Evaluating Indoor Localization Performance on an IEEE 802.11ac Explicit-feedback-based CSI Learning System

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***Abstract*—There is a demand for device-free user location estimation with high accuracy in order to realize various indoor applications. This paper proposes an IEEE 802.11ac explicit feedback-based channel state information (CSI) learning system which can be used for device-free user location estimation. The proposed CSI learning system captures CSI feedback from off-the-shelf Wi-Fi devices and extracts 624 features from a CSI feedback frame defined in IEEE 802.11ac. We evaluated the proposed system using location estimation with six patterns: different combinations of device-free user movement and access point antenna orientation. The evaluation results show that the machine learning based localization achieves approximately 96% accuracy for seven positions of the user, and the divergence of CSI improves localization performance.**

***Index Terms*—Channel State Information, Device-free Location Estimation, Wi-Fi, IEEE 802.11ac, Machine Learning.**

I. Introduction

User location information plays an essential role in location-based applications such as navigation, augmented reality, and home automation. There are many studies on indoor localization using a camera [1], ultrasound [2], infrared rays [3], received signal strength indication (RSSI) [4]–[6], and channel state information (CSI) [7], [8]. However, each localization method individually has a problem. The details of these problems and related works are discussed in Section II.

This paper proposes an IEEE 802.11ac explicit-feedback-based CSI learning system and shows the location estimation evaluation results using the CSI learning system. The proposed CSI learning system utilizes compressed angles with an access point (AP), a station (STA), and capture device without replacing the Wi-Fi cards of the AP and STA, and realizes device-free user location estimation using only off-the-shelf Wi-Fi devices. We evaluated the proposed CSI learning system with a device-free user, seven learning positions, and six learning datasets. These datasets include different combinations of device-free movement and AP antenna orientation. The evaluation results show that average accuracy is approximately 90% or more with the highest accuracy.

The rest of the paper is organized as follows. Section II discusses the requirements and related works. Section III proposes the IEEE 802.11ac explicit feedback-based CSI learning system. Section IV shows the evaluation of the localization performance of the proposed CSI learning system. Finally, Section V concludes this paper.

II. Related Works

The indoor localization system needs to satisfy the following requirements:

- device-free
- low deployment cost.

Device-free estimation is desirable for user's burden. If a user needs to carry around a specific device, then problems may arise such as battery exhaustion and device failure. The low development cost includes the financial cost when deploying a localization system. It is desirable to deploy the system as cheaply and easily as possible to a target place.

Indoor location estimations using a camera [1], ultrasound [2], or infrared rays [3] have achieved high location estimation accuracy. However, these methods have problems such as high installation cost, line-of-sight (LOS) requirement, and the need for many sensors to cover a large area.

To solve the problem on the number of sensors, radio-based approaches [4]–[18] are attracting increased attention because of their ubiquitousness in smartphones, electrical appliances, and laptops. For example, location estimation using RSSI have been proposed [4]–[6]. Location estimation using RSSI has the advantage that infrastructure cost is low because we can use deployed wireless devices. However, RSSI is difficult to improve indoor location estimation accuracy because RSSI is coarse-grained and unstable information [19].

CSI is considered fine-grained information compared with RSSI. Indoor localization using CSI is classified into two categories: fingerprinting-based systems and time-of-arrival (ToA)/angle-of-arrival (AoA)-based systems. Fingerprinting-based systems include PhaseFi [13] and LiFS [7]. PhaseFi and LiFS acquire 30 subcarriers using CSI Tool [20] and creates a database. LiFS utilizes user trajectories to obtain fingerprint values with multiple APs, and achieves higher accuracy than RSSI-based systems. However, PhaseFi and LiFS require special wireless devices such as Intel 5300 network interface cards and universal software radio peripherals.

ToA/AoA-based systems include Chronos [16] and SpotFi [18]. Chronos measures the ToA while SpotFi measures the AoA for indoor localization. For example, Chronos measures ToA using CSI on 35 channels and computes each propagation delay. However, ToA/AoA-based systems require users to have a wireless device.

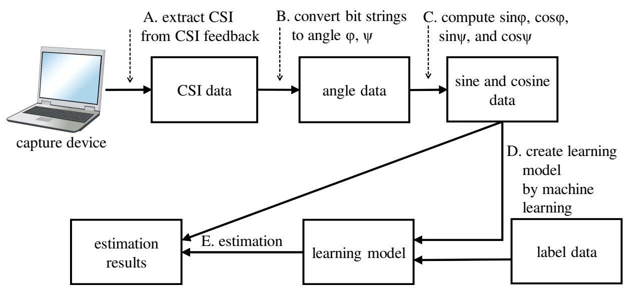

Fig. 1. Learning and estimation processes using the proposed CSI learning system

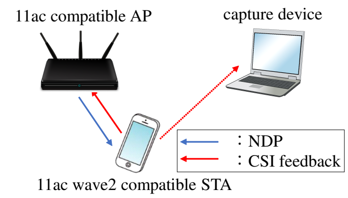

Fig. 2. Components of the proposed CSI learning system

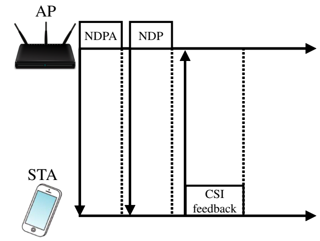

Fig. 3. Frame sequence for acquiring CSI

III. IEEE 802.11ac Explicit-Feedback-based CSI Learning System

To realize a localization system that satisfies device-free and low deployment cost requirements, we designed an IEEE 802.11ac explicit-feedback-based CSI learning system. Fig. 1 shows the learning and estimation processes using the proposed CSI learning system. The processes are as follows: 1. extract CSI from CSI feedback; 2. convert bit strings to angle ϕ, ψ; 3. compute $\sin\phi$, $\cos\phi$, $\sin\psi$, and $\cos\psi$; and 4. create database by machine learning, 5. estimation.

A. Capture CSI feedback

The proposed CSI learning system easily extends the number of APs and STAs because a single capture device can capture CSI feedback from multiple APs and STAs. Additionally, the proposed CSI learning system can also capture CSI from off-the-shelf wireless devices because it only uses standardized packets in IEEE 802.11ac.

Fig. 2 shows the components and Fig. 3 shows the frame sequence at an AP and STA to capture CSI feedback. The AP and the STA are specified in IEEE 802.11ac. First, the AP transmits a null data packet announcement (NDPA) and null data packet (NDP). The NDPA is a frame to announce the start of channel sounding, and the NDP is a frame to estimate channel information. After the STA receives the NDP, the STA transmits CSI feedback to the AP. The CSI feedback is a frame to feedback the CSI based on the NDP. Finally, the capture device acquires CSI by capturing the CSI feedback from the STA to the AP. NDPA, NDP, and CSI feedback are defined in the IEEE 802.11ac standard.

B. Convert bit strings into angle ϕ, ψ

A captured CSI feedback frame includes fifty-two subcarriers, and each subcarrier has different ϕ and ψ which represent compressed angles. ϕ is the phase difference among antennas, and ψ is the relative amplitude among antennas. Equations (1) and (2) represent ϕ radian and ψ radian, respectively [21].

$$\phi = \frac{k\pi}{2^{b_\phi - 1}} + \frac{\pi}{2^{b_\phi}} \tag{1}$$

$$\psi = \frac{k\pi}{2^{b_\psi + 1}} + \frac{\pi}{2^{b_\psi + 2}} \tag{2}$$

$$k = 0, 1, \ldots, 2^{b_\psi} - 1$$

TABLE I
ϕ and ψ in CSI feedback matrix [21]

Size of matrix	Number of angles	The order of angles
2×1	2	ϕ_{11}, ψ_{21}
2×2	2	ϕ_{11}, ψ_{21}
3×1	4	ϕ_{11}, ϕ_{21}, ψ_{21}, ψ_{31}
3×2	6	ϕ_{11}, ϕ_{21}, ψ_{21}, ψ_{31}, ϕ_{22}, ψ_{32}
3×3	6	ϕ_{11}, ϕ_{21}, ψ_{21}, ψ_{31}, ϕ_{22}, ψ_{32}
4×1	6	ϕ_{11}, ϕ_{21}, ϕ_{31}, ψ_{21}, ψ_{31}, ψ_{41}
...	...	...

k is the resolution of ϕ and ψ, and b_ϕ and b_ψ are the number of bits of ϕ and ψ, respectively. b_ϕ and b_ψ are defined in multiple-input multiple-output control of a CSI feedback [21] and vary depending on whether the feedback type is single-user or multi-user. The proposed CSI learning system uses single-user feedback. If the feedback type is single-user, then (b_ϕ, b_ψ) will be (4, 2) or (6, 4), and the proposed CSI learning system uses (6, 4) as (b_ϕ, b_ψ). The range of ϕ and ψ are $\frac{\pi}{64} \leq \phi \leq \frac{127\pi}{64}, \frac{\pi}{32} \leq \psi \leq \frac{31\pi}{64}$, respectively.

The proposed CSI learning system acquires 312 angles. The number of ϕ and ψ vary depending on the size of the CSI feedback matrix, which is $N_r \times N_c$. N_r is the number of rows of the CSI feedback matrix and N_c is the number of columns of the CSI feedback matrix. Table I shows the relationship between the CSI feedback matrix size and the number of angles. Since $N_r = 4$ and $N_c = 1$, the CSI feedback matrix is 4×1. From Table I, the proposed CSI learning system acquires ϕ_{11}, ϕ_{21}, ϕ_{31}, ψ_{21}, ψ_{31}, and ψ_{41} for each subcarrier. There are $52 \times 6 = 312$ data from a CSI feedback frame.

C. Compute $\sin\phi$, $\cos\phi$, $\sin\psi$, and $\cos\psi$

The ϕ and ψ are not directly used for machine learning because they are angles with the unit radian. For example, although both 0.1 radian and $2\pi - 0.1$ radian mean almost the same in CSI, there are large distance in view of angle.

To solve the discontinuity of ϕ and ψ, the proposed CSI learning system used sine and cosine by computing $\sin\phi$, $\cos\phi$, $sin\psi$, and $\cos\psi$, and $312 \times 2 = 624$ features were extracted from 312 angle data.

D. Create learning model by machine learning

The proposed CSI learning system created a learning model from the calculated sine and cosine with label data. The label

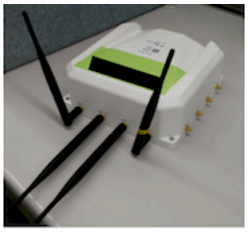

Fig. 4. AP used in this evaluation

TABLE II
CONDITIONS OF EXPERIMENT

Variables	Explanation
Capture time	1 minute
CSI feedback interval	average 10 ms
Frequency	5.2 GHz
Machine learning	k-nearest neighbor
	random forest
	support vector machine

data can be anything such as the number of people in a space, temperature, or the open/closed state of a door. For example, Section IV uses the location of a user as label data.

Additionally, we can choose any machine learning method. For example, Section IV uses k-nearest neighbors, random forest, and support vector machine.

E. Estimation

The proposed CSI learning system estimates a label from captured CSI. For example, Section IV estimates the location of a user using k-nearest neighbors, random forest, and support vector machine.

IV. Experimental Evaluation for Location Estimation

A. Experimental settings

We considered the following six datasets for evaluating the influence to location estimation accuracy by direct waves, reflected waves, and user movement. Fig. 4 shows the AP used in this evaluation. We assumed that the STA receives a direct wave easily if the antenna is upright, and receives a reflected wave easily if the antenna is laid. The six datasets are as follows:

- Four antennas are upright and the user is staying at seven learning positions in Fig. 5 (four upright staying),
- Four antennas are upright and the user is walking on the spot at seven learning positions in Fig. 5 (four upright walking),
- Four antennas are laid and the user is staying at seven learning positions in Fig. 5 (four laid staying),
- Four antennas are laid and the user is walking on the spot at seven learning positions in Fig. 5 (four laid walking),
- Two antennas are upright and the other two are laid, and the user is staying at each of the seven learning positions in Fig. 5 (two upright two laid staying), and
- Two antennas are upright and the other two are laid, and the user is walking on the spot at each of the seven learning positions in Fig. 5 (two upright two laid walking).

Table II shows the evaluation settings. The proposed CSI learning system acquired approximately 1400 CSI feedback packets per dataset: the capture time was 1 min per place, and the average CSI feedback interval was 10 ms. The channel frequency band was 5.2 GHz. We used three machine learning methods: k-nearest neighbor, random forest, and support vector machine.

Fig. 5 shows the experimental environment. The red square is the location of the AP and the red triangle is the location of the STA. The experiment was conducted at the NTT Yokosuka R&D Center 1F. The number in Fig. 5 is the learning positions of the device-free user. The size of the experimental environment is 10.8 m $\times$ 13.2 m.

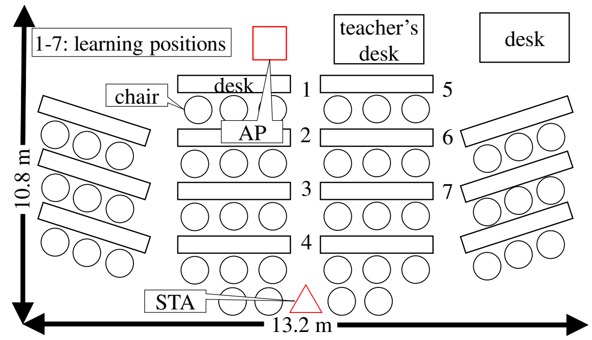

Fig. 5. Experimental environment

TABLE III
AVERAGE ACCURACY OF TABLE IV– IX

Location estimation	k-nearest neighbor	random forest	support vector machine
four upright staying	21	20	33
four upright walking	53	62	69
four laid staying	53	53	50
four laid walking	63	66	61
two upright two laid staying	66	39	55
two upright two laid walking	88	89	95

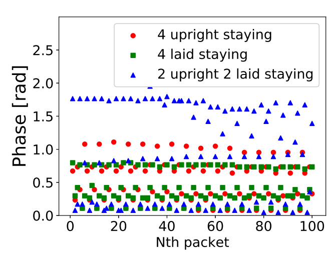

Fig. 6. ϕ_{11} while the user was staying

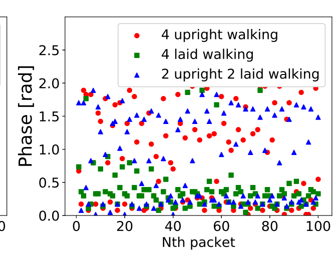

Fig. 7. ϕ_{11} while the user was walking

TABLE IV
CONFUSION MATRIX: LOCATION ESTIMATION RESULT OF FOUR UPRIGHT STAYING

	k-nearest neighbor							random forest							support vector machine						
	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
1	68	5	0	22	3	2	0	70	0	0	30	0	0	0	73	0	0	27	0	0	0
2	3	62	33	1	1	0	0	2	52	28	17	0	0	0	23	70	7	0	0	0	0
3	1	27	4	68	0	0	0	88	4	5	3	0	0	0	1	0	0	99	0	0	0
4	3	49	33	15	0	0	0	72	3	12	13	0	0	0	11	0	4	85	0	0	0
5	0	85	3	12	0	0	0	34	46	20	0	0	0	0	0	0	0	100	0	0	0
6	0	47	28	25	0	0	0	22	37	41	0	0	0	0	0	0	0	100	0	0	0
7	0	97	0	3	0	0	0	32	39	29	0	0	0	0	0	0	0	100	0	0	0

TABLE V
CONFUSION MATRIX: LOCATION ESTIMATION RESULT OF FOUR UPRIGHT WALKING

	k-nearest neighbor							random forest							support vector machine						
	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
1	31	0	0	5	22	19	23	38	0	0	8	20	17	17	38	0	0	8	5	11	38
2	31	69	0	0	0	0	0	13	87	0	0	0	0	0	1	99	0	0	0	0	0
3	2	9	44	1	20	10	14	3	9	43	4	17	7	17	2	9	44	4	14	2	25
4	1	4	29	33	14	9	10	1	5	6	57	15	4	12	1	3	7	59	6	1	23
5	0	0	0	0	81	1	18	0	0	0	0	83	0	17	0	0	0	0	95	0	5
6	0	0	0	0	11	65	24	0	0	0	0	16	63	21	0	0	0	0	9	67	24
7	0	0	0	0	27	22	51	0	0	0	0	18	20	62	1	0	0	0	8	11	80

TABLE VI
CONFUSION MATRIX: LOCATION ESTIMATION RESULT OF FOUR LAID STAYING

	k-nearest neighbor							random forest							support vector machine						
	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
1	71	6	22	1	0	0	0	66	12	11	11	0	0	0	55	23	19	3	0	0	0
2	14	33	15	36	0	1	1	17	36	25	22	0	0	0	8	39	36	15	0	0	2
3	0	0	81	19	0	0	0	0	0	95	5	0	0	0	0	0	76	23	0	0	1
4	5	11	6	73	0	2	3	9	8	10	72	0	0	1	0	13	7	76	0	0	4
5	5	8	0	0	26	22	39	15	10	0	0	18	27	30	7	23	0	0	14	32	24
6	3	8	0	0	3	61	25	4	4	0	0	6	53	33	2	12	0	0	3	63	20
7	14	20	0	6	5	29	26	19	17	1	7	4	22	30	9	27	1	6	2	28	27

TABLE VII
CONFUSION MATRIX: LOCATION ESTIMATION RESULT OF FOUR LAID WALKING

	k-nearest neighbor							random forest							support vector machine						
	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
1	92	5	1	1	0	1	0	95	3	1	1	0	0	0	88	2	6	3	0	1	0
2	13	50	16	2	5	5	9	11	56	16	4	6	4	13	5	35	21	3	7	2	27
3	8	10	60	6	5	6	5	8	11	66	0	7	4	4	6	8	71	3	6	1	5
4	1	5	16	69	3	4	2	3	4	24	63	2	2	2	0	2	26	66	1	4	1
5	0	0	0	0	62	9	29	0	0	0	0	60	13	27	0	0	1	0	52	29	18
6	2	12	3	1	11	50	21	5	12	2	2	13	54	12	2	11	7	3	15	50	12
7	0	0	0	22	6	11	61	0	2	0	21	4	8	65	0	0	0	24	1	7	68

B. Results

Table III shows the average accuracy of location estimation using the six datasets and three machine learning methods. Table IV– IX show the location estimation results of the six datasets. The columns and rows are the actual and estimated positions of the user, respectively. The unit of the table elements is percentage.

In Table IV– IX, we can make observations: First, two upright two laid walking with the support vector machine achieved the best performance.

Second, the datasets with walking are better than those with staying. Table IX shows the confusion matrices of two upright two laid walking, and Table VIII shows that of two upright two laid staying. In Table VIII, the datasets with staying tend to induce errors when the actual user position is at 5, 6, or 7, which is out of the LoS between the AP and STA.

Third, the direction of the antenna is important: two upright two laid is better than four upright and four laid. Table IX shows the confusion matrices of two upright two laid walking, Table V shows that of four upright walking, and Table VII

TABLE VIII
CONFUSION MATRIX: LOCATION ESTIMATION RESULT OF TWO UPRIGHT TWO LAID STAYING

	k-nearest neighbor							random forest							support vector machine						
	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
1	100	0	0	0	0	0	0	92	8	0	0	0	0	0	100	0	0	0	0	0	0
2	80	18	2	0	0	0	0	80	18	2	0	0	0	0	24	64	2	0	0	0	0
3	0	43	57	0	0	0	0	0	43	57	0	0	0	0	0	0	44	56	0	0	0
4	0	0	0	100	0	0	0	0	0	0	100	0	0	0	0	0	0	100	0	0	0
5	0	0	0	16	84	0	0	0	0	0	100	0	0	0	0	0	0	100	0	0	0
6	0	0	0	51	0	0	49	50	0	5	45	0	0	0	0	0	0	100	0	0	0
7	0	0	0	0	0	0	100	0	0	38	32	0	0	30	0	0	21	0	0	0	79

TABLE IX
CONFUSION MATRIX: LOCATION ESTIMATION RESULT OF TWO UPRIGHT TWO LAID WALKING

	k-nearest neighbor							random forest							support vector machine						
	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
1	80	1	15	0	0	0	0	82	6	10	2	0	0	0	91	0	9	0	0	0	0
2	1	87	12	0	0	0	0	1	87	12	0	0	0	0	1	99	2	0	0	0	0
3	5	0	91	4	0	0	0	5	0	91	4	0	0	0	0	0	100	0	0	0	0
4	0	1	3	96	0	0	0	0	1	3	96	0	0	0	0	0	7	93	0	0	0
5	0	0	0	0	89	9	2	0	0	0	0	89	9	2	0	0	0	0	97	3	0
6	0	0	0	0	16	82	2	0	0	0	0	16	82	2	0	0	0	0	2	89	9
7	0	0	0	0	4	0	96	0	0	0	0	4	0	96	0	0	0	0	4	0	96

shows that of four laid walking. Although four upright walking and four laid waking datasets have errors at almost every position, two upright two laid walking successfully estimates every position.

As described above, two upright two laid antennas and user walking improve localization accuracy. The improved accuracy indicates that the divergence of CSI improves the performance of machine learning.

In order to check whether there is CSI divergence in the two upright two laid walking dataset, we plotted ϕ_{11} on time series. Fig. 6 and Fig. 7 show the ϕ_{11} while a user was staying and while a user was walking at position 1, respectively. The horizontal axis is the time of CSI feedback packets, and the vertical axis is the phase. From Fig. 6 and Fig. 7, two observations can be made. First, walking datasets include larger divergence than staying datasets. Second, two upright two laid datasets include larger divergence than four upright datasets and four laid datasets.

The finding is interesting: the divergence of CSI improves machine learning performance. Previous studies such as PhaseFi [13] and PADS [14] have used linear transformation for localization, and described that stable phases improve localization accuracy.

V. CONCLUSION

In this paper, we proposed an IEEE 802.11ac explicit-feedback-based CSI learning system. Our CSI learning system uses only off-the-shelf WiFi devices. The proposed CSI learning system utilizes six compressed angles for a device-free user location estimation. We evaluated the proposed CSI learning system using six datasets by considering the AP's antenna orientation and movements of the user. The evaluation results showed that location estimation using the data while two-upright two-laid walking had the highest accuracy among the proposed location estimation. Location estimation using data while the user was walking showed higher accuracy than data while the user was staying, and the divergence of CSI improves localization performance.

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