kNR-tree: A novel R-tree-based index for facilitating Spatial Window Queries on any k relations among N spatial relations in Mobile environments[*]

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ABSTRACT
The ever-increasing popularity of mobile applications coupled with the prevalence of spatial data has created the need for efficient processing of spatial queries in mobile environments. While different types of spatial queries (e.g., spatial select queries, spatial join queries and nearest neighbour queries) need to be addressed in mobile environments, this work specifically addresses the processing of spatial select queries (i.e., window queries) on any k relations among N spatial relations. We designate such window queries on any k relations among N spatial relations as kNW queries. Notably, the processing of kNW queries is much more challenging in mobile environments than in traditional environments primarily due to the mobility of the clients which issue the queries to the respective base stations. The main contribution of this work is the proposal of the kNR-tree, a *single* integrated novel R-tree-based structure for indexing objects from N different spatial relations. Notably, the kNR-tree facilitates efficient processing of kNW queries. Our performance evaluation demonstrates that our proposed technique, which is based on the kNR-tree, is indeed effective in reducing the response times of kNW queries in mobile environments.

1. INTRODUCTION
The ever-increasing popularity of mobile applications coupled with the prevalence of spatial data has created the need for efficient processing of different types of spatial queries (e.g., spatial select queries, spatial join queries and nearest neighbour queries) in mobile environments. Such mobile environments typically comprise a set of base stations, each of which is responsible for storing and managing the data of mutually disjoint spatial regions, and mobile clients that issue queries to the base stations within their communication range. This work focusses on the processing of spatial select queries (i.e., window queries) on any k relations among N spatial relations in mobile environments. We designate such window queries on any k relations among N spatial relations as kNW queries.

The reason for addressing kNW queries instead of just considering window queries on a single relation is that in practice, a single client may be interested in objects from a number of different relations and different clients may be interested in different numbers as well as different kinds of relations. This is more so in case of mobile environments where there are likely to be multiple relations and the demographics of the client population may vary considerably. For example, a particular mobile client X may wish to issue the following query: *Find all bookshops, restaurants and car-parks which I will encounter* **nearby me** *during my next 10 minutes of travelling.* Another mobile client Y may issue the following query: *Find all bus stations and shopping centres which I will encounter* **nearby me** *during my next 15 minutes of travelling.* Notably, during the time interval between the time of issuing the query and the time of the client receiving the results, since the client is continuously moving, there may be some objects of interest to the client nearby him, but the client would only know about these objects after receiving the query results by which time the client may have already moved past these objects. Hence, to ensure the *usefulness* of the results to the client, reduction of query response time is of paramount importance.

Our work differs from existing works in two major ways. First, since we do *not* have a priori knowledge of the mobile client's position when the query results would be ready, the window of the query is speculative (not known in advance) i.e., the processing done by some of the base stations may *not* contribute to the final results that are returned to the client. Second, while existing works investigate issues concerning a single spatial relation, we examine issues concerning objects from N different spatial relations.

The main contribution of this work is the proposal of the kNR-tree, a *single* integrated novel R-tree-based structure for indexing objects from N different spatial relations. Notably, the kNR-tree facilitates efficient processing of kNW

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queries. Our performance evaluation demonstrates that our proposed technique, which is based on the kNR-tree, is indeed effective in reducing the response times of kNW queries in mobile environments. The remainder of this paper is organized as follows. Section 2 presents an overview of the problem, while Section 3 discusses the processing of kNW queries in mobile environments. The kNR-tree index structure is proposed in Section 4. Section 5 reports the performance evaluation and Section 6 discusses relevant existing works. Finally, we conclude in Section 7 with directions for future work.

2. PROBLEM FORMULATION

This section discusses the formulation of the problem. The problem statement is as follows: *Given a set of base stations, each of which stores and manages the data (from N spatial relations) of mutually disjoint spatial regions and a set of mobile clients, the mobile client wishes to find the results of spatial window queries (on any k of the N relations) nearby himself within the duration of the next T time units.*

In our proposed system, the universe is divided into a set of *mutually disjoint* rectangular spatial regions, the data of each spatial region being stored and managed by *only one* particular base station. We define a region R as being within the *domain* of a base station B_R if B_R is responsible for storing and managing the data associated with R. Figure 1 depicts an illustrative example of how the universe is statically divided into four rectangular spatial regions. In Figure 1, suppose regions 1, 2, 3, 4 are within the domains of base stations B_1, B_2, B_3, B_4 respectively. Moreover, we assume that a mobile client M currently in region R can communicate *only* with the base station B_R within whose domain R is in i.e., all other base stations are outside the communication range of M. For example, in Figure 1, M issues a query from point P_{Issue} (in B_1's domain), so M has to issue the query to B_1.

All the base stations can communicate among themselves. We define two base stations as *neighbours* if their round-trip communication time is less than a pre-defined threshold. We assume that each base station has an index for tracking mobile objects within its domain. Any existing index structure for mobile indexing [7, 6, 5, 9] can be used for this purpose.

We assume that all objects are points in space. In particular, note that the objects are static, but the clients who issue queries to the objects are mobile. The spatial relations are numbered as 1 to N. Each object is of the form (OID, Loc, O_{bitmap}) where OID represents the *unique* identifier associated with the object. OID is generated by concatenating the base station's identifier with a unique integer generated by the base station within whose domain the object is located. Loc specifies the coordinates where the object is located, while O_{bitmap} is the object bitmap which is an array of N bits, each entry position of which corresponds to a specific spatial relation i.e., position 1 of O_{bitmap} relates to relation 1, position 2 is associated with relation 2 and so on. For each relation associated with the object, the corresponding entry in the bitmap is marked as '1', all other entries being '0'. Note that we number bitmap positions starting from 1 (*not* from 0).

For practical reasons, we allow an object to belong to multiple relations e.g., a bookshop that has a cafeteria would belong to both relations, *Bookshop* and *Cafeteria*. Interestingly, even though we view the problem as that of indexing N different spatial relations, an alternative perspective of this problem could be to view the problem as that of indexing only one spatial relation with the type of the object as a scalar attribute of the space.

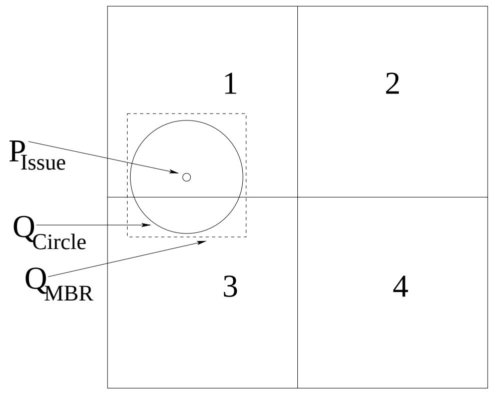

Figure 1: Problem description

Client queries are of the form ($queryID$, $clientID$, P_{Issue}, $Speed_{Max}$, Q_{bitmap}, δ, τ) where $queryID$ is the unique identifier for a query, $clientID$ is the unique identifier of the client M, P_{Issue} is the point (location) from which the query was issued, and $Speed_{Max}$ specifies M's maximum speed. Q_{bitmap} is the query bitmap (an array of N bits), whose structure is *exactly* the same in terms of entry positions of relations as that of the object bitmap. Entries in Q_{bitmap} corresponding to query-related relations are marked as '1', the others being marked as '0'. δ quantifies the distance from M's current location which M considers to be 'nearby' himself. Understandably, the notion of 'nearby' can vary significantly between mobile clients. τ indicates the duration of time (after issuing the query) during which the client would wish to receive the query results.

3. WINDOW QUERY PROCESSING IN MOBILE ENVIRONMENTS

We define $\mathbf{Q_{circle}}$ as a circle drawn with P_{Issue} as centre and ($\tau \times Speed_{Max} + \delta$) as radius. Let us refer to the MBR of Q_{circle} as $\mathbf{Q_{MBR}}$. An illustrative example of Q_{circle} and Q_{MBR} is shown in Figure 1. Q_{circle} encompasses the entire spatial region that can *possibly* be associated with the client's query, thereby implying that Q_{MBR} should be specified as the window query for the client's next τ time units of travelling. However, given that the client may *not* be travelling at his maximum speed in all directions at once, Q_{MBR} is a speculative and conservative estimate of the query window, thereby indicating that some of the processing done by the base stations would be unnecessary.

Intuitively, it is possible for Q_{MBR} to intersect with the domains of base stations other than the base station from whose domain the query had been issued. For example, Figure 1 indicates that Q_{MBR} intersects with the domains of both B_1 and B_3, even though the query had been issued from within B_1's domain. Hence, given that a mobile client M issues a query to a base station B_i within its communication range, we have the following two cases:

1. *Q_{MBR} falls completely within B_i's domain:* B_i processes Q_{MBR} on its own and sends results to M. We defer the discussion concerning how Q_{MBR} is processed by an individual base station to Section 4.

2. *Q_{MBR} intersects with the domain of at least one base station other than B_i:* B_i determines the set R of base stations with whose domains Q_{MBR} intersects. For each member r of R, B_i determines the intersecting rectangular part between Q_{MBR} and r's domain, and sends the intersecting rectangular part to each r. Let us refer to such intersecting rectangular parts as $subQ_{MBR}$s. After processing its respective $subQ_{MBR}$, each r sends a *COMPLETE* message to indicate that it has completed processing its $subQ_{MBR}$. Incidentally, during the time interval between the time that the query was issued and the time of B_i receiving the *COMPLETE* message from each r, M may have moved into the domain of any *one* of the members of R. Hence, B_i sends a message to each r enquiring whose domain M is currently in. Each r checks its index for tracking mobile objects to determine whether M is currently in its domain and the member $r_{current}$ of R which determines that M is currently in its domain sends a message to B_i. B_i sends a message to each r asking them to send their results to $r_{current}$. Now $r_{current}$ receives all the results from every r, checks the time t that has elapsed since the query was issued and computes a circle using the client's current location as the centre and $((\tau\text{-}t) \times Speed_{Max} + \delta)$ as radius. Then $r_{current}$ runs the MBR of this circle as a spatial select condition on the results to obtain the result set, which is returned to the client.

4. kNR-TREE: A SINGLE INTEGRATED INDEX FOR OBJECTS FROM N DIFFERENT SPATIAL RELATIONS

This section presents the kNR-tree, a *single* integrated R-tree-based structure for indexing objects from N spatial relations.

Non-leaf nodes of the kNR-tree contain entries of the form *(ptr, mbr, N_{bitmap})* where *ptr* is a pointer to a child node in the kNR-tree and *mbr* is the MBR that covers all the MBRs in the child node. N_{bitmap} consists of array of N entry bits, each of which corresponds to a specific spatial relation. Notably, the structure of N_{bitmap} is exactly the same as that of the object bitmaps and the query bitmaps in terms of the entry positions of the spatial relations. If the node contains *at least one* object from a particular relation, the corresponding entry in its N_{bitmap} is marked as '1', otherwise it is marked as '0'. Leaf nodes of the kNR-tree contain entries of the form *(oid, loc, N_{bitmap})*, where *oid* is a pointer to an object in the database and *loc* is the location of the object. The structure of N_{bitmap} for the leaf nodes of the kNR-tree is essentially the same as that of the structure of N_{bitmap} for the non-leaf nodes.

Creation of the kNR-tree uses the R-tree insertion algorithm [4], the only difference being that whenever an object to be inserted traverses down the kNR-tree, an OR operation should be executed between the object's bitmap and the existing bitmap at the nodes which fall in the path of the object's top-down kNR-tree traversal. Insertion and deletion algorithms for the kNR-tree also follow standard R-tree algorithms with the handling of node bitmaps being the only difference. Notably, while insertion of objects into the kNR-tree can be expected to be fairly efficient, we can expect deletion of objects to be expensive, especially in cases where updates to the node bitmaps need to be propagated all the way upto the root node of the kNR-tree. We intend to investigate efficient deletion of objects from the kNR-tree in the near future. Moreover, observe that the kNR-tree is not dynamic in the sense that if a new relation is added to the universe, the index needs to be rebuilt. We leave the issue of incorporating dynamism in the kNR-tree to further study.

Figure 2 depicts an illustrative example of the kNR-tree. In Figure 2, the universe is divided into three rectangular spatial regions A, B and C. As depicted in the figure, H, P, J and S stand for hotel, presentation room, jacuzzi and shopping centre respectively. The root node's bitmap H,P,J,S = (0,1,1,1) indicates that the universe comprising A,B and C contains a presentation room, a jacuzzi and a shopping centre, but not a hotel. For the sake of convenience, we have used this notation throughout this figure. A is further divided into three rectangular spatial regions D, E and F respectively. The figure indicates that the region covered by D, E and F also contains a presentation room, a jacuzzi and a shopping centre without having any hotel. D is further divided into three rectangular spatial regions O, Q and R. The figure displays that the region encompassed by O, Q and R contains a presentation room and a jacuzzi, but neither a hotel nor a shopping centre. Similarly, B and C are further divided into G, I, K and L, M, N respectively.

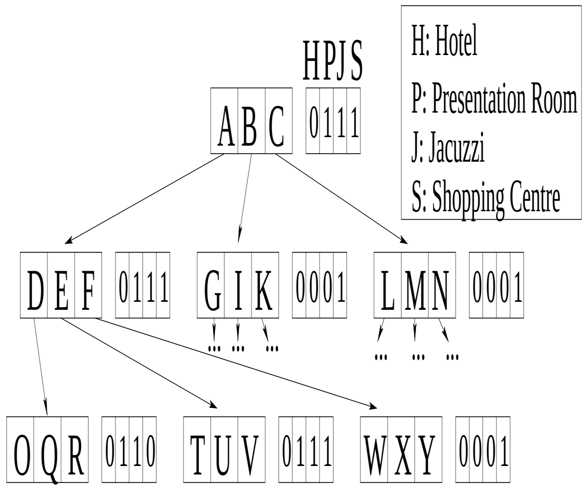

Figure 2: Illustrative example for the kNR-tree

kNW Query Processing using the kNR-tree

Our strategy for processing *kNW* queries using the kNR-tree comprises a top-down traversal involving only those nodes whose MBRs intersect with the query window such

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**Algorithm Spatial_ Window ( $R$, $W$, $Q_{bitmap}$ )**
**Inputs:** 1) A kNR-tree whose root node is $R$.
        2) A query window $W$
        3) $Q_{bitmap}$, the query bitmap
**Output:** Results of the $kNW$ query
if $R$ is not a leaf node
  if $R$ satisfies $Q_{bitmap}$
    Find each MBR entry $M$ of $R$ intersecting $W$
    for each $M$
      execute **Spatial_ Window ( $Childptr$, $W$, $Q_{bitmap}$ )**
      /* Childptr is the pointer to M's child node */
else
  if $R$ satisfies $Q_{bitmap}$
    Find a list $L$ of MBR entries of $R$ that intersect $W$
    for each MBR entry $M$ in $L$
      Check each object within $M$
      Add each object satisfying $Q_{bitmap}$ to the result set
**end**
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Figure 3: *kNW* query processing algorithm for the kNR-tree

that the bitmap of every node, which falls in the path of the top-down kNR-tree traversal, is checked against the query bitmap to decide whether to go further down the branches emanating from the node. The result set consists of k linked lists, each linked list storing the objects retrieved for one of the k relations. Whenever any object is retrieved, the algorithm first determines which relation(s) it belongs to and then adds the object to the linked list(s) associated with the object. The implication is that if an object belongs to multiple relations, it will appear in the linked lists of all the relations that it belongs to. The kNW query processing algorithm for the kNR-tree is presented in Figure 3. In Figure 3, we define a node as *satisfying* a query bitmap if the node contains at least one of the k relations associated with the query.

5. PERFORMANCE STUDY

This section reports the performance evaluation of our proposed techniques. The machine used for the experiments had processing capacity of 1.7 GHz (Pentium-4), main memory of 768 Mbytes and disk space of 40GB. We ran the experiments under the Redhat Linux (version 7.3) operating system. Due to space constraints, in this paper, we show the performance of the kNR-tree at only one base station, even though we have conducted experiments using 16 base stations (each of which indexed the objects in its domain using the kNR-tree).

We conducted our experiments using different real-life datasets. In the interest of space, here we present only the results of our experiments that were performed using a specific *real-life* dataset *'Greece Roads'*[3]. The *'Greece Roads'* dataset contains 23268 rectangles representing the data of roads in Greece. First, we computed the centroid of these rectangles to obtain a dataset of 23268 points before enlarging this dataset by translating and mapping the data. The base station used for this experiment had more than 200000 points (objects), each point being associated with *at least one* spatial relation from the set of 20 relations used for our experiments. We assumed that one kNR-tree node fits in a disk page (page size = 4096 bytes). Hence, kNR-tree node capacity is the same as page size in our case. We used a fan-out of 64 for the kNR-tree.

We define the size of a query **QSIZE** as the percentage of the area of the base station's domain that a query covers. For example, QSIZE = 20 implies that the query covers 20% of the area associated with the base station's domain. The interarrival time between queries was fixed at 5 seconds.

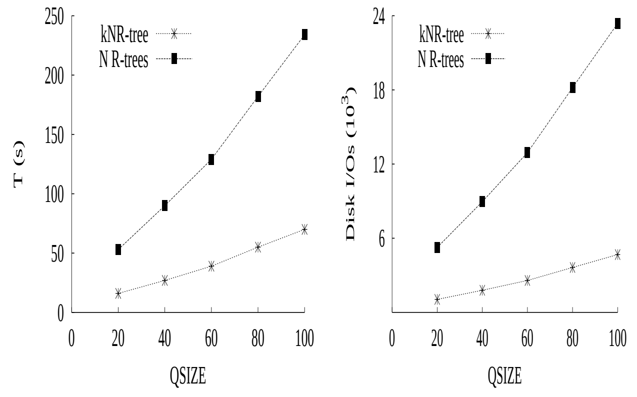
We numbered the relations as 1 to N. Each object was associated with at most 3 relations. For deciding the number of relations associated with a particular object, we generated a random number q between 1 and 3 so that the object belongs to q relations. Then we generate q *distinct* random numbers between 1 and N and assign the object to the q relations whose relation numbers match with these generated numbers. For generating queries, we see the value of k in a particular query Q and associate k relations with Q by choosing k *distinct* random numbers between 1 and N. Then we select a point randomly in the domain of the base station under consideration and draw a rectangle of area QSIZE using the point as the centroid of the rectangle. This rectangle is our query window.

Performance of the kNR-tree

To understand the performance of the kNR-tree, let us now focus on a kNR-tree at a specific base station. Notably, different values of $Speed_{Max}$ and τ result in window queries of different sizes (areas). In our experiments, variations in $Speed_{Max}$ and τ are modeled by varying the respective query window sizes characterized by QSIZE. Moreover, for this set of experiments, the query windows were selected such that they completely overlap with the domain of the base station under consideration. As reference, we adopt a traditional approach which uses N different R-trees to index N relations i.e., one R-tree for each relation. Let us designate it as the *'N R-trees'* approach.

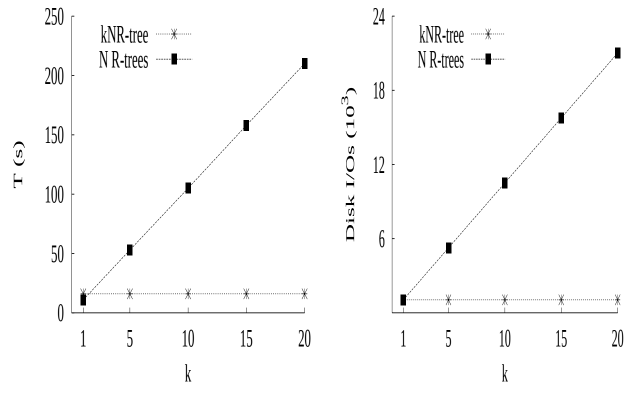
Figure 4 shows the effect of variations in QSIZE when k is fixed. Figures 4a and 4b presents the results concerning query response time T and total number of disk I/Os incurred for k=5. When QSIZE increases, more branches of the index structures need to be traversed, thus explaining the reason for higher number of disk I/Os and consequently higher query response times for increasing values of QSIZE. While the kNR-tree requires only one traversal from its root node to its leaf nodes, the 'N R-trees' approach needs to make one traversal from the root node to the leaf nodes for *each* of the R-trees corresponding to the queried relations, thereby incurring significantly higher number of disk I/Os (shown in Figure 4b) and hence much higher response times (depicted in Figure 4a) than the kNR-tree. Moreover, if an object satisfies q relations, it would be retrieved only once in case of the kNR-tree, while it would be retrieved q times from q different R-trees in case of the 'N R-trees' approach.

Figure 5 depicts the effect of variations in k when QSIZE is fixed. Figures 5a and 5b show the query response times T and disk I/Os for QSIZE=20. As k increases, kNR-tree's performance gain over the 'N R-trees' approach also increases due to lower number of disk accesses incurred by



(a) T for $k = 5$ (b) Disk I/Os for $k = 5$

Figure 4: Effect of variations in QSIZE



(a) T for QSIZE = 20 (b) Disk I/Os for QSIZE = 20

Figure 5: Effect of variations in k

the kNR-tree as discussed above. Interestingly, the results in Figure 5a indicate that the kNR-tree performs slightly worse than the 'N R-trees' approach when k=1. A detailed examination of the experimental results log revealed that this may be attributed to two reasons. First, the height of the kNR-tree can be expected to be larger than at least some of the individual R-trees in the 'N R-trees' approach. Second, unlike the 'N R-trees' approach, the kNR-tree needs processing time to handle the bitmaps of its nodes during the traversal.

6. RELATED WORK

Traditional R-tree-based indexes such as the R-tree [4], the R$^+$-tree [2] and the R*-tree [8] are *not* adequate for indexing mobile objects because such indexing entails frequent updates causing a large number of node-splits and/or node-merges. Hence, several R-tree-based structures such as the Spatio-Temporal R-tree (STR-tree) and Trajectory-Bundle tree (TB-tree) [6], the time-parameterized R-tree (TPR-tree) [7], Lazy Update R-tree (LUR-tree) [5], and the Multi-version 3D R-tree(MV3R-tree) [9] have been proposed specifically for indexing moving objects. A good survey on spatio-temporal databases can be found in [1].

7. CONCLUSION

The increasing popularity of mobile applications coupled with the prevalence of spatial data has created the need for efficient processing of spatial queries in mobile environments. In this paper, we have addressed the processing of spatial select (window) queries on any k relations among N spatial relations. Our solution involves the use of our proposed kNR-tree. Our performance evaluation has demonstrated the effectiveness of our proposed kNR-tree-based technique in reducing the response times of kNW queries in mobile environments. In the near future, we intend to make more detailed performance comparisons between our proposed kNR-tree-based technique and relevant existing techniques and also we wish to examine the effect of the spatial density of the dataset on our proposed technique. Moreover, we aim at investigating effective load-balancing among the base stations.

8. ACKNOWLEDGEMENTS

The authors would like to thank the JSPS (Japanese Society for Promotion of Science) for funding this work.

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