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Predictive Query Indexing for Ambiguous Moving Objects in Uncertain Data Mining

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Abstract

Indexing and query processing is a developing examination field in spatio-temporal data. The majority of the continuous applications, for example, area based administrations, armada administration, movement expectation and radio recurrence recognizable proof and sensor systems depend on spatiotemporal indexing and query preparing. All the indexing and query processing applications is any of the structures, for example, spatio file get to and supporting inquiries or spatio-transient indexing technique and bolster query or temporal measurement, while in spatial data it is considered as the second need. The majority of the current overview takes a shot at spatio-fleeting depend on indexing techniques and query preparing, yet exhibited independently. Probabilistic range query is an essential kind of query in the region of dubious data administration. A probabilistic range query restores every one of the articles inside a particular range from the query question with a likelihood no not as much as a given edge. A query protest is either a specific question or an indeterminate question demonstrated by a Gaussian appropriation. We propose a few sifting systems and a U-tree-based list to effectively bolster probabilistic range questions over Gaussian items. Broad tests on genuine data exhibit the proficiency of our proposed approach.

Keywords: Uncertain Data, Constrained space, probabilistic range query, uncertain moving objects, obstacles, query processing.

I. Introduction

As of late, uncertain data administration has gotten significant consideration in the database group. It includes an extensive assortment of true applications, going from versatile mechanical autonomy, sensor systems to area based administrations. Among every one of the issues in the zone of indeterminate data administration, probabilistic range query is an essential one for processing dubious data in certifiable applications. A probabilistic range query restores every one of the data protests that show up inside the given pursuit locale with probabilities no not as much as a given likelihood limit. For example, consider a self-explored portable robot moving in a remote situation. The robot constructs a guide of the earth by watching close-by milestones through gadgets, for example, sonar and laser go discoverers. Because of the inalienable confinement achieved by sensor exactness and flag commotions, the area data procured from measuring gadgets is not generally exact. In the meantime, the robot additionally leads probabilistic limitation [1] to gauge its own particular area self-sufficiently by coordinating its development history and the point of interest data. This can bring about inaccuracy in the area of the robot, as well. In result, likelihood inquiries have developed to handle such uncertainty; e.g., "discover historic points existing in 5 meters from my present area with a likelihood no less than 80%". Regularly for such applications, questionable articles are put away in the databases and related with likelihood appropriations. A generally utilized circulation for such a reason for existing is a multi-dimensional Gaussian dispersion which is broadly embraced in measurements, design acknowledgment [7] and restriction in apply autonomy [9]. In this paper we concentrate the situation where the areas of data items are questionable, while the area of the query protest is either correct or uncertain. In particular, data question are depicted by Gaussian disseminations with various parameters to show their disparities in vulnerability. A query protest can be either a specific point in the multi-dimensional space or an indeterminate area spoken to by a multi-dimensional Gaussian dispersion. We take care of the probabilistic range query issue as per the above setup. A direct way to deal with this issue is to process the appearance

likelihood [8] for every data question and yield it if this likelihood is no not as much as the limit. In any case, the likelihood calculation for the most part requires exorbitant numerical joining for precise outcome [6], rendering it restrictively costly to process for every one of the data questions and check if the query limitation is fulfilled. In this manner, such calculations ought to be decreased however much as could be expected. There have been answers for probabilistic range questions that can deal with Gaussian-based dubious data, yet in light of particular suppositions. For instance, U-tree [2] accept that each indeterminate question is situated inside a pre-characterized instability area. It builds a list for all articles in view of this area to lessen the quantity of hopefuls that require the costly numerical coordination. In addition, Gauss-tree [3] is proposed for probabilistic recognizable proof inquiries, however the Gaussian dispersions they take after must be autonomous in each measurement. At the point when these suspicions are disregarded, these arrangements at no time in the future work. One issue of U-tree is that it is difficult to choose a reasonable degree of the instability district for a certifiable protest. In this paper we take care of these issues with nonexclusive Gaussian circulations with no of these suppositions; i.e., the items can situate in an endless space rather than U-tree, or have connections between's measurements instead of Gauss-tree.

II. Related Work

Query Processing on Imprecise Data Early research fundamentally concentrates on different data models for precisely catching the areas of moving articles. In this specific circumstance, query calculations go for limiting the measure of data transmission (for refreshing the focal server) to guarantee the exactness of database esteems. Cheng et al. [4] are the first to detail questionable recovery all in all areas. They display an intriguing scientific classification of novel query sorts, together with the comparing preparing techniques. An I/O effective calculation for closest neighbor pursuit is proposed in [5]. Nothing from what was just mentioned works considers prob-go recovery. Cheng et al. [6] build up a few answers for prob-extend inquiries which, in any case, target 1D space as it were. They contend that range seek in unverifiable databases is intrinsically more troublesome than that on conventional exact questions, and bolster their cases by giving two hypothetical methodologies that accomplish (practically) asymptotically ideal execution. All things considered, the practicability of these techniques is restricted since (i) they can't bolster objects with subjective pdfs (e.g., one strategy targets just uniform pdfs), and (ii) they may bring about expansive real execution overhead because of the concealed constants in their unpredictability ensures. Dalvi and Suciu [8] examine "probabilistic databases", where each record is the same as a tuple in a customary database, aside from that it is related with an "existential" likelihood. For instance, a 60% existential likelihood implies that a tuple may not exist in the database with a 40% possibility; in the event that it does, nonetheless, its esteems are exact. Henceforth, probabilistic databases are not the same as indeterminate databases (the theme of this paper), where each protest unquestionably exists however its solid esteems take after a probabilistic dispersion. A productive stream mining calculations was planned in [17] to mine regular examples successfully and effectively from such spilling data.In [18], a tree-based mining calculation was created that used to mine continuous examples from dynamic indeterminate data stream in light of time-blurring and historic point models.An proficient Skyline query calculation was composed in [19] of questionable moving stream data yet the execution is neglected to utilize list structures, for example, lattice, R tree et cetera. A novel calculation was viably composed in [20] to mine the questionable gathering designs that enhance the mining productivity however it not proficient to deal with more unpredictable examples. The previously mentioned challenges related with various data mining procedures hard to handle the data instability issue viably. Henceforth, a novel approach called Fusion Layer Topological Space Query (FLTS) Indexing system is acquainted with take care of the questionable data mining issue on preparing the client asked for query. The concise clarification about the FLTS Indexing procedure is introduced in next segment.

III. Data Uncertainty and Probabilistic Queries

In [7][9], a data representation scheme known as *probabilistic uncertainty model* was proposed. The model requires that at the time of query execution, the range of possible values of the attribute of interest, and their distributions, are known. For notational convenience, we assume that a real-valued attribute a of a set of database objects T is queried. The ith object of T is named T_i, and the value of a for T_i is called $T_i.a$ ($i = 1,...,|T|$), where $T_i.a$ is treated as a

continuous random variable. The *probabilistic uncertainty* of $T_i.a$ consists of two components:

Definition 1 *An* **uncertainty interval** *of $T_i.a$, denoted by U_i, is an interval $[L_i,R_i]$ where $L_i,R_i \in <$, and the conditions $R_i \geq L_i$ and $T_i.a \in U_i$ always hold.*

Definition 2 *An* **uncertainty pdf** *of $T_i.a$, denoted by $f_i(x)$, is a pdf of $T_i.a$, such that $f_i(x)=0$ if $x \in/ U_i$.*

This simple model provides flexibility where the exact model of uncertainty is determined by applicationdependent assumptions. A simple example is the modeling of sensor measurement uncertainty, where each U_i is an error range containing the mean value, and $f_i(x)$ is a normal distribution. Another example is the modeling of one-dimensional moving objects based on [20], where at any point in time, the actual location is within a certain bound, d, of its last reported location value. If the actual location changes further than d, then the sensor reports its new location value to the database and possibly changes d. In this case, U_i contains all the values within a distance of d from its last reported value. For $f_i(x)$, one may assume that $T_i.a$ is uniformly distributed, i.e., $f_i(x) = 1/[R_i - L_i]$ for $T_i.a \in U_i$. Treating $f_i(x)$ as a uniform pdf models the scenario where $T_i.a$ has an *equal* chance of locating anywhere in U_i. Due to its simplicity, a uniform distribution facilitates ease of analysis and efficient index design, as illustrated in subsequent sections.

Alternatively, one may perform an estimation of the pdf based on time-series analysis, the discussion of which is beyond the scope of this paper. Interested readers are referred to [5] for details. Also notice that we limit our discussion of uncertainty to interval data. A comprehensive discussion of different types of uncertainty can be found in [21].

A *probabilistic threshold query* (PTQ), proposed in [9], is a variant of probabilistic query, where only answers with probability values over a certain threshold p are returned. The PTQ that we study specifically in this paper is defined formally below.

Definition 3 Probabilistic Threshold Query *(PTQ) Given a closed interval $[a,b]$, where $a,b \in <$ and $a \leq b$, a PTQ returns a set of tuples T_i, such that the probability $T_i.a$ is inside $[a,b]$, denoted by p_i, is greater than or equal to p, where $0 < p \leq 1$.*

Simply speaking, a PTQ can be treated as a range query, operating on probabilistic uncertainty information, and returns items whose probabilities of satisfying the query exceed p.

A Simple Uncertainty Index

A naive method to evaluate a PTQ is to first retrieve all T_i's, whose uncertainty intervals have some overlapping with $[a,b]$, into a set S. Each T_i in S is then evaluated for their probability of satisfying the PTQ with the following operation:

$$p_i = \int_{OI} f_i(x)dx \qquad (1)$$

where p_i is the probability that T_i satisfies the PTQ, and OI is the interval of overlap between $[a,b]$ and U_i.

The answer only includes T_i's whose p_i's are larger than p.

Two problems can be seen from this approach. First, how can we find the elements of S i.e., U_i's that overlap with $[a,b]$? It can be very inefficient if each item T_i is retrieved from a large database and tested against $[a,b]$. A typical solution is to build an index structure over U_i's (which are intervals) and apply a range search of $[a,b]$ over the index. This problem is known as the interval indexing problem, and has been well studied [17][15].

The second problem is that the probability of each element in S needs to be evaluated with Equation 1. This can be a computationally expensive operation. Notice that the bottleneck incurred in this step is independent of whether we use an interval index or not. In particular, the interval index does not help much if many items overlap with $[a,b]$, but most have probability less than p. In this situation, we still need to spend a lot of time to compute the probability values for a vast number of items, only to find that they do not satisfy the PTQ after all.

Probability Threshold Indexing

The above problems illustrate the inefficiency of using an interval index to answer a PTQ. While the range search is being performed in the interval index, only uncertainty intervals are used for pruning out intervals which do not intersect $[a,b]$. Another piece of important uncertainty information, namely the uncertainty pdf, has not been utilized at all in this searching-andpruning process. As a result, a large number of items may overlap with $[a,b]$, while in fact

only a small fraction of them contribute to the results of PTQ.

Our goal is to redesign index structures so that probabilistic uncertainty information is fully utilized during an index search. This structure, called *Probability Threshold Indexing* (PTI), is based on the modification of a one-dimensional U-tree, where probability information is augmented to its internal nodes to facilitate pruning. To illustrate our idea, let us review briefly how a range query is performed on an U-tree. Starting from the root node, the query interval [*a*,*b*] is compared with the maximum bounding rectangle (MBR) of each child in the node. Only children with MBRs that overlap with [*a*,*b*] are further followed. We thus save the effort of retrieving nodes whose MBRs do not overlap [*a*,*b*]. We can generalize this idea by constructing *tighter* bounds (that we call *x*-bounds) than the MBR in each node, by using uncertainty information of intervals, so as to further reduce the chance of examining the children of the node. Let M_j denote the MBR/uncertainty interval represented by the *j*th node of an U-tree, ordered by a pre-order traversal. Then the *x*-bound of M_j is defined as follows.

Definition *An* **x-bound** *of an MBR/uncertainty interval M_j is a pair of lines, namely left-x-bound*

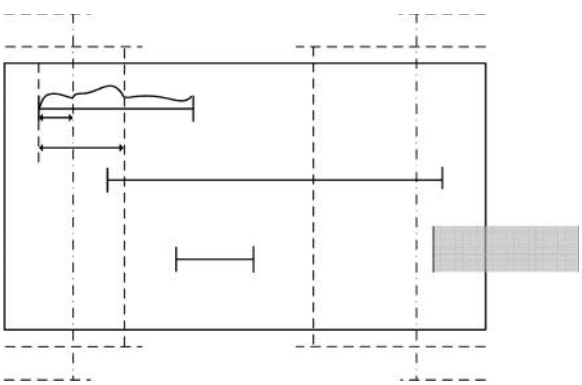


Figure 1: Inside an MBR M_j, with a 0.2-bound and 0.3-bound. A PTQ named *Q* is shown as an interval.

(denoted by $M_j.lb(x)$) and right-x-bound (denoted by $M_j.rb(x)$). Every interval $[L_i,R_i]$ contained in this MBR is guaranteed to have a probability of at most x (where $0 \le x \le 1$) of being left of the left-xbound and being right of the right-x-bound. That is to say, if $L_i \le M_j.lb(x)$ and $R_i \ge M_j.rb(x)$, then the following must hold: $\int_{L_i}^{M_j.lb(x)} f_i(y)dy \le x$ *and*

$\int_{M_j.rb(x)}^{R_i} f_i(y)dy \le x$.

Using the definition of an *x*-bound, the MBR of an internal node can be viewed as a 0-bound, since it guarantees all intervals in the node are contained in it with probability one i.e., no interval lies beyond the 0-bound. Figure 1 illustrates three children MBRs (*A*,*B*,*C*), in the form of one-dimensional intervals, contained in larger MBR M_j. A 0.2-bound and a 0.3bound for M_j are also shown.

As Figure 1 shows, an *x*-bound is a pair of lines where at most a fraction of *x* of each interval in the MBR cross either of them. For illustration, the uncertainty pdf of *A* is shown, where we can see that

$\int_{L_A}^{j} M.lb(0.2)$ $\int_{L_A}^{j.r\ (0.3)} f_i(x)dx \le M\ b\ f_i(x)dx \le$ 0.2, and 0.3. For interval *B*, the constraint on the right-0.3bound is $\int_{M_j.rb(0.3)}^{R_B} f_i(x)dx \le 0.3.$ Interval *C* does not crosses either the 0.2-bound and the 0.3-bound, so it satisfies the constraints of both *x*-bounds. Furthermore, we require an *x*-bound to be unique, where the left-*x*-bound and right-*x*-bound are pushed towards the center of the MBR as much as possible, without violating their definitions.

The whole purpose of storing the information of the *x*-bound in a U-tree node is to avoid investigating the contents of a node. If we can avoid this probing, a considerable amount of I/Os can be saved. Furthermore, we do not need to compute the probability values of those intervals, which cannot satisfy the query anyway. To illustrate how this idea works, let us look at Figure 1 again. Here a range query *Q*, represented as an interval, is tested against the internal node. Without the aid of the *x*-bound, *Q* has to (i) examine which MBR (i.e., *A*, *B*, or *C*) overlaps with *Q*'s interval, (ii) for the qualified MBRs (*B* in this example), further retrieve the node pointed by *B* until the leaf level is reached, and (iii) compute the probability of the interval in the leaf level.

The presence of the *x*-bound allows us to decide with ease whether an internal node contains any qualifying MBRs, without further probing into the subtrees of this node. In this example, we first test *Q*'s range against the left-0.2-bound and the right-0.2bound. As shown in Figure 1, it intersects none of these bounds. In particular, although *Q* overlaps the MBR, its overlapping region is somewhere between the right-0.2-bound and the right boundary of M_j's MBR. Recall that a 0.2-bound allows at most an accumulated pdf of 0.2 of any interval in an MBR.

This implies that the portion of the intervals (interval *B*) that passes through the 0.2-bound cannot exceed a probability of 0.2. Therefore, the probability of intervals in the MBR that overlap the range of *Q* cannot be larger than 0.2. Assume *Q* has a probability threshold of 0.3 i.e., *Q* only accepts intervals with an overlapping probability of at least 0.3. Then we can be certain that *none* of the intervals in the MBR satisfies *Q*, without further probing the subtrees of this node. Compared with the case where no *x*-bounds are implanted, this represents a significant saving in terms of number of I/Os and computation time.

In general, given an *x*-bound of a MBR M_j, we can eliminate M_j from further examination if the following two conditions hold:

1. $[a,b]$ does not intersect left-*x*-bound or right-*x*bound of M_j i.e., either $b < M_j.lb(x)$ or $a > M_j.rb(x)$ is true, and
2. $p \geq x$

If no *x*-bound in M_j satisfies these two conditions, the checking of intersections with M_j is resumed, where the contents of the node represented by M_j are loaded, and the range searching process is done in the same manner for an U-tree.

IV. A Simple Uncertainty Index

Answer Range Queries over Imprecise Data

In this section, we show how to answer the two range queries described earlier. Although the process is straightforward, the format of results is important for further discussions in the later sections. Here different objects may have different imprecision *e*. Note although we assume a uniform probability distribution of object location across the uncertain area, any type of known probability distribution is applicable.

Return Objects in a Given Range

The task of returning objects within a given query range can be accomplished by modifying the traditional spatial query processing technique that deploys tree structures. The first modification is that the point objects are now represented by objects with non-zero extents—the uncertain area with radius *e*(see figure 1). To handle the fact that some objects are not fully contained in the region, another modification is needed to associate each returned object with a probability value(p_i) to indicate how likely the object can really be in the query region.

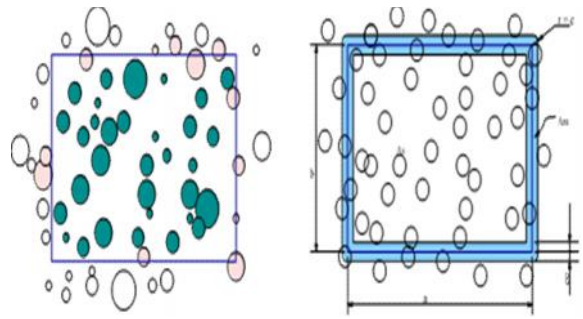


Fig.2 Range Query over Imprecise **Fig.3** Effect of Imprecision *e* in Range

Data (sets differentiated by colors) Query

Probability value p_i is 1.0 for those objects whose uncertainty area is completely contained by the given query region. For objects whose uncertainty areas overlap with query region, p_i could be computed as the cumulative probability represented by the overlapping area. Under the assumption of uniform probability distribution, we have: $p_i = \frac{A_i}{\pi e^2}$, where A_i is the overlap area that can be computed from geometric parameters.

Return COUNT of Objects in a Given Range

To answer *COUNT* queries, the format of answers needs to be specified first. Possible options are $\{min,max\}$, $\{min,max,mean\}$, $\{min,max,mean,var\}$, and $\{(min,P_{min}),(min + 1,P_{min+1}),...,(max,P_{max})\}$. Note that here we use upper case *P* to represent the probability that *COUNT* takes a specific value. Lower case *p* is used to represent the probability with which an object could be in a query region. A server can produce all the information needed in the above answer formats, given its capability to answer the query discussed in section 3.1. Here we summarize the process to compute the above answers.

Let the first N_s objects in the answer set be the ones from *MUST* set. Then, we know $p_i = 1$ for all $1 \leq i \leq N_s$. An immediate result is that $min = |MUST| = N_s$ and $max = |MUST|+|MAY| = N_s + N_m$. *Mean* is summation of p_i's of all relevant objects. And *variance* can be evaluated as:

Ns+Nm

$$variance = \text{X } P(COUNT = k)(k - mean)^2 \qquad (1)$$

k=0

The probability for individual *COUNT* value can be computed by summation of probabilities of events that yield the *COUNT*. For example, below is the probability that *COUNT* takes value of *min* + 1.

Ns+Nm

$P(COUNT = N_s + 1) = X\ p_i[Y(1 - p_j)]$ (2)

$i,j=N_s+1\ j6=i$

Among the four answer formats, the more detailed formats require more computation as well as larger answer sizes. Choosing a proper format should be a task of database server based on user requirements. In next section, we base our discussion on the second format.

R-tree Based CPA Join

Given these caveats, perhaps the most natural choice for the CPA Join is the R-tree. The R-tree is a hierarchical, multi-dimensional index structure that is commonly used to index spatial objects. The join problem has been studied extensively for R-trees and several spatial join techniques exist that leverage underlying R-tree index structures to speed-up join processing. Hence, our fi inclination is to consider a spatiotemporal join strategy that is based on R-trees. The basic idea is to index object histories using R-trees and then perform a join over these indices.

The R-Tree Index

It is a very straightforward task to adapt the R-tree to index a history of moving object trajectories. Assuming three spatial dimensions and a fourth temporal dimension, the four-dimensional line segments making up each individual object trajectory are simply treated as individual spatial objects and indexed directly by the R-tree. The R-tree and its associated insertion or packing algorithms are used to group those line segments into disk-page sized groups, based on proximity in their four-dimensional space. These pages make up the leaf level of the tree. As in a standard R-tree, these leaf pages are indexed by computing the minimum bounding rectangle that encloses the set of objects stored in each leaf page. Those rectangles are in turn grouped into disk-page sized groups which are themselves indexed. An R-tree index for 3 line segments moving through 2-dimensional space is depicted in Figure 4.

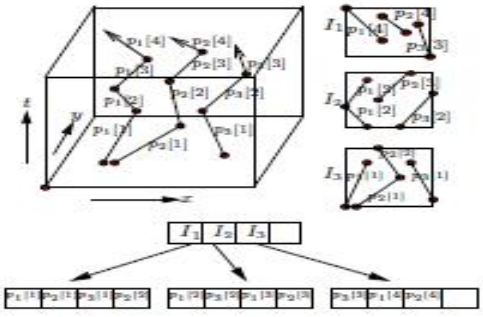


Figure 4. Example of an R-tree

Basic CPA Join Algorithm Using R-Trees

Assuming that the two spatiotemporal relations to be joined are organized using R-trees, we can use one of the standard R-tree distance joins as a basis for the CPA Join. The common approach to joins using R-trees employ carefully controlled synchronized traversal of the two R-trees to be joined. The pruning power of the R-tree index arises from the fact that if two bounding rectangles R1 and R2 do not satisfy the join predicate then the join predicate is not satisfied between any two bounding rectangles that can be enclosed within R1 or R2.

In a *synchronized* technique, both the R-trees are simultaneously traversed retrieving object-pairs that satisfy the join predicate. To begin with, the root nodes of both the R-trees are pushed into a queue. A pair of nodes from the queue is processed by pairing up every entry of the fi node with every entry in the second node to form the candidate set for further expansion. Each pair in the candidate set that qualifies the join predicate is pushed into the queue for subsequent processing. The strategy described leads to a BFS (Breadth-First-Search) expansion of the trees. BFS-style traversal lends itself to global optimization of the join processing steps and works well in practice.

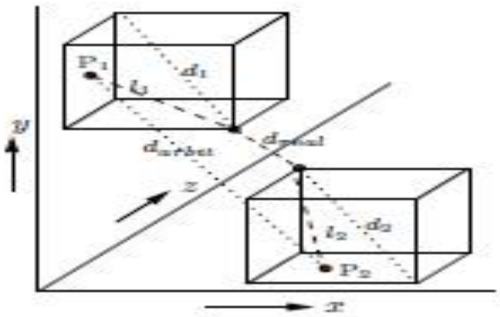


Figure 5. Heuristic to speed up distance computation

V. Proposed Methodology

The distance routine is used in evaluating the join predicate to determine the distance between two bounding rectangles associated with a pair of nodes. A node-pair qualifies for further expansion if the distance between the pair is less than the limiting distance *d* supplied by the query. Objects moving in a constrained 2D space where objects are forbidden to be located in some specific areas such specific areas as restricted areas, and dub the query above the Constrained Space Probabilistic Range Query (CSPRQ). The CSPRQ can also find many applications as objects moving in a constrained 2D space are common in the real world. For example, the tanks in the digital battlefield usually cannot run in lakes, forests and the like, the areas occupied by those obstacles can be naturally regarded as restricted areas. The key idea of proposed solution is to use a strategy called pre-approximation that can reduce the initial problem to a highly simplified version, implying that it makes the rest of steps easy to tackle. The optimizations are mainly based on two insights: (i) the number of effective subdivisions is no more than 1, we utilize this insight to improve the power pruning restricted areas; and (ii) an entity with the larger span is more likely to subdivide a single region, this insight motivates us to sort the entities to be processed according to their spans. In addition to the main insights above, we also realize two other facts and utilize them. Specifically, two mechanisms are developed: postpone processing and lazy update.

VI. Performance Evaluation

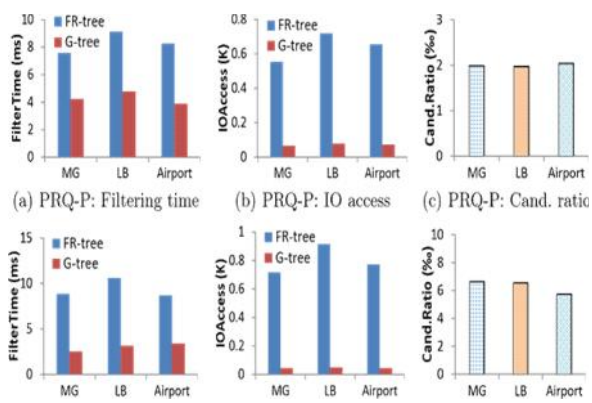
The average query response time of 200 PRQ-P (resp. PRQ-G) queries (10K samples are used for numerical integration) is 0.242 seconds (1.250 seconds resp. PRQ-G) for G-tree, and 120.764 seconds (236.725 seconds resp. PRQ-G) for Scan, almost 500 (190 resp. PRQ-G) times that of G-tree. Among the overall response time, the integral computation takes up 0.237 seconds (1.246 seconds resp. PRQ-G) for G-tree, and 120.692 seconds (236.577 seconds resp. PRQ-G) for Scan. This indicates that probability integration dominates the overall query processing and is computationally expensive. Consequently, it is important to reduce candidate objects which need to perform integration as much as possible.

Among 50,747 objects in LB, the average candidate number of G-tree is 93 for PRQ-P (335 for PRQ-G). The number of validated objects by integration is 65 for PRQ-P (156 for PRQ-G). So for PRQ-P 69.9% (46.6% for PRQ-G) of the candidates identified by our approach are real results. This demonstrates the effectiveness of our proposed filtering techniques.

In the sequel, we exclude the integral part from query processing and focus on evaluating the filtering and indexing performance of FR-tree and G-tree.

We run the two algorithms to process 10K queries on the three datasets and show the average filtering time and IO access of PRQ-P (resp. PRQ-G) in Fig. 6(a) – 6(b) (resp. Fig. 6(d) – 6(e)). For PRQ-P, the filtering time of G-tree is half of that of FR-tree, because the IO access of G-tree is 90% less than that of FR-tree, though the segmented bounding boxes in G-tree are more complex to process than those in FR-tree. The reduction on PRQ-G is more substantial. The filtering time of G-tree on MG and LB is 71% less than that of FR-tree, and 61% on Airport. The IO access of G-tree of three datasets is 6% that of FR-tree.

As a ρ_{max} is adopted to process queries with any θ, the bounding boxes in FR-tree are very loose. This causes more IO accesses and increases filtering time. On the other hand, since the bounding boxes in G-tree are constructed in a parametric fashion, they can be calculated dynamically for arbitrary θ and hence are compact. Another interesting observation is that the IO access almost resembles the candidate number, indicating most IOs are spent on retrieving data objects.



(a) PRQ-P: Filtering time (b) PRQ-P: IO access (c) PRQ-P: Cand. ratio

Fig. 6(c) and Fig. 6(f) shows the candidate ratio of PRQ-P and PRQ-G, which is calculated by dividing the candidate number by the total number of objects. The candidate number of FR-tree and G-tree is the

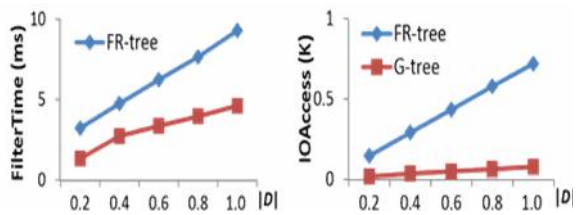
same since we equip FR-tree with our filtering techniques.

(d) PRQ-G: Filtering time (e) PRQ-G: IO access (f) PRQ-G: Cand. ratio

Fig.6. Performance of PRQ-P and PRQ-G Queries

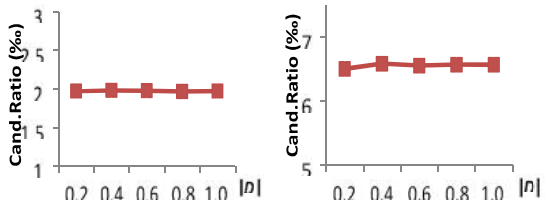
The candidate ratio is around 2‰ for PRQ-P and 6‰ for PRQ-G on the three datasets. This reveals that only a very small percentage of data objects will become candidates owing to our filtering techniques.

Varying Dataset Size. To evaluate the scalability of our approach, we randomly extract 20%, 40%, 60%, 80% and 100% of LB dataset and show the filtering time and IO access of two methods in Fig. 7(a) – 7(b) on PRQ-P queries. The performance on PRQ-G queries reveals a similar trend and hence is omitted here due to space limit. As the dataset size becomes larger, the filtering time and IO access of FR-tree almost increase linearly. G-tree displays a steady increasing trend and always outperforms FT-tree.



(a) PRQ-P: Filtering time (b) PRQ-P: IO access

Fig. 7 Varying [D]: Filtering time and IO access (PRQ-P)

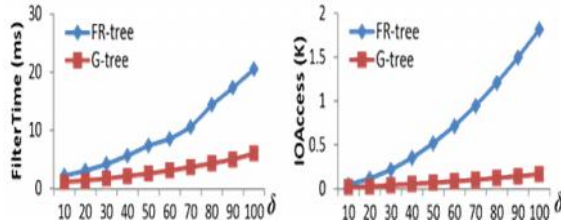


(a) PRQ-P: Candidate ratio (b) PRQ-G: Candidate ratio

Fig.8. Varying |D|: Candidate ratio

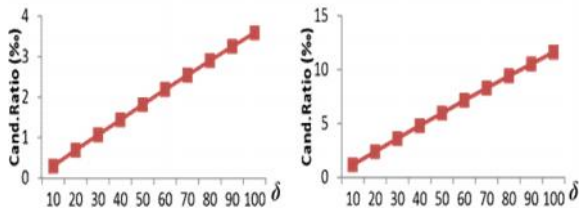
As shown in Fig. 8(a) – 8(b), the candidate ratio of PRQ-P retains 2‰ when varying the dataset size |D|, and 6.5‰ for PRQ-G, demonstrating the steadiness and scalability of our approach with respect to the dataset size.

Varying Query Range. We vary the query range δ from 10 to 100 by 10 and show the performance on PRQ-P queries in Fig. 9(a) – 9(b). The performance on PRQ-G queries is similar and hence omitted. As δ increases, FR-tree consumes much more time and more IO accesses on filtering processing. In contrast, Gtree exhibits much slower increasing trends. Fig. 10(a) – 10(b) shows that the candidate ratio of both PRQ-P and PRQ-G also increases with δ, but for PRQ-P it is only 3.4% (11.6% for PRQ-G) even if achieves 100.



(a) PRQ-P: Filtering time (b) PRQ-P: IO access

Fig. 9. Varying: Filtering time and IO access (PRQ-P)



(a) PRQ-P: Candidate ratio (b) PRQ-G: Candidate ratio

Fig.10. Varying δ: Candidate ratio

Varying Probability Threshold. We vary θ from 0.1 to 0.9 and show the performance in Fig. 11(a) – 12(b) for both PRQ-P and PRQ-G queries. For PRQ-P, the filtering time and IO access of both FR-tree and G-tree decreases gradually with θ when it is less than 0.5. When θ exceeds 0.5, the filtering time slightly rebounds. This is consistent with our filtering condition which assigns $\rho = 1 - 2\theta$ if $\theta < 0.5$ and $\rho = \theta$ if $\theta \geq 0.5$. Because when $\theta < 0.5$, ρ decreases when θ moves towards larger values, and bounding boxes shrink. So most of non-candidates can be filtered quickly and and less IO accesses are needed, and hence it accelerates filtering.

On the contrary, when $\theta \geq 0.5$, ρ increases with θ, each bounding box enlarges and consequently the filtering time and IO access rises. However, an object needs to satisfy the constraint that the center must be located within the query region, and thus the increase

in filtering time is not obvious in this case. The reason also accounts for the trend of G-tree on candidate ratio in Fig. 10

VII. Conclusion

The CSPRQ for uncertain moving objects. The deliberate analyses offer insights into the problem considered, and show that to process the CSPRQ using a straightforward method is infeasible. We propose the targeted solution and demonstrate its efficiency and effectiveness through extensive experiments. An additional finding is the precomputation based method has a non-trivial preprocessing time (although it outperforms our preferred solution in other aspects), which offers an important indication sign for the future research. We conclude this paper with several interesting research topics: (i) how to process the CSPRQ in 3D space (ii) if the location update policy is the time based update, rendering that the uncertainty region u is to be a continuously changing geometry over time, how to process the CSPRQ in such a scenario (iii) if the query issuer is also moving, the location of query issuer is also uncertain, how to process the location based CSPRQ.

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