Abnormal human behavior detection based on VAE-LSTM hybrid model in WiFi CSI with PCA

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***Abstract*—Recently, It is easy to find network access points(APs), which can be used for more than simply connecting devices to the Internet. For example, the waveform of a WiFi signal changes when a human action is performed between the two APs. In previous research, we demonstrated how changes in an electric wave affect the channel state information of a signal and how deep learning can utilize this information to detect and predict human behavior. In this paper, we proposed a method to detect human behavior. The proposed method improves the performance of detection of human behavior and effective in a changing environment. We found that using a VAE-LSTM hybrid model with PCA is useful in terms of detecting abnormal human behavior Experimental results demonstrate that the proposed method can detect general abnormal behavior with $>$-79% overall precision in a changing environment.**

keywords: LSTM, VAE, CNN, CSI, autoencoder, PCA, RNN, Smart City, IOT.

I. Introduction

With advances in network ,technologies to realize the Internet of Things, we know that mobile devices can receive WiFi signals in many locations while moving around a city. It is great to use this without wasting WiFi AP signals and should be helpful for many situations [1]. Channel State Information(CSI) comes from the network AP and contains information about the WiFi signal, and we can use and advance this information to develop many skills.

In this study, we used two Intel WiFi Link 5300 wireless NICs to extract CSI data and a transceiver used three antennas to receive the WiFi signal. Multiple antennas is used in WiFi for each subcarrier in the MIMO-OFDM system. The channels can be represented as follows.

$$Signal_i = H_i X_i + N_i \in \{1, ...S\} \tag{1}$$

Here, X_i and Y_i are the i-th subcarriers among S subcarriers, respectively. These comprise the I_T-dimensional transmit vector and the I_R-dimensional receive vector for the carrier, where I_T is the number of transmitting antennas, and I_R is the number of receiving antennas. In addition, H_i is an I_T*I_R-dimensional CSI matrix, and N_i is an I_R-dimensional noise vector. Matrix H_i can be expressed as follows.

$$H_i = \begin{bmatrix} h_{11} & h_{12} & ... & h_{1I_R} \\ h_{21} & h_{22} & ... & h_{2I_R} \\ ... & ... & ... & ... \\ h_{I_T1} & h_{I_T2} & ... & h_{I_TI_R} \end{bmatrix} \tag{2}$$

They can be reflected or diffracted by various objects, e.g., buildings and vehicles. However, problems can occur due to hardware noise or weak signal fading. In addition, using off-the-shelf NICs that were not originally designed to measure CSI introduces hardware-induced noise. Previous studies have demonstrated that PCA filtering is efficient to reduce noise and improve the speed of an AI model's training processes. However, there is a critical problem to adjust CSI in general situations. There are a lot of many changeable things when CSI is used. Because the world contains many objects in various environments; thus, significant noise occurs due to the absence of hardware responsibility. And even if a tiny environmental composition is changed, the ability of an AI model based on a supervised learning technique, e.g., LSTM [2] and CNN-LSTM [3] to recognize human behavior decreases. Thus, we must increase the performance so that we can apply these technologies in a practical environment. So that we we can apply such technologies in a practical environments. Here, an unsupervised learning approach is needed because, when the environment changes, the model learns as it changes and finds the correct answer. Therefore, this paper proposes an unsupervised learning VAE-LSTM model with PCA preprocessing to detect changing CSI information for a variable environment. For example, the proposed model can detect abnormal human behavior while recognizing human behavior with CSI.

The remainder of this paper is organized as follows. Section II describes the results and limitations of previous studies and methods. Real-world WiFi CSI-based human activity recognition and prediction experiments are performed in a controlled environment. Section II also discusses the accuracy and speed of recognizing human activity. Here, we demonstrate that it cannot be guaranteed to recognize many human behaviors in general variable situations even with PCA.

In Section III, we discuss the proposed PCA and VAE-LSTM model and how it identifies abnormal human behavior in a variable environment. Experimental results are described in Section IV, and the paper is concluded in Section V.

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II. PREVIOUS RESULTS AND LIMITATIONS

A previous study (Hwang, 2021) demonstrated that a supervised learning based method can be applied to human behavior recognition [4]. Figure 1 shows a misclassification table indicating that the model has $>$ 86% accuracy. The advantage of using deep learning over traditional machine learning techniques is that deep learning can discriminate between a wider variety of activities and is more resistant to changes or surroundings. However, supervised deep learning methods, e.g., LSTM or CNN methods, cannot train a variable space. For example, in a room of inside a building if someone who has different characteristics such as height and volume comes in then, the previous signal dataset would not be sufficiently strong to extract new characteristic features.

Behavior	Number of sample	Accuracy
Bed	657	86.4%
Fall	443	94.3%
Walk	1465	98%
Sit down	299	86.5%

Figure 1. Accuracy of Behavior

PCA is can be used to increase the accuracy of a deep learning model and the training speed of the data. In addition, classifying only two classes can keep the accuracy sufficiently high when using PCA [5]. Figure 2 shows how works when classifying with PCA a small number of classes.

	Default	PCA processed
Acurracy (4 Classes)	90%	72%
Acurracy (2 Classes)	90%	87%

Figure 2

By tracking the principal component, the changing data are transformed into fit principal components. Thus, changing characteristics can be reflected easily in learning. but this also cannot be guaranteed in general variable situations. However, using PCA with VAE-LSTM, is effective in terms of finding anomalous behavioral data by simply classifying the data in variable environment.

III. METHODOLOGY

3.1. Principal Component Analysis

PCA is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. Thus PCA can be used to reduce dimensionality or filter noise. Figure 3 shows two straight axes changing to a single axis. If we have n observations with p variables, the number of distinct principal components is min(n-1,p). Here, the resulting vectors are an uncorrelated orthogonal basis set.

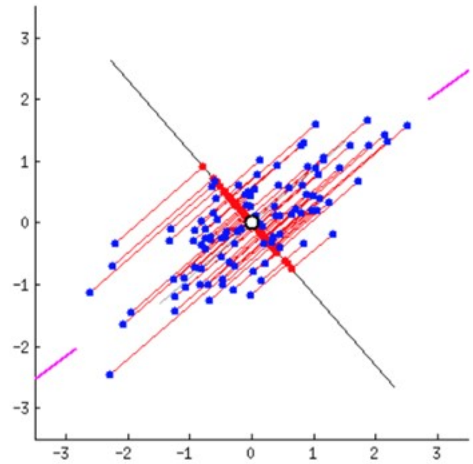

Figure 3. PCA

To obtain the principal component, from dataset X, we define principal component W_1. such that, we can maximize the variance.

$$W_1 = argmax_{\|w\|=1} E\{(W^T X)^2\} \tag{3}$$

$$\hat{X}_k = X - \sum_{i=1}^{k-1} W_i W_i^T X \tag{4}$$

$$W_k = argmax_{\|w\|=1} E\{(W^T \hat{X}_k)^2\} \tag{5}$$

Here, W^T is a matrix of basis vectors, with a single vector per column, where each basis vector is one of the eigenvectors of a covariance matrix. In Figure 3, the linear function is a basis vector, and the blue spots represent dataset X; thus, $W^T X$ means the variance of the projected vector. If we find the basis vector that maximizes the variance, then the dataset can be projected into that basis vector, and that is a principal component. To calculate other components, the kth component can be found by subtracting the first k-1 principal components from X. This means that from dataset X, subtract fratures that is already extracted, and find a kth component out of it. As a result, we can find the kth conponent.

3.2 VAE-LSTM

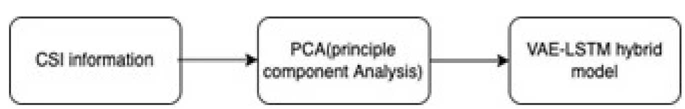

Figure 4. WiFi CSI Process on VAE-LSTM

Given time-series data X = $x_1, x_2, , x_n$, where $x_i \in R^1$ is a one-dimensional channel converted by PCA about different channels at the x_i time stamp that contains channel statement information. The purpose of the encoder in VAE is to turn the input space into an easy-to-draw multi-Gaussian space, and then the code is sampled from zero-mean Gaussian rather than from what the encoder provides. If the decoder makes it right, it creates a new image effectively. Such autoencoder structures [6] are used to reconstruct time-series data by receiving various feedback and applying constraints. The hybrid VAE-LSTM model [7] detects anomalies over a sequence of k consecutive windows or a given time series. Here, the I-th window is encoded into a low-dimensional embedding e^i, which is then input to an LSTM model to predict the next window's embedding e^{i+1}. The predicted embedding is then decoded to reconstruct the original window. The reconstruction error serves as the anomaly detection score. The embedding is then decoded to reconstruct the original window w^{i+1}. Meanwhile, reconstruction errors score anomaly detection. A hybrid model typically involves using a representational learning module to extract spatial information from a single image frame. Thus, a general approach for video analysis is applied to a sequential module to model temporal correlations in a series of frames image. Figure 5 illustrates these the models.

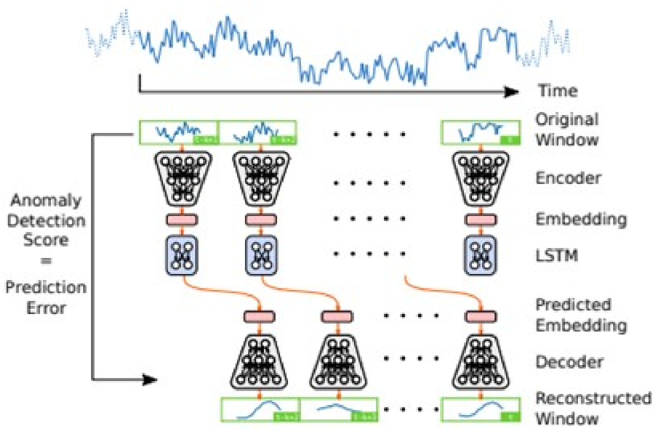

Figure 5. VAE-LSTM

IV. EXPERIMENT AND RESULT

In an experiment, we combined 50 laying data with 25 walking data, and 50 laying data with 25 sitting data to create a timestamp of approximately 1000 seconds. Then, anomaly detection performed using the walking and sitting data in the test set with two sets of 500 times training sets and 500 sampling tasks. This experiment was conducted to detect when lying down and performing other actions occurs. Here, the window size was 24 timestamps, the batch size was 32, the number of hidden units was 512, and the number of hidden units of the LSTM was 64. Figure 6 shows the results.

Data	**Precision**	**Recall**	**F1**
Lay and walk	0.80	0.99	0.96
Lay and sit	0.79	0.994	0.96

Figure 6. Results

V. CONCLUSION

Based on unsupervised deep learning methodology is not supervised learning. Thus if new characteristic emerge, it can be easier to train new feature. Then the model will automatically find abnormal features, e.g., human behavior, by making comparisions with previous data. This approach can be also considered in localization in unlabeled users domain by WiFi [8]. In conclusion, VAE-LSTM with PCA model can be used to recognize abnormal behavior so that classifying classes in variable environments.

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