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센서 레지스트리 시스템을 위한 개선된 센서 필터링 기법

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Improved Sensor Filtering Method for Sensor Registry System

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요 약

센서 레지스트리 시스템(Sensor Registry System, SRS)은 이기종 센서 네트워크에서 의미적 상호운용성 유지를 위해 개발되었다. SRS는 위치 정보를 기반으로 주변 센서와 모바일 기기와의 연결 여부를 확인하며, 연결이 되었을 때 센서의 메타데이터를 제공한다. 성공적으로 연결되는 주위의 센서를 식별하는 과정을 센서 필터링이라고 정의한다. 이러한 센서 필터링의 성능 개선이 SRS 연구의 핵심 주제 중 하나이다. 실제 상황에서, GPS에서 제공된 잘못된 위치 정보로 인해 센서 필터링이 실패하는 경우가 발생한다. 따라서 이 논문에서는 지리적 임베딩과 뉴럴 네트워크 기반 경로 예측을 이용한 새로운 센서 필터링 방법을 제안하고 몬테카를로 접근방법을 통해 서비스 제공률을 평가한다. 실증 연구에서, 제안 방법이 위치 정보 이상 문제를 개선하고 SRS 센서 필터링에 효과적인 모델임을 보였다.

ABSTRACT

Sensor Registry System (SRS) has been devised for maintaining semantic interoperability of data on heterogeneous sensor networks. SRS measures the connectability of the mobile device to ambient sensors based on positions and only provides metadata of sensors that may be successfully connected. The step of identifying the ambient sensors which can be successfully connected is called sensor filtering. Improving the performance of sensor filtering is one of the core issues of SRS research. In reality, GPS sometimes shows the wrong position and thus leads to failed sensor filtering. Therefore, this paper proposes a new sensor filtering strategy using geographical embedding and neural network-based path prediction. This paper also evaluates the service provision rate with the Monte Carlo approach. The empirical study shows that the proposed method can compensate for position abnormalities and is an effective model for sensor filtering in SRS.

키워드 : 지리 임베딩, 뉴럴 네트워크, 경로 예측, 센서 필터링, 센서 레지스트리 시스템

Keywords : Geographical embedding, Neural network, Path prediction, Sensor filtering, Sensor registry system

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Ⅰ. Introduction

Ambient sensors are a crucial element of intelligent manufacturing and the Internet of Things. Recently, an ambient sensors have developed rapidly for edge computing devices in intelligent services. Different types of ambient sensors obtain heterogeneous data. Edge computing devices, such as mobile devices, must combine the raw data acquired with the metadata of the sensors to produce meaningful information. Therefore, We use the Sensor Registry System (SRS) which registers semantic metadata of sensors and devices. The SRS is based on ISO/IEC 11179 and resolve the semantic interoperability problem [1]. In the ambient sensor environment, the data delivery process have two connections. When a user use mobile device which wants to receive data from the ambient sensors, the mobile device reqeust metadata of the sensors to SRS as the first connection. After receiving the semantic metadata from SRS, the mobile device can collects sensory data from the sensors as the second connection. Through the two connections, the mobile device can provide intelligent services by acquiring heterogeneous data with properties.

The process of acquiring heterogeneous sensing data is position-based. In the first connection, the mobile device requires a link to the SRS. The connection is usually over the cellular network. The mobile device should be within the cell coverage area of the base station. Similarly, for the second connection, the mobile device should connect with the circumferential sensors. Consequently, it also needs to be located within the communication range of the corresponding ambient sensors. In general, the positions of cellular base stations and ambient sensors are stationary. Therefore, the intelligent application determines the connectability of the two links by the mobile device's status. It only tries to get data from the sensors that may be connected. The process of getting the potential connected sensors is called sensor filtering. Optimizing sensor filtering for better service request success is one of the major problems of the SRS workflow.

There are several existing methods to optimizing the first connection. If the mobile device enter a denial-of-service area, it may not be able to communicate with SRS. It occurs that the mobile device cannot obtain metadata from SRS as well as sensory data from ambient sensors, then the services are failed. There are several researches about improvement of reliability to acquire the metadata using path prediction [2-4]. The path predicition algorithms need the historical trajectory of users to predict the next position, and the mobile device can receive metadata of sensors nearby the predicted path before entering the denial-of-service area. However, these researches do not consider the fact that the Global Positioning System (GPS) causes some errors. Also, the SRS needs to be evaluated quantitatively for performance.

This paper uses the dual collaboration stratege based on geographical embedding [5] and path prediction to improve connection success between mobile device and sensors in the second connection phase. The sensor filtering method uses two positions from the GPS and path prediction algorithm simultaneously. If one of them is correct, the service will be successful.

We also improve the service provision rate simulation flow. Existing Monte Carlo-based methods are likely to evaluate the service provision rate with historical trajectories. The collected historical trajectories are employed as input one by one to simulate the performance of SRS. Historical spatial-temporal positions are queried together with randomly generated sensor nodes in PostGIS to determine if the connection is successful probabilistically. Indeed, sensors in wireless sensor networks can communicate between themselves, and mobile devices can indirectly acquire data from the sensors network in a multi-hop approach. We have added a breadth-first search (BFS) algorithm in the Monte Carlo-based simulation flow to group the separate sensors into sensor networks. The simulated service provision rate is much more realistic.

Ⅱ. Methodology

2.1. Communication Model

In the SRS workflow, a mobile device should connect with ambient sensors to acquire raw data. The ambient sensors also need to connect to compose a sensor network for multi-hop data delivery. The connectivity is an essential issue in the study of the evaluation of SRS. We use the binary model to evaluate the connectivity. In the binary model, each device has a communication area. A device can receive the signal from the other device if and only if the device is located at the communication area [6]. The communication area is a disk. Fig. 1 illustrates the schematic diagram for the communication disk of the sensor node. o is the position of the sensor. The circle is the communication disk. Device A is inside the disk so that it can make a connection with sensor o. On the contrary, device B is outside the disk, so it can not connect with sensor o.

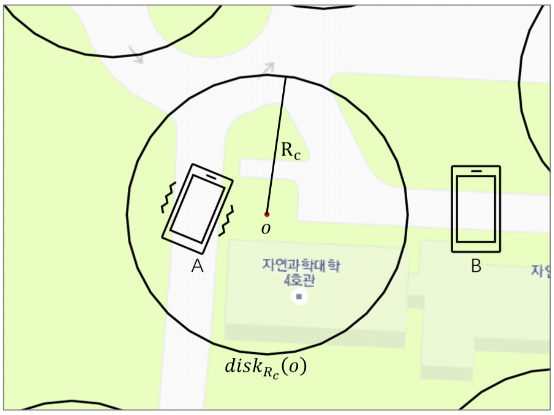

Fig. 1 Schematic diagram for the communication disk of sensor node

2.2. Communication Model

For security reasons, the device should not know the entire sensor network. It is a common strategy. Only a limited number of sensors are known. As shown in Fig. 2, a user at p1 can make a connection with s8. So the user should know the metadata of the sensor s8. For sensor s7, and s6, the user is not in the communication disk, so he does not need the metadata of s7 and s8. How to decide the list of sensors is called sensor filtering.

In reality, GPS sometimes shows the wrong position. For example, if a user is at p1 but the GPS shows that the user is at p2. It leads to the SRS do not send the metadata of the sensor s8 to the user. We employ a dual collaboration strategy for effective sensor filtering. Both positions from GPS and path prediction are used for sensor filtering. As shown in Fig. 2, the dashed line is the historical trajectory. After path prediction, the SRS obtain the position p1. The SRS will send the metadata associated with the predicted position p1 and the position p2 from GPS to the user. In this way, the incorrect GPS position does not affect the final service. The GPS reliability is a hardware-dependent constant. Therefore, we focus on path prediction. A practical path prediction algorithm is essential.

Fig. 2 Example of path prediction-based sensor filtering with dual collaboration strategy

Path prediction is available in two categories: segment-based and cell-based. Segment-based path prediction maps the collected spatial-temporal points into manually designed segments. The Grid-based algorithm directly divides the research area into square cells, which has better flexibility. We use the gird-based mapping method in this work. We captured participants' positions in their daily lives to compose the dataset and used the cell to represent the historical trajectories. In detail, the collected data is a collection of spatial- temporal points. Spatial-temporal point p is a tuple of timestamp t and geographical coordinate g, i.e., $p=g_{lon},g_{lat},t,e$. Our research area is a university campus and the living areas near it. The research area is divided into 117×90 cells. A cell is a 10m×10m square, and each cell has an identifier. After the grid-mapping, the spatial-temporal p is converted to q, which is a tuple of timestamp t and cell identifier c, i.e., q=t,c. Given a user identifier u, a trajectory sequence S is a spatial-temporal point sequence, i.e., $S_u=q_1,q_2,\cdots,q_n$. The path prediction algorithm in the sensor filtering module predicts based on fixed-length historical trajectories in the SRS workflow. Therefore, we convert the trajectory sequence into fixed-length trajectories by sliding window. Given a trajectory sequence S and a time window t_w, a trajectory is a subsequence $S_{tw}=q_i,q_{i+1},\cdots,q_{i+k}$ of S in the time window t_w, if $\forall 1<j\leq k, t_{qj}$ belongs to t_w. In the sensor filtering module, the target of path prediction is to predict the next cell. A trajectory with length k is divided into two parts. The first part $q_i,q_{i+1},\cdots,q_{i+k-1}$ is used as the input to the algorithm, and the second part, of length 1, is the output. Thus the task of path prediction is converted into a time series multi-classification problem.

2.3. Monte Carlo-based Simulation Flow

Service provision rate is the probability of successfully providing services to a mobile device when requested, as shown in equation (1).

$$R_{SP}=\frac{\sum provided\,services}{\sum of\,service\,requests} \tag{1}$$

The service provision rate is measured by a Monte Carlo based simulator which we developed. The simulator performs SRS using historical trajectories of users. It is a two-step approach.

In the first step, many sensors are randomly generated in the research area. Some of the sensors are relatively close and can communicate with each other. Algorithm 1 is based on a breadth-first search (BFS) algorithm that groups the sensors using queues. After grouping, sensors that are close to each other form a sensor network. A mobile device can obtain data from all sensors within the sensor network through multiple hops.

Algorithm 1: sensor_network_grouping

```
Input:
S: A set of sensors
Q: An empty list
Output:
N: A dictionary of sensor networks

i ← 0
While (len(S) > 0)
  s ← S.pop()
  N[i].append(s)
  Q.append(s)
  While (len(Q) > 0)
    a = Q.pop()
    Temp ← A
    For each sensor sj∈Temp:
      o ← the center of the disk a
      If ST_Intersects(sj, o)
        N[i].append(sj)
        Q.append(sj)
        S.remove(sj)
      End If
    End For
  End While
  n ← n + 1
End While
```

For the second step, the simulator evaluates the service provision rate with historical trajectories. The sensor has communication range which generated randomly as fixed radius disk. If a mobile device enters the disk, the mobile device and sensor start communication. It means that the cell having shaded area can indicate the percentage of the service provision. For example, in Fig. 3, CELL5800 is entirely covered by a communication disk, meaning the mobile device inside CELL5800 can successfully connect with the corresponding sensor. Any communication disk does not cover CELL5685. It implies that the mobile device within CELL5685 cannot be connected to any sensor. CELL6035 is in between the two cases, half-covered by disk, indicating that the device in CELL6035 has half possibility to connect successfully. According to the proposed method, the cells from the GPS and the path prediction are used simultaneously, and the service is requested in actual position to success.

The simulation process is repeated several times using historical trajectories by randomly generating sensing networks. To obtain the service provision rate, the results of the random investigation is finally statistically averaged.

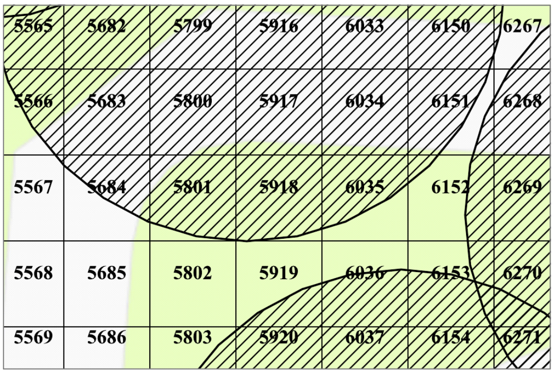

Fig. 3 Indicating the connectivity by the area ratio

Ⅲ. Experiment and Evaluation

3.1. Dataset

To experiment our proposal, we collect GPS trajectories by smart devices such as smart phone and smart watch. There are 59 participants for our experimentation, and they collect 900 million GPS positions from their daily activities in 6-months. And the collected data are refined by a preprocessing method [7]. After all filtering, 35,234 trajectories from 240 million GPS positions are remained for experimentation. The total distances of trajectories are 1,588 km with 3,300+ hours.

3.2. Experimental Settings

We designed three neural network models to compare the achieved prediction accuracy with the traditional Collective Behavior Pattern (CBP) to evaluate the results better. They are G-CNN (Gated Convolutional Neural Network) [8], LSTM (Long Short-Term Memory), and Transformer [9]. As with the general time series multi-classification problem approach, these models consist of three parts: an embedding layer, a neural network model, and a classifier layer. A CBOW (Continuous Bag Of Word) Word2vec model is used to construct the cell embedding. It provides a meaningful representation of cells based on the users' behavior patterns, defining an intuitive impression for the metric of behavioral distance. The classifier includes a dropout layer and several fully connected layers with the ReLU (Rectified Linear Unit) activation function. The training process is based on the negative log-likelihood loss, mini-batches, and Adam optimizer. While collecting the collection, we found that users always move within the area they are habitual to and rarely move to other places. It leads to an unbalanced distribution of the collected data. Therefore, we changed the percentage of the validation set and test set. The preprocessed historical trajectories were randomly split into a training set, a validation set, and a test set containing 40%, 30%, and 30% of the data.

3.3. Experimental Result and Evaluation

In multi-classification problems, there are two ways to calculate the recall: the macro-average and weighted-average. Macro-average directly averages the evaluation metrics (e.g., precision, recall, f1-score) of different classes. The weights of all classes are the same. It can handle each class equally, but its value is affected by the minority classes. Instead, the Weighted-average approach gives different weights to each class. It considers the imbalance problem of the dataset, and its value is more susceptible to the majority class. As shown in Table. 1, there is a significant difference between macro recall and weighted recall. It's consistent with intuition. People tend to move within their comfort zone and rarely go to other places. The data we collected is unbalanced, with some cells appearing frequently and others rarely.

The comparison results are reported in Table 1. CBP is the baseline for path prediction-based SRS in previous work. We evaluate the CBP with G-CNN, LSTM, and Transformer. Three neural network models outperform the CBP, yielding a 15% improvement. Of these metrics, precision focuses on False Positive (FP), and recall concerns False Negative (FN). In path prediction, FP means that the actual position is not in the current cell, but the predicted one is. It is not a severe problem because it only causes a waste of system resources as the mobile device tries to connect to sensors out of the communication range. In contrast, FP indicates that the actual position is in the current cell, but the predicted result is another cell. Such a mistake results in the mobile device not connecting to the correct sensor, which consequently causes the intelligent service to fail. It should be avoided as much as possible. Therefore, we focus on recall.

Table. 1 Overall performance comparison

Items / Methods	Weighted Precision (Macro Precision)	Weighted Recall (Macro Recall)	Weighted F1-Score (Macro F1-Score)
CBP	0.4811(0.4064)	0.5102(0.4254)	0.4803(0.3976)
G-CNN	0.6810(0.6947)	0.6678(0.6450)	0.6610(0.6420)
LSTM	0.6807(0.6233)	0.6793 (0.5747)	0.6709(0.5755)
Transformer	0.6614(0.5746)	0.6574(0.5416)	0.6464(0.5323)

Comparing the recall, G-CNN outperforms the other methods. The macro recall and weighted recall are about 22% and 15% better, respectively. The weighted recall of the three neural network models is similar, and all can be 15% higher than the traditional CBP. However, for macro recall, G-CNN shows 7% and 10% higher than LSTM and Transformer. The stacked residual blocks have good generalization capability.

Each sensor has a communication area. A sensor can send data to another one if the latter lies inside the communication disk of the former. A set of sensors form a communication network in which data is traveled in multiple hops. After randomly generating sensors, we use Algorithm 1 to group these sensors into communication networks. As shown in Fig. 4, the communication network marked with dots consists of two sensors. Other networks are made of a single sensor. We use these communication networks to perform spatial calculations with cells to simulate whether a connection is successfully established probabilistically.

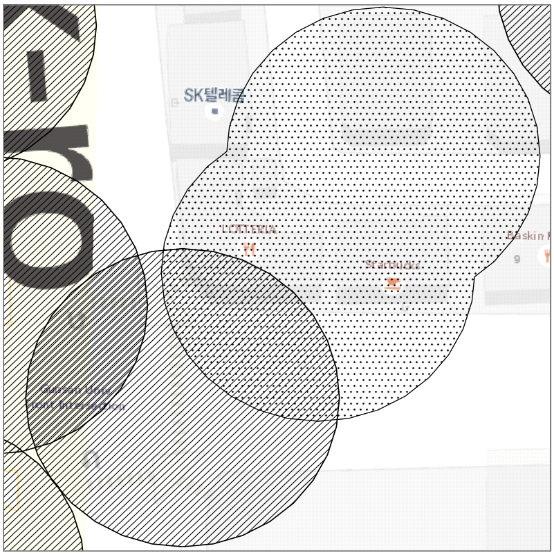

Fig. 4 Example of the sensor communication network

Besides, we examine the service provision rate by the Monte Carlo method. The ideal scenario of a completely accurate mobile device position determines the upper limits of the service provision rate, and the lower limit is the case when GPS positioning is sometimes wrong. The service provision rate reinforced by the dual collaboration strategy is distributed between the ideal scenario and the actual situation.

Table 2 shows the service provision service rates. In Table 2, unlike the machine learning metrics such as recall, the four path prediction algorithms have similar performance in the Monte Carlo simulation with the dual collaboration strategy. We consider grid-based path prediction as a time-series multi-classification problem to predict the cell corresponding to the user's current position from a historical trajectory. In machine learning metrics, if the input cell is different from the expected label, the predicted result is wrong. However, in service provision rate evaluation, the expected communication area covers more than one cell. It is possible to establish a successful connection when the predicted wrong cell is within the expected communication area. It implies that the predicted cell does not have to be strictly correct. Suppose it is spatially close to the expected label. In that case, there is a high probability that the predicted cell is within the expected communication area. Thus a successful service request is obtained. Monte Carlo is a more realistic measurement. By applying the dual collaboration strategy with path prediction algorithms, the effect of mobile device position error can be compensatory. The evaluations are close to the ideal scenario under a variety of coverage conditions.

Table. 2 Service provision rate for sensor counts of 20, 30, 50, 100, and 200

# of sensros	Ideal scenario	Scenario for RG=0.9	CBP	G-CNN	LSTM	Transformer
20	0.681	0.618	0.675	0.677	0.679	0.678
30	0.675	0.608	6.669	6.670	6.673	0.672
50	0.687	0.618	0.680	0.683	0.684	0.683
100	0.692	0.622	0.685	0.687	0.688	0.688
200	0.708	0.638	0.702	0.704	0.706	0.705

Ⅳ. Conclusion

In this work, we investigated the problem of sensor filtering indicating the wrong location of GPS. We used a dual collaboration strategy to provide effective sensor filtering in SRS. It integrates position information obtained from GPS and predicted by historical trajectory to improve the service provision rate. The neural network models such as G-CNN, LSTM, and Transformer learn movement patterns from long-range cell sequences based on practical grid-based path prediction algorithms. Comparatively, G-CNN has better generalization capability. A Monte Carlo-based simulation flow is used for measuring the service provision rate. The path prediction algorithm may predict an expected cell or a cell adjacent to the expected cell. These features show results in the SRS, which has different performance from machine learning indicators. The four path prediction algorithms have similar performance for sensor filtering of the SRS.

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