Transform-Space View: Performing Spatial Join in the Transform Space Using Original-Space Indexes

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Abstract—Spatial joins find all pairs of objects that satisfy a given spatial relationship. In spatial joins using indexes, original-space indexes such as the R-tree are widely used. An original-space index is the one that indexes objects as represented in the original space. Since original-space indexes deal with extents of objects, it is relatively complex to optimize join algorithms using these indexes. On the other hand, transform-space indexes, which transform objects in the original space into points in the transform space and index them, deal only with points but no extents. Thus, optimization of join algorithms using these indexes can be relatively simple. However, the disadvantage of these join algorithms is that they cannot be applied to original-space indexes such as the R-tree. In this paper, we present a novel mechanism for achieving the best of these two types of algorithms. Specifically, we propose the new notion of the transform-space view and present the transform-space view join algorithm. The transform-space view is a virtual transform-space index based on an original-space index. It allows us to “interpret” or “view” an existing original-space index as a transform-space index with no space and negligible time overhead and without actually modifying the structure of the original-space index or changing object representation. The transform-space view join algorithm joins two original-space indexes in the transform space through the notion of the transform-space view. Through analysis and experiments, we verify the excellence of the transform-space view join algorithm. The transform-space view join algorithm always outperforms existing ones for all the data sets tested in terms of all three measures used: the one-pass buffer size (the minimum buffer size required for guaranteeing one disk access per page), the number of disk accesses for a given buffer size, and the wall clock time. Thus, it constitutes a lower-bound algorithm. We believe that the proposed transform-space view can be applied to developing various new spatial query processing algorithms in the transform space.

Index Terms—Transform-space view, adaptive row major order, spatial join, corner transformation, databases.

1 INTRODUCTION

Spatial joins (or simply joins) find all pairs of objects that satisfy a given spatial relationship. An example of a spatial join is “finding all the roads that overlap with rivers.” Since spatial joins require a significant cost of processing, much effort has been made to develop efficient algorithms [4], [12], [20], [25], [28].

Existing spatial join algorithms can be classified into those that use indexes on both files and those that do not. Join algorithms that do not use indexes on both files include the Partition-Based Spatial Merge Join [25], Spatial Hash Join [20], Seed Join [19], Sort/Sweep Spatial Join [8], Unified Approach for Indexed and Non-Indexed Spatial Joins [1], Iterative Spatial Join [13], and Slot Index Spatial Join [21]. These join methods are best used when there is no preexisting index on the files to be joined or there exists an index on only one file. However, when there are indexes on both files, these algorithms are slower than those that use indexes. Therefore, in this paper, we limit our discussion to join algorithms that use indexes on both files (we call them index join algorithms).

Index join algorithms are classified into those whose indexes are created in the original-space (o-space) and those whose indexes are created in the transform-space (t-space). O-space index join algorithms use indexes that consider the extents of objects in the o-space. On the other hand, t-space index join algorithms use indexes in which objects with extents in the o-space have been transformed into points with no extents in the t-space.

O-space index join algorithms include the Depth-First Traversal R-tree Join [4] and the Breath-First Traversal R-tree Join [12]. Both are based on the R-tree family [2], [9]. The Depth-First Traversal R-tree Join is a representative algorithm widely used for comparing the performances of other join algorithms. It performs the join by traversing two R-trees in the depth-first order. Since it optimizes only a part of the sequence of accessing disk pages (page access sequence) for joining two R-trees, it only achieves local optimization [12], [28]. The Breath-First Traversal R-tree Join achieves global optimization by optimizing the page
access sequence for the entire join. This is done by traversing the two R-trees in the breadth-first order. However, it has a drawback of incurring disk or memory overhead to store the entire page access sequence before performing join.

T-space index join algorithms include the Transformation-Based Spatial Join [28]. It is based on the Multi-Level Grid File (MLGF) [17], [29]. This algorithm achieves global optimization by utilizing special characteristics of the t-space. Due to this global optimization, it shows performance comparable to or better than that of the Depth-First Traversal R-tree Join. Besides, since the algorithm does not store the entire page access sequence, unlike the Breadth-First Traversal R-tree Join, it does not incur as much disk or memory overhead. Thus, it shows a performance comparable to or better than that of the Breadth-First Traversal R-tree Join. But, it has a drawback in that it cannot be applied to joining two o-space indexes or joining a t-space index with an o-space index.

Each class of index join algorithms has some advantages and disadvantages. O-space index join algorithms have an advantage in that they can be applied to widely used index structures such as the R-tree family in the o-space. The disadvantage is that, since the algorithms deal with the extents of the objects, it is relatively complex to optimize them. In particular, doing global optimization requires significant disk or memory overhead. In contrast, since t-space index join algorithms deal with only points but no extents, optimization is relatively straightforward and a global optimization is possible without significant overhead. However, the disadvantage is that they cannot be applied to widely used index structures such as the R-tree.

In this paper, we propose a novel mechanism for achieving the best of these two types of approaches. Specifically, we propose a technique that can apply a t-space index join algorithm to an o-space index. Our approach is based on the new notion of the transform-space view (t-space view), which is a virtual t-space index for an o-space index. The importance of the t-space view is that it allows us to dynamically "interpret" or "view" an existing o-space index as a t-space index without modifying its original structure and with no space and negligible time overhead. This allows us to apply conventional t-space index join algorithms to widely used R-trees. Second, we propose a new join algorithm based on the t-space view. Third, we show that the formal analysis and the ARM order for the Transformation-Based Spatial Join algorithm [18] are also usable for the proposed algorithm. Fourth, through experiments, we show that applying a t-space index join algorithm to R-trees through the t-space view is faster than applying o-space index join algorithms to R-trees in the o-space for all the data sets tested, thus rendering it a lower-bound algorithm.

The rest of this paper is organized as follows: Section 2 describes related work covering o-space and t-space index join algorithms. Section 3 defines the concept of the t-space view and Section 4 presents our t-space view join algorithm. Section 5 explains a formal analysis of the effect of the space filling curve on the one-pass buffer size and Section 6 introduces the ARM order. Section 7 presents the experimental results for performance evaluation of the algorithm. In Section 8, we summarize and conclude the paper.

2 RELATED WORK

In this section, we describe representative join algorithms that use indexes. Section 2.1 describes o-space index join algorithms based on R-trees. Section 2.2 explains t-space index join algorithms.

2.1 O-Space Index Join Algorithms

We consider two R-tree based join algorithms depending on the traversal method used: the Depth-First Traversal R-tree Join algorithm proposed by Brinkhoff et al. [4] and the Breadth-First Traversal R-tree Join algorithm proposed by Huang and Jing [12]. Here, we briefly explain the structure of the R-tree [9] and define some notation. The R-tree is a height balanced tree structure storing multidimensional

1. Examples to which the t-space view method cannot be applied are P-Tree [14] and Cell-Tree [7].

2. To the extent of the authors’ knowledge, these are the only R-tree based spatial join algorithms reported in the literature. Other algorithms are their variants or do not require indexes on both files.
rectangles. A nonleaf page of an R-tree contains entries of the form \(<\text{mbr}, \text{ref}>\), where \(\text{mbr}\) is the minimum bounding rectangle (MBR) containing all MBRs of the entries in a child page and \(\text{ref}\) is the pointer to the child page. A leaf page contains entries of the form \(<\text{mbr}, \text{oid}>\), where \(\text{mbr}\) is the MBR of a spatial object and \(\text{oid}\) refers to the spatial object in the database.

The Depth-First Traversal R-tree Join finds all pairs of MBRs that overlap with each other from nonleaf pages of the two given R-trees by traversing depth first. The algorithm minimizes the search space by using the property that, when a pair of MBRs do not overlap with each other, their child pages will not overlap either and it thereby excludes them from further traversal.

It is necessary to control the page access sequence to prevent pages from being reread frequently from the disk. The Depth-First Traversal R-tree Join uses some heuristics, such as local plane-sweeping and local Z-ordering, to minimize disk accesses. Since these heuristics optimize the page access sequence of the child pages of only one pair of nonleaf pages that overlap with each other at a time, they tend to find a local optimum rather than finding the global optimum [12], [28].

If we generate and optimize the page access sequence of the child pages of as many pairs of overlapping nonleaf pages as possible simultaneously, then a near-global optimum can be found. Based on this observation, the Breadth-First Traversal R-tree Join generates the page access sequence of the entire set of pages by traversing breadth first, optimizing the sequence, and performing the join. However, because this algorithm incurs a significant overhead for keeping track of the entire sequence, the algorithm has a lower performance than the Depth-First Traversal R-tree Join in small or large buffers depending on the techniques of managing the sequence. That is, when the page access sequence is stored in main memory (Combo2 strategy), it, in effect, causes a reduction in the buffer size. Since an insufficient buffer significantly drops the performance of join, the algorithm performs worse for small buffers. When the page access sequence is stored on the disk (Combo1 strategy), a performance drop caused by insufficient buffer does not occur. However, this strategy always causes extra disk accesses to store and access the entire page access sequence to the disk; thus, the algorithm performs worse for large buffers.

2.2 T-Space Index Join Algorithms

T-space index join algorithms use t-space indexes that manage points. These points are transformed from the objects with extents in the o-space by using a transformation technique. A typical transformation technique used is corner transformation [24], [27]. Corner transformation transforms each object in the \(n\)-dimensional o-space into a single point in the \(2n\)-dimensional t-space by using \(2n\) parameters. These points are subsequently indexed by a multidimensional point access method. The coordinates of a point in the \(2n\)-dimensional space are determined by the minimum and maximum values of the MBR on each of the \(n\) axes in the o-space. For example, a one-dimensional object whose minimum and maximum values on the x-axis are \(lx\) and \(rx\), respectively, is transformed into the point \(<lx, rx>\) in the two-dimensional t-space.

When we use the t-space index to process an o-space query, we must transform the o-space query into a t-space query. Fig. 1 shows t-space regions used for transforming o-space queries into t-space queries [24], [28]. Fig. 1a shows a query region \(q\) in the o-space and Fig. 1b shows six t-space regions A to F having different spatial relationships with the query region \(q\). In Fig. 1b, region A contains all the points that are contained by \(q\); regions B, C, and D contain those that overlap with \(q\); regions E and F contain those that do not overlap with \(q\). Using these t-space regions, an o-space query that finds objects overlapping with \(q\) in the o-space is transformed into a t-space query that finds points in the union of t-space regions A, B, C, and D. Since finding points with no extents in a region is conceptually more straightforward than finding objects with extents that satisfy a spatial relationship with a region, processing queries in the t-space can be more concisely done than in the o-space [6], [28]. We can also process spatial join more concisely in the t-space.

Some transformation techniques [26] transform \(n\)-dimensional objects into one-dimensional points. These points are then indexed by a one-dimensional access method. These methods first partition the space into grid cells. Each grid cell is labeled with a unique number given by the Z-order or the Hilbert order. Objects are then indexed by a \(B^*\)-tree according to the label of the grid cell in which the objects are contained. It is known that these techniques are not favorable for spatial join since they have an obvious disadvantage in that, if the grid structures of the two indexes are not compatible, they cannot be joined unless the labels of one of them are recomputed [6].

The Transformation-Based Spatial Join [28] uses the MultiLevel Grid File (MLGF) [17], [29] as the index. This algorithm joins two MLGF indexes R and S that contain points that have been transformed by corner transformation. Here, we briefly explain the structure of the MLGF and define some
notation. The MLGF is a height-balanced index tree that stores multidimensional point data. A nonleaf page in an MLGF contains entries of the form \(<\text{region}, \text{ref}\>\), where \(\text{ref}\) is the pointer to the child page and \text{region} contains all the regions represented by the entries of the child page pointed by \(\text{ref}\). A leaf page contains entries of the form \(<\text{point}, \text{oid}\>\), where \text{point} is the coordinate of the points in the t-space and \text{oid} is the identifier of the object stored in the database.

The Transformation-Based Spatial Join finds a pair of points whose original objects overlap by comparing the points in all the leaf-pages of indexes \(R\) and \(S\). Here, the two t-space regions of \(S\) that are to be joined with two adjacent t-space regions of \(R\) have considerably overlapping areas. By taking advantage of this characteristic, together with the LRU buffer policy, the algorithm globally optimizes the number of disk accesses. On the other hand, the drawback of the algorithm is that it cannot be directly applied to the data stored in and managed by an o-space index.

3 T-SPACE VIEW

A t-space view is a virtual t-space index mapped from an o-space one by the transformation technique. Using the t-space view, an o-space index can be interpreted or viewed as a t-space index without modifying the structure of the o-space index. Thus, the t-space join algorithms can be directly applied to the t-space views of the o-space index. Fig. 2 illustrates the process of performing a join using t-space views. In the figure, two o-space indexes \(R\) and \(S\) are interpreted as virtual t-space views \(TV(R)\) and \(TV(S)\), respectively, and a t-space index join algorithm is applied to \(TV(R)\) and \(TV(S)\).

The t-space view is interpreted by mapping the structure of the o-space index into that of the t-space index. We first informally describe the mapping using the R-tree for the o-space index and the MLGF for the t-space index. As shown in Section 2, an entry in a nonleaf page of the R-tree has the form \(<\text{mbr}, \text{ref}\>\) and the one in the MLGF has \(<\text{region}, \text{ref}\>\). Here, \text{mbr} represents an \(n\)-dimensional o-space region and \text{region} represents a \(2n\)-dimensional t-space region. Thus, we map an \text{mbr} of the R-tree into a \text{point} of the MLGF. Using these mappings, we can interpret an R-tree as an MLGF, without physically materializing a new index.

We now formally define the mapping of the \(2n\)-dimensional t-space view for an \(n\)-dimensional o-space index. We use corner transformation for the mapping. Here, we assume that the o-space index is tree-structured and regions and objects stored in the index are represented as MBRs.

**Definition 1.** Suppose objects and regions in the \(n\)-dimensional o-space are represented in the form

\[
[l_1, r_1] \times [l_2, r_2] \times \cdots \times [l_n, r_n],
\]

where \(l_i\) is the minimum value and \(r_i\) is the maximum value on the \(i\)th axis. The \(2n\)-dimensional t-space view for an \(n\)-dimensional o-space index is interpreted as follows:

a. **Mapping of o-space objects.** An object \([l_1, r_1] \times [l_2, r_2] \times \cdots \times [l_n, r_n]\) in the \(n\)-dimensional o-space is mapped into the point \(<l_1, r_1, l_2, r_2, \cdots, l_n, r_n>\) in the \(2n\)-dimensional t-space.

b. **Mapping of o-space regions.** A region \([l_1, r_1] \times [l_2, r_2] \times \cdots \times [l_n, r_n]\) in the \(n\)-dimensional o-space is mapped into the region \([l_1, r_1] \times [l_2, r_2] \times \cdots \times [l_n, r_n] \times [l_1, r_1] \times [l_2, r_2] \times \cdots \times [l_n, r_n]\) in the \(2n\)-dimensional t-space.

The mapping of o-space objects in Definition 1 follows the definition of corner transformation. The mapping of o-space regions is an extension of the corner transformation modified in such a way that the containment relationships between objects and regions in the o-space are preserved in the t-space. That is, the mapping guarantees that the t-space region corresponding to an o-space region is the region that contains all the t-space points corresponding to the objects contained in the o-space region. We need the preservation of the containment relationship to maintain a proper search structure in the t-space view. Suppose a one-dimensional o-space object \([lx', rx']\) contained in the one-dimensional o-space region \([lx, rx]\) (i.e., \(lx \leq lx' \leq rx' \leq rx\)) is mapped into the two-dimensional t-space point \(P <lx', rx'>\). Then, \(P\) exists in the t-space region \([lx, rx] \times [lx, rx]\) by the relationship \(lx \leq lx' \leq rx\) and \(lx \leq rx' \leq rx\). Therefore, the relationships between the objects and regions in the o-space are preserved in the t-space as well after mapping.

**Example 1.** Fig. 3 illustrates an example of a one-dimensional R-tree and its two-dimensional t-space view. Fig. 3a shows a one-dimensional R-tree in the o-space. Fig. 3b shows the two-dimensional t-space view.
view mapped from the R-tree in Fig. 3a. Fig. 3c shows the representation of o-space objects and regions of Fig. 3a in the one-dimensional o-space. Fig. 3d shows the representation of the corresponding point objects and regions in the two-dimensional t-space. The R-tree in Fig. 3a consists of two leaf pages, A and B, and one nonleaf page, Root. Leaf pages store o-space objects $a$, $b$, $c$, $d$, and $e$. The mapping is done as follows: By Definition 1a, the o-space object $a$, represented as $[0.1, 0.3]$ in Fig. 3c, is interpreted as the t-space point $<0.1, 0.3>$ in Fig. 3d. Other o-space objects $b$, $c$, $d$, and $e$ can be interpreted similarly. By Definition 1b, the o-space region A, represented as $[0.1, 0.6]$ in Fig. 3c, is interpreted as the t-space region $[0.1, 0.6] 	imes [0.1, 0.6]$ in Fig. 3d. The region B, represented as $[0.4, 0.9]$ in Fig. 3c, is similarly interpreted as the t-space region $[0.4, 0.9] 	imes [0.4, 0.9]$ in Fig. 3d.

Since the t-space view is defined in the t-space, all the properties of the t-space are applied to the t-space view. Thus, the relationships for the t-space in Fig. 1b are also effective for the t-space view. In addition, the t-space view has the following properties: The first property is that the mapping from an o-space index to a t-space view has no space and negligible time overhead since each entry of an o-space index is mapped into an entry of a t-space view through mere "interpretation" or "viewing." Thus, we can apply efficient t-space join algorithms to o-space indexes through the t-space view without additional cost. The second property is that the t-space view does not generate horizontally adjacent regions of pages because regions in a t-space view are always squares and on the diagonal from Definition 1. We take advantage of this property in the t-space view join algorithm that we present in Fig. 9. Using this property, we omit the process of grouping horizontally adjacent pages needed to perform spatial join in the t-space. Details are explained in Section 4.

4 T-SPACE VIEW JOIN ALGORITHM

The t-space view join algorithm spatially joins two t-space views TV(R) and TV(S) of o-space indexes R and S. For ease of explanation, we first explain the algorithm in the
The two SJW's in TS(S) for two adjacent regions in TS(R) significantly overlap due to two properties. This overlap allows us to minimize the number of disk accesses by retaining the pages of the SJW to be reread in the buffer.

The first property is that SJWs for two horizontally adjacent regions have the containment relationship. In Fig. 5a, illustrating two adjacent regions, let the one far from the diagonal line be \( P_1 \) and the one near the diagonal line be \( P_2 \). Then, as shown in Fig. 5b, the relationship \( SJW(P_1) \supset SJW(P_2) \) holds. If we join \( P_2 \) and \( SJW(P_2) \) after we join \( P_1 \) and \( SJW(P_1) \), \( SJW(P_2) \) has already been read into the buffer and, thus, extra disk access can be avoided. Therefore, we use the notion of the horizontal strip enclosing horizontally adjacent regions and those regions in a horizontal strip are joined consecutively.

The second property is that, between two vertically adjacent horizontal strips \( HSTR_1 \) and \( HSTR_2 \), \( SJW(HSTR_1) \) and \( SJW(HSTR_2) \) significantly overlap. In Fig. 6, if we join \( HSTR_2 \) and \( SJW(HSTR_2) \) after we join \( HSTR_1 \) and \( SJW(HSTR_1) \), the former join can be processed with only incremental disk accesses because most of \( SJW(HSTR_2) \) has already been read into the buffer. Therefore, we perform the join by selecting vertically adjacent horizontal strips consecutively.

Using these two properties, we define the t-space view join algorithm as in Fig. 7. The algorithm takes two t-space views TV(R) and TV(S) and a space filling curve SFC as the input. Since a t-space view is a virtual structure defined in the t-space, all the properties of the t-space, including the SJW and its two properties, are also preserved in the t-space view. In the explanation of the algorithm, we assume that TV(R) and TV(S) have the same properties of TS(R) and TS(S). The space filling curve [15] is a way of linearly ordering regions in a space. Here, the curve is used to select horizontal strips in a sequence. In a two-dimensional t-space, the SFC is the vertical axis RX. The case of 2\( n \)-dimensional t-space will be discussed at the end of this section.

In Fig. 7, the t-space view join algorithm consists of two loops. The first loop in Line 1 selects the region \( r_{region} \) of a leaf page in TV(R) using the function \( Next_{Leaf}_{Region} \) in Fig. 8. The function \( Next_{Leaf}_{Region} \) returns the region corresponding to each leaf page in TV(R) following the order of SFC. The function discards the regions in TV(R)
that are not to be joined with any region in TV(S) as soon as possible. By doing this, it prevents the algorithm from reading unnecessary pages from TV(R). For SFC, the function can use any space filling curve defined recursively. In the first loop, we use each region as a horizontal strip because 1) there are no horizontally adjacent pages in a t-space view according to the properties identified from Definition 1 and 2) objects are not duplicated in the intersecting regions according to the properties of o-space indexes like the R-tree. Line 2 sets \( r_{\text{page}} \) to the page corresponding to \( r_{\text{region}} \). The second loop in Line 3 selects each leaf page \( s_{\text{page}} \) from the set of pages in SJW(\( r_{\text{region}} \)) in TV(S). Line 4 joins the two selected leaf pages, \( r_{\text{page}} \) and \( s_{\text{page}} \), using the function Join_Pages.

Fig. 8 shows the function Next_Leaf_Region. It takes two t-space views TV(R) and TV(S) and a space filling curve SFC as the input and returns the region corresponding to each leaf page in TV(R) following the order of SFC. By exploiting the hierarchical structure of the t-space view, the function can select regions of the leaf pages in a sorted order according to SFC with minimal overhead. In the hierarchical structure of the t-space view, the region of the parent page always comes before the region of a child page. That is, the region of the page will not be selected by SFC until the region of the parent page is selected. Using this property, we can significantly reduce the number of the regions to be sorted at a time. Since the regions to be sorted are dynamically changing as the selection proceeds, we use a heap\(^4\) to maintain the SFC-sorted order and heap sort\(^16\) to incrementally add and subtract regions maintaining the sorted order. We call this technique hierarchical region-based sorting and elaborate on this in Fig. 8. The concept of this technique has been derived from a similar technique used by Hjaltason and Samet\(^{[11]}\) to find \( k \)-nearest neighbors incrementally using R-trees. Here, pages are selected incrementally in the order of the distance between the query point and the region of each page.

In Fig. 8, the function Next_Leaf_Region initializes heap with the region of the root page in TV(R) (Lines 1, 2). For each subsequent Next_Leaf_Region call, the function subtracts a region \( r_{\text{region}} \) (Lines 4, 5) and checks whether any page exists in SJW(\( r_{\text{region}} \)) in TV(S). If no page exists in SJW(\( r_{\text{region}} \)), we simply discard the \( r_{\text{region}} \) (Line 7). By doing this, we can discard any \( r_{\text{regions}} \) that are not going to participate in the join, thus avoiding unnecessary page accesses. If the \( r_{\text{region}} \) is a leaf region, we simply return the page for \( r_{\text{region}} \) (Lines 8, 9). If it is not a leaf region, we add all the child regions of \( r_{\text{region}} \) (Lines 10, 11). The size of heap is very small since each region in the heap does not expand into regions of the child pages until it is selected by SFC. In our extensive experiments, the size of the heap has been less than 4 Kbytes in all the cases.

We have so far explained the two-dimensional t-space view join based on the two-dimensional spatial join windows, horizontal strips, and space filling curves. We now extend them to \( 2n \)-dimensional cases.

We define the spatial join window in the \( 2n \)-dimensional space as the Cartesian product of \( n \) number of two-dimensional spatial join windows. That is, for a hyper-rectangular region \( P \) in the \( 2n \)-dimensional TS(R), let \( q \) be \( < \ld_1, \ld_2, \ld_n, r\_d_1, r\_d_2, ..., r\_d_n > \), where \( \ld_j \) is the minimum value on the \((2i-1)\)th axis and \( r\_d_j \) is the maximum value on the \(i\)th axis. Then, the \( 2n \)-dimensional SJW(P) is the region \([0, r\_d_1] \times [\ld_1, 1] \times [0, r\_d_2] \times [\ld_2, 1] \times ... \times [0, r\_d_n] \times [\ld_n, 1]\).

We define the \( 2n \)-dimensional horizontal strip as the Cartesian product of \( n \) number of two-dimensional horizontal strips. Then, the space filling curve for ordering the horizontal strips is defined in the \( n \)-dimensional subspace consisting of the Cartesian product of \( n \) number of vertical

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**Algorithm:** Transform_Space_View_Join(TV(R), TV(S), SFC)

1. for each region \( r_{\text{region}} \) returned from Next_Leaf_Region (TV(R), TV(S), SFC) do
2. let \( r_{\text{page}} \) be the page corresponding to \( r_{\text{region}} \)
3. for each page \( s_{\text{page}} \) from the set of pages in SJW(\( r_{\text{region}} \)) in TV(S) do
4. Join_Pages(\( r_{\text{page}} \), \( s_{\text{page}} \))
5. end
6. end

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**Function:** Next_Leaf_Region (TV(R), TV(S), SFC)

1. if heap has not been initialized then
2. add the region of the root page of TV(R) into heap
3. end
4. while heap is not empty do
5. let \( r_{\text{region}} \) be a region subtracted from heap
6. let \( r_{\text{page}} \) be the page corresponding to \( r_{\text{region}} \)
7. if the set of pages in SJW(\( r_{\text{region}} \)) in TV(S) is not empty then
8. if \( r_{\text{page}} \) is a leaf page then
9. return \( r_{\text{region}} \)
10. else /* if \( r_{\text{page}} \) is a non-leaf page then */
11. add all the regions of the children in \( r_{\text{page}} \) into heap
12. end
13. end
14. end
15. return null

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Fig. 7. The t-space view join algorithm.

Fig. 8. The Next_Leaf_Region function using hierarchical region-based sorting.

heap: a global variable where elements are maintained to be sorted by SFC

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3. In the case of joining o-space indexes where objects are duplicated, duplicated join pairs can occur in the result. Thus, we need to eliminate them after the join is completed. However, we note that this step is also needed even if we use an o-space join algorithm.

4. The heap is implemented using a complete binary tree. It has \( O(\log_2 n) \) time complexity for adding and subtracting regions.
axes of two-dimensional spaces. This is an extension of the space filling curve for the two-dimensional case, which is simply the (one-dimensional) vertical axis. We can use any space filling curve that is able to order the strips in the $n$-dimensional space. Examples of such space filling curves are the row major order, Z-order [23], and Hilbert order [10]. In Sections 5 and 6, through a formal analysis, we propose a new space filling curve that minimizes the one-pass buffer size and the number of disk accesses.

The t-space view join achieves global optimization by considering the entire page access sequences of two t-space views, TV(R) and TV(S). Here, we take advantage of the properties of the spatial join window and the LRU buffer replacement policy. By exploiting the hierarchical structure of the TV(R) and the heap whose elements are ordered by SFC, the ordering of the page access is done with little overhead, resulting in global optimization in the t-space view join. Therefore, it always outperforms the Breadth-First Traversal R-tree Join that needs significant overhead for global optimization. It also outperforms the Depth-First Traversal R-tree Join that only does local optimization.

We also have solved the problems of the Transformation-Based Spatial Join algorithm—an earlier t-space index join algorithm. The t-space view join has the following advantages: First, it can be applied to o-space indexes, while the Transform-Based Spatial Join cannot. Second, the t-space view join does not access unnecessary leaf pages of the outer index, while the Transform-Based Spatial Join does.

## 5 SPACE FILLING CURVES AND ONE-PASS BUFFER SIZE

The order of accessing disk pages makes a significant impact on the performance of joins [4], [12], [18], [28] in terms of the one-pass buffer size and the number of disk accesses. Here, the one-pass buffer size is the minimum buffer size necessary for processing joins while accessing the pages to be joined only once. In this section, we adapt the analysis [18] of the effect of the space filling curve on the one-pass buffer size, when used with the Transformation-Based Spatial Join algorithm [28], to the t-space view join algorithm. We first explain a method that calculates the one-pass buffer size for a given space filling curve and calculate one-pass buffer sizes for typical space filling curves by using this method. We then conclude which space filling curve is preferable for the t-space view join.

To make analysis easy, we make a few assumptions for data distributions, which we call uniform data and page distribution assumptions. We assume the distribution of data is uniform in terms of the positions and sizes of objects in the two-dimensional o-space, that the sizes of the regions corresponding to the leaf pages of the o-space index are equal, and that their center positions have a uniform distribution. Finally, we use the LRU buffer replacement policy commonly used in DBMSs.

Fig. 9 shows the process of joining the pages of TV(R) and TV(S) in the t-space view join algorithm. Here, the pages in TV(R) are read consecutively following the order of SFC. $P_i$ represents the $i$th page read from TV(R) and SJWP($P_i$) represents the set of pages corresponding to the region SJWP($P_i$) in TV(S).

Among the pairs of pages whose SJWPs overlap in Fig. 9, let $P_s$ and $P_e$ be the pair whose difference between the two values $s$ and $e$ is the maximum. Then, to guarantee one-pass, the t-space view join algorithm needs an LRU buffer whose size is equal to the total number of pages read in when doing the join starting from $P_s$ to $P_e$. This constitutes the one-pass buffer. If the buffer is smaller than the one-pass buffer, due to LRU buffer replacement, not all the pages that have been read in when the join is processed for $P_s$ are guaranteed to remain in the buffer until the join is processed for $P_e$. Equation (1) calculates the average one-pass buffer size:

$$
(1 + |SJWP(P_s)|) + \sum_{i=1}^{MAXLDIST-1} (1 + AVG(|\Delta SJWP|)).
$$

In (1), $(1 + |SJWP(P_s)|)$ represents the number of pages read in for $P_s$ and SJWP($P_s$). $(1 + AVG(|\Delta SJWP|))$ represents the average number of pages read in for each page $P_i$ processed after $P_s$ and the incremental SJWP($P_i$) that is newly read in. MAXLDIST is the maximum linear distance between any two pages whose SJWPs overlap. In Fig. 9, MAXLDIST is $|e - s + 1|$.

According to (1), MAXLDIST is the most dominant factor of the one-pass buffer size. To obtain MAXLDIST, we first define in Fig. 10 a scheme for identifying pages in the four-dimensional t-space by two-dimensional coordinate values. Fig. 10a and Fig. 10b show the LX-RX and LY-RY planes that are t-spaces of the X and Y axes, respectively. Here, a rectangle represents the region corresponding to a disk page. In Fig. 10c, we project the four-dimensional space onto the RX-RY plane (the Cartesian product of two vertical axes as described in Section 4), where the regions are to be selected according to the space filling curve. For simplicity, Fig. 10c represents these regions projected onto the RX-RY plane in an array-like fashion in order to identify them.

---

**Fig. 9.** The process of joining pages in the t-space join algorithm.
clearly. Next, we assign the two-dimensional coordinate value \( (u, v) \) to the region in the RX-RY plane whose coordinate in the RX axis is \( u \) and in the RY axis is \( v \). Since each region corresponds to a page, a page is identified by the coordinate of the region.

A space filling curve \( C \) represents the order using a linearization function \( L_C \). The linearization function \( L_C \) is a function that maps the page whose coordinate is \( (u, v) \) to the order number \( i \). This is denoted as \( L_C(u, v) = i \). When the coordinates of two pages \( P_1 \) and \( P_2 \) are \( (u_1, v_1) \) and \( (u_2, v_2) \), the distance between the two pages for a space filling curve \( C \) is calculated as \( |L_C(u_2, v_2) - L_C(u_1, v_1)| + 1 \).

To obtain \( \text{MAXLDIST} \), we now define the notion of page adjacency.

**Definition 3.** The page adjacency of an index is defined as the minimum constant \( c \) satisfying \( |u_1 - u_2| \leq c \) and \( |v_1 - v_2| \leq c \) for all pairs of pages \( (u_1, v_1) \) and \( (u_2, v_2) \) whose SJWPs overlap, i.e., if \( |u_1 - u_2| > c \) or \( |v_1 - v_2| > c \), then the SJWPs of the pages \( (u_1, v_1) \) and \( (u_2, v_2) \) do not overlap.

Using the page adjacency defined above, we calculate \( \text{MAXLDIST} \)’s for typical space filling curves: the row major order, Z-order, and Hilbert order. For other space filling curves, \( \text{MAXLDIST} \) can be calculated similarly. We first explain the cases when the page adjacency is 1. We then explain them when the page adjacency is greater than 1.

**Lemma 2.** Under uniform data and page distribution assumptions, for the row major order, \( \text{MAXLDIST}_{RM} = \sqrt{n} + 2 \) when the page adjacency is 1 and \( n \geq 4 \).

**Proof.** See Appendix B, which can be found on the Computer Society Digital Library at http://computer.org/tkde/archives.htm.

**Lemma 3.** Under uniform data and page distribution assumptions, for the Z-order, \( \text{MAXLDIST}_Z = \frac{n}{4} + 2 \) when the page adjacency is 1 and the number of pages \( n \geq 4 \).

**Proof.** See Appendix C, which can be found on the Computer Society Digital Library at http://computer.org/tkde/archives.htm.

**Lemma 4.** Under uniform data and page distribution assumptions, for the Hilbert order, \( \text{MAXLDIST}_{Hilbert} = \frac{10n + 8}{12} \) when the page adjacency is 1 and the number of pages \( n \geq 4 \).

**Proof.** See Appendix D, which can be found on the Computer Society Digital Library at http://computer.org/tkde/archives.htm.

**Example 3.** Fig. 11 shows \( \text{MAXLDIST} \)’s for the row major order, Z-order, and Hilbert order when the number of pages \( n = 64 \) and the page adjacency is 1. Two pages with the linear distance between them being \( \text{MAXLDIST} \) are represented as gray rectangles and the path of the space filling curve between the two pages as black curves. In each figure, the length of the curve is \( \text{MAXLDIST} \). For the row major order, \( \text{MAXLDIST}_{RM} = \sqrt{64} + 2 = 10 \), for Z-order, \( \frac{12}{2} + 2 = 34 \), and for Hilbert order, \( \frac{10 \cdot 64 + 8}{12} = 54 \).

Now, we consider the case where the page adjacency \( c > 1 \). For the row major order, \( \text{MAXLDIST}^{RM} = c \times \sqrt{n} + c + 1 \) from (4) in Appendix B, which can be found on the
In Lemmas 2, 3, and 4, we have formally derived MAXLDISTs of typical space filling curves. We observe that MAXLDIST of the row major order is $O(\sqrt{n})$ while the others are $O(n)$. Therefore, the row major order has the smallest one-pass buffer size when $n \gg 1$. Hence, to minimize the one-pass buffer size, using the row major order is preferable. However, when the given buffer is smaller than the one-pass buffer, the row major order abruptly incurs a lot of disk accesses. In the next section, we analyze this problem and present a solution. As the solution, we introduce a new space filling curve, called the adaptive row major order, that has been proposed in [18].

6 Adaptive Row Major Order

As shown in Section 5, the row major order is the space filling curve that has the smallest one-pass buffer size. But, it has the problem of reading some pages more than once when the buffer is smaller than the one-pass buffer. We analyze this problem as follows.

In the row major order, when the given buffer is even slightly smaller than the one-pass buffer, we may have to reread SJWPs of all the pages that have been processed. When page adjacency = $c$, if we let $(u,v)$ be the $i$th page, then $(u + c, v + c)$ is identified as the $i + \maxLDist_{\text{RM}}$th page. Since the linear distance between them is $\maxLDist_{\text{RM}}$ and the buffer is smaller than the one-pass buffer determined by $\maxLDist_{\text{RM}}$ from (1), the SJWP of $(u,v)$ must have been swapped out by the time the page $(u + c, v + c)$ is processed. However, since the SJWP of $(u + c, v + c)$ overlaps that of $(u,v)$ (note that page adjacency = $c$), we need to reread the SJWP of the $i$th page from disk. In this way, for each $i$, we may have to reread the SJWP of the $i$th page $(u,v)$ from disk when joining the $(i + \maxLDist_{\text{RM}})$th page $(u + c, v + c)$ if the LRU buffer given is smaller than the one-pass buffer determined by $\maxLDist_{\text{RM}}$.

The linear distance between $(u,v)$ and $(u + c, v + c)$ is proportional to $\sqrt{n}$, which is the horizontal width of the row major order. Thus, we can solve the problem by controlling the horizontal width. For this purpose, we use a new space filling curve, the adaptive row major order (ARM order), proposed in [18]. The formal definition is stated in Definition 4.

Definition 4. The linearization function of the ARM order $L_{\text{ARM}}$ is defined as (2):

$$L_{\text{ARM}}(u,v) = \left\{ \begin{array}{ll}
v \times \sqrt{n} + u & \text{if } u < \frac{\sqrt{n}}{k} \text{ and } k > 0 \\
\vdots & \\
v \times \sqrt{n} + (u - \frac{i\sqrt{n}}{k}) + \frac{i^2}{k} & \text{for } 1 \leq i < k - 1 \text{ if } \frac{i\sqrt{n}}{k} \leq u < \frac{(i+1)\sqrt{n}}{k} \text{ and } k > 2 \\
\vdots & \\
v \times \sqrt{n} + (u - \frac{(k-1)\sqrt{n}}{k}) + \frac{(k-1)^2}{k} & \text{if } u \geq \frac{(k-1)\sqrt{n}}{k} \text{ and } k > 1. \end{array} \right.$$ 

Example 4. Equation (3) and Fig. 12 show the ARM order when $n = 36$ and $k = 2$. This ARM order consists of two components, each traversed in the row major order. In general, the ARM order consists of $k$ number of components of width $\sqrt{n}$, each traversed in the row major order. The left part $(u < 3)$ has a width of 3 and is described by the linearization function $v \times 3 + u$. The right part $(u \geq 3)$ also has a width of 3 and is described by the linearization function $v \times 3 + (u - 3) + 18$.

$$L_{\text{ARM}}(u,v) = \left\{ \begin{array}{ll}
v \times 3 + u & \text{if } u < 3 \\
v \times 3 + (u - 3) + 18 & \text{if } u \geq 3. \end{array} \right.$$ 

In the ARM order, we determine $k$ in such a way that, given a buffer of a specific size $B$ and page adjacency $c$, the one-pass buffer size determined by $\maxLDist$ within one component ($\maxLDist_{\text{component}}$) is equal to or smaller than $B$. Here, $\maxLDist_{\text{component}} = c \times \frac{\sqrt{n}}{k} + c + 1$. From (1), we determine $k$ as the minimum one satisfying $(1 + |\text{SJWP}(P_0)|) + (1 + \text{AVG}(|\text{SJWP}|)) \times (\maxLDist_{\text{component}} - 1) \leq B$.

7 EXPERIMENTS

In this section, we first compare the performances of the t-space view joins using different space filling curves and parameters, $|\text{SJWP}(P_0)|$, $\text{AVG}(|\text{SJWP}|)$, and $c$, can be measured or predicted by sampling nonleaf pages. To handle the worst case in the nonuniform distribution, we sample some nonleaf pages in the densest region identified from the index with a small overhead. Nevertheless, these nonleaf pages tend to remain in the buffer without (or with only a few for small buffers) extra disk accesses. The extra cost for measuring these parameters has been added in the experimental results in Section 7.
verify the analytic results in Sections 5 and 6. We then compare the performance of the t-space view join with those of o-space index join algorithms—the First Traversal R-tree Join and the Breadth-First Traversal R-tree Join (Compo1 and Compo2). Table 1 summarizes the algorithms compared.

We perform experiments using the three measures: the one-pass buffer size, the number of disk access, and the wall clock time. We use three distributions of data: uniform, exponential, and real distributions. The data and distributions are identical to those used in [28]. Data sets U1 and U2 have uniform distributions; data sets E1 and E2 exponential distributions. Each data set has 130,000 MBs (3.5 MBytes). The center points of the MBs in U1 and U2 are uniformly distributed in the o-space, and those in E1 and E2 are exponentially distributed with an average value of 1/4 along each axis in the o-space. The number of join results for U1 and U2 is 87,434 and that for E1 and E2 is 87,346. The real data set consists of Tiger1 and Tiger2, which are identical to those used by Brinkhoff et al. [4] and Huang and Jing [12]. Tiger1 contains 131,461 MBs of streets in an area of California (3.8 MBytes); Tiger2 contains 128,971 MBs of rivers and railway tracks (3.4 MBytes). The number of join results of Tiger1 and Tiger2 is 86,094. The all the data sets used for the experiments are in the two-dimensional o-space. For spatial join algorithms, performances in the two-dimensional o-space are most important since almost all spatial applications deal with two-dimensional data—for example, maps.

We conduct all the experiments on a Sun Ultra 60 workstation. To avoid the buffering effect of the file system and to guarantee actual disk I/Os, we use raw disks for indexes. Indexes used in the experiments are R*-trees, which are identical to those used by Brinkhoff et al. [4]. The page size of the R*-trees is 4 Kbytes. We use the LRU buffer replacement policy.

### 7.1 Performance Comparison among T-Space View Join Algorithms Using Different Space Filling Curves

We verify the analysis in Sections 5 and 6 on the one-pass buffer size of the t-space view join algorithms using different space filling curves for uniform data sets. We also compare the results for other data sets: exponential and real ones. Fig. 13 summarizes the one-pass buffer sizes. The results show that TSVJ-RM and TSVJ-ARM have the smallest one-pass buffer size as we have analytically predicted in Sections 5 and 6. Compared to TSVJ-Z, TSVJ-RM and TSVJ-ARM reduce the one-pass buffer size by up to 14.0 times for different data sets. Compared to TSVJ-Hilbert, they reduce the one-pass buffer size by up to 21.3 times.

For uniform data sets, the results show that the ratio of one-pass buffer sizes for TSVJ-RM, TSVJ-Z, and TSVJ-Hilbert is 71.885:1480 = 0.040:0.59:1.00. This ratio is very close to the ratio 69.973:1615 = 0.040:0.60:1.00 calculated from (1) and Lemmas 2, 3, and 4 when using the parameters $|SJWP(P_i)| = 4$, AVG($|\Delta SJWP|$) = 1.12, the page adjacency $c = 1$, and the number of pages $n = 913$. These parameters have been measured by sampling pages of the t-space view. This result indicates that the analysis for uniform data sets is highly accurate. We also observe that the results are similar for exponential and real ones, indicating that the analysis based on uniform data sets is a reasonable approximation.

Fig. 14 shows the number of disk accesses the t-space view join algorithms incur as the buffer size is varied for the uniform, exponential, and real data sets. In the figure, the bottom horizontal line represents the optimal number of disk accesses obtained with the one-pass buffer. In Fig. 14, we observe that TSVJ-ARM outperforms other TSVJ algorithms regardless of the buffer size. TSVJ-RM incurs the same number of disk accesses as TSVJ-ARM when the buffer is larger than the one-pass buffer. TSVJ-RM, however, has the problem of causing excessive disk accesses when the buffer is smaller than the one-pass buffer. This experimental result matches the analytic result in Sections 5 and 6. To summarize the performance improvement of TSVJ-ARM compared to the others, we distinguish two cases: those using a small buffer and those using a large buffer. A small buffer has a size of 1 ~ 2 percent of the combined size of the two indexes joined. A large buffer has a size of 5 ~ 6 percent of the same. We observe that TSVJ-ARM outperforms other TSVJ algorithms by up to 3.95 times for the small buffer and by up to 1.31 times for the large buffer.

### 7.2 Performance Comparison of T-Space View Join Algorithm with O-Space Index Join Algorithms

This section, we compare our TSVJ-ARM with DFRJ and BFRJ. We choose TSVJ-ARM because it has the best performance among TSVJ algorithms.

#### 7.2.1 Comparison of TSVJ-ARM with DFRJ

Figs. 15, 16, and 17 summarize the results of experiments for TSVJ-ARM and DFRJ using the uniform, exponential, and real data sets. The results show that TSVJ-ARM always
outperforms DFRJ in terms of the three measures for all the data sets tested.

Fig. 15 shows that, compared to DFRJ, TSVJ-ARM reduces the one-pass buffer size by up to 15.7 times. Fig. 16 compares the numbers of disk accesses as the buffer size varies. Fig. 16 shows that, with the small buffer, TSVJ-ARM reduces the number of disk accesses by up to 1.55 times and, with the large buffer, by up to 1.16 times. Fig. 17 shows the result of the wall clock time with curves similar to those in Fig. 16. The results using the uniform and exponential data sets are omitted since they are similar to those using the real data sets.

The reason why TSVJ-ARM has a better performance than DFRJ is that TSVJ-ARM formally controls the order of page accesses by employing global optimization that takes advantage of the characteristics of the spatial join windows in the t-space. On the other hand, DFRJ controls the order of page accesses by using heuristics such as local plane-sweeping and local Z-ordering, resulting in local optimization.

### 7.2.2 Comparison of TSVJ-ARM with BFRJ

BFRJ-Combo2 controls the LRU buffer by using the method of pin/unpin, which helps the buffering efficiency. The pin operation fixes the pages that are expected to be reread in the buffer and assures that they remain in the buffer until they are reread. The unpin operation undoes the pin

![Fig. 13. One-pass buffer sizes of TSVJs when using different space filling curves.](image-url)

![Fig. 14. The number of disk accesses of TSVJs with various space filling curves for uniform, exponential, and real data sets. (a) Uniform data set. (b) Exponential data set. (c) Real data set.](image-url)

![Fig. 15. One-pass buffer sizes of DFRJ and TSVJ-ARM.](image-url)
operation. This method can be applied to any algorithms that do global optimization since, in these algorithms, we can predict which pages are to be pinned or unpinned. This method can also be applied to TSVJ-ARM. But, since TSVJ-ARM carefully reads pages to assure that they are not unnecessarily reread from the disk, TSVJ-ARM with and without this method show almost the same performance. Therefore, we DO NOT apply this method to TSVJ-ARM.

Fig. 16 compares the one-pass buffer sizes of TSVJ-ARM and BFRJ-Combo2 for the uniform, exponential, and real data sets. Since BFRJ-Combo1 uses external disk sort, it always reads disk pages more than once. Thus, we have not been able to obtain the one-pass buffer size of BFRJ-Combo1 and compare it with that of TSVJ-ARM. Fig. 16 shows that, compared to BFRJ-Combo2, TSVJ-ARM reduces the one-pass buffer size by up to 1.14 times.

Figs. 19 and 20 show the numbers of disk accesses and the wall clock times of BFRJ-Combo1, BFRJ-Combo2, TSVJ-RM, and TSVJ-ARM as the buffer size varies. Fig. 19 additionally shows the results of TSVJ-RM since they have some similarities compared to those of BFRJ-Combo2. These similarities are due to the ordering methods used in these algorithms. BFRJ-Combo2 orders the regions primarily by the $x$ coordinate value of the $o$-space regions and TSVJ-RM orders regions primarily by the $ry$ coordinate value and secondarily by the $rx$ coordinate value of the $t$-space regions. Since the regions in both algorithms are primarily ordered by one coordinate value of the regions, they show similar performance.

Fig. 19 shows that TSVJ-ARM always outperforms BFRJ-Combo1 and BFRJ-Combo2. Compared to BFRJ-Combo1, with the small buffer, TSVJ-ARM reduces the number of disk accesses by up to 1.87 times; with the large buffer, by up to 1.31 times. Compared to BFRJ-Combo2, with the small buffer, TSVJ-ARM reduces the number of disk accesses by up to 2.89 times; with the large buffer, the two algorithms

13. Recently proposed spatial join algorithms, the Sort/Sweep Spatial Join [8] and the Unified Approach for Indexed and Non-Indexed Spatial Joins [1], also use a similar ordering to optimize the sequence of accessing pages globally. Thus, they are expected to have a similar performance with TSVJ-RM and BFRJ-Combo2. But, we did not perform a direct comparison of them since the type of the algorithms [1], [8] is different from that of TSVJs and BFRJs: These algorithms [1], [8] join a nonindexed file with an indexed file; TSVJs and BFRJs join two indexed files. We also note that the plane sweeping technique uses a similar ordering.
show almost the same performance since the buffer size is close to the one-pass buffer sizes.

Fig. 20 shows the result of the wall clock time with curves similar to those in Fig. 19. We note that the number of disk accesses in Fig. 19 for BFRJs is similar with TSVJ-ARM, but the wall clock time in Fig. 20 for BFRJs is worse than TSVJ-ARM. The reason is that TSVJ-ARM uses less CPU time than BFRJ: TSVJ takes advantage of the partial sort result that the index already contains; on the other hand, BFRJs do not use such pre-sorted result. But, we note that overall trends in Figs. 19 and 20 are similar. The results using the uniform and exponential data sets are omitted since they are similar to those using the real data sets.

TSVJ-ARM outperforms both BFRJ-Combo1 and BFRJ-Combo2 regardless of the buffer size because it does not need extra disk or memory overhead for global optimization. In contrast, BFRJ-Combo1 needs extra disk accesses to store the join sequence of the entire pages, causing extra disk access overhead. Thus, it performs worse for large buffers. BFRJ-Combo2 needs memory overhead to store the join sequence, effectively reducing the buffer size. Thus, it performs worse for small buffers. It is a disadvantage of BFRJs that any single algorithm is not efficient for all the range of buffer sizes. TSVJ-ARM solves this problem. In addition, TSVJ-ARM reduces the number of disk accesses by adaptively controlling the order for a given buffer size, while BFRJs do not.

8 Conclusions

In this paper, we first have proposed the new notion of the t-space view. A t-space view is a virtual t-space index of an o-space index. The novel aspect of this notion is that it allows us to dynamically interpret an existing o-space index such as the R-tree as a t-space index with no space and negligible time overhead and without modifying its original structure. The idea of the t-space view can be applied to any o-space index where regions and objects stored in the index are represented as minimum bounding rectangles (e.g., R-tree [9], R*-tree [2], X-tree [3], and SKD-Tree [22]).

Next, we have presented the t-space view join algorithm based on the notion of the t-space view. The algorithm
globally optimizes the order of accessing the entire pages of indexes by utilizing the special characteristics of the t-space without much extra overhead in terms of memory or disk access time, providing advantages over existing o-space index join algorithms. It also solves the drawbacks of the Transformation-Based Spatial Join algorithm [28], which is a t-space index join algorithm.

Next, we have adapted the formal analysis [18] of the effect of the space filling curves on the performance of the Transformation-Based Spatial Join algorithm [28] to the t-space view join algorithm. Experimental results show that the analysis is highly accurate. We have also applied the ARM order [18] to the t-space view join algorithm. The ARM order adaptively controls the order of accessing pages for a given buffer size. Experiments show that the ARM order also works well (or even better) with the t-space view join algorithm, significantly reducing all three measures used: the one-pass buffer size, the number of disk accesses for a given buffer size, and the wall clock time.

Last, through extensive experiments, we have verified the excellence of the t-space view join. It has been shown that the t-space view join always outperforms the existing spatial join algorithms that use R-trees in the o-space (the Breadth-First Traversal R-tree Join and the Depth-First Traversal R-Tree Join) for all data sets tested. Thus, it constitutes a lower-bound algorithm. Specifically, it reduces the one-pass buffer size by up to 1.14 times for the Breadth-First Traversal R-tree Join and 1.57 times for the Depth-First Traversal R-Tree Join. It reduces the number of disk accesses by up to 2.89 times for the Breadth-First Traversal R-tree Join and 1.55 times for the Depth-First Traversal R-Tree Join. We have shown that the wall clock time has a similar trend. The reason why the proposed algorithm shows a superior performance is that it performs a global optimization without significant overhead while the others either do only a local optimization or do a global optimization with certain overhead.

The most important contribution of this paper is to show that we can use o-space indexes such as the R-tree in the t-space through the notion of the t-space view. As further study, based on this new notion, we are expecting to develop various new spatial query processing algorithms in the t-space using conventional o-space indexes.

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