Flexible RFID Location System Based on Artificial Neural Networks for Medical Care Facilities

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Abstract

RFID location systems are often used in real-time location systems that come up with the problems like multipath phenomenon and layout changing. These make locating difficult because most of the location systems are based on fixed mathematical calculation that cannot take these situations into account. Using artificial neural network, our location scheme can learn the geography features to adapt to the real world. It could avoid multipath phenomenon effect and be flexibly applied to any environment. The experimental processes and result are shown in the end of the paper.

Keywords: Real-time location system (RTLS), Radio frequency identification (RFID), Back propagation network (BPN), Received signal strength indicator (RSSI).

1. Introduction

Radio Frequency Identification (RFID) is a fast growing automatic data retrieval technology that has become very popular in supply chain, retail logistics, and other applications [1]. Nowadays, RFID location and tracking application is also important that can be helpful to support the asset tracking and equipment management.

RFID location systems are often be used in Real-time location systems (RTLSs). Location systems come up with the problems that signal reflection of walls, ground, and objects are received from various directions over a multiplicity of paths, called multipath phenomenon [1][2]. Moreover, the layout of objects is likely to be changed in many cases. These make locating difficult because that most of the location systems [3][4][5] are based on fixed mathematical calculation that the calculation model should be reconstructed when the layout of objects changing.

Artificial neural network is a learning algorithm that can automatically learn the features of input and create appropriate output. In this paper, we locate the user's position by applying the Back Propagation Network (BPN).

The rest of the paper is organizes as follows. In section 2, the brief introduction of Received Signal Strength Indicator (RSSI) and the Artificial Neural Networks (ANNs) will be given. Section 3 describes our proposed scheme. The experimental processes and result are discussed in section 4. Finally, we provide some conclusions in the last section.

2. Related Works

In this section we brief introduce the Received Signal Strength Indicator (RSSI) and the Artificial neural networks (ANNs).

2.1 Received Signal Strength Indicator (RSSI)

Many location systems use the Received signal strength indicator (RSSI) to calculate the distance between user and reader. RSSI is the signal strength received from the reader antenna [1]. RSSI decrease by the distance between the user and reader according to the path loss model. But the path loss model is not fixed, it impacted by geography condition, reflection of walls, ground, and even layout of objects like barriers or a big desk. That is, maybe two RSSIs are the same, but indeed their distance to reader are different. These features make the fixed mathematical model difficult to construct. Moreover, if we use fixed mathematical model to locating the user's position, we may have to reconstruct a new model for location when the geography condition changing manually.

2.2 Artificial neural networks (ANNs)

Artificial Neural Networks (ANNs) are information processing tools inspired by the learning ability of the human brain. About the theories and functions we can find in Hecht-Nielsen's paper [6]. ANNs can automatically learn the features of inputs and create appropriate outputs that users don't need to know the hidden processes between them.

There are three layers in the ANNs: the input layers, the hidden layer, and the output layer. In this paper, the ANN used is the Back propagation network (BPN). There are two phases in BPN, the training phase and the predicting phase. When we get the training data set, we define the input and the corresponded expected output. BPN would automatically create the model that satisfies the training data set as much as it can, calls the training phase. After the model is created, we can use it to predict the outputs corresponded to the new inputs, calls the predicting phase.

Using this feature, we collect the RSSIs of RFID readers as the inputs of BPN, and let the corresponded position be the expected outputs to train the collecting data. After the model is created, we apply it to predict the positions by giving new RSSIs. Therefore, our scheme doesn’t compute the mathematical model and virtually take the geography condition into account because that the RSSIs in the specific zone is the result of multipath phenomenon and other condition effect.

3. Proposed Scheme

Proposed scheme locating the user’s position by using BPN modeling that can real-time locate which zone the user is. Proposed scheme can be divided into three phases: the data collection and pre-processing phase, the neural network training phase, and the neural network predicting phase. The three phases are described in the following paragraphs.

3.1 The Data Collection and Pre-processing Phase

We put three RFID readers in the location area, and all of them can sense the signals in the whole location area. Firstly, we divide the location area to predefined *n* zones, calls Z_1 to Z_n. For example, we divide the location area to 2x3 zones, shown in Figure 1. The marked numbers 1 to 6 are the dividing zones of the location area Z_1 to Z_6, and R_1 to R_3 are RFID readers.

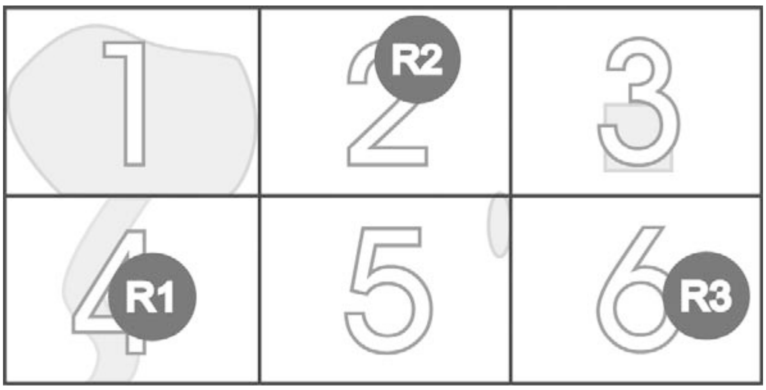

Figure 1: Example of the location area map

Then we record the RSSIs of each reader in every zone. There are two ways to collect the training data: one is going around in the whole zone to collect real data, and another is stay in the center of zone to get more intensive data. In our experiment, stay in the center of zone make the location more accurate than the another one.

We should normalize the collecting data because that data input and output in BPN are in the range of 0 to 1. We perform the normalization to the received RSSIs according to the following Equation (1). The variable x_i is the original received RSSI, and x_i' is the normalized RSSI. $x_{\max}$ and $x_{\min}$ are the maximum and minimum of all the received RSSIs in the whole location area.

$$x_i' = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

3.2 The Neural Network Training Phase

BPN is a learning model that consists of three layers: the input layers, the hidden layer, and the output layer. In this paper, the input units are the received RSSIs of the readers R_1, R_2 and R_3. The output units represent the user's position. We use the normalized RSSIs calculated in previous phase as the input unit so that there are 3 units in the input layer, corresponded to the three readers.

We use the zone number of the location area as the output of BPN. If the location area is divided to *n* zones, there *n* units in the output layer, corresponded to the *n* zones. The value 1 represents that the user's position is the corresponded zone, whereas the value 0 means that the user is not in the corresponded zone. For example, if the zone number is 1 and the location area is divided into 6 zones, the output units should be 100000; if the zone number is 2, the output units should be 010000.

The number of hidden layer unit is generally defined by the following two approaches:

$$Nhidden = \frac{Ninput + Noutput}{2} \tag{2}$$

$$Nhidden = \sqrt{Ninput \times Noutput} \tag{3}$$

In our scheme, the number of hidden layer unit is defended according to the Equation (3).

In this example, there are 3 units in the input layer, 4 units in the hidden layer, and 6 units in the output layer. The structure of BPN is shown in Figure 2.

Then we can use the data set collected in the previous phase to train the BPN, and after training we would get the locating model of this location area.

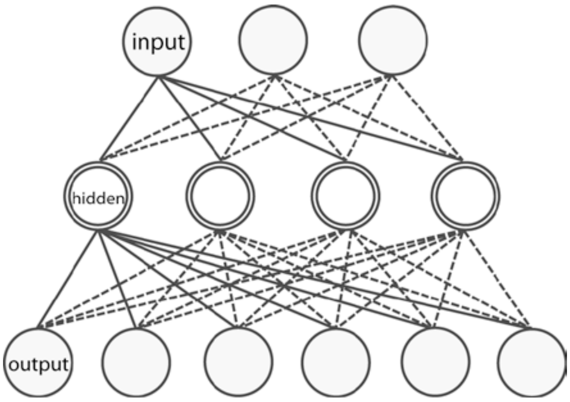

Figure 2: Example of Neural Network Structure

3.3 The Neural Network Predicting Phase

After the locating model created, we can use the model to predict the user's position. Firstly, we load the parameters of the model to BPN, and then normalize the newly received RSSIs as the input. The output is the prediction of the user's position.

When the geography or layout of objects is changed, we can simply retrain the BPN to get the new model, and then load the new model to locate the user's position. These processes can be automatically done so that we don't need to reconstruct the mathematical model manual.

4. Experimentation

Our experimental location area is in the outdoor lawn, the ground has dimension of 9 m by 18.3 m. The location area is divided into 6 zones that each zone has dimension of 4.5 m by 6.1 m, as Figure 1 shown. The gray marked regions are trees, stones and other big barriers, and R_1 to R_3 are RFID readers. The users take the RFID tags in the hand and stay in the center of zone to record the RSSIs. In each zone, we record 10 sets of RSSIs and then go to the next zone. The specification of RFID readers and tags we use are shown in Figure 3, Table 1 and Table 2.

The 60 sets of RSSIs are used to train the BPN. There are 3 units in the input layer, 4 units in the hidden layer, and 6 units in the output layer. The structure of BPN is shown in Figure 2.

In our experimentation, the correct rate is instable, generally between 60% and 90%. We find out that the accuracy is decreased when the weather change. For example, the model created in a dry and hot day performs well in the sunny days whereas performs poor in the raining days. The temperature and humidity would be important features in our experimentation that affect the accuracy of model. In the future work, the temperature and humidity should be taken into account. The inputs of BPN should be the RSSIs, temperature and humidity.

Figure 3: RFID readers and tags in experimentation

Table 1: Specification of experimental RFID readers

Communication	2.45 GHz Support read and write
Frequency	2.40~2.48 GHz
Channel	255
Address	65536
RSSI	0-255
LQI	0-255
Programmable	Set Parameter
LED	Reader action or R/W status
Ethernet	10BASE-T/100BASE-TX port, 10/100Mbps auto-sensing
RS232	RX,TX
RS485	+,-
Protocols	ICMP, ARP, IP, TCP(Server/Client), UDP, DHCP, HTTP
Baud Rate	2,400 bps ~ 115,200 bps
Power Input	7.5 VDC ~ 28 VDC
Action Current	500 mA @ 9 VDC MAX
Operating Temperature	-20 $^{\circ}$C to 65 $^{\circ}$C, 5 to 95%RH
Storage Temperature	-30 $^{\circ}$C to 85 $^{\circ}$C, 5 to 95%RH
Dimension	107W x 138H x 30D (mm)

Table 2: Specification of experimental RFID tags

Frequency	2.45GHz support read/write
Channel	256
Address	65536
RSSI	0-255
ID	64 bit
LED	Indicates the status of the signal transmission and battery power
Replaceable Batteries	CR2032 3VDC * 2
Operational Life	1 ~ 3 years
Operational Temperature	-20°C to 60°C, 5 to 95%RH
Storage Temperature	-30°C to 70°C, 5 to 95%RH
Dimension	86W*54H*6D (mm)

5. Conclusion

Using artificial neural network, our location scheme can learn the geography features to adapt to the real world. It would take the geography and reflection of walls, ground, and layout of objects into account. Therefore, it could avoid multipath phenomenon effect and be flexibly applied to any environment. If the geography or layout of objects is changed, we can simply retrain the BPN to get the new model to locate the user's position. In the experimentation, the accuracy of scheme is generally between 60% and 90%. We find out that the temperature and humidity would be important features that should be taken into account. In the future work, the inputs of BPN should be the RSSIs, temperature and humidity.

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