An Indoor Knowledge Graph Framework for Efficient Pedestrian Localization

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Abstract—A large amount of information including indoor spatial structure information and smartphone sensor information can be utilized for indoor localization. However, it remains an open challenge to efficiently organize and effectively integrate this data to achieve accurate indoor localization. Knowledge Graphs have powerful intuitive data representation capabilities, semantic and relational processing capabilities, and efficient data storage and feedback mechanisms. Introducing Knowledge Graphs to indoor localization can effectively improve positioning accuracy and subsequently, enrich indoor location-based services. This article presents a Knowledge Graph framework that integrates the basic structure of the indoor environment and various types of smartphone sensing data for indoor localization. This framework consists of two sections: indoor space ontology and mobile sensing data. The indoor space ontology expresses the indoor spatial structure and relationship data, while the sensor sensing data includes a large amount of sensor information generated by pedestrians during indoor activities. Experimental results confirm that the proposed Knowledge Graph framework can achieve efficient indoor localization with good scalability and flexibility under various indoor circumstances.

Index Terms—Indoor navigation, sensor fusion, knowledge representation.

I. INTRODUCTION

CONVENIENT and pervasive indoor localization technology is of great significance for promoting indoor location-based Internet of Things (IoT) applications. Unlike the tremendously successful outdoor localization applications that utilize the Global Navigation Satellite Systems (GNSS), indoor location-based services are still in their infancy. Driven by the proliferation of smartphones with rich built-in sensors, various indoor localization technologies have been developed for location-based applications and services. Information supporting indoor localization includes spatial structure information provided by maps or indoor special models, as well as smartphone sensing information such as WiFi strength, magnetic field strength (MFS) and inertial navigation data [1], [2]. However, it remains an open challenge on how to efficiently organize and effectively integrate various information sources for indoor location-based services.

The Knowledge Graph is a large network of interconnected entities constructed from associating different kinds of knowledge [3]. Its efficient structure and relational information are key resources for many applications. At present, it has been successfully applied in many areas including semantic searching, natural language processing and intelligent question answering. Moreover, the Knowledge Graph has good flexibility and expansibility, which can be incrementally improved and enriched with additional information acquired over a period of time.

Introducing Knowledge Graphs to indoor localization can effectively improve localization accuracy and subsequently, enrich indoor location-based services. More specifically, an indoor Knowledge Graph can integrate various existing indoor information sources (such as spatial model, objects of interest, user profiles, environmental information and semantic descriptions) while supporting knowledge search and relational expression [4]. As a result, a successful indoor Knowledge Graph is able to achieve accurate and efficient indoor localization services in a variety of complex indoor scenes.

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However, several challenges have to be overcome before Knowledge Graphs can be practically utilized in indoor localization. First, structural and relationship information has to be well organized and expressed even in complex indoor environments. Second, successful integration of smartphone sensing data with spatial structure data is very critical. To cope with the challenges above, a node-edge schema is designed in this work to express the spatial structure and relationship information in the indoor environment. More importantly, the indoor Knowledge Graph can fuse all kinds of smartphone sensing information, which can be used to enrich and extend various indoor location-based services.

As a result, the proposed framework makes the tasks of collecting, expanding and updating the sensor data using smartphones more effective. The specific contributions of this work can be summarized as follows:

- An indoor ontology composed of nodes and edges is developed in this work. The ontology is capable of expressing indoor spatial structure and relationship information;
- In addition, an indoor Knowledge Graph with good scalability and flexibility is proposed to fuse the basic structure of the indoor environment and various types of smartphone sensing data;
- Finally, an efficient and stable scheme combining action matching, WiFi strength matching and MFS sequence matching for indoor localization is established based on the proposed indoor Knowledge Graph.

The remainder of this article is organized as follows: Section II briefly reviews the related studies while Section III introduces the indoor Knowledge Graphs. After that, Section IV elaborates the method of indoor localization using Knowledge Graphs. Finally, experimental results and discussions are provided in Section V followed by the conclusions in Section VI.

II. RELATED WORKS

In 2012, Google proposed the concept of Knowledge Graphs to enhance its search engine services. Since then, Knowledge Graphs have been widely employed in intelligent search engines, intelligent question and answer, personalized recommendations and other fields. The predecessor of Knowledge Graphs was actually the Semantic Network. The Semantic Network is a structured way to represent knowledge by using graphs composed of nodes and edges with nodes representing objects or concepts while edges the relations between them. By establishing a universal information exchange medium that can be understood by computers, the Semantic Network is able to greatly improve the search efficiency and reasoning ability of the network. Despite that it is easy to understand and use, the Semantic Network, it is difficult to integrate multi-source data in the Semantic Network. Furthermore, it is non-trivial to define labels for nodes and edges in the Semantic Network.

In contrast, Knowledge Graphs can aggregate information gathered from a variety of sources, making information resources easier for computation, comprehension and evaluation. As a result, Knowledge Graphs can form a series of semantic knowledge bases. In particular, linked open data (LOD) is an important source of Knowledge Graph data, which has a broad coverage with emphasis on integrating more entity data including Freebase, Wikidata, DBpedia and YAGO [5–8]. In contrast, there exist some industry knowledge bases, also known as vertical knowledge bases. These vertical knowledge bases are usually constructed from specific industry data with a more focused coverage. Typical examples of these vertical knowledge bases include the internet movie database (IMDB) [9] and an open music encyclopedia (MusicBrainz) [10]. The introduction of Knowledge Graphs has exerted a positive impact on many industries including the indoor localization services.

Indeed, many indoor spatial models had been studied and developed before the introduction of Knowledge Graphs. According to the modeling approach, indoor spatial models can be categorized into geometric spatial models and symbolic spatial models. Geometric spatial models represent indoor space by points, lines and areas while symbolic spatial models focus on the description and connection of objects. The geometric spatial model provides accurate location information but lacks the capability of incorporating context-awareness information. In contrast, the symbolic spatial model reveals the connectivity and reachability between spatial entities but is unable to offer an accurate indoor structure [11], [12]. Thus, the hybrid spatial model that combines the advantages of the geometric and symbolic approaches is considered to be a promising alternative [13], [14]. However, the spatial model alone remains insufficient for indoor localization services. Recently, the indoor ontology has received much attention with its advantages in semantic and relational expressions. By exploiting its ontology model, [15] develops an indoor shopping recommendation system capable of localizing shoppers and providing the most suitable shopping route. To extend the scope of the indoor ontology model, an indoor activity ontology focusing on semantic queries and data management is established in [16]. In addition, the ontology for both indoor localization and navigation has also been studied. For instance, OntoNav is an ontology-based navigation system for indoor environments. The system can express the user’s cognitive characteristics and the semantic information of various indoor elements [17]. In [18], an Indoor Navigation Ontology (INO) is designed for presentation tasks and path searches. Furthermore, an INO-based spatial ontology associated with the actual content and basic elements of the path selection is proposed in [18]. In [19], various special requirements and the corresponding routing algorithms are derived.

Some recent studies have attempted to utilize the indoor spatial models for indoor localization [20]. In general, indoor localization methods can be categorized into two approaches, namely infrastructure-based and infrastructure-free approaches [20]. For infrastructure-based methods, special equipment is deployed to help indoor position estimation [21], [22]. In contrast, the infrastructure-free approach takes advantage of already existing systems such as WiFi strength and magnetic field strength [23], [24]. For instance, Zee is designed to perform user tracking by exploiting the sensors built in the cellphone and the floorplan [25]. After a user walks...
a sufficiently long distance, Zee can determine a unique trajectory by mapping the sensor data onto the floorplan. During this process, Zee also simultaneously collects WiFi information for WiFi fingerprinting-based localization. FOLLOWME is another well-known infrastructure-free solution that exploits multiple sensors to guide the users to the same destination taken by “an earlier leader” [26]. The leader’s reference trajectory is obtained by combining features extracted from sensor data with the leader’s walking pattern. Despite its many advantages, FOLLOWME requires a prior reference trace with the same origin and destination.

As suggested by the discussions above, most existing indoor localization methods either overlook sensing information or ignore indoor entity information. In this work, we design an ontology that can integrate indoor entity information and sensor sensing information. Based on this Knowledge Graph, we can perform indoor localization by fusing a variety of sensors, and can handle the difficulties in indoor localization such as initial position determination and short-range walking trajectory tracking. In a recent study, the authors proposed an indoor localization method based on a landmark graph [27]. Many landmarks include acceleration landmarks, gyroscope landmarks, barometer landmarks, WiFi landmarks, and light landmarks are introduced to construct and update the landmark graph. This makes the localization accuracy of this system subject to the density and stability of these landmarks. In contrast, the proposed entity-based graph, which is extracted through a map, has a stable structure and is able to correlate with various types of virtual information to provide more stable positioning services in indoor environments in different situations.

III. INDOOR KNOWLEDGE GRAPHS

A. Framework

The proposed framework is able to describe the basic elements and relationships in the indoor environment, as well as basic data collected by smartphone sensors. This article introduces an indoor Knowledge Graph framework for indoor pedestrian localization. The proposed framework includes indoor space ontology and sensor data, as shown in Fig. 1.

The defined indoor space ontology is mainly composed of nodes and edges. The nodes are divided into four categories, namely turn nodes, stair nodes, elevator nodes and door nodes. Furthermore, the edges include individual edges and combined edges. The starting or end point of each edge is also a node. In addition to nodes and edges, the proposed framework is designed to incorporate sensor data obtained from smartphone built-in sensors including accelerometers, gyroscopes, magnetometers and WiFi receivers. As a result, the proposed framework can combine indoor structural information with sensor information through pedestrian activities. Specifically, in the process of pedestrian indoor activities, a large amount of sensor data collected by smartphones can be organized and stored through the indoor space ontology. By exploiting the indoor ontology in data relation expression and reasoning, the proposed framework can improve the accuracy and efficiency of pedestrian indoor localization.

B. Description of the Indoor Knowledge Graph

A triple is the most general representation of a Knowledge Graph [28]. The basic forms of triples include (entity - relationship - entity) and (entity - attribute - attribute value).
The proposed indoor Knowledge Graphs are also organized in the same way.

1) Indoor Knowledge Entity: Indoor knowledge entities include real location points and routes in an indoor environment. These special location points and routes are defined as nodes and edges in the proposed ontology. As previously discussed, nodes are divided into four categories, namely turn nodes, stair nodes, elevator nodes and door nodes. Each node can inherit the attributes of its parent node. Furthermore, each node entity may be associated with multiple types of functional data, including WiFi, magnetic, inertial and other information. As shown in Fig. 2, ID and Name are the identities of an entity, where ID is unique. Action stores actions that pedestrians may perform at the entity, a node entity usually has multiple actions in an indoor environment. WiFi Strength refers to the WiFi signal information that can be received at the entity node. WiFi Strength is stored in the form of a dictionary, such as [AP1 : RSSI1], [AP2 : RSSI2], [AP3 : RSSI3]. The WiFi dictionary can contain one or more entries. Furthermore, entries can be added to the dictionary continuously in practical applications. Finally, relative coordinates are measured and calculated according to the indoor map.

Similarly, edge entities also have attributes such as ID, Name and Action as shown in Fig. 3. The difference is that the edge entity is associated with sequence data, which is more recognizable. For example, an MFS sequence can be expressed as [MFS1, MFS2, MFS3, ...]. Distance represents the length of the edge entity. The direction attribute of data is given by the direction of data acquisition. In addition, each entity can store multiple data samples to improve its data stability.

2) Indoor Knowledge Relationship: The relationship between entities mainly defines inclusion and adjacency. Each edge entity contains a starting node and an end node. If the end node of one edge entity is the starting node of another edge entity, then the two entities are adjacent as shown in Fig. 4. In addition, a combined edge entity consists of two or more adjacent individual edge entities with the same direction information, as shown in Fig. 5. Relational data is of great significance for improving the efficiency and stability of information. In the process of information retrieval, relational data can greatly reduce the scope of the search. For example, when a user arrives at a node entity, it only needs to match the information collected afterward and the entity associated with the node to determine the user’s next location. On the other hand, relational data can infer search results even with partial information.

3) Indoor Knowledge Rules: Specific rules should be followed in the construction and use of indoor Knowledge Graphs. Entities in Knowledge Graphs can be extracted from existing indoor maps while the corresponding actions of the entities can be obtained according to the map features. Each entity contains one or more directional actions. Other information associated with the entity needs to be obtained through the smartphone sensors. The information collected through multiple smartphone sensors can be utilized to continuously update and supplement the Knowledge Graph during the positioning process. Therefore, the proposed indoor Knowledge Graph can be constructed and improved through crowdsourcing technology, which provides a convenient and efficient way of utilizing the collected data.

IV. INDOOR PEDESTRIAN LOCALIZATION USING THE PROPOSED FRAMEWORK

A. Smartphone Sensor Data Collection

The data collected by the smartphone sensors include the geometric information provided by the inertial sensor, the triaxial magnetic field data and the MFS sequence data collected by the magnetometer, the Media Access Control (MAC) address and the strength data collected by the WiFi receiver.

1) Inertial Sensor Data: Based on the data collected by the built-in inertial sensor of the smartphone, the relative trajectory of pedestrians walking indoors can be easily obtained by the pedestrian dead reckoning (PDR) algorithm [29]. More specifically, the steps can be detected according to the peak value of the acceleration. Similarly, the magnitude of the
acceleration change can be used to estimate the step length. The step length in Step $k$ can be computed as

$$l_k = \mu^4 \sqrt{a_{\text{max}}(k) - a_{\text{min}}(k)},$$

where $\mu$ denotes the pedestrian’s stride length parameter, $a_{\text{max}}(k)$ and $a_{\text{min}}(k)$ stand for the maximum and minimum synthetic acceleration values in this step, respectively.

After obtaining steps and step-lengths, the distance information can be easily derived as follows:

$$D(\mathcal{M}) = \sum_{k=1}^{N_{\text{step}}} l_k,$$

where $N_{\text{step}}$ is the total number of steps.

In addition to the inertial sensor, the gyroscope in the smartphone is also utilized to obtain angular changes during walking. The angular value $\theta$ of each step obtained by the gyroscope is given as follows:

$$\theta = \sum_{i=1}^{N_{\text{sample}}} \rho_i \cdot \Delta t,$$

where $\rho_i$ and $\Delta t$ stand for the angular velocity value of each sample and the sampling interval, respectively. $N_{\text{sample}}$ represents the number of samples in a step.

2) WiFi Data: WiFi networks have been widely deployed in indoor environments. It is very convenient to use smartphones to collect WiFi information, including the MAC address and the received signal strength. Each node entity stores the WiFi signal information derived from different WiFi Access Points (APs). In order to collect WiFi data, we perform a WiFi signal scan at each node entity to obtain the Basic Service Set IDentifier (BSSID) and strength information of the WiFi signal. The WiFi data derived from Node$_i$ is represented in the following format:

$$\text{Node}_i(x_i, y_i) : \{\text{Bssid}_{i1}, \text{Level}_{i1}\}, \{\text{Bssid}_{i2}, \text{Level}_{i2}\}, \cdots, \{\text{Bssid}_{iK}, \text{Level}_{iK}\},$$

where $(x_i, y_i)$ represents the node coordinates while Bssid$_{ik}$ and Level$_{ik}$ indicate the existing WiFi address and the received signal strength of the $k$-th BSSID for $k = 1, 2, \cdots, K$ with $K$ being the total number of BSSID’s that Node$_i$ observes.

3) Magnetometer Data: Magnetic field data can be collected anywhere by a magnetometer at high frequency and low energy consumption. These characteristics of magnetometer data make it a good choice for indoor localization. However, such magnetometer data has only three dimensions, which makes it challenging to uniquely characterize a large number of locations. To cope with this obstacle, we propose to utilize MFS sequences as they are more stable and distinguishable.

In this work, we collect MFS sequence data for the edge entity. Despite that the MFS value changes with time, but the trend of an MFS sequence remains consistent. Therefore, the MFS sequence data can provide long-term stable localization support.

In the collected MFS data, each edge entity in the Knowledge Graph corresponds to multiple MFS sequences. As edge entities may have different lengths, they usually have different sample numbers as well. Even for the same edge entity, different sequences may comprise different sample numbers because of different step lengths and walking speeds. Fig. 6 shows the MFS sequences of three consecutive edge entities.

A low-pass filter is applied to smooth the MFS data and remove the spurious peaks. Fig. 7 shows that the sequences of the same entity share strong similarities while the sequences between different edge entities are highly distinguishable, which makes the collected data suitable for the matching purposes.

B. Construct an Indoor Knowledge Graph

Neo4j is the current mainstream database for constructing Knowledge Graphs [30]. Its advantages include that it can easily represent both connected and semi-structured data as well as quickly retrieve and traverse data. Furthermore, Neo4j has good scalability in handling large-scale nodes, relationships and attributes. These characteristics make Neo4j ideal for expressing and managing indoor elements.

Next, we extract entity information from indoor maps. Fig. 7 shows the floorplan of the experimental site and the extracted entities. The red dots represent the elevator nodes while the yellow and green dots indicate the turn nodes and the door nodes in the experimental site, respectively. The lines between two adjacent nodes are edge entities that are considered to be directional in our experiments.
After extracting entities, we associate the entities through simple relationships including parent-child relationship and start-end relationship. Subsequently, the attributes of each entity are added to enrich the entity content. These attributes include the ID and name of the entity itself, the actions extracted from the indoor map, the WiFi and magnetic field data collected by the sensors. For instance, part of the Knowledge Graph constructed in this scenario is shown in Fig. 8. After extracting the map information and adding a small amount of collected WiFi and MFS information, the attribute information of these entities is shown in Table I and Table II. A node entity usually contains multiple actions while an edge entity has direction as well as distance. Furthermore, even though different edge entities have the same attributes, their corresponding MFS still have large differences, as expressed in the form of graphs in Table III. The WiFi and magnetic data of each entity can contain one or more entries that can be added continuously.

### C. Pedestrian Localization Based on Indoor Knowledge Graph

The proposed indoor Knowledge Graph is designed to provide pedestrian location services in a variety of situations. For different situations, we develop different pedestrian indoor positioning solutions based on the proposed indoor Knowledge Graph.

### 1) Indoor Localization Based on WiFi

A smartphone can localize itself by first measuring the WiFi strength. Since the WiFi strength information is stored in the node entity, WiFi signal matching can be used to determine the user’s position. The data in the node entity is used as the fingerprint database. Furthermore, the newly collected data is used to calculate the Euclidean distance from each data point in the database. The node corresponding to the shortest distance is considered to be the estimated location point. In practice, arbitrary points are selected as starting points each of which contains WiFi data as follows:

\[
\text{Unknown Point}_i = [\text{Bssid}_1, \text{Level}_1], [\text{Bssid}_2, \text{Level}_2], \ldots, [\text{Bssid}_m, \text{Level}_m],
\] (5)
where \( m \) denotes the number of stable WiFi signals detected in the experimental environment. However, due to the limited density of node entities, this method can only achieve coarse positioning. In the following, inertial sensor data can be further used to derive the initial position.

2) Indoor Localization Based on WiFi and Action Information:
If a pedestrian walks indoors for a short distance, it is highly likely that he passes some special points such as a door, a staircase or an elevator point. By exploiting the inertial sensor data, special points in the trajectory can be efficiently identified \[31\]. After these special points are detected, we can combine the pedestrian action information with the WiFi information in the framework. More specifically, these special points correspond to node entities in the indoor Knowledge Graph. Therefore, we use the information obtained at these nodes such as action and WiFi information to match the information stored in the Knowledge Graph to localize pedestrians.

3) Indoor Localization Based on Multi-Sensor Information:
While a pedestrian is walking indoor, sensors including accelerometers, magnetometers, gyroscopes and WiFi can collect a large amount of raw data. By analyzing this data, information corresponding to entity attributes in the Knowledge Graph can be derived, e.g., distance, direction, action, WiFi and MFS sequence information. The association between the entity and the sensor is shown in Table IV.

Based on the detected special points, a trajectory can be divided into multiple trajectory segments. These special points and trajectory segments correspond to node entities and edge entities in the indoor Knowledge Graph, respectively. For example, as shown in Fig. 10, four special points in a trajectory are detected, including three turn nodes (Node 1 - Node 3) and one door node (Node 4). Thus, the trajectory is divided into five segments (Segment 1 - Segment 5). Except for the first segment (Segment 1) and the last segment (Segment 5), each segment should have a corresponding edge entity.

According to its characteristics, the collected information with different priorities is processed to achieve efficient indoor positioning. The generated action sequence is first used to match the information in the Knowledge Graph. After that, distance, WiFi and MFS sequence information is used sequentially to determine a unique trajectory. Specifically, our proposed scheme performs the following procedures:

![Fig. 8. Part of the indoor Knowledge Graph.](image)

![Fig. 9. Variation of sensors for different actions.](image)

![Fig. 10. Trajectory segmentation.](image)
TABLE IV
ENTITY AND SENSOR DATA ASSOCIATION

<table>
<thead>
<tr>
<th>Entity</th>
<th>Name</th>
<th>Description</th>
<th>Associated sensors</th>
<th>Corresponding changes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Node</td>
<td>Action</td>
<td>Common indoor actions include walking, turning, going up(or down) the stairs, opening a door. WiFi signal strength collected at each node, i.e. WiFi fingerprint dataset.</td>
<td>Accelerometer, gyroscope, magnetometer</td>
<td>Different sensor changes correspond to different actions, as shown in Fig. 9. The WiFi data collected at the current location matches the closest WiFi fingerprint.</td>
</tr>
<tr>
<td>WiFi Strength</td>
<td></td>
<td></td>
<td>WiFi</td>
<td></td>
</tr>
<tr>
<td>Edge</td>
<td>Action</td>
<td>Walking</td>
<td>Accelerometer, gyroscope, magnetometer</td>
<td>Based on the sensor data, the PDR is able to obtain the walking distance. The measured MFS sequence matches the most similar stored sequence.</td>
</tr>
<tr>
<td></td>
<td>MFS sequence</td>
<td>Stores the MFS sequence corresponding to each edge.</td>
<td>Magnetometer</td>
<td></td>
</tr>
</tbody>
</table>

1) Action matching: In this first step, we propose to match the action information in trajectory with the constructed Knowledge Graph. Taking the trajectory in Fig. 10 as an example, we can obtain the action sequence of the trajectory as: “walking (east), turn right (east-south), walking (south), turn right (south-west), walking (west), turn right (west-north), walking (north), opening a door (north)”. After this procedure, six matching results are identified. With reference to Fig. 11, these six matching results are represented as
- \( T_1: (S_1, t_{27}, t_{25}, t_{28}, d_{17}) \),
- \( T_2: (S_2, t_{27}, t_{25}, t_{18}, t_{22}, d_{16}) \),
- \( T_3: (S_2, t_{25}, t_{18}, t_{21}, d_{15}) \),
- \( T_4: (S_2, t_{25}, t_{18}, t_{20}, d_{14}) \),
- \( T_5: (S_2, t_{25}, t_{18}, t_{20}, d_{13}) \).

2) Screening based on a distance threshold: The distance of each trajectory segment in Fig. 10 can be calculated from the data acquired by the inertial sensor. The distance values of the five trajectory segments (Segment 1 - Segment 5) are 3.47 m, 8.33 m, 5.38 m, 0.98 m, 1.47 m, respectively. Since the distance estimated by the inertial sensor contains certain errors, a threshold \( \mu \) is set to determine whether the distance condition is satisfied. In Fig. 10, except for the first segment (Segment 1) and the last segment (Segment 5), each segment (Segi) should have a corresponding edge entity (Edgei). Denote by \( \text{Dis}(Segi) \) and \( \text{Dis}(Edgei) \) the distance of the segment and entity, respectively. Then, \( \text{Dis}(Segi) \) and \( \text{Dis}(Edgei) \) should meet the following conditions defined with \( \mu \):

\[
(1 - \mu)\text{Dis}(Segi) \leq \text{Dis}(Edgei) \leq (1 + \mu)\text{Dis}(Segi).
\]

Using the distance threshold above, we have found three trajectories, namely \( T_1, T_2 \) and \( T_4 \), that meet the requirement above.

3) WiFi signal strength matching: Received WiFi signal strength at nearby locations, e.g. \( d_{17} \) and \( d_{18} \), are expected to be similar, which makes the matching result prone to errors. Therefore, we only regard distant points (more than three meters) as matching targets. Among the possible three trajectories obtained in the previous step, Node 2 may correspond to node entities t_{25} or t_{18}. By matching the WiFi list obtained at Node 2 with the WiFi information stored in the two node entities, it is easy to exclude node entity t_{18}. Therefore, after WiFi signal strength matching is performed, only two trajectories, namely \( T_1 \) and \( T_2 \), satisfy the conditions and are kept.

4) MFS sequence matching: Each trajectory segment has a corresponding MFS sequence that has to be matched to the magnetic data stored in the entity. We propose
to use the Dynamic Time Warping (DTW) algorithm for MFS sequence comparison in this work due to its capability of comparing sequences of different lengths. More specifically, the DTW distance between the MFS sequence corresponding to Segment 4 and the existing MFS sequence in edge entities (\(t_{28} - d_{18}\) and \(t_{29} - d_{17}\)) is calculated as shown in Fig. 12. The entity corresponding to the shortest DTW distance is the matching result of Segment 4. After the MFS sequence matching, we can identify the unique trajectory (\(T_2\)).

5) Starting and end position estimation: Since we do not limit the starting and end positions, the first and last trajectory segments usually do not correspond to the complete entities. Therefore, we use the determined node entities (e.g., \(t_{27}\) and \(d_{17}\)) to calculate the starting and end positions. Position estimation error will be further analyzed in the next section.

It is worth noting that the magnetometer and WiFi do not perform positioning alone, but take full advantage of their respective strengths to assist in positioning. For example, when matching WiFi signal strength, we only regard distant points (more than three meters) as matching targets. On the other hand, we only use MFS sequence matching to determine the position when the two trajectories are in the adjacent areas and are very similar.

V. DISCUSSIONS

A. Experiment Setup

To better illustrate the proposed Knowledge Graph framework as well as its applications in indoor localization, we collected data for the fourth floor of a building on the campus of the Chinese University of Hong Kong, Shenzhen in China. The total floor space of the experimental site is about 2,500 square meters and is featured with elevators, stairs, doors, and rooms. Furthermore, multiple Mi 6 smartphones produced by the Xiaomi Corporation were used in the experiments. The Mi 6 smartphone is equipped with all aforementioned sensors including the accelerometer, gyroscope, magnetometer, and WiFi. In addition, the phone is empowered by a Snapdragon 835 processor with 6 GB RAM. In order to collect WiFi information for the node entity, the pedestrian holds the smartphone and stays at each node entity for about 30 seconds to collect WiFi signals. On the other hand, pedestrians walked inside the building to collect magnetometer data for each edge entity. Data is collected by a proprietary data collection APP running on the smartphone. The collected data includes WiFi receiver, three-axis acceleration, three-axis gyroscope, and three-axis magnetometer information.

We extract entity information from indoor maps. In addition to the geometric information that can be directly inferred from the map, the entity’s associated information also includes sensor information collected at each entity using a smartphone. While a pedestrian is walking indoor, sensors including accelerometers, magnetometers, gyroscopes, and WiFi can collect a large amount of raw data. By analyzing this data, information corresponding to entity attributes in the Knowledge Graph can be derived. In general, we first build a database based on the Knowledge Graph and then compare the new data with it to get the best match.

As a fingerprint database for subsequent matching, we need to first manually correlate the entities with the MFS and WiFi data. Similar to most fingerprint matching methods, the construction of the fingerprint database is time-consuming work. Fortunately, the structure of the Knowledge Graph is not complex and can effectively reduce this consumption. Specifically, there are 54 individual edges and 54 node entities in the Knowledge Graph. In other words, we only need 108 data collections to complete the database construction. The average length of the individual edge entities was 4.5 meters, and the data collection time for each edge was approximately 4 seconds based on the walking speed of the pedestrians. Similarly, for each node entity, it takes approximately 5 seconds to collect WiFi data. Therefore, this time spent is acceptable for a total floor area of approximately 2500 square meters.

The proposed solution consists of two phases: offline training and online localization. In the offline phase, we extract entities from the indoor map and add geometric information to those entities. In addition, we collect virtual information in the indoor environment at each entity through the sensor that comes with the smartphone. The data collected by the smartphone sensor includes inertial data and WiFi data. Subsequently, this information is used to construct an indoor Knowledge Graph. In the online phase, five processes are used to determine the position of indoor pedestrians, which are action matching, screening based on a distance threshold, WiFi signal strength matching, MFS sequence matching, starting and end position estimation.

B. Matching Accuracy Analysis

Clearly, matching the collected WiFi and magnetic data with the Knowledge Graph is very critical. In Fig. 10, we have collected ten sets of the WiFi signal strength data for each node entity and ten sets of MFS sequence data for each edge entity. In order to evaluate the performance of the proposed
matching method, 10-fold cross-validation has been used. Table V shows the matching accuracy as well as the entities that are prone to matching errors.

Inspection of the experimental results has revealed that mismatches frequently occurred to those WiFi data collected in adjacent areas. In contrast, MFS sequence matching is more accurate, even in adjacent areas. This characteristic of the MFS sequence makes it advantageous in matching similar trajectories. As shown in Fig. 13, two similar trajectories (T_a and T_b) have exactly the same direction, distance and actions. Moreover, it is difficult to distinguish them using WiFi signals because they are too close to each other. However, their magnetic sequences are clearly distinguishable as shown in Fig. 14.

Therefore, the MFS sequence is very suitable for identifying similar trajectories. By incorporating various data sources, we can effectively localize indoor pedestrians using the proposed Knowledge Graph with high matching accuracy in various indoor situations.

An example of the trajectory matching and localization performance obtained with the proposed method is shown in Fig. 15. The starting and end points of this trajectory are S_1 and E_1, respectively. Five turning nodes (u_1 - u_5) and one door node (o_1) in the trajectory divide the trajectory into seven segments. Using the proposed matching and positioning method, trajectory segments Seg(u_1 - u_2), Seg(u_2 - u_3), Seg(u_3 - u_4), Seg(u_4 - u_5) and Seg(u_5 - o_1) were matched to Edge(t_1 - t_3), Edge(t_3 - t_4), Edge(t_4 - t_10), Edge(t_{10} - t_{11}) and Edge(t_{11} - d_1), respectively. Subsequently, the corresponding map locations of the first (Seg(S_1 - u_1)) and last (Seg(o_1 - E_1)) trajectory segments were estimated by PDR. The ground truth of the starting and end points of the trajectory is represented by red triangle S_r and cross shape E_r, respectively. The Euclidean distance between S_r and S_1 is the initial position error, while the Euclidean distance between E_r and E_1 is the end position error. The initial and end position errors of trajectory M_1 are 0.3 m and 0.56 m, respectively.

C. Comparison With Existing Methods

First, we compare the proposed Knowledge Graph framework against those ontology-based methods proposed in the literature, namely OntoNav [17], ONALIN [19] and University Activity Ontology (UAO) [16], in terms of “Expressed data”, “Functions” and “Emphasis”. As shown in Table VI, those ontology-based methods were customized for very specific indoor services. In sharp contrast to those existing works that focused on specific indoor services, our proposed Knowledge Graph framework provides a general framework for efficient indoor localization services in various situations.

Next, we compare our proposed method with the infrastructure-free indoor localization systems, namely Zee and FOLLOWME as shown in Table VII. Clearly, the proposed method outperforms the other two methods in terms of its capability of handling various scenarios and determining the initial position.

Finally, we employ the same set of experiment data to compare the localization performance of the proposed method against two most representative infrastructure-free methods,
TABLE VI

<table>
<thead>
<tr>
<th>Framework</th>
<th>Expessed data</th>
<th>Functions</th>
<th>Emphasis</th>
</tr>
</thead>
<tbody>
<tr>
<td>OntoNav</td>
<td>Geometric information, semantics bound to building areas and user profiles.</td>
<td>Navigation service, geometric path computation service, semantic path selection service</td>
<td>Navigation services.</td>
</tr>
<tr>
<td>ONALIN</td>
<td>The concept and relationship of common indoor objects, ADA standards.</td>
<td>Routing for individuals with various needs and preferences</td>
<td>Special user needs.</td>
</tr>
<tr>
<td>UAO</td>
<td>The geometry model, the 3D network based topological data model, indoor activity information.</td>
<td>Route analysis, manage and query semantic data.</td>
<td>Activity information.</td>
</tr>
<tr>
<td>The proposed framework</td>
<td>Indoor spatial structure data, indoor object properties and relational data, various types of smartphone sensing data.</td>
<td>Indoor localization in various situations, indoor environmental information expression.</td>
<td>Indoor localization.</td>
</tr>
</tbody>
</table>

TABLE VII

<table>
<thead>
<tr>
<th>Name</th>
<th>Zee FOLLOWME</th>
<th>The Proposed Approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>Requirement</td>
<td>Floorplan</td>
<td>Leader’s reference trajectory</td>
</tr>
<tr>
<td>Sensors</td>
<td>Acc., Gyro, Mag. (WiFi)</td>
<td>Acc., Gyro, Mag. (Baro.)</td>
</tr>
<tr>
<td>User participation</td>
<td>None</td>
<td>Some</td>
</tr>
<tr>
<td>Positioning capability in various scenarios</td>
<td>Moderate</td>
<td>Weak</td>
</tr>
<tr>
<td>Capability of determining the initial position</td>
<td>Moderate</td>
<td>Weak</td>
</tr>
</tbody>
</table>

TABLE VIII

<table>
<thead>
<tr>
<th>Method</th>
<th>[23]</th>
<th>[24]</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average localization error (m)</td>
<td>1.48</td>
<td>0.91</td>
<td>0.71</td>
</tr>
</tbody>
</table>

where accurate estimates should be close to the red triangles. First, the solid square symbol indicates the location obtained by [23] using the WiFi fingerprinting technique. Since the WiFi signal strength is collected only at the reference points, [23] can only localize the initial position to the closest reference point, which incurs a large matching error. In addition, the asterisk symbol “*” represents the position estimated with [24], i.e. the fusion of WiFi and PDR. Despite that [24] utilizes both PDR and WiFi intensity matching over multiple time periods to obtain its position estimation, it is unable to cope with the WiFi mismatch. As a result, its performance improvement is limited as compared to [23]. In contrast, since the proposed method utilizes all available sensing data by exploiting the proposed knowledge graph framework, it provides significant performance improvement as indicated by the cross symbols “+” in Fig. 16. The cumulative distribution function (CDF) of the initial localization error obtained with these three methods is shown in Fig. 17 while the average localization errors in Table VIII. It should be emphasized that the proposed method uses fewer WiFi reference points than the other two methods, but can achieve better positioning results. Thus, the positioning

namely the WiFi fingerprinting-based method [23] and the joint PDR and WiFi fingerprinting-based method [24]. Since the performance of [23], [24] depends heavily on the density of the reference points and the WiFi signal strength fluctuations in the indoor environments, [23], [24] require significantly more reference points in the field to measure the WiFi signal strength as compared to the proposed method. In Fig. 16, the red circles indicate the reference points employed by the proposed method while the blue circles the additional reference points required to increase the density of the WiFi fingerprint database for [23], [24]. It is worth noting that the proposed method requires 50% less reference points as compared to [23], [24].

For performance comparison purposes, ten trajectories with various lengths were collected from different locations on the same floor. These trajectories contain at least three trajectory segments with their initial and end positions being arbitrarily selected. The red triangles ($M_1 - M_{10}$) in Fig. 16 indicate the true starting positions of these trajectories. Results of initial position estimation by different methods are shown in Fig. 16,
results obtained by the proposed method are satisfactory and encouraging.

D. Efficiency Analysis

Finally, we evaluate the efficiency of the proposed method based on the following two considerations, namely efficient data usage and efficient computation. First, in the process of the traditional fingerprint matching method used to achieve meter-level localization accuracy, a large amount of fingerprint data has to be collected in advance. In contrast, using the proposed indoor Knowledge Graph-based localization method, only the relevant data corresponding to the nodes and edges in the Knowledge Graph is required. As a result, the proposed method can substantially reduce the labor-intensive data collection processes, and subsequently improve the efficiency of data usage.

Second, we carry out efficient indoor positioning computation based on the proposed Knowledge Graph. The computational advantage of the proposed method is achieved by reducing the number of matches performed to find the best match in the fingerprinting database. As mentioned in the third point of Section IV, Part C, five processes are used to determine the position of indoor pedestrians, namely action matching, screening based on a distance threshold, WiFi signal strength matching, MFS sequence matching, starting and ending position estimation. This design enables the proposed method to achieve localization accuracy at reduced computational complexity. Specifically, the action matching employs string alignment for linked open data, with time complexity of $O(n)$ where $n$ is the number of actions, while the shortest distance method is utilized for the WiFi strength matching with computational complexity of $O(m^2)$ with $m$ being the number of WiFi APs in the experiment. In addition, the DTW algorithm is used in the MFS sequence matching with the time complexity is $O(pq)$, where $p$, $q$ are the length of two MFS sequences for comparison, respectively. Due to the high computational complexity of MFS matching, we try to reduce the number of MFS matches that may be required. Therefore, the proposed method carries out action matching followed by the WiFi strength matching while the MFS sequence matching is finally performed only on those trajectories satisfying the first two matches. This design can ensure the proposed method to achieve localization accuracy at reduced computational complexity.

VI. CONCLUSION

Effective utilization of various information sources for indoor localization can promote IoT indoor applications. In this work, an indoor Knowledge Graph framework has been developed for indoor localization. In contrast to the conventional methods, the proposed indoor Knowledge Graph framework is able to integrate the spatial information and various types of smartphone sensing data including the inertial sensor data, the WiFi and magnetic field data. For more accurate and efficient indoor localization, a scheme combining the action matching, the WiFi strength matching, and the MFS sequence matching has been developed. Extensive experimental results have confirmed that the proposed indoor localization method can achieve high positioning accuracy, regardless of the indoor infrastructure. Experimental results have confirmed that the proposed scheme can achieve efficient indoor localization in various indoor situations. In our future work, real scene images will be added as important information and we will consider identifying more complex activities.

REFERENCES


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