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Indoor Localization Based on CFR Environment Awareness

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Abstract. Accurate amplitude information provides the possibility for indoor localization, it is easy to acquire and does not require complex corrections like phase. However, the amplitude information is sensitive to the environment, which reduces the localization accuracy. This paper proposes an indoor localization method based on environment awareness. First, using the variance of phase difference to judge whether there is anyone walking in the environment. Second, we create amplitude images as the input to Convolution Neural Network without the person walking to train localization model in the offline. Third, online localization using localization model.

Keywords: Indoor localization, Convolution Neural Network, phase difference, amplitude, CFR.

1. Introduction

Due to the complicated indoor environment, there are serious multipath effects and non-line-of-sight transmission, which makes GPS not well applied. With the rapid development of wireless network technology, Wi-Fi has also been widely used. Indoor localization, environment awareness, and human body posture detection based on Wi-Fi have become research hot-spots. At present, there are two main systems based on Wi-Fi indoor localization, one of them is to use the received signal strength (RSS), the other is to use the characteristics of the wireless channel state information (CSI) for indoor localization [1,3,4].

Received signal strength is easy to obtain and related to the distance between the transceiver, so we can calculate it according to propagation loss model, then use geometric relationships for indoor localization. However, this method requires multiple APs to be installed, thereby increasing the cost of the equipment. To overcome this problem, RSS based fingerprinting system has aroused everyone's attention, Horus [2], employs the K-nearest neighbor method to indoor localization. Another RSS based system use machine learning methods to minimize the error of localization, such as SVM, Neural Network [3] and so on. In fact, the received signal strength is not suitable for indoor localization because the indoor environment is more complicated, and RSS is the value of multipath superposition, which can only provide rough channel information.

Recently, CSI-based localization systems are increasingly popular, Spotfi [4] employs MUSIC to compute the AOA and TOF of every path and find the direct one. CSI can be described as the impulse response of the wireless channel in the time domain, which also can be described as the frequency response of the wireless channel (CFR). CFR can be obtained from computers and routers equipped with Wi-Fi network interface cards, which can provide more fine-grained channel state information and describe changes of every subcarrier in a packet.

In this paper, an indoor localization based on environment awareness is proposed，which includes the following three steps:

1) Because amplitude information is susceptible to environmental changes, it is necessary to perform personnel inspection before location. We introduce the variance of phase difference to sense whether there is anyone walking between the AP and receiver;
2) We extract amplitude information from collected CFR under no one walking, and then create amplitude images as the input of CNN;
3) As we all know, CNN have a wide range of applications in image recognition and has a good performance. So, we can construct a CNN localization model and using the amplitude image as input of the CNN in the offline training.

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2. System Model

2.1 Environment Awareness.

CFR of each antenna at the receiver can be extracted from NIC, which includes values from 30 out of the 56 subcarriers for a 20MHz or 40MHz channel [3] and can be defined as:

$$CFR = \left[CFR_1, CFR_2, ..., CFR_{30}\right] \tag{1}$$

Each component of CFR represents the frequency response of wireless channel, it is a complex value and can be described as:

$$CFR_i = \left\|CFR_i\right\| \exp\left(j\angle CFR_i\right) \tag{2}$$

$\left\|CFR_i\right\|$ and $\angle CFR_i$ indicate the amplitude and phase of the CFR corresponding to the $i-th$ subcarrier respectively. There are two main reasons for using the variance of the phase difference between two antennas to sense the environment [5]:

1) The phase difference is relatively stable with respect to phase, the raw phase information $\angle RCFR_i$ extracted from the NIC can be expressed as:

$$\angle RCFR_i = \angle CFR_i + 2\pi \frac{m_i}{N} \Delta t + \delta + z \tag{3}$$

Where $\angle CFR_i$ represents the real phase of the $i-th$ subcarrier, m_i is the index of the $i-th$ subcarrier, Δt represents the delay caused by packet detection delay and frequency offset, δ represents the unknown phase offset caused by the center frequency, z is the environment noise [5]. The phase difference between the two adjacent antennas of the $i-th$ subcarrier in the same packet eliminate the phase delay caused by Δt, so it becomes more stable than phase [3].

2) The variance of the phase difference is more sensitive to the environment than phase, if the phase offset and environment noise are not considered and assume the signals from different antennas are independent [5], the variance of phase difference $\sigma^2_{\Delta\angle CFR_{i,j}}$ between two antennas can be derived as:

$$\sigma^2_{\Delta\angle CFR_{i,j}} = \sigma^2_{\Delta\angle CFR_i} + \sigma^2_{\Delta\angle CFR_j} \tag{4}$$

Where, the variance of the phase difference of two antennas is the sum of individual variance on each antenna, so the latter is smaller than the former. However, considering the influence of the phase difference of the sudden change of the antenna and the subcarrier, the Hamper filter is used to detect the outlier before calculating the variance [5].

Also, the threshold method is used to judge that there is someone walking between the AP and receiver, the variance of the phase difference is better than the variance of phase, which can be seen in Fig. 1, where phase1 and phase2 represent the phase variance at two scenarios respectively, phase diff1 and phase diff2 represent the variance of phase difference at two scenarios respectively.

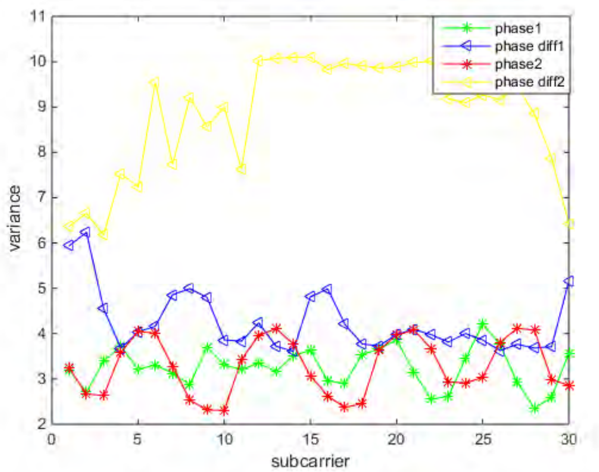

Fig. 1 The variance of phase and phase difference at two scenarios

2.2 Create Amplitude Images.

When the AP is in a different position, the amplitude of the CFR collected by the receiver will be different. The CFR amplitude of 90 packets of three antennas extracted from the NIC is taken as the pixel value of the picture [6], so the size of the picture is 90*90. In order to better utilize the amplitude images to distinguish different locations, we binarize the image as in Fig. 2:

1) Calculate the average of all pixels in the image, expressed by p;
2) Pixel value greater than p is 255 while pixel value less than p is 0.

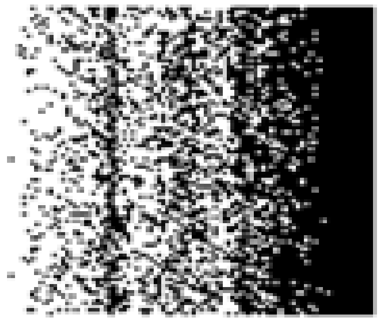

Fig. 2 Amplitude binary image of one location

2.3 Localization Based on CNN.

The convolutional neural network includes input layer, convolutional layer, pooling layer, and fully-connected layer. Amplitude picture as input to CNN and the number of location as output to CNN. The other three main components of CNN in the following.

Offline training: The convolutional layer can extract feature maps within local regions in the previous layer’s feature maps. For each input image in the first convolutional and pooling layer, we employ 40 convolutional filter with size 7*7 to obtain the same number of feature maps with size 84*84, In order to reduce the complexity of the operation, we can get the same number of feature maps with 42*42 from the pooling layer [3]. Then like this, 10 feature maps with 1*1 can be obtained, which can be used as input to the fully-connected layer to train the weights based on BP algorithm. The squared error loss function defined as:

$$Error = \frac{1}{2N}\sum_{i=1}^{N}\left(y_i - r_i\right)^2 \tag{5}$$

Where N is the number of training locations, y_i is the CNN output for the $i-th$ location, r_i is the true label for the $i-th$ location. We use 10 training locations and 10 test locations.

Online test: We employ KNN method to predict the location of AP, select the three locations closest to the test position number and calculate the average of their position coordinates as the coordinates of the test position.

3. Accuracy of Location Estimation

Fig. 3 presents the training error over iteration of the CNN in the laboratory of 6m*6m , with respect to guarantee successful training and get a well localization model, we set the threshold of training error to 0.05, the corresponding number of iteration is about 500 times. The location accuracy with 50% error is of about 1.5m in the laboratory.

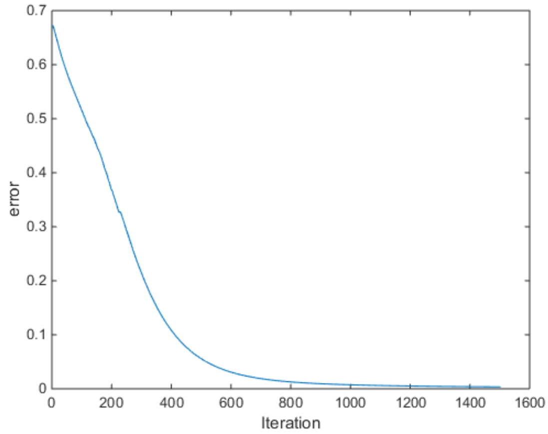

Fig. 3 Error over iteration of the CNN

4. Summary

In this paper, an indoor localization based on environment awareness is proposed. We first using the variance phase difference to judge whether there is anyone walking in the environment，then the amplitude information extracted from CFR under no one walking can be used to construct amplitude picture, which are used as the input of CNN. Finally, we estimate the positioning accuracy through experiments.

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