JOURNAL OF INFORMATION SCIENCE AND ENGINEERING 31, 1831-1848 (2015)

Continuous Monitoring of Top-*k* Spatial Keyword Queries in Road Networks*

YANHONG LI[1], GUOHUI LI[2], LIHCHYUN SHU[3], QUN HUANG[4] AND HONG JIANG[5]
[1]*College of Computer Science*
South-Central University for Nationalities
Wuhan, 430074 P.R. China
[2]*School of Computer Science and Technology*
Huazhong University of Science and Technology
Wuhan, 430074 P.R. China,
[3]*College of Management*
National Cheng Kung University
Tainan City, 701 Taiwan
[4]*709th Research Institute*
China Shipbuilding Industry Corporation
Wuhan, 430079 P.R. China
[5]*Naval University of Engineering*
Wuhan 430033 P.R. China
E-mail: liyanhong@mail.scuec.edu.cn; anddylee@163.com

Recently, spatial keyword queries (SKQ) have become a hot topic in database field. However, Most of the existing SKQ methods are limited in Euclidean space or assume that objects (and queries) are static. This paper addresses the issue of processing continuous top-*k* spatial keyword queries over moving objects (CMTkSK) in road networks. To efficiently index moving geo-textual objects in road networks, a novel index structure called TPR^{gt}-tree is proposed. Based on the index, an efficient CMTkSK query processing method which includes three main phases, namely *generating initial result set phase*, *pruning phase*, and *continuous monitoring phase*, is proposed. The proposed method can deal with the situation where the query client and geo-textual objects move continuously in the road network. By finding the result change time points, the method can continuously monitor CMTkSK queries and keep the query result set up-to-date with a small price. Finally, experiment results show that the proposed method is much more efficient and precise than its competitor

Keywords: top-*k* spatial keyword query, moving object, road network, continuous monitoring, algorithm

1. INTRODUCTION

With the popularization of the geographical applications and services, spatial data query issues are becoming more and more important [1-5]. In recent years, spatial keyword queries (SKQ), which consider both spatial proximity and textual relevance between the query client and geo-textual objects, have become a new research topic in database area. Researchers have started to address SKQ processing, and some important research results have been published, *e.g.*, [6-20].

Received July 31, 2014; revised November 5, 2014; accepted March 18, 2015.
Communicated by Vincent S. Tseng.
* This work was supported by the National Natural Science Foundation of China under Grant No. 61309002.

Zhou [12] *et al.* discussed the issue of SKQ query processing and proposed two geo-textual indices that integrates inverted files and R*-trees loosely, *i.e.*, inverted file-R*-tree (IF-R*) and R*-tree-inverted file (R*-IF). IF-R* is a spatial-first index, while R*-IF is a text-first geo-textual index. Felipe *et al.* [13] proposed an index structure called IR^2-tree which integrates an R-tree and signatures files. The signature file, in the form of bitmap, is stored for each node of the IR^2-tree. Cong *et al.* [14] proposed an index structure called IR-tree which incorporates the inverted files and R*-tree. The IR-tree combines these two indexes to jointly prune the search space, thus it is more efficient than the methods in [12]. Wu *et al.* [15] and Huang *et al.* [16] studied continuously moving top-*k* spatial keyword queries. The former proposed an efficient algorithm for computing safe zones that guarantee correct result, and the latter calculated a safe region such that if a new query falling into the safe region the answer set remains the same. Chen [17] presented the first all-around evaluation of geo-textual indices, and offered a new insight into the properties and relative merits of the geo-textual indices.

However, these above algorithms are restricted to Euclidean space. In Euclidean space, the distance between two objects is decided by their coordinates. While in road networks the object-object distance is determined by the connectivity of the road network. Thus, the query methods in Euclidean space cannot be applied to road networks. João *et al.* [18] first studied top-*k* spatial keyword query processing in road networks and described how to rank objects with respect to both network distance and text relevance. The author proposed the indexing structure and utilized overlay network for efficient query processing. However, they focused on snapshot SKQ queries in road networks. In [19], the authors investigated continuous top-*k* spatial keyword queries in road network, and proposed two methods that can monitor moving queries in an incremental manner. However, they assumed all the geo-textual objects are static.

Up to now, there is still few research effort on continuous monitoring of spatial keyword queries in road networks, where both the query and geo-textual objects can move continuously in road networks which arises naturally in a travel environment. Consider the following scenario: Bob was walking on the street on one Wednesday afternoon and wanted to take a taxi to downtown. Due to heavy traffic in the city nowadays, many new traffic rules are being rolled out. For example, on Monday, Wednesday and Friday, only vehicles whose license numbers end with odd numbers are allowed to travel on the three bridges that lead to downtown. Thus, Bob would submit a spatial keyword query with keywords "odd vehicle license number, taxi" as he walked on the street. If continuous spatial keyword queries were supported, he could keep walking and receiving up-to-date results until a satisfactory taxi appears.

This paper addresses the issue of processing continuous top-*k* spatial keyword queries over moving objects (CMT*k*SK) in road networks and can deal with the situation where the query client and geo-textual objects move continuously within the road network. Moreover, the textual information of the object (or query) may change during the movement. To efficiently index moving geo-textual objects in road networks, a novel index structure called TPR^{gt}-tree is proposed. TPR^{gt}-tree is a two-level structure. Its top level gives the spatial information of the road network. The second level of TPR^{gt}-tree consists of three tables, which are edge table T_{edge}, node table T_{node}, and geo-textual object table T_{obj}. Even the geo-textual objects move continuously in the road network, we can maintain the correctness of our index structure by simply modifying the pointers

between the objects and the edges where they move.

Based on the index, an efficient CMTkSK query processing method which includes three main phases, namely *generating initial result set phase*, *pruning phase*, and *continuous monitoring phase*, is proposed. In the first phase, an efficient method is used to search qualified objects of query q. Specifically, starting from q, it expands the road network for searching top-k spatial keyword (*TkSK*) objects and examines nodes and edges in the exact order they are encountered. In the second phase, based on the network distance calculating model and the formula for calculating the ST score of geo-textual object which considers both road network distance and text relevance, a pruning network distance $ND_{pruning}$ is calculated. We are sure that if an object o whose network distance at time t_s is larger than $ND_{pruning}$, o is impossible to be the TkSK object of query q within the monitoring time period. Finally, in the third phase, an efficient algorithm called *M*onitor*CMTkSK* is proposed. By finding the result change time points (t_{Change}), we can continuously monitor CMTkSK queries and keep TkSK result set up-to-date with a small price.

The major contributions of this paper are as follows:

1. Our work remedies the major drawbacks of the past related works and provides a more practical and efficient solution for the continuous top-k spatial keyword query processing in road networks.
2. A novel index called TPR^{gt}-tree is proposed to efficient index the moving geo-textual objects in the road network.
3. A continuous top-k spatial keyword query processing algorithm (*CMTkSK*) in the road network is proposed, to efficiently find the *TkSK* objects of the moving query client within the monitoring time period.
4. Simulation experiments are conducted to evaluate the performance of the CMTkSK algorithm on a real road network and a geo-textual object set.

2. PROBLEM DEFINITION AND DATA STRUCTRUES

2.1 Problem Definition

It is assumed that each geo-textual object has a point location and a set of keywords, and the issue of processing continuous top-k spatial keyword queries over moving objects (***CMTkSK***) in road networks on such objects is considered here.

Dataset Setting Let D be a set of geo-textual objects, where each object $o \in D$ has spatial location $o.l$ and a textual description (or a set of keywords) $o.\psi$.

Top-*k* Spatial keyword Query (TkSK) Given a TkSK query $q = \langle l, \psi, k\rangle$ on the road network, where $q.l$ is q' location, $q.\psi$ is a set of query keywords, and $q.k$ is the number of requested objects, **TkSK**(q), contains k spatial-textual objects ranked according to the following score (ST) which considers both road network distance and text relevance.

Continuous top-*k* Spatial keyword query over moving objects in road networks (CMT*k*SK) Given a CMT*k*SK $q=\langle l, \psi, k, [t_s, t_e]\rangle$, where $q.l$, $q.\psi$ and $q.k$ have the same

meanings with that in **TkSK,** and $[t_s, t_e]$ is a query time period, the result of q, CMTkSK(q) consists of several tuples $<[t_i, t_j], D_i>$ (i = 1, 2, 3, ….). In particular, $t_i, t_j \in [t_s, t_e]$, and D_i contains k spatial-textual objects ranked according to the following score (ST) within the sub-period $[t_i, t_j]$.

$$ST(o,q) = \frac{\theta(o.\varphi, q.\varphi)}{1 + \alpha.\delta(o.l, q.l)} \tag{1}$$

where $\delta(o.l, q.l)$ reflects the network proximity between $o.l$ and $q.l$, $\theta(o.\varphi, q.\varphi)$ reflects the text relevance between $o.\varphi$ and $q.\varphi$, and $\alpha \in [0, +\infty]$ is a preference parameter to define relative importance of one measure over the other. For example, $\alpha > 1$ increases the weight of textual relevance over network proximity.

The network proximity can be defined as the network distance between $o.l$ and $q.l$.

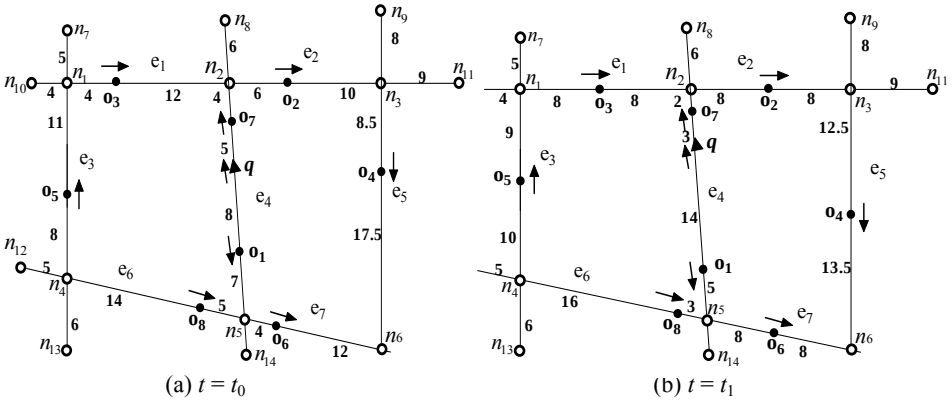
$$\delta(o.l, q.l) = d_N(o.l, q.l) \tag{2}$$

As for the textual relevance, the well-known cosine similarity model [20] is adopted.

$$\theta(o.\varphi, q.\varphi) = \frac{\sum_{t \in q.\varphi} w_{t,o.\varphi} w_{t,q.\varphi}}{\sqrt{\sum_{t \in o.\varphi} (w_{t,o.\varphi})^2 \cdot \sum_{t \in q.\varphi} (w_{t,q.\varphi})^2}} \tag{3}$$

In particular, the weight $w_{t,o,\varphi} = 1 + ln(f_{t,\, o.\psi})$, where $f_{t,\, o.\psi}$ is the number of occurrences (frequency) of term t in $o.\psi$; and the weight $w_{t,\, q.\psi}$ equals $ln(1+|O|/df_t)$, where $|O|$ is the cardinality of object set and df_t is the number of objects in O whose description containing term t. The value of θ is in the range of [0, 1] (property of cosine). There are many other relevance measures for textual relevance, such as the language model [4] and Okapi BM25 [10]. Our method can also support these measures.

To illustrate this **CMT*k*SK** problem clearly, we consider an example in Fig. 1, where a set of geo-textual objects o_1 to o_8 and a query object q move continuously in a road network. Here both query clients (queries for short) and geo-textual objects (objects for short) belong to the data set D. Assume that a moving query $q = \langle l, \psi, k, [t_s, t_e]\rangle$, where $q.\psi = \{pizza, cheap\}$ and $q.k = 2$. As shown in Fig. 1 (a), object o_1 and o_2 are the



(a) $t = t_0$ (b) $t = t_1$

Fig. 1. An example of CMT*k*SK query in road network.

Obj	Terms and term frequencies	v	Obj	Terms and term frequencies	v
o_1	(restaurant,3)(pizza,5)(cheap,2)	1	o_5	(pizza, 4)(Italian,5)(coffee,2)	1
o_2	(pizza,5)(Italian,5)(cheap, 1)	1	o_6	(Italian,4)(coffee,3)(cheap,1)	2
o_3	(coffee,4)(Italian,2)(cheap,4)	2	o_7	(Italian,4)(restaurant,3)(cheap,2)	-1
o_4	(coffee,4)(Italian,4)(cheap,3)	-2	o_8	(pizza,4)(restaurant,3)(cheap,2)	1
q	{pizza, cheap}	-2			

(c) Text information of objects.

Fig. 1. (Cont'd) An example of CMT*k*SK query in road network.

two nearest objects of q whose text description contains all the query keywords. Thus, o_1 and o_2 are the top-2 objects according to ST value, and the query result at time t_0 is $\{o_1, o_2\}$. Similarly, as shown in Fig. 1 (b), o_2 moves closer to q than o_1 at time t_1. Thus, the query result at time t_1 is $\{o_2, o_1\}$. Finally, the CMT*k*SK query result will consist of several tuples $<[t_0, t_1], \{o_1, o_2\}>$, $<[t_1, t_2], \{o_2, o_1\}>$…., where t_i ($i = 0, 1, \ldots$) is a time point.

2.2 Data Structure

In our system, we use graph model to simulate road networks to process CMT*k*SK queries. In particular, the road network is represented as an undirected weighted graph consisting of a set of nodes and edges. We maintain a set of moving CMT*k*SK queries (queries for short) and a set of moving geo-textual objects (objects for short) in the road network. Here, each object (or query) moves with fixed speed in the road network and the textual information of the object (or query) may change during the movement.

People often use TPR-tree [21] like index to keep the information of objects to support location based query processing over moving objects. In our system, an index structure called TPR^{gt}-tree is proposed to efficiently index moving geo-textual objects with fixed speed in the road network, where gt indicates geo-textual objects.

As shown in Fig. 2, TPR^{gt}-tree is a two-level structure. Its top level gives the spatial information of the road network, where each leaf node consists of the edges included in

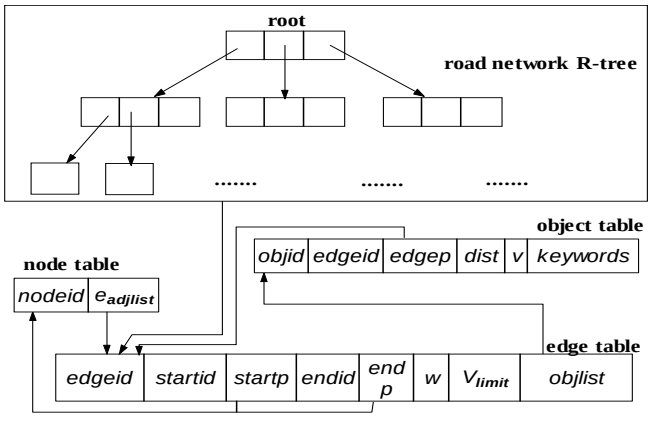


Fig. 2. The structure of TPR^{gt}-tree.

the corresponding MBR. Thus, we can identify the edge where an object (or query) lies according to the position of the object (or query).

The second level of TPR^{gt}-tree consists of three tables, which are edge table T_{edge}, node table T_{node}, and geo-textual object table T_{obj}. For each edge in the leaf node of the top level of TPR^{gt}-tree, there is a pointer pointing to the entry corresponding to this edge in T_{edge}. In this way, the detail information of an edge where an object (or query) lies can be retrieved. Each entry of T_{edge} consists of the edge *id* (*e.id*), the id of its starting node (*e.startid*), the pointer to the entry of its starting node in T_{node}, the id of its ending node (*e.endid*), the pointer to the entry of its ending node in T_{node}, its weight (*e.w*), its velocity limitation($e.v_{limit}$), and the list of objects on it (*e.objlist*). In particular, for each item in *e.objlist*, it includes the object *id* and the pointer to the entry of this object in T_{node}. Secondly, each entry of T_{node} consists of the node *id* (*n.id*) and the set of edges adjacent to the node *n* ($n.e_{adjlist}$), where each entry of this adjacent list includes the id and the address of the edge in T_{edge}. Thirdly, each entry of T_{obj} consists of the object *id* (*obj.id*), the id of the edge where the object lies (*obj.edgeid*), the address of the edge where *obj* lies in T_{edge} (*obj.edgep*), the distance from *obj* to the start node of the edge where it resides (*obj.dist*), its moving velocity (*obj.v*), and the set of keywords of *obj* (*obj.keywords*).

Based on the TPR^{gt}-tree structure, it is efficient to update the moving object information. Here considers two common situations: (1) object keyword update. Then we only need to modify the keywords of the object in T_{obj} correspondingly, which is rather easy to do; (2) an object *o* moves from one edge e_i to another edge e_j. Then, (a) locate the entry for object *o* in T_{obj}, and modify the fields *edgeid* and *edgep* to the *id* and the address for edge e_j in T_{edge}, respectively; (b) delete *o* from the *objlist* of edge e_i in T_{edge}; (c) insert *o* together with its address in T_{obj} into the *objlis*t of edge e_j in T_{edge}.

Definition 1: Given two different edges e_i and e_j, if the shortest distance between every pair of two points, one from e_i and another from e_j, is always determined by the same path, then we say e_i and e_j are **distance determinate [22]**.

To efficiently evaluate these predicates, we construct a matrix *DD*, with each element DD_{ij} having one of the following five values: the value Φ means that e_i and e_j are distance indeterminate; otherwise, e_i and e_j are distance determinate and there is a shortest path connecting e_i and e_j. There are four sub cases, in particular, the value <0, 0> (<–1, –1>, <0, –1>, <–1, 0>, resp.) means the two endpoints of the shortest path are $e_i.startid$ ($e_i.endid$, $e_i.startid$, $e_i.endid$, resp.) and $e_j.startid$ ($e_j.endid$, $e_j.endid$, $e_j.startid$, resp.)

To further speed up the network distance calculation, we construct another matrix ***ND*** where ND_{ij} is the shortest distance between nodes n_i and n_j.

2.3 Network Distance Calculation

When an object *o* moves with a fixed speed, its location at time *t*, denoted as *o*(*t*), is calculated as $o(t) = o.dist + o.v * (t - t_0)$, where *o.dist* is the start location of *o* represented as its distance from the starting node of the edge it resides, *o.v* is the moving speed, and t_0 is the start time. Given a moving object *o* and a query *q*, There are two possible cases for the distance between *o* and *q*, that is $d_{q,o}(t)$, depending on whether they are moving on the same edge:

Case 1: q and o move on the same edge e

Assume both q and o are moving on the edge (n_i, n_j), $d_{q,o}(t)$ can be easily calculated.

$$d_{q,o}(t) = |(o.dist - q.dist)+(o.v - q.v)*(t - t_0)| \quad (4)$$

Case 2: q and o move on two different edges.

Assume that q is moving on edge e_i which starts from n_k and ends at n_l, and o is moving on edge e_j which starts from n_m and ends at n_n. There are two different sub cases. Based on the notion of **distance determinate** proposed before, even if o and q move on two different edges, it becomes much easier to calculate their distance in most cases.

(1) e_i and e_j *are* distance determinate.

By Definition 1, there is a shortest path connecting e_i and e_j. Without loss of generality, we assume the two nodes connecting this shortest path are n_l and n_n.

we can see that no matter o and q move toward or away from the shortest path connecting e_i and e_j, $d_{q,o}(t)$ is equal to the sum of $d(q.l(t), n_l)$, $DN_{l,n}$, and $d(o.l(t), n_n)$, where $d(q.l(t), n_l)$ is the distance from $q.l(t)$ to n_l, $ND_{l,n}$ is the network distance between n_l and n_n. Recall our use of the matrix DD in which the entry DD_{ij} with $<value_0, value_1>$ is used to represent different relations between e_i and e_j in terms of distance determinate. Note that when n_l is $e_i.startid$ (the $value_0$ of DD_{ij} is 0), $d(q.l(t), n_l) = q.dist+q.v*(t-t_0)$; when n_l is $e_i.endid$ (the $value_0$ of DD_{ij} is −1), $d(q.l(t), n_l)= e_i.w-(q.dist+q.v*(t-t_0))$. Thus $d(q.l(t), n_l)$ can be uniformly represented by $|q.dist+ q.v*(t-t_0)+DD_{ij}.value_0*e_i.w|$, no matter whether n_l is $e_i.startid$ or $e_i.endid$. As a result, we have

$$d_{q,o}(t)=|q.dist+q.v*(t-t_0)+DD_{ij}.value_0*e_i.w|+ND_{l,n}+ |o.dist+o.v*(t-t_0)+DD_{ij}.value_1*e_j.w| \quad (5)$$

(2) e_i and e_j are *distance indeterminate*.

Note that the possible locations of q and o are within two edges, *i.e.* e_i and e_j, respectively. Thus, the shortest path between any pair of points in these two edges should pass through their end nodes, *i.e.* n_k (or n_l) and n_m (or n_n). Therefore, we need to take into account four network distances, *i.e.*,

$$\begin{aligned}
&d^1_{q,o}(t)=d(n_k, q)+ND_{k,m}+d(n_m, o)=(q.dist+q.v*(t-t_0))+ND_{k,m}+(o.dist+o.v*(t-t_0))\\
&d^2_{q,o}(t)=d(n_k, q)+ND_{k,n}+d(n_n, o)=(q.dist+q.v*(t-t_0))+ND_{k,n}+(e_j.w-(o.dist+o.v*(t-t_0)))\\
&d^3_{q,o}(t)=d(n_l, q)+ND_{l,m}+d(n_m, o)=(e_i.w-(q.dist+q.v*(t-t_0)))+ ND_{l,m}+(o.dist+o.v*(t-t_0))\\
&d^4_{q,o}(t)=d(n_l, q)+ND_{l,n}+d(n_n, o)=(e_i.w-(q.dist+q.v*(t-t_0))+ND_{l,n}+(e_j.w-(o.dist+o.v*(t-t_0)))\\
&d_{q,o}(t)=\min(d^1_{q,o}(t), d^2_{q,o}(t), d^3_{q,o}(t), d^4_{q,o}(t))
\end{aligned} \quad (6)$$

Now we use the objects in Fig. 1 as an example to illustrate the calculation of $d_{q,o}(t)$. Here we consider three different cases: object o_1 and query q that are on the same edge; object o_2 and query q that are on two different edges which are distance determinate; object o_5 and query q that are on two different edges which are distance indeterminate. We obtain the following functions of $d_{q,o}(t)$ with respect to different pairs of objects and query during different time intervals:

$0 \le t \le 4.5 \quad dq, o_1(t) = 8 + 3t$

$0 \le t \le 4.5$ dq, $o_2(t) = 15-t$
$0 \le t \le 1$ dq, $o_5(t) = 36+3t$
$1 \le t \le 4.5$ dq, $o_5(t) = 42-3t$

Observe that dq, $o(t)$ is a linear function of time t, except that when q and o move on two edges which are distance indeterminate, dq, $o(t)$ could be a poly-line which consists of one segment with an upward slope and another segment with a downward slope.

3. CMT*k*SK ALGORITHM

In this section, we present the CMT*k*SK query monitoring algorithm in the road network. The query in question may choose a different edge in the road network to travel or change its direction at road intersection, and in this case the distance functions of all related objects will change. Thus, we only consider the time period from t_s to the earliest time instance t_e, when the query reaches an intersection. For the time after t_e, we consider a new time period to be monitored. For the same reason, we also consider the time point, when q change its moving speed, as the beginning of a new period. Besides, when a query changes its query keywords, the ST functions for every candidate objects will change, thus it is considered as a new query of course. However, when one of the related object arrives at a road intersection, changes its moving speed, or changes its keywords, its distance function (or ST function) is modified correspondingly. Next, we propose a continuous *TkSK* query monitoring method which is composed of three phases, *generating initial result set phase*, *pruning phase* and *continuous monitoring phase*.

3.1 Phase 1: Generating the Initial TkSK Query Result

In order to get the initial query result set, we use an algorithm called *InitTkSK* to search qualified objects of query q. Specifically, starting from q, InitTkSK expands the road network for searching T*k*SK objects and examines nodes and edges in the exact order they are encountered.

InitTkSK uses the heaps *nodeL* and *optL*, which are both initialized to empty, to organize the nodes and *TkSK* candidate objects met during network expansion, respectively. By using the TPR^{gt}-tree, InitTkSK first locates the edge e where query q locates. Then, (1) it locates the entry for edge e in edge table T_{edge}, and retrieves the detail information of e; (2) by using the *objid*s and pointers in *e.objlist*, it retrieves the location and the set of keywords of each object on edge e from object table T_{obj}; (3) calculates ST score for each object o on edge e, by using formula 1 in section 2.1, and inserts object o together with its ST score into *optL* in descending order of ST value.

If there are k objects in *optL* (o_k is used to represent the object ranked kth in the list), and the distance from q to the two end points of edge e is both larger than $(1-\mathrm{ST}(o_k))/(\alpha*\mathrm{ST}(o_k))$, then the network expansion is stop and the first k objects in *optL* form the query result set. Since ST value is depended on both the network distance and keyword reference between query q and objects, we enlarge the expansion distance to $(1-\mathrm{ST}(o_k))/(\alpha*\mathrm{ST}(o_k))$, which is denoted as d_k, to avoid pruning candidate objects by mistake. In this way, we ensure that for an object o whose distance from q is larger than d_k, the ST value of o, $\mathrm{ST}(o)$, cannot be larger than $\mathrm{ST}(o_k)$, even its keyword set includes all the

keywords of query q. Otherwise, we insert *e.startid* and *e.endid* into *nodeL* in ascending order of distance from q.

Next, InitTkSK iteratively de-heaps nodes from *nodeL*. For each de-heaped node n: (1) for each adjacent node n_{adj} of n except its predecessor (lines 11-22): ①calculates $d(n_{adj,}\, q)$; ②further checks whether (d($n_{adj,}\, q$)<=d_k). If *true*, 1) for each object o on this edge e(n, n_{adj}), calculate its ST value (ST(o)), inserts o together with ST(o) into *optL* in descending order of ST value; 2) inserts n_{adj} into *nodeL* together with d($n_{adj,}\, q$); Otherwise, 1) calculates the point n' in edge e(n, n_{adj}) where d(n', q) = d_k; 2) for each object o on this sub edge e(n, n'), calculate its ST value, inserts o together with ST(o) into *optL* in descending order of ST value. The iteration continues until *nodeL* is empty and the first k objects in *optL* form the query result set. The detail step of the phase is shown in Algorithm 1.

Algorithm 1: InitTkSK (q)

```
1.  Heap optL=Ø, nodeL=Ø; float d_k=∞, ST(o_k)=0;
2.  Search TPR^gt-tree  to locate the edge e containing q;
3.  For each object o on edge e{
4.        Calculate ST(o);
5.        Insert (o, ST(o)) into optL in ascending order of ST value;}
6.  Let ST(o_k) to be ST value of the kth object in optL;
7.  d_k=(1-ST(o_k))/(α* ST(o_k));
8.  Insert e.startid (e.endid) together with its distance to q into nodeL, if the distance value is
    smaller than d_k;
9.  While nodeL is not empty {
10.    De-heap node n from nodeL;
11.    For (each adjacent node n_adj of n except its predecessor) {
12.          d(n_adj, q)=d(n, q)+nn_adj.w ;
13.          if (d(n_adj, q)<=d_k) {
14.                For each object o in edge e(n, n_adj){
15.                      Insert the objects o together with ST(o) into optL;}
16.                d_k =(1-ST(o_k))/(α* ST(o_k));
17.                Insert n_adj into nodeL with d(n_adj, q);}
18.          else {
19.                Calculate the point n' in edge e(n, n_adj) where d(n', q)=d_k;
20.                For each object o in sub-edge e(n, n'){
21.                      Insert the objects o together with ST(o) into optL;}
22.                d_k = (1-ST(o_k))/(α* ST(o_k)); }}}
23. Choose the first k objects in optL to form the TkSK_Set;
24. Output TkSK _Set;
```

Fig. 1 gives an example of CMTkSK query. As shown in Fig. 1 (a), query q which is denoted by a solid triangle is moving on edge e_4. Assume that $q.k$ is 2 and $q.\psi$={*pizza*, *cheap*}. For ease of presentation, we assume that α=1 and the textual relevance of an object o ($o.\theta$) is the number of occurrences of the query keywords in $o.\psi$ divided by the number of query keywords in $q.\psi$. The algorithm first accesses the network R-tree to find that query q is moving on edge e_4. There are two objects, o_1 and o_7, on edge e_4. Thus,

the algorithm calculates their ST values as follows.

$$ST(o_1) = \frac{\theta(o_1.\varphi, q.\varphi)}{1+\alpha \bullet d_N(o_1, q)} = \frac{1}{1+8} = \frac{1}{9} \quad ST(o_7) = \frac{\theta(o_7.\varphi, q.\varphi)}{1+\alpha \bullet d_N(o_7, q)} = \frac{0}{1+5} = 0$$

o_1 and o_2 together with their ST values are inserted into *optL* in descending order of ST value. Thus *optL* equals {(o_1, 1/9), (o_7, 0)}, and d_k=(1−ST(o_7))/(α* ST(o_7)). Since the distance values from both the starting node and the end node of edge e_4 to query q are smaller than d_k which equals infinite at this moment, these two nodes together with their distances to query q are inserted into *nodeL* sequentially (line 8). Here *nodeL* equals {(n_2, 9), (n_5, 15)}. Then, the first element of *nodeL*, which is n_2, is de-heaped, and edge e_1 and e_2 are processed. The ST values of object o_3 on edge e_1 and o_2 on edge e_2 are calculated, respectively. In particular, ST(o_3)=1/40 and ST(o_2)=1/16. Next, o_2 and o_3 are inserted into *optL*={(o_1, 1/9), (o_2, 1/16), (o_3, 1/40) (o_7, 0)}. Since each adjacent node of n_2 is either outside the distance range d_k=(1−ST(o_2))/(α* ST(o_2)) of query q, which is 15 at this moment, or is a boundary node of the road network, neither of them is inserted into *nodeL*.

Next, n_5 is de-heaped from *nodeL*. Since the distance of n_5 to query q is equal to d_k, none of its adjacent edges is processed. Now, *nodeL* is empty and the processing is stopped, and the first two objects in *optL* forms the *TkSK_Set* = {(o_1, 1/9), (o_2, 1/16)}.

3.2 Phase 2: Pruning Phase

The main goal of this phase is to find a pruning network distance, denoted as $ND_{pruning}$, to ensure that if an object o whose network distance at time t_s is larger than $ND_{pruning}$, then o is impossible to be the TkSK object of query q within the interval [t_s, t_e]. In Phase 1, we have gotten ST(o_k) which is the ST value of the kth result object of query q at time t_s, and d_k equals (1−ST(o_k))/(α* ST(o_k)). In particular, for an object o whose distance from q is larger than d_k at time t, the ST value of o, ST(o), cannot be larger than ST(o_k) at this time point, even if its keyword set includes all the keywords of query q. Since objects and the query are moving continuously in the road network, the objects outside the pruning distance of q at time t_s may move into the distance range d_k within the period [t_s, t_e], thus we enlarge the pruning distance by ($q.v$+v_{max})*(t_e−t_s). Here, v_{max} is the largest *vlimit* of the edges within the distance range d_k of q. Then, the pruning distance, $ND_{pruning}$, is set to be d_k+($q.v$+v_{max})*(t_e−t_s). Thus, for each object o within $ND_{pruning}$ of query q at time t_s, if $o.\varphi$ includes any query keyword in $q.\varphi$, o is regarded as the candidate objects and put into Cand_Set; otherwise, o is regarded as the monitored objects and put into Monitor_Set. All other objects can be pruned safely.

Continue the example in Fig. 1, we have already gotten the value of d_k which is 15. As shown in Fig. 3, query q moves with a speed of -2m/sec toward n_2 and its distance to node n_2 is 9, it takes 4.5 sec for q to reach node n_2. Hence, t_e is set to be 4.5sec. Moreover we add (2+2)*4.5=18 to $ND_{pruning}$, which increases $ND_{pruning}$ from 15 to 33. Note that both the moving speed of q and the largest speed of the edges within $ND_{pruning}$ of q are 2 here. There are six moving objects o_1, o_2, o_3, o_6, o_7 and o_8 within the pruning range and $o_7.\varphi$ doesn't include any query keyword. Thus the Cand_Set is {o_1, o_2, o_3, o_6, o_8} and Monitor_Set is {o_7}.

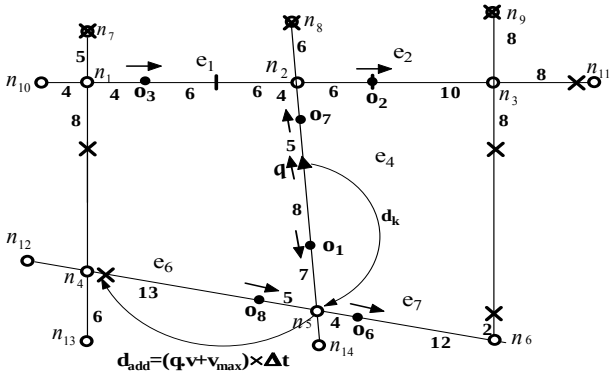


Fig. 3. The pruning phase of *CMTkSK* query processing.

3.3 Phase 3: Continuous Monitoring for CMTkSK Queries

Since queries and objects can move continuously in the road network, the *TkSK_Set* for a query q may be overdue after some time. To keep the *TkSK_Set* correct continuously, an algorithm called *M*onitor-*CMTkSK* is proposed to continuously monitor *CMTkSK* queries and keep *TkSK_Set* up-to-date. Remember that for query q at time instance t_s, there is an object that ranks kth among all the objects in Cand_Set in terms of their ST values, from largest to smallest; we call this object kth object. The goal of phase 3 is to determine the *query result change time points* (t_{Change}s) within $[t_s, t_e]$ such that the query has the same *TkSK* result within two consecutive t_{Change}s, and find the corresponding *TkSK_Set* at each t_{Change}. Algorithm 2 is for this purpose.

Firstly, Algorithm *MonitorCMTkSK* (1) sets two variables, t_a and t_b, which are both initialized to t_s, to record the beginning and the end of the sub-periods being processed within $[t_s, t_e]$, respectively; and (2) uses set CMTkSK_Set to organize the TkSK result which includes a set of tuples: <sub-period, the corresponding *TkSK_Set*>. Then, we consider each object $o \in Cand\_Set$. Remember that *Cand_Set* includes all the objects o whose $ND_{q,o}(t)$ is smaller than $ND_{pruning}$ at t_s and $o.\varphi$ includes any query keyword. If the ST function of o intersects with that of kth object at a time point $t \in [t_s, t_e]$, we use variable t_c to keep this time point. If there are several this kind of time points, t_c equals the earliest one.

Then we replace t_a with t_b and t_b with t_c to form a new time period (line 7). Since *TkSK_Set* remains unchanged within the newly formed time period, the tuple $<[t_a, t_b]$, $\{TkSK\_Set\}>$ represents part of the query result and is inserted into *CMTkSK*_Set(line 8). Then the *TkSK_Set* is modified discriminately: if o is not in current *TkSK_Set*, o is included into *TkSK_Set* (line 10); otherwise switch the order of o and the old o_k in *Cand_set* and *TkSK_Set* to let o be the new kth object (lines 12-13). The modified *TkSK_Set* will be used in the next sub-period. Next, repeat the steps in lines 3-5 to get the next t_{Change}. The processing repeats until all the t_{Change}s are found and processed, and then the final *CMTkSK_Set* is obtained.

Algorithm 2: *MonitorCMTkSK*
Input: *TkSK_Set, Cand_Set*, d_k and ST(o_k) at time instance t_s, and the time period $[t_s,t_e]$
Output: *CMTkSK*_Set

1. Begin{
2. set *CMTkSK*_Set=Φ; $t_a=t_s$; $t_b=t_s$; $t_c=t_a$;
3. For (each object $o \in Cand\_Set\text{-}o_k$)
4. {If ($ST_{q,o}(t)$ intersects $ST_{q,ok}(t)$ at a time instance $t \in [t_a,t_b]$ and ($t>t_c$))
5. $\{t_c=t;\}\}$
6. While ($t_c<t_e$)
7. $\{t_a=t_b$; $t_b=t_c$;
8. Insert the tuple <$[t_a,t_b]$,{*TkSK_Set*}> into *CMTkSK*_Set ;
9. If (*o* is not in *TkSK_Set*)
10. {Replace the *k*th object in *TkSK_Set* with *o*;}
11. Else
12. {Switch the position of *o* and the old o_k in *Cand_Set* and *TkSK_Set*;
13. let o_k be *k*th object in *Cand_Set*;}
14. Repeat lines 3-5;}
15. Insert the tuple <$[t_b,t_e]$,{*TkSK_Set* }> into *CMTkSK*_Set ;
16. Return *CMTkSK*_Set ;}

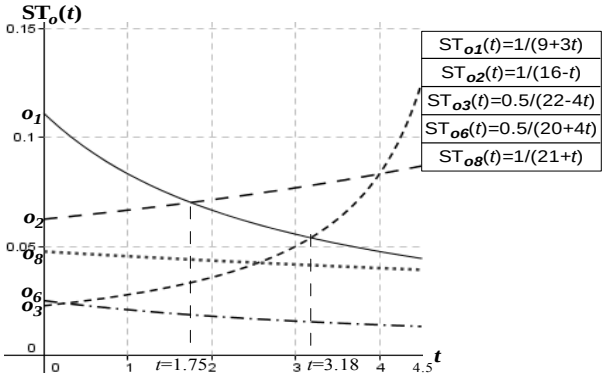


Fig. 4. The continuous monitoring phase.

As shown in Fig. 4, at time t_0, *TkSK_Set* is {o_1, o_2} and o_k is o_2. Then, the ST functions of o_1 and o_2 intersect with each other at time t=1.75, thus o_1 replaces o_2 as the *k*th object. Next, the ST function of o_3 intersects that of o_1 which is the *k*th object at time t=3.18, thus o_3 replaces o_1 as the *k*th object and *TkSK_Set* becomes {o_2, o_3}. Here time instances t=1.75 and 3.18 are t_{Change}s and all these t_{Change}s within time period [0, 4.5] divide this time period into several sub-periods. Finally, all the sub-periods together with their *TkSK_Sets* form the *CMTkSK*_Set of query *q*, which consists of four tuples: <[0, 1.75], {o_1, o_2}>, <[1.75, 3.18], {o_2, o_1}>, <[3.18, 4], {o_2, o_3}>, and [4, 4.5], {o_3, o_2}.

4. PERFORMANCE EVALUATION

4.1 Experimental Settings

This section presents the performance evaluation of our *CMTkSK* query processing

method. To simulate the real world road network, we use the real data of the traffic network of Oldenburg in Germany [23], which consists of 6105 nodes and 7035 edges. We use the generator proposed in [24] to obtain a set of geo-textual objects and queries. The description of the objects (queries) is obtained from Twitter (http://twitter.com), one tweet per object. Fig. 5 depicts the real road network of Oldenburg and the date objects in it, with roads and data objects represented by blue lines and red points, respectively. Remember that the index and data structure of our proposed method consists of a road network R-tree and three relational tables. Fig. 6 depicts the storage cost when we vary the number of objects in the system, and this figure shows that the storage space for keeping the index and data structure is small and can be kept in memory. Moreover, these three tables include some pointer fields to make them interrelated, thus the time for searching related items (edges, nodes, or objects) within the tables can be saved. To further speed up the network distance calculation, we construct two matrixes *DD* and *ND* (refer to section 2.2. The total storage space needed for these two matrixes constructed for Oldenburg is 93.1M, thus can also be kept in memory). As a result, the total query processing time can be low.

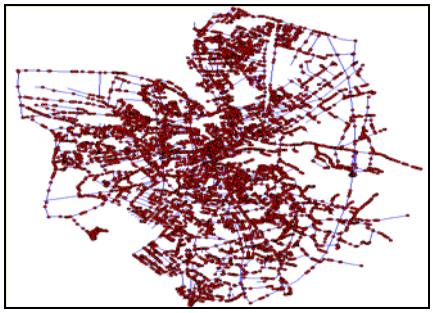


Fig. 5. Oldenburg and data set.

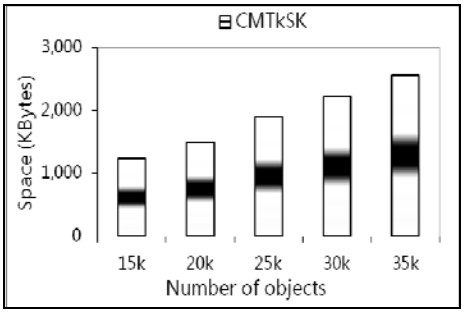


Fig. 6. Storage cost for index and data structure.

Here, we will compare our method with the *CMA* method [25], which uses a combined expansion tree to keep the monitoring area of a TkSK query. Each query requires continuously monitoring of their *TkSK_Sets* for 100 timestamps. The CMA algorithm re-evaluates the snapshot *TkSK* query when location updates of objects (and/or the query) occur. The update interval (*UI*) of CMA is set to 5 and 10 time units in this experiment which are denoted as CMA(UI=5) and CMA(UI=10), respectively. Besides, we use *CMTkSK* to denote our proposed method. We measure the average running time for processing *CMTkSK* queries in road networks. Moreover, we investigate the precision of these two algorithms by evaluating the percentage of retrieved *TkSK* objects that are real. Let $TkSK_{get}$ be the set of *TkSK* objects which are retrieved by these two algorithms. Besides, we let $TkSK_{real}$ be the set of objects which are the real *TkSK*s of query q. Then, precision is represented as follows.

$$\text{Precision} = \frac{\#(TkSK_{get} \bigcap TkSK_{real})}{\#(TkSK_{real})} \tag{7}$$

The input and distance-calculations of these two compared methods are the same.

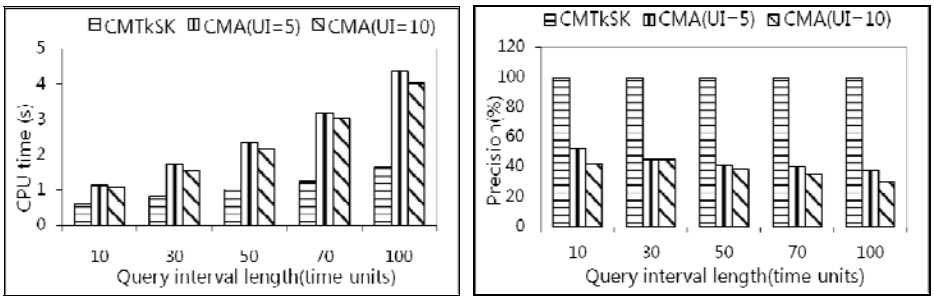
Table 1 includes the parameters under investigation and the values in bold face are the default values in the following experiments.

Table 1. Dataset Parameters

Parameter	values
Query time interval	10, 30, **50**, 70, 100
Number of keywords	1, 2, **3**, 4, 5
Value of *k*	10, 15, **20**, 25, 30
Number of objects	15k, 20k, **25k**, 30k, 35k

4.2 Experimental Results

Firstly, Fig. 7 evaluates the effect of query interval length on the CPU time and the precision of CMTkSK and CMA. As shown in Fig. 7 (a), the CPU time of these two algorithms increases as query interval length becomes longer. For our CMTkSK, this is because a longer query interval length implies more queries and objects reaching the network nodes and/or changing their keywords, hence more queries are launched or modified. For CMA, this is due to the fact that a larger query interval length incurs more location updates of objects and queries, resulting in more maintenance cost. Clearly, CMTkSK has a better performance at all time intervals, compared to CMA (Both for UI = 5 and 10). Fig. 7 (b) shows that the precision of CMTkSK is always 100% under different query interval lengths. If CMA is adopted to answer the query, the precision is at best 54% and a large part of the query results are unknown due to the nature of CMA's discrete location updates. Moreover, as shown in the figures, if UI increases, which means the time span between two location updates becomes longer, the total update processing cost will decrease. However, the precision will decrease too.



(a) CPU time (b) Precision

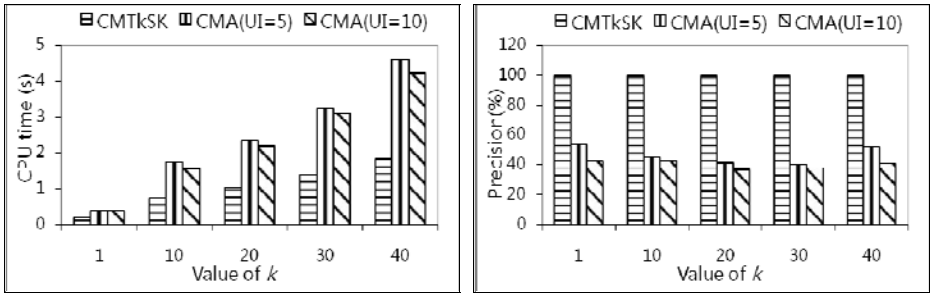
Fig. 7. Effect of query interval length on algorithm performance.

The second set of experiments measures the effect of *k* value on the performance of the methods. Fig. 8 (a) shows that the CPU time for both algorithms grows as *k* increases. This is because that as *k* becomes larger, the number of candidate objects increases so that the monitoring range and ST value comparisons between these candidate objects also increase. Fig. 8 (b) studies how the value of *k* affects the precision of the methods.

The precision of the CMTkSK algorithm remains 100% for different *k* values. However, the precisions of CMA is low no matter UI=5 or UI=10.

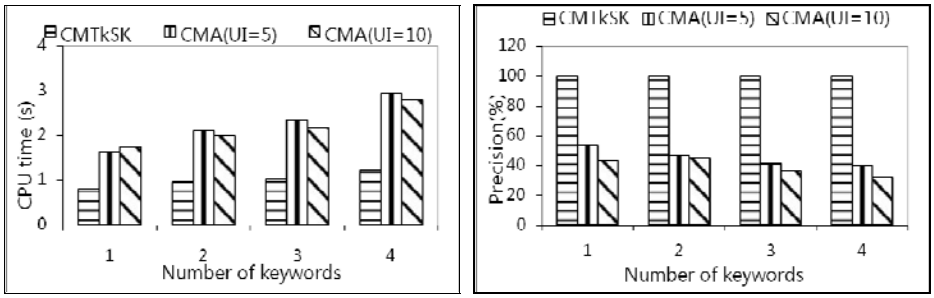
Fig. 9 plots the CPU time and precision as a function of keyword number. As shown in Fig. 9 (a), the CPU cost of these two methods increases as the number of keywords increases. This is because that more query keywords result in more candidate objects and more ST value comparisons. Fig. 9 (b) shows that similar to Figs. 7 (b) and 8 (b), the precision of our CMTkSK maintains 100% for different keyword numbers, and the precision of CMA is still low and changes slightly when the keyword number varies.

Finally, Fig. 10 evaluates the effect of object cardinality on the CPU time and the



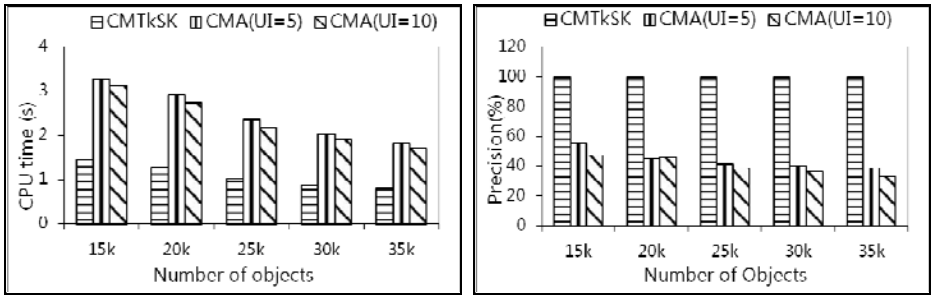
(a) CPU time (b) Precision

Fig. 8. Effect of *k* value on algorithm performance.



(a) CPU time (b) Precision

Fig. 9. Effect of number of keywords on algorithm performance.



(a) CPU time (b) Precision

Fig. 10. Effect of number of objects on algorithm performance.

precision of CMTkSK and CMA. As shown in Fig. 10 (a), the CPU time of these two algorithms decreases as the number of objects becomes larger. For CMA, as the number of objects increases, the object density increases correspondingly, thus the network expansion needed for searching candidate objects decreases. As a result, the running time decreases. For CMTkSK, as the object density increases, the monitoring range of a query decreases, thus the running time decreases. As shown in Fig. 10 (b), the precision of CMA is at best 56% and decreases slightly as the number of moving objects increases.

5. CONCLUSIONS

This paper addressed the issue of processing continuous top-*k* spatial keyword queries over moving objects in road networks (CMTkSK). The TPR^{gt}-tree index is proposed to efficiently index the moving geo-textual objects in road networks. Based on the index, an efficient CMTkSK query processing method is proposed. Finally, experimental study on a real road network demonstrates the efficiency of our proposed method. The result shows that our method is about 1.28 times more efficient than the CMA method. Moreover, the precision of our method maintains 100% at any time instance, while the precision of the compared method is at best 56%.

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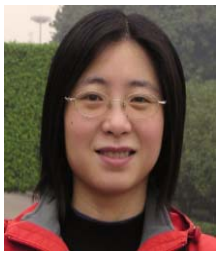
Yanhong Li (李艳红) received her Ph.D. degree in Computer Science from Huazhong University of Science and Technology, China in 2011. She has been on the faculty at South-Central University for Nationalities, and she is currently an Associate Professor in the Department of Computer Science. Her research interest is spatial information and communication.

Guohui Li (李国徽) received his Ph.D. degree in Computer Science from Huazhong University of Science and Technology in 1999. He is a Full Professor in School of Computer Science and Technology, Huazhong University of Science and Technology. His research interests mainly include advanced data management, mobile computing and real-time computing.

LihChyun Shu (徐立群) received her Ph.D. degree in Computer Science from Purdue University in 1994. He is a Fully Professor in the College of Management, National Cheng Kung University. His research interest is methods for design and analysis of software, especially software for concurrent and distributed systems, as well as real-time systems.



Qun Huang (黄群) has been on the faculty at 709th Research Institute, China Shipbuilding Industry Corporation, and she is currently a Senior Engineer in the Department of Engineering. Her research interests include spatial information and communication, and multimedia network communication technology.

Hong Jiang (蒋宏) received his Master degree in Automation from Huazhong University of Science and Technology, China in 2008. He has been on the faculty at Naval University of Engineering, and he is currently an Associate Professor in the Department of Electrical and Electronic Engineering. His research interest is advanced data management.