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대규모 사물 인터넷을 위한 DNN 알고리즘 활용 FM 지문 실외 위치 추적

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FM-Based Outdoor Fingerprint Location Using DNN Algorithm for Large-Scale Internet of Things

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요 약

오늘날 무선 네트워크와 통신 기술의 급속한 성장과 함께 위치 측정 기술의 발전은 인간의 삶과 과학 기술의 발전에 큰 영향을 끼치고 있다. 사물 인터넷(IoT) 기술은 모든 계층의 삶과 인간의 일상까지 스며 들고 있다. 정보의 교환과 공유를 위해 점점 더 많은 물리적 장치가 네트워크에 연결되고 있는데, 대규모 사물 인터넷 장치 및 서비스를 지원하기 위해 여러 IoT 기술과 저전력 광역 네트워크 기술이 개발되고 있다. 본 논문에서 제안한 FM 신호 기반의 지문 실외 위치 측정 기술은 대규모 사물 인터넷 장치에 적응하기 위한 저비용이며, 저에너지를 소비하는 위치 측정 방법이다. 지문 데이터베이스와 훈련 데이터를 구성하기 위해 수신되는 FM 신호의 강도를 측정하며, 위치 정보의 정확도를 높이기 위하여 심층 신경망을 사용하여 오차를 줄이는 효과적인 정보를 구성하여 최종 위치 정보를 얻을 수 있다. 실험을 통해 이 방법은 실외 위치 측정에 있어 최고 95% 이상의 정확도를 보였고 효과적으로 향상시킬 수 있음을 입증하였다.

Key Words : FM radio, Fingerprints, Deep Learning, Positioning, Internet of Things

ABSTRACT

The generation of positioning technology has a great impact on human life and the development of science and technology, especially with the rapid growth of wireless networks and communication technology today. The Internet of Things (IoT) technology has penetrated all walks of life and even the daily life of human beings. More and more physical devices are connected to the network for information exchange and sharing. To enable large-scale IoT devices and services, several newly developing IoT technologies, Low Power Wide Area Network(LPWAN) have emerged. The FM signal based fingerprint outdoor positioning technology in this paper is a low-cost and low energy consumption positioning method to adapt to large-scale IoT devices. Through collecting FM signal strength and other effective information, fingerprint databases are constructed and the data are trained by using Deep Neural Networks(DNN) to reduce accuracy differences. The Final location information can be obtained by this method. Experimental results show that the accuracy of this method is 95.57%, which can effectively improve the accuracy of FM outdoor positioning.

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Ⅰ. Introduction

It is becoming more and more important to obtain the location of mobile or sensor devices through various location technologies and to provide information resources and services for them through mobile Internet. Now the most widely used and most mature outdoor positioning technology is the Global Positioning System (GPS)[1] and base station positioning technology of cellular system. GPS is a positioning system based on artificial earth satellites with high precision radio navigation. It can provide accurate geographic position, vehicle speed and accurate time information anywhere in the world and near-earth space. It has the advantages of high precision, all-weather, global coverage, convenience, and flexibility. With the rapid development of communication technology, the traditional way of mobile communication is changing from the connection between people and things to the connection between people and things or between things, and the interconnection of all things has become an inevitable trend. To adapt to the wide connection with low energy consumption and low cost, the broadband of the LPWAN[2] is low, the base station construction is immature, and the positioning accuracy is poor. Therefore, the positioning technology still applies the traditional GPS positioning system[3,4]. However, GPS is characterized by high energy consumption and high cost, which is contrary to the original intention of the development of large-scale IoT.

Therefore, based on this problem, this paper proposes a fingerprint positioning technology through Frequency Modulation(FM) signal. As is known to all, FM radio has a long history and is now very mature. It has many advantages such as having transmitting base stations, wide-coverage, stable signal, small interference, and low receiving cost. At present, most of the research are mainly based on the signal strength characteristics of FM broadcast for localization[5], and there are two main methods. One is to establish signal propagation models such as Angle of Arrival[6], Time Difference of Arrival[7,8] and Time of Arrival, and the other is the fingerprint localization method[9]. At present, fingerprint positioning method is widely used in indoor positioning, generally using Wi-Fi as fingerprint location information. However, in a complex outdoor environment, Wi-Fi cannot fully cover the area and the signal is vulnerable to interference. On the contrary, FM signals are almost fully covered and compared with multiple routers required by Wi-Fi, FM also requires less cost and is less affected by other bands. Therefore, FM is selected as the fingerprint feature in this paper and used DNN algorithm for region-level localization. DNN algorithm is now a more popular algorithm, the effect is excellent. The second part of this paper is related work, the third part is the experimental process, the fourth part is the comparative analysis of the experiment, the fifth part is the conclusion.

Ⅱ. Related Work

Research and experiment on positioning technology have always been a hot topic. In recent years, there have been a lot of indoor and outdoor positioning studies using fingerprint algorithm, but most of them use Wi-Fi signals as signal features[10], and fewer use FM signals, or use the method of combining FM and Wi-Fi to locate.

Because WIFI is greatly affected by the environment and the communication distance is short, we mainly introduce the location method based on FM signal.

The first work[11] presents an indoor positioning system based on FM and Wi-Fi which can be positioned when mobile devices make requests. In this method, signal strength databases of FM and Wi-Fi are constructed and trained, and tested by the K-Nearest Neighbor (KNN) algorithm. The system has strong portability and high positioning accuracy.

The second work[12] is a low-cost and easy to implement fingerprint positioning method based on FM for indoor positioning. This work solved some difficulties in using FM signals. No additional infrastructure is required, and fingerprint identification is independent of the timing of the FM signal and has the advantage of not being affected by multiple paths. This experiment selects the Received Signal Strength (RSS) data of nine FM radio stations in the typical indoor office environment and evaluates and analyzes them using KNN and K-Weighted Nearest Neighbor(KWNN) algorithms.

The third work[13] proposed a positioning method using FM. In this paper, a longitudinal study of indoor frequency modulation is carried out, and the received signal strength is used as a fingerprint feature for localization. At the same time, the long-term performance of FM-based indoor positioning under changing environmental conditions is also understood. This experiment selected three different indoor environments, collected a large number of RF original sample data and signal strength data, and built a database. This method not only uses the general KNN classification method but also uses the random forest and support vector machine (SVM) algorithm in the data processing. Through the test, the accuracy of the support vector machine algorithm is the highest among the three methods, which is 78.8%.

The above three experiments are basically based on the KNN algorithm for indoor positioning. The fourth work[14] is based on Long-Term Evolution (LTE) signal as fingerprint feature, combined with DNN algorithm for outdoor environment positioning. Developed a fingerprint representation method that converts LTE signals into fingerprint images, using mixed-position grayscale fingerprint images for positioning. It can overcome LTE signal fluctuations and provide satisfactory positioning accuracy.

Combining these four works, we can find that most methods use FM signals as fingerprint features and are used for indoor positioning, and we can find the KNN algorithm are mostly used. The fourth study provides a new idea that DNN algorithm can be combined with FM signal fingerprint characteristics for outdoor positioning. This method is convenient and simple to implement and can improve positioning accuracy.

Ⅲ. FM-Based Fingerprint Outdoor Location

3.1 Experiment Definition

The structure of this experiment is divided into two parts as Fig. 1 shows the flow chart of FM-based fingerprints positioning architecture, one is the data training stage, the other is the data testing stage. In our experiment, the data training phase is mainly to collect the signal strength, stereo, and other attributes as fingerprint characteristics and stored in the database to train the data through the DNN algorithm. In the data testing phase, the location algorithm is used to solve the position.

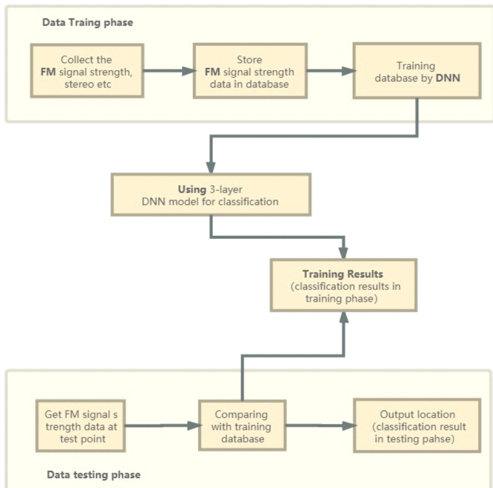


Fig. 1. The flow chart of FM based fingerprints positioning architecture.

3.2 Data Collection

In the acquisition and construction stage of the feature database of FM broadcast signal, the reliability, accuracy, and adaptability of the data collected by the acquisition equipment and the acquisition location have a great impact on the accuracy of the data for the positioning application. So, two issues need to be considered: the selection of the acquisition equipment and the selection of the acquisition location.

However, the experiment of this paper is mainly applied to large-scale connected IoT devices, so the selection of acquisition equipment is also low cost and low precision FM Radio TEA5767 module which is connected to Raspberry Pi for the acquisition of data. Fig. 2 is the composition of the experimental equipment. The device measures the FM signal strength and stereo of six FM radio stations around it.

As the coverage area of FM radio signal is very wide, this study is mainly applied to the application of outdoor region-level positioning. And as the most of acquisition area has obvious environmental characteristics, the collected signal data need to be purified. For the our experiment, five different locations are selected in five areas within the Daegu campus of Kyungpook National University. Each area has distinct environmental characteristics. Fig. 3 identifies the five signal acquisition areas of our experiment.

In this experiment, a total of 7,500 FM broadcast characteristic data were collected from six radio stations in 25 locations.

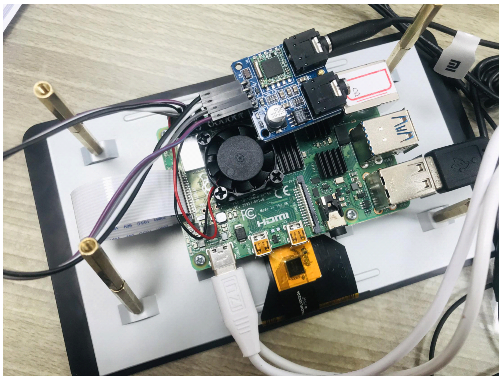


Fig. 2. Data acquisition system

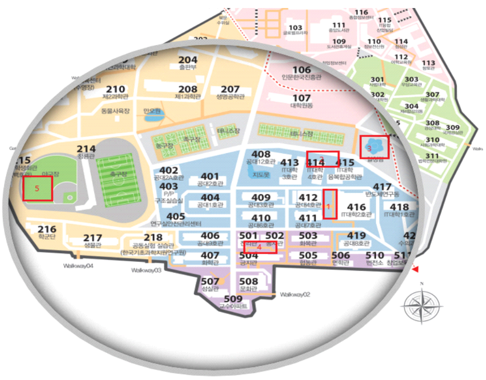


Fig. 3. Data acquisition area

3.3 Training Data by DNN Algorithm

This experiment uses a DNN algorithm to train and test the data. The neural networks can be used for classification and regression tasks and it is based on the extension of the perceptron. The perceptron is a model with several inputs and one output. The single-layer perceptron model shown in Figure 4.

It learns the linear relationship between output and input and obtains the intermediate weight in this linear relationship. Then the desired result is obtained through the neuron activation function, and the output is 1 or -1 to indicate whether this is the case or not. However, this model can only be used for binary classification, and can not learn more complex nonlinear models, so it can not be used in the industry. The neural network extends the perceptron model and adds hidden layer to enhance the expression ability of the model. This hidden layer can have many layers, and the neurons in the output layer can also have multiple outputs. The activation function has also been expanded, so that it can be flexibly applied to classification and regression, dimensionality reduction, and clustering. DNN is sometimes called multilayer perceptron. The neural network inside DNN can be divided into three categories, input layer, hidden layer, and output layer. The layers are fully connected. The output layer of multiple neurons output corresponds to Fig. 5.

In this experiment, after filtering extreme values and preprocessing, there are a total of 2250 RSS data. The DNN model is then set up with one input layer, two hidden layers, and one output layer. The

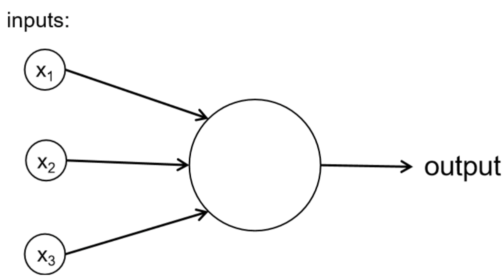


Fig. 4. The single-layer perceptron model

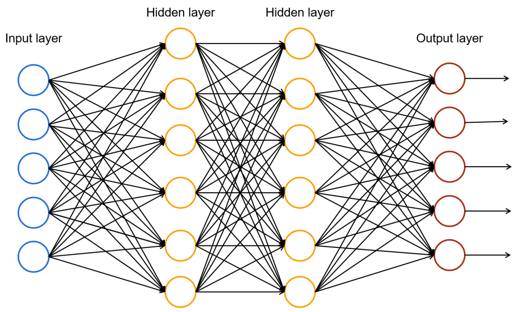


Fig. 5. The output layer of multiple neurons output

input data of the input layer is 1000, the Rectified Linear Unit (ReLU) is used as the activation function, and the input dimension is the number of stations is 6. The hidden data of the hidden layer is 500 and 100 respectively, and the activation function also uses the ReLU. The output number of the output layer is five different reference points selected from the five regions, a total of 25. The activation algorithm uses Softmax for classification. The optimizer uses Adam. Generally speaking, ReLU is the linear rectification function that refers to the ramp function in mathematics. In the context of artificial neural networks, the ReLU function is an activation function defined as the positive part of its argument as formula (1):

$$f(x) = x^{+} = \max(0, x) \tag{1}$$

where x is the input to a neuron.

Softmax is typically used as the last activation function of a neural network to normalize the network output to the probability distribution on the predicted output category.

The standard (unit) softmax function σ: R^K -> R^K is defined by the formula (2):

$$\sigma(\vec{z})i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{\beta z_j}} for\, i = 1, ..., K \text{and} z = (z_1, ... z_K) \in R^K \tag{2}$$

where,

z : The input vector to the softmax function, made up of (z_0, ... z_k).

z_i : The input vector elements of softmax function that can take any real number, positive, zero, or negative.

e^{z_i} : The standard exponential function. It is applied to each element of the input vector. This gives a positive value above 0, which will be very small if the input was negative, and very large if the input was large. However, it is still not fixed in the range (0, 1) which is what is required of a probability.

$\sum_{j=1}^{K} e^{z_j}$: The term on the bottom of the formula is the normalization term. It ensures that all the output values of the function will sum to 1 and each be in the range (0, 1), thus constituting a valid probability distribution.

K : The number of classes in the multi-class classifier.

Ⅳ. Experiment Results and Analysis

4.1 The Comparison of Different Groups

Regional positioning is essentially a problem of regional classification. Therefore, this research mainly uses the DNN positioning algorithm[15] and divides a total of 2250 signal strength data pre-processed after measurement into three cases for experiments.

This experiment contains the location number of a total of 25 reference nodes and 50 continuous RSS of the six radio channels that can be received at the reference node, and whether it is stereo.

Due to the accuracy of the equipment, the original data obtained were very unstable and had extreme values. Therefore, all the data were filtered first by calculating the average value. Twenty data with the smallest average difference are selected as the first group from the 50 times of data in each station at each location. A signal strength is divided by sixteen levels from 0 to 15 level. Assume that a set of values indicated by a signal in this experimental equipment are 7, 8, 9, 6, 7, 7, 8, 9, 10, 7. If we need to filter the five of the values, then can get a mean of 7.8 using the square variance formula (3). In this way we can get the next five values as 7, 8, 7, 7, 8.

$$(MD) = \frac{\sum |x - \overline{x}|}{n} \tag{3}$$

Where, (MD) is mean deviation, Σ is the symbol of the total, x is the variable. $\vec{x}$ is the arithmetic mean of the variable, and n is the number of the value of the variable.

By the same way, fifteen data are filtered out as the Group 2 on the basis of group 1. Then group 3 of 10 data filtered on the basis of group 2. After using the DNN positioning algorithm, we got three sets of results as Table 1 shows. And all the data were randomly divided into the training set and the test set at a ratio of 7:3 in DNN model.

The purpose of grouping the raw data is to determine to what extent the filtering can achieve the greatest accuracy.

In the first group, there were still several extreme values. The maximum accuracy of training is 87.14%, while the maximum accuracy of testing can only reach 74.66%, with large errors, high loss rate and unsatisfactory accuracy.

In the second group, the extreme value was reduced by further filtering, and the accuracy of training was up to 97.32%, and the accuracy of test was also up to 95.58%. The second group has small error, small loss rate and high accuracy.

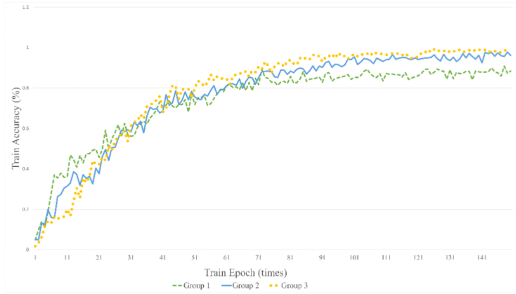
After the third group of filtering, the data value becomes very stable, and the training accuracy rate is very high, reaching 97.14%. However, the actual test accuracy rate fluctuates greatly, with the highest only reaching 93.33% and the lowest even reaching about 80%. It is speculated that it may be overfitting phenomenon, but the actual situation remains to be verified later. Fig. 6 show The test and train accuracy of three groups with DNN algorithm.

It can be seen from the above Fig. 5 that the second group has the highest test accuracy. When

Table 1. The accuracy of three groups of DNN

	group 1	group 2	group 3
Accuracy on training data	87.14%	97.32%	97.14%
Accuracy on test data	74.66%	95.58%	93.33%

(a) The test accuracy



(b) The train accuracy

Fig. 6. The test and train accuracy of three groups with DNN algorithm

the accuracy of the device itself is not enough, to get more accurate results, the original complex data (signal level) needs to be properly filtered. However, in my opinion, too many extreme values should not be included. In addition, the data is too stable due to filtering, and some data fluctuations of normal measurement chamber are missing. In addition to measuring signal strength, the equipment used in this experiment can also recognize whether it is stereo. But when the stereo was added as the fingerprint feature, the effect did not change much.

4.2 The Comparison of Different Algorithm

Several experiments mentioned in the related works[11-13] study are indoor positioning tests using KNN method.

Therefore, this paper also uses KNN method to test outdoor positioning, and the accuracy is shown in the figure 7 below.

As can be seen from the above, the accuracy rate is the highest when the K value is 11, and the accuracy rate of the second group can reach 95%. When the k value is small, the third group repeats

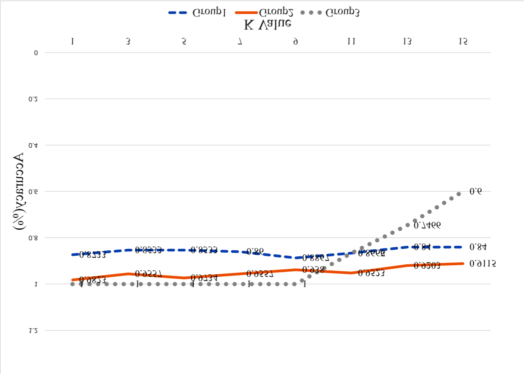


Fig. 7. The accuracy of three groups with KNN

100% accuracy many times, and when the k value is larger, the accuracy rate is lower, even reaching 60%. The accuracy of the first group is lower.

Table 2 is the accuracy of using DNN and KNN algorithm. Therefore, we can get both DNN and KNN algorithms can be used for outdoor fingerprint location based on FM in this experiment, and both can achieve good results. However, the data of this experiment is prone to over-fitting when KNN algorithm is used, compared with DNN algorithm, which is better.

The measuring of signal strength was affected by many parameters of the environments. Nowadays, more and more applications in large-scale IoT environments require the high positioning precision of its devices. By the above analysis, the combining of signal strength parameters of FM radio signals, the fingerprint oriented localization algorithm, and DNN method has high precision for a mobile or sensor device to get a positioning information in large-scale IoT environments, and it has the advantages of low cost and low energy consumption.

Table 2. The accuracy of DNN and KNN

	group 1	group 2	group 3
Accuracy on DNN	74.66%	95.58%	93.33%
Accuracy on KNN	86.68%	95.23%	86.68%

V. Conclusion

This paper proposed a method for FM signal based fingerprint outdoor positioning technology. This method uses the signal strength parameters of the FM broadcast signal, the fingerprint positioning method and the DNN positioning algorithm for the positioning of a device. It has the advantages of low cost, low energy consumption, convenient installation, and etc., which can be well adopted to the positioning needs of the current large-scale IoT era. Due to the limitations of the equipment itself, there still exists some problems such as inaccurate signal strength measurement and too few parameters that can be measured. Therefore, in the following experiment, we will choose equipment with better quality for measurement, compare the environments, and carry out indoor positioning plan through this method.

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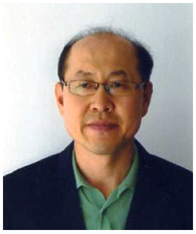

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