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Human Detection with WiFi CSI

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Abstract: *Human detection in a place or an area is an important technique to obtain the information whether a human or humans exist there or not. Typically, it is done with censor cameras but its cost is relatively high and many people are disturbed with potential privacy infringement. In this project, we employ WiFi CSI with machine learning techniques instead of censor cameras. Our technique is expected to be employed for various situations including environmental measurement. In this paper we conduct human posture estimation experiments and discuss the accuracy of the estimation. We confirmed that posture extimation accuracy achieved over 99%.*

Keywords: Channel State Information, Machine Learning, IoT

1. INTRODUCTION

Infection disease epidemics and crowd accidents in big events happen and crowd monitoring becomes an important scientice topic. Moreover, crowd monitoring contributes to an over-tourism solution and the optimal service delivery for custormers. Human detection is a crucial technology for these crowd monitoring systems.

Monitoring systems using image processing with surveillance cameras have been proposed (Razalli et al., 2019; Chen et al., 2021). Methods using surveillance cameras involve the use of human images, which poses a risk of privacy invasion. Human detection methods has been proposed to detect persons near a sensor using packet RSSI (Yanagimoto et al., 2018; Depatla et al., 2018; Yanagimoto et al., 2022). RSSI represents signal length, which theoretically decreases with the distance between the transmitter and receiver. However, due to multipass effect, it often does not follow theoretical decrease in real world. These approaches require persons to wear devices that periodically transmit packets. So, they are not device-free approaches. Methods using Channel State Information (CSI), which reprensents the radio wave propagation conditions between a transmitter and a receiver, have been proposed (Liu, 2019; Ma, 2022; Yanagimoto, 2023; Yanagimoto 2023). CSI is represented as a vector, unlike RSSI, which is a scalar, and can avoid troubles related to multipath effect.

In this paper, we propose a human posture detection system using CSI measurement system with M5Stacks. The

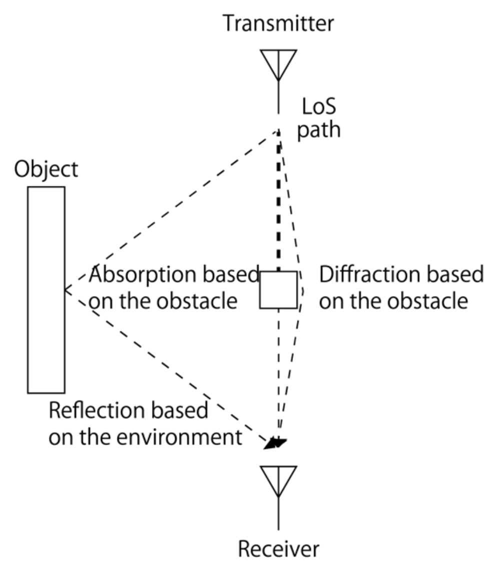

Fig.1. An example of multipass effect

system detects whether a person between a transmitter and a receiver is standing or squatting. The system offers a device-free and privacy-proof service that does not require cameras and special WiFi devices. This approach supports various applications such as monitoring the elderly. Evaluation experiments confirmed that using machine learning achieved an accuracy rate of over 99%.

The organization of this paper is as follows: Section 2 explain CSI and the proposed CSI measurement system. Section 3 reports experiments: 3.1. discuss measured CSI; 3.2 describes posture estimation with machine learning. Section 4 is conclusions.

2. Human Detection with Channel State Information

2.1 Channel State Information (CSI)

In the wireless communication, the placement of objects within the propagation area can lead to absorption, reflection, and diffraction of radio waves and change the received signal strength in complicated ways. Fig. 1 shows an example of multipass effect. Channel State Information (CSI) measures the radio wave progation condition depending on the propagation environment. Hence, based on measured CSI, we can estimate object existence within the propagation area. CSI is measured by WiFi devices compiled with IEEE802.11a/g/n/ac and is related to Orthogonal Frequency Division Multiplex (OFDM). OFDM devides the radio frequency band into multiple orthogonal subcarriers for parallel transmission to increase transimission speed. CSI can be measured from each subcarrier and is represented as a multi-dimensional complex vector.

Radio waves emitted from the transmitter arrive at the receiver in various ways after reflecting off objects in the communication environment. Assuming that the transmitted signal has reached the receiver via *M* different paths, it can be modeled as follows.

$$h(t;\tau) = \sum_{i=0}^{M-1} a_i e^{j\phi_i} \delta\,(t-\tau_i) \qquad (Eq.1)$$

where, a_i denotes the amplitude attenuation when a radio wave passes through the *i*th path. ϕ_i is the phase shift when a radio wave passes through the *i*th path. τ_i is the propagation delay depending on the distance of the *i*th path. $\delta()$ is a delta function.

In signal processing, the impulse response, $h(t;\tau)$, is represented as frequency domain representation. Speaking concretely, $h(t;\tau)$ is transformed by the Fourier transform.

$$H(f) = \sum_{i=0}^{M-1} a_i e^{j\phi_i} e^{-j2\pi f\tau_i} \qquad (Eq.2)$$

where, $H(f)$ is a measured CSI. $H(f)$ can be rewritten below.

$$H(f) = \|H(f)\| e^{j\angle H(f)} \qquad (Eq.3)$$

where, $\|H(f)\|$ means an amplitude and $\angle H(f)$ is the phase.

Because the CSI is measured from each subcarrier, an observed CSI is defined below.

$$H(\boldsymbol{f}) = [H(f_1), H(f_2), \cdots, H(f_N)] \qquad (Eq.4)$$

In this case, we assume N subcarriers.

2.2 CSI Measurement System

We constructed a CSI measurement system with a pair of M5Stacks. In the conventional systems, Intel WiFi Link 5300 is used but the WiFi device is widely not available in the current market. So, it is difficult to obtain it. Fig. 2 shows a picture of a transmitter constructed with M5Stack.

M5Stack uses IEEE802.11n and employs 2.4GHz as a carrier frequency and single antenna. So, by using M5Stack, CSi can be measured as a 197-dimensional complex vector. We neglect some pilot signals and obtain 174-dimensional complex vector eventually. It means that $H(\boldsymbol{f})$ in (*Eq.* 4*)* is a 1x174 matrix. The transmitter sends packet for CSI measurement every 10ms and the receiver accepts 100 packets every second theoretically. However, pakec loss occurs frequently and we cannot observe 100 CSI values every second.

Fig.2. Transmitter with M5Stack

2.3 Posture Estimation with Machine Learning

CSI values change as observed environment changes. So, the presence or absence of a person indoors can be detected by changes in the observed CSI values. For human detection, machine learning is commonly employed. Moreover, it is possible to detect differences in human posture and whether a person is walking or running. Detecting the presence or posture of a person generally estimates the state itself. Hence, each CSI is used as a feature.

In posture estimation, each CSI is used as feature inputs for machine learning. Decision Tree (Quinlan; 1987) is a mathine learning by splitting the training data set into subsets base do the values of the features according to their labels. Random forests (Breiman; 2001) is a type of ensenmble learning that combines multiple decision tree and can construct more complex decision boundaries. Logistic Regression (Cox; 1958) is a type of generalized linear model that can express the output as a probability. Support Vector Machine (Vapnik; 1963) is a method that construct non-linear decision boundaries without increasing computational cost by utilizing the kernel trick. Gradient Boosting Decision Tree (Friedman; 2001) is an ensemble learning method that uses boosting and decision tree and achieves high accuracy in various classification tasks.

3. Experiments

We carried out a human posture estimation experiment as one of human detection tasks with CSI. Especially, the experiment aims to detect situations where someone may be squatting due to illness or discomfort.

3.1 CSI Measurement

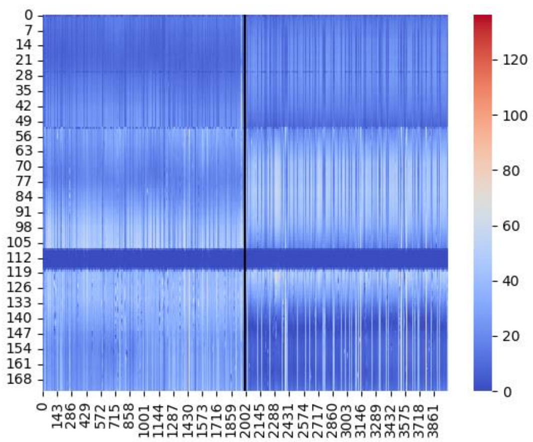

Fig.3. Heatmap of CSI amplitude for standing and squatting.

In this experiment, a transmitter and a receiver were set up in a room. Between them, a person took two poses, standing and squatting and we measured CSI values for two poses. The CSI, which changed with human movement, was measured during enough time to ensure measurement in stable situation. In evaluation experiment, we used a part of the measurement. Speaking concretely, we extracted 2,000 data for standing and squatting from all observations. Since the transmitter sends about 50 packets per second, the data is constructed from observations taken over approximately 30 seconds.

Fig. 3 shows a heatmap of the measured CSI amplitudes. Because the measured CSI is a complex number, we convert the complex number to an amplitude as following.

$$a = \sqrt{Re[H(f)]^2 + Im[H(f)]^2} \qquad (Eq. 5)$$

where, $Re[]$ and $Im[]$ are a real part of a complex number and a imaginary part of a complec number, respectively. In Fig. 3 the left half represents measurements taken while standing, and the right half represents measurement taken while squatting. This means that the differences in posture are reflected in the variations of the CSI patterns.

Table 1. Prediction accuracy for test data.

Method	Accuracy
Decision Tree	0.978
Logistic Regression	0.991
Random Forest	0.997
Support Vector Machine	0.994
Gradient Boosting Decision Tree	0.997

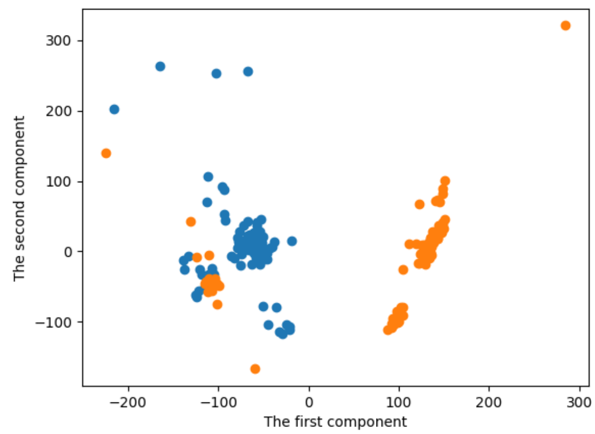

Fig. 4. The data distribution reduced to lower dimensions with PCA.

3.2 Posture Estimation with Machine Learning

We made a dataset from the observed data for machine learning, randomly splitting 70% of the data into a training data and 30% into test data. Especially, we predicted human posture depending on a CSI value obtained from each packet.

We employe 5 machine learning; Decision Tree, Logistic Regression, Random Forest, Support Vector Machines, and Gradient Boosting Decision Tree. Table 1 shows the prediction accuracies for 5 classifiers.

Nonlinear classifiers such as Random Forest, Support Vector Machines, and Gradient Boosting Decision Tree achieves higher prediction accuracies than a linear classifier such as Decision Tree.

Fig. 4 shows the distirbution of measured CSIs depending on standing and squatting. Some of the data overlaps, making it impossible to separate with a linear boundary. Therefore, it appears that a nonlinear classifier achieved higher recognition accuracy.

This experiment result demonstrated that using M5Stack to measure CSI and applying machine learning can accurately estimate human posture. That shows that it is possible to construct a privacy-conscious human detection systems that is preferable to methods using cameras.

4. CONCLUSIONS

In this paper, we constructed a CSI measurement system using M5Stack and proposed a system for estimating human posture without any cameras. The estimation accuracy achieve was over 99%. This means that a human detection system can be build using CSI and machine learning.

Future work will include developing systems to detect not only human posture but also movements and the crowd couting. Moreover, we will explore other machine learning such as deep learning, to further improve estimataion accuracy.

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