to R -Tree and furthermore in few cases the space consumption of the proposed R -Tree is lower than the original R -Tree. Besides, in the worst case scenario, the proposed R -Tree uses 4% more memory than R -Tree. Furthermore, as more increase in leaf node size compared to non-leaf node size, the space consumption is also increases. In average case the proposed scheme takes 1.1% more space than the original R -Tree.

4. Performance Evaluation

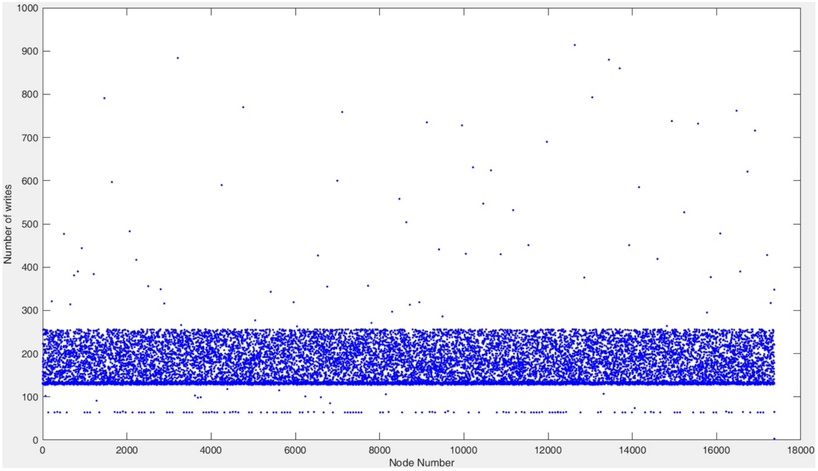
In this section, we compare the proposed R -Tree scheme with the original R -Tree by using both large synthetic and benchmark datasets presented in Section 3.1. Comparison is based on the number of writes per node, as well as performance in terms of processing time for insert, delete, and search operations.

4.1. Synthetic Dataset

In contrast to Figures 2, Figure 7 presents the number of writes per node when the synthetic dataset has been inserted into the proposed R -Tree. Due to the similarity of results and space limitations, we show only the results for 64 and 256 maximum fill factor values. It is obvious that the proposed R -Tree Scheme noticeably decreases the number of writes, as well as proportionally distributes the writes among the PCM cells, which increases PCM lifetime. Table 4 presents the results from Figures 2 and 7 in more details by showing the minimum and maximum number of writes among nodes, average number of writes per node and standard deviation of number of the writes per node. According to Table 4, the maximum and minimum number of writes in proposed R -Tree scheme is much lower than the original R -Tree. Based on Table 4, in average the minimum number of writes using the proposed R -Tree scheme is 12 times lower than the original R -Tree and the maximum number of writes using the proposed R -Tree scheme is 2144 times lower that the original R -Tree. The same could also be said about the average number of writes per node, where in average it has been decreased by 68 times. All this shows that the proposed R -Tree scheme improves the lifetime of PCM by increasing the leaf



(a) per node with 64 maximum fill factor value



(b) per node with 256 maximum fill factor value

Fig. 7. The number of write operations per node when inserting three million objects with 64 and 256 maximum fill factor values into the proposed R -Tree.

node size and updating parent node only once. Furthermore, the standard deviation of the number of writes per node is much lower than the average number of writes per node for the proposed R -Tree scheme, showing that the number of writes are clustered closely around the average. This proves that the number of writes per node are well distributed among all the nodes.

Table 4. Detailed analysis based on number of writer per node.

Tree	Min. value	Max. value	Average	Standard Deviation
R -Tree ff64	32	82608	973	1293
Prop. R -Tree ff64(2x)	10	219	46	17
R -Tree ff256	128	2348790	14052	25647
Prop. R -Tree ff256(2x)	3	914	175	48

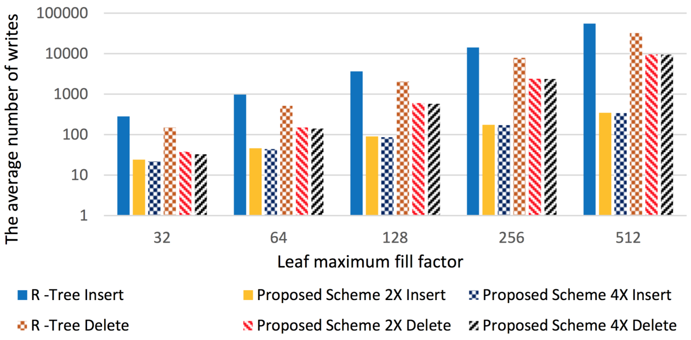


Fig. 8. The average number of writes per node when inserting the synthetic dataset and deleting a random 500,000 objects. Logarithmic scale graph (base 10).

To show how the proposed scheme outperforms the original R -Tree, Figures 8 shows the average number of writes per node while inserting the synthetic dataset (Insert) and when inserting the synthetic dataset and removing a random 500 thousand objects (Delete) for both the original R -Tree and the proposed R -Tree scheme. The logarithmic scale graph base to 10 has been used in order to clearly show the results. According to results, the proposed scheme requires at least 11 times fewer writes per node compared to original R -Tree and in average case consumes 109 times less writes, while inserting synthetic dataset. Postponing the split operation by increasing the leaf node size, proposed novel parent node update mechanism helps to keep PCM cells usable as long as possible. Furthermore, replacing the split node with blank node (available node with minimum number of writes), spreads the number of writes among all PCM cells proportionally. In all the results with the increase of maximum fill factor value, the number of writes increases. This happens due to the reason that the large the node is more writes is required while splitting that node(in case of sorting the node before split and more data objects needs to be inserted to other existing nodes). Moreover with more increasing the leaf node size, the number of writes slightly decreases as the number of splits decreases.

Also, the proposed scheme decreases the number of writes during deletion by not merging nodes when the minimum fill factor requirement does not met, as well as updating the parent nodes only once. According to Figure 8, with the increase of maximum fill factor value, the average number of writes per node increases. Based on results, the increase in the size of leaf nodes decreases the number of writes during deletion. In average, the number of writes per node is decreased by 3 times by using the proposed R -Tree Scheme for delete operation.

Figure 9 shows the average number of writes per record when inserting the synthetic dataset and deleting a random 500,000 objects. According to the results, in average the number of writes has been decreased by 25 times for insertion and 12 times for deletion.

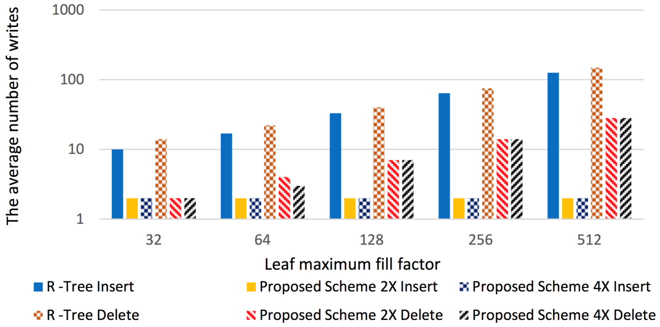


Fig. 9. The average number of writes per record when inserting the synthetic dataset and deleting a random 500,000 objects. Logarithmic scale graph (base 10).

Table 5. The standard deviation of number of writes per leaf and internal nodes when synthetic dataset is used.

Tree	Maximum fill factor 64		Maximum fill factor 256	
	Leaf node	Internal node	Leaf node	Internal node
R -Tree	1210	3058	18522	210024
Prop. R -Tree 2X	10	58	41	214
Prop. R -Tree 4X	10	29	44	125

Table 5 shows the standard deviation of number of writes per leaf and internal nodes when synthetic dataset is used. The results show that the proposed R -Tree scheme decreases the number of writes to both leaf and internal nodes. Moreover with the increase of the leaf node size compared to the internal node size, the number of writes to the internal nodes noticeably decreases.

Since our second goal is to improve the performance in terms of processing time, Table 6 shows the results where the proposed R -Tree is compared with the original one.

Postponing the Split operation by increasing the leaf node size improves the insert performance and in average the insert performance have been improved 20%. According to the results the increase in maximum fill factor value slightly degrades the performance both for R -Tree and proposed R -Tree. Also for each maximum fill factor value, the insert performance of proposed R -Tree 4X is better than the performance of proposed R -Tree 2X due to the decrease in number of splits.

For search performance, as the leaf node size is increased, when the maximum fill factor is low (32) the proposed scheme takes slightly more time. This happens because by inserting huge dataset to the tree with low maximum fill factor value, the tree must hold large quantity of nodes, which does not let the proposed R -Tree to decrease the tree height. However, as the leaf node size gets larger the decrease in height of the proposed R -Tree helps to improve the search performance. In average case the proposed R -Tree scheme improves the search performance 6%. The location of the data in leaf node that we search for, causes slight the difference in pattern between proposed Scheme 2X and 4X as shown in Table 6. As the nodes are not sorted in R -Tree, elements of an appropriate nodes must be searched one by one until the data is found.

Delete performance is quite similar to the search performance. The reason for that is in R -Tree, before deleting an element we need to search for it and most of the delete time is consumed finding the element in the tree. According to Table 6, the delete time in original R -Tree is higher than search, as the node needs to merge with other nodes if the minimum fill factor requirement not met. As it was with search performance, the proposed R -Tree takes slightly more time (3%) for deletion when the maximum fill factor is 32. However, in case of proposed R -Tree, the delete time is quite identical to search time as we never need to merge the nodes. Moreover, for R -Tree with larger maximum fill factor values (128, 256 and 512) the delete performance gets better than the search. This happens due to the reason that after each deletion the number of the remaining elements in a large R -Tree nodes decreases making the search faster. In average case the proposed R -Tree scheme improves the delete performance by 15%.

Table 6. Execution times while using the synthetic dataset for insertion, search, and deletion. All times shown are in seconds.

Maximum fill factor		32	64	128	256	512
Insertion	R -Tree	36.3	42.1	57.4	78.5	128.7
	Prop. R -Tree 2X	32.4	36.0	45.5	64.7	99.3
	Prop. R -Tree 4X	31.2	34.9	43.2	60.6	94.2
Search	R -Tree	31,091.4	31,113.8	27,520.7	24,341.4	23,659.1
	Prop. R -Tree 2X	32,848.3	26,423.5	25,294.2	23,560.0	22,064.4
	Prop. R -Tree 4X	32,844.2	27,908.9	23,424.2	23,668.7	21,637.4
Deletion	R -Tree	31,994.8	32,536.8	30,491.0	26,985.3	26,540.8
	Prop. R -Tree 2X	32,904.6	26,424.2	25,064.6	23,068.9	21,303.3
	Prop. R -Tree 4X	32,844.2	28,059.5	23,312.1	23,246.1	20,884.2

We went beyond to compare the proposed R -Tree scheme with and without merging while deletion (Table 7) in order to check how efficient is not to merge nodes that do not fulfill the minimum fill factor requirement. The results shows that the standard deviation of the number of writes in average reduced by 12% when we do not merge the proposed R -Tree scheme while deletion. Furthermore, the no merge version of proposed R -Tree improves the delete performance in terms of processing time as there is no need to reinsert the element of the node that do not fulfill the minimum fill factor requirement. In average, the proposed no merge version of R -Tree decreases the delete performance in terms of processing time by 19%.

Table 7. Comparison of standard deviation of writes per node and time spend while deletion for Proposed R -Tree scheme with and without merge operation by using the synthetic dataset.

Tree	Merge while deletion		Do not merge while deletion	
	Stan. Deviation	Time(sec.)	Stan. Deviation	Time(sec.)
Prop. R -Tree (2X) ff64	116	30,887.0	93	26,424,2
Prop. R -Tree (2X) ff256	1562	30,320.0	1254	23,068.9
Prop. R -Tree (4X) ff64	101	33,024.1	96	28,059.5
Prop. R -Tree (4X) ff256	1322	30,648.1	1273	23,246.1

4.2. Benchmark Dataset

This section presents the experimental results when the benchmark dataset (introduced in Section 3.1) is used. For search and deletion, we used a random 20,000 objects among the inserted ones.

Similar results were observed when using the benchmark dataset as seen for synthetic dataset. Figures 10, respectively shows the average number of writes per node while inserting the benchmark dataset (Insert) and when inserting the benchmark dataset and removing a random 20 thousand objects (Delete) for both the original R -Tree and the proposed R -Tree scheme. For the insert operation, the number of writes per node decreased by at least 10 times and in average case is decrease by 92 times. It should also mentioned that with the increase of the maximum fill factor value the proposed R -Tree scheme consumes much less number of writes than the original R -Tree. This happens so, because the leaf node is increased compared to the original R -Tree, which delays the split operation. Moreover, in every change in leaf nodes, the parent nodes are updated only once.

According to the results (Figure 10) the number of writes per node decreases in case of deletion as well. In average the number of writes is decreased by 20 times while using the proposed R -Tree scheme. The decrease in number of writes while deletion happens due to disabling the minimum fill factor requirement in R -Tree, as well as due to proposed novel parent node update algorithm. As we have observed for synthetic dataset, also in case of benchmark dataset increase in leaf node size decreases the number of writes.

Table 8 shows the performance results when inserting the benchmark dataset into R -Tree and the proposed R -Tree. Based on the results, on average, for the five different maximum fill factor values, the proposed R -Tree improves performance by 20% for insertion. With the increase of the maximum fill factor value, both R -Tree and proposed R -Tree requires more time for insertion. However by more increasing the leaf node size

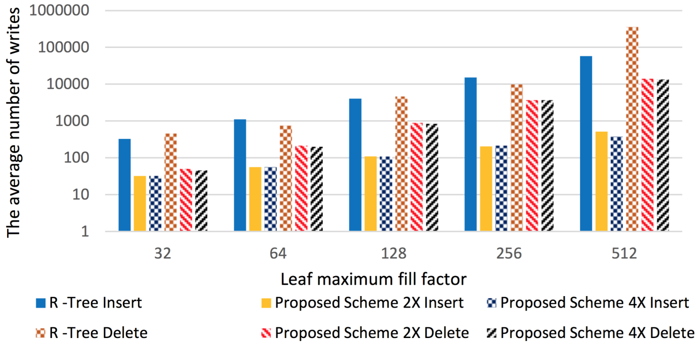


Fig. 10. The average number of writes per node when inserting the benchmark dataset and deleting a random20,000 objects. Logarithmic scale graph (base 10).

less time is used by insert operation. In average the search performance is improved by 21%, which happens as the height of the tree is decreased. Finally in case of deletion, the average performance is improved by 29% when the proposed R -Tree scheme have been used, that mainly due to disabling the minimum fill factor requirement in the proposed scheme. For searching and deletion, the performance improvement of the proposed R -Tree is higher when the maximum fill factor value is small (e.g. 32, 64). This is due to fact that the larger nodes require more time to search. Also, even though the delete operation takes more time than search for R -Tree, in case of the proposed R -Tree delete is faster than the search. This happens because we do not need to merge the nodes when the minimum fill factor requirement does not meet for delete operation and with every deletion, the performance of search operation (as the quantity of data that tree stores decreases) gets better. The results for search and deletion do not have any pattern with the change of the maximum fill factor value, which is due to the location of the data that needs to be searched or deleted in leaf nodes. Obviously, more the data that we are searching for near the beginning of the node, less time is required by search and delete operations.

The results of the benchmark dataset are quite similar to the results of the synthetic dataset in case of the average number of writes per node while insertion and as well as deletion. With the increase of the maximum fill factor value the number of writes also increases both for insert and delete operations. According to the results, the proposed R -Tree 4X consumes slightly less writes than the 2X version of the proposed R -Tree. Also, the shape of the insert performance in terms of processing time is similar by using both dataset. Moreover, according to the results of R -Tree and proposed R -Tree, with the increase of the maximum fill factor, insert operation gets slower by using both synthetic and benchmark datasets. Furthermore, for the proposed R -Tree scheme, increasing the leaf node size 4 times (4X) shows better results than increasing the leaf node size 2 times (2X) for insert performance in terms of processing time. For search and delete performance the shapes of two datasets are not identical. By using the synthetic dataset with maximum fill factor 32, the proposed R -Tree scheme takes more time than the R -Tree. However, when the benchmark dataset is used, even for small maximum fill factor value such as 32, the proposed R -Tree scheme improves the performance over the R -Tree. Based on our analysis this happened because the synthetic dataset is much larger than the benchmark dataset. So, more nodes must be created for storing the elements of the synthetic dataset in the tree, which makes the proposed R -Tree to grow higher making the search and delete performance slower.

Table 8. Execution times while using the benchmark dataset for insertion, search, and deletion. All times shown are in seconds.

Maximum fill factor		32	64	128	256	512
Insertion	R -Tree	1.07	1.15	1.44	1.99	2.8
	Prop. R -Tree 2X	0.89	0.99	1.18	1.55	2.18
	Prop. R -Tree 4X	0.87	0.93	1.15	1.46	2.17
Search	R -Tree	16.04	19.02	16.48	12.79	18.57
	Prop. R -Tree 2X	9.62	12.94	16.76	14.63	18.13
	Prop. R -Tree 4X	10.85	8.43	10.16	15.38	13.33
Deletion	R -Tree	16.36	17.45	17.16	16.41	19.63
	Prop. R -Tree 2X	8.81	12.06	15.64	13.78	17.49
	Prop. R -Tree 4X	10.0	7.72	9.74	14.43	12.65

5. Conclusion

Phase change memory is a byte-addressable type of non-volatile memory. Compared to other storage systems, PCM is two to four times denser than DRAM, and it has better read latency than NAND Flash memory. Although the write endurance of PCM is 10 times better than NAND Flash memory, it is still limited to 10^6 times per PCM cell. Currently, many existing applications use spatial data (for example, location information); therefore, storing spatial data in memory is significant. R -Tree is a well-known data structure that can handle spatial data; we propose using it over PCM. However, R -Tree invokes a lot of writes, and moreover, its performance is low, especially for insertion. We propose a novel PCM-aware R -Tree algorithm. By doubling the leaf node size, writing a split node to a blank node, updating parent nodes only once and not merging the nodes after deletion when the minimum fill factor requirement does not meet, the proposed R -Tree achieves dramatic improvement in the number of writes, and at the same time, improves performance. According to our experimental results when we used both large synthetic and benchmark datasets, the proposed novel scheme dramatically reduced the number of write operations to PCM cells and also improved the performance in terms of processing time for insert, search and delete operations. These results suggest our new method outperforms existing ones in addressing the PCM endurance problem.

The limitation is that R -Tree (at the application level of the S/W stack) cannot become aware of the write count number for each PCM cell. Therefore, R -Tree needs to ask the kernel (at the OS level or the H/W level) for the write count number. Then, R -Tree can select memory cells with the lowest count number while creating a new node, as well as replacing the split node with the node that has smallest number of writes. As this paper deals with endurance problem of PCM in application level, we hope that the next generation of PCM can provide information about the exact number of writes on each PCM cell to Operation System or various applications. One possible solution to this problem is to propose a new PCM translation layer.

The proposed R -Tree scheme can improve the lifetime of PCM. By using the proposed R -Tree scheme, PCM can be used for in memory databases to store spatial data or spatial applications. So PCM will penetrate or commercialized in server or computer system. Our future work is to implement proposed R -Tree scheme in real spatial database applications. We will also apply the proposed scheme to other spatial tree variants that are similar to R -Tree, such as quadtee and k-d tree.

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