Hybrid Fusion for 802.11ax Wi-Fi-based Passive Radars Exploiting Beamforming Feedbacks

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***Abstract*—Passive Wi-Fi-based radars (PWRs) are devices that enable the localization of targets using Wi-Fi signals of opportunity transmitted by an access point. Unlike active radars that optimize their transmitted waveform for localization, PWRs align with the 802.11 amendments. Specifically, during the channel sounding session preceding a multi-user multiple-input multiple-output downlink transmission, an access point isotropically transmits a null data packet (NDP) with a known preamble. From these known symbols, client user equipments derive their channel state information and transmit an unencrypted beamforming feedback (BFF) back to the access point. The BFF comprises the right singular matrix of the channel and the corresponding stream gain for each subcarrier, which allows the computation of a beamforming matrix at the access point. In a classical PWR processing, only the preamble symbols from the NDP are exploited during the channel sounding session. In this study, we investigate multiple target localization by a PWR exploiting hybrid information sources. On one hand, the joint angle-of-departure and angle-of-arrival evaluated from the NDP. On another hand, the line-of-sight angle-of-departures inferred from the BFFs. The processing steps at the PWR are defined and an optimal hybrid fusion rule is derived in the maximum likelihood framework. Monte-Carlo simulations assess the enhanced accuracy of the proposed combination method compared to classical PWR processing based solely on the NDP, and compare the localisation performance between client and non-client targets.**

***Index Terms*—Passive Wi-Fi Radar, Beamforming Feedback, MU-MIMO, Multitarget Localization, Maximum Likelihood**

I. Introduction

Passive Wi-Fi-based Radars (PWRs) are devices employed for target localization utilizing Wi-Fi signals transmitted by an Access Point (AP) [1]. The communication signal emitted by the AP to its clients within the environment is reflected off the targets and received by the PWR. The PWR captures and demodulates known preamble orthogonal frequency division multiplexing (OFDM) modulated symbols to estimate the localization parameters of the targets. Unlike active radars which optimize their transmitted waveform for localization, the design of PWRs is intrinsically linked to the evolution of the 802.11 standard [2]. Consequently, any wireless communication technology specified within the Wi-Fi standard presents an opportunity to enhance PWR localization capabilities.

In particular, the initiation phase of a multi-user multiple-input multiple-output (MU-MIMO) downlink transmission between an AP and multiple client user equipments (UEs) could be leveraged. To determine its beamforming coefficient, an 802.11ax AP initiates a channel sounding session during which null data packets (NDP) containing known OFDM symbols are transmitted to the client UEs. Based on the NDP, the client UEs can evaluate their channel state information (CSI) and transmit back unencrypted beamforming feedback (BFF) to the AP. These MU-MIMO BFFs comprise a subcarrier-averaged stream gain and, for each subcarrier, the right singular matrix of the channel and the quantized delta streams, enabling the AP to compute its beamforming matrix [3]. However, traditional processing methods employed by PWRs during the channel sounding session solely rely on the known preambles provided by the NDP.

Previous works in the literature explore the utilization of the BFF for various purposes. For instance, an experimental investigation conducted by [4] focuses on BFF-based angle-of-departure (AoD) estimation. The study demonstrates that the estimation error of AoD using BFF is comparable to that achieved through CSI-based estimation methods. In [5], the right singular vectors contained within the BFF are sniffed at a PWR to reconstruct the precoded MIMO preamble signals. This approach enables the localization of targets using the beamformed Wi-Fi signals. However, to the best of the author's knowledge, there has been no investigation into the hybrid combination of the CSI evaluated at a PWR during the channel sounding session with the information provided by the BFF to enhance the localization accuracy of the radar system. Additionally, there is no previous work leveraging the delta signal-to-noise ratio (SNR) transmitted in the MU-MIMO BFF for this purpose.

In this study, our focus lies on the localization of K targets by a PWR exploiting a hybrid source of information: the joint AoDs and angles-of-arrival (AoAs) extracted from the NDP transmitted by an AP, and the line-of-sight (LoS) AoD inferred from the BFF transmitted by the client UEs. Consequently, the PWR must implement a combination rule for the optimal exploitation of both sources of information.

The maximum likelihood (ML) framework enables the derivation of an optimal joint AoD/AoA-based fusion rule. However, in scenarios involving the detection of multiple targets, the complexity of the ML algorithm increases, as its brute force implementation requires a $2K$-dimensional search across the positions of all targets [6]. In our previous analysis [7], we introduced a fusing methodology for a multistatic OFDM radar localization based on known preambles only, effectively decoupling the $2K$-dimensional ML estimator into K per-target two-dimensional searches. The proposed alternating summation method relies on a pre-estimation of the targets' parameters acquired via the multiple signal classification (MUSIC) algorithm. This method takes into account the varying ability of the different radar pairs constituting the multistatic configuration to localize different targets.

The aim of this paper is to explore the advantages of utilizing the BFFs at a PWR for localizing multiple targets. Our contributions are outlined as follows:

- We detail the processing steps at a PWR to extract both the CSI from the NDP transmitted by the AP and the BFFs transmitted by the client UEs during the MU-MIMO channel sounding session.
- We formulate the ML estimator for localizing multiple targets through the hybrid fusion of the CSI and the BFFs. We demonstrate that the alternating summation method proposed in [7] for a multistatic radar configuration can be adapted by computing an approximated sample covariance matrix of the channel using the right singular vectors and the quantized subcarrier stream gain contained in the BFF.
- Numerical simulations demonstrate the benefits of exploiting the BFFs compared to localization based solely on the CSI. Furthermore, the localization improvement is compared for client and non-client targets.

The structure of the paper is organized as follows: Section II presents the sensing steps at the PWR during the channel sounding session. Section III describes the system model. Section IV details the mathematical formulation of the hybrid radar processing at the PWR. In Section V, numerical results are provided to evaluate the benefit of the proposed fusion.

A. Notations

The vectors and matrices are defined as $\mathbf{a}$ and $\mathbf{A}$, respectively. The trace, the transpose and the Hermitian transpose are denoted by $\mathrm{Tr}\{\mathbf{A}\}, \mathbf{A}^{\mathrm{T}}$ and $\mathbf{A}^{\mathrm{H}}$, respectively. The Moore-Penrose inverse is defined as $\mathbf{A}^{+} = \left(\mathbf{A}^{\mathrm{H}}\mathbf{A}\right)^{-1}\mathbf{A}^{\mathrm{H}}$. The vector and the Frobenius matrix norm are written $\|\mathbf{a}\|$ and $\|\mathbf{A}\|_{\mathrm{F}}$. The identity matrix is denoted by $\mathbf{I}$ and the Kronecker product is denoted by $\otimes$.

II. Channel Sounding Session Sensing

In this study, we investigate the sensing capability of a PWR during the channel sounding session defined by the 802.11ax amendment. The scenario is illustrated in Fig.1.

From a communication standpoint, the AP initiates a downlink MU-MIMO transmission with the client UEs. To compute or update its beamforming steering matrix, the AP initiates an explicit channel sounding session with the following steps:

C1) The AP isotropically transmits an NDP to the client UEs.

C2) The client UEs evaluate their CSI for each transmitting-receiving antenna pairing from known high efficiency long training fields (HE-LTF) in the NDP.

C3) Each client UE performs a singular value decomposition (SVD) of the obtained channel matrix to extract the right singular matrix of the channel and the quantized delta stream for each subcarrier, along with a subcarrier-averaged stream gain. These parameters are subsequently transmitted back to the AP in an unencrypted and compressed BFF.

C4) The AP decompresses the BFFs and computes its precoding matrix for beamformed data transmission.

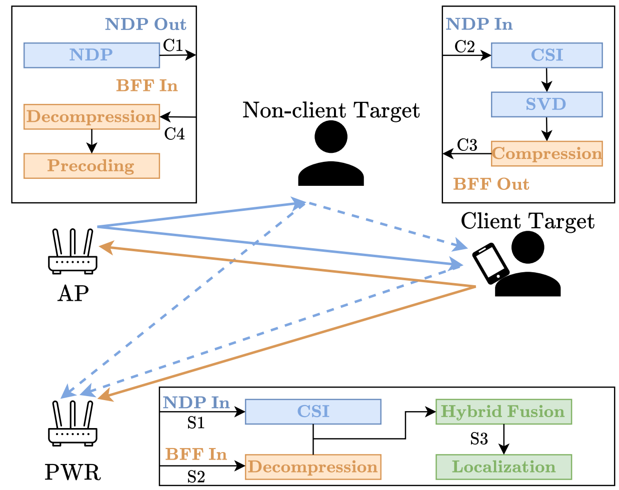


Fig. 1: Illustration of the scenario. The hybrid configuration comprises an AP, a PWR, multiple client and non-client targets. In the illustration, solid lines represent the incident waveforms, while dashed lines denote the reflected waveforms. Blue lines represent the NDP, and orange lines depict the BFF.

From a sensing perspective, the PWR aims to localize the clients and other potential targets within its coverage area. To achieve this, the PWR operates as follows:

S1) It evaluates its CSI from the NDP transmitted isotropically by the AP.

S2) It sniffes the BFFs transmitted by the client UE and uncompresses their content.

S3) It combines the estimated CSI with the information contained in the BFFs to enhance the localization of the targets.

III. System Model

In this section, we provide the system model for the configuration depicted in Fig. 1. On one hand, the AP initiates a channel sounding session to conduct a downlink MU-MIMO transmission to the client UEs. As described in Section II, the AP isotropically transmits an NDP to obtain feedback from the client UEs, from which the beamforming steering matrix can be evaluated. If the AP has N_A antennas, then the NDP comprises N_A known HE-LTF OFDM symbols on Q subcarriers with a subcarrier spacing of Δ_f.

On the other hand, the PWR intends to exploit this NDP to localize C clients and $K-C$ non-client targets within its coverage area. The positions of these K targets are defined by the vectors $\mathbf{x} = [x_1 \ \dots \ x_K]^{\mathrm{T}}$ and $\mathbf{y} = [y_1 \ \dots \ y_K]^{\mathrm{T}}$, where indices $k = 1 \dots C$ correspond to the positions of the client UEs. The AP, the PWR and the client UEs are all equipped with uniform linear arrays of respectively N_A, N_P and N_u antennas, where $u = 1 \dots C$. For simplicity, we assume that the arrays of the AP and the PWR are oriented towards the coverage area and have half-wavelength spacing. To express the channel model, we assume that only multipath signals featuring a single reflection on a target significantly impact the observed channel model. In this single-bounce model, signals with multiple reflections are thus omitted [8].

In the remainder of this section, we describe the radar channel model between the AP and the PWR, as well as the communication channel model between the AP and the client UEs.

A. Passive Radar Channel Model

To describe the radar channel between the AP and the PWR, we assume that the direct LoS signal, along with clutter contributions, are effectively suppressed from the estimated channel. This can be obtained by exploiting previously transmitted known preamble symbols. The resulting radar channel is thus defined by the K multipath components resulting from reflections on the client and non-client targets. The AoD and the AoA corresponding to the k^{th} target are denoted by φ_k and ϑ_k, respectively. All angles are defined between the wavefront and the normal vector of their corresponding antenna array. The corresponding complex steering vectors are thus given by $\mathbf{a}(\varphi_k) = [1 \; e^{j\pi \sin(\varphi_k)} \dots \; e^{j\pi(N_A-1)\sin(\varphi_k)}]^{\text{T}}, \in \mathbb{C}^{N_A \times 1}$ and $\mathbf{a}(\vartheta_k) = [1 \; e^{j\pi \sin(\vartheta_k)} \dots \; e^{j\pi(N_P-1)\sin(\vartheta_k)}]^{\text{T}}, \in \mathbb{C}^{N_P \times 1}$. The set of all AoDs and AoAs are denoted by $\mathbf{\Phi}$ and $\mathbf{\Theta}$, respectively. Throughout this paper, for the sake of notation simplicity, we do not explicitly denote the dependence of the angle on $(\mathbf{x}, \mathbf{y})$. The baseband equivalent channel matrix for the radar channel is defined for each subcarrier q as follows

$$\mathbf{H}_q^r = \mathbf{A}(\mathbf{\Theta}) \; \mathbf{B}_q^r \; \mathbf{A}^{\text{H}}(\mathbf{\Phi}), \; \in \mathbb{C}^{N_P \times N_A}, \tag{1}$$

where $\mathbf{A}(\mathbf{\Phi}) = [\mathbf{a}(\varphi_1) \; \dots \; \mathbf{a}(\varphi_K)] \in \mathbb{C}^{N_A \times K}$ is the AoD steering matrix, $\mathbf{A}(\mathbf{\Theta}) = [\; \mathbf{a}(\vartheta_1) \; \dots \; \mathbf{a}(\vartheta_K)] \in \mathbb{C}^{N_P \times K}$ is the AoA steering matrix, and $\mathbf{B}_q^r \in \mathbb{C}^{K \times K}$ is the radar channel coefficient diagonal matrix. The diagonal entries of the matrix are defined by the channel vector $\boldsymbol{\beta}_q^r = [\beta_{q,1}^r \; \dots \; \beta_{q,K}^r]^{\text{T}}, \in \mathbb{C}^{K \times 1}$. The received signal model at the PWR is thus given by

$$\mathbf{Z}_q^r = \mathbf{H}_q^r \mathbf{S}_q + \mathbf{N}_q^r, \tag{2}$$

where $\mathbf{N}_q^r \in \mathbb{C}^{N_P \times N_A}$ denotes the radar Additive White Gaussian Noise (AWGN) matrix, and $\mathbf{S}_q \in \mathbb{C}^{N_A \times N_A}$ is the transmitted signal per subcarrier. The columns of $\mathbf{S}_q$ represent the different HE-LTF OFDM symbols, and the rows represent the different AP antennas. Both the client UE and the PWR know the structure of the transmitted $\mathbf{S}_q$ matrix from the information contained in the preamble of the NDP, as it is well defined in the 802.11ax amendment [3].

B. Communication Channel Model

The communication channel between the AP and the u^{th} client UE consists of the LoS link and $K_u{-}1$ multipath components resulting from reflections on other targets and the clutter. In this scenario, the clutter contributions cannot be effectively removed from the communication channel, as the client UE does not perform any suppression before computing its BFF. However, it is assumed that the LoS link is the strongest. The LoS AoD is denoted by φ_u and the set $\mathbf{\Phi}_u$ comprises all multipath AoDs including the reflection on both the other $K-1$ targets and the clutter. The baseband equivalent channel matrix for the communication channel of the u^{th} client UE is defined for each subcarrier q as follows

$$\mathbf{H}_{u,q}^c = \boldsymbol{\beta}_{u,q}^c \mathbf{a}^{\text{H}}(\varphi_u) + \mathbf{B}_{u,q}^c \; \mathbf{A}^{\text{H}}(\mathbf{\Phi}_u), \in \mathbb{C}^{N_u \times N_A}, \tag{3}$$

where $\boldsymbol{\beta}_{u,q}^c \in \mathbb{C}^{N_u \times 1}$ and $\mathbf{B}_{u,q}^c \in \mathbb{C}^{N_u \times (K_u - 1)}$ represent the LoS and multipath communication channel coefficients, respectively. Each column represents a different path, while the rows represent the different antennas of the UE. These coefficients encompass the linearly increasing phases across subcarriers and across receiving antennas, attributed to the range and AoA of the paths, respectively, as well as the attenuation defined by the radar range equation. The received signal model at the client UE is given by

$$\mathbf{Z}_{u,q}^c = \mathbf{H}_{u,q}^c \mathbf{S}_q + \mathbf{N}_{u,q}^c, \tag{4}$$

where $\mathbf{N}_{u,q}^c \in \mathbb{C}^{N_u \times N_A}$ denotes the AWGN matrix.

IV. Hybrid Radar Processing

We formulate the ML combination rule at the PWR for determining the positions of the K targets based on the sniffed BFFs and the processing of the NDP. In multitarget localization scenarios, we seek the set of (x, y) positions of the K targets that maximizes the sum of the log-likelihood function of each independent source of information. Therefore, the brute-force maximization implies solving a $2K$-dimensional problem. In our previous work [7], we demonstrated that in a multistatic scenario comprising multiple AP/PWR radar pairs, the $2K$-dimensional log-likelihood functions can be approximately decoupled into K per-target two-dimensional functions. This method relies on a pre-estimate of the target angles $(\widehat{\mathbf{\Phi}}, \widehat{\mathbf{\Theta}})$ at each radar pair using the MUSIC algorithm. Furthermore, this so-called alternating summation method relies only on the sample covariance matrices.

In this section, we develop the ML estimator based on the received signals for the radar channel in (2) and the communication channels in (4) to show how the alternating summation method presented in [7] for a multistatic scenario can be adapted to the hybrid fusion considered in this paper.

A. Maximum Likelihood Fusion

As described in Section III, the PWR and the client UEs exploit the HE-LTF symbols transmitted isotropically by the AP to evaluate the radar and communication channel matrices, respectively. The CSI matrices estimated by the PWR and the client UEs are thus obtained by multiplying the received signals in (2) and (4) by $\mathbf{S}_q^{\text{H}}$ since $\mathbf{S}_q \mathbf{S}_q^{\text{H}} = N_A \mathbf{I}$.

To localize the K targets in the scene, the PWR exploits a hybrid source of information: the joint AoD/AoA extracted from the NDP and the LoS AoD from the BFFs. This is highlighted in the ML formulation by expressing the estimated CSI matrices as

$$\widetilde{\mathbf{h}}_q^r = \mathbf{A}'(\mathbf{\Phi}, \mathbf{\Theta})\ \boldsymbol{\beta}_q^r + \mathbf{n}_q^{r\prime}, \tag{5}$$

$$\widetilde{\mathbf{H}}_{u,q}^c = \boldsymbol{\beta}_{u,q}^c \mathbf{a}^{\mathrm{H}}(\varphi_u) + \mathbf{N}_{u,q}^{c\prime}, \tag{6}$$

where $\widetilde{\mathbf{h}}_q^r \in \mathbb{C}^{N_A N_P \times 1}$ is the vector obtained by vectorizing the radar CSI matrix, $\mathbf{n}_q^{r\prime}$ and $\mathbf{N}_{u,q}^{c\prime}$ are the noise vector and matrix of variances σ_r^2 and σ_u^2 resulting from the symbol equalization, and $\mathbf{A}'(\mathbf{\Phi}, \mathbf{\Theta}) = [\mathbf{a}'(\varphi_1, \vartheta_1)\ \ldots\ \mathbf{a}'(\varphi_K, \vartheta_K)] \in \mathbb{C}^{N_A N_P \times K}$ represents the joint AoD/AoA matrix in which $\mathbf{a}'(\varphi_k, \vartheta_k) = \mathbf{a}(\varphi_k) \otimes \mathbf{a}(\vartheta_k), \mathbb{C}^{N_A N_P \times 1}$. Observe that in (6), the multipath term $\mathbf{B}_{u,q}^c\ \mathbf{A}^{\mathrm{H}}(\mathbf{\Phi}_u)$ is omitted from the model of the observations as only the LoS AoD will be retrieved from the BFFs. This model mismatch has thus an impact on the ML estimator but can not be avoided in this scenario.

The parameters to be estimated are defined by the vector $\boldsymbol{\gamma} = [\mathbf{x}^{\mathrm{T}} \mathbf{y}^{\mathrm{T}} \{\boldsymbol{\beta}_q^r\}_{q=1\ldots Q} \{\boldsymbol{\beta}_{u,q}^c\}_{q=1\ldots Q}^{u=1\ldots C}]^{\mathrm{T}}$. It is assumed that the number of targets to be localized is known, as methods for estimating K are available in the literature [9]. Notice that our study solely focuses on angle-based ML localization and does not utilize range information. Therefore, each channel coefficient vector $\boldsymbol{\beta}_q^r, \boldsymbol{\beta}_{u,q}^c$ is independently estimated, as the linear phase increase across subcarriers, defined by the range of each target, is not exploited. Considering independent noise contributions for the estimated CSIs, the combined likelihood function is derived as the product of individual Gaussian density functions. After taking the natural logarithm of the combined likelihood function, the following expression must be maximized

$$\widehat{\boldsymbol{\gamma}} = \arg\max_{\boldsymbol{\gamma}} \mathcal{L}(\boldsymbol{\gamma}) = \arg\max_{\boldsymbol{\gamma}} \mathcal{L}^r(\boldsymbol{\gamma}) + \sum_{u=1}^{C} \mathcal{L}_u^c(\boldsymbol{\gamma}), \tag{7}$$

where the log-likelihood from the PWR and the clients CSIs are respectively given by

$$\mathcal{L}^r(\boldsymbol{\gamma}) = \frac{-1}{2\sigma_r^2} \sum_{q=1}^{Q} \|\widetilde{\mathbf{h}}_q^r - \mathbf{A}'(\mathbf{\Phi}, \mathbf{\Theta})\ \boldsymbol{\beta}_q^r\|^2, \tag{8}$$

$$\mathcal{L}_u^c(\boldsymbol{\gamma}) = \frac{-1}{2\sigma_u^2} \sum_{q=1}^{Q} \|\widetilde{\mathbf{H}}_{u,q}^c - \boldsymbol{\beta}_{u,q}^c \mathbf{a}^{\mathrm{H}}(\varphi_u)\|_{\mathrm{F}}^2, \tag{9}$$

First, we maximize with respect to the channel coefficients $\boldsymbol{\beta}_q^r$ and $\boldsymbol{\beta}_{u,q}^c$ to obtain closed-form expressions as function of the angles. Following the solution of the resulting linear least squares problem, the ML estimate of the channel coefficients for every subcarrier q is expressed as $\widehat{\boldsymbol{\beta}}_q^r(\mathbf{\Phi}, \mathbf{\Theta}) = (\mathbf{A}'(\mathbf{\Phi}, \mathbf{\Theta}))^+\ \widetilde{\mathbf{h}}_q^r$ and $\widehat{\boldsymbol{\beta}}_{u,q}^c(\varphi_u) = \widetilde{\mathbf{H}}_{u,q}^c\,(\mathbf{a}^+(\varphi_u))^{\mathrm{H}}$.

Substituting these estimates back into (8) and (9), and after performing some mathematical manipulations, the two log-likelihood functions can be reformulated as

$$\mathcal{L}^r(\boldsymbol{\gamma}) = \frac{Q}{2\sigma_r^2} \operatorname{Tr}\left\{\mathbf{A}'(\mathbf{\Phi}, \mathbf{\Theta})\,(\mathbf{A}'(\mathbf{\Phi}, \mathbf{\Theta}))^+\ \widetilde{\mathbf{R}}^r\right\}, \tag{10}$$

$$\mathcal{L}_u^c(\boldsymbol{\gamma}) = \frac{Q N_u}{2\sigma_u^2} \operatorname{Tr}\left\{\mathbf{a}(\varphi_u)\mathbf{a}^+(\varphi_u)\ \widetilde{\mathbf{R}}_u^c\right\}, \tag{11}$$

in which the sample covariance matrices of the channel averaged over the subcarriers are given by

$$\widetilde{\mathbf{R}}^r = \frac{1}{Q} \sum_{q=1}^{Q} \widetilde{\mathbf{h}}_q^r\ (\widetilde{\mathbf{h}}_q^r)^{\mathrm{H}}. \tag{12}$$

$$\widetilde{\mathbf{R}}_u^c = \frac{1}{Q N_u} \sum_{q=1}^{Q} (\widetilde{\mathbf{H}}_{u,q}^c)^{\mathrm{H}}\ \widetilde{\mathbf{H}}_{u,q}^c, \tag{13}$$

B. Channel State Information and Beamforming Feedback

As described in Section II, the PWR does not have access to the full CSI from the client UEs, but only to the BFFs. Each client UE constructs this feedback by evaluating the SVD of the estimated CSI matrix, yielding:

$$\widetilde{\mathbf{H}}_{u,q}^c = \widetilde{\mathbf{U}}_{u,q}^c \widetilde{\mathbf{\Sigma}}_{u,q}^c (\widetilde{\mathbf{V}}_{u,q}^c)^{\mathrm{H}}, \tag{14}$$

where $\widetilde{\mathbf{U}}_{u,q}^c$ and $\widetilde{\mathbf{V}}_{u,q}^c$ represent the left and right unitary singular matrices, respectively, and $\widetilde{\mathbf{\Sigma}}_{u,q}^c$ is the singular values diagonal matrix. As defined in the 802.11ax standard [3], the MU-MIMO BFF contains the compressed right singular vectors $\widetilde{\mathbf{V}}_{u,q}^c$ for each subcarrier, the subcarrier-averaged stream gain and for each stream and subcarrier the delta signal-to-noise (SNR) with respect to this subcarrier-averaged stream gain. This gives access to a quantized version of the singular value matrix $\widetilde{\mathbf{\Sigma}}_{u,q}^c$. Details on the compression can be found in [3]. Assuming the LoS link between the AP and the client UE to be much stronger than the multipath components, it can be shown that the sample covariance matrix in (13) can be approximated from the BFF as follows:

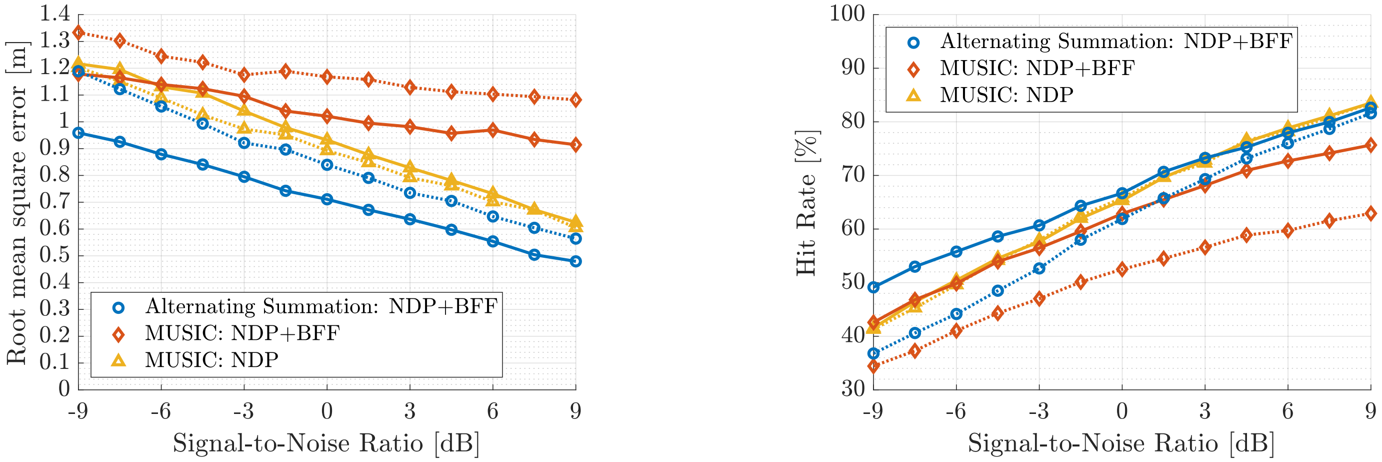
$$\widetilde{\mathbf{R}}_u^c \approx \frac{1}{Q N_u} \sum_{q=1}^{Q} \widetilde{\mathbf{V}}_{u,q}^{c,1} \widetilde{\mathbf{\Sigma}}_{u,q}^{c,1} (\widetilde{\mathbf{V}}_{u,q}^{c,1})^{\mathrm{H}}. \tag{15}$$

where $\widetilde{\mathbf{V}}_{u,q}^{c,1}$ and $\widetilde{\mathbf{\Sigma}}_{u,q}^{c,1}$ are obtained by keeping only the strongest stream of the SVD. The alternating summation method with an association step is thus evaluated at the PWR from the sample covariance matrices defined in (12) and (15).

V. Simulation Results

This section evaluates the enhancement brought by the exploitation of the BFFs at the PWR on the accuracy of the radar in localizing targets within its coverage area. The joint NDP and BFF processing outlined in Section IV is compared through $30,000$ simulations with a MUSIC algorithm based on the NDP only. It is also compared to a sum of the MUSIC pseudo-spectrums obtained from the NDP and the BFFs. The following performance metrics are studied:

1) **Hit Rate:** A hit is acknowledged when a peak is detected within a vicinity of 2 meters from the true target position; otherwise, it is considered a miss.
2) **RMSE:** The root mean square error (RMSE) is computed between the true target position and the corresponding detected position. To ensure a fair comparison between the methods, only the targets resulting in a hit by all methods are considered in the evaluation of the RMSE.



(a) RMSE

(b) Hit Rate

Fig. 2: The impact of the signal-to-noise ratio on the performance metrics of the various methods is depicted. The solid and dashed lines correspond to the localization performance for the client and non-client targets, respectively.

For each simulation, we analyze a fixed AP and PWR setup designated to locate two client targets and a non-client target randomly positioned. The number of antennas are $N_A = N_u = N_P = 4$ and the number of subcarriers is $Q = 512$. Fig. 2 depicts the results obtained for the hit rate and the RMSE for the client and non client targets as functions of the SNR. The SNR is defined here as the mean of the quotient of the radar channel coefficients of each path by the noise variance. Note that the same noise variance is considered at the clients and the PWR. It is observed that for both the client and the non-client target, the hybrid fusion of the NDP and the BFF based on the alternating summation method enhances the achievable RMSE compared to the exploitation of the NDP only. However, the hybrid fusion rule must be well defined, as a simple combination of MUSIC pseudo-spectrums deteriorates the RMSE. Furthermore, it can be observed that only the alternating projection method achieves an improved RMSE for the client target compared to the non-client one. This results from the improved ability of the alternating summation method to account for the varying localization ability of the NDP and the BFF. Regarding the hit rate, the alternating summation presents similar performance at high SNRs as the NDP-based MUSIC. At low SNRs, we observe that it improves the hit rate for the client targets. However, it can decrease the hit rate of the non-client target since the association step is not always well performed at low SNRs. Globally, these results confirm the benefit of the hybrid combination when the fusion rule ùis appropriately chosen.

VI. Conclusion

In this paper, we investigate the multitarget localization capabilities of a PWR during the MU-MIMO channel sounding session initiated by an AP. Both the joint AoD/AoA extracted from the NDP transmitted by the AP and the LoS AoD extracted from the BFFs transmitted by the client UEs are explored for their potential utility by the PWR. The proposed hybrid radar fusion method is derived from the maximum likelihood framework. It is shown to solely rely on the computation, for all source of information, of the approximated sample covariance matrices of the channel state information. Numerical simulations presented in this study validate the effectiveness of the proposed approach. The results highlight the benefits of exploiting BFF in a hybrid fusion for target localization compared to classical PWR processing based solely on NDPs. In future works, the exploitation of range information from the NDP would further enhance localization accuracy.

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