

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 8, August 2015

# A Web Based Queries Search Key Word for Spatial Objects

R.Karthikeyan<sup>1</sup>, V.Khanna<sup>2</sup>

Assistant Professor, Department of Computer Science Engineering, Bharath University, Chennai, Tamil Nadu, India<sup>1</sup>

Dean, Department of Information Technology, Bharath University, Chennai, Tamil Nadu, India<sup>2</sup>

### rkarthikeyan1678@gmail.com

**ABSTRACT:** In this paper, we have a tendency to gift new system to guage Location-Dependent spatial search Queries that searches for victimisation keywords. Here it providing Distance classification technique and providing a dynamic object mapping mechanism, during this spatial Object search is extremely economical and versatile for varied forms of queries, namely, vary search and nearest neighbor search, on objects over large-scale networks. In spatial object search, an outsized road network is organized as a hierarchy of interconnected regional sub-networks increased with 1) shortcuts for fast network traversals; and 2) object abstracts for guiding traversals. during this paper, we have a tendency to gift (i) the look and implementation of the only and multisource classification technique, (ii) economical object search algorithms, and that we conducted intensive experiments with real spatial object search on road networks. The experiment result shows the prevalence of road over the progressive approaches.

### I. INTRODUCTION

Open GIS (Geographical Information System) is full Integration spatial data that is providing location-based services. Many vendors start to provide map and navigation services (Google Map, MapQuest, Yahoo! Map etc.) along with convenient geo-tagging tools that enable the content providers (e.g., retail stores, facilities and general users) to publish location-dependent information on digital maps. Here, we refer to location-dependent information (e.g., point of interest, traffic, and local events) as spatial objects (or objects for short). We define queries that search for spatial objects with respect to user-specified locations as location-dependent spatial queries (LDSQs). For people participating a conference as an example, some useful LDSQs include Q1: find hotels within one mile from the conference venue; Q2: locate the nearest bus station to the conference venue; and Q3: find a restaurant closest to the hotels of the conference.

Although existing applications based on this model can display objects tagged on a map and point-to-point directions search, common LDSQs like finding the nearest bookstores from a given location based on network distance or current traffic condition have not yet been supported. Tomeet the enormous Web and mobile user needs for LBSs, the support for efficient LDSQ processing is needed. Thus, there is a great demand on a system framework that can i) flexibly and efficiently accommodate diverse objects (in terms of contents, types, and formats) on maps, ii) efficiently support various LDSQs, and iii) effectively support different distance metrics such as road network distance, travel time, toll, etc to be considered for LDSQs. As objects and user trajectories are constrained by road networks, search of spatial objects should be based on *network distances*. In recent years, a trend for LBS deployment has been growing quickly on the Web. Spatial objects from content providers (e.g., stores, average users etc) and digital maps from map service providers (e.g., GoogleMap, MapQuest, MS Virtual Earth, Yahoo! Map1) are coupled to quickly deploy LBSs on the fly. Figure 1 shows a map from Google Map on which a bus station and a conference site (as spatial objects) are tagged by the conference web master (i.e., a content provider).Conference bus station



(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 8, August 2015

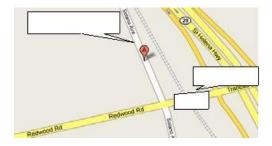


Figure 1: Spatial Object tagged on digital map

In processing LDSQs on a road network, two basic operations, namely, network traversal and object lookup, are involved. The former visits network nodes and edges according to network proximity, while the latter accesses and checks the attributes of objects located at traversed nodes or edges against object search criteria. Objects collected during the course of a traversal form a query result. Logically, the more network traversals and object lookups are involved, the larger the query processing overhead is incurred. As network traversals and object placements are constrained by the network topology, nodes and edges (i.e., the entire network) conceptually form an object search space. Observing some search subspaces (e.g., the middle portion bounded by a dashed line in Fig. 2) do not have objects of interest, we could facilitate network traversals by pruning those subspaces without objects of interest. This observation inspires an idea of search space pruning, based on which we design a novel, efficient, and extensible system framework, for processing LDSQs on road networks.

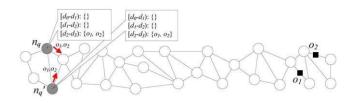


Figure 2: Distance Index

### **II. EXISTING SYSTEM**

Existing works on processing LDSQs on road networks are categorized as solution-based approaches and extended spatial database approaches, which are reviewed below. Solution-based approaches and Distance Index) utilize some precomputed results to evaluate LDSQs. WhileVN3, UNICONS, SPIE only cater for NNqueries, Distance Index supports both range and NN queries. Distance Index precomputes for all nodes the distances and pointers to subsequent nodes on paths toward individual objects, and encodes them as distance signatures. To reduce the storage overhead of distance signatures, distance ranges, rather than precise distances, are adopted such that distances within one range share the same signature. Fig. 2 illustrates the distance signatures on objects o1 and o2 stored at nq and nq0, with d0 < d1 < d2 < d3. As we can observe, distance ranges maintained about objects located at nearby nodes can be very similar or even identical, thus consuming redundant storage. This, in fact, incurs impractically large storage overhead.

In general, the pitfalls of solution-based approaches include high precomputation overhead, massive storage overhead, and expensive result maintenance cost. Besides, they adapt poorly to other types of queries, and to objects and network updates.

*Extended spatial database approaches* incorporate road networks to existing spatial databases. Two basic search strategies were studied[1]. The first strategy is based on the idea *of Euclidean distance*. By this strategy, approaches first identify candidate objects that have Euclidean distances to the query point bounded by a distance threshold. Then,



(An ISO 3297: 2007 Certified Organization)

### Vol. 3, Issue 8, August 2015

they determine network distances between individual candidate object and the query point based on shortest path algorithms or materialized distances and finally, they discard false candidates whose network distances actually are larger than the threshold[2].

The second strategy is based on network expansion that gradually expands a search range on a network until all the nodes and edges that satisfy the search criteria are visited. Objects on those visited nodes and edges form the result set. Although more efficient than Euclidean distance bound approaches, network expansion approaches are still inefficient due to the slow node-by-node expansion toward all directions.

### III. PROPOSED SYSTEM

In this section, we present the concept, design and implementation of our Spatial Object Search. We first introduce Rnets, shortcuts and object abstracts, i.e., the key design in support of search space pruning in Spatial Object., and then discuss Rnet hierarchy formation. More, we present *Route Overlay* and *Association Directory*, the two core components in LDSQ implementation.[3]

Definition 1. **Rnet**. In a network N = (N,E), an Rnet R = (NR,ER,BR) represents a search subspace, where

NR, ER and BR stand for nodes, edges and border nodes in

R, and

(1)ER E, (2)NR =  $\{n/(n, n') ER$  (n', n)

ER}, and

 $(3)BR = NR \cap \{n | (n, n') E' (n', n) \}$ 

E'},

Where E' = E - ER.

Definition 2. Object Abstract. The object abstract of an Rnet R, O(R), represents all the

objects residing on edges in ER, i.e.,  $O(R) = \_e ERO(e)$ .

Definition 3. **Shortcut**. The shortcut, S(b, '), between border nodes b and b' (BR) of an Rnet R bears the shortest path SP(b,b') and its distance ||b, b'||. It is noteworthy that the edges that contribute to SP(b, b') might not necessarily be included in ER..[4]

To find objects in terms of their network distances and attributes, a search algorithm may implicitly form a search tree originated at the query node. Following the topology of the network, the portion of the network covered by a search tree conceptually represents a search space. Scanning an entire search space incurs significant traversal overheads. Skipping some search subspaces that do not contain objects of interest from detailed examinations presents an optimization opportunity.[5]

This *search space pruning* technique is expected to be very effective in road networks because spatial objects are often clustered and concentrated in some areas, e.g., hotels and resorts are likely to be in business and scenic areas,



(An ISO 3297: 2007 Certified Organization)

### Vol. 3, Issue 8, August 2015

respectively. Thus, many subspaces do not contain objects of interest and can be pruned.[6] Though well received in various database searches, to the best of our knowledge, the idea of search space pruning has not been exploited in the context of object search on road networks.[7]

### A). Route Overlay and Association Directory

To facilitate network traversals that explore a network in a node-by-node fashion, we adopt a node-oriented storage scheme that associates nodes with edges and their corresponding distances to their neighboring nodes. As the network is formulated as a hierarchy of Rnets, one straightforward storage scheme is to store all Rnets where border nodes and shortcuts are nodes and edges as separate networks in addition to the original network .[8] This implementation, however, has to maintain separate structures and thus may complicate the search traversals, since search mechanisms need to switch between different networks. Based on Definition 4 that the border nodes in parent Rnets are always the border nodes in some of their child Rnets, our novel index structure, namely *Route Overlay*, that naturally flattens a hierarchical network into a plain network can effectively avoid all the shortcomings of the separate[9]

### B). Search Algorithm

We, in this paper, focus on k-nearest neighbor (kNN) queries and range queries. A kNN query (e.g., Q2 in Section 1) returns the k objects of interest closest to nq. A range query (e.g., Q1 in Section 1) sets a distance range and retrieves all objects of interest with their distances from nq within the range. Our algorithms based on the idea of network expansion upon object search can perform searches efficiently since it navigate Rnets in detail only if they contain objects of interest; otherwise it bypasses them.

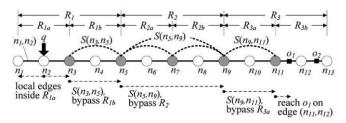


Figure 4: Example of Single Source NN Query

Next, a longer shortcut S(n5, n9) at n5 is taken to skip R2 from detailed traversal. Further, the search at n9 reaches n11via S(n9, n11).[10] Now, as R3b contains objects, the traversal follows the physical edges and the object o1 is found after exploring n11. From the figure, we can see the search only takes three jumps from n3 to n11, that significantly saves the traversal cost, compared with traversing physical edges between the query node and the objects[11].

A multisource LDSQ finds objects with respect to m query nodes, i.e., nq1; ... nqm (m > 1). A multisource kNN query finds k objects whose maximum distances from all query nodes are the minimum, A multisource range query retrieves all objects of interest within distance range r with respect to all query nodes In the literature, suggests to process multisource LDSQs as euclidean distance bound approach that first estimates candidate objects based on their euclidean distances and eliminates false candidates based on IR network distances. This approach, however, covers a larger search space and incurs longer processing times than necessary.[12]

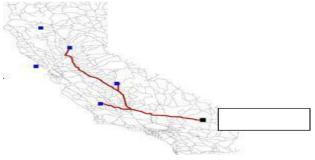


(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 8, August 2015

Algorithn Input. Local.	a MultiSource <i>k</i> NNSearch( <i>RO</i> , <i>AD</i> , $\{n_{q_1}, \dots, n_{q_m}\}$ , <i>k</i> ) Route Overlay ( <i>RO</i> ), Association Directory ( <i>AD</i> ), A set of <i>m</i> query nodes ( $\{n_{q_1}, \dots, n_{q_m}\}$ ), #NNs ( <i>k</i> ) Priority Queue ( <i>P</i> ), Rnet Visited Set ( <i>RV</i> ), Object Visited Set ( <i>OV</i> ), Border Visited Set ( <i>BV</i> );
Output.	Result set ( <i>Res</i> )
Begin	
	each $n_{q_i} \in \{n_{q_1}, \cdots n_{q_m}\}$ do
2. enqueue $(P, (n_{q_i}, 0, q_i))$ ; 3. while (P is not empty AND $ Res  < k$ ) do	
	$(d, q_i) \leftarrow \text{dequeue}(P);$
	( $\epsilon$ is marked "visited by $q_i$ ") then goto 3;
	( $\epsilon$ is a node) then
7. (	$O \leftarrow \text{SearchObject}(AD,\epsilon);$ // find objects with $\epsilon$
	foreach $(o, \delta(o, \epsilon)) \in O$ do
9.	enqueue( $P$ , $(o, d + \delta(o, \epsilon), q_i)$ );
10. <b>f</b>	<b>foreach</b> Rnet R containing $\epsilon$ , add $(R, q_i)$ to RV;
	foreach Rnet R visited by all subqueries then
12.	get $(R, \epsilon', d', q')$ in $BV$ , $\epsilon'$ is the border nodes of $R$ ;
13.	enqueue( $P$ , ( $\epsilon'$ , $d'$ , $q'$ ));
14.	mark $\epsilon'$ "unvisited by $q'''$ ; // this allows revisit to $\epsilon'$ .
15. N	MultiSourceChoosePath( $RO$ , $AD$ , $\epsilon$ , $q_i$ , $d$ , $P$ , $RV$ , $BV$ );
16. els	se $// \epsilon$ is an object.
17. a	adding $(\epsilon, q_i)$ to $OV$ ;
	<b>f</b> ( $\epsilon$ is visited by all subqueries) <b>then</b>
19.	$Res \leftarrow Res \cup \{\epsilon\};$
20. m	ark $\epsilon$ "visited by $q_i$ ";
	put Res;
End.	





Query object

Figure 6: Distance Index of Spatial Objects



(An ISO 3297: 2007 Certified Organization)

### Vol. 3, Issue 8, August 2015

### **IV.PERFORMANCE EVALUATION**

This section evaluates our proposed spatial object searches on framework in terms of both indexing overhead and query performance. We applied Spatial object on four real road networks, namely, CA, NA, SF, and PRS.5 CA and NA consist of highways in California and North America, respectively. SF and PRS correspond to streets and roads in San Francisco and Paris, respectively. We generated 100 to 100,000 objects following either uniform distribution or clustered distribution over these road networks. To simulate clustered distribution, we select a set of nodes as cluster centroids and distribute equal numbers of objects within 10 nodes around them

### A. Index Construction

The first experiment set evaluates the index construction time and index sizes for all the approaches with various numbers of objects and networks. Here, we use the default p and l for ROAD and leave the evaluation of their impacts in the final set of experiments.

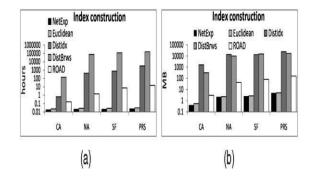


Figure 7: Index Construction (a). IndexConstruction Time (b). Index Size

### B. Query Performance

The second set of experiments evaluate the search performance of particular locations and other approaches in answering singlesource LDSQs and multisource LDSQs on the following factors:

- 1. Network path
- 2. Numbers of objects,
- 3. Object distributions,
- 4. Query parameters, and
- 5. The number of sources for multiple-source LDSQs.

In the experiments, we generate 100 random queries and report the average query processing time. B. Experiments on Single-Source kNN Query First, we conduct evaluations for single-source kNN queries. As depicted in Fig. 15a, euclidean performs the worst because of exhaustive shortest path searches for a possibly large number of candidate objects, consistent with the observations made in further, both DistIdx and DistBrws perform worse than NetExp and due to the excessive accesses to distance signatures and shortest path quad-trees and slow node-by-node network traversals. As expected, consistently performs the best. For clustered objects, It can effectively bypass those Rnets with no object of interest.



(An ISO 3297: 2007 Certified Organization)

### Vol. 3, Issue 8, August 2015

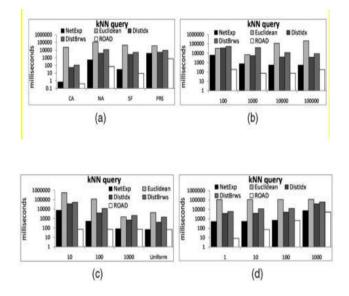
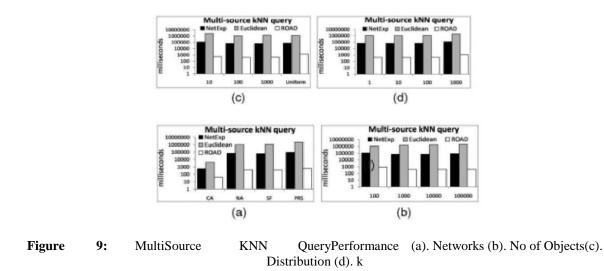


Figure 8: Source KNN Query Performance (a). Networks (b). No of Objects (c). Distribution(d). k

As there are no approaches on top of DistIdx and DistBrws presented in the literature supporting multisource LDSQs, we ignore them in this and next experiments. In the first four experiments, we fix m at two (i.e., two-source kNN queries), as shown in Fig. 9a, 9b, 9c, and 9d, and the last experiment studies the impact of m with k set to one (i.e., multisource NN queries), as shown in Fig. 17e. As observed from the results, ROAD consistently performs better than NetExp and euclidean. This is because NetExp has to explore all the subnetworks (i.e., edges and nodes) around query points; while euclidean has to invoke multiplenetwork traversals to determine the network distances of candidate objects. Differently, ROAD can effectively prune away some search spaces that have no result objects



### V. CONCLUSIONS

The on-going trend of web-based LBSs demands a system that can be extended to accommodate diverse objects, provide efficient processing of various location dependent spatial objects, and support different distance metrics.[20] In



(An ISO 3297: 2007 Certified Organization)

### Vol. 3, Issue 8, August 2015

response to these needs, we propose a new system Extensible Fast Nearest Neighbor Search with Keywords for KNN processing, in this paper. The design of Location dependent achieves a clear separation between objects and network for better system extensibility. It also exploits search space pruning, a powerful technique for efficient object search.[21] Upon the framework, efficient search algorithms for single source and multisource LDSQs are devised. Via a comprehensive performance evaluation on KNN Search by keywords, the new system LDSO is shown to significantly outperform the state-of-the-art techniques

### REFERENCES

[1] H. Hu, D.L. Lee, and J. Xu, "Fast Nearest Neighbor Search on Road Networks," Proc. 10th Int'l Conf. Extending Database Technology (EDBT), pp. 186-203, 2006.

[2] Kalaiselvi V.S., Prabhu K., Ramesh M., Venkatesan V., "The association of serum osteocalcin with the bone mineral density in post menopausal women", Journal of Clinical and Diagnostic Research, ISSN : 0973 - 709X, 7(5) (2013) pp.814-816.

[3] H. Hu, D.L. Lee, and V.C.S. Lee, "Distance Indexing on Road Networks," Proc. Int'l Conf. Very Large Data Bases (VLDB), pp. 894-905, 2006

[4] Jayalakshmi T., Krishnamoorthy P., Kumar G.R., Sivamani P., "The microbiological quality of fruit containing soft drinks from Chennai", Journal of Chemical and Pharmaceutical Research, ISSN : 0975 – 7384, 3(6) (2011) pp. 626-630.

[5] Ken C.K. Lee, Wang-Chien Lee, Baihua Zheng, and Yuan Tian ROAD: A New Spatial Object Search Framework for Road Networks. IEEE transactions on knowledge and data engineering, vol. 24, no. 3, March 2012

[6] H.-J. Cho and C.-W. Chung, "An Efficient and Scalable Approach to CNN Queries in a Road Network," Proc. Int'l Conf. Very Large Data Bases (VLDB), pp. 865-876, 2005.

[7] Kaliyamurthie K.P., Parameswari D., Udayakumar R., "QOS aware privacy preserving location monitoring in wireless sensor network", Indian Journal of Science and Technology, ISSN : 0974-6846, 6(S5) (2013) pp.4648-4652.

[8] H. Samet, J. Sankaranarayanan, and H. Alborzi, "Scalable Network Distance Browsing in Spatial Databases," Proc. SIGMOD Conf., pp. 43-54, 2008.

[9] M.L. Yiu, N. Mamoulis, and D. Papadias, "Aggregate Nearest Neighbor Queries in Road Networks," IEEE Trans. Knowledge and Data Eng., vol. 17, no. 6, pp. 820-833, 2005.

[10] Sharmila D., Muthusamy P., "Removal of heavy metal from industrial effluent using bio adsorbents (Camellia sinensis)", Journal of Chemical and Pharmaceutical Research, ISSN : 0975 – 7384, 5(2) (2013) pp.10-13.

[11] M.R. Kolahdouzan and C. Shahabi, "Voronoi-Based K Nearest Neighbor Search for Spatial Network Databases," Proc. 30th Int'l Conf. Very Large Data Bases (VLDB), pp. 840-851, 2004.

[12] Udayakumar R., Khanaa V., Saravanan T., Saritha G., "Retinal image analysis using curvelet transform and multistructure elements morphology by reconstruction", Middle - East Journal of Scientific Research, ISSN : 1990-9233, 16(12) (2013) pp.1781-1785.

[13] R. Dechter and J. Pearl, "Generalized Best-First Search Strategies and the Optimality of A," J. ACM, vol. 32, no. 3, pp. 505-536,

[14]Dr.A.Muthu Kumaravel, KNOWLEDGE BASED WEB SERVICE, International Journal of Innovative Research in Computer and Communication Engineering, ISSN(Online): 2320-9801,pp 5881-5888, Vol. 2, Issue 9, September 2014

[15]Dr.A.Muthu Kumaravel, Data Representation in web portals, International Journal of Innovative Research in Computerand Communication Engineering, ISSN(Online): 2320-9801, pp 5693-5699, Vol. 2, Issue 9, September 2014

[16]Dr.Kathir.Viswalingam, Mr.G.Ayyappan, A Victimization Optical Back Propagation Technique in Content Based Mostly Spam Filtering International Journal of Innovative Research in Computer

and Communication Engineering ,ISSN(Online): 2320-9801 , pp 7279-7283, Vol. 2, Issue 12, December 2014

[17]Kannan Subramanian, FACE RECOGNITION USINGEIGENFACE AND SUPPORT VECTOR

MACHINE, International Journal of Innovative Research in Computerand Communication Engineering, ISSN (Online): 2320-9801, pp 4974-4980, Vol. 2, Issue 7, July 2014.

[18]Vinothlakshmi.S,To Provide Security & Integrity for Storage

Services in Cloud Computing International Journal of Innovative Research in Computer and Communication Engineering ISSN(Online): 2320-9801 , pp 2381-2385 , Volume 1, Issue 10, December 2013.