ABSTRACT In the field of WiFi sensing, as an alternative sensing source of the channel state information (CSI) matrix, the use of a beamforming feedback matrix (BFM) that is a right singular matrix of the CSI matrix has attracted significant interest owing to its wide availability regarding the underlying WiFi systems. In the IEEE 802.11ac/ax standard, the station (STA) transmits a BFM to an access point (AP), which uses the BFM for precoded multiple-input and multiple-output communications. In addition, in the same way, the AP transmits a BFM to the STA, and the STA uses the received BFM. Regarding BFM-based sensing, extensive real-world experiments were conducted as part of this study, and two key insights were reported: Firstly, this report identified a potential issue related to accuracy in existing uni-directional BFM-based sensing frameworks that leverage only BFMs transmitted for the AP or STA. Such uni-directionality introduces accuracy concerns when there is a sensing capability gap between the uni-directional BFMs for the AP and STA. Thus, this report experimentally evaluates the sensing ability disparity between the uni-directional BFMs, and shows that the BFMs transmitted from the STA achieve higher sensing accuracy compared to the BFMs transmitted from the AP when the sensing target values are estimated depending on the angle of departure of the AP. Secondly, to complement the sensing gap, this paper proposes a bi-directional sensing framework, which simultaneously leverages the BFMs transmitted from the AP and STA. The experimental evaluations reveal that bi-directional sensing achieves higher accuracy than uni-directional sensing in terms of the human localization task.

INDEX TERMS Wireless sensing, channel state information, beamforming feedback, bi-directional.

I. INTRODUCTION

WiFi sensing [1], [2] has attracted notable interest as a technology that adds value to existing wireless local area networks (WLANs) beyond the communication infrastructure, which is under standardization by IEEE 802.11bf task group [3]. In WiFi sensing, a widely used radio frequency (RF) information is channel state information (CSI). It is used in multiple-input multiple-output orthogonal frequency-division multiplexing (MIMO-OFDM) systems [1]. CSI is generally measured in the MIMO-OFDM communication procedures and includes high sensing capacity to facilitate CSI-based sensing with low implementation cost and high sensing accuracy.

CSI-based sensing is associated with an issue regarding the applicability of the underlying WLAN system. Generally, access to the physical layer (PHY) component is necessary to obtain the CSI. However, only a few wireless chips permit such access to the PHY layer [4]–[6]. Therefore, CSI-based sensing cannot necessarily be applied to most existing WLAN systems. To extend their applicability, a new RF information, beamforming feedback matrix (BFM), has been utilized for sensing purposes [7]–[11]. In the IEEE
BFM for AP: \( \mathbf{V}_{\text{STA}} \)
BFM for STA: \( \mathbf{V}_{\text{AP}} \)
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BFM for AP: \( \mathbf{V}_{\text{AP}} \)
BFM for STA: \( \mathbf{V}_{\text{STA}} \)

(a) Previous uni-directional sensing framework.

(b) Proposed bi-directional sensing framework.

FIGURE 1: Overview of previous and proposed BFM-based sensing frameworks. The previous framework uses only the uni-directional BFM (i.e., either \( \mathbf{V}_{\text{AP}} \) or \( \mathbf{V}_{\text{STA}} \)) and ignores other directional BFM. The proposed framework uses the bi-directional BFM (i.e., both of \( \mathbf{V}_{\text{AP}} \) and \( \mathbf{V}_{\text{STA}} \)).

802.11ac/ax standard [12], [13], the BFM, which is a right singular matrix of the CSI matrix, is transmitted from a station (STA) to an access point (AP) and is used for the precoding procedure in the AP for MIMO transmissions. Moreover, in the same way, the AP transmits BFM to the STA, and the STA uses the received BFM for the precoding procedure in some scenarios, such as the STA that acts as a relay station. The BFM transmission procedure is conducted without any encryption. Thus, BFM-based sensing can be only conducted by capturing the BFM with a media-access-control (MAC) frame capture tool, without any access to the PHY layer of the communication pair. This fact enables us to utilize most WLAN devices for BFM-based sensing.

We show an existing BFM-based sensing framework [7]–[11] in Fig. 1(a). Let the BFM transmitted from the STA to the AP and the BFM transmitted from the AP to the STA be denoted by \( \mathbf{V}_{\text{AP}} \) and \( \mathbf{V}_{\text{STA}} \), respectively. In these studies, the frame capture acquires BFM and estimates the sensing target values (e.g., human locations [7]–[9], device location [8], [9], and respiratory rate [10]) by feeding BFM to machine learning (ML) models. The existing BFM-based sensing frameworks [7]–[11] are referred to as uni-directional sensing, and they leverage either \( \mathbf{V}_{\text{AP}} \) or \( \mathbf{V}_{\text{STA}} \). Therefore, even when the AP and STA transmit BFM to each other, the existing works [7]–[11] leverage only uni-directional BFM (i.e., either of \( \mathbf{V}_{\text{AP}} \) or \( \mathbf{V}_{\text{STA}} \)) and ignore the other directional BFM.

Regarding the existing uni-directional sensing, our concern is that there may be a sensing capability disparity between the usage of \( \mathbf{V}_{\text{AP}} \) and \( \mathbf{V}_{\text{STA}} \), resulting in the risk of using a BFM with a low sensing capability among \( \mathbf{V}_{\text{AP}} \) and \( \mathbf{V}_{\text{STA}} \). Regarding the sensing capability gap between the two uni-directional BFM, our previous work [14] proved that \( \mathbf{V}_{\text{AP}} \) informs the AP’s angle of departure (AoD) under strict assumptions regarding the channel model and antenna array. Instead, to account for the accuracy disparity, there are two limitations in [14] as follows. Firstly, the evaluation and discussion of the sensing ability regarding the AP’s AoD estimation using \( \mathbf{V}_{\text{STA}} \) were not presented. Secondly, [14] used strict assumptions regarding the propagation model and antenna array; for example, the AP and STA are assumed to be equipped with linear antenna arrays. Such strict assumptions are not necessarily satisfied in most WLAN systems.

To account for the accuracy disparity, we experimentally evaluate the sensing ability gap between \( \mathbf{V}_{\text{AP}} \) and \( \mathbf{V}_{\text{STA}} \) for the AP’s AoD estimation task in a real environment using off-the-shelf equipment, which are equipped with non-linear antenna arrays. The experimental evaluation confirmed that sensing using \( \mathbf{V}_{\text{AP}} \) resulted in a higher AoD estimation accuracy than sensing based on \( \mathbf{V}_{\text{STA}} \). Moreover, this difference in the accuracy of AoD sensing implies that there is an accuracy difference for practical sensing tasks in which the sensing target values to be estimated depend on the AP’s AoD. Specifically, we experimentally evaluate the difference in accuracy between sensing with \( \mathbf{V}_{\text{AP}} \) and \( \mathbf{V}_{\text{STA}} \) using a human localization task in which the angle from the human to the AP corresponds to the AP’s AoD of the human-reflected path. The experimental results confirm the existence of a sensing accuracy disparity between the uni-directional BFM.

Furthermore, in this report, a simple but powerful method called bi-directional sensing is proposed to address the potential accuracy concern. An overview of the bi-directional sensing process is shown in Fig. 1(b). In this method, the uni-directional BFM are integrated into an input feature and are fed to the ML model. Our experimental evalu-
tions reveal that the proposed bi-directional sensing achieves higher sensing accuracy than the previous uni-directional sensing. Moreover, it is determined that when the ML model is trained using the bi-directional BFMs, it leverages more appropriate BFMs of the uni-directional BFMs. Specifically, if the sensing with $V^{AP}$ achieves higher accuracy than sensing with $V^{STA}$, the ML model with bi-directional BFMs assigns higher importance metrics to the input features generated from $V^{AP}$ compared to those of $V^{STA}$, and vice-versa. Note that the importance metrics indicate the contribution of each input feature to the sensing accuracy.

The contributions of this study are summarized as follows:

1) We experimentally validate that $V^{AP}$ achieves superior sensing accuracy than $V^{STA}$ for the AP’s AoD estimation.

2) We experimentally validate the difference in the sensing accuracy between $V^{AP}$ and $V^{STA}$ for a human localization task, which is caused by the difference in sensing accuracy for the AP’s AoD estimation. This finding highlights potential accuracy risks in existing BFM-based sensing schemes, which are not found in previous works that used only uni-directional BFM (i.e., either $V^{AP}$ or $V^{STA}$). To the best of our knowledge, in-depth discussions on the difference between uni-directional BFMs in terms of sensing accuracy have not been presented in the BFM-based sensing literature.

3) We propose a novel BFM-based sensing framework called bi-directional sensing. In this approach, $V^{AP}$ and $V^{STA}$ are integrated into an input feature, which is fed to the ML model. We experimentally validate that the proposed bi-directional sensing achieved higher accuracy than the preexisting uni-directional sensing for a human localization task.

In this study, our main objective is to show that the sensing abilities of the BFM transmitted for an AP and STA are different, and that the bi-directional BFM-based sensing framework is beneficial in terms of sensing accuracy when compared to uni-directional BFM-based sensing. Namely, our focus is on the difference in the directivities of BFMs in BFM-based sensing frameworks. Thus, the comparison of the proposed framework to other RF-information-based sensing frameworks (e.g., CSI-based sensing and received-power-based sensing) is out of the scope of this report. Moreover, we should note that the BFM-based sensing framework is explicitly different from other RF-information-based sensing frameworks in terms of its system requirements. Specifically, the BFM-based sensing can be conducted using frame capture without access to the AP and STA, whereas the other RF-information-based sensing frameworks generally require such accessibility.

II. RELATED WORKS

Traditionally, owing to its ease of availability and broad applicability, the received signal strength indicator (RSSI) has been used for WiFi sensing, such as human detection [15], human tracking [16], and human localization [17]. Considering the spread of the MIMO system in WLAN, CSI-based sensing has attracted notable interest in terms of the improvement of the sensing capacity. Since the CSI includes more fine-grained information than the RSSI, specifically CSI includes the attenuation between each transmit-receive antenna pair for each OFDM subcarrier. CSI-based sensing achieves higher sensing accuracy [18]–[21] and success in more complex sensing tasks [22]–[25] than RSSI-based sensing. In the existing CSI-based sensing literature, either of the firmwares [4]–[6] have been mainly used for CSI extraction. However, they can only be used on a few wireless chips. Therefore, there are device limitations in the realization of CSI-based sensing.

Compared to CSI-based sensing, BFM-based sensing is a firmware-agnostic wireless sensing method [8]–[11]. As mentioned in the previous section, BFMs can be collected via MAC-layer frame capture without any special constraints regarding the firmware. Although a vast number of studies addressed CSI-based sensing [1], there are few studies on BFM-based sensing; human detection [7]–[9], respiratory rate estimation [10], and camera image estimation [11]. Moreover, these experimental studies [7]–[11] addressed sensing tasks using uni-directional BFM (i.e., either $V^{AP}$ or $V^{STA}$). In contrast to those investigations [7]–[11], this report focuses on the difference between the BFM transmitted for an AP and STA and leverages bi-directional BFMs to improve sensing accuracy.

III. PRELIMINARIES: MIMO-OFDM

This section describes a MIMO-OFDM communication system using Eigen beam space division multiplexing (ESDM) [26]. The system consists of a transmitter (TX) and a receiver (RX) that are compliant with IEEE 802.11ac/11ax [12], [13]. The TX sends frames to the RX using MIMO-OFDM. The RX estimates the CSI, computes the BFM based on the CSI, and transmits the BFM to the TX. The TX uses the BFM as a precoding matrix.

Formally, let the CSI matrix from the TX to the RX at the $k$th subcarrier be denoted by $H[k] \in \mathbb{C}^{N_t \times N_r}$, where $N_t$ and $N_r$ are the number of antennas of the TX and RX, respectively. The CSI matrix is estimated at the RX using the pilot signals (e.g., null data packet) at each OFDM subcarrier. From the CSI matrix, the RX calculates a right singular matrix $V[k]$ of $H[k]$ using singular value decomposition, as

$$H[k] = U[k] \Sigma[k] V[k]^H,$$  \hspace{1cm} (1)

where $V[k]$ and $U[k]$ are unitary matrices, and $\Sigma[k]$ is a diagonal matrix with singular values. Subsequently, the RX transmits the right singular matrix $V[k]$, which is referred to as a BFM, to the TX using the BFM frame. In the TX, the BFM is used for the precoding procedure. Given a transmitting data vector $x[k]$, the transmitted signal vector $s[k]$ is denoted by

$$s[k] = V[k] x[k].$$  \hspace{1cm} (2)
In addition to $V[k]$, the subcarrier-averaged upstream substream gain $\Sigma$ is transmitted from the RX to the TX via the IEEE 802.11ac/11ax protocol [12], [13], where

$$\Sigma = \frac{1}{K} \sum_{k=1}^{K} \Sigma[k], \quad (3)$$

where $K$ is the number of subcarriers.

The BFM transmission procedure of the IEEE 802.11ac/11ax [12], [13] is quantized in the RX using the Givens transform to reduce the communication payload size of the BFM frame. In this process, the BFM $V[k]$ is represented as an $M$-dimensional vector $v[k] \in \mathbb{R}^M$, where $M$ is determined by $N_t$ and $N_r$. For shorthand notation, let the $M \times K$ matrix $V'$ denote the coordination of $(v[k])_{k=1}^{K}$. Moreover, the quantized BFM calculation function from the CSI matrices is denoted as $f^B$, where

$$V' = f^B((H[k])_{k=1}^{K}). \quad (4)$$

It should be noted that $V'$ represents information obtained via frame capture and is used for BFM-based sensing.

### IV. BI-DIRECTIONAL BEAMFORMING FEEDBACK MATRIX SENSING

#### A. SYSTEM MODEL

Fig. 2 shows the system model, which consists of an AP, an STA, and a frame capture device. The AP and the STA periodically transmit MIMO frames between each other. For the MIMO transmission, the BFM frames are transmitted from the AP to the STA, and from the STA to the AP over the air without encryption. The frame capture obtains both the BFM transmitted from the AP and STA. More formally, the CSI matrices from the AP to the STA and from the STA to the AP at the subcarrier $k$ are denoted as $H^\text{AP}[k]$ and $H^\text{STA}[k]$, respectively. Based on Section III the BFM are transmitted from the AP and STA are denoted as $V^{\text{AP}}$ and $V^{\text{STA}}$, respectively, where

$$V^{\text{AP}} = f^B((H^\text{AP}[k])_{k=1}^{K}), \quad (5)$$

$$V^{\text{STA}} = f^B((H^\text{STA}[k])_{k=1}^{K}). \quad (6)$$

In this report, based on existing BFM-based sensing methods, an ML-based sensing technique is developed. Thus, the system has two-time phases: a training phase and a testing phase. In the training phase, the frame capture obtains BFM and the ground-truth target label (e.g., actual measured location of a human subject), and the BFM are used as input features. The ML model is trained using a training dataset consisting of the input features and target labels. In the testing phase, whenever the frame capture obtains the BFM frame, it estimates the target label by feeding the BFM to the trained ML model.

#### B. MATHEMATICAL ESTIMATION OF ANGLE OF DEPARTURE FROM BEAMFORMING FEEDBACK MATRIX

This section summarizes the AP’s AoD estimation method based on $V^{\text{AP}}$ under strict assumptions [14]. The assumptions are as follows: the CSI is represented using a discrete physical propagation model [27], the AP and STA are equipped with a linear antenna array, the distance between consecutive antenna elements is less than half of the wavelength, and the number of propagation paths is smaller than the number of antenna elements of the AP and that of the STA. Based on these assumptions, the AP’s AoD is estimated using the BFM of an arbitrary subcarrier $V^{\text{AP}}[k]$ and the subcarrier-averaged substream gain $\Sigma$. Specifically, noise subspace vectors are estimated as the row vector of $V^{\text{AP}}$ with a subcarrier-averaged stream gain of zero, then the AoD of the AP is estimated from the noise subspace vectors using multiple signal classification spectrum [28]. Moreover, this concept [14] is equivalent to estimating the AoD of the STA from the BFM transmitted from the STA under the aforementioned assumptions.

To account for the accuracy gap, there are two limitations [14] as follows. Firstly, [14] investigated the sensing capability of $V^{\text{AP}}$ in the AP’s AoD estimation, however, the sensing capability of $V^{\text{STA}}$ is unknown. Secondly, some of the assumptions in [14] differ significantly from the situations in actual WiFi systems. Specifically, the distance between consecutive antennas is generally larger than half of the wavelength to improve MIMO communication efficiency. Moreover, the requirement of six to eight antennas [29] is generally more than that of off-the-shelf WiFi APs and STAs. Therefore, the objective is to experimentally validate the difference in the sensing ability between $V^{\text{AP}}$ and $V^{\text{STA}}$ for AoD estimation using off-the-shelf WiFi devices.

### V. EXPERIMENTAL SETUP

We experimentally evaluate the accuracy of BFM-based sensing methods for two sensing tasks: AoD estimation and human localization, using off-the-shelf WiFi devices in an

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1 In this report, $V[k]$ denotes the right singular matrix of the CSI matrix at the $k$th subcarrier, and $V$ denotes the payload of the BFM matrix.
outdoor environment. These sensing tasks are formulated as classification problems. For shorthand notation, we denote $V_{AP}$ sensing and $V_{STA}$ sensing as uni-directional sensing with $V_{AP}$ and $V_{STA}$, respectively.

### A. SYSTEM COMPONENTS

As depicted in Fig. 3, the system consists of an AP, an STA, and frame capture. The AP and STA are equipped with four antennas. All the equipment is on-the-shelf devices. The AP and STA are in compliance with IEEE 802.11ax and send BFM frames approximately every 0.1 s. Since the number of antennas of the AP and STA is identical, the dimension of the BFM at each subcarrier is the same among $V_{AP}$ and $V_{STA}$. In this evaluation, the number of subcarriers $K$ and the dimension of the BFM at each subcarrier $M$ are 64 and 12, respectively, resulting in the shape of the BFM of $12 \times 64$. The details of the experimental setup are shown in Table 1.

### B. EXPERIMENTAL SCENARIO

#### AoD estimation

This evaluation aims to assess the accuracy difference of the AP’s AoD estimation on the realistic environment of two uni-directional sensing approaches: sensing using $V_{AP}$ and sensing using $V_{STA}$. Specifically, we estimate the AoD of the antenna array of the STA was fixed at the position $(6 \text{ m}, 90^\circ)$, while a human stands at any of the 21 points and is depicted as black dots in Fig. 3(b).

#### Human localization

This evaluation aims to assess the accuracy of the uni-directional sensing and the proposed bi-directional sensing approaches on more practical sensing tasks than AoD estimation. Fig. 4(b) shows an overview of the experimental environment. We generated a dataset wherein a human was located at any of 21 positions. The 21 positions are denoted using the distance $r$ and the angle $\theta$ to the AP. As such, the target label is represented by a two-dimensional vector $(r, \theta)$. In this scenario, two ML models are trained to estimate the angle $\theta$ and the distance $d$. The positions of the STA are fixed, and the distance between the AP and STA is 6 m. It should be noted that $\theta$ corresponds to the AP’s AoD of the human-reflected path in this experimental scenario. We obtained 12,600 data samples, wherein 600 samples corresponded to each position.

The classification accuracy for human localization is evaluated using three parameters: angle accuracy, distance accuracy, and position accuracy. The angle/distance accuracy is defined as the test sample ratio for which the estimated angle/distance matches the ground truth. The position accuracy is defined as the ratio of the test samples for which the estimated angle and distance match the ground truth. According to these definitions, the position accuracy is less than the angle/distance accuracy.

### C. MACHINE LEARNING

Three ML models are utilized: a random forest (RandF) [30], a light gradient boosting machine (LightGBM) [31], and support vector machine (SVM) [32]. The AoD estimation and the human localization are formulated as the classification problem. In this evaluation, the dataset is randomly divided into training and testing datasets with a ratio of 9:1. When using the RandF and LightGBM, we performed 10-fold leave-one-out cross-validation for ten trials with a different random seed. When using the SVM, we did not conduct cross-validation and the ML model was trained only once.

### Table 1: Experimental equipment.

| Component     | Description                                      |
|---------------|--------------------------------------------------|
| AP            | Buffalo, WXR-5700AX7S                              |
| STA           | Buffalo, WXR-5700AX7S                              |
| Frame capture | NVIDIA Jetson nano with Intel AX200                |
| Protocol      | IEEE 802.11ax                                     |
| Wireless band | 104 ch                                           |
| Bandwidth     | 20 MHz                                           |

![FIGURE 3: Layout of experimental setup. AP, STA, and frame capture are at a height of 75 cm](image1)

![FIGURE 4: Equipment deployment. Preparation of a polar coordinate system centered on the AP. The antenna array of the AP is placed parallel to the zero-degree direction. For the AoD estimation task, the STA is located at any of 21 points, and is depicted as black dots in Fig. 4(a). For the human localization task, the STA is fixed at the position (6 m, 90\(^\circ\)), while a human stands at any of the 21 points and is depicted as black dots in Fig. 4(b).](image2)
The hyperparameters are selected as follows unless otherwise indicated. For the RandF, the maximum depth, the splitting criterion, and the number of trees are selected as 5, Gini impurity, and 50, respectively. For the LightGBM, the maximum depth, the splitting criterion, the number of trees, and the learning rate are selected as infinite, multi-class log loss, 5, and 0.1, respectively. For the SVM, the regularization parameter and the kernel are selected as 1.0, and the Gaussian kernel, respectively.

D. FEATURE GENERATION

In bi-directional sensing, the bi-directional BFMs are integrated to generate an input feature. Specifically, given that \( V^{AP} \) and \( V^{STA} \) are captured within a time interval of less than \( t_0 \), they are flattened and concatenated. The input feature vector with a dimension of 1,536 is then generated. In the experimental evaluation process, \( t_0 \) is set to 0.15 s.

However, in uni-directional sensing, either \( V^{AP} \) or \( V^{STA} \) is used. To allow for a fair comparison between uni-directional sensing and bi-directional sensing, the former uses the input feature, for which the dimension is the same as that of bi-directional sensing. Thus, two BFMs that were captured within a time interval of less than \( t_0 \) are flattened and concatenated, and the input feature vector is then generated.

VI. RESULT

A. ANGLE OF DEPARTURE ESTIMATION

In this section, the results show that a higher accuracy was obtained for \( V^{AP} \) sensing in the process of the AP’s AoD estimation compared to \( V^{STA} \) sensing, which validates the main points in Section I. As shown in Table 2(a), regardless of the ML model, \( V^{AP} \) sensing achieved higher accuracy compared to \( V^{STA} \) sensing in the AP’s AoD estimation. Moreover, the accuracy of \( V^{AP} \) sensing is higher than 0.98 for three ML models, which indicates that the performance is almost perfect. Table 2(b) shows the average error for AoD estimation using three ML models. The average error for \( V^{AP} \) sensing is much smaller compared to that of \( V^{STA} \) sensing, regardless of the ML model that is used. Specifically, regardless of the ML models, the average error for \( V^{AP} \) sensing is lower than 0.3\(^\circ\), whereas that of \( V^{STA} \) sensing is larger than 4.0\(^\circ\). Fig. 5 shows the empirical cumulative distribution function (CDF) of the AoD estimation error. Regardless of the ML model, in the case of \( V^{AP} \) sensing, more than 99\% of the test samples had an error less than 30\(^\circ\), whereas for \( V^{STA} \) sensing, less than 92\% of the samples met this criterion. In addition, the effect of the ML hyperparameters on accuracy in the RandF model is shown in Fig. 6. This finding is consistent with the results described so far; the accuracy for \( V^{AP} \) sensing is higher than that of \( V^{STA} \) sensing, regardless of the number of trees. Thus, we can conclude that \( V^{AP} \) sensing achieves higher AP AoD sensing accuracy compared to \( V^{STA} \) sensing.

### TABLE 2: Classification accuracy of seven classes and the average error of AoD estimation using three ML models. \( V^{AP} \) sensing achieved higher AP AoD accuracy compared to \( V^{STA} \) sensing.

|       | \( V^{AP} \) sensing | \( V^{STA} \) sensing |
|-------|----------------------|----------------------|
| RandF | 98.7\%               | 56.6\%               |
| LightGBM | 99.7\%               | 78.0\%               |
| SVM   | 99.9\%               | 87.0\%               |

![FIGURE 5: Empirical CDF of estimation error in AoD estimation using three ML models. The red and green lines represent the results for \( V^{AP} \) and \( V^{STA} \) sensing, respectively.](image)

![FIGURE 6: Effect of the number of trees of RandF on AoD estimation accuracy.](image)

B. HUMAN LOCALIZATION

Accuracy comparison. In this section, the accuracy of the three BFM-based sensing methods (i.e., \( V^{AP} \) sensing, \( V^{STA} \) sensing, and \( V^{AP} \) sensing) is validated. According to Table 2(a), \( V^{AP} \) sensing achieved the highest classification accuracy for all seven classes, whereas \( V^{STA} \) sensing achieved the lowest. The accuracy of \( V^{AP} \) sensing compared to \( V^{STA} \) sensing is almost perfect. Moreover, the accuracy of \( V^{AP} \) sensing is much smaller compared to that of \( V^{STA} \) sensing, regardless of the ML model that is used. Specifically, regardless of the ML models, the average error for \( V^{AP} \) sensing is lower than 0.3\(^\circ\), whereas that of \( V^{STA} \) sensing is larger than 4.0\(^\circ\). Fig. 5 shows the empirical cumulative distribution function (CDF) of the AoD estimation error. Regardless of the ML model, in the case of \( V^{AP} \) sensing, more than 99\% of the test samples had an error less than 30\(^\circ\), whereas for \( V^{STA} \) sensing, less than 92\% of the samples met this criterion. In addition, the effect of the ML hyperparameters on accuracy in the RandF model is shown in Fig. 6. This finding is consistent with the results described so far; the accuracy for \( V^{AP} \) sensing is higher than that of \( V^{STA} \) sensing, regardless of the number of trees. Thus, we can conclude that \( V^{AP} \) sensing achieves higher AP AoD sensing accuracy compared to \( V^{STA} \) sensing.
sensing, and bi-directional BFM-based sensing) was evaluated based on a human localization task. These parameters were considered as part of the evaluation including the angle, distance, and position.

Table 3 shows the three accuracy metrics for the three BFM-based sensing methods. In the case of the angle accuracy, which is shown in Table 3(a), \( V^{AP} \) sensing achieved higher accuracy than \( V^{STA} \) sensing, regardless of the ML model. Considering that the angle \( \theta \) corresponds to the AP’s AoD of the human-reflected path in the experimental setup, the difference in angle accuracy is because \( V^{AP} \) includes more useful information for the AP’s AoD compared to the BFM \( V^{STA} \), as indicated in Section VI-A. Owing to the difference in angle accuracy, \( V^{AP} \) sensing achieved a higher position accuracy than \( V^{STA} \) sensing, as shown in Table 3(c). Thus, we can conclude that there is a difference in the accuracy metrics and ML models, which validates 3 in Section I.

As shown in Table 3, bi-directional sensing achieves higher accuracy compared to uni-directional sensing in terms of the accuracy metrics and ML models, which validates 3 in Section I. This difference in accuracy is because the ML model that is trained based on bi-directional BFMs leverages the more appropriate BFM of the two uni-directional BFMs, which is validated in the following section. The difference in accuracy between bi-directional and uni-directional sensing is more robustly validated in terms of the localization error in the following section.

### Localization error comparison

This section validates that the proposed bi-directional sensing achieves lower human-localization error than uni-directional sensing. Table 4 shows the average error of human localization tasks, wherein the error is defined as the Euclidean distance between the estimated and ground-truth locations. Regardless of the ML model, bi-directional sensing achieved a lower average error compared to uni-directional sensing. For example, when using the SVM model, the average error of bi-directional sensing is lower than 0.1 m, whereas that of uni-directional sensing is larger than 0.15 m. Figure 7 shows the empirical CDF of the human-localization error of three ML models. Comparing the ratio of the test sample, which has an error less than 1 m, that of bi-directional sensing is higher compared to that of uni-directional sensing. For example, when the RandF model is used, the errors associated with bi-directional sensing, \( V^{AP} \) sensing, and \( V^{STA} \) sensing are 74.4%, 65.2%, and 59.0%, respectively. Thus, we can conclude that bi-directional sensing achieves higher accuracy than uni-directional sensing, which is consistent with the results presented in this section and further validates 3 in Section I.

### Feature importance comparison

Table 5 shows the feature importance of the RandF and LightGBM models that were trained using bi-directional BFMs. The feature importance is defined in decision tree models such as the RandF and LightGBM models. This parameter is assigned to each feature element, and indicates the contribution of each feature to the reduction of the Gini coefficient. A higher importance indicates a greater contribution of the corresponding feature.

Since bi-directional sensing uses the input feature of \( V^{AP} \) and \( V^{STA} \), Table 5 represents the importance assigned to the feature generated from \( V^{AP} \) and that from \( V^{STA} \). Note that since the target vector is two-dimensional (i.e., angle and distance), the ML model includes two groups of trees (i.e., angle estimation trees and distance estimation trees); Thus, we show the feature importance for the two tree groups.

### Table 3: Classification accuracy of human localization.

|                  | \( V^{AP} \) | \( V^{STA} \) |
|------------------|-------------|-------------|
| (a) Angle accuracy: \( \theta \) |            |             |
| RandF            | 87.3%       | 82.4%       |
| LightGBM         | 94.8%       | 93.4%       |
| SVM              | 98.5%       | 96.6%       |

| (b) Distance accuracy: \( d \) |            |             |
|--------------------------------|-------------|-------------|
| RandF                         | 83.6%       | 78.4%       |
| LightGBM                      | 90.6%       | 86.2%       |
| SVM                           | 96.7%       | 93.3%       |

| (c) Position accuracy: \( r, \theta \) |            |             |
|---------------------------------------|-------------|-------------|
| RandF                                 | 74.4%       | 65.2%       |
| LightGBM                              | 86.1%       | 81.0%       |
| SVM                                   | 95.2%       | 90.5%       |

### Table 4: Average localization error for the human localization task.

|                  | \( V^{AP} \) | \( V^{STA} \) |
|------------------|-------------|-------------|
| Bi-directional   | 0.526 m     | 0.677 m     |
| LightGBM         | 0.289 m     | 0.369 m     |
| SVM              | 0.090 m     | 0.184 m     |
TABLE 5: Feature importance of the ML model trained using bi-directional BFMs. The importance of the feature generated from the $V^{AP}$ and that from $V^{STA}$ are represented separately.

|                              | $V^{AP}$ | $V^{STA}$ |
|------------------------------|----------|-----------|
| **(a) Angle estimation trees**|          |           |
| RandF                        | 0.692    | 0.308     |
| LightGBM                     | 0.601    | 0.399     |
| **(b) Distance estimation trees**|        |           |
| RandF                        | 0.548    | 0.452     |
| LightGBM                     | 0.426    | 0.574     |

VII. CONCLUSION

In this investigation, it was experimentally validated that the sensing accuracy of two cases of sensing using the BFM transmitted for the AP and sensing based on the BFM transmitted for the STA are different for human localization and the AP’s AoD estimation tasks. The results imply that there exist a potential accuracy degradation in uni-directional BFM-based sensing, which uses either BFM transmitted for the AP or BFM transmitted for STA. To overcome the potential accuracy degradation, we propose a bi-directional BFM sensing, which simultaneously uses BFMs transmitted for the AP and STA. We experimentally established that the proposed bi-directional BFM sensing achieved higher sensing accuracy than uni-directional BFM sensing.

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