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AN IMPROVEMENT OF CSI-BASED HUMAN DETECTION WITH DC COMPONENT ELIMINATION

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Abstract. *Human detection and movement tracking has been in more demand for various purposes, and they are expected to invade privacy as well as to be realized at a low cost. Although sensor camera-based approaches have been widely investigated, such expectations want other approaches. One of the promising approaches is CSI-based machine learning. Channel State Information (CSI), originally developed for efficient Wi-Fi transmission since around 2015, represents Wi-Fi propagation conditions, which can be used to detect environmental changes. In this paper, we employ CSI commodity sensors, M5Stack and construct a classification system with gradient boosting decision tree. However, while CSI-based classification achieves high accuracy, it is often too sensitive and existence detection of different persons suffers substantial degradation of accuracy. Our proposal is to employ DC component elimination as preprocessing. Evaluation is done with experiments: we measure CSI for 1) a man's existence, 2) a woman's existence, 3) no person under a man's existence sensor setting, and 4) no person under a woman's existence sensor setting. We combine the four types of observations and predict whether a person exists or not. It is known that accuracy becomes very low when training and test data are generated with different persons. However, our proposal using DC component elimination as preprocessing, almost 100% accuracy is achieved. Prospective applications are also discussed to clarify the proposed method's coverage and advantages.*
Keywords: Channel state information, Human detection, IoT, Signal processing

1. **Introduction.** Nowadays, human detection, movement tracking, and crowd counting are more in need. For example, during the COVID-19 pandemics, the number of the people in a place was supposed to be limited. In the aging society like Japan, censoring systems to detect any abnormal behavior of the elderly are in high demand both at home and at hospitals. A realistic improvement against pollution issues is to keep people away from the polluted areas, and it is also useful if the exposed amount of pollutive materials can be estimated, which is at least partially supported by good human detection in areas. A monitoring system with surveillance cameras [1, 2] is one of the approaches to realizing crowd monitoring. However, the system inherently has a good possibility to invade privacy because the system recognizes each person in a monitoring area by analyzing videos taken from surveillance cameras. Simply, no one wants to always be observed, and surveillance cameras raise such concerns, and it is practically impossible to obtain formal acceptance and agreement for such systems from all people in camera

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visions. Thus, human detection with cameras keeps its advantage in many cases, but other mechanisms with less invasion of privacy are also expected. Another approach is to detect packets of wireless communication [3, 4]. In urban areas, in particular, almost all people have their mobile devices with them, and thus the number of detected wireless devices can be considered to be a good estimation of the number of people in an area when the task targets crowd counting. Wi-Fi and Bluetooth signals have both been investigated. In most cases, their MAC addresses have been the target of identification.

Another approach is a sensing system that detects packets for wireless communication [3, 4]. The sensing system captures probe packets from Wi-Fi mobile devices and Bluetooth devices and detects how many persons exist in a monitoring area by identifying devices that submit the packets. The systems recognize the packets based on their source MAC addresses and neglect some packets according to their Received Signal Strength Indicator (RSSI) [5]. However, such has crucial issues. First, an MAC address is linked to an individual device, and thus privacy invasion cannot be avoided. Second, considering this danger, recent devices adopt the frequent randomization of MAC address, which decreases the danger of privacy invasion but makes it impossible to count exactly how many devices exist. Third, RSSI is very sensitive to environmental changes and it is very difficult to determine a threshold for classifying the packets inside or outside of the target area. Fourth, as probe packet submission timing varies among devices, there is no guarantee that the system can receive probe packets from all devices during the observation. Fifth, an increasing number of people have more than one such device with them nowadays, and thus the device-based estimation of the number of people has been more inaccurate. All these issues are difficult or impossible to solve.

Yet another approach, since around 2015, is a method based on Channel State Information (CSI) [6]. CSI includes the partial information on signal attenuation and phase for carrier wave frequency and changes according to environmental changes. Instead of counting the number of the sources of CSI, the changes of CSI can be the source of human detection, as the (in)existence of humans is part of environmental changes. Human detection and other tasks along this method are a classification task with supervised machine learning, or abnormal detection for some tasks. In fact, CSI has been investigated for human activity recognition [7, 8], crowd counting [9, 10], and human presence detection [11]. Many of those studies achieved a high accuracy, and CSI-based approaches are much more privacy-proof. Especially, CSI-based systems are privacy-proof and device-free. Furthermore, CSI-based human detection can also employ multiple antenna situations to collect more features with good consideration of possible interferences among antennas.

In previous studies, we proposed improved methods of human place detection in an indoor situation using CSI [12]. However, it was found that CSI-based classification is often too sensitive, and accuracy tends to fall down when the training and test datasets consist of different persons. When the tracking target is a unique person, like in the case of elderly tracking at home, it is rather an advantage that it distinguishes the target person and others. However, when a more public space is a target place to detect humans, this is a crucial issue to solve.

The purpose of this paper is to propose the employment of DC component elimination as part of preprocessing to improve classification accuracy when the data are of more than one person. For CSI collection, a low-cost commodity device, M5Stack is used. The experiment targets two different persons in a way that the training dataset contains a person and the test dataset contains the other, and constructs models to detect whether a person is in a place or not. The amplitude and phase of measured CSI is used as features, and our classifier adopts Gradient Boosting Decision Tree (GBDT) [13]. Our proposal of the employment of DC component elimination as part of preprocessing achieved a significant improvement of accuracy even when the training and test datasets consist of data of different persons.

Our contributions are as follows.

- Phase information contributes to improving CSI-based human detection.
- DC component elimination prevents specifying individual recognition and contributes to constructing a general human detection system.

This paper is organized as follows: Section 2 describes channel state information and Gradient Boosting Decision Tree (GBDT). Section 3 reports experimental results. Especially, we compare datasets with DC component elimination preprocessing with datasets without the preprocessing. Section 4 is the conclusions.

2. **Human Presence Detection with Channel State Information.**

2.1. **Channel state information.** In wireless communication, the received signal is distorted because of multipath propagation. The multipath propagation causes due to reflection, diffraction, and scattering in a monitoring area. Figure 1 shows an example of multipath propagation in the real world. Basic propagation is a Line-of-Sight (LoS) path, where radio is directly sent from a transmitter to a receiver. Other propagation is caused by reflection because there are many objects in the observation area. Hence, the multipath propagation distorts and attenuates the signal. Channel State Information (CSI) measures the distortion and the attenuation by using a predefined signal communication.

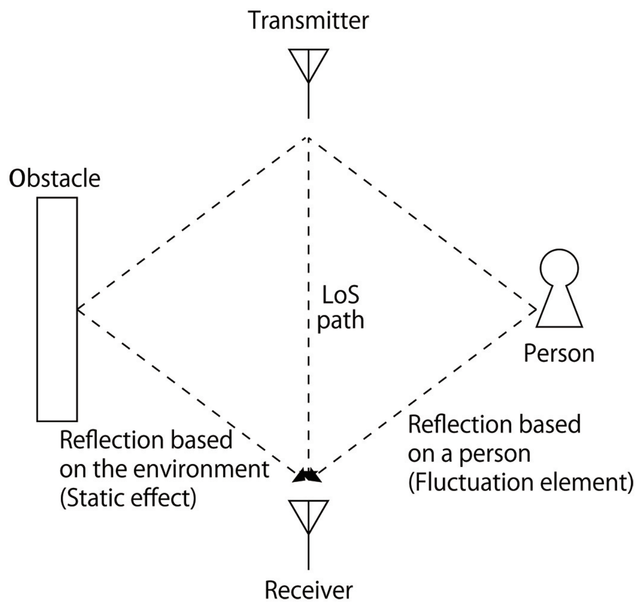

FIGURE 1. An example of multipath propagation in the real world

First, we model multipath propagation. This measurement is regarded as a received signal for an impulse signal.

$$h(t, \tau) = \sum_{i=1}^{M} a_i e^{j\phi_i} \delta(t - \tau_i) \tag{1}$$

a_i denotes power attenuation in the ith path and ϕ_i is a phase in the ith path. τ_i is a propagation delay in the ith path. In this case, we assume M different propagation paths. So, when the environment changes, M changes according to the number of multiple propagations.

Then, the impulse response is rewritten as a frequency domain representation with Fourier transformation.

$$H(t; f) = \sum_{i=1}^{M} a_i e^{j\phi_i} e^{-j2\pi f \tau_i} \tag{2}$$

Wi-Fi devices built according to the IEEE 802.11 a/g/n/ac protocols use Orthogonal Frequency Division Multiplexing (OFDM) [14] as a modulation method to increase transmission speed. OFDM divides a carrier wave into some subcarriers and sends information in parallel. Because each subcarrier is orthogonal mutual, we do not need to consider any interference among the subcarriers. Figure 2 shows wireless communication based on OFDM.

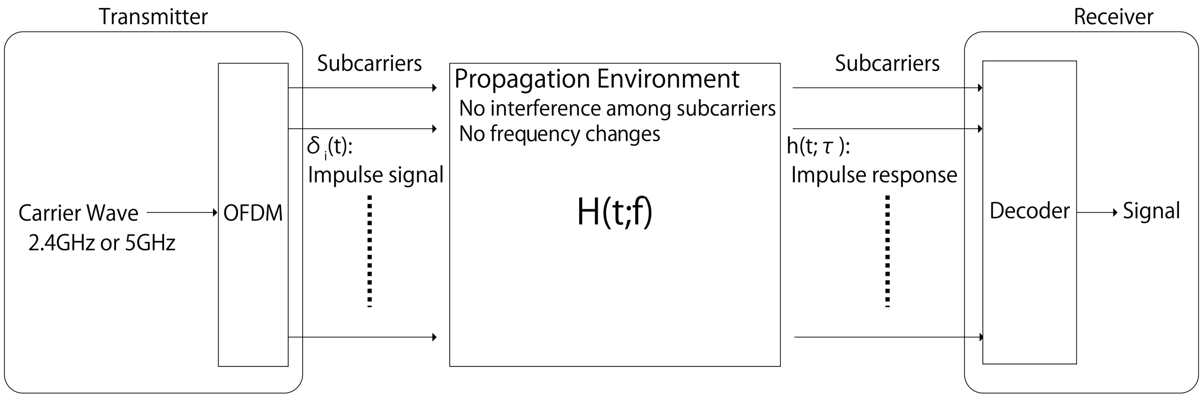

FIGURE 2. Wireless communication with OFDM. Subcarriers do not affect each other and subcarrier frequency does not change by the environment.

CSI consists of a set of responses on the subcarrier frequencies and is represented as a vector of a complex number.

$$H(t) = [H(t; f_1), H(t; f_2), \ldots, H(t; f_N)] \tag{3}$$

N means the number of subcarriers in OFDM. Each $H(t; f_i) = \|H(t; f_i)\|e^{\angle H(t;f_i)}$ has an amplitude and a phase. In this study, we use the amplitude and the phase of the observed complex number as CSI.

The CSI is observed in every received packet and the whole CSI is represented as an $N \times T$ matrix.

$$H = \begin{pmatrix} H(0; f_1) & \cdots & H(T; f_1) \\ \vdots & \ddots & \vdots \\ H(T; f_1) & \cdots & H(T; f_N) \end{pmatrix} \tag{4}$$

2.2. **Gradient boosting decision tree.** In this study, we judge whether a person exists or not in a place based on observed CSIs. We employ Gradient Boosting Decision Tree (GBDT) as a classifier for human detection. GBDT is one of the ensemble learning algorithms and employs a regression tree as a weak learner. The regression trees are integrated with a boosting strategy.

The regression tree is constructed with CART [15]. CART divides training data based on a feature of the training data and clusters the training data based on the target value. As a regression tree, the output of the regression tree is an average of target values in a cluster.

The target values are defined as the difference between the target value and a prediction value with the classifier.

3. **Experiments.** We measured CSI in a real situation with the proposed measurement system and predicted human presence based on the observed CSI. For this purpose, we constructed a CSI measurement system with commodity sensors: a pair of M5Stacks including a small microcomputer module with an EPS32 Microcontroller. Figure 3 shows a picture of a transmitter constructed with M5Stack. In our experiment, both the transmitter and the receiver are constructed with M5Stack. The receivers receive packets from the transmitter and extract CSI from the received packets. The transmitter transmits

Figure 3. A transmitter constructed with M5Stack

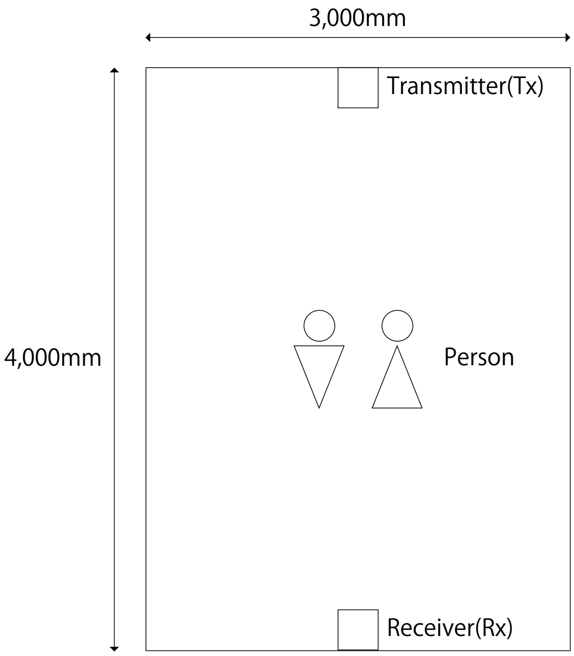

Figure 4. A room layout for experiments

packets every 10 ms and the receiver generates 100 CSIs every minute theoretically. The Wi-Fi module in M5Stack is based on IEEE802.11n and has only a single antenna. Hence, from this measurement system, we get CSI as a 178-dimension vector by OFDM and H is represented as a 178×1 matrix.

Figure 4 shows the sensor settings and human location in the experiments. We carried out the experiments in a rectangular room and there is no equipment in the room. We measured each CSI for 2 minutes when a man and a woman are in the room and there is no person. These measurements are carried out at different hours because we consider the difference in measurement environment. Additionally, we set the sensors again in two measurements. Our observation includes some noises derived from the observation settings. We theoretically obtain 24,000 CSIs for each situation but some packet loss occurs in this measurement. The number of the observed CSI is about 7,000. Table 1 shows the content of measurements in the experiments.

Table 1. The number of observations in the experiments

Experiments	The number of data
No person in measurement 1	6,761
Man in measurement 1	8,580
No person in measurement 2	6,337
Woman in measurement 2	8,265

In Figure 5, we visualized amplitudes and phases for observed CSIs. Amplitude and phase are calculated below.

$$a = \sqrt{x^2 + y^2} \tag{5}$$

$$p = \tanh^{-1} \frac{x}{y} \tag{6}$$

In this case, CSI is a complex number, $x + jy$. The upper figures show measurement 1, where we measured CSI for no person and a man. On the other hand, lower figures show measurement 2, where we measured CSI for no person and a woman. Figures for amplitude have a similar pattern. When a person is between sensors, CSI amplitude is low because a person prevents wave transmission. On the other hand, when a person is between them, various reflection occurs and complex phase patterns are shown in the visualization.

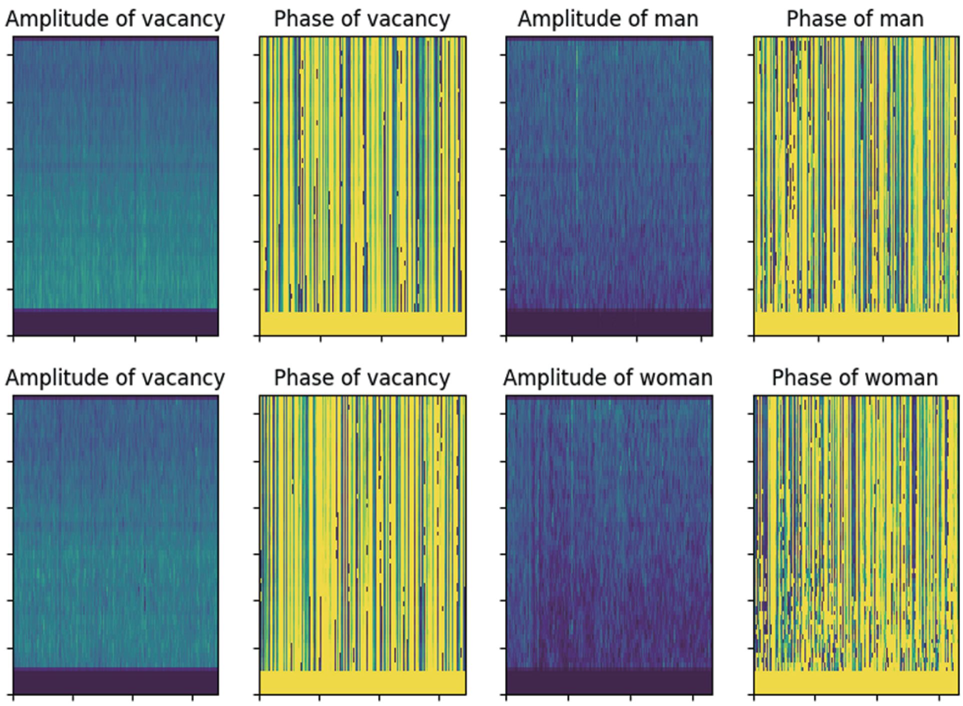

Figure 5. Heatmap of amplitude and phase for observed CSI

In the first experiment, we predict whether a person exists or not using data split. In this case, training data and test data are generated from the same person. The prediction accuracy obtained with the experiments is shown in Table 2. The observation data is divided into 70% training data and 30% test data randomly. It means that prediction accuracy is high without any preprocessing. Moreover, there is no large difference using only amplitude as a feature.

In the second experiment, we predict whether a person exists or not using training data and test data generated from different persons. Table 3 shows prediction accuracies. In all settings, the prediction accuracies are worse than Table 2. It means that CSI is very

Table 2. Prediction accuracy with training data and test data generated from the same person (first experiment)

Features	Accuracy
Measurement 1 with amplitude	0.970
Measurement 1 with amplitude and phase	0.968
Measurement 2 with amplitude	0.853
Measurement 2 with amplitude and phase	0.861

Table 3. Prediction accuracy with training data and test data generated from the same person (second experiment)

Features	Accuracy
Training data from a man and Test data from a woman with amplitude	0.565
Training data from a man and Test data from a woman with amplitude and phase	0.566
Training data from a woman and Test data from a man with amplitude	0.508
Training data from a woman and Test data from a man with amplitude and phase	0.541

Table 4. Prediction accuracy with training data and test data generated from the same person (third experiment)

Features	Accuracy
Measurement 1 with amplitude and phase	1.0
Measurement 2 with amplitude and phase	1.0
Training data from a man and Test data from a woman with amplitude and phase	1.0
Training data from a woman and Test data from a man with amplitude and phase	1.0

sensitive to observed persons and the differences between persons are emphasized. For applying CSI-based human detection to various tasks, we have to ease the sensitivity.

In the third experiment, we improved the performance for training data and test data generated from different persons with DC component elimination. We think a reason for worse prediction accuracy is derived from bias based on different persons. So, we set averages of amplitude and phases during human existence and human absence. Table 4 shows the prediction accuracies. All accuracies achieve 1.0 and the system can carry out classifications perfectly. However, this performance is restricted for this experiment setting and we should discuss how accurately the proposed system can predict for various experimental settings. From these results, we think DC component elimination contributes to the improvement of prediction accuracy.

4. **Conclusions.** We propose a CSI-based human detection system with a commodity sensor: M5Stack. We use amplitude and phase as features, which are calculated from a complex number of CSI. Additionally, we apply DC component elimination to observed data to ease CSI sensitivities. After this preprocessing, the prediction accuracies are improved dramatically and we achieve the perfect prediction in this experiment.

We will discuss the proposed method's coverage to apply it to various tasks because in this experiment the accuracies achieve 100% but it is not true for all tasks. However, DC component elimination is confirmed to contribute to lessening unwanted excessive sensitivity. Based on this result, we investigate crowd counting using CSI where much more number of persons are the targets to detect.

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