Fog Computing-based Approximate Spatial Keyword Queries with Numeric Attributes in IoV

Yanhong Li, Rongbo Zhu, *Member, IEEE*, Shiwen Mao, *Fellow, IEEE*, and Ashiq Anjum, *Member, IEEE*

***Abstract*—Due to the popularity of on-board geographic devices, a large number of spatial-textual objects are generated in Internet of Vehicles (IoV). This development calls for Approximate Spatial Keyword Queries with numeric Attributes in IoV (A^{2}SKIV), which takes into account the locations, textual descriptions, and numeric attributes of spatial-textual objects. Considering huge amounts of objects involved in the query processing, this paper comes up with the ideal of utilizing vehicles as fog-computing resource, and proposes the network structure called FCV, and based on which the fog-based Top-k A^{2}SKIV query is explored and formulated. In order to effectively support network distance pruning, textual semantic pruning, and numerical attribute pruning simultaneously, a two-level spatial-textual hybrid index STAG-tree is designed. Based on STAG-tree, an efficient Top-k A^{2}SKIV query processing algorithm is presented. Simulation results show that, our STAG-based approach is about 1.87x (17.1x, resp.) faster in search time than the compared ILM (DBM, resp.) method, and our approach is scalable.**

***Keywords*—Approximate spatial keyword query, Fog computing, IoV, Numeric attribute, Traffic network**

I. Introduction

As an important paradigm to realize intelligent transportation system, Internet of Vehicles (IoV) enables vehicles to communicate with road side units (RSUs), and remote cloud servers [1]. For real-time perception and geographic distribution, cloud computing is clearly not the best choice to provide communication and computing resources, since it is completely centralized [2]. Fog computing, by contrast, complements cloud computing by extending computing and caching capabilities to the edges of the network, and it facilitates localization decisions and rapid response.

As a kind of fog computing, vehicle fog computing (VFC) is considered as a promising method for supporting applications in IoV, which uses vehicles as infrastructure to make full use of vehicle communication and computing resources. In particular, VFC utilizes a large number of cooperative end-user clients or near-user edge devices to perform huge amounts of communication and computation [3], which differs from other existing technologies in its proximity to end users, dense geographic distribution, and support for mobility [4], [5]. In order to enhance the computing and storage capabilities of the network edge, recently, a new network structure, named fog computing-based IoV (FC-IoV) [6], is proposed, which deploys fog servers at downtown intersections and accident-prone roads to enhance the computing and storage capabilities of the network edge.

Recently, lots of efforts are made to explore different kinds of issues on fog-based IoV, such as the optimal deployment and dimensionality for autonomous driving [7], reasonable and feasible resource allocation in real time [8]. However, there is few work on processing spatial-textual information generated in IoV to obtain user interested information. In real life, due to the popularity of on-board geographic devices, huge numbers of spatial-textual objects are generated in IoV. To effectively process the massive data collected and obtain the information that users are interested in, spatial keyword query (SKQ) has been proposed and discussed [9]–[13], which uses a set of keywords and a spatial constraint to express user's interest in exploring useful information.

The existing work on SKQ query processing can be divided into two categories: SKQ in Euclidean space [11] and SKQ in traffic networks [14]. For SKQ in traffic networks, the schemes use real traffic network distance rather than Euclidean distance in Euclidean space, thus can better meet the requirements of real-time applications in IoV. Moreover, considering that some previous work focuses on SKQ requiring exact keyword matching, and may result in too few results returned due to the diversity of textual expressions, recently, approximate spatial keyword query (ASKQ) was explored. ASKQ can handle spelling errors and conversional spelling difference (for example, *color* vs. *colour*), which appear in real applications frequently.

However, in many applications of IoV, such as mobile e-commence, various items are generated with textual descriptions, different attributes, and spatial locations. Correspondingly, the requirement of a user could include a set of keywords, attribute-value pairs, distance limitation or the number k of results, for example, "oxford", "dictionary", publish year=2018 & price=1000, and k=5 (means the top-5 results). To capture the requirements of users, a spatial keyword search with numeric attributes is needed. Meanwhile, the more queries and objects involved, the more complex the

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query processing, which makes efficient query processing and fast feedback on query results a challenge. This calls for approximate spatial keyword query (A^2SK) with locations, textual descriptions and numeric attribute requirement simultaneously. To this end, we also need to make full use of the potential communication and computing power around query users in IoV, in addition to efficient query processing methods.

To address the issues mentioned above, this paper explores the fog computing-based A^2SK queries in traffic networks of IoV (A^2SKIV), which poses three major challenges. Firstly, query users and textual-spatial objects may distribute within a large traffic networks with millions vertices and edges in IoV. How to efficiently calculate the network distances between queries and objects is the first issue need to be handled. Secondly, with millions of textual-spatial objects in IoV, we need to consider a large number of keywords and attribute-value pairs. Moreover, approximate keyword match rather than exact keyword match is considered which makes A^2SKIV search more complex. Thirdly, many users may initiate queries simultaneously, the proposed matching method should be effective enough to significantly reduce the cost of query processing.

To support network distance pruning, keyword pruning, and numeric attribute-value pruning simultaneously, a novel spatial-textual hybrid index structure should be designed, which should consider the relative invariance of traffic network structure and the dynamic variation of textual-spatial objects and queries. Firstly we need a spatial index to keep the traffic network structure in IoV, thus given the positions of an object and a query, the network distance between them can be calculated quickly, while maintaining a reasonable and acceptable amount of storage space. Meanwhile, a textual & numeric index on the textual-spatial objects of each traffic network region (subgraph) is required too. In order to save space consumption, the textual information and numeric information need to be organized efficiently and smartly. Moreover, in order to improve the processing efficiency of a huge amount of unqualified textual-spatial objects, some efficient pruning rules are also needed.

In order to meet the requirements mentioned above, this paper explores A^2SKIV comprehensively, and the main contributions of the paper are as follows.

1. The A^2SKIV problem is formulated, which distinguishes itself from existing SKQ query efforts in that it takes into account textual similarity, numeric similarity, and spatial proximity in traffic network space, simultaneously.

2. A two-level spatial-textual hybrid index STAG-tree is presented. In addition, several lemmas are presented to prune a huge amount of unrelated objects. A Top-k A^2SKIV query processing algorithm based on STAG-tree index is designed. In addition, we discuss how to extend the proposed method for supporting numeric attributes with interval values.

3. Simulation using two traffic networks together with their spatial-textual object sets is performed to evaluate the effectiveness of the proposed STAG-tree index and query processing algorithm.

The rest of this paper is organized as follows. In Section II, we review the related work. Section III presents the system model and problem definitions. In Section IV, we introduce a hybrid index in detail. Top-k A^2SKIV query processing algorithm is proposed in Section V. Section VI discusses extending the method for supporting attributes with interval values. Section VII gives the experimental evaluation, and finally, Section VIII concludes the paper.

II. Related Work

A. Fog Computing in IoV

In 2012, Cisco came up with the concept of fog computing. Since then, many efficient schemes were proposed [15]–[20]. An object cloud communication architecture [3] based on fog computing and intelligent gateway was proposed . Later, Aazam et al. [21] proposed a system called fog micro data center, where the fog plays an important role in resource management, data filtering, preprocessing, data processing and security measures. Meanwhile, Hou et al. [22] proposed a new concept of vehicle fog computing (VFC), using vehicles as infrastructure to take full advantage of their communication and computation resources. An intelligent VFC system combining parking assistance and intelligent parking was discussed [7]. In particular, A vehicle reservation auction method based on VFC perception was designed to guide the vehicle to the available parking space with less effort during driving. Meanwhile, the vehicle's fog ability was utilized to compensate the vehicle's service cost through monetary reward, thus helping to delay the sensitive computing service. Yu et al. [6] discussed the optimal deployment and dimensionality (ODD) of fog computing-based IoV infrastructure for autonomous driving. Two different architectural patterns, namely, coupling pattern and decoupling pattern, were proposed, and the ODD problem was transformed into two integer linear programming formulas to reduce the deployment cost. Such efforts improve the computing and storage capabilities of IoV and enable lots of applications. In edge-enabled networks, the geographic diversity of resources and various hardware configurations need to be carefully managed to ensure efficient utilization of resources. Lamb et al. [8] analyzed the moving edge calculation of vehicle networks, and introduced an architecture of evaluating available resources and allocating the most reasonable and feasible resources in real time.

B. SKQ Querying in Traffic Networks of IoV

In order to meet user's interests in IoV, lots of efforts are made to deal with moving Top-k SKQ processing, direction-aware SKQ processing, interactive Top-k SKQ querying, keyword search based on distributed graphs [23], Why-not Range-Based Skyline Queries [24], and location-aware error-tolerant keyword search [25]. In order to accelerate the calculation of long road network distance, a multi-hop distance labeling scheme (DBM) was proposed [26], which is based on Dijkstra method. Guo *et al.* [14] discussed the distributed SKQ search on the traffic network, and proposed a new distributed index. By using this index, each machine independently evaluates search operations in a distributed manner. Gao et al. [27] discussed reverse Top-k Boolean SKQ search in traffic networks, which shows how to use arbitrary k to answer the query

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without anticipatory computing. Zhao et al. [28] explored time-aware SkQ queries on traffic network. They proposed a novel TG index and several algorithms to efficiently process this type of queries. To support mobile search and targeted location-aware advertising, an inverted index-based solution (ILM) is proposed to improve query performance [29]. Li et al. [30] studied the intelligent augmented keyword search in real-life IoVs. A hybrid index called ASKTI was proposed. In ASKTI, the information of traffic network structure, keywords, boolean expressions, and spatial information of objects are smartly organized, so as to prune unqualified traffic network space as early as possible. Abeywickrama et al. [31] discussed how to efficiently process SKQ Queries on traffic networks, and proposed K-SPIN, a versatile framework that avoids keyword separated indexes to reduce latency and avoid expensive operations.

To improve query processing performance in IoV, there are many similarity functions such as edit distance, Jaccard, and n-gram [32]. To handle the inconsistencies and errors in queries and data, Alsubaiee *et al.* [33] proposed a natural index structure, which enhances the approximate keyword search ability of the spatial index based on tree. An approximate n-gram matching method was proposed [34], which uses the long but approximate n-gram matching as the basis for pruning k nearest neighbour candidates. Zheng *et al.* [35] explored approximate keyword search in semantic track database, and proposed a hybrid index called Giki. Giki consists of two components, which are SQ-Tree part using n-grams and K-Ref part using edit distance.

Although there are many effective query processing methods in IoV, most schemes face the following limitations: 1) Focus on exact keyword match, while ignore approximate keyword match, which can handle spelling errors and traditional spelling differences that often occur in practical applications; 2) Only keyword matching and attribute-value matching are considered, ignoring spatial constraints; 3) Limited to Euclidean space, and the query search cannot be processed in traffic networks in IoV, a realistic application scenario. This paper fills this gap by developing a two-level spatial-textual hybrid index, which can overcome the limitations mentioned above in IoV.

III. System Model and Problem Definitions

This section first gives the system model, and then formulates Top-k A^{2}SKIV queries. Table I lists the notations that we use in the paper.

A. System Model

To meet the requirements of efficient query processing and fast feedback on query results, a fog computing-based network structure FCV is adopted to utilize the computing and storage capabilities of edge devices, which is a hierarchical structure consists of three layers. Fig. 1 illustrates the system overview and scenarios of FCV with moving and parked vehicles' service and applications.

The proposed FCV considers four scenarios of vehicle behaviour states. Fog computing has the natural advantage of being closer to vehicle endpoints and mobile devices, thus avoiding the high latency associated with complex system responses and service failures associated with remote routing to remote cloud servers. To address communication and computing power issues, FCV employs vehicles and mobile devices as the infrastructures, making full use of their communication and computing resources. Moreover, RSUs and fog devices are adopted and deployed. In general, the deployment of RSUs and fog devices focuses on intersections in the city centre and some road-sides on busy roads.

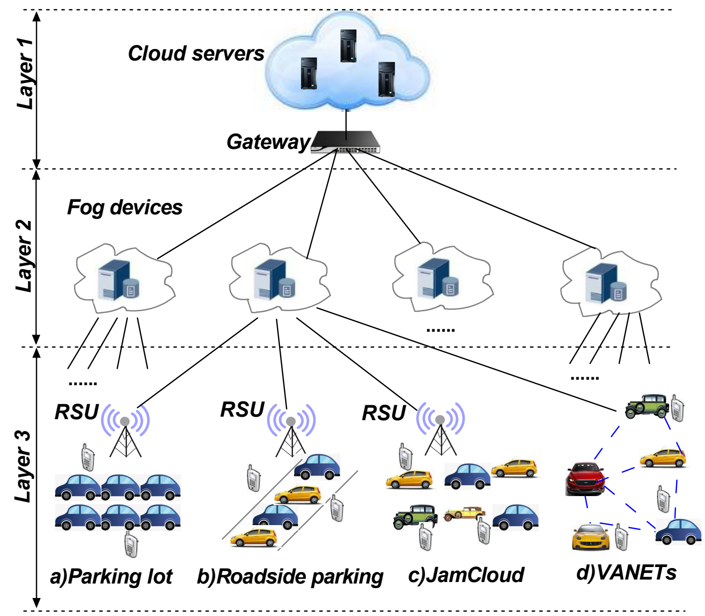

Fig. 1. An Illustration of the system model.

As shown in Fig. 1, the first layer of FCV is cloud computing layer which includes cloud servers and gateways. In particular, the gateway communicates with other heterogeneous networks and can also send the filtered underlying data to cloud servers.

The second one is fog computing layer, including lightweight fog devices at network edges. Fog devices temporarily cache and process the raw-date collected, and upload the filtered data to the cloud servers for further processing. And fog devices can also store some frequently accessed data for rapid-response processing.

The third layer is accessing layer, which includes RSUs, vehicles and mobile devices. RSUs provide open service access points for fog computing vehicles and mobile devices. Note that although RSUs and fog devices are deployed in similar locations, we will deploy them separately, taking into account the flexibility of deployment. RSUs, nearby vehicles and mobile devices communicate wirelessly, exchanging information and collaborating on computing tasks. However, RSUs communicate with fog devices via wired connection. There are four types of scenarios in the third layer, as described below.

Fig. 1(a) and (b) illustrate parked vehicles and mobile devices as infrastructures. A huge number of parked vehicles are scattered across the traffic network in IoV. These vehicles and mobile devices become a rich computing infrastructure,

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TABLE I
SYMBOLS AND DEFINITIONS

Notation	Definition
o	A textual-spatial object
q	An A^{2}SKIV query
$q.V(o.V)$	A set of attribute-value pairs for q (o)
$q.L(o.L)$	The location of q (o)
$D_{td}(q,o)$	The textual distance between o and q
$D_{nd}(q,o)$	The numeric distance between o and q
$D_{tr}(q,o)$	The travel distance between o and q
$D_{tns}(q,o)$	The textual-numeric-spatial distance between o and q
$D^{LB}_{tns}(q,\mathcal{G}_i)$	The lower-bound textual-numeric-spatial distance between subgraph $\mathcal{G}_i$ and q
$d^{LB}_{ed}(q_i,w_i)$	The lower-bound edit distance between word w_i and query keyword q_i

providing powerful computing resources and storage space. When joining the FCV, they can be used as a small data center to deal with a variety of complex tasks. Fig. 1(c) and (d) illustrate moving vehicles working as infrastructures. In urban areas, traffic is usually slow. In addition, most vehicles travel very slowly when entering the urban area, especially during rush hours, and there is good communication between nearby mobile vehicles and devices. Moving vehicles can constantly transmit information by establishing new connections. When nearby moving vehicles join the FCV, they can collaborate and connect with each other, and complete tasks using local computing and communication resources.

B. Problem Definition

1) A Traffic Network of IoV: A traffic network of IoV is modeled as a undirected weighted graph G=(V, E), where V is a set of vertices, and E is a set of edges. A vertice $v \in V$ represents a road intersection or endpoint in the traffic network. An edge $e(v_i, v_j, l) \in E$, represents the road segment between two vertices v_i and v_j ($i \neq j$), and l represents the length of the road segment. Our model can be extended to support the directed weighted graph, which represents unidirectional traffic, by simply allowing the length of $e(v_i, v_j)$ be set different from that of $e(v_j, v_i)$.

2) Spatial-textual Objects with Numeric Attributes and Approximate Spatial Keyword Queries:

Definition 1. *Spatial-textual objects with numeric attributes in traffic networks of IoV (object for short).*

Object o is defined as o = ($o.tags$, $o.V$, $o.L$), where $o.tags$ is related descriptive tags containing a set of keywords, $o.V$ is a set of attribute-value pairs, and $o.L$ is a spatial point on the edge of the traffic network. The size of $o.V$ is the number of attribute-value pairs represented by n, and so o can be represented as:

$$o = \{tags, A_1 = v_1 \bigcap A_2 = v_2 \bigcap ... \bigcap A_n = v_n,\ o.L\}.$$

Definition 2. *Approximate spatial keyword queries with numeric attributes in IoV (A^{2}SKIV).*

An A^{2}SKIV query q is defined as q = ($q.W$, $q.V$, $q.L$), where $q.W$ is the relevant keywords, $q.V$ is a set of user-given attribute-value pairs, $q.L$ is a spatial point on the edge of the traffic network. The size of $q.V$ is the number of attribute-value pairs represented by m, and so q can be represented as:

$$q = \{q.W, A_1 = v_1 \bigcap A_2 = v_2 \bigcap ... \bigcap A_m = v_m,\ q.L\}.$$

3) Match Semantics: For A^{2}SKIV query q and object o, to measure the relevance between q and o, there are three aspects should be considered, i.e., textual distance, numeric attribute distance, and traffic network distance between q and o.

Definition 3. *Keyword mapping. For A^{2}SKIV query q and object o, a keyword mapping from q to o, i.e., q.KM(o), is a set of keywords, in which each keyword is textual closest to q among all keywords contained by o in terms of edit distance[1], i.e., $w_i = argmin_{w_j \in o.tags}\{d_{ed}(q_i, w_j)\}$.*

Definition 4. *Textual distance. Given A^{2}SKIV query q and object o, we first calculate the sum of edit distance between each keyword $w_i \in q.KM(o)$ and corresponding keyword $q_i \in q.W$. To normalize the sum of edit distance calculated to range [0, 1], the max$\{|q.W|,\ |o.tags|\}$, which is the greater one between $|q.W|$ and $|o.tags|$, is also considered as follows:*

$$D_{td}(q,o) = \sum_{q_i \in q.W} \frac{d_{ed}(q_i, w_i)}{|q.W| \times max\{|q.W|, |o.tags|\}}. \tag{1}$$

Next, let's discuss how to calculate the numeric distance between query q and object o. Numeric attribute distance refers to the degree of difference between the values of q and o under the same numeric attribute, which is expressed as the size of difference.

For q and o, the numeric distance between q and o under each numeric attribute A_j ($1 \leq j \leq m$) can be expressed as follows:

$$d_j = \begin{cases} d(q.A_j, o.A_j), & \text{if } o.A_j \text{ exists} \\ +\infty. & \text{otherwise} \end{cases} \tag{2}$$

Then we normalize each numeric attribute distance to range [0, 1], and comprehensively consider the influence of each numeric attribute distance to calculate the total numeric distance between q and o.

Definition 5. *Numeric distance. For each query attribute $A_j \in q.V$, let M_j = Max(A_j)-Min(A_j) = $\beta_j \times 10^{c^j}$, where Max(A_j) and Min(A_j) are the maximum and minimum values of attribute A_j for all objects in object set O, and $1.0 \leq \beta_j \leq$* 10.0. *Let e_j= $c_j + 1 \geq 1$, the numeric distance $D_{nd}(q,o)$ between q and o can be defined as follows:*

$$D_{nd}(q,o) = \frac{1}{|q.V|} \sum_{A_j \in q.V} (\frac{d_j}{M_j})^{\frac{1}{e_j}}. \tag{3}$$

Note: if there is any query attribute that is not in $o.V$, $D_{nd}(q,o)$=+∞.

[1]The edit distance between the two strings s_1 and s_2, $d_{ed}(s_1, s_2)$, can be defined as the minimum number of edit operations (i.e., insertion, deletion, or substitution), required to convert from s_1 to s_2. The n-gram is a common technique for estimating edit distance between strings. For a string s, the n-grams can be obtained by sliding a window of length n from the beginning to the end of the string. In particular, Minhash method [36] can be used to estimate set similarity.

Travel distance is another aspect for query effort measurement, which is the length of the shortest path from query q to object o, i.e., $D_N(q.l, o.l)$.

Definition 6. *Travel distance. Since the value of Sigmoid function changes rapidly in the case of small variables, this is consistent with the intuition that user satisfaction is generally more sensitive to travel distance in the case of short distance. Therefore, we use the Sigmoid function to normalize travel distance to range* $[0, 1]$*:*

$$D_{tr}(q, o) = \frac{2}{1 + e^{-\rho \times D_N(q.l, o.l)}} - 1, \tag{4}$$

where $0 < \rho \leq 1$ *is the distance adjustment parameter.*

Finally, we adopt the concept of textual-numeric-spatial distance and combine the measurement of spatial, textual, and numeric relevance between q and o by using a simple linear interpolation. In particular, the textual-numeric-spatial distance between q and o is a linear combination of the spatial, textual, and numeric relevance between q and o, each weighted with parameter α, β and γ, respectively.

Definition 7. *Textual-numeric-spatial distance. Formally, given q and o, the textual-numeric-spatial distance is denoted as* $D_{tns}(q, o)$*, which is defined as:*

$$D_{tns}(q, o) = \alpha \times D_{td}(q, o) + \beta \times D_{nd}(q, o) + \gamma \times D_{tr}(q, o) \tag{5}$$

where $\alpha, \beta, \gamma \geq 0$*, and* $\alpha + \beta + \gamma = 1$.

C. Problem Statement

By using the textual-numeric-spatial distance $D_{tns}(q, o)$ to measure the combined proximity between query q and object o, we can formally define Top-k A^{2}SKIV query below.

Definition 8. *Top-k A^{2}SKIV query. Given a spatial-textual object dataset O, a Top-k A^{2}SKIV query* q=($q.W$, $q.V$, $q.L$, k) *retrieves a set of objects* $\widehat{O} \subseteq O$*, such that* $|\widehat{O}|$=k *and* $\forall o \in \widehat{O}$ *and* $o' \in O - \widehat{O}$, $D_{tns}(q, o) < D_{tns}(q, o')$.

Example 1. *Fig. 2 illustrates an example of Top-k A^{2}SKIV query on the traffic network in IoV, with 10 spatial-textual objects and 1 query located on the edges. Each object has a set of keywords and a set of attribute-value pairs to provide its description information, and a spatial point on the edge of the traffic network to describe its location. The query q contains four items: a set of query keywords* $\{Theater, coffee\}$*, attribute-value pairs for "*A_1 = 4.4 & A_2=45*", a spatial point* q_l *for its current location, and a value* $k = 1$ *for top-1 related objects wanted. Note* A_1*="rating", and* A_2*= "pcc (per capita consumption)". We first consider* o_5, o_6, o_7 *and* o_9*, whose network distances from query q are the four most shortest ones among all the objects in O.*

Assume M_1=Max(A_1)-Min(A_1)=5-0=5, M_2=Max(A_2)-Min(A_2)=200-0=200, e_1=1, e_2=3, ρ=0.1, *and* $\alpha = \beta = \gamma = \frac{1}{3}$*, we can get:*

$D_{tns}(q, o_6)$=$\frac{1}{3} \times \frac{1}{2} \times (\frac{1}{7} + 0)$ + $\frac{1}{3} \times \frac{1}{2} \times (\frac{0.1}{5} + 0)$ + $\frac{1}{3} \times (\frac{2}{e^{-0.1*7}} - 1)$ = 0.1631.

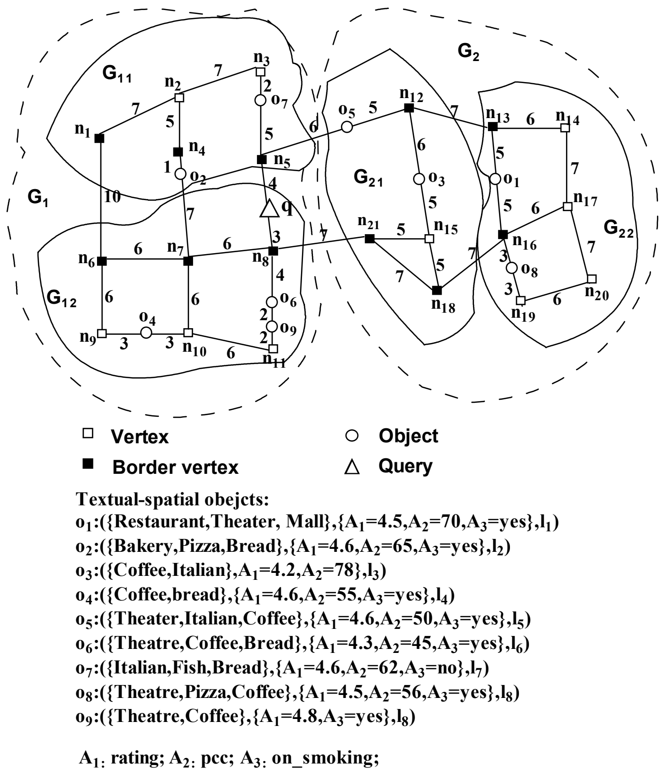

Fig. 2. An example of Top-k A^{2}SKIV query.

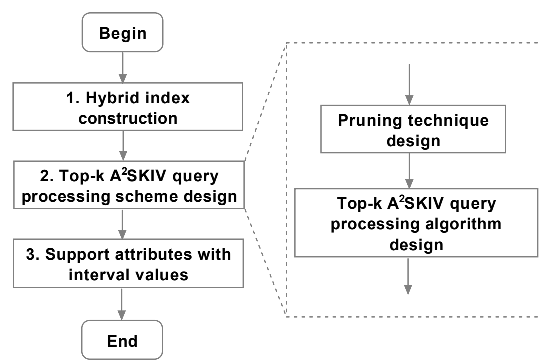

Fig. 3. The flowchart of Top-k A^{2}SKIV query processing.

Similarly, we can get $D_{tns}(q, o_5)$=0.1649, $D_{tns}(q, o_7)$= 0.1682, *and* $D_{tns}(q, o_9)$=$+\infty$. *Note that* $D_{nd}(q, o_9)$=$+\infty$ *since* o_9 *does not have query attribute* A_2*, thus* $D_{tns}(q, o_9)$ *equals* $+\infty$*. Then, object* o_6 *is the top-1 result object of q at this moment, and other objects can be evaluated similarly.*

In the following three sections, the detail method for Top-k A^{2}SKIV query processing is proposed, which includes hybrid index construction, Top-k A^{2}SKIV processing scheme design, and extending our index constructed to support attributes with interval values. Top-k A^{2}SKIV processing scheme consists of pruning techniques and query processing algorithms. The query processing flowchart is then shown in Fig. 3.

IV. Hybrid Index for A^{2}SKIV Query Processing

To improve query performance and efficiently prune irrelevant objects for A^{2}SKIV queries as many as possible, a novel

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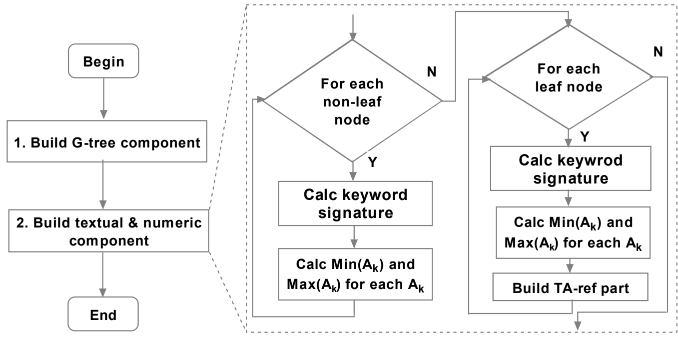

Fig. 5. The flowchart of building the STAG-tree index.

two-level spatial-textual hybrid index structure STAG-tree is proposed as shown in Fig. 4, which supports network distance pruning, textual pruning, and numeric attribute pruning simultaneously. STAG-tree also considers the relative invariance of traffic network structure and the dynamic variation of objects and queries. Then, the flowchart of building the STAG-tree is illustrated in Fig. 5.

A. Build G-tree Component

G-tree [37] is an assembly-based index and can efficiently support location-based queries on traffic network in IoV. A traffic network is modeled by an undirected weighted graph $\mathcal{G} = \{V, E\}$ as mentioned before, and G-tree can be constructed by using graph partitioning. Firstly, the graph $\mathcal{G}$ is marked as the root of G-tree, and then $\mathcal{G}$ is partitioned into f equal-sized subgraphs $\mathcal{G}_1, \mathcal{G}_2, ..., \mathcal{G}_f$, i.e., $|V_{\mathcal{G}_1}|, |V_{\mathcal{G}_2}|, ...|V_{\mathcal{G}_f}|$ are almost the same, and works as the parent node of these subgraphs. Note for $\mathcal{G}_i$ may exist $u \in V_i$ such that $\exists(u, v) \in E$ and $v \notin V_i$, such node u is called a border, and $B_{\mathcal{G}_i}$ is used to represent the border set in graph $\mathcal{G}_i$. Thus, $\mathcal{G}_i$ can be denoted by $\mathcal{G}_i$=$\{E_{\mathcal{G}_i}, V_{\mathcal{G}_i}, B_{\mathcal{G}_i}\}$, where $E_{\mathcal{G}_i}$, $V_{\mathcal{G}_i}$, and $B_{\mathcal{G}_i}$ denote the vertices, edges, and borders in $\mathcal{G}_i$ which meet the following conditions: 1) $\bigcup_{1\geq i\geq f} V_{\mathcal{G}_i}$=$V$; 2) For $i \neq j$, $V_{\mathcal{G}_i} \bigcap V_{\mathcal{G}_j} = \emptyset$; 3) For $\forall u, v \in V_{\mathcal{G}_i}$, if $(u, v) \in E_{\mathcal{G}_i}$, then $(v, u) \in E_{\mathcal{G}_i}$; 4) For $\forall u \in V_{\mathcal{G}_i}, \exists(u, v) \in E$ and $v \notin V_i$, then $u \in B_{\mathcal{G}_i}\}$. Then, subgraph $\mathcal{G}_i$ is partitioned recursively, and the steps are repeated until each subgraph has no more than τ vertices. Note that f and τ are adjustable parameters. For example, as shown in Fig. 2, the traffic network $\mathcal{G}_0$ is first divided into two subgraphs $\mathcal{G}_1$ and $\mathcal{G}_2$. Then $\mathcal{G}_1$ ($\mathcal{G}_2$, resp.) is divided into $\mathcal{G}_{11}$ and $\mathcal{G}_{12}$ ($\mathcal{G}_{21}$ and $\mathcal{G}_{22}$, resp.). Assume $f = 2$ and $\tau = 6$, the G-tree structure of the traffic network in Fig. 2 can be obtained as shown in Fig. 4(a). Note that the numbers under the ID of each subgraph are the IDs of its borders.

To accelerate the shortest path calculation, G-tree keeps the distance metrics (DM) which include the shortest-path distance between each border-border pair (border-vertice pair, resp.) for non-leaf nodes (leaf nodes, resp.). Particularly, an efficient bottom-up method is adopted to accelerate the distance computation. In this way, the DMs of the G-tree in Fig. 4(a) can be obtained, and the DM of each subgraph (or graph) is given next to it. The total space complexity of G-tree is $O(log_2 f * \sqrt{\tau} * |V| + log_f \frac{|V|}{\tau} * log_2^2 f * |V|)$, where $|V|$ is total number of vertices in graph $\mathcal{G}$, f is the fan-out of non-leaf G-tree nodes for graph $\mathcal{G}$, and τ is maximum number of vertices contained in each leaf node of G-tree. Note that log_2^2, $\sqrt{\tau}$, and $log_f \frac{|V|}{\tau}$ are small numbers, thus the size of G-tree is scalable. Please refer to [37] for details.

B. Build Textual & Numeric Component

Secondly, as shown in Fig. 4(b), the dynamic part of the index, i.e., a textual & numeric index on objects, is constructed. For each non-leaf subgraph (node) $\mathcal{G}_i$:

1) ID of the subgraph $\mathcal{G}_i$ is stored;

2) Calculate and keep, a) the keyword signature of all the objects within $\mathcal{G}_i$; and b) the $Min(A_k)$ and $Max(A_k)$ of each numeric attribute A_k, which are the minimum and maximum values of A_k for all the objects in $\mathcal{G}_i$. If no object in $\mathcal{G}_i$ has attribute A_k, $Max(A_k) = Min(A_k) = +\infty$;

3) The entries pointing to the subgraphs of $\mathcal{G}_i$ is stored.

For each leaf subgraph (node) $\mathcal{G}_i$, we also calculate and keep the first two items similar to the non-leaf subgraph:

1) ID of $\mathcal{G}_i$;

2) The keyword signature, and $Min(A_k)$ and $Max(A_k)$ for each numeric attribute A_k.

The third item of the non-leaf subgraph is not required in the leaf subgraph, since it does not have any subgraphs. In addition, for each leaf subgraph we also construct and keep the TA-ref index part as follows.

TA-ref index. TA-ref index, as shown in Fig. 4(c), is used to organize the textual and numerical information of the objects in each nonleaf subgraph, to facilitate textual distance and numeric distance calculation of objects in subgraphs. TA-ref index consists of two parts: T-ref and A-ref.

T-ref part. As far as we know, it is unfeasible calculating the edit distance during query processing by directly using Wagner-fisher algorithm [32]. Thus, for each leaf subgraph $\mathcal{G}_i$, we construct the T-ref part to index the edit distance of the objects within $\mathcal{G}_i$. For $\mathcal{G}_i$, we select a set of reference keywords R($\mathcal{G}_i$)= $\{w_r^{\mathcal{G}_i}\}$ to index the edit distances between the keywords contained in the objects within $\mathcal{G}_i$ and R($\mathcal{G}_i$).

To construct the T-ref part for $\mathcal{G}_i$, we need to divide the keywords contained in all the objects within $\mathcal{G}_i$ into N clusters, and select a reference keyword $w_{r_n}^{\mathcal{G}_i}$ for each cluster, thus to minimize the mathematical expectation of editing distance in each cluster. To this end, k-means clustering algorithm is adopted to obtain each cluster and its corresponding reference keyword. Thus, each object o_i within $\mathcal{G}_i$ is indexed in a B$^+$-tree by the key y(o_i^n). The key y(o_i^n) is calculated according to the edit distance between the keyword w_i^j and the reference keyword $w_{r_n}^{\mathcal{G}_i}$, i.e., y(o_i^n)=$d_{ed}(w_{r_n}^{\mathcal{G}_i}, w_i^j)$+$n \times C$ $(0 \leq n \leq N)$, where C equals the maximum edit distance between the reference keyword of the cluster and the keywords belonging to the cluster. To facilitate the edit distance calculation in query processing, we also calculate and keep the distance lower limit $DL(w_{r_n}^{\mathcal{G}_i})$ and the distance upper limit $DU(w_{r_n}^{\mathcal{G}_i})$ for each cluster.

Example 2. *Fig. 4(c) gives the T-ref for subgraph $\mathcal{G}_{12}$, where the keywords of objects within $\mathcal{G}_{12}$ are partitioned into three*

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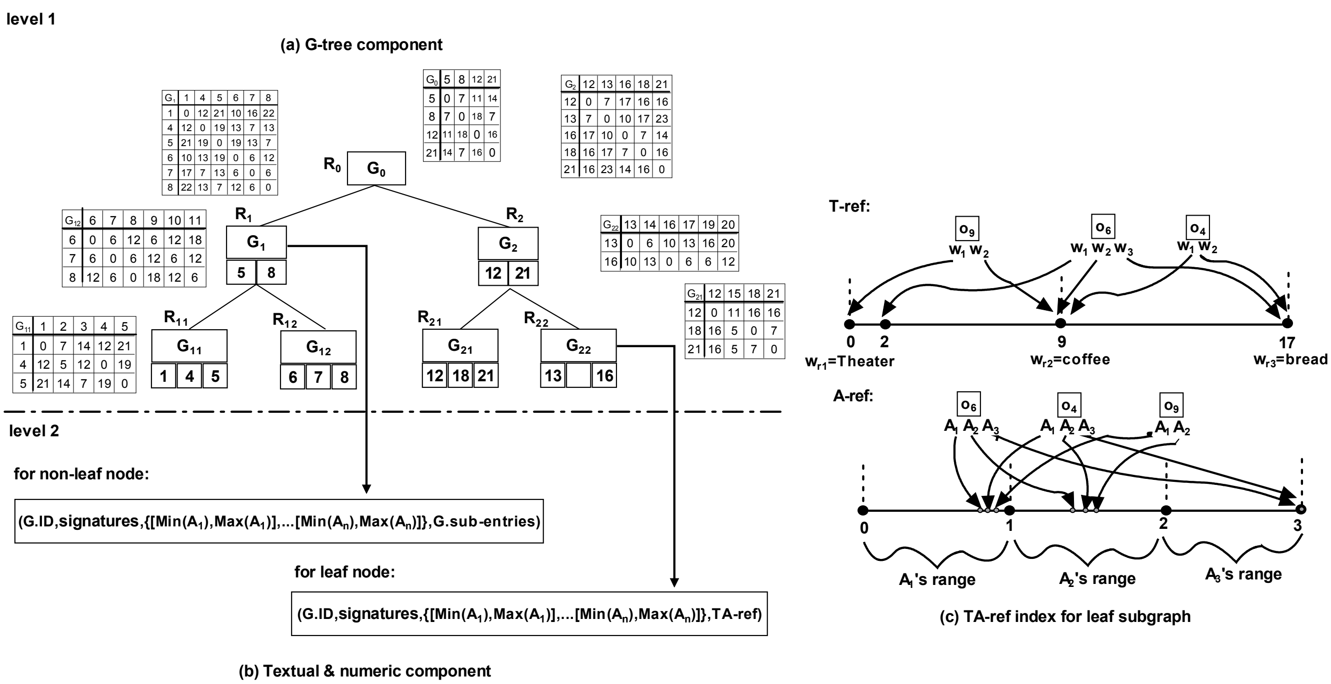

Fig. 4. The STAG-tree index.

clusters, whose reference keyword is "Theater", "coffee", and "bread", respectively.

A-ref part. A-ref part is to facilitate the numeric distance calculation of the objects in subgraphs. For each numeric attribute A_k ($1 \leq k \leq n$) of the system, we use $[k-1, k)$ to represent the value range of the objects with attribute A_k. To map the attribute values of objects to the value ranges of attributes, each object o_i within $\mathcal{G}_i$ is indexed in a B$^+$-tree by the key y(o_i^k). The key y(o_i^k) is calculated according to its attribute value, i.e., y(o_i^k)=$\frac{o_i.V_k}{M_k} + k - 1$ ($0 \leq k \leq n$), where $o_i.V_k$ is the attribute value of object o_i for A_k, and $M_k = Max(A_k) - Min(A_k)$. Note that $Max(A_k)$ and $Min(A_k)$ are the maximum and minimum values of attribute A_k for all the objects in O.

Example 3. *Fig. 4(c) also gives the A-ref for subgraph $\mathcal{G}_{12}$, where the numeric attributes of objects within $\mathcal{G}_{12}$ are partitioned into three clusters, whose value range is [0, 1), [1, 2), and [2, 3), respectively. For example, the attribute value for A_2 of o_6 is 45, and M_2=100, and then we have y(o_6^2)=$\frac{45}{100} + 2 - 1$ = 1.45.*

Remember we partition the traffic network into equally sized subgraphs, while minimizing the number of border vertices at the same time. And then, the index part of each subgraph is constructed accordingly. To allocate the workload among different fog-devices in the second layer of our FCV structure, the information of STAG-index is partitioned, each corresponding to a sub-graph. For a fog-server, the index part of the subgraph on which it resides and the subgraphs surrounding it will be stored in the server.

V. Process A^{2}SKIV Queries in IoV

This section introduces the Top-k A^2SKIV query processing method based on STAG-tree index.

A. Pruning Techniques

Firstly, several lemmas are introduced to efficiently prune the unrelated traffic network space and unqualified spatial-textual objects in IoV.

Lemma 1. *Given a Top-k A^2SKIV query q=($q.W$, $q.V$, $q.L$, k) and a subgraph $\mathcal{G}_i$, $\mathcal{G}_i$ can be ignored if*

$$d_N^{\min}(\mathcal{G}_i, q) > -\frac{1}{\rho}\ln(\frac{2}{\frac{D_{tns}(q,o_k)}{\gamma}+1} - 1),$$

where o_k is the k-th nearest neighbor of q.

Proof: For any object o in $\mathcal{G}_i$, we have

$$\begin{aligned} D_{tns}(q,o) &= \alpha \times D_{td}(q,o) + \beta \times D_{nd}(q,o) + \gamma \times D_{tr}(q,o) \\ &\geq \gamma \times D_{tr}(q,o), \end{aligned}$$

$$if \qquad d_N^{\min}(\mathcal{G}_i, q) > -\frac{1}{\rho}\ln(\frac{2}{\frac{D_{tns}(q,o_k)}{\gamma}+1} - 1),$$

through transformation, for each $o \in \mathcal{G}_i$ we have:

$$D_{tr}(q,o) > \frac{D_{tns}(q,o_k)}{\gamma}.$$

Thus, we have:

$$D_{tns}(q,o) \geq \gamma \times D_{tr}(q,o) > D_{tns}(q,o_k).$$

As a result, any object o in $\mathcal{G}_i$ can not be a Top-k result object. Thus, $\mathcal{G}_i$ can be ignored. ∎

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Lemma 2. *Given a Top-k A^2SKIV query q=(q.W, q.V, q.L, k) and a subgraph $\mathcal{G}_i$, if $\forall q_j \in q.W$, $q_j.signature \cap \mathcal{G}_i.signature = \emptyset$, then $\mathcal{G}_i$ can be ignored.*

Proof: For $\mathcal{G}_i$, if $\forall q_j \in q.W$, $q_j.signature \cap \mathcal{G}_i.signature = \emptyset$, which means that for any query keyword q_j, there is no object in $\mathcal{G}_i$ textual similar with q_j, hence, $\mathcal{G}_i$ can be ignored. ■

Lemma 3. *Given a Top-k A^2SKIV query q=(q.W, q.V, q.L, k) and a subgraph $\mathcal{G}_i$, if $\exists A_j \in q.V$, such that $Max(A_j)(or Min(A_j))$ for $\mathcal{G}_i$ equals +∞, then $\mathcal{G}_i$ can be ignored.*

Proof: For subgraph $\mathcal{G}_i$, if $\exists A_j \in q.V$, whose $Max(A_j)$ (or $Min(A_j)$) for $\mathcal{G}_i$ equals +∞, it means $\mathcal{G}_i$ does not include any object containing attribute A_j, which also means that the numeric distance d_j for any object o in $\mathcal{G}_i$ equals +∞. Thus $D_{nd}(q,o)$ equals +∞, which in turn makes $D_{tns}(q,o)$ equal +∞. Any object o in subgraph $\mathcal{G}_i$ can not be a Top-k result object. Thus, $\mathcal{G}_i$ can be ignored. ■

Lower bound distance computation. The pruning strength of the above three lemmas is relatively limited. In order to further reduce unrelated subgraphs, for any subgraph $\mathcal{G}_i$, we calculate $D^{LB}_{tns}(q,\mathcal{G}_i)$ as follows:

1) $\mathcal{G}_i$ is nonleaf subgraph.
   - If $\mathcal{G}_i$ is not pruned by lemmas 1, 2 or 3, we reduce $D^{LB}_{tns}(q,\mathcal{G}_i)$ by assuming $D_{td}(q,\mathcal{G}_i)$ equals 0.
   - To calculate $D^{LB}_{nd}(q,\mathcal{G}_i)$, for each query attribute A_k, we compare its value for A_k, i.e., $q.A_k.v$, with the value range $[Min(A_k),\ Max(A_k)]$ of $\mathcal{G}_i$. If $q.A_k.v$ falls in $[Min(A_k), Max(A_k)]$, assume that $d_k = 0$; otherwise d_k = min$\{|q.A_k.v$ - $Min(A_k)|$, $|q.A_k.v$-$Max(A_k)|\}$. Then, $D^{LB}_{nd}(q,\mathcal{G}_i)$ is obtained by formula (3).
   - To calculate $D^{LB}_{tr}(q,\mathcal{G}_i)$, we use the shortest network distance between q and the border vertices of $\mathcal{G}_i$, if q does not belong to $\mathcal{G}_i$; otherwise $D^{LB}_{tr}(q,\mathcal{G}_i)$=0.

   Finally, $D^{LB}_{tns}(q,\mathcal{G}_i) = \alpha \times 0 + \beta \times D^{LB}_{nd}(q,\mathcal{G}_i) + \gamma \times D^{LB}_{tr}(q,\mathcal{G}_i)$.
2) $\mathcal{G}_i$ is leaf subgraph.
   - The calculation of $D^{LB}_{nd}(q,\mathcal{G}_i)$ and $D^{LB}_{tr}(q,\mathcal{G}_i)$ is the same as that of the nonleaf subgraph.
   - The TA-ref index of leaf subgraph $\mathcal{G}_i$ will be used to calculate $D^{LB}_{tns}(q,\mathcal{G}_i)$, whose focus is the calculation of $d^{LB}_{ed}(q_i,w_i)$ for each query keyword $q_i \in q.W$ and its most mapping keyword w_i for objects in $\mathcal{G}_i$. We will detail how to determine w_i and its corresponding object o_i as follows.

     Calculating $d^{LB}_{ed}(q_i,w_i)$ for q_i. Since the edit distance follows the triangle inequality, we make use of the edit distances between q and reference keywords of the T-ref part in TA-ref index for $\mathcal{G}_i$.

     Firstly, the edit distance between q_i and each reference keyword $w^{\mathcal{G}_i}_{r_j}$, i.e., $d_{ed}(q_i, w^{\mathcal{G}_i}_{r_j})$, is calculated. If $d_{ed}(q_i, w^{\mathcal{G}_i}_{r_j}) \in [DL(w^{\mathcal{G}_i}_{r_j}), DU(w^{\mathcal{G}_i}_{r_j})]$, let $d^{LB}_{ed}(q_i,w_i)$ =0, and the processing for k_i completes.

     Otherwise, we choose $w_r = argmin_{0 \le j \le n}$ $\{d_{ed}(q_i, w^{\mathcal{G}_i}_{r_j})\}$ and its two bounding values $DL(w^{\mathcal{G}_i}_r)$ and $DU(w^{\mathcal{G}_i}_r)$, and let $d^{LB}_{ed}(q_i,w_i)$ equal $\min((d_{ed}(q_i,w^{\mathcal{G}_i}_r) - DL(w^{\mathcal{G}_i}_r)),\ d_{ed}(q_i,w^{\mathcal{G}_i}_r) - DU(w^{\mathcal{G}_i}_r)))$.

     Then, by using all the $d^{LB}_{ed}(q_i,w_i)$, $D^{LB}_{td}(q,\mathcal{G}_i)$ can be obtained through formula (1).

   Finally, $D^{LB}_{tns}(q,\mathcal{G}_i)$ = $\alpha \times D^{LB}_{td}(q,\mathcal{G}_i) + \beta \times D^{LB}_{nd}(q,\mathcal{G}_i) + \gamma \times D^{LB}_{tr}(q,\mathcal{G}_i)$.

Lemma 4. *Given a Top-k A^2SKIV query q=(q.W, q.V, q.L, k) and a subgraph $\mathcal{G}_i$, if $D^{LB}_{tns}(q,\mathcal{G}_i) > D_{tns}(q,o_k)$, where o_k is with the same meaning of Lemma 1, and $D^{LB}_{tns}(q,\mathcal{G}_i)$ is the lower bound of the textual-numeric-spatial distance between query q and any object o in $\mathcal{G}_i$, $\mathcal{G}_i$ can be ignored.*

Proof: Since $D^{LB}_{tns}(q,\mathcal{G}_i) > D_{tns}(q,o_k)$, for any object $o \in \mathcal{G}_i$, there exist at least k objects whose textual-numeric-spatial distance between query q is smaller than that of o, thus o can not be a Top-k result object. Hence, $\mathcal{G}_i$ can be ignored. ■

B. A^2SKIV Query Processing Algorithm

Now we are ready to discuss the A^{2}SKIV query processing algorithm using STAG-tree index, which is called A^{2}S^{2}KG. It takes as inputs a STAG-tree $\mathcal{ST}$ and an A^{2}SKIV query q=($q.W$, $q.V$, $q.L$, k), and outputs the result object set S_{result}. A^{2}S^{2}KG progressively accesses the nearest subgraphs and retrieves the most relevant objects. Finally, the k objects with the smallest textual-numeric-spatial distance value, $D_{tns}(q,o)$, form the query result set.

The detailed steps of A^{2}S^{2}KG algorithm are shown in Algorithm 1. Firstly, a min-heap *HG* is initialized to empty for organizing the nodes (subgraphs) or objects to be visited. Moreover, a set S_{result} is adopted to keep the result objects for query q, and a float D_{tsk} is initialized to be +∞ for keeping the textual-numeric-spatial distance of the current k-th nearest neighbor from query q. In particular, *HG* is an ordered structure and $D^{LB}_{tns}(q,P_{node})$ is the key of a node (subgraph) P_{node} in *HG*.

A^{2}S^{2}KG first locates the leaf node (subgraph), leaf(q), where q lies in. For each object o in leaf(q), it inserts o together with its $D_{tns}(q,o)$ into heap HG, and updates D_{tsk} accordingly, if $D_{tns}(q,o)$ is no larger than D_{tsk} (lines 4-6). Then, it uses pointer P_{node} to keep the upper-most node (subgraph) visited of $\mathcal{ST}$ and uses variable P_{LB} to keep the lower bound of the textual-numeric-spatial distance between query q and P_{Node}, i.e., $D^{LB}_{tns}(q,P_{Node})$. Let P_{node} point to leaf(q) and P_{LB} be $D^{LB}_{tns}(q,P_{Node})$ (line 7), and then visit $\mathcal{ST}$ in a bottom-up manner (lines 8-23). If HG is empty, the Adjust function is called to move P_{node} to its parent node and update P_{LB} accordingly (line 10). Adjust function will also process each unvisited child nodes of new P_{node}. The detail steps of Adjust function are shown in Algorithm 2.

Next, a tuple (c, dis) is popped-out from *HG*. Note that (c, dis) is the head element of *HG*, and *HG* is ordered by the (lower bound of) textual-numeric-spatial distances of its elements from query q. If dis, which is the (lower bound of) distance of head element c from query q, is larger than P_{LB},

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Algorithm 1: A^2S^2KG algorithm

input : STAG-tree $\mathcal{STAG}$, A^2SKIV query q=($q.W$, $q.V$, $q.L$, k)
output: Set S_{result}
1 **begin**
2 S_{result}=$\emptyset$; float $D_{tsk} = +\infty$; $HG = \emptyset$;
3 Locate the leaf node (subgraph) leaf(q) where q lies;
4 **for** *each object $o \in$ leaf(q)* **do**
5 **if** $D_{tns}(q, o) \leq D_{tsk}$ **then**
6 HG.push($O, D_{tns}(q, o)$); //update D_{tsk} accordingly;
7 P_{Node}=leaf(q); $P_{LB} = D^{LB}_{tns}(q, P_{Node})$;
8 **while** $|S_{result}| < k$ && ($HG \neq \emptyset$ || $P_{Node} \neq R_0$) **do**
9 **if** HG=$\emptyset$ **then**
10 Adjust(P_{Node}, P_{LB}, HG);
11 (c, dis)=HG.pop();
12 **if** $dis > P_{LB}$&$P_{node} \neq R_0$ **then**
13 Adjust(P_{Node}, P_{LB}, HG);
14 **else**
15 **if** *c is an object* **then**
16 insert c into S_{result};
17 **else**
18 **if** *c is a non-leaf subgraph* **then**
19 **for** *each unvisited child node $s \in c$* **do**
20 Gjudge(s);
21 **else**
22 **for** *each object $o \in c$* **do**
23 Ojudge(o);

then the query answer may be existed in the parent node of P_{node}, thus Adjust function is called to move P_{node} to its parent node and update P_{LB} accordingly (line 13). Otherwise ($dis <= P_{LB}$), there are three cases: 1) c is an object, then c is a result object since c is the object with the minimum textual-numeric-spatial distance (lines 15-16); 2) c is a non-leaf subgraph, then for each unvisited subgraph s of c, function Gjudge (shown in Algorithm 3) is called to process each s; 3) c is a leaf subgraph, then for each object o of c, function Ojudge is called to process o.

The detailed steps of $Adjust$ function are shown in Algorithm 2. It first moves P_{node} to its parent node (line 2). Then, for each unvisited child node s of P_{node}, Gjudge function (Algorithm 3) is called to check if s possibly contains result objects, and if true, we calculate the lower bound of the textual-numeric-spatial distance between s and query q, i.e., $D^{LB}_{tns}(q, s)$. Finally, P_{LB}, which keeps the minimum value of $D^{LB}_{tns}(q, s)$ for all the child nodes of P_{node}, is returned.

The pseudo-code of $Gjudge$ function is shown in Algorithm 3. For node s, $Gjudge$ uses Lemmas 1, 2 and 3, respectively, to check if s is a qualified subgraph, otherwise s is safely pruned and 1, which is the uppermost limit of $D_{tns}(q, s)$, is returned. If s is not pruned, we 1) calculate $D^{LB}_{tns}(q, s)$; 2) push s together with $D^{LB}_{tns}(q, s)$ into HG (update D_{tsk} accordingly), and return $D^{LB}_{tns}(q, s)$ if $D^{LB}_{tns}(q, s) \leq D_{tns}(q, o_k)$; otherwise s is pruned by Lemma 4 and 1 is returned, since if $D^{LB}_{tns}(q, s) > D_{tns}(q, o_k)$, s can not contain any result object. The processing step of Ojudge function is similar to that of

Algorithm 2: Adjust function

input : P_N, P_{LB}, HG
output: P_{LB}
1 **begin**
2 P_{Node}=P_{Node}.Parent;
3 **for** *each unvisited child node s of P_{Node}* **do**
4 D_{tns}=Gjudeg(s);
5 **if** $D_{tns} < P_{LB}$ **then**
6 P_{LB}=D_{tns};

Gjudge function, and we omit the discuss for space limitation.

Time complexity analysis. Finally, we discuss the time complexity of the A^2S^2KG algorithm. Given an object o and a Top-k A^2SKIV query q=($q.W$, $q.V$, $q.L$, k), o is a candidate result object for q if 1) $o.V$ contains all the numeric attributes of $q.V$, i.e., $\forall q.V.A_j, 1 \leq i \leq m, \exists o.V.A_i = q.V.A_j$, whose probability can be represented as $Pr_{AM}(o)$; 2) $\exists q_j \in q.W$, $q_j.signature \cap \mathcal{G}_i.signature \neq \emptyset$, whose probability can be represented as $Pr_{KM}(o)$.

Thus, the total probability of an object o being a candidate object of q, $Pr_{cand}(o)$, equals $Pr_{AM}(o) * Pr_{KM}(o)$. Note here k result objects are required, the total number of objects visited is $\frac{k}{Pr_{cand}(o)}$. For each object o being visited, the time costs for computing its $D_{td}(q, o)$ and $D_{nd}(q, o)$ are $O(|q.W| * |o.tags|)$ and $O(|q.V| * |o.V|)$, respectively. Assume W_{dis} and V_{dis} are the total numbers of distinct keywords and distinct numeric attributes in the system, respectively. Thus the time complexity for textual and attribute matching in query processing is $O(\frac{k}{Pr_{cand}(o)} * (W^2_{dis} + V^2_{dis}))$.

To estimate the value of $Pr_{AM}(o)$, assume m and n are the numbers of numeric attributes for o and q, respectively, and $m \geq n$, we have: $Pr_{AM}(o)$= $C^n_n * \frac{C^{m-n}_{V_{dis}-n}}{C^m_{V_{dis}}} = \frac{C^{m-n}_{V_{dis}-n}}{C^m_{V_{dis}}}$. Here C^i_j is the number of combinations of taking i elements from a set of j.

For object o and query q, it is difficult to calculate exact value of $Pr_{KM}(o)$, thus we use the probability of $o.tags$ containing at least one keyword in $q.W$ to approximate $Pr_{KM}(o)$. Assume m and n are the numbers of keywords for o and q, respectively, and $m \geq n$. Thus we have:

$$Pr_{KM}(o) \approx \begin{cases} 1 - \frac{C^m_{W_{dis}-n}}{C^m_{W_{dis}}}, & \text{if } m \leq W_{dis} - n \\ 1, & \text{otherwise} \end{cases}$$

Since we use the G-tree to compute the shortest path distances, the time cost for computing $D_{tr}(q, o)$ is $O(\tau * log\tau + log_f \frac{|V|}{\tau} * log^2_2 f * |V|)$ [37]. To sum up, the time complexity of A^2S^2KG algorithm is $O(\frac{k}{Pr_{cand}(o)} * (W^2_{dis} + V^2_{dis}) + \tau * log\tau + log_f \frac{|V|}{\tau} * log^2_2 f * |V|)$.

VI. Support Attributes with Interval Values

In real applications, the attribute value of an object is not necessarily a specific value, but usually an interval of values. In this section, we discuss extending our STAG-tree index to handle this situation, where the attribute value of the object is an interval of values.

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Algorithm 3: Gjudge function

input : $\mathcal{STAG}$, A^{2}SKIV query q, node s
output: $D^{LB}_{tns}(q, s)$
begin
  if $d_N^{\min}(q, s) > -\frac{1}{\rho}\ln(\frac{2}{\frac{D_{tsk}}{\gamma}+1} - 1)$ **then**
    return 1; //s is pruned by Lemma 1;
  if $\forall q_k \in q.W$, $q_k.signature \cap s.signature = \emptyset$ **then**
    return 1; //s is pruned by Lemma 2;
  if $\exists A_k \in q.V$, *such that* $Max(A_k)(or Min(A_k))$ *for* $\mathcal{G}_i.SGA$ *equals* $+\infty$ **then**
    return 1; //c is pruned by Lemma 3;
  if $D^{LB}_{tns}(q, s) > D_{tsk}$ **then**
    return 1; //s is pruned by Lemma 4;
  else
    HG.push(c, $D^{LB}_{tns}(q, s)$); //update D_{tsk} accordingly;
    return $D^{LB}_{tns}(q, s)$;

A. Modification of Numeric Distance Calculation

Firstly, we modify the calculation of the numeric distance between query q=($q.W$, $q.V$, $q.L$, k) and object o=($o.tags$, $o.V$, $o.L$), for objects with attributes of interval values (IV for short). Remember that numeric attribute distance refers to the degree of difference between the values of query q and object o under the same numeric attribute.

For query q and object o, the numeric distance d_k between q and o for attribute A_k of interval values, can be expressed as follows:

$$d_k = \begin{cases} +\infty, & \text{if } o.A_k \text{ not exists} \\ 0, & \text{if } o.A_k.IV \subseteq q.A_k.IV \\ M_k, & \text{if } o.A_k.IV \text{ does not intersect} \\ & \text{with } q.A_k.IV \\ |o.A_k.IV| - & \\ |o.A_k.IV \cap q.A_k.IV|, & \text{otherwise} \end{cases} \tag{6}$$

Then, by using formula (3), we normalize each non-infinite numeric attribute distance to range [0, 1], and comprehensively consider each non-infinite numeric attribute distance to calculate the total numeric distance between q and o.

Note: 1) M_k = $Max(A_k)$-$Min(A_k)$; 2) if there is any query attribute not existing in $o.V$, the numeric distance between q and o, i.e., $D_{nd}(q, o)$, equals $+\infty$.

B. Index Modification

Next, we discuss extending STAG-tree index to support queries and objects with attributes of interval values. In particular, the A-ref part needs to be modified to accommodate the interval values of numeric attributes for objects and queries.

Remember in Subsection IV.A, for each numeric attribute A_k ($1 \leq k \leq n$), we use $[k-1, k)$ to represent attribute value range of A_k. Moreover, we map $o_i.V_k$, which is the attribute value for A_k of object o_i within $\mathcal{G}_i$, to the value range of A_k by the key y(o_i^k)=$\frac{o_i.V_k}{M_k}+k-1$ ($1 \leq k \leq n$). To accommodate the interval values for attribute A_k, we use $o_i.V_k.L$ and $o_i.V_k.R$ to represent the left and right bound of the interval values for $o_i.A_k$, respectively. Then, map $o_i.V_k.L$ and $o_i.V_k.R$ to the value range of A_k by the key y($o_i^k.L$)=$\frac{o_i.V_k.L}{M_k}+k-1$ and y($o_i^k.R$)=$\frac{o_i.V_k.R}{M_k}+k-1$ ($1 \leq k \leq n$), respectively.

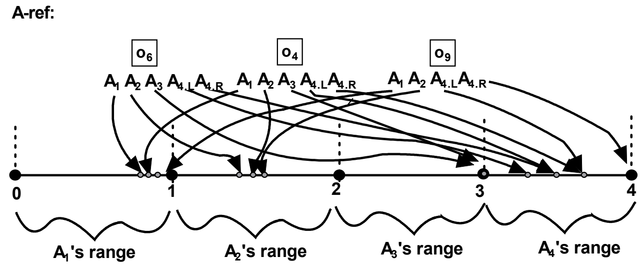

Fig. 6. A-ref modification.

TABLE II
CHARACTERISTICS OF THE DATA SETS

Attribute	FL	CAL
Number of vertices	1,070,376	21,048
Number of edges	1,356,399	21,693
Number of objects	10M	200k
Avg. number of keywords in objects	6.1	5.2
Avg. number of attributes in objects	4.3	4.1
Number of queries	1k	1k

Example 4. *As shown in Fig. 6, we add the fourth numeric attribute, i.e., A_4 (business hours), for the objects in the system, and the value range of A_4 is [3, 4). Assume that the business hours for o_6 are from 8:00 to 12:00, and M_4=24 since there are 24 hours in a day. Thus we have y($o_6^4.L$)=$\frac{8}{24}+4-1$ = 3.33, and y($o_6^4.R$)=$\frac{12}{24}+4-1$ = 3.50.*

The query processing steps are similar to that in Section V, except for the calculation of $D_{nd}(q, o)$.

VII. PERFORMANCE EVALUATION

A. Experimental Settings

1) Datasets: We use two datasets, Florida (FL for short) and California (CAL for short), to test the performance of the proposed methods. FL and CAL consist of the traffic network, the users, and points of interest (POIs) of Florida and California, respectively. The object information for CAL comes from the Geographic Names Information System in the United States (geonames.usgs.gov/domestic). Each object includes an object ID, a textual description, and a location within the road traffic network. For FL dataset, we use the objects extracted from Twitter (www.twitter.com), and each object includes an object ID, a Twitter message, a time of publication, and a location in the Florida transportation network. The detail information of FL and CAL is shown in Table II.

2) Queries: To evaluate the performance of A^{2}SKIV, we generate a set queries including locations, keywords, and attribute-value pairs. The keywords and attributes of A^{2}SKIV queries are also obtained from Twitter. In addition, attribute values are randomly selected and range from 1 to 1000. The number of query keywords and query attributes ranges from 1 to 5 and 1 to 4, respectively, with a default value of 2.

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TABLE III
EVALUATION PARAMETERS USED IN THE EXPERIMENT

Parameter	Values
Object cardinality ($\|D\|$)	FL: 2,4,**6**,8,10 (M) CAL: 10,50,**100**,150,200 (K)
Number of query results (k)	5,10,**15**,20,25
Number of query keywords ($\|q.W\|$)	1,**2**,3,4,5
Number of query attributes ($\|q.V\|$)	1,**2**,3,4
Preference parameter α	0.1,0.2,**0.33**,0.4,0.5
Preference parameter β	0.1,0.2,**0.33**,0.4,0.5
Preference parameter γ	0.1,0.2,**0.33**,0.4,0.5

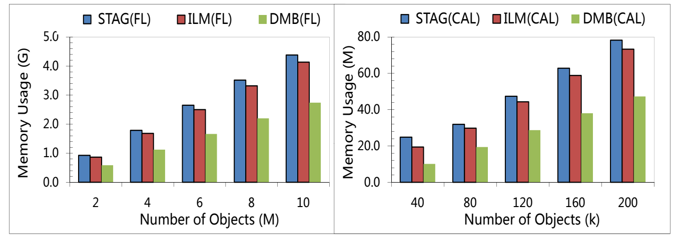
3) Algorithms: Our STAG-tree based method (STAG for short) will be compared with two baseline methods, DBM [26] and ILM [29], in terms of memory consumption and processing time. Specifically, DBM is based on Dijkstra method. Starting from query q, DBM performs network expansion for candidate objects, and calculates the textual-numeric-spatial distance of the object o encountered from query q, i.e, $D_{tns}(q, o)$. In order to accelerate the calculation of long road network distance, a multi-hop distance labeling scheme is adopted. ILM is an inverted-list based scheme. For each keyword w, let the set of n-grams [32] contained in w be S_w. Thus, for object o, we have S_o=$\cup_{w \in o.tags} S_w$. For each n-gram ζ, a list l_ζ containing the ID of objects, whose n-grams contain ζ, can be obtained. For each query keyword $q_i \in q.W$, S_{q_i} is computed, and then by using the Heap Algorithm [38], the object lists l_{ζ_j}s (for each $\zeta \in S_{q_i}$) are merged, to get a new list l_{q_i} of objects for q_i, whose objects are sorted in descending order of $|S_{q_i} \cap S_o|$. Thus, the objects sharing no common n-gram with q can be safely pruned. Similarly, for each query attribute A_i, we also have a list l_{A_i} containing the ID of objects which contain attribute A_i. Thus, the objects do not contain all the attributes $A_i \in q.V$ are ignored.

B. Efficiency Measurement

This subsection evaluates the performance of three methods by varying the object cardinality, number of query results (k), number of query keywords, number of query attributes, and the values of preference parameters (α, β, and γ). The memory space for query processing is also studied. The main parameters and their values are shown in Table III.

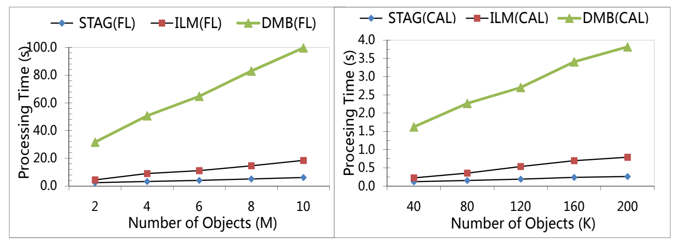
1) Memory Consumption: The memory consumption of three methods is shown in Fig. 7, which increases as the number of objects increases. The more objects, the more storage space they take up. Generally speaking, STAG and ILM consume more memory resource than that of DBM for both FL and CAL data sets. For ILM, the reason is that it builds an inverted list for each keyword and attribute, and the object IDs store multiple copies in inverted lists. As for STAG, we build T-ref and A-ref part to keep the textual and numeric information of each object.

2) Effect of $|D|$: The running time of methods w.r.t. the number of objects in the system is shown in Fig. 8. It is observed that STAG outperforms its competitors. On average, STAG-based approach is about 1.87x (17.1x, resp.) faster in processing time than the compared ILM (DBM, resp.) method. It is due to the fact that STAG can prune huge amounts



(a) FL data set (b) CAL data set

Fig. 7. Effect of $|D|$ on memory consumption.



(a) FL data set (b) CAL data set

Fig. 8. Effect of $|D|$ on processing time.

of unpromising objects based on network distance, textual similarity and attribute similarity, simultaneously. Fig. 8 also shows that the running time of three methods increases as the object cardinality increases. It is natural since more related objects need to be considered when there are more objects in IoV. Moreover, STAG and ILM are much more scalable on FL and CAL datasets than DBM, because DBM checks objects in the order being encountered. On the contrary, STAG and ILM arrange the objects according to keywords and attributes. Therefore, objects that do not contain all query attributes (or do not have any keyword similar to any query keyword) can be pruned securely, which makes both approaches more scalable than DBM.

3) Effect of k: The effect of value k (number of results wanted) on the running time of STAG, ILM, and DBM is evaluated. Fig. 9 shows that STAG significantly outperforms ILM and DBM, since it uses STAG-tree index to prune large parts of unqualified objects. On the contrary, DBM performs the worst because it examines all the objects in the order being encountered and then computes their textual-numeric-spatial distance values. As for the stability of methods when the value of k varies, all methods incur higher cost with larger k, because the larger k is, the more related objects need to be examined. For STAG, the increase of k value has no obvious effect on the performance due to the effective pruning scheme.

4) Effect of $|q.W|$: We also evaluate the query performance when the number of query keywords, $|q.W|$, varies. Fig. 10 shows that the running time of all methods increases with the increment of $|q.W|$. For STAG and ILM, the reason is that an object with any keyword similar to any query keyword has a chance to be one of the query results, thus more qualified objects need to be considered with larger $|q.W|$. The processing time of DBM increases slightly with larger $|q.W|$, because it requires more computation time to calculate the textual-numeric-spatial distance values of objects.

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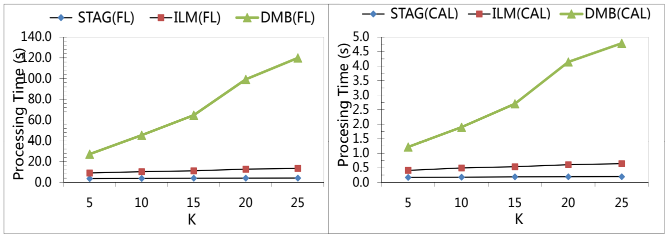
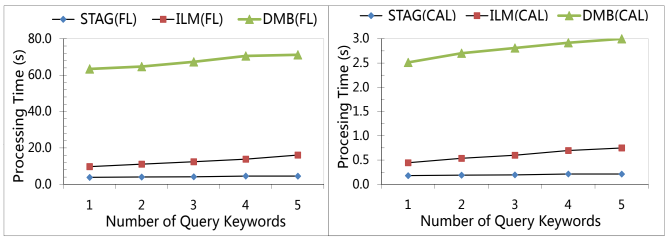


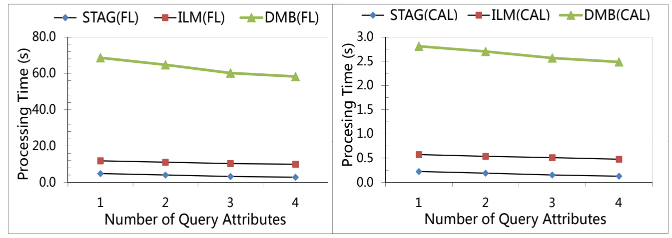
(a) FL data set (b) CAL data set

Fig. 9. Effect of k on processing time.



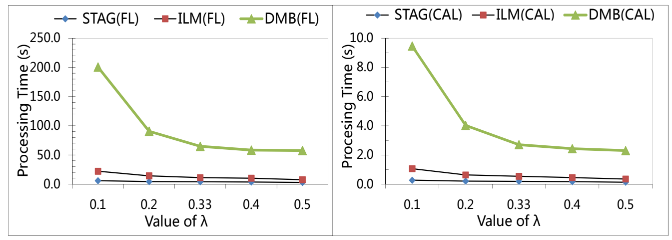
(a) FL data set (b) CAL data set

Fig. 10. Effect of $|q.W|$ on processing time.



(a) FL data set (b) CAL data set

Fig. 11. Effect of $|q.V|$ on processing time.



(a) FL data set (b) CAL data set

Fig. 12. Effect of γ on processing time.

Not surprisingly, STAG gets the best performance of three methods. For example, STAG requires only 36.4% (6.3%, resp.) processing time of ILM (DBM, resp.) when $|q.W|$ equals 3 for FL data set.

5) Effect of $|q.V|$: Now we continue to evaluate the impact of number of query attributes, $|q.V|$, on performance of three schemes. Fig. 11 shows that all methods incur less processing time with larger query attributes. The reason is twofold. On one hand, a candidate object is needed to contain all query attributes, and the more query attributes there are, the fewer eligible objects there are. On the other hand, the calculation of numeric distance values for candidate objects is little more difficult with more query attributes. Overall, the former outweighs the latter, so the total processing cost of the methods decreases as the number of query attributes increases. It is worth noting that the decreasing tendency of STAG is more obviously than its competitors due to its significant pruning ability, i.e., most of the cells (subgraphs) in STAG tree can be ignored as more attributes are queried.

6) Effect of α, β, and γ: Parameters α and β control the importance of textual and numeric similarity between queries and objects, respectively. When the value of α or β changes separately, there is no fixed impact pattern on the performance of query processing. As a result, we do not give the results of α and β for effective measurement, and only show the impact of γ on query efficiency. Note that varying the value of γ means varying the sum of α and β. Fig. 12 gives the query performance of these three methods for different γ values. Again, our STAG significantly outperforms its competitors. On average, it incurs only 38.0% (6.5%, resp.) query time of ILM (DBM, resp.) for CAL data set. As for the stability of methods when the value of γ varies, three methods incur lower cost with larger γ, since larger γ means the spatial proximity between the query and objects becomes more important, thus the candidate objects may locate within a more concentrate range and fewer relevant objects need to be considered.

VIII. Conclusion

This paper formulates and solves fog computing-based A^{2}SKIV in IoV. A fog-based network structure FCV is adopted to improve query processing efficiency and reduce query feedback time. To deal with A^{2}SKIV queries, a two-level hybrid index STAG-tree is proposed, whose first level is a G-tree which accelerates the calculation of the network distance between objects and the query, and whose second level is the textual & numeric component which efficiently organizes the information of objects within the subgraphs of traffic network in IoV. In addition, several lemmas are presented to prune a huge number of unqualified textual-spatial objects, and an efficient Top-k A^{2}SKIV query processing algorithm is presented. The effectiveness of the proposed index and query processing algorithm is verified by extensive experimental evaluation using real and composite data sets. The results also show that the proposed scheme is effective in applications like mobile search and targeted location-aware advertising in IoV.

References

[1] R. Yu, Y. Zhang, S. Gjessing, W. Xia, and K. Yang, “Toward cloud-based vehicular networks with efficient resource management,” *IEEE Network*, vol. 27, no. 5, pp. 48–55, 2013.

[2] J. Li, J. Jin, Y. Dong, and H. Zhang, “Virtual fog: A virtualization enabled fog computing framework for internet of things,” *IEEE Internet of Things Journal*, vol. 5, no. 1, pp. 121–131, 2018.

[3] M. Aazam and E. N. Huh, “Fog computing and smart gateway based communication for cloud of things,” in *International Conference on Future Internet of Things and Cloud*, 2014, pp. 464–470.

[4] K. Dan, K. Piratla, and C. J. Matthews, “Towards sustainable water supply: Schematic development of big data collection using internet of things,” *Procedia Engineering*, vol. 118, pp. 489–497, 2015.

[5] G. Li, C. Zhou, J. Li, and B. Guo, “Maintaining data freshness in distributed cyber-physical systems,” *IEEE Transactions on Computers*, vol. 68, no. 7, pp. 1077–1090, 2019.

[6] C. Yu, B. Lin, P. Guo, W. Zhang, S. Li, and R. He, "Deployment and dimensioning of fog computing-based internet of vehicle infrastructure for autonomous driving," *IEEE Internet of Things Journal*, vol. 6, no. 1, pp. 149–160, 2019.

[7] Y. Zhang, C.-Y. Wang, and H.-Y. Wei, "Parking reservation auction for parked vehicle assistance in vehicular fog computing," *IEEE Trans. Vehicular Technology*, vol. 64, no. 4, pp. 3126–3139, 2019.

[8] Z. Lamb and D. Agrawal, "Analysis of mobile edge computing for vehicular networks," *Sensors*, vol. 19, pp. 1303–1323, 2019.

[9] D. Zhang, K. L. Tan, and A. K. H. Tung, "Scalable top-k spatial keyword search," in *International Conference on Extending Database Technology*, 2013, pp. 359–370.

[10] Q. Zhou, G. Li, J. Li, and C. Deng, "Execution-efficient response time analysis on global multiprocessor platforms," *IEEE Transactions on Parallel & Distributed Systems*, vol. 29, no. 12, pp. 2785–2797, 2018.

[11] Y. E. Carlsson, "Keyword search on spatial network databases: Road network indexing for efficient query processing," *Master Thesis. Norwegian University of Science and Technology, Trondheim, Norway*, pp. 1–63, 2011.

[12] Q. Zhou, G. Li, J. Li, L. C. Shu, C. Zhang, and F. Yang, "Dynamic priority scheduling of periodic queries in on-demand data dissemination systems," *Information Systems*, vol. 67, pp. 58–70, 2017.

[13] L. Kuang, L. T. Yang, J. Chen, H. Fei, and C. Luo, "A holistic approach to distributed dimensionality reduction of big data," *IEEE Transactions on Cloud Computing*, vol. 6, no. 2, pp. 506–518, 2018.

[14] L. Guo, J. Shao, H. H. Aung, and K. L. Tan, "Efficient continuous top-k spatial keyword queries on road networks," *GeoInformatica*, vol. 19, no. 1, pp. 29–60, 2015.

[15] Z. Kuang, L. Li, J. Gao, L. Zhao, and A. Liu, "Partial offloading scheduling and power allocation for mobile edge computing systems," *IEEE Internet of Things Journal*, vol. 6, no. 4, pp. 6774–6785, 2019.

[16] F. Kong, J. Li, B. Jiang, and H. Song, "Short-term traffic flow prediction in smart multimedia system for internet of vehicles based on deep belief network," *Future Generation Computer Systems*, vol. 93, pp. 460–472, 2019.

[17] G. Mastorakis, E. Pallis, C. X. Mavromoustakis, L. Shu, and J. J. P. C. Rodrigues, "Special issue on multimedia services provision over future mobile computing systems," *IEEE Systems Journal*, vol. 12, no. 1, pp. 12–15, 2018.

[18] M. Mukherjee, S. Lei, and W. Di, "Survey of fog computing: Fundamental, network applications, and research challenges," *IEEE Communications Surveys and Tutorials*, vol. 20, no. 3, pp. 1826–1857, 2018.

[19] C. Sheng, W. Liao, C. Luo, L. Ming, and L. Pan, "Cril: An efficient online adaptive indoor localization system," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 5, pp. 4148–4160, 2017.

[20] S. Salinas, C. Luo, X. Chen, W. Liao, and P. Li, "Efficient secure outsourcing of large-scale sparse linear systems of equations," *IEEE Transactions on Big Data*, vol. 4, no. 1, pp. 26–39, 2018.

[21] M. Aazam and E. N. Huh, "Dynamic resource provisioning through fog micro datacenter," in *IEEE International Conference on Pervasive Computing and Communication Workshops*, 2015, pp. 105–110.

[22] X. Hou, Y. Li, M. Chen, D. Wu, D. Jin, and S. Chen, "Vehicular fog computing: A viewpoint of vehicles as the infrastructures," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 6, pp. 3860–3873, 2016.

[23] Y. Yuan, X. Lian, L. Chen, J. Yu, G. Wang, and Y. Sun, "Keyword search over distributed graphs," *IEEE Transactions on Knowledge and Data Engineering*, vol. 29, no. 6, pp. 1212–1225, 2017.

[24] X. Miao, Y. Gao, G. Su, and C. Gang, "On efficiently answering why-not range-based skyline queries in road networks," *IEEE Transactions on Knowledge & Data Engineering*, vol. 30, no. 9, pp. 1697–1711, 2018.

[25] J. Yang, Y. Zhang, X. Zhou, J. Wang, H. Hu, and C. Xing, "A hierarchical framework for top-k location-aware error-tolerant keyword search," in *Proceedings - International Conference on Data Engineering*, 2019, pp. 986–997.

[26] L. Chang, J. X. Yu, L. Qin, H. Cheng, and M. Qiao, "The exact distance to destination in undirected world," *Vldb Journal*, vol. 21, no. 6, pp. 869–888, 2012.

[27] Y. Gao, X. Qin, B. Zheng, and G. Chen, "Efficient reverse top-k boolean spatial keyword queries on road networks," *IEEE Transactions on Knowledge and Data Engineering*, vol. 27, no. 5, pp. 1205–1218, 2015.

[28] J. Zhao, Y. Gao, C. Gang, and C. Rui, "Towards efficient framework for time-aware spatial keyword queries on road networks," *Acm Transactions on Information Systems*, vol. 36, no. 3, pp. 1–48, 2017.

[29] D. Zhang, Y. Li, X. Cao, J. Shao, and H. T. Shen, "Augmented keyword search on spatial entity databases," *Vldb Journal*, vol. 27, no. 2, pp. 225–244, 2018.

[30] Y. Li, M. Wang, R. Zhu, and A. Anjum, "Intelligent augmented keyword search on spatial entities in real-life internet of vehicles," *Future Generation Comp. Syst.*, vol. 2019, no. 94, pp. 697–711, 2019.

[31] T. Abeywickrama, M. A. Cheema, and A. Khan, "K-spin: Efficiently processing spatial keyword queries on road networks," *IEEE Transactions on Knowledge and Data Engineering*, vol. PP, no. 99, pp. 1–1, 2019.

[32] L. Gravano, P. G. Ipeirotis, H. V. Jagadish, N. Koudas, S. Muthukrishnan, and D. Srivastava, "Approximate string joins in a database (almost) for free," in *VLDB*, 2001, pp. 491–500.

[33] S. Alsubaiee, A. Behm, and L. Chen, "Supporting location-based approximate-keyword queries," in *Sigspatial International Conference on Advances in Geographic Information Systems*, 2010, pp. 61–70.

[34] X. Wang, X. Ding, A. K. H. Tung, and Z. Zhang, "Efficient and effective knn sequence search with approximate n-grams," *Proceedings of the VLDB Endowment*, vol. 7, no. 1, pp. 1–12, 2013.

[35] B. Zheng, N. J. Yuan, K. Zheng, X. Xie, S. Sadiq, and X. Zhou, "Approximate keyword search in semantic trajectory database," in *Proceedings - International Conference on Data Engineering*, 2015, Seoul, South Korea, pp. 975–986.

[36] B. Yao, F. Li, M. Hadjieleftheriou, and K. Hou, "Approximate string search in spatial databases," in *Proceedings - International Conference on Data Engineering*, 2010, pp. 545–556.

[37] R. Zhong, G. Li, K. L. Tan, and L. Zhou, "G-tree: an efficient index for knn search on road networks," *ACM International Conference on Information and Knowledge Management*, pp. 39–48, 2013.

[38] S. Sarawagi, S. Sarawagi, A. Kirpal, and A. Kirpal, "Efficient set joins on similarity predicates," *Proc. of the Acm Sigmod Intl. conf. on Management of Data*, pp. 743–754, 2004.

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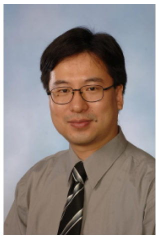

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