MULTI-BASE STATIONS BLUETOOTH LOCATION METHOD BASED ON FULL CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT:

Bluetooth positioning system has attracted much attention in the field of indoor navigation due to its high precision, low power consumption and small size. In order to solve the problem that geometric analysis cannot accurately solve the tag position, a multi-base stations Bluetooth location method combined with signal space score map and full convolutional neural network is proposed in the paper. The method generates a signal space score map based on pixels. The signal space score map inputs into the trained full convolutional neural network to output the score map of label position space. The predicted label position is obtained by mapping the pixel point with the maximum value to real spatial coordinates. It's worth mentioning that the actual distance represented by two adjacent pixels is the minimum positioning accuracy. The sigmoid function is used as the activation function in the fully convolutional neural network, so the neural network can represent the predicted uncertainty of tag position in the tag position space score map. The experimental results prove that the system improves the positioning accuracy and the robustness of navigation system.

1. INTRODUCTION

Nowadays, people demand to indoor positioning service is increasing in real life. Indoor positioning technology is receiving more and more attention. In this paper, the application of Bluetooth technology to achieve indoor positioning is mainly based on the following points: 1) Short distance wireless communication to meet the general indoor application scenarios; 2) Low cost and low power consumption are conducive to the construction of a low-cost positioning sensor network; 3) A large number of devices with Bluetooth modules, such as mobile phones, PDAs and other portable devices, come out in a rush, meeting the application requirements in the ubiquitous computing environment. With the promulgation of Bluetooth 5.1 protocol, the accuracy of Bluetooth positioning system is greatly improved. However, the accuracy of Bluetooth positioning system is not only affected by hardware, but also related to base station registration, algorithm and other factors.

As shown in Table 1, traditional wireless indoor positioning algorithms can be roughly divided into three categories: propagation modeling method, fingerprint positioning method and geometric feature method. The propagation modeling method obtains the distance between base station and tag by the attenuation relationship of RSSI with distance. At present, there are mainly three propagation models: Free-space model, Two-ray ground reflection model and Shadowing model. However, due to the occlusion between the tag and the base station, ranging cannot be conducted directly. Therefore, this method is rarely used indoor. Fingerprint positioning method includes offline and online two stages. In the offline stage, the fingerprint database was established. In the online stage, the actual information was compared with the parameters in the database. The position corresponding to the signal strength with the smallest mean square error was the coordinate of the target node. However, there exists interference from other signals in most indoor positioning systems. Fingerprint positioning method cannot measure the parameter value of label. In geometric feature method, triangulation method is often used for Bluetooth positioning. The method forms a circle around the access point. when there are three or more access points in a certain range, the intersection point can be obtained through geometric analysis. This intersection is the exact analytic solution of the label's position in space. However, Tag positions cannot be resolved by geometric parsing because of transmission loss, communication interference and other factors.

Wireless location	Propagation modeling	Fingerprint locating	Geometric feature
pros	Simple operation, easy to implement	Without reference to measuring points	Low cost low complexity
cons	Obstructing objects will lead to inability to directly measure distance and low positioning accuracy	Big workload interfered by other signals, calibration is required, and error accumulation exists	At least three base stations, tag positions may Unable to determine

Table 1. Traditional wireless indoor location algorithm.

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At present, with the rapid rise of deep neural network, deep neural network is more and more widely used in the navigation and positioning field. For example, Bai using recurrent neural network (RNN) framework to better achieve the Wi-Fi fingerprints of indoor positioning mobile users. However, there are many training parameters, which can easily cause gradient dissipation or gradient explosion. Khan and Wang studied a wireless signal processing algorithm based on deep neural networks (DNN). The input of DNN is channel impulse response (CSI) - Angle-of-Arrival (AOA) image. CSI is susceptible to noise, shadow and small-scale fading, leading to large positioning errors. M Comiter introduced a positioning method based on convolution neural network (CNN). This method has good robustness for AOA estimation with noise influence in two-dimensional space. Haji Z studied in the realization of high-precision tracking of mobile agent based on CNN-AOA technology in three-dimensional space. However, only feature vectors of fixed length can be obtained in CNN. The computational efficiency is low. While full convolutional networks (FCN) recover the category of each pixel from the abstract features. In other words, FCN extends from image-level classification to pixel-level classification. At present, there are few references about deep neural network in Bluetooth location. Therefore, a multi-base stations Bluetooth location method combined with signal space score map and full convolutional neural network is proposed in the paper. The method generates a signal space score map based on pixels. The signal space score map inputs into the trained full convolutional neural network to output the score map of label position space. The predicted label position is obtained by mapping the pixel point with the maximum value to real spatial coordinates. It's worth mentioning that the actual distance represented by two adjacent pixels is the minimum positioning accuracy.
The rest of this paper is organized as follows: In Section 2, the theoretical basis of Bluetooth location and FCN is introduced; Section 3 introduces the method proposed in this paper. Section 4 gives experimental verification; Finally, Section 5 concludes the paper.

2. RSSI BLUETOOTH LOCALIZATION THEORY BASED ON FCN

2.1 Measurement of Bluetooth system error

According to the Bluetooth signal propagation model:

$$P(d) = P(d_0)\text{-}10n\log(\frac{d}{d_0})\text{+}X, \tag{1}$$

Where d= distance between the unknown node and the beacon node
d_0=distance from the reference node to the beacon node
P(d)= RSSI of the target node
P(d_0)=RSSI of the reference node
n=Path loss factor
X=Occlusion factor random error

Multiple Bluetooth base stations are arranged. The distance between the base station and the tag can be obtained by the signal receiving intensity between the tag and the base station in space. In an ideal experimental environment, according to the performance of the base station, the furthest distance and the nearest measurement distance of the base station are divided into several equal parts. The labels are placed on the distance of equal points in turn for data collection. Due to the existence of system error, the ranging data fluctuates up and down in the process of data collection. The data presents the normal distribution style. According to the actual distance value collected, the mean standard deviation of the normal distribution of data at each equinoctial point can be obtained statistically, denoted as. The mean of the standard deviation of the normal distribution of the data is obtained by the actual distance acquired, denoted as σ. The distance corresponding to the probability interval $(-3\sigma,3\sigma)$ is denoted as the range width of the base station signal distribution interval φ. The system error parameters of the base station are obtained as σ and φ. (When multiple base stations are used for positioning, the system error parameters of each base station shall be determined separately in advance.)

2.2 Full convolutional neural network

FCN is the first time to extend end-to-end convolutional network to semantic segmentation tasks. Subsequently, many successful image segmentation deep learning technologies are based on FCN network structures, such as U-Net. FCN transforms the height and width of the feature map of the middle layer back to the size of the input image by transpose the convolution layer, so that the prediction results correspond to the spatial dimension (height and width) of the input image one by one. As long as the position on the spatial dimension is given, the output of the channel dimension is the category prediction of the corresponding pixel of that position. Among them, three techniques are mainly used: convolution, deconvolution, and skip layer. Convolution adapts to any size input, output low resolution segmentation picture; Deconvolution refers to up-sampling low-resolution images and outputting segmented images with the same resolution; Skip Layer refers to the combination of up-sampling and upper-level convolutional pooling data to fill in the missing detail data and restore the image. Convolutional neural network realizes the transformation from image category to pixel category in FCN framework.

3. CONSTRUCTION OF RSSI BLUETOOTH POSITIONING SYSTEM BASED ON FCN

The framework of multi-base station Bluetooth positioning based on FCN is shown in Figure 1. Specifically, there are three steps in this method: Firstly, collect the distance data between tags and each base station in space through wireless communication; Secondly, according to the collected distance data, the coordinates of each base station and the system error parameters, the signal space score map is generated; Finally, the generated signal space score map is input into the fully trained convolutional neural network, and the tag position space score map is output, so as to obtain the tag position information in space.

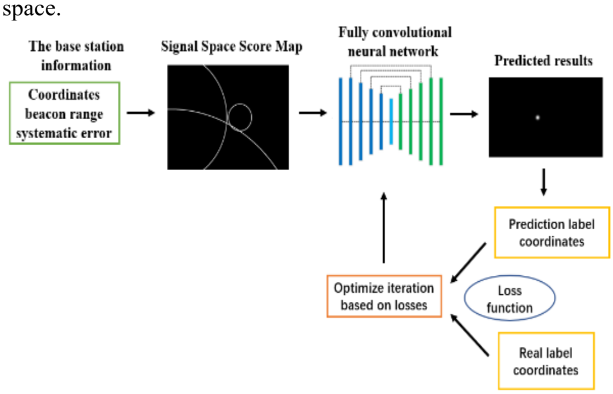


Figure 1. Overall flow chart.

The system proposed in this paper is mainly divided into two stages: signal space score map based on RSSI and the position estimation based on FCN algorithm, as follows:

3.1 Signal space score map based on RSSI

For the convenience of subsequent description, "signal space score map" is defined in this paper. The signal space score map is a signal space score map in a certain space constructed based on the pixel point size, There are three steps to implement the map as follows:

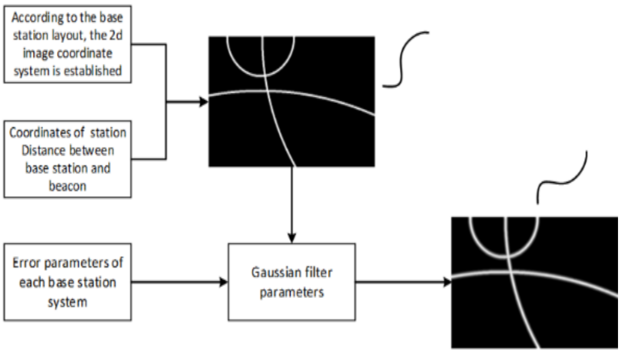


Figure 2. Signal space score map generation flow chart.

1) As shown in Figure 2, a two-dimensional image coordinate system is established according to the layout of the base stations. The desired canvas size is intercepted in its second quadrant.
2) The distance between the base station and the tag measured by the base station is recorded as r. The circle is drawn inside the canvas with the coordinates of the base station as the center. $r-\frac{\varphi}{2}$ and $r+\frac{\varphi}{2}$ are the radii of inner and outer, respectively. Repeat this step for all the used base stations to draw their respective circles in the canvas.
3) Apply a two-dimensional Gaussian filter to each pixel point in the canvas to obtain a signal space score map. The standard deviation of the Gaussian filter is the mean value of the system error parameter σ for each base station, denoted as σ; the size of the Gaussian filter can be calculated by the following equation:

$$filterwidth = roof(4 * \overline{\sigma}), \tag{2}$$

roof( ) is an upward rounding operation.

3.2 Location estimation based on FCN algorithm

3.2.1 Architecture

As shown in Figure 3, the U-Net network architecture has been improved in two aspects. The convolutional layer for adjusting the number of channels is removed at the end. Sigmoid is used as the activation function in each convolution operation.
The basic components of FCN are the convolutional block, the upper convolutional block, and the lower convolutional block. As shown in Figure 4, the width, height and number of channels of the feature graph are W, H and C_{in}. After the feature map is input into the convolution block, the end of the convolution block gets output feature map that the width and height are the same as the input feature diagram. The number of channels is C_{out}. The details of each convolution operation in the convolution block are shown in Table 2. The upper convolution block is obtained by adding an upsampling operation before the convolution operation 1 in the convolution block, The lower convolution block is obtained by adding a maximum pooling operation before the convolution operation 1 in the convolution block. After each down-convolution operation, the W and H of the output feature map become half of the input feature map; after each up-convolution operation, the W and H of the output feature map become twice of the input feature map.
The output label position space score map is the same size as the input signal space score map in FCN. Each pixel in the label position space score map can be directly mapped to the two-dimensional image coordinate system in real space. The predicted tag position is obtained by traversing the position space score graph to find the pixel coordinates of the highest value, noted as (x_{pd}, y_{pd}).
On this basis, the uncertainty of the predicted tag position is obtained in the position space score plot because of the Sigmoid function. For some application scenarios, the positioning uncertainty can be quantified. On the basis of obtaining (x_{pd}, y_{pd}), the variance parameter of gaussian distribution can be obtained by statistical analysis of the values around the point.

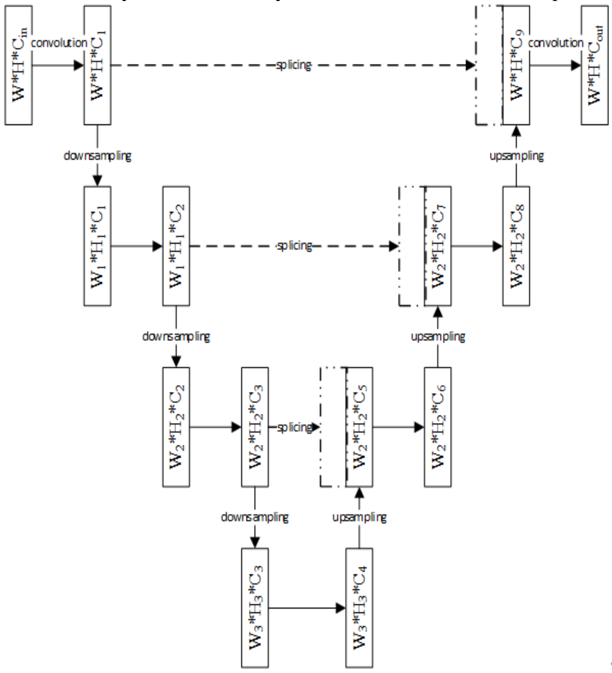


Figure 3. Structural diagram of full convolutional neural network.

operation 1	operation 2	operation 3	operation 4
1*1	3*3	1*1	1*1
step =1	step =1	step =1	step =1
Edge padding=0	Edge padding=1	Edge padding=0	Edge padding=0
channels= C_{mid}	channels= C_{mid}	channels= C_{out}	channels= C_{out}
BatchNorm	BatchNorm	BatchNorm	BatchNorm
Sigmoid	Sigmoid	Sigmoid	Sigmoid

Table 2. Details of each convolution operation in the convolution block.

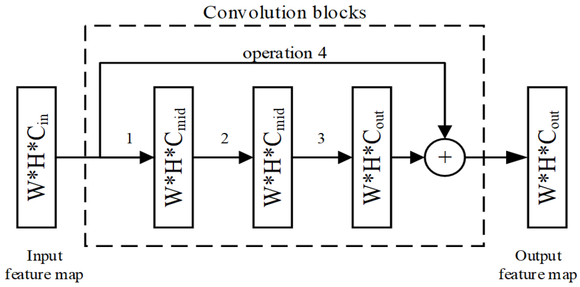


Figure 4. Convolutional block structure diagram.

3.2.2 Training method

In order to train the full convolutional neural network used in this, the spatial score map of the label location predicted by the untrained neural network shall be obtained, and (x_{pd}, y_{pd}) shall be obtained and compared with the actual label coordinates, and the error shall be passed to the neural network for weight correction. In this paper, the error of the neural network is the Euclidean distance between the predicted obtained coordinates and the actual real coordinates, and thus the training objective of the neural network used in this method can be transformed to minimize the following mathematical model.

$$Z = \min(\sqrt{(x_{pd} - x_{gt})^2 + (y_{pd} - y_{gt})^2}), \qquad (3)$$

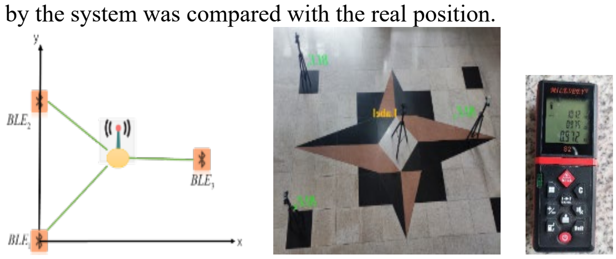
where $(x_{gt}, y_{gt})$are the actual label coordinates.

Further, the method of augmenting the data set during the training of the full convolutional neural network in said step three is as follows.

Under the condition that the label coordinates are within the range of the canvas, the canvas is translated and rotated to obtain a variety of signal space score maps, and finally the purpose of enhancing the dataset is achieved. Due to the geometric transformation of the canvas, the same transformation needs to be applied to the actual label coordinates to obtain the correct true values for loss calculation.

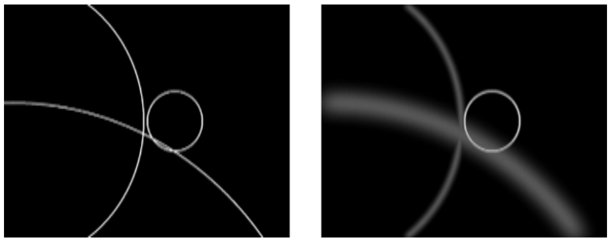
4. EXPERIMENTAL VALIDATION

In order to validate the proposed method in this paper, experiments were carried out in real scenarios. The experiment site was as follows: the first-floor hall of Xiangtan University information building. Bluetooth chip used Nrf 52832. There were three Bluetooth base stations and one Bluetooth tag. The experimental site size 5 * 3 (m) rectangular area, as shown in Figure 5 (a) (b). The three base stations and one tag placed in the same horizontal plane with a bracket, the horizontal height of 1m. As is shown in Figure 5 (c), the experimental calibration instrument used laser rangefinder that had a high ranging sensitivity (±1.5mm+d*5 per 100,000), and the position solved by the system was compared with the real position.



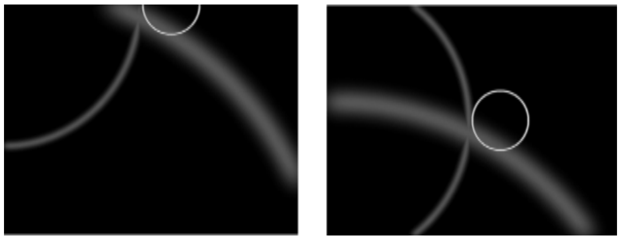
(a) (b) (c)

Figure 5. (a) Experimental data acquisition framework of RSSI Bluetooth positioning framework based on FCN. (b) Actual environment for data collection. (c) Laser rangefinder



(a) (b)

Figure 6. (a) Signal space score map generated by setting parameters such as beacon distance. (b) The results of correcting the circles plotted for each base station using the confidence parameter.

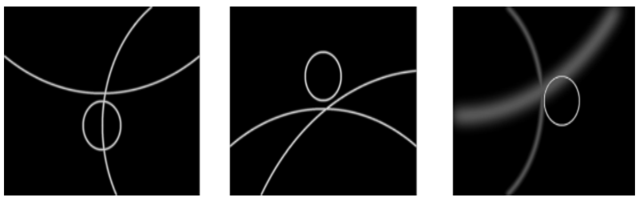


(a) (b)

Figure 7. (a) Signal space score map generated by setting parameters such as beacon distance. (b) Calculated canvas offset given the true coordinates of the label, corrected signal space score.

(a) (b) (c)

Figure 8. Signal space score map generated by different tag positions for the same base station layout. (a) The horizontal coordinate of the label was 1.6m. (b) The horizontal coordinate of the label was 1.8m. (c) The horizontal coordinate of the label was 2.0m.



(a) (b) (c)

Figure 9. Signal space score generated by different base station layouts for the same tag location. (a) A base station was at the same level as the tag. (b) Two base stations were on the same level as the tag. (c) Two base stations were on the same level with the tag, and the system error parameters were changed.

Locating method	RSSI	CNN	The proposed method
RMSE	3.24m	2.13m	1.58m

Table 3. Results of different positioning methods.

To implement the signal space score map based on RSSI, the systematic error of each base station needs to be obtained. As shown in Figure 5 (b), the RSSI of the base stations and tag at the same distance was continuously collected in the real environment. The distance between the base stations and the tag were acquired through using the Shadowing signal propagation model to generate continuous distance variation. Finally, the system error parameters of different base stations were obtained. The base station coordinates were preset and the distance between the base stations and the label was measured for many times to get the mean value. The input parameters of the signal space score map were obtained by moving the label position. Finally, the obtained signal space score maps were used as the input map of FCN.

From Figure 6 (a) (b), the method in this paper took the systematic error parameter as one of the input parameters of the signal space score graph for calculation, deepened the ring ambiguity, and thus improved the confidence of the signal space score graph. Further, it can be seen from Figure 7 (a) (b) that the method in this paper obtained the label position in the center of the canvas by considering the calculation of the canvas offset. In the next stage we used the signal space score maps as the input to the FCN framework.

In order to verify the universality of the proposed method, two schemes of hardware layout change were adopted in the experiment. In Scheme 1: Change the label position through fixed base station coordinates; In scheme 2: base station layout and system error parameters of base station were changed by fixed tag position. As shown in Figure 8 (a) (b) (c), the coordinates of the three Bluetooth base stations and the abscissa of the tag were fixed in the experiment. The ordinate of the tag accumulated 0.2m successively from 1.6m to obtain different signal space score maps. The second method was to fix the label coordinates and change the number of base stations that had the same ordinate as the label to form a different layout. Change the system error parameters of the base station, as shown in Figure 9 (c). The rings intersect more thoroughly because of the increase in ambiguity. The generation of signal space score map determines the final positioning effect to a large extent. From Figure 9 (a) (b), the Signal space score map realized by only using three base stations also has incomplete intersection. To solve this problem, Follow-up studies need to collect more base station positioning data for further optimization.

In addition, in order to evaluate the reliability of this method, the experiment adopted traditional RSSI three-point positioning and RSSI positioning method based on CNN structure under the same conditions. It can be seen that compared with traditional RSSI positioning, the positioning method using deep neural network has improved its accuracy to some extent in Tables 3. In the Bluetooth positioning method based on FCN framework, most of the tag measurements were close to the real values in the Bluetooth positioning framework based on FCN.

5. CONCLUSION

In this paper, an multi-base stations Bluetooth location method based on full convolutional neural network method was proposed. There are two main parts in the approach: 1) The signal space score map was generated from distance data, coordinates of each base station and system error parameters in space; 2) The signal space score map input into the trained full convolutional neural network to output the score map of label position space. After the preceding steps, the label position information can be obtained. For the traditional geometric analytic multi-base station wireless localization method, the number of base stations are not limited. For the existing positioning methods using CNN structure, the signal space score map with arbitrary resolution can be used as input in the Bluetooth localization algorithm based on FCN. Achieve classification from image level to pixel level.

At the same time, the method has a good tolerance for ranging errors and can quantify the uncertainty of localization results. It is experimentally demonstrated that the method convenient to deploy, has stronger robustness and the positioning accuracy.

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