Accuracy Evaluation of Person Position Estimation Using Compressed CSI Under Temporary Shielding

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***Abstract*—Person position estimation using cameras can fail when the view is temporarily blocked. Prior work used camera images and received signal strength indicator (RSSI) to estimate positions during such shielding, while channel state information (CSI) may provide richer wireless propagation information. However, compressed CSI has not been sufficiently evaluated for person position estimation under temporary physical shielding. This paper evaluates compressed CSI by varying recording date, shielding condition, person position, occluder type, occluder position, and room layout. The mean estimation error was 35.9 cm when training and test data were recorded on the same day and 95.2 cm when they were recorded on different days. For same-day data, the mean error was approximately 8.9 cm under matched shielding conditions and 53.1 cm under mismatched conditions. Differences associated with person position and room layout were larger than those associated with occluder type and occluder position. These results suggest that robustness to recording-session and shielding-condition differences is important for person position estimation using compressed CSI under temporary shielding.**

***Index Terms*—compressed CSI, person position estimation, temporary shielding, wireless sensing.**

I. Introduction

In public spaces, cameras may fail to observe the position of a person when the camera view is temporarily blocked by people or objects. Estimating the position of the person during such temporary shielding is important for continuous observation in spaces where people gather. To address this problem, a method combining camera images with received signal strength indicator (RSSI) obtained from wireless devices has been proposed for person position estimation under temporary shielding [1]. This method automatically collects pairs of person positions estimated from camera images and RSSI values when no shielding exists, and estimates the position of the person using RSSI when the camera view is blocked.

In addition to RSSI, channel state information (CSI) has been used for wireless human sensing. CSI provides wireless propagation information across subcarriers and antenna pairs, and may provide richer cues for human sensing than RSSI [2]. Previous studies have investigated CSI-based human detection [3] and indoor localization [4]. However, compressed CSI has not been sufficiently evaluated for person position estimation in spaces where temporary physical shielding occurs between wireless devices. This point is important because such shielding may affect both visual observation and wireless propagation. Moreover, many studies using CSI rely on specific devices or tools for obtaining raw CSI, such as the Linux 802.11n CSI Tool [5] and the Atheros CSI Tool [6]. Raw CSI also has a large data size, which may increase storage and processing costs.

This paper evaluates compressed CSI used in IEEE 802.11ac/ax environments as a wireless feature for person position estimation under temporary shielding. We vary the recording date and shielding condition of the training and test data, as well as person position, occluder type, occluder position, and room layout. This study provides a systematic empirical evaluation of compressed CSI for person position estimation under temporary shielding across these training and test conditions and environmental conditions. The experimental results show that larger estimation errors were observed for different recording dates and mismatched shielding conditions, whereas occluder type and occluder position showed smaller mean differences.

II. Person Position Estimation Using Compressed CSI

A. System Overview

This paper evaluates the accuracy of person position estimation using compressed CSI in an environment with temporary shielding. Compressed CSI is used as the feature, and person position estimation is formulated as a regression problem. The evaluation uses training and test data. For the training data, compressed CSI at each time instant is paired with the corresponding person position to construct a regression model. For the test data, compressed CSI at each time instant is input to the constructed regression model to estimate the person position. Fig. 1 shows an overview of this study. The camera shown in Fig. 1 illustrates the target application scenario and was not used for person position estimation in the present experiment.

B. Compressed CSI Feature Construction

In compressed beamforming feedback, the right singular vector matrix obtained by singular value decomposition of the channel matrix is represented using quantized angle parameters through Givens rotations. In this study, the angle parameters ψ and ϕ are used as compressed CSI features. In the wireless-device configuration used in the experiment, ten angle elements were obtained for each subcarrier. These ten elements were concatenated across 64 subcarriers, yielding a feature vector with $64 \times 10 = 640$ dimensions. Each 640-dimensional compressed CSI feature vector is used for person position estimation at each time instant.

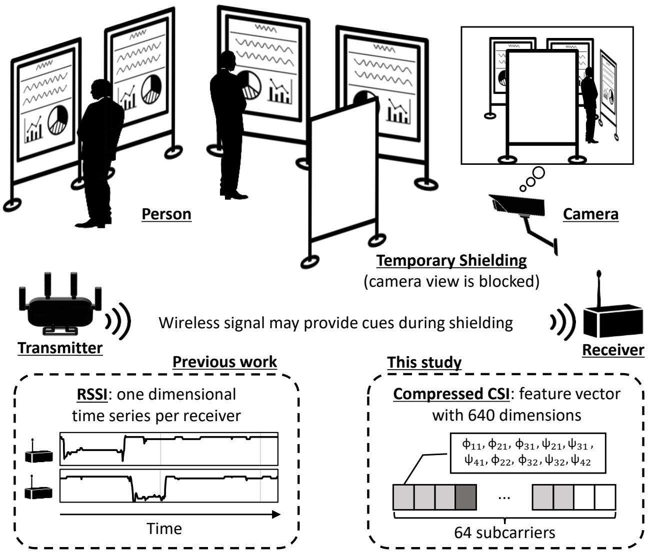

Fig. 1. Overview of the accuracy evaluation using compressed CSI for person position estimation under temporary shielding.

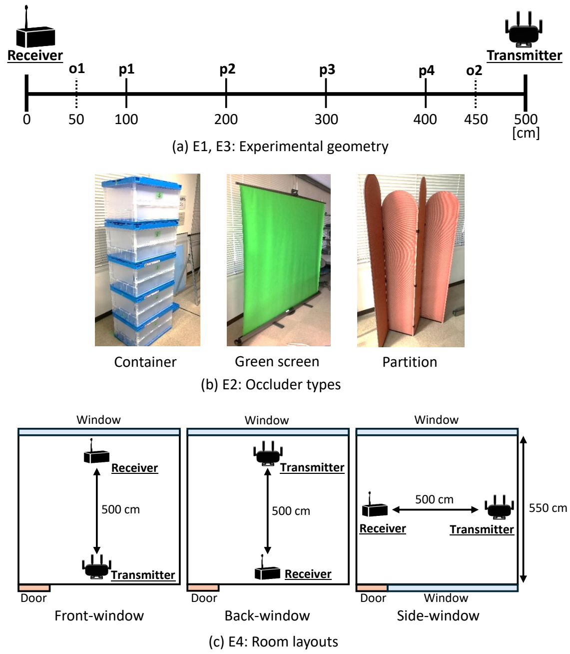

Fig. 2. Experimental conditions for E1–E4: (a) experimental geometry, (b) occluder types, and (c) room layouts.

C. Position Estimation

A k-nearest neighbor (kNN) regression model is used with $k = 3$; Euclidean distance is used in the feature space, and the estimated position is calculated as the average position of the three nearest training samples. During training, each 640-dimensional compressed CSI feature vector is paired with the corresponding person position. This estimation process is applied to each time instant in the test data.

III. Experimental Setup

A. Measurement Setup

The experiments used a Buffalo WXR-5700AX7S, an NVIDIA Jetson equipped with an Intel Desktop Wireless M.2 2230 Kit and a directional BINGFU Wi-Fi 6 antenna, and a separate laptop running Ubuntu 20.04 with Wireshark v4.2.2 for packet capture. Beamforming was enabled, and communication was performed in the 5 GHz band. The wireless devices were placed 500 cm apart at a height of 70 cm. Compressed CSI for 64 subcarriers was collected for 10 s in five trials per condition. The mean packet capture rate was 9.2 packets per second.

B. Evaluation Conditions

We evaluated different combinations of training and test data. We varied the recording date and shielding condition of the training and test data. L1 denotes four combinations of shielding conditions in the training and test data: without shielding → without shielding, with shielding → with shielding, without shielding → with shielding, and with shielding → without shielding. L2 indicates whether the training and test data were recorded on the same day or on different days. For the same-day condition, the training and test data were collected 1 h 27 min to 2 h 07 min apart, with a mean interval of 1 h 49 min. For the different-day condition, the interval ranged from 23 h 47 min to 30 h, with a mean of 24 h 19 min. We also varied the person position, occluder type, occluder position, and room layout as experimental conditions. These conditions are denoted as E1, E2, E3, and E4, respectively. Fig. 2 summarizes the experimental conditions.

In E1, the person positions were set at 100 cm, 200 cm, 300 cm, and 400 cm from the receiver and denoted as $p1$ to $p4$, respectively. A single participant carrying no wireless device stood still at the four predefined positions between the transmitter and receiver throughout the experiment. These predefined positions were used as the reference positions for evaluating the estimation error. In E2, three types of occluders were used: stacked containers, a green screen, and a folding partition. In E3, the occluder positions were set at 50 cm and 450 cm from the receiver and denoted as $o1$ and $o2$, respectively. In E4, three room layouts were evaluated: front-window, back-window, and side-window, in which the windows were located in front of, behind, and on both sides of the transmitter, respectively.

The estimation error is calculated as the Euclidean distance between the estimated position and the corresponding reference position.

IV. Results and Discussion

A. Effects of Training and Test Conditions

Fig. 3 shows the mean estimation error for each condition. The error bars indicate standard deviations.

Among the training and test conditions, the largest difference in mean estimation error was observed between the same-day and different-day conditions. The mean error was 35.9 cm

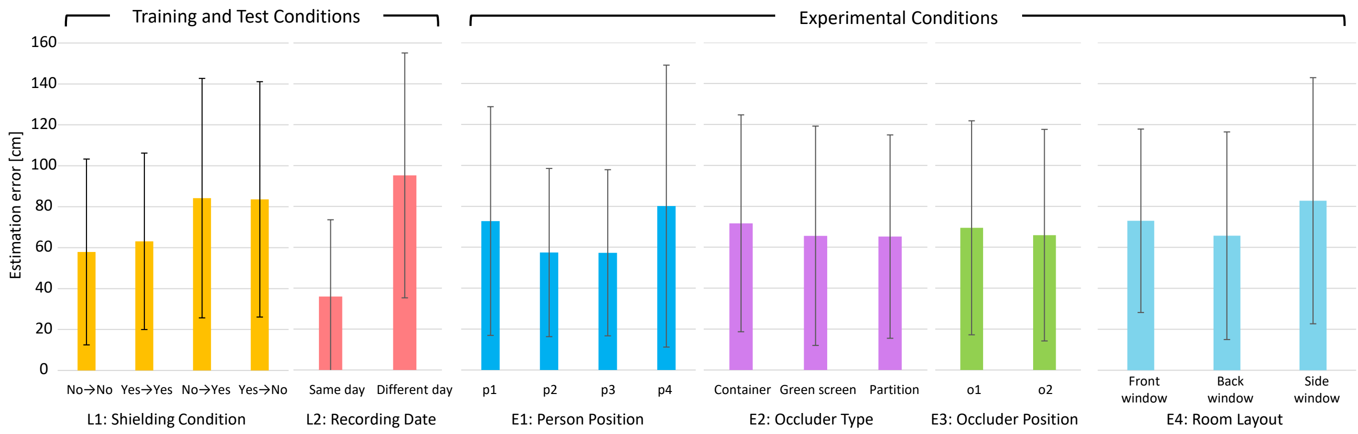

Fig. 3. Mean estimation error using compressed CSI under different training and experimental conditions. L1 and L2 represent training and test conditions, while E1–E4 represent experimental conditions. In L1, each label indicates the shielding condition of the training data → test data; No and Yes denote without shielding and with shielding, respectively. Error bars indicate standard deviations.

for the same-day condition and 95.2 cm for the different-day condition. The difference between these conditions was 59.3 cm. In addition, the mean error was approximately 60.5 cm when the shielding conditions matched between the training and test data and approximately 83.9 cm when they did not match. The difference between the matched and mismatched conditions was approximately 23.4 cm. Under the present experimental conditions, the difference in mean estimation error between the recording-date conditions was larger than that between the matched and mismatched shielding conditions.

To further examine the effect of shielding condition while reducing the effect of recording-date differences, L1 was additionally evaluated using only training and test data recorded on the same day. Fig. 4 shows the mean estimation error for the four shielding-condition combinations using only same-day data.

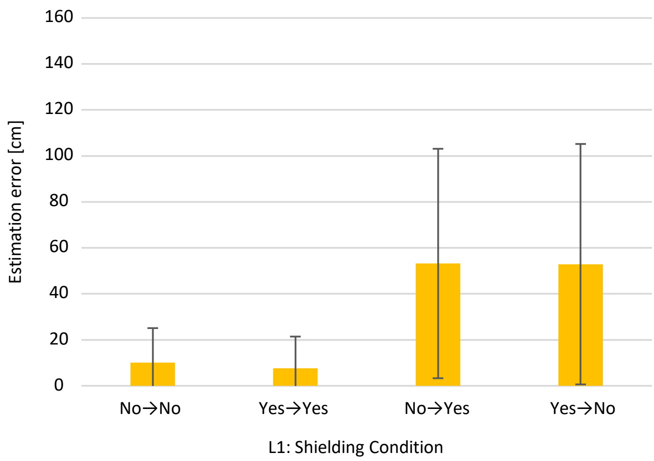

Fig. 4. Mean estimation error for the four shielding-condition combinations using only same-day data. Each label indicates the shielding condition of the training data → test data. No and Yes denote without shielding and with shielding, respectively. Error bars indicate standard deviations.

The mean errors were 10.1 cm and 7.6 cm for the No → No and Yes → Yes conditions, respectively. In contrast, the mean errors increased to 53.2 cm for the No → Yes condition and 52.9 cm for the Yes → No condition. The average error was approximately 8.9 cm for the matched conditions and 53.1 cm for the mismatched conditions, corresponding to a difference of approximately 44.2 cm. These results show that substantially larger estimation errors were observed under mismatched shielding conditions even when the analysis was restricted to same-day data.

B. Effects of Experimental Conditions

For the experimental conditions, the errors at $p1$ and $p4$ tended to be larger than those at $p2$ and $p3$. The maximum difference among the person-position conditions was 22.8 cm. The side-window condition showed a larger mean error than the other room-layout conditions, and the maximum difference among the room-layout conditions was 17.1 cm. In contrast, the maximum differences among the occluder-type and occluder-position conditions were 6.5 cm and 3.6 cm, respectively. Thus, the differences associated with occluder type and occluder position were smaller than those associated with person position and room layout. However, because the standard deviations were large under several conditions, further evaluation is required to clarify the effects of environmental conditions.

C. Discussion

Among the evaluated conditions, the largest difference in mean estimation error was observed between the recording-date conditions. Even when the wireless-device settings and positions were unchanged, larger estimation errors were observed when the training and test data were recorded on different days than when they were recorded on the same day. This result suggests that person position estimation using compressed CSI may be affected by changes in wireless propagation conditions between measurement dates.

The estimation error was also larger when the shielding conditions of the training and test data did not match. The same-day analysis further showed average errors of approximately $8.9\ \mathrm{cm}$ under matched shielding conditions and $53.1\ \mathrm{cm}$ under mismatched conditions. This result shows that mismatched shielding conditions were associated with substantially larger estimation errors even when the analysis was restricted to same-day data. The presence or absence of an occluder may change the distribution of compressed CSI features, resulting in a difference between the feature distributions used for training and testing. When training data collected without shielding are used for person position estimation under temporary shielding, reducing this distribution difference may therefore be important.

For context, our previous RSSI-based study reported a mean estimation error of $15.9\ \mathrm{cm}$ using kNN for the condition with one participant under temporary shielding [1]. In the present compressed CSI experiment, the mean error was $53.2\ \mathrm{cm}$ for the same-day condition in which the training data were collected without shielding and the test data were collected with shielding. Thus, a larger mean error was observed in the present compressed CSI evaluation than in the previous RSSI-based study. However, these values should not be interpreted as a direct performance comparison because the two studies used different experimental settings, feature constructions, preprocessing procedures, kNN configurations, and evaluation protocols. The RSSI-based study used four receivers and temporal RSSI sequences, whereas the present study uses a 640-dimensional compressed CSI feature at each time instant.

The previous RSSI-based study applied preprocessing including receiver-specific baseline correction, and the mean error of kNN decreased from $17.9\ \mathrm{cm}$ to $15.9\ \mathrm{cm}$ after preprocessing [1]. In the present study, the substantially larger error observed when the training and test data were recorded on different days suggests that compressed CSI features may also be sensitive to session-dependent changes in the propagation environment. Normalization or calibration across measurement sessions should therefore be investigated. In addition, although compressed CSI contains richer channel information than RSSI, not all components of the 640-dimensional feature vector are necessarily informative for person position estimation. Components that are sensitive to recording date or shielding condition may affect nearest-neighbor selection. Future work will therefore investigate feature normalization, selection and transformation, temporal feature integration, and multiple receivers to improve robustness to these condition differences.

Among the environmental conditions, the differences associated with person position and room layout were larger than those associated with occluder type and occluder position. However, because the standard deviations were also large, the effects of individual environmental factors cannot be clearly separated from the present results alone.

The present evaluation used a fixed transmitter–receiver distance of $500\ \mathrm{cm}$ and a single wireless-device configuration. Further evaluation with different device configurations, transmitter–receiver distances, and measurement environments is therefore required to assess the generality of the observed trends.

V. Conclusions

This paper evaluated compressed CSI for person position estimation under temporary shielding by changing the recording date, shielding condition, person position, occluder type, occluder position, and room layout. The mean estimation error was $35.9\ \mathrm{cm}$ when the training and test data were recorded on the same day and $95.2\ \mathrm{cm}$ when they were recorded on different days. The same-day analysis further showed mean errors of approximately $8.9\ \mathrm{cm}$ for matched shielding conditions and $53.1\ \mathrm{cm}$ for mismatched conditions.

Among the environmental conditions, the differences associated with person position and room layout were larger than those associated with occluder type and occluder position. However, because the standard deviations were large under several conditions, further evaluation is required to clearly separate the effects of individual environmental factors.

These results suggest that improving robustness to changes in recording date and shielding condition is important for person position estimation using compressed CSI. Future work will investigate methods to improve robustness to these condition differences and evaluate generalization under different environmental conditions.

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