Target Tracking with Integrated Sensing and Communications in IEEE 802.11bf

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***Abstract*—The IEEE 802.11bf amendment is aimed to provide Wi-Fi networks with essential support for their potential sensing capability, in addition to their renowned communications paradigm. Taking advantage of both sensing and communications, integrated sensing and communications (ISAC) is a promising direction for Wi-Fi that has been less investigated in the existing literature. Therefore, in this paper, we propose a novel method for target tracking with ISAC in IEEE 802.11bf. Particularly, the Kalman filter is adopted for tracking the state of the target and the Cramér-Rao lower bound (CRLB) is employed to develop a proper performance metric for trilateration, where the access point (AP) needs a selection of three stations (STAs). By solving a discrete convex optimization problem, the AP decides between sensing and communications within each TXOP and selects the three STAs for trilateration if sensing is conducted. Simulation results confirm that the proposed method strikes a good balance between the sensing and communications performance. Moreover, the sensing performance of the proposed method improves as the number of STAs increases.**

***Index Terms*—IEEE 802.11bf, integrated sensing and communications (ISAC), target tracking, Kalman filter, Cramér-Rao lower bound (CRLB)**

I. Introduction

Renowned for its communications paradigm, Wi-Fi has been a prevalent wireless local area network (WLAN) technology widely deployed around the globe. It is envisioned that the global economic value of Wi-Fi would reach around 5 trillion USD by 2025 [1]. In addition to conventional communications tasks, Wi-Fi demonstrates its great potential for sensing applications, which render Wi-Fi more versatile [2].

To fully unleash the potential of Wi-Fi for sensing, the IEEE 802.11bf amendment is proposed to provide essential PHY and MAC support for Wi-Fi sensing purpose [3]. In the IEEE 802.11bf amendment, an access point (AP) or a station (STA) serves as a sensing initiator (SI) or a sensing responder (SR), where the SI initiates a sensing procedure involving the SR in the goal of sensing the environment with Wi-Fi waveforms and channels. Even before the release of the IEEE 802.11bf amendment, there has been abundant prior research on how Wi-Fi sensing can be used in real-world applications, such as respiration sensing [4] and human identity recognition [5].

With the communications paradigm and sensing capability, integrated sensing and communications (ISAC) is a promising but less explored topic in the context of Wi-Fi. While the ISAC functionality of a Wi-Fi network can be fully supported by the IEEE 802.11bf amendment [6], the few previous works on ISAC of Wi-Fi focus only on early Wi-Fi amendments (e.g., IEEE 802.11ad/ay/ac) without consistent sensing specifications. With ISAC in IEEE 802.11ad, [7] investigates the self-interference cancellation for short-range and long-range sensing. The authors of [8] develop a joint beamforming training and energy allocation algorithm with ISAC in IEEE 802.11ay. In [9], the authors explore the unified channel state information (CSI) extraction with ISAC in IEEE 802.11ac. Despite their proposed Wi-Fi ISAC schemes, the previous works suffer from a lack of consistent sensing procedure, which makes a generalization challenging.

In this paper, we propose a novel method for target tracking with ISAC in IEEE 802.11bf, keeping track of the state of a moving target. Through the proposed method, the AP adopts the Kalman filter [10] for target tracking with trilateration, which requires a selection of three STAs, and leverages a trilateration performance metric based on the Cramér-Rao lower bound (CRLB) [11]. By solving a discrete convex optimization problem, the proposed method guides the AP on how to decide between sensing and communications within each transmit opportunity (TXOP) and how to select the three STAs for trilateration if sensing is conducted.

The remainder of this paper is organized as follows. We present the system model and problem formulation in Sec. II. In Sec. III, we introduce the proposed method in detail. Simulation results and discussions are covered in Sec. IV. Finally, Sec. V concludes the paper.

Notations: Boldfaced capital and lowercase letters denote matrices and column vectors, respectively. Given a vector $\mathbf{a}$, we use diag$(\mathbf{a})$ to denote the diagonal matrix containing $\mathbf{a}$ on its diagonal. Given a matrix $\mathbf{A}$, we denote Tr$\{\mathbf{A}\}$, $\mathbf{A}^T$, and $\mathbf{A}^{-1}$ its trace, transpose, and inverse, respectively. For any matrices $\mathbf{A}$ and $\mathbf{B}$, we use $\mathbf{A} \otimes \mathbf{B}$ to denote their Kronecker product. We define $\mathbf{I}_p$ to be the $p \times p$ identity matrix. We use $\mathbf{S}^p_{++}$ to denote the set of symmetric positive definite $p \times p$ matrices. For any set $\mathcal{A}$, we use $[\mathcal{A}]^p$ to denote its p-subsets. We denote the multivariate normal distribution with mean vector μ and covariance matrix $\mathbf{\Phi}$ as $\mathcal{N}(\mu, \mathbf{\Phi})$.

II. System Model and Problem Formulation

In this section, we describe the system model and problem formulation of target tracking with ISAC in IEEE 802.11bf.

Consider an ISAC-enabled IEEE 802.11bf Wi-Fi network composed of an AP, M STAs, and a moving target (to be tracked) on a 2D area with uplink (UL) sensing and downlink (DL) communications, as illustrated in Fig. 1. Denote the set of STA indices as $\mathcal{M} = \{1, 2, ..., M\}$. Through the ISAC functionality supported by IEEE 802.11bf, the AP is allowed to conduct either sensing or communications within an obtained TXOP.

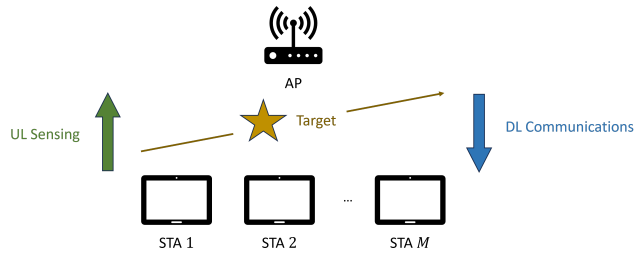

Fig. 1. An illustration of ISAC-enabled IEEE 802.11bf Wi-Fi network

At some time t, the AP obtains a new TXOP and needs to decide whether to conduct sensing or communications. Suppose by time t, the AP has conducted sensing within N_s previous TXOPs and communications within N_c previous TXOPs. Creating a measurement of the target within each sensing TXOP, the AP has N_s measurements at time t. With N_s measurements, the AP needs to generate a predicted state of the target. Define a binary variable u_c of value 0 when the AP conducts sensing and of value 1 when the AP conducts communications. Accordingly, the AP needs to determine the value of $u_c \in \{0, 1\}$.

If the AP decides to conduct sensing ($u_c = 0$), then it will experience the $(N_s + 1)$th sensing TXOP. Within this $(N_s + 1)$th sensing TXOP, the AP executes UL sensing to create a measurement for tracking the corresponding state of the target, expressed as

$$\mathbf{x}[N_s+1] = [x[N_s+1]\, \dot{x}[N_s+1]\, y[N_s+1]\, \dot{y}[N_s+1]]^T, \quad (1)$$

where $(x[N_s+1], y[N_s+1])$ and $(\dot{x}[N_s+1], \dot{y}[N_s+1])$ are the corresponding position and velocity of the target, respectively. Denote the time at which the N_sth sensing TXOP occurs as t'. Then, the time duration between the N_sth and $(N_s + 1)$th sensing TXOPs is $T' = t - t'$. Following the nearly constant velocity (CV) model [12], the state transition of the target between the N_sth and $(N_s + 1)$th sensing TXOPs can be written as

$$\mathbf{x}[N_s + 1] = \mathbf{F}\mathbf{x}[N_s] + \mathbf{v}[N_s + 1], \quad (2)$$

where $\mathbf{F} = \mathbf{I}_2 \otimes \begin{bmatrix} 1 & T' \\ 0 & 1 \end{bmatrix}$ and $\mathbf{v}[N_s + 1] \sim \mathcal{N}(\mathbf{0}, \mathbf{Q}_v)$ is the process noise with $\mathbf{Q}_v = v_s \mathbf{I}_2 \otimes \begin{bmatrix} T'^3/3 & T'^2 \\ T'^2 & T' \end{bmatrix}$, where v_s is the process noise intensity. Particularly, the AP creates a measurement in terms of target position with trilateration, which requires the AP interact with three STAs (as the interaction between the AP and a single STA leads to a range estimate and trilateration requires three range estimates). For the mth STA, denote its position as $(\bar{x}_m, \bar{y}_m)$ and the signal-to-noise ratio (SNR) of its link connected to the AP as ξ_m. Depending on STA position $\{(\bar{x}_m, \bar{y}_m)\}_{m\in\mathcal{M}}$ and link SNR $\{\xi_m\}_{m\in\mathcal{M}}$, the AP needs to select three STAs of indices $\mathcal{I} = \{i_1, i_2, i_3\} \in [\mathcal{M}]^3$ for trilateration in UL sensing. In IEEE 802.11bf, the AP serves as the SI to initiate UL sensing involving the three STAs of indices $\mathcal{I}$ as SRs. The UL sensing includes two phases, polling and trigger frame (TF) sounding, as illustrated in Fig. 2. In the polling phase, the AP sends a Sensing Polling TF to the three STAs of indices $\mathcal{I}$, which respond with clear to send (CTS)-to-self frames. In the TF sounding phase, the AP sends an SR2SI Sounding TF to the three STAs of indices $\mathcal{I}$, which respond with SR2SI null data packets (NDPs). With received SR2SI NDPs from the three STAs of indices $\mathcal{I}$, the AP obtains three range estimates and creates a measurement in terms of target position, written as

$$\mathbf{z}[N_s + 1] = \mathbf{H}\mathbf{x}[N_s + 1] + \mathbf{w}_{\mathcal{I}}[N_s + 1], \quad (3)$$

where $\mathbf{H} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$ and $\mathbf{w}_{\mathcal{I}}[N_s + 1] \sim \mathcal{N}(\mathbf{0}, \mathbf{Q}_{w_{\mathcal{I}}})$ is the measurement noise with $\mathbf{Q}_{w_{\mathcal{I}}} = \mathrm{diag}([\sigma_{\mathcal{I}}^2\, \sigma_{\mathcal{I}}^2]^T)$, where $\sigma_{\mathcal{I}}^2$ is the noise variance dependent on $\mathcal{I}$. For UL sensing, the required time is a constant which can be expressed as

$$\tau_s = 3\tau_{SIFS} + 2\tau_{TF} + \tau_{CTS} + \tau_{SR2SI}, \quad (4)$$

where τ_{SIFS}, τ_{TF}, τ_{CTS}, and τ_{SR2SI} are the time duration for short interframe space (SIFS), TF transmission, CTS-to-self frame transmission, and SR2SI NDP transmission, respectively.

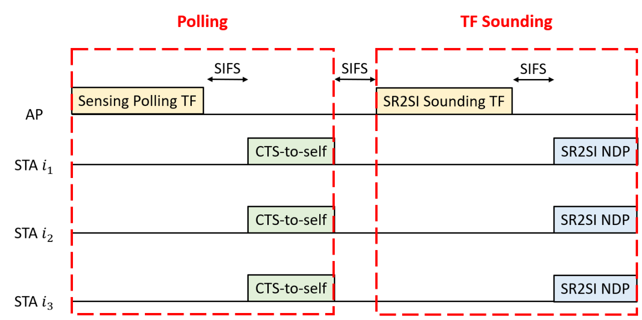

Fig. 2. An illustration of UL sensing with AP and three STAs of indices $\mathcal{I}$

If the AP decides to conduct communications ($u_c = 1$), then it will experience the $(N_c + 1)$th communications TXOP. Within this (N_c+1)th communications TXOP, the AP executes DL communications and delivers DL data of amount B_m to the mth STA, $m \in \mathcal{M}$. Denote the required time for DL communications in the n_cth communications TXOP as $\tau_c[n_c]$, $n_c = 1, 2, ..., N_c, N_c + 1$.

Consequently, we formulate the following problem of target tracking with ISAC in IEEE 802.11bf: For a new TXOP at time t, given N_s measurements $\{\mathbf{z}[n_s]\}_{n_s=1}^{N_s}$, STA position $\{(\bar{x}_m, \bar{y}_m)\}_{m\in\mathcal{M}}$, link SNR $\{\xi_m\}_{m\in\mathcal{M}}$, and required time $\tau_s, \{\tau_c[n_c]\}_{n_c=1}^{N_c+1}$, generate a predicted state $\hat{\mathbf{x}}$ of the target and determine the value of $u_c \in \{0, 1\}$ along with STA indices $\mathcal{I} \in [\mathcal{M}]^3$ for trilateration in UL sensing (when $u_c = 0$).

III. Proposed Method

In this section, we propose a novel method for the problem of target tracking with ISAC in IEEE 802.11bf formulated in

Sec. II. Specifically, we present a comprehensive overview of the proposed method in the following subsections.

A. Target Tracking and Trilateration Performance Metric

For the AP, it needs to track the state of the target with trilateration in UL sensing, and its trilateration performance can be quantified with a proper performance metric.

With regard to target tracking, we adopt the Kalman filter [10], which consists of two steps: prediction and update. Essentially, the AP generates a predicted state with prediction mean squared error (MSE) matrix in the prediction step within each TXOP and an updated state with update MSE matrix in the update step within each sensing TXOP. Denote the updated state and update MSE matrix within the N_sth sensing TXOP as $\tilde{\mathbf{x}}'$ and $\tilde{\mathbf{\Delta}}'$ (dependent on N_s measurements $\{\mathbf{z}[n_s]\}_{n_s=1}^{N_s}$), respectively. At time t, the predicted state of the target can be computed in the prediction step as

$$\hat{\mathbf{x}} = \mathbf{F}\tilde{\mathbf{x}}' = [\hat{x}\ \hat{\dot{x}}\ \hat{y}\ \hat{\dot{y}}]^T, \tag{5}$$

where $(\hat{x}, \hat{y})$ and $(\hat{\dot{x}}, \hat{\dot{y}})$ are the predicted position and velocity of the target, respectively, with prediction MSE matrix $\hat{\mathbf{\Delta}} = \mathbf{F}\tilde{\mathbf{\Delta}}'\mathbf{F}^T + \mathbf{Q}_v$. If the AP decides to conduct sensing ($u_c = 0$), then it will experience the (N_s+1)th sensing TXOP and creates a measurement $\mathbf{z}[N_s+1]$. Then, the updated state of the target can be computed in the update step as

$$\tilde{\mathbf{x}} = \hat{\mathbf{x}} + \mathbf{K}(\mathbf{z}[N_s+1] - \mathbf{H}\hat{\mathbf{x}}) \tag{6}$$

with update MSE matrix $\tilde{\mathbf{\Delta}} = (\mathbf{I}_4 - \mathbf{K}\mathbf{H})\hat{\mathbf{\Delta}}$, where $\mathbf{K} = \hat{\mathbf{\Delta}}\mathbf{H}^T(\mathbf{Q}_{w_\mathcal{I}} + \mathbf{H}\hat{\mathbf{\Delta}}\mathbf{H}^T)^{-1}$ is the Kalman gain matrix. Hence, the AP generates a predicted state $\hat{\mathbf{x}}$ with (5) at time t and an updated state $\tilde{\mathbf{x}}$ with (6) if sensing is conducted ($u_c = 0$).

To quantify the trilateration performance of the AP, we choose a proper performance metric based on the CRLB [11], which is the minimum variance of any unbiased estimate. Following the CRLB analysis in [13], the CRLB of range estimate and trilateration estimate in the context of UL sensing (as illustrated in Fig. 2) can be derived. To begin with, the CRLB of range estimate between the AP and the mth STA can be obtained as

$$l_{r,m} = \frac{3c^2}{8\pi^2\eta W^2\xi_m}, \tag{7}$$

where c is the speed of light, η is the number of high efficiency-long training field (HE-LTF) repetitions in an SR2SI NDP, and W is the signaling bandwidth. With STA indices $\mathcal{I} = \{i_1, i_2, i_3\} \in [\mathcal{M}]^3$ selected by the AP and corresponding STA position $\{(\bar{x}_m, \bar{y}_m)\}_{m\in\mathcal{I}}$, the CRLB of trilateration estimate between the AP and the three STAs of indices $\mathcal{I}$ can be obtained by extending (7) as

$$l_{tri,\mathcal{I}} = \mathrm{Tr}\{(\mathbf{\Gamma}_\mathcal{I}\mathbf{D}_\mathcal{I}\mathbf{\Gamma}_\mathcal{I}^T)^{-1}\}, \tag{8}$$

where $\mathbf{D}_\mathcal{I} = \mathrm{diag}([l_{r,i_1}^{-1}\ l_{r,i_2}^{-1}\ l_{r,i_3}^{-1}]^T)$ and $\mathbf{\Gamma}_\mathcal{I} = \begin{bmatrix} \frac{x-\bar{x}_{i_1}}{d_{i_1}} & \frac{x-\bar{x}_{i_2}}{d_{i_2}} & \frac{x-\bar{x}_{i_3}}{d_{i_3}} \\ \frac{y-\bar{y}_{i_1}}{d_{i_1}} & \frac{y-\bar{y}_{i_2}}{d_{i_2}} & \frac{y-\bar{y}_{i_3}}{d_{i_3}} \end{bmatrix}$ with (x, y) being the target position and $d_{i_j} = \sqrt{(x-\bar{x}_{i_j})^2 + (y-\bar{y}_{i_j})^2}$ being the distance between the target and the i_jth STA, $j = 1, 2, 3$. At time t, since the target position (x, y) is unknown, we replace the target position (x, y) with the predicted target position $(\hat{x}, \hat{y})$ in (5) and obtain the predicted CRLB of trilateration estimate as

$$\hat{l}_{tri,\mathcal{I}} = \mathrm{Tr}\{(\hat{\mathbf{\Gamma}}_\mathcal{I}\mathbf{D}_\mathcal{I}\hat{\mathbf{\Gamma}}_\mathcal{I}^T)^{-1}\}, \tag{9}$$

where $\hat{\mathbf{\Gamma}}_\mathcal{I} = \begin{bmatrix} \frac{\hat{x}-\bar{x}_{i_1}}{\hat{d}_{i_1}} & \frac{\hat{x}-\bar{x}_{i_2}}{\hat{d}_{i_2}} & \frac{\hat{x}-\bar{x}_{i_3}}{\hat{d}_{i_3}} \\ \frac{\hat{y}-\bar{y}_{i_1}}{\hat{d}_{i_1}} & \frac{\hat{y}-\bar{y}_{i_2}}{\hat{d}_{i_2}} & \frac{\hat{y}-\bar{y}_{i_3}}{\hat{d}_{i_3}} \end{bmatrix}$ with $\hat{d}_{i_j} = \sqrt{(\hat{x}-\bar{x}_{i_j})^2 + (\hat{y}-\bar{y}_{i_j})^2}$ being the distance between the predicted target position and the i_jth STA, $j = 1, 2, 3$. Therefore, with selected STA indices $\mathcal{I}$, we choose the predicted CRLB of trilateration estimate $\hat{l}_{tri,\mathcal{I}}$ in (9) to quantify the trilateration performance of the AP.

B. ISAC and STA Selection for Trilateration in UL Sensing

When the AP obtains a new TXOP at time t, it needs to decide whether to conduct sensing or communications, i.e., determine the value of $u_c \in \{0, 1\}$. If the AP decides to conduct sensing ($u_c = 0$), then it needs to select three STAs of indices $\mathcal{I} \in [\mathcal{M}]^3$ for trilateration in UL sensing.

For a decision between sensing and communications with the ISAC functionality, we consider the total sensing duration and total communications duration. Recall that the AP has experienced N_s sensing TXOPs and N_c communications TXOPs by time t. Over all TXOPs up to the current one given $u_c \in \{0, 1\}$, the total sensing duration can be expressed as $(N_s + 1 - u_c)\tau_s$, while the total communications duration can be expressed as $(\sum_{n_c=1}^{N_c} \tau_c[n_c]) + u_c\tau_c[N_c+1]$. Define a control variable $\alpha \in (0, 1)$ for the ratio of total sensing duration to total communications duration, which avoids an excessive delay due to a large sensing overhead. Accordingly, the AP conducts sensing ($u_c = 0$) when the total sensing duration is no larger than α times the total communications duration and conducts communications ($u_c = 1$) otherwise.

To achieve the best trilateration performance in UL sensing, the AP selects three STAs of indices $\mathcal{I}$ with minimum predicted CRLB of trilateration estimate $\hat{l}_{tri,\mathcal{I}}$ in (9). Let $\hat{\mathbf{\Psi}}_\mathcal{I} = \hat{\mathbf{\Gamma}}_\mathcal{I}\mathbf{D}_\mathcal{I}\hat{\mathbf{\Gamma}}_\mathcal{I}^T$, which is a symmetric positive definite matrix since $\hat{\mathbf{\Gamma}}_\mathcal{I}$ is a full rank matrix and $\mathbf{D}_\mathcal{I}$ is a diagonal matrix with all diagonal entries being positive. Then, $\hat{l}_{tri,\mathcal{I}}$ in (9) can be rewritten as $\mathrm{Tr}\{\hat{\mathbf{\Psi}}_\mathcal{I}^{-1}\}$. Note that selecting the best $\mathcal{I}$ is equivalent to selecting the best $\hat{\mathbf{\Psi}}_\mathcal{I}$.

In consequence, the AP obtains u_c^* (which is a decision between sensing and communications) and $\hat{\mathbf{\Psi}}_\mathcal{I}^*$ (which leads to STA indices $\mathcal{I}^*$ for trilateration in UL sensing) by solving the optimization problem (10) below ($\mathcal{I}^*$ is of interest only when $u_c^* = 0$):

$$\min_{u_c, \hat{\mathbf{\Psi}} \in \mathbf{S}_{++}^2} \quad u_c + \mathrm{Tr}\{\hat{\mathbf{\Psi}}^{-1}\} \tag{10a}$$

$$\text{subject to} \quad (N_s + 1 - u_c)\tau_s \le \alpha[(\sum_{n_c=1}^{N_c} \tau_c[n_c]) + u_c\tau_c[N_c+1]] \tag{10b}$$

$$u_c \in \{0, 1\} \tag{10c}$$

$$\hat{\mathbf{\Psi}} \in \{\hat{\mathbf{\Psi}}_\mathcal{I} : \mathcal{I} \in [\mathcal{M}]^3\} \tag{10d}$$

The objective function (10a) results in the STA indices with minimum predicted CRLB of trilateration estimate while encouraging sensing whenever possible, being convex in u_c and $\hat{\boldsymbol{\Psi}}$ (note that the trace function of the inverse of a symmetric positive definite matrix is convex). The constraint (10b) imposes a requirement for the total sensing duration and total communications duration, being convex in u_c and $\hat{\boldsymbol{\Psi}}$. The constraints (10c) and (10d) specify the set of choices for u_c and $\hat{\boldsymbol{\Psi}}$, respectively. As a result, the optimization problem (10) is a discrete convex optimization problem, which can be solved efficiently with practical discrete convex optimization techniques (e.g., [14] and [15]).

C. Solution Framework

With the critical components of the proposed method presented in Secs. III-A and III-B, we summarize the solution framework in Algorithm 1.

Initially, the AP obtains a new TXOP at time t. With (5), the AP generates a predicted state $\hat{\mathbf{x}}$ of the target. Based on the predicted target position $(\hat{x}, \hat{y})$ in the predicted state $\hat{\mathbf{x}}$, the AP solves the discrete convex optimization problem (10) to obtain $u_c^* \in \{0, 1\}$ and $\hat{\boldsymbol{\Psi}}_{\mathcal{I}}^*$ with STA indices $\mathcal{I}$ (which is of interest only when $u_c^* = 0$). If $u_c^* = 0$, then the AP conducts UL sensing with the three STAs of indices $\mathcal{I}^*$ and create a measurement $\mathbf{z}[N_s + 1]$ as (3). With (6), the AP generates an updated state $\tilde{\mathbf{x}}$ of the target. On the other hand, if $u_c^* = 1$, then the AP conducts DL communications with the M STAs.

Algorithm 1: Solution Framework

Input:
$\{\mathbf{z}[n_s]\}_{n_s=1}^{N_s}, \{(\bar{x}_m, \bar{y}_m)\}_{m\in\mathcal{M}}, \{\xi_m\}_{m\in\mathcal{M}}, \tau_s, \{\tau_c[n_c]\}_{n_c=1}^{N_c+1}$
Output:
Generate predicted state $\hat{\mathbf{x}}$ with (5).
Obtain u_c^* and $\hat{\boldsymbol{\Psi}}_{\mathcal{I}}^*$ (which leads to $\mathcal{I}^*$) by solving (10) ($\mathcal{I}^*$ is of interest only when $u_c^* = 0$).
if $u_c^* = 0$
  Conduct UL sensing with three STAs of indices $\mathcal{I}^*$.
  Create measurement $\mathbf{z}[N_s + 1]$ as (3).
  Generate updated state $\tilde{\mathbf{x}}$ with (6).
else if $u_c^* = 1$
  Conduct DL communications with M STAs.
end

IV. Simulation

In this section, we evaluate the performance of the proposed method from both the sensing and communications perspectives. Specifically, we compare the sensing and communications performance of the proposed method and two random baseline methods, and we examine the effect of number of STAs on the sensing performance. The evaluations are simulated with an ISAC-enabled IEEE 802.11bf Wi-Fi network in MATLAB.

The two random baseline methods (reduced from the proposed method) are as follows:

- **Random STA selection for trilateration (RSST)**: The STA index set $\mathcal{I}$ is randomly selected from $[\mathcal{M}]^3$.
- **Random decision between sensing and communications (RDSC)**: The value of binary variable u_c is randomly chosen from $\{0, 1\}$.

A. Parameter Settings

On a 2D area, the Wi-Fi network consists of an AP and M STAs which are randomly located with x and y coordinates uniformly selected from $[-10, 10]$ m and a moving target with an initial position at origin $(0, 0)$ and an initial velocity of 1 m/s in a random direction. The carrier frequency is 5.25 GHz, and the channel bandwidth is 80 MHz. For brevity, the key Wi-Fi network parameter settings are summarized in Table I.

TABLE I
Wi-Fi Network Parameter Settings

Parameter	Value
AP and STA position	Random
Target initial position	$(0, 0)$
Target initial velocity	1 m/s in random direction
Carrier frequency	5.25 GHz
Channel bandwidth	80 MHz
Simulation time	1 minute
DL data amount B_m	1500 bytes
(τ_{SIFS}, τ_{TF}, τ_{CTS}, τ_{SR2SI})	(16, 10.8, 4.6, 44+8$\rho\eta$) μs
# HE-LTF symbol ρ	4
# HE-LTF repetition η	4
Process noise intensity v_s	0.1
Channel model	IEEE 802.11be indoor
(AP Tx power, STA Tx power)	(43, 23) dBm
Multiple-input multiple-output (MIMO)	4×2

In the simulation, we carry out three evaluations over $\alpha = \{0.005, 0.025, 0.05, 0.2, 0.8\}$. For the first evaluation, we assess the sensing performance in terms of MSE between target position (x, y) and predicted target position $(\hat{x}, \hat{y})$ with number of STAs $M = 8$. Next, we assess the communications performance in terms of throughput with number of STAs $M = 8$ for the second evaluation. For the third evaluation, we inspect how number of STAs M affects the sensing performance in terms of MSE between target position (x, y) and predicted target position $(\hat{x}, \hat{y})$ across $M = \{4, 8, 12\}$.

B. Simulation Results

Fig. 3 shows the results of the first evaluation (sensing performance), demonstrating the MSE between target position (x, y) and predicted target position $(\hat{x}, \hat{y})$ under the three methods (Proposed, RSST, and RDSC) with number of STAs $M = 8$. As the RDSC method randomly chooses between sensing and communications without α, its MSE remains a constant over α. On the other hand, the MSE of the proposed and RSST methods decreases as α increases, since a larger α leads to an increased total sensing duration. It can be observed that the proposed method always outperforms the RSST method in terms of MSE, since the proposed method selects the three STAs which lead to the minimum predicted CRLB of trilateration estimate. Compared to the RDSC method with a fixed sensing performance, the proposed method can meet different sensing performance requirements by flexibly configuring α.

The results of the second evaluation (communications performance) are shown in Fig. 4, which demonstrates the

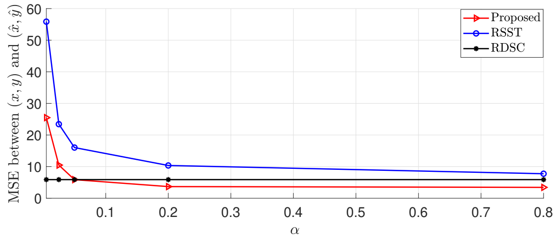

Fig. 3. MSE between target position (x, y) and predicted target position $(\hat{x}, \hat{y})$ under different methods with number of STAs $M = 8$

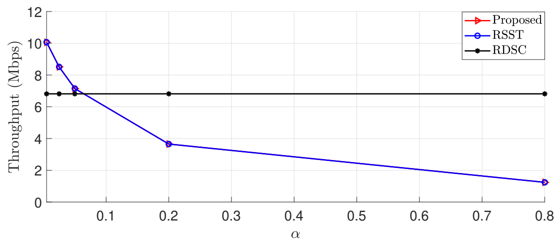

Fig. 4. Throughput under different methods with number of STAs $M = 8$

throughput under the three methods (Proposed, RSST, and RDSC) with number of STAs $M = 8$. Since the proposed and RSST methods follow the same procedure for a decision between sensing and communications within each TXOP, they achieve the same throughput. Similarly, the RDSC method results in a fixed communications performance, while the proposed method can leverage the flexible configuration of α to meet different communications performance requirements.

From the first and second evaluations, it can be inferred that the proposed method strikes a better balance between the sensing and communications performance than the RSST method (which suffers from an inferior sensing performance) and the RDSC method (whose sensing and communications performance is fixed).

For the third evaluation (effect of number of STAs M on sensing performance), its results are shown in Fig. 5, which demonstrates the MSE between target position (x, y) and predicted target position $(\hat{x}, \hat{y})$ of the proposed method across $M = \{4, 8, 12\}$. Similarly, across $M = \{4, 8, 12\}$, the MSE of the proposed method drops with an increased α. Besides, it can be found that the MSE drops as the number of STAs M increases, since it is more likely to select the three STAs with a smaller predicted CRLB of trilateration estimate when there are more STA candidates.

V. Conclusion

In this paper, we propose a novel method for target tracking with ISAC in IEEE 802.11bf. To track the target state, the proposed method adopts the Kalman filter, with which the AP generates a predicted state within each TXOP and an updated state within each sensing TXOP. For trilateration which requires a selection of three STAs, the proposed method develops a trilateration performance metric based on the CRLB for the AP. Through the proposed method, the AP solves a discrete convex optimization problem to decide between UL sensing and DL communications within each TXOP and

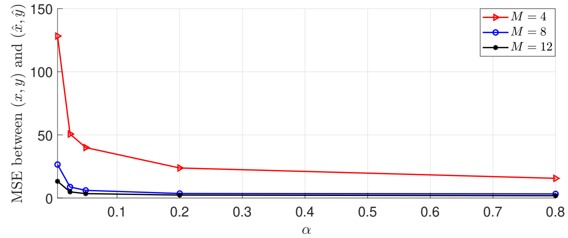

Fig. 5. MSE between target position (x, y) and predicted target position $(\hat{x}, \hat{y})$ of proposed method under different numbers of STAs $M = \{4, 8, 12\}$

selects the three STAs for trilateration if UL sensing is conducted. Simulation results verify the good flexibility between the sensing and communications performance of the proposed method. Besides, the proposed method achieves an improved sensing performance with an increased number of STAs.

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