A CNN Approach of Activity Recognition via Channel State Information(CSI)

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Abstract*—In this paper, we propose a model using computer vision technology CNN to process wireless sensor measurements. Wireless sensing, as a popular research program in the intelligent application of the Internet of things(IoT), has drawn increasing attention from researchers of all over the community in recent years. With the special tool named iwl5300 coming out in 2010,Channel State Information(CSI), a more precise and accurate measurement data, has replaced Received Signal Strength Indicator (RSSI) and become a rather helpful tool to study WiFi signal and commit experiments. In recent years, with the flourish development of computer vision technology, image recognition technology has been rather qualified to process many kind of images, as so the application of image recognition technology be used in wireless sensing data processing is a reasonable innovation. By this means, not only the calculation cost has been saved, but also both the accuracy and the scale of the problem has been improved. In this paper, a model called C-WiFi is proposed, which is brand-new. In this model, the traditional method of Dynamic Time Warping(DTW) is declined and with the CSI measurements converted into the spectrum diagram. As the result, we can see that C-WiFi has achieved gratifying results in identifying activity at the same time and has made contributions to further improving human-computer interaction ability.

Keywords*：*CNN, CSI, IoT，Gesture Recognition.

I. Introduction

With the booming development of information technology, the era of the Internet of things industry can also be seen flourishing. As an important part of new computer technology, Internet of things has played a very important role in the whole process of development of information technology application. The so-called Internet of things is essentially the Internet between things. The Internet of things is also an extension of the Internet network, which can not only improve people's ability to perceive the surrounding environment, but also help understand the state of things. Owing to this, the IoT technology truly bring much convenience to our daily life. Secondly, in the process of using the Internet of things, we can find that the client extension and expansion of the Internet of things have been satisfied with information exchange and communication between various items. By applying sensors to the Internet of things, we can create a better network environment. In the whole wireless sensor network, we can collect and monitor the information that needs to be applied through the sensor nodes. With the constant development of information technology, the emergence of the Internet of things brought great convenience for people's daily life. What's more, as a kind of wireless sensor network ensuring the safety of network information transmission network, only by fully combined it with the Internet of things, will it better meets requirements that become higher and higher.

The purpose of IoT is to develop green and all-wireless technologies, including perception and communication, which requires extremely low power consumption, wireless coverage, reliable connection and secure communication. When we apply Internet of things technology to real life, we need to consider security, cost and practicality. As far as home application is concerned, it needs to be very convenient to install, to use and to maintain. Smart space combined with IoT technology is the embodiment combination of high and new technologies. It is a rising industry with extensive application needs. It has become an irresistible technology development trend to apply IoT technology to smart space. Technologies like computer vision, light recognition, infrared technology, are known as smart space technology applications, however its shortcomings are also very obvious. Computer vision technology based on equipment like cameras. First of all, the camera installation consumes a certain cost, and the practice of indoor camera installation is generally not accepted by individuals, considering there is also a great risk of information leakage. Besides, light-based IoT perception relies heavily on light intensity. Also, it has strict requirements for indoor structures and cannot deal with shielding and other complex situations. The advanced infrared technology is mostly used in remote control, and requires the help of specific tools, making it difficult to be used in the Internet of things without devices.

Diverse from those technologies mentioned above, wireless sensing not only reduces the risk of privacy leak, and at the same time reduces the installation costs. In addition, wireless sensing also overcome shortcomings of Visible-light identification technology that it's affected much by the extent of the field of vision. On a lot of application of smart space, wireless sensing technology is low-cost, easy to install and modify, and the ability of recognition is of high precision. All these functions based on a low labor costs and even no labor cost. And therefore in smart space combined with technology of Internet of things, such a device-free technology couldn't be more popular. By receiving the Channel State Information of radio waves after scattering, diffraction and other physical phenomena, wireless sensing can realize the recognition of human activities, gait, gestures and even lip language. And the realization of all these

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recognition capabilities only based on two signal ends, which greatly improves the comfort of the intelligent space.

In the community, researchers used to utilize Dynamic Time Warping (DTW) to process CSI measurements, however with the mature technology of image recognition, the CNN method can be applied to CSI measurements classify. As one of the core algorithm for image recognition, CNN is a special deep feedforward network. In this paper, we process the SI measurements, convert it to the temporal-frequency images, thus we can input the images into the model for training, and then the CNN model extracts the fine-grained features. In method like this we can save labor of modeling the features and consume less time. As far as the results is concerned, our model performs better than the two models in the community in terms of accuracy and problem scale, making contributions to further improving the human-computer interaction ability.

II. Overview

In this section, we will introduce the framework of this paper, the experimental process and so on.

In section 3, related work about CSI and CNN will be introduced. In section 4, information about Channel State Information will be introduced. In section 5, information as well as the structure of CNN model will be described. In section 6, there is a complete experiment, and in section 7, the result is been discussed. In section 8, a conclusion is stated.

A. Experiment equipment

According to the China smart space equipment industry market outlook and investment strategy planning report released by the prospective research, up to 2018, China's smart space market scale is initially estimated to exceed 170 billion RMB. Transform your ordinary house into a smart home thus is a hot issue in the community. However the way of the transform goes, it should follw the MMM principle(Minimum cost and Minimum change in Minimum time). Based on this view, this experiment equipment adopted only one transmitter (wireless router) and one receiver. Transmitter USES a NetGear R7000 wireless router, receiver USES a mini PC, which is 4G memory, and a Intel 5300 NIC. The experiment measurements is collected within 5G frequency band in a normal office room.

B. Data collection

In this paper, we collect the measurements of 16 kinds of activities of six volunteers. 30 groups of samples has been collected for each of the object. First, the transmitter and receiver are installed on two platforms, and the platform is 85cm high and is set 1. 9m apart. To collect the CSI measurements, the receiver(mini PC) pings the transmitter in 1000 package per second. Each collection continues about 4 sec.

C. Data processing

First, the raw measurements collected by iwl5300 needs to be standardized. A channel has 30 subcarriers. This means that there are 30 data structure in each sample. In order to simplify the calculation process, we need to reduce the dimensionality of the measurements. In the dimensionality reduction method, principal component analysis (PCA) is utilized to extract the data with high scores in the first K dimension, and then form a new data set with the result, and then the time temporal- frequency diagram is drawn to be used as the input dataset of the CNN model.

D. CNN model training

Load the dataset into the C-WiFi model after obtaining the processed measurements, and then the C-WiFi model will start mathematical model, analyze and identify in replace of labor work. CNN model here is used to train CSI data, and 70/30 ratio is used for training and verification. Cross-validation is used for training and parameter adjustment, and thus a high-performance C-WiFi model with appropriate parameters is finally obtained. The C-WiFi model schematic diagram is proposed in Fig. 1.

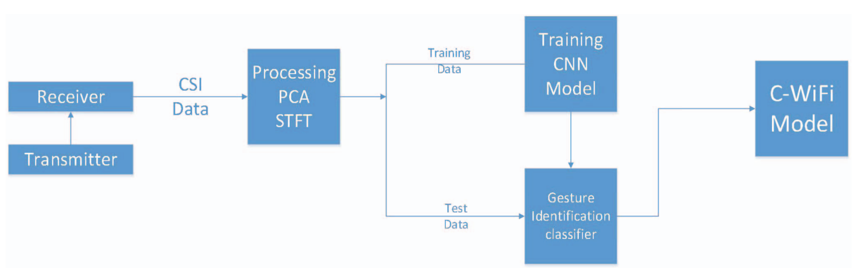

Figure 1. C-WiFi model schematic diagram

III. Related Work

Initially, Dynamic Time Warping(DTW) has been used to identify and analyze the amplitude-frequency feature of the radio signal[27,28]. 2010, CSITOOL iwl5300 technology came out, and the research work of using CSI information for identification scrambled to come out. For example, gesture recognition, gait recognition, and lip recognition[2,7,8,11,36]. In addition, researches on fall detection based on tag are also carried out[37].

With the flourish development of computer vision technology, image recognition technology has been rather qualified to process many kind of images. As one of the core algorithm of image recognition, CNN has attracted the attention of many researchers due to its excellent features such as local connection, weight sharing, pooling operation and multi-layer structure. CNN reduces the number of weights that need to be trained and reduces the computational complexity of the network through weight sharing. At the same time, it makes the network invariant to the local transformation of input, such as translation invariance, scaling invariance, etc. through pooling operation, which improves the generalization ability of the network. CNN directly inputs the original data into the network, and then implicitly carries out network learning from the training data, avoiding the shortcomings of manually extracting features, which leads to the accumulation of errors, and the whole classification process is automatic.

IV. CSI

When the WiFi signal is transmitted under the standard protocol 802. 11 or 802. 11ac, it USES the modulation method of Orthogonal Frequency Division Multiple (OFDM), and the CSITOOL can extract the channel state information from the commercial Intel 5300 NIC[24]. CSI is fine-grained physical information, more sensitive to the environment than RSSI, so that the CSI measurements applied much better to gesture recognition, gait recognition, keystroke identification, tracking, and other fields. It describes the decay factor in the transmission path of each factor, namely the channel gain matrix H (sometimes referred to as the channel matrix, the channel fading matrix) of each element in the values, such as signal Scattering , environment decay(fading,Multipath fading or shadowing fading), energy decay of distance, etc. CSI can make the communication system adapt to the current channel conditions and provide a guarantee for the communication with high reliability and high rate in the multi-antenna system. CSI is a fine-grained feature of MAC layer, which can reflect signal attenuation, including refraction, reflection, diffraction, power attenuation and other information.

Wireless channels generally use Channel Impulse Response (CIR) to describe Channel multipath effect. Under the assumption of linear time invariance, Channel Impulse Response can be expressed as follows:

$$h(t) = \sum_{i}^{N} \eta_i e^{-j\theta_i} \sigma(t - t_i) \tag{1}$$

The multipath propagation of a radio signal in the temporal domain is shown as time delay extension, whilst in the frequency domain, it will cause selective fading of the signal. Therefore, the frequency response of a wireless channel can be used to describe the multipath propagation of a signal respectively from the amplitudes and frequencies and the phases. Under the condition of infinite bandwidth, CFR and CIR are Fourier transforms to each other. The frequency response of the channel can be expressed as follows:

$$H(m) = \|H(m)\| e^{j\angle H(m)} \tag{2}$$

V. CNN

CNN is one of the core algorithm of image recognition. The basic structure of CNN consists of the input layer, the convolution layer, the pooling layer (also known as the sampling layer),the full connection layer and the output layer[16,19]. In general, the convolutional layer and pooling layer are selected to be set of several pairs , and the setting of alternating convolutional layer and pooling layer is adopted. That is to say, a convolutional layer is connected with a pooling layer, and a convolutional layer is connected with a pooling layer in a roll, and so on. Since each neuron in the output characteristic surface of the convolution layer is locally connected with its input, and the input value of the neuron is obtained through the weighted sum of the corresponding connection weight and local input plus the bias value, the process is equivalent to the convolution process, hence come the name CNN.

Convolutional neural network has the characteristics of local connection and weight sharing[20], in which a large number of neurons are organized in a certain way to respond to overlapping areas in the field of vision. The local connection, weight sharing and pooling operation of convolutional neural network can effectively reduce the complexity of the network, reduce the number of training parameters, and make the model invariant to translation, distortion and scaling to a certain extent, with strong robustness and fault tolerance, and also easy to train and optimize. Based on these superior characteristics, it performs better in various signal and information processing tasks than the standard full-connected neural network.

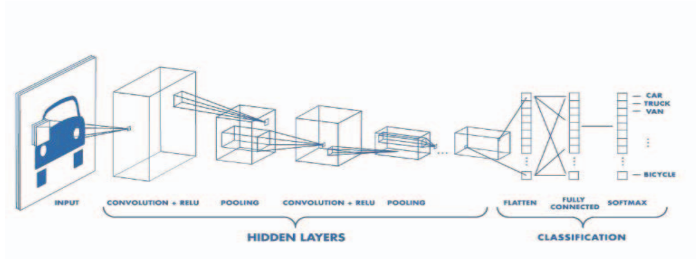

Figure 2. CNN flow chart

As is shown in Fig. 2,

(1)Convolution layer

In the convolution layer, the feature map of the upper layer is convolved by a learnable convolution kernel, and then the output Feature map can be obtained by an Activation function:

$$a_k^n = \varphi(\chi_k^n) \tag{3}$$

$$\chi_k^n = \sum_{i \in D_k} a_i^{n-1} * \mu_{ik}^n + \beta_k^n \tag{4}$$

χ_k^n means the Net activation in kth channel of the nth layer;

a_k^n means the output in kth channel of the nth layer;

μ_{ik}^n means the convolution kernel matrix;

β_k^n means the bias.

(2)Pooling

Pooling is an important operation in the convolutional neural network, which can reduce features while maintaining local invariance of features. Common Pooling operations are: Spatial pyramid Pooling (SPP), Max Pooling, Mean Pooling, Stochastic Pooling, etc. .

$$\chi_k^n = \omega_k^n \rho(a_i^{n-1}) + \beta_k^n \tag{5}$$

χ_k^n means the Net activation in kth channel of the nth layer;

ω_k^n means the weight of the pooling layer;

$\rho(\cdot)$ means the pooling function.

(3)The activation function

The commonly used kinematic functions are ReLU, Leakly ReLU, Parametric ReLU, Randomized ReLU, ELU, etc.

(4)Loss function

The selection of loss function plays an important role in the convolutional neural network. The representative loss functions are: square error loss, cross entropy loss, Hinge loss and so on.

(5)The fully connection layer

In the full-connected network, the feature images of all two-dimensional images are spliced into one-dimensional features as the input of the full-connected network. The output of the full-connected layer n can be obtained by weighted summation of the input and response of the activation function:

$$a^n = \varphi(\chi^n) \tag{6}$$

$$\chi^n = \omega^n a^{n-1} + \beta^n \tag{7}$$

χ^n means the net activation of the full connection layer n, which is obtained by weighting and bias of the output characteristic graph a^{n-1} of the previous layer;

ω^n means the weight coefficient of the fully connected network;

β^n is a bias term for the full connection layer n.

VI. EXPERIMENTS

A. Data Collection

In this experiment, only one pair of transmitter (wireless router) and receiver is used. Transmitter USES a NetGear R7000 wireless router, receiver USES a mini PC, which is 4G memory, and Intel 5300 NIC. The experiment measurements is collected within 5G frequency band (when in 2. 4G frequency band ,there is high interference and the packet loss rate is over 40%). A total of 16 groups of activities of 6 volunteers were collected, with 30 samples for each group of movements, and a total of 2880 samples were collected.

The indoor environment is as shown in the Fig. 3. It is a common office room. The volunteers performed various gestures in the gray measurement area. At first, the we make the mini PC(receiver) pings the wireless router(transmitter), and after receiving the feedback from the transmitter to confirm the channel is connected, the data is ready to be collected. Create a new command window aside by the original one on the mini PC , and input the command to receive channel state information. The receiving rate is 1000 package/ SEC. At the same time, the volunteer start to make special gestures for about three seconds, and then the volunteer stop gesturing, leave the measurement area, and in mini PC we stop receiving channel state information, thus a sample is collected. Through routines like this,we collected 2880 samples.

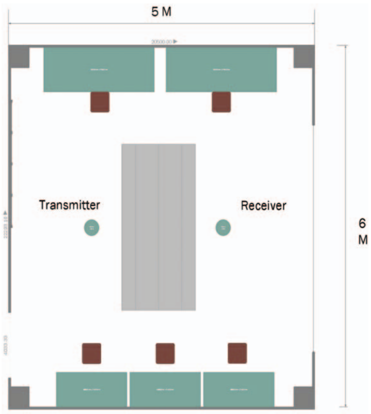

Figure 3. Experiment environment which is a office room

B. Data Processing

The CSITOOL iwl5300 is used to receive CSI measurements, and relevant programs are used to load structure data on MATLAB platform, and the channel gain matrix is obtained, including RSSI of each antenna, packet frequency and so on. In the 802. 11 or 802. 11ac wireless network protocol, the physical layer USES OFDM technology, and the channel is divided into 30 subcarriers, each of which carries packets for information transmission. Draw the diagram of the radio waveform on the MATLAB,it can be observed that the raw measurement has enormous noise and the waveform features are not at all obvious, which is difficult for CNN model to analysis its essence of measurements distribution.

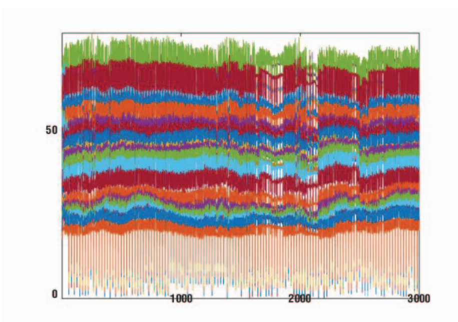

Figure 4. Waveform drawn by raw measurements

As is vividly depicted in Fig. 4, the waveform of 30 channels is shown above. Over all we can see that the 30 channels have roughly the same up and downs, different color represent different channel waveform, and the color of each channel is randomly generated. The channel noise, as well as the interference, disturbs a lot when input into the CNN model, will be a holdback for image recognition.

To better observe the feature of the waveform, the butterworth lowpass filter is used to filter the measurements, thus a clear and intuitive image can be obtained. And in Fig. 5,it can be easily observed that in the 500ms of the beginning,the measurement received is distorted, and this part of the measurement will be cut off in data processing.

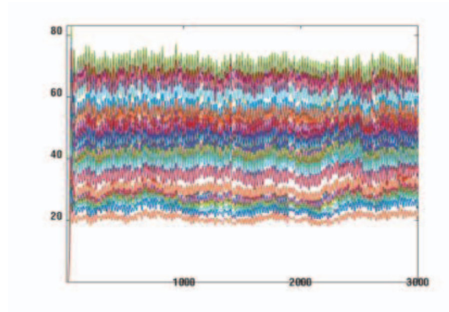

Figure 5. Waveform drawn by filtered measurements

On the other hand, with the time fleets about 2500ms, the observation target has taken back the gesture and left the measuring area, so that the measurements after this time point are invalid,also needs to be removed when processing data. Through this routine, each sample roughly guarantees the effective data around 2500ms, saving a lot of computing costs for the subsequent model training. According to the observed number of subcarriers, that is, 30, CSI data presents a structure data with a unit number of 30. The direct application of such data to model training is too complicated. The Principal Component Analysis(PCA) is used to reduce the dimensionality of the data. After dimensionality reduction, the pre-k column data is obtained according to the score, and the time-frequency chart is drawn by spectrogram to generate the training set.

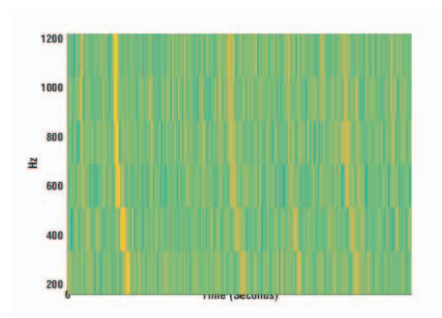

Figure 6. Temporal-frequency domain diagram

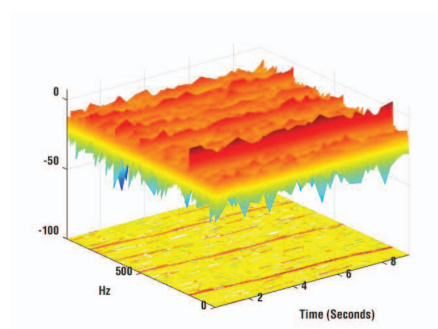

Figure 7. Temporal-frequency domain 3D diagram

As is shown in Fig. 6, use STFT to process the principle data , a spectrum diagram is drawn as one of the sample's dataset. The horizontal axis represents the change in time, and the vertical axis represents the change in frequency. For better analysis the feature of the spectrum, we draw a 3D diagram, in which we can easily evaluate the quality of the data, and removed the sample of low-quality in time.

C. Model training

The basic structure of CNN consists of input layer, convolution layer, pooling layer (also known as sampling layer), full connection layer and output layer. The alternative Settings of convolutional layer and pooling layer are adopted, that is to say, a convolutional layer is connected to a pooling layer, and a convolutional layer is connected after the pooling layer in a roll, and so on. Since each neuron in the output feature plane in the convolutional layer is locally connected with its input, and the input value of the neuron is obtained through the weighted sum of the corresponding connection weight and local input plus the bias value.

VII. Experimental Result

During the process of training, the number of hidden layers in the model structure was changed. As is shown in Fig. 8,the number of hidden layers increased from 3 to 10, the accuracy gradually increased to 90. 43% -- 92. 17%,and in Table 1 is the numbering of the each gesture.

The accuracy of each gesture recognition when the number of convolution kernel fixed to 10 is shown in Fig. 9. The highest accuracy is the classification of gesture "sit down",and the lowest accuracy for classification is from gesture "two hands wave", and the accuracy is 92. 17% and 90. 43% respectively.

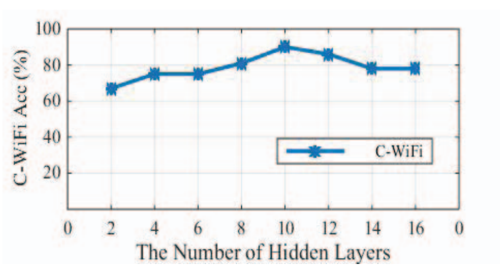

Figure 8. Impact of hidden layers

However, when the number of hidden layers goes from 10 to 16, the accuracy decreased to about 80. 70%. As is shown in Fig. 10,the number of hidden layer is fixed at 10,and with the target gesture increases, the accuracy of C-WiFi remains at a stable high level. However as the control group, two classic models---Wig and WiAG[7,8]---in the community gradually show a decrease in the recognition accuracy as the problem scale increases.

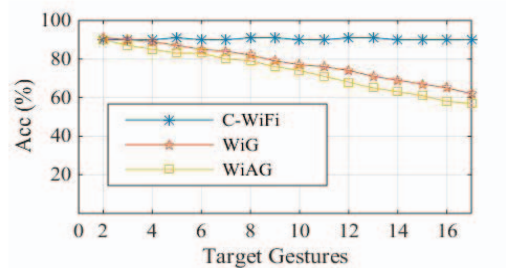

Figure 9. Performance of increasing number of gestures of three different models

VIII. Conclusion

The C-WiFi model proposed in this paper, is a image recognition method based classifier for CSI measurements, can put the CSI measurements detected indoor from the receiver into the CNN model for training after simple data processing. This image recognition method saves the steps of manual mathematical modeling and also saves time and labor. This proposed model can identify 16 activities of human,and reach the accuracy of 90. 43% -- 91. 07%. In the results, we can see that when the hidden layer of CNN reaches 10, the model performs better than the two models in the community in terms of accuracy and problem scale. The results show that the image recognition technique from computer vision can be applied to extract features of CSI measurements and classify them, making contributions to further improving the human-computer interaction ability. However, there also leaves some limitations to be solved. One is that the experimental environments is not various enough. The other is that the distribution of other network(such as campus wireless network) can not be neglected,which makes data collection inefficiency and of bad effect. And the model training stage consumes most of the time spending besides data collecting, up to the date we didin't solve the problem.

Table 1. Target Gesture Numbering

1	2	3	4	5	6	7	8
horizon arm wave	high arm wave	two hands wave	high throw	draw x	draw tick	toss paper	forward kick
9	10	11	12	13	14	15	16
side kick	bend	hand clap	walk	phone call	drink water	sit down	squat

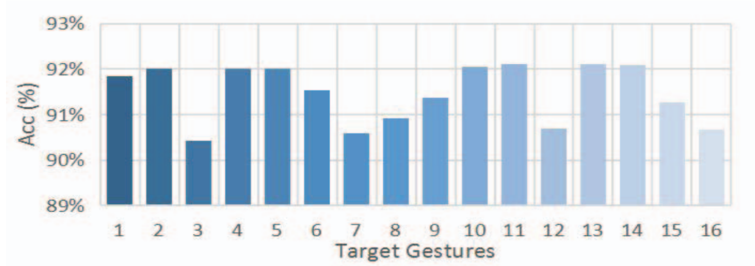

Figure 10. Accuracy of each target gesture

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