Wau: A User Authentication System Based on Channel State Information and Deep Neural Networks

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Abstract. Recently, user authentication techniques have attracted more attention and played a more important role in human-computer interaction applications. In this paper, we propose a user authentication system based on CSI (channel state information) called Wau. This system works in a device-free way and has no privacy violation because it facilitates the crucial characteristics of CSI that the unique CSI variation from different user activity can be measured and recognized. We adopt deep neural networks to realize the authentication of 8 people in three environments, including a through-the-wall scenario. The highest recognition accuracy reaches up to 98%. These results validate the feasibility and effectiveness of the user authentication system using CSI and deep neural networks.

1. Introduction

In recent years, user authentication has attained more consideration due to the wide demand for smart home, intrusion detection, and network security. Many applications employ fingerprint recognition [1] and face recognition [2] techniques to implement user authentication. Although these systems achieve high authentication accuracy, they have certain shortcomings, such as private violation or deployment cost. Therefore, identity authentication using a device-free work pattern is becoming increasingly popular. With the widespread application of WiFi hotspot, many intelligent applications using the WiFi signal is becoming more prevalent. As a result, user authentication based on WiFi signals has gained more attention. Among the signals from WiFi devices, CSI (channel state information) describes communication link qualifications and can be affected by person motions. Thereby, it can be utilized to recognize user identity. According to existing applications, we find that CSI can be used to identify people using different actions, including gait [3-6], activity [7], hand gesture [8], stillness [9,10]. Among these applications, gait-based and activity-based approaches are more popular because gait and activity are coarse-grained actions and can be measured and analyzed easily.

Traditional user authentication application usually needs to extract accurate features to implement user recognition. However, this system has to apply some complicated feature extraction methods since these features will determine recognition results significantly. Therefore, automatic extraction and recognition methods are becoming more popular. Deep learning approaches can implement complicate data classification since they utilize neural networks to extract features and classify data. As a result, more and more deep learning models are widely used in various applications.

Human action can generate complex CSI variations. It is difficult to analyze and explain the fluctuation using traditional approaches. Therefore, we can utilize deep learning approaches to process these variations. In this paper, we propose a system called Wau to recognize personal identity. It
realizes device-free user authentication and does not violate privacy. Specifically, it not only can identify a user identity in the general environment but also can recognize a user under a through-the-wall environment. The whole process of user authentication contains three parts, including signal collection, signal processing, and classification. Firstly, we apply a router and a laptop equipped with Intel 5300 NIC to collect CSI signals. We conduct the experiment in a hall, corridor, and reference room, respectively. Secondly, we transform the data into a matrix that is suitable for neural network input. Thirdly, we build deep learning models and use them to determine people’s identity.

In summary, the contributions of this paper are listed as follows. Firstly, we propose a device-free passive user authentication system called Wau, and it can work both in a general indoor environment and through-the-obstacles environment. Secondly, we use CNN (Convolutional Neural Network), LSTM (Long Short-Term Memory), and GRU (Gated Recurrent Unit) to handle measurement data and realize higher authentication accuracy compared to existing systems. The results validate that deep neural networks can effectively process CSI data and implement accurate user authentication.

The rest of this paper is organized as follows. In section 2, we introduce the background of CSI signals and models used to process signals. In section 3, we describe the framework of this system. Section 4 evaluates the authentication performance of this system. In section 5, we conclude the paper with some future studies.

2. Related background theories
This paper focuses on user authentication based on CSI and deep learning models. Therefore, this section mainly introduces CSI and some typical models used in this paper.

2.1. Channel state information
CSI is a metric used to estimate the channel characteristics of a wireless communication link. It depicts how a signal propagates through a channel, combines multiple effects such as delay, amplitude attenuation, and phase offset, and describes the amplitude and phase of each subcarrier in the frequency domain space. CSI comes from the physical layer and has high stability at different subcarrier. In the frequency domain, the wireless channel state can be described as:

\[ Y = H \times X + N \]  

Y, X, H, N represent received signal vector, transmitted signal vector, channel matrix, and Gaussian white noise, respectively. And channel matrix H can be described as:

\[ H(i) = |H(i)|e^{j\angle H(i)} \]  

\( H(i) \) represents the value of CSI for the subcarrier, and it contains the information of amplitude and phase. Specifically, \( |H(i)| \) and \( \angle H(i) \) represent the amplitude and phase value of the \( i^{th} \) subcarrier, respectively.

2.2. Signal processing methods
Signal processing methods play an essential role in the user authentication procedure. The raw data is collected, and it must be processed to meet the input criterion for deep neural networks. The CSI data contain two complex values that can be used to calculate the amplitude and phase of a subcarrier. Since the phase reflects more fine-grained information and contains more noise, it must be calibrated before usage. On the contrary, the amplitude depicts more coarse-grained information and more robust to noise. Therefore, we apply the amplitude of CSI as input data. In addition, since deep learning models usually process matrix data, we change the data into a typical matrix pattern.

In this system, we use several deep neural networks to process CSI data and recognize user identity. Next, we will introduce these typical neural network models.
2.2.1. **CNN.**

CNN is a deep feedforward artificial neural network. As shown in Figure 1, the structure of CNN contains the input layer, hidden layer, and output layer. The input layer can process multidimensional data. The hidden layer includes the convolutional layer, pooling layer, and fully connected layer. The convolutional layer of the neural network is to retain the local features of the image. The data after convolution needs to be calculated by the activation function, such as sigmoid, tanh, and ReLU. The pooling layer is used to reduce the size of the feature map generated by the convolutional layer. Standard pooling methods include max-pooling and mean-pooling. After the fully connected layer, we can obtain one dimension vector. Finally, the output layer usually utilizes the softmax function to output classification results.

![Figure 1. The principle of CNN.](image)

2.2.2. **LSTM.**

LSTM realizes the retention of important content and the removal of unimportant content by using the structure of the gate. LSTM includes three gates, i.e., input gate, forget gate, and output gate. The forget gate determines what information is discarded from the cell state at the last moment; the input gate determines how many network inputs can be saved to the cell state; the output gate determines the output information.

2.2.3 **GRU.**

GRU also uses the gate structure to control the information of memory and input. It contains two gates, i.e., reset gate and update gate. The function of the update gate in GRU is similar to the input gate and forget gate in LSTM; the reset gate is used to control how much the previous state information is brought into the current state. Compared to LSTM, GRU has one less gate than LSTM, and its structure is simpler. In the case of large training data, GRU can save a lot of time.

3. **System framework**

In this section, we introduce the system of user authentication in detail. It mainly includes two aspects, i.e., the principle of CSI-based user authentication and experimental environments.

![Figure 2. The framework of user authentication.](image)

3.1. **The principle of CSI-based user authentication**

The fundamental principle of CSI-based user authentication can be explained as follow. The user motion has a certain impact on CSI when they do actions within the range of WiFi signal coverage. Specifically, it will cause the change of signal propagation path and channel interference. Therefore, we can identify each person according to their different influence on CSI.

| Input shape | The number of epochs | Batch_size | Learning rate | Activation function | Optimizer |
|-------------|----------------------|------------|---------------|---------------------|-----------|

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As shown in Figure 2, the whole process of signal processing includes the signal collection, signal processing, and classification. CSI signal variation caused by people’s movement is acquired by using a router as AP and a laptop as PC equipped with Intel 5300 NIC. And we select amplitude as a base signal in this paper. Next, the CSI signals will be transformed and fed into a neural network model. Specifically, we build the CNN including four convolutional layers, three max-pooling layers, and two fully connected layers, the LSTM including three memory layers and one fully connected layer, and the GRU including three gate recurrent unit layers two fully connected layers. The specific parameters of these three networks are shown in Table 1.

3.2. Experimental environments
In this experiment, the router is equipped with one antenna, and the laptop is equipped with three antennas, i.e., $N_t=1$ and $N_r=3$. Usually, we can acquire 30 subcarriers from every antenna. Thereby, we can obtain 3 data streams from each data packet since we used three receiving antennas. The dimensions of CSI information we acquired are $30\times3$:

$$CSI = \begin{bmatrix}
H_{1,1} & \cdots & H_{1,30} \\
\vdots & \ddots & \vdots \\
H_{30,1} & \cdots & H_{30,30}
\end{bmatrix} \quad (3)$$

We collect data in 3 different scenarios, including hall, corridor, and reference room, respectively. We use the action data of 8 student volunteers aged 20-25. In experiment 1, the transmitter and receiver are placed on a table of 0.8 m high and 2 m apart, as shown in Figure 3 (a). And we ask eight volunteers to walk from the direction perpendicular to AP and PC. Each volunteer needs to walk 8 m and provides 100 samples. In the meanwhile, the laptop receives CSI signal contiguously. In experiment 2 and 3, the laptop and router are placed on both sides of the wall or bookshelf, and participants perform actions between them to collect data. Other experiment settings are the same as experiment 1. The experimental environments of 2 and 3 are shown in Figure 3 (b) and (c).

4. Performance evaluation
This system uses deep learning models to achieve user authentication. We verify its authentication accuracy in different situations, such as different environments, different classification approaches, and other actions. Next, we will analyze the authentication accuracy from these three aspects.

4.1. User authentication in three environments
We evaluate the identification accuracy of our system in three different environments. We test the model using the following two ways. The first one is that we evaluate the CNN model for each test scenario. Since we have three test environments, we have three different model parameters. The second one is that we validate the CNN model using all samples collected in three scenarios. The two test results validate the effectiveness of identity authentication using CSI and CNN, as shown in Figure 4. Specifically, the recognition accuracy of specific environments is 89%, 88%, and 74% from
case1 to case3, respectively. The recognition accuracy of case4 using all samples is 87%. The results show that CNN model using more samples can decrease the environmental effect and improve recognition accuracy. Compared with traditional systems using machine learning technology, such as WiFi-ID [4] that achieves recognition accuracy of 77% to 93% from 6 to 2 people, our system achieves better performance in the number of identifying people and scenarios.

Figure 4. The authentication accuracy in four sample cases.

4.2. User authentication using other deep learning models

This system chooses the deep learning model as the classifier since it can handle complex data and achieve better classification performance. To validate the effectiveness of the neural network model, we compare the classification performance of three deep learning approaches, including CNN, LSTM, and GRU. The test is conducted in the hall. The training procedures of CNN, LSTM, and GRU are shown in Figure 5(a), (b), and (c), respectively. Therefore, we find that they can achieve above 80% recognition accuracy, and CNN can realize better authentication results compared with LSTM and GRU.

Figure 5. The authentication accuracy of CNN, LSTM, and GRU.

Figure 6. The authentication results based on raising the arm.
4.3. User authentication based on activity
Different from some user authentication only based on gait, this system can realize authentication using different activities. Specifically, we collect CSI data when a person raises her arms. By applying CNN, we realize the authentication accuracy above 98%, as shown in Figure 6. The recognition accuracy based on activity is higher than that of gait because the activity of each person has a bigger motion range, which leads to a more complex effect of CSI signal. As a result, the fluctuations are effectively captured and utilized by the neural networks model.

5. Conclusion
To determine user identity using the complex CSI variation from different persons, we design a CSI-based user authentication system using the deep learning model. This system can identify a personal identity in the general environment and some environments with obstacles. Three deep learning neural networks are applied to train data and validate the system. The results show CNN has the best authentication accuracy for different test environments. The test results also indicate that we can effectively benefit from complicated CSI fluctuations using deep neural networks. Besides, this system can work well for some environments with some obstacles. We validate the authentication accuracy in the corridor and reference room where the wall and bookshelf hinder the signal propagation. We also evaluate the experimental performance when the user raises his arms. All these test scenarios, including different person actions, test environments, neural network models, verify the effectiveness of our system. In the future, we will concentrate on studies about identity authentication using more user activities and more through-the-wall scenarios.

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