Joint Tracking of Multiple Beams in Beamspace MIMO Systems

Liza Afeef, Murat Karabacak, Member, IEEE, and Huseyin Arslan, Fellow, IEEE

Abstract—In millimeter-wave (mmWave) systems, beamforming is needed to overcome harsh channel environments. As a promising beamforming solution, lens antenna array (LAA) implementation can provide a cost-effective solution without notable performance degradation compared to its counterpart. However, an appropriate beam selection is a challenge since it requires efficient channel estimation via an extensive beam training process for perfect beam alignment. In this paper, we propose a high mobility beam and channel tracking algorithm based on the unscented Kalman filter (UKF) to address this challenge, where the channel changes can be monitored over a certain time. The proposed algorithm tracks the channel changes after establishing a connection with an appropriate beam. The algorithm is first introduced in a multi-user beamspace multiple-input multiple-output (MIMO) system with LAA where a single beam is tracked at the user side at downlink transmission. Then, it is employed for multi-beam joint-tracking at the base station side in the uplink transmission. The analysis indicates that under different channel variation conditions, the proposed algorithm outmatches the popular extended Kalman filter (EKF) in both single-beam and multi-beam tracking systems. While it is common to individually track the beams in a multi-beam system scenario, the proposed joint tracking approach can provide around 62% performance enhancement compared to individual beam tracking using the conventional EKF method.

Index Terms—Beam Tracking, Joint-Tracking, LAA, mmWave, Mobility, UKF, Sigma Points.

I. INTRODUCTION

Millimeter-wave (mmWave) communication is considered as a promising technology to support the envisioned high data rate in next-generation wireless networks [1]. However, mmWave signals suffer from a severe path loss problem due to harsh propagation conditions including blockage at high frequencies [2], [3]. Therefore, multiple-input multiple-output (MIMO) beamforming implementation is merged in mmWave communications to achieve highly directional beams and mitigate such path loss effects. Apart from combating the path loss problem, beamforming also reduces interference, boosts capacity, enhances security [4], and offers better coverage at the cell edge [5], [6].

Despite the traditional beamforming approach of phase shifters for each antenna aperture which causes high power consumption, the studies in [7]–[9] uses a lens on top of the antenna array, and with switches in the place of phase shifters. Such implementation of a lens into antenna array, referred to as lens antenna array (LAA), exhibits some distinctive properties [10]: 1) It focuses signal power at the front-end to achieve high directivity, 2) it concentrates signal power directed to a sub-region of the antenna array, and 3) it replaces the phase shifters with switches which reduce the cost. Owing to these properties and advantages, lens antenna systems are highly considered to be an effective solution for mmWave communications in terms of cost and performance [11]. LAA systems can also offer high gain and relatively low sidelobes in different directions without any significant performance loss [12], [13].

Designing an LAA system whose aperture phase distribution equalized in a scanning plane is a straightforward procedure [14]. Additionally, an increased level of channel sparsity in mmWave LAA systems, makes it possible to improve the channel estimation using dictionary-based sparse estimators [15]. Besides, By employing the LAA, the spatial channel representation can be converted to the beamspace channel model [12].

The sparse nature of the beamspace MIMO channel allows selecting a small number of beams and thus reduces the number of radio-frequency (RF) chains in the system. However, an accurate channel state information (CSI) is needed in beamspace MIMO systems [16] which require to have frequent estimating for the channel leading to a huge overhead and large loss of throughput [17], [18]. Such often channel estimation can be avoided using tracking algorithms to track the channel parameters, i.e. channel coefficient, angle of arrival (AoA), and angle of departure (AoD). The beam tracking algorithms are significantly fast, reliable, and robust which allow efficient data transfer between transmitters and receivers in mmWave communications. In high dynamic communication networks, channel tracking can overcome the performance degradation of physical layer authentication [19].

A. Prior works

Several works are proposed regarding beam tracking techniques for mmWave communication. The first work in this direction is presented in [20], where an analog beamforming strategy is selected and an extended Kalman filter (EKF) based tracking algorithm for a sudden change detection method is proposed to track AoA/AoD while assuming constant channel coefficient in a mmWave system. This filter uses Jacobian matrices to transform the non-linear system into linear approximations around the current state. The results show that

Copyright may be transferred without notice, after which this version may no longer be accessible.
the use of the EKF algorithm causes a gracious decaying in the system performance with the acquisition error while requiring a low signal-to-noise ratio (SNR) and low pilot overhead. The method has difficulties to track in a fast-changing channel environment since it requires pre-requisites for a full scan that causes long time measurement. To decrease the measurement time and provide a more suitable tracking algorithm, the authors in [21] proposed an alternative solution that requires only a single measurement with EKF estimation and a beam switching design. As an extension for the work in [21], the authors in [22] proposed a joint minimum mean square error (MSE) beamforming with the help of EKF tracking strategy. Using same filter, [23] proposes a beam tracking model for motion tracking (position, velocity, and channel coefficient) in mmWave vehicular communication system. The main different of this model is shown in its state variables where approximate linear motion equations are derived from the beam angles to avoid the nonlinearity of using angles in the state variables which reduces the complexity in calculating the Jacobians matrix.

However, the above-discussed techniques are limited to the scenarios where only a single beam is considered or multiple beams with uncorrelated paths. In [24], a Markov jump linear system (MJLS) and an optimal linear filter are designed to track the dynamics of the channel with two beams considering the correlation between them. This system iteratively tracks the AoA of the incoming beams only, taking into account the channel gain correlation between different paths. However, the computational complexity of this method increases exponentially with the number of target beams. In a faster angle variation environment, [25] proposes a tracking algorithm based auxiliary particle filter (APF) that displays optimal performance using 32 antennas. Although APF shows improved performance, this approach requires a high processing time compared to EKF approach. In [26], angle tracking strategies for wideband mmWave systems are proposed where pairs of auxiliary beams are designed as the tracking beams to capture the angle variations, toward which the steering directions of the data beams are adjusted. The proposed methods are independent from a particular angle variation. However, their analysis show that the method is sensitive to radiation pattern impairments.

In mmWave beamspace MIMO system with multiple user equipment (UE)s, only the work in [27] proposes a channel tracking algorithm by exploiting the temporal correlation of the time-varying channels to track the line-of-sight (LoS) path of the channel. Considering a motion model for the UEs, a temporal variation law of the AoA and AoD of the LoS path is excavated and tracked based on the sparse structure of beamspace MIMO system. However, a large number of pilots are implemented to employ the tracking with the presented method.

B. Our contribution

Despite of the benefit of utilizing LAA in MIMO systems, the literature lack the sufficient analysis of tracking approaches in these systems. Although few researches paid attention to various types of channel tracking filters [21], [22], [25], none of them spots the light on tracking multi-beam jointly in a multi-beam beamspace MIMO systems to provide multiple users support at the same time. In this paper, we introduce multiple user support while implementing multi-beam tracking with a reduced complexity algorithm based on unscented Kalman filter (UKF). The contributions of this paper are summarized as follows:

- LAA concept is considered as a practical solution for the future mmWave communication systems since it can provide less hardware complexity and high antenna gains. However, such beamforming systems still in need of beam tracking algorithms for efficient usage of the beams. Thus, in this paper for the first time, a beam tracking algorithm is implemented in an LAA system to the best of authors’ knowledge.
- Due to the ability of the UKF algorithm to adapt in a high dynamic state estimation, for the first time, UKF is adapted to track channel parameters (i.e. AoA, AoD, and directional channel coefficients) of a multi-user beamspace MIMO communication system, where the algorithm parameters and steps are optimized to properly work on this system.
- The tracking algorithm is adapted to beamspace MIMO communication by optimizing the sigma points spreading parameters of the UKF to provide optimized solution for downlink (DL) and uplink (UL) transmission scenarios where single-beam and multi-beam tracking are applied, respectively.
- The performance of the UKF algorithm-based tracking is compared with the EKF algorithm. Evaluation results indicate that the proposed UKF algorithm outperforms the conventional EKF algorithm while having the same complexity.

C. Organization and notation

This paper is organized as follows. In Section II the system model is presented for DL and UL transmission where the beamspace channel transformation is introduced also. The frame structure and evolution models of the whole system along with the proposed strategy of the UKF approach are provided in Section III. In Section IV simulation results for each approach are carried out to evaluate the performance of the algorithm compared to those by conventional EKF. Finally, conclusions and future vision are given in Section V.

Notation: Matrices are denoted by bold uppercase letters (e.g. $\mathbf{A}$), and vectors are denoted by bold lowercase letters (e.g. $\mathbf{a}$). $\mathbf{A}^T$ and $\mathbf{I}_Z$ denote the Hermitian (conjugate transpose) of matrix $\mathbf{A}$ and $\mathbf{Z} \times \mathbf{Z}$ identity matrix, respectively. $\text{sinc}(\cdot)$ is the “sinc” function defined as $\text{sinc}(x) = \sin(\pi x)/(\pi x)$, and for a real number $A$, $\lceil \cdot \rceil$ denotes a floor operation. Furthermore, $E\{\cdot\}$ denotes the expectation operator.

II. System Model

A typical mmWave beamspace MIMO system is considered where the base station (BS) employs $N_{\text{BS}}$ antennas and $N_{\text{RF}}$
Considering all the assumptions, the received noisy vector at the UL mode of the system where all users during the tracking, we propose to track the beams at the BS side at each UE.

The received noisy signal for user at time slot is given as

\[
y_{k,t} = w_k^H H_{k,t} p_k s_k + w_k^H H_{k,t} \sum_{i=1,i \neq k}^K p_i s_i + w_k^H v_t,
\]

where \( w_k \in \mathbb{C}^{N_k \times 1} \) is the combiner vector for the \( k \)-th user, \( H_k = [H_{1,t}, H_{2,t}, \ldots, H_{K,t}] \) is the channel matrix, \( H_{k,t} \) is the channel matrix between the BS and the \( k \)-th user, \( P = [p_1, p_2, \ldots, p_K] \) is the hybrid beamformer matrix, \( s = [s_1, s_2, \ldots, s_K] \) are the transmitted symbol for all users with normalized power, and \( v \sim \mathcal{C} \mathcal{N}(0, \sigma_v^2) \) is the additive white Gaussian noise.

In general, it is considered that the channel between BS and each UE \( H_k \) follows a geometrical narrowband slow time-varying channel model \([2]\), given as

\[
H_{k,t} = \sqrt{N_{\text{BS}} N_k \lambda / L_k} \sum_{l=1}^{L_k} \alpha_{k,l,t} a(\theta_k, \phi_k, \theta_l) a^H(\theta_k, \phi_k, \theta_l),
\]

where \( L_k \) is the number of resolvable channel paths between the BS and user \( k \), \( \alpha_{k,l,t} \) is the complex channel coefficient, and \( \theta_k, \phi_k \) and \( \theta_l, \phi_l \) are the AoA and AoD for path \( l \) of user \( k \). \( a \) represents the steering vector for uniform linear array (ULA) antenna which is given as \([28]\)

\[
a = \frac{1}{\sqrt{N}} e^{-j \frac{2\pi}{\lambda} \frac{(N-1)}{2} d \sin(\theta)} \ldots e^{-j \frac{2\pi}{\lambda} \frac{(N-1)}{2} d \sin(\theta)}^T,
\]

where \( \lambda \) is the carrier wavelength and \( d \) is the antenna spacing satisfying \( d = \lambda / 2 \). \( N \in \{N_{\text{BS}}, N_k\} \), \( \theta \in \{\theta_k, \phi_k\} \).

In order to decrease the effect of the users interference during the tracking, we propose to track the beams at the BS side at the UL mode of the system where all users are transmitted to be received at the same time by the BS. Considering all the assumptions, the received noisy vector \( y_t \) from all \( K \) users at time slot \( t \) becomes

\[
y_t = W^H H_p P D s + v_t,
\]

where \( D = \text{diag} \left( \frac{1}{\sqrt{p_1}}, \ldots, \frac{1}{\sqrt{p_K}} \right) \) describes the average path loss between the BS and each UE.

A. Beam space channel transformation

In order to transfer the conventional spatial channel to a beamspace one, a LAA is carefully designed at the BS and UE sides. Therefore, the channel in (2) is transformed into beamspace channel as \([7]\)

\[
H_{b,t} = [H_{b,1,t}, H_{b,2,t}, \ldots, H_{b,K,t}],
\]

\[
= U H_{d,t} U^H,
\]

where \( H_{b,k,t} \) is the beamspace channel of the \( k \)-th UE and \( U = \frac{1}{\sqrt{N}} [u(\psi_1), u(\psi_2), \ldots, u(\psi_{N-1})]^T \) is a unitary discrete Fourier transform (DFT) matrix that uses to transform the spatial channel into beamspace channel where \( u(\psi) \) represents the virtual steering vector at specific virtual angle \( \psi \).

In general, the beamspace channel between each UE and the BS, either in UL or DL transmission, can be written as

\[
H_{b,k,t} = \sqrt{N_{\text{BS}} N_k \lambda / L_k} \sum_{l=1}^{L_k} \alpha_{k,l,t} H_{k,l,t},
\]

where it can be assumed that the transmitted side has \( N_k \) antenna elements and the received side has \( N_r \), and \( H_{k,l,t} \) is given as

\[
H_{k,l,t} = U a(\theta_k, \phi_k, \theta_l) a^H(\theta_k, \phi_k, \theta_l) U^H
\]

\[
= \frac{1}{N_r N_k} \times \begin{bmatrix}
    f(\phi_A, \phi_D, \psi_{t,0}, \psi_{r,0}) & \cdots & f(\phi_A, \phi_D, \psi_{t,0}, \psi_{r,N-1}) \\
    \vdots & \ddots & \vdots \\
    f(\phi_A, \phi_D, \psi_{r,v}, \psi_{r,v}) & \cdots & f(\phi_A, \phi_D, \psi_{r,v}, \psi_{r,N-1}) \\
    \vdots & \ddots & \vdots \\
    f(\phi_A, \phi_D, \psi_{r,N-1}, \psi_{r,N-1}) & \cdots & f(\phi_A, \phi_D, \psi_{r,N-1}, \psi_{r,N-1})
\end{bmatrix},
\]

where \( \phi_A = \frac{\pi}{\lambda} \sin(\theta_k, \phi_k, \theta_l), \phi_D = \frac{\pi}{\lambda} \sin(\theta_k, \phi_k, \theta_l) \).

From the power-focusing ability of Dirichlet sinc function, it can be concluded that the power of \( H_{b,k,t} \) is concentrated on a small number of elements \([29]\). Thus, when considering the UL transmission, the transmission of each user happens mainly through that small number of elements at the BS side which reduces the interference between the UEs.

III. THE PROPOSED BEAM TRACKING ALGORITHM

In this section, the frame transmission structure is presented first. Then, the evolution model is presented, while the beam tracking algorithm is proposed after that.

A. Frame structure

The frame structure for the proposed beamspace MIMO system is similar to the structure in \([30]\), where one total slot is allocated for beamspace channel estimation. Then, assuming that all the UEs are synchronized, in each time-slot, one pilot is allocated for beam and channel tracking in either UL or DL transmissions. Note that the proposed algorithm is also designed to work with only one pilot to update its parameters.
The proposed frame structure for the tracking procedure is illustrated in Fig. 2.

### B. Evolution model

In this work, three parameters are considered to track the beam; complex channel coefficients, AoA, and AoD. Therefore, in order to prepare the system for tracking, two evolution models should be presented; state and generic models.

In the state-evolution model, the state-space vector for all channel paths at time $t$ can be given as

$$
\mathbf{x}_t = \begin{bmatrix} \alpha_{R,t} & \alpha_{I,t} & \alpha_{D,t} & \alpha_{A,t} \end{bmatrix}^T,
$$

(8)

where we separate the channel coefficient into real $\alpha_R$ and imaginary $\alpha_I$ parts to make sure that the angles are real along with the tracking procedures. Since Gauss–Markov model is widely adopted as a simple and effective model to characterize the fading process [31], the evolution model for the channel coefficients can be assumed as a first-order Gauss-Markov [21], [32] given as

$$
\alpha_t = \rho \alpha_{t-1} + \xi_{t-1},
$$

(9)

where $\rho$ is the channel fading correlation coefficient that characterizes the degree of time variation, and $\xi \sim \mathcal{C}\mathcal{N}(0, \sigma^2)$ [22]. The generic-evolution model for AoA and AoD follows the Gaussian process noise model [20], [21] and given by

$$
\theta_{t,i} = \theta_{t-1,i} + \xi_{i,t-1},
$$

(10)

with $\xi \sim \mathcal{C}\mathcal{N}(0, \sigma^2)$, $i \in \{A, D\}$.

Note that $\sigma^2$ and $(1-\rho^2)$ determines the channel variations. Higher values of $\sigma^2$ and $(1-\rho^2)$ imply fast fading channel, while lower values are used for slow fading channels.

Based on these evolution models, the state-evolution can now be written as

$$
\mathbf{x}_t = \mathbf{F} \mathbf{x}_{t-1} + \mathbf{u}_{t-1},
$$

(11)

where $\mathbf{F}$ is a function of the generic-evolution models for complex channel coefficients, AoAs and AoDs as in [9] and [10], $\mathbf{u} \sim \mathcal{C}\mathcal{N}(0, \mathbf{Q})$ representing the distribution of $\zeta$ and $\xi$ with $\mathbf{Q} = \text{diag}([1-\rho^2]/2, (1-\rho^2)/2, \sigma^2, \sigma^2)$ since the channel parameters are considered independent.

### C. Proposed unscented Kalman tracking filter

In this subsection, the proposed UKF algorithm is applied to the system models that described in Section II for beam and channel tracking. UKF is considered as an advantageous to EKF due to its ability to adapt to model changes and to overcome the weaknesses of the EKF while having the same complexity as explained in [33]–[35]. This preference was proved in [36], [37], where the performances of UKF and EKF were compared for an autonomous underwater vehicle navigation system. Moreover, UKF is quite suitable for a heavily nonlinear system since its estimation characteristic is not concerned by the level of nonlinearity, which makes the algorithm commonly used in many engineering fields such as integrated navigation [38], autonomous underwater vehicle navigation [36], [37], system identification [39], target tracking [40], and location tracking [41].

In this paper, UKF based algorithm is employed to track the beam. In order to start the tracking, a perfect channel estimation is assumed and the state space vector $\mathbf{x}$ is initialized from the estimated beam/channel parameters. The input of the proposed algorithm is the state space vector at time $t$ represented by its mean $\bar{x}_t$ and covariance $\Sigma_{x,t}$. The measurement/observed symbol $y_t$ is needed as an input to update the algorithm.

The state distribution for the algorithm is represented by a Gaussian random variable specified utilizing a minimal set of carefully chosen sample points. These points are called sigma points and they completely capture the true mean and covariance of $\bar{x}_t$ and $\Sigma_{x,t}$. Noting that when these points propagated through the real-time non-linear system, they can obtain the posterior mean and covariance correctly unlike the EKF algorithm where the nonlinearity is approximated to a linear using Jacobian matrix. These sigma points are given as

$$
\mathbf{\chi}_{t-1} = \begin{bmatrix} \bar{x}_{t-1} & \bar{x}_{t-1} + \sqrt{(m+\Lambda)\Sigma_{x,t-1}} & \bar{x}_{t-1} - \sqrt{(m+\Lambda)\Sigma_{x,t-1}} \end{bmatrix}
$$

(12)

where $m$ is the number of state-space elements in $\mathbf{x}$ and $\Lambda$ is a scaling parameter such that $(\Lambda + m) \neq 0$ and it can control the amount sigma points spreading around the mean. These sigma points are then propagated through the process model given in [11] returning in the end a cloud of transformed points $\bar{x}_t$. The new estimated mean $\bar{x}_t$ and covariance $\Sigma_{x,t}$ are then computed from the transformed points $\mathbf{\chi}_t$ as

$$
\bar{x}_t = \sum_{i=0}^{2m} \bar{\omega}_i^{(m)} \mathbf{\chi}_{t,i},
$$

(13)

$$
\Sigma_{x,t} = \sum_{i=0}^{2m} \bar{\omega}_i^{(c)} (\mathbf{\chi}_{t,i} - \bar{x}_t)(\mathbf{\chi}_{t,i} - \bar{x}_t)^T + \mathbf{Q}_t,
$$

(14)

where $\bar{\omega}_i^{(m)} = \bar{\omega}_i^{(c)} = \frac{1}{2(m+\Lambda)}$ for $i = 1, 2, \cdots, 2m$ while $\bar{\omega}_0^{(m)} = \frac{\Lambda}{\Lambda + m}$ and $\bar{\omega}_0^{(c)} = \frac{\Lambda}{\Lambda + m} + (1-\gamma^2 + \beta)$, noting that the weights are normalized to satisfy $\sum_{i=0}^{2m} \bar{\omega}_i = 1$. $\beta$ is used to incorporate prior knowledge of the distribution of $\mathbf{x}$, which
is set to 2 as an optimum value for a Gaussian distribution \cite{42}, while \( \gamma \in [0, 1] \) is a scaling parameter used to identify \( \Lambda \) given that \( \Lambda = \gamma^2 (m + \kappa) - m \) where \( \gamma \) and \( \kappa \) are scaling parameters that are responsible of determining the spreading of sigma points around the mean \( \bar{X} \).

The transformed sigma points \( \chi_t \) are then propagated through the nonlinear observation model \( g(\chi_t) \). Considering the system is tracked in the DL mode, based on \ref{1}, the observation function in a beamspace domain is given as

\[
Z^{(DL)}_i = g_{DL}(\chi_t) = \omega_k^H H_{b,k,t}(\chi_t) p_k,
\tag{15}
\]

where \( s_k \) is considered as a unit pilot symbols.

For the UL beamspace transmission, the BS is responsible of tracking multi-beam simultaneously. Therefore, referring to \ref{4}, the observation function will lead to multi measurements and is given as

\[
Z^{(UL)}_i = g_{UL}(\chi_t) = W^H b_{k,t}(\chi_t) PD.
\tag{16}
\]

This class of filter can be relevant even when there is a disconnectedness in nonlinear functions \( F \) and \( g \).

The mean \( \bar{z}_t \) and covariance \( \Sigma_{z,t} \) of the transformed observations are measured as

\[
\bar{z}_t = \sum_{i=0}^{2m} \omega_i^{(m)} Z_{t,i},
\tag{17}
\]

\[
\Sigma_{z,t} = \sum_{i=0}^{2m} \omega_i^{(c)} (Z_{t,i} - \bar{z}_t)(Z_{t,i} - \bar{z}_t)^T + \sigma_v^2.
\tag{18}
\]

After that, in order to measure the filter gain \( K_t \), the cross covariance between the transformed observation and the transformed sigma points is needed and can be expressed as follow

\[
\Sigma_{xz,t} = \sum_{i=0}^{2m} \omega_i^{(c)} (\chi_{t,i} - \bar{x}_t)(Z_{t,i} - \bar{z}_t)^T.
\tag{19}
\]

Therefore, the gain is defined as

\[
K_t = \Sigma_{xz,t} \Sigma_{z,t}^{-1}.
\tag{20}
\]

Lastly, the posterior state-space vector and its covariance are updated as

\[
\bar{x}_t = \bar{x}_t + K_t (y_t - \bar{z}_t),
\tag{21}
\]

\[
\Sigma_{x,t} = \Sigma_{x,t} + K_t \Sigma_{z,t} K_t^T.
\tag{22}
\]

The tracking will be repeated for each measurement update on \( t \)-th time index until the algorithm fails to track due to extreme changes on the channel and new channel parameter estimation is performed.

It should be noted that the algorithm addresses the approximation issues of the EKF by using unscented transformation (UT). This concept is generated under the fact that the approximation of a given distribution, by using a fixed number of parameters, is easier than approximating an arbitrary nonlinear function \cite{43}. Following this approach, the UT obtains a set of \( 2m + 1 \) sigma points, deterministically chosen as presented in \ref{12}. The uniqueness of the UKF algorithm is in the way of selecting these points: numbers, values, and weights. The sigma point method results in a more accurate computation of the nonlinear system tracking where the accuracy is increased as the set of sigma points increases. However, the amount to pay is a significant increase in computational cost as \( 2m + 1 \) parameters are additionally performed in the system. Therefore, since the spreading of the sigma points can control the accuracy of the UKF algorithm, in this work, the spreading of these sigma points are controlled so that the modified UKF algorithm provides better performance during the tracking time without additional performed parameters.

The effect of different sigma points spreading around the true mean is illustrates in Fig. 3 where it is clearly shown that choosing different spreading can lead to different mean and covariance than the true ones.

In order to optimize the spreading of the sigma points, optimal values for the scaling parameters \( \gamma \) and \( \kappa \) are chosen so that the innovation in \ref{21} is minimized, and it is formulated as

\[
\{ \gamma_t^+, \kappa_t^+ \} = \min_{\gamma_t, \kappa_t} \{ y_t - \bar{z}_t \}.
\tag{23}
\]

The proposed UKF tracking algorithm scheme is summarized in Algorithm 1.

\begin{algorithm}
1. **Estimate** the total beamspace channel \( H_b \).
2. for \( t = 1, 2, 3, \ldots \) do
3. **Optimize** the \( \gamma_t \) and \( \kappa_t \) using \ref{23} for the first time slot only.
4. **Calculate** \( \chi_{t-1} \) as in \ref{12}.
5. **Update** \( \chi_{t-1} \) to \( \chi_t \) using \ref{11}.
6. **Propagate** \( \chi_t \) through \( g(\chi_t) \) using \ref{15} for DL transmission or \ref{16} for UL transmission.
7. **Calculate** the filter gain \( K_t \) using \ref{20}.
8. **Update** the state-space \( x_t \) and its covariance \( \Sigma_{x,t} \) using \ref{21} and \ref{22}.
9. **Return** \( x_t, \Sigma_{x,t} \).
\end{algorithm}

Fig. 3: Effect of sigma points spreading on the transformed procedure in UKF algorithm.
IV. NUMERICAL RESULTS

In this section, the numerical results are presented to examine the performance of the proposed tracking algorithm in several scenarios. We explore the impact of different number of UEs in the system and provide a comparison with EKF based tracking algorithm \[20, 21\]. The performance of each tracking method is shown by calculating the MSE for the angles which is given as

$$J_k = E \left[ |\hat{\theta}_t - \theta_t|^2 \right],$$

(24)

where $\hat{\theta}_t$ is the tracked angles while $\theta_t$ is the estimated angles considering no tracking is hired in the system. The channel fading correlation $\rho$ for the system is set to be $\rho = 0.99$ corresponds to slow fading in channel coefficient. A random initialization for the tracking parameters $\theta_A$ and $\theta_D$ is given from a uniform distribution $U(\theta, \pi)$, and $\alpha$ as a complex standard normal distribution. Due to the similarity in performance for AoA and AoD, only the AoA performance is given. It is assumed that the number of RF chains at BS side is equal to the number of served UEs in both DL and UL transmissions ($N_{\text{RF}} = K$). Since a reliable high-data transmission in mmWave can be provided with only a few number of path components \[44\], the DL and UL transmissions are assumed to have one path component between each user and the BS during the analysis. As well, based on the sparse nature of the beamspace channel at mmWave frequencies, we can select only a small number of dominant beams to reduce the effective dimension of MIMO system without obvious performance loss. So, few UEs are served in the system. Each MSE plot is obtained by averaging over 10000 simulation runs.

A. Beam and channel tracking in the DL transmission

In this subsection, the proposed algorithm is used for tracking at the user side, where the BS can serve multiple UEs. The system parameters setup is given in Table I.

B. Beam and channel tracking in the UL transmission

In this subsection, the UL transmission system is provided where the UEs are assumed to transmit at same power level

---

**TABLE I: Simulation configuration in the DL transmission.**

| Parameters                      | Value   |
|---------------------------------|---------|
| Operating frequency $f_o$       | 28 GHz  |
| Channel paths for the tracked user $L_k$ | 1, 5    |
| Channel paths for other UEs $l$ | 1       |
| Antenna array elements at BS $N_{\text{BS}}$ | 16      |
| Antenna array elements at all UEs $N_k$ | 8       |
| Distance between antenna elements $d$ | $\lambda/2$ |
| Angle speed variation $\sigma_A = \sigma_D = \sigma^2$ | $(0.25)^2$, $(0.5)^2$ |
| Tracking duration               | 20 time slot |
| Channel fading correlation coefficient $\rho$ | 0.99    |
| SNR                             | 20 dB   |
| Number of UEs in the system $K$ | 1, 4    |

---

Fig. 4 depicts the MSE beam tracking performance for single- and multi-user system in the DL transmission at different speed variation angles. It is seen that as the variation $\sigma^2$ increases from 0.25$^2$ to 0.5$^2$, the measured error of the proposed tracking algorithm increases from $10^{-4}$ to $5 \times 10^{-3}$ for single user scenario. Although the proposed algorithm performs poorly when the number of UEs increases in the system, it can beat the performance of the conventional EKF algorithm. It is clearly shown the proposed algorithm outperforms the conventional EKF up to 85% performance enhancement in a high speed variation system.

Fig. 4b illustrates the channel tracking performance for both the proposed and the conventional EKF algorithms for a single-user system $K = 1$ at angle speed variation of $\sigma^2 = (0.25)^2$. It is noticed that the proposed algorithm gives up to 44% performance enhancement in tracking single path, while it reaches around 66% enhancement for tracking the LoS path and more than 80% for tracking the non-line-of-sight (NLoS) paths in a user that has 5 resolvable channel paths.
Fig. 5: The MSE of (a) AoA for different number of UEs, and (b) its channel tracking at the UL transmission.

TABLE II: Simulation configuration in the UL transmission.

| Parameters                                    | Value       |
|-----------------------------------------------|-------------|
| Operating frequency $f_c$                    | 28 GHz      |
| Channel paths between each UE and the BS $L_k$| 1           |
| Antenna array elements at BS $N_{BS}$        | 16          |
| Antenna array elements at all UEs $N_k$      | 8           |
| Distance between antenna elements $d$        | $\lambda/2$|
| Angle speed variation for all UEs $\sigma_\alpha = \sigma_\phi = \sigma^*$ | $0.35^2$   |
| Tracking duration                             | 20 time slot|
| channel fading correlation coefficient $\rho$| 0.99        |
| Averaged SNR from each UE                    | 0 dB        |
| Number of UEs in the system $K$              | 1, 2, 4     |

The proposed algorithm is optimized its parameters according to receiving the UEs’ signals together. So that all UEs have been tracked jointly and simultaneously. However, the EKF algorithm in this case is employed to track each user channel separately in the presence of receiving signal from other UEs. The system parameters setup for the UL transmission are given in Table II.

Fig. 5a demonstrates the MSE performance of AoA beam tracking for the single- and multi-user beamspace MIMO systems while Fig. 5b illustrates the channel tracking performance for the same system at the UL transmission. According to Fig. 5a, the effectiveness of the proposed algorithm in tracking multiple beams jointly is clearly shown with 62% performance enhancement compared to the conventional EKF method. As well, the degradation in performance between different number of UEs in the system is negligible. However, as shown in Fig. 5b, the performance gap between the proposed algorithm in a single-user system and multi-user system is notable where there is around 90% reduction in performance between one-user system and two-user system. Noting that the gap between the proposed algorithm and the conventional EKF based method is increased as well.

V. CONCLUSION

A novel multi-beam joint-tracking algorithm based on UKF filter was designed for multi-user beamspace MIMO systems using LAA. The proposed algorithm is employed to track the channel parameters; AoA, AoD, and channel coefficient, of multi-beam jointly. The algorithm avoids Jacobian and/or Hessian matrices computation to provide a linear estimator without any approximation as it is the case in the conventional EKF based method. Two implementations were investigated for the beam and channel tracking using the proposed algorithm: 1) single-beam tracking at the UE side in the DL transmission in the presence of other UEs’ beams interference, and 2) multi-beam joint-tracking at the BS side in the UL transmission system. Note that the proposed algorithm optimized the sigma points spreading parameters of UKF method which enables us to efficiently track multiple UEs simultaneously. This leads to enhancing the tracking performance by reducing overall interference in the UL transmission. The numerical results showed that the proposed algorithm can provide up to 85% performance enhancement in tracking performance compared to conventional EKF based method in high mobility systems. The proposed algorithm can be implemented in a highly mobile environment to enhance mobility support by detecting changes in the channel for high-speed users. Also, the proposed algorithm is feasible for devices with limited computation and processing capabilities. As a future work, performance analysis of the presented works can be utilized in a laboratory environment.

ACKNOWLEDGEMENT

The work of H. Arslan was supported by the Scientific and Technological Research Council of Turkey under Grant No. 116E078.
APPENDIX A
ANALYSIS OF $f$

Given that $\Phi_A = \frac{d}{\lambda} \sin(\theta_{k,A},t)$, $\Phi_D = \frac{d}{\lambda} \sin(\theta_{k,D},t)$, and $U(\theta_{k,A},t) = 0$ if $\theta_{k,A},t \neq (2\pi q + \pi) \frac{\lambda}{d}$, the power in which has the same capabilities of the original Dirichlet sinc $N$ of $\psi_{f}(...)$ is equal to

$$H_{k,t} = \begin{bmatrix} H_{u}(\psi_{r,0}) \vspace{1em} \vdots \vspace{1em} H_{u}(\psi_{r,N-1}) \end{bmatrix} \begin{bmatrix} u(\Phi_A) \times \end{bmatrix} \begin{bmatrix} u(\psi_{t,0}) \vspace{1em} \vdots \vspace{1em} u(\psi_{t,N-1}) \end{bmatrix}$$

Therefore, each element in the matrix can be given as

$$[H_{k,t}]_{v,c} = \sum_{q} e^{-j2\pi \sin(\pi \varphi_{A}) \frac{\lambda}{d} \sin(\pi \varphi_{A}) - \varphi_{D} \frac{\lambda}{d} \sin(\pi \varphi_{A}) - \psi_{r,v}}$$

Simplifying (25) as

$$[H_{k,t}]_{v,c} = \sum_{q} e^{-j2\pi \sin(\pi \varphi_{A}) \frac{\lambda}{d} \sin(\pi \varphi_{A}) - \varphi_{D} \frac{\lambda}{d} \sin(\pi \varphi_{A}) - \psi_{r,v}}$$

where $f_N(\varphi)$ is the Dirichlet sinc function with a maximum of $N$ at $\varphi = 0$. It is noticed that each element in $H_{k,t}$ is a summation of Dirichlet function with a phase shift of $\psi_{r,v}$ which has the same capabilities of the original Dirichlet sinc function. Therefore, the power in $H_{k,t}$ is concentrated only on a small number of elements due to the power-focusing ability of $f_N(\varphi)$. 

REFERENCES

[1] Z. Pi and F. Khan, “An introduction to millimeter-wave mobile broadband systems,” IEEE Communications Magazine, vol. 49, no. 6, pp. 101–107, 2011.
[2] R. W. Heath, N. Gonzalez-Prelcic, S. Rangan, W. Roh, and A. M. Sayeed, “An overview of signal processing techniques for millimeter wave MIMO systems,” IEEE Journal of Selected Topics in Signal Processing, vol. 10, no. 3, pp. 436–453, 2016.
[3] S. Doğan, M. Karabacak, and H. Arslan, “Optimization of antenna beamwidth under blockage impact in millimeter-wave bands,” in 2018 IEEE 29th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC). IEEE, 2018, pp. 1–5.
[4] B. Peköz, M. Hafez, S. Kose, and H. Arslan, "Reducing precoder/channel mismatch and enhancing secrecy in practical MIMO systems using artificial signals," IEEE Communications Letters, 2020.
[5] I. Ahmed, H. Khammari, A. Shahid, A. Musa, K. S. Kim, E. De Poorter, and I. Moerman, "A survey on hybrid beamforming techniques in 5G: Architecture and system model perspectives," IEEE Communications Surveys & Tutorials, vol. 20, no. 4, pp. 3060–3097, 2018.
[6] A. F. Molisch, V. V. Ratnam, S. Han, Z. Li, S. L. H. Nguyen, L. Li, and K. Haneda, “Hybrid beamforming for massive MIMO: A survey,” IEEE Communications Magazine, vol. 55, no. 9, pp. 134–141, 2017.
[7] J. Brady, N. Behdad, and A. M. Sayeed, “Beamspace MIMO for millimeter-wave communications: System architecture, modeling, analysis, and measurements,” IEEE Transactions on Antennas and Propagation, vol. 61, no. 7, pp. 3814–3827, 2013.
[8] Y. Zeng and R. Zhang, “Millimeter wave MIMO with lens antenna array: A new path division multiplexing paradigm,” IEEE Transactions on Communications, vol. 64, no. 4, pp. 1557–1571, 2016.

[9] M. A. Al-Joumayly and N. Behdad, “Wideband planar microwave lenses using sub-wavelength spatial phase shifters,” IEEE Transactions on Antennas and Propagation, vol. 59, no. 12, pp. 4542–4552, 2011.
[10] J. Cho, G.-Y. Suk, B. Kim, D. K. Kim, and C.-B. Chae, “RF lens-embedded antenna array for mmWave MIMO: Design and performance,” IEEE Communications Magazine, vol. 56, no. 7, pp. 42–48, 2018.
[11] O. Quevedo-Teruel, M. Ibrahimouni, and F. Gharsaem, “Lens antennas for 5G communications systems,” IEEE Communications Magazine, vol. 56, no. 7, pp. 36–41, 2018.
[12] Y. Zeng, R. Zhang, and Z. N. Chen, “Electromagnetic lens-focusing antenna enabled massive MIMO: Performance improvement and cost reduction,” IEEE Journal on Selected Areas in Communications, vol. 32, no. 11, pp. 1194–1206, 2014.
[13] T. Kwon, Y.-G. Lim, B.-W. Min, and C.-B. Chae, “RF lens-embedded massive MIMO systems: Fabrication issues and codebook design,” IEEE Transactions on Microwave Theory and Techniques, vol. 64, no. 7, pp. 2256–2271, 2016.
[14] P. Y. Lau, Z. N. Chen, and X. Qing, “Electromagnetic field distribution of lens antennas,” in Proc. Asia-Pacific Conference on Antennas Propagation, 2013.
[15] M. Nazzal, M. A. Aygul, A. Gorcın, and H. Arslan, “Dictionary learning-based beamspace channel estimation in millimeter-wave massive MIMO systems with a lens antenna array,” in 2019 15th International Wireless Communications & Mobile Computing Conference (IWCMC). IEEE, 2019, pp. 20–25.
[16] X. Wei, C. Hu, and L. Dai, “Deep learning for beamspace channel estimation in millimeter-wave massive MIMO systems,” IEEE Transactions on Communications on, 2020.
[17] L. Yang, Y. Zeng, and R. Zhang, “Channel estimation for millimeter-wave MIMO communications with lens antenna arrays,” IEEE Transactions on Vehicular Technology, vol. 67, no. 4, pp. 3239–3251, 2017.
[18] X. Li, J. Fang, H. Li, and P. Wang, “Millimeter wave channel estimation via exploiting joint sparse and low-rank structures,” IEEE Transactions on Wireless Communications, vol. 17, no. 2, pp. 1123–1133, 2017.
[19] L. Bai, L. Zhu, J. Liu, J. Choi, and W. Zhang, “Physical layer authentication in wireless communication networks: A survey,” Journal of Communications and Information Networks, vol. 5, no. 3, pp. 237–264, 2020.
[20] C. Zhang, D. Guo, and P. Fan, “Tracking angles of departure and arrival in a mobile millimeter wave channel,” in Proc. IEEE International Conference on Communications (ICC). IEEE, 2016, pp. 1–6.
[21] V. Va, H. Vikalo, and R. W. Heath, “Beam tracking for mobile millimeter wave communications systems,” in Proc. IEEE Global Conference on Signal and Information Processing (GlobalSIP). IEEE, 2016, pp. 745–747.
[22] S. Jayaprakasam, X. Ma, J. W. Choi, and S. Kim, “Robust beam-tracking for mmWave mobile communications,” IEEE Communications Letters, vol. 21, no. 12, pp. 2654–2657, 2017.
[23] S. Shaham, M. Ding, M. Kokshoorn, Z. Lin, S. Dang, and R. Abbas, “Fast channel estimation and beam tracking for millimeter wave vehicular communications,” IEEE Access, vol. 7, pp. 141104–141118, 2019.
[24] Y. Fan, J. B. Li, H. Li, and C. Tian, “A stochastic framework of millimeter wave signal for mobile users: Experiment, modeling and application in beam tracking,” in Proc. 11th Global Symposium on Millimeter Waves (GSMW). IEEE, 2018, pp. 1–8.
[25] J. Lim, H.-M. Park, and D. Hong, “Beam tracking under highly non-linear mobile millimeter-wave channel,” IEEE Communications Letters, vol. 23, no. 3, pp. 450–453, 2019.
[26] D. Zhu, J. Choi, Q. Cheng, W. Xiao, and R. W. Heath, “High-resolution angle tracking for mobile wideband millimeter-wave systems with antenna array calibration,” IEEE Transactions on Wireless Communications, vol. 17, no. 11, pp. 7173–7189, 2018.
[27] L. Dai and X. Gao, “Priori-sided channel tracking for millimeter-wave beamspace massive MIMO systems,” in 2016 URSI Asia-Pacific Radio Science Conference (URSI AP-RASC). IEEE, 2016, pp. 1493–1496.
[28] Z. Wang, M. Li, X. Tian, and Q. Liu, “Iterative hybrid precoder and combiner design for mmWave multiuser MIMO systems,” IEEE Communications Letters, vol. 21, no. 7, pp. 1581–1584, 2017.
[29] A. Sayeed and N. Behdad, “Continuous aperture phased MIMO: Basic theory and applications,” in 2010 48th Annual Allerton Conference on Communication, Control, and Computing (Allerton). IEEE, 2010, pp. 1196–1203.
[30] J. Li, Y. Sun, L. Xiao, S. Zhou, and C. E. Koksal, “Fast analog beam tracking in phased antenna arrays: Theory and performance,” arXiv preprint arXiv:1710.07823, 2017.
[31] M. Medard, “The effect upon channel capacity in wireless communications of perfect and imperfect knowledge of the channel,” IEEE Transactions on Information theory, vol. 46, no. 3, pp. 933–946, 2000.
[32] J. M. Wooldridge, *Introductory econometrics: A modern approach*, 6th ed. Nelson Education, 2016.

[33] S. Lu, L. Cai, L. Ding, and J. Chen, “Two efficient implementation forms of unscented Kalman filter,” in *2007 IEEE International Conference on Control and Automation*. IEEE, 2007, pp. 761–764.

[34] C. Montella, “The Kalman filter and related algorithms: A literature review,” Dec. 2011. [Online]. Available: https://www.researchgate.net/publication/236897001_The_Kalman_Filter_and_Related_Algorithms_A_Literature_Review

[35] S. Thrun, “Probabilistic robotics,” *Communications of the ACM*, vol. 45, no. 3, pp. 52–57, 2002.

[36] B. Allotta, A. Caiiti, L. Chisci, R. Costanzi, F. Di Corato, C. Fantacci, D. Fenucci, E. Meli, and A. Ridolfi, “An unscented Kalman filter based navigation algorithm for autonomous underwater vehicles,” *Mechatronics*, vol. 39, pp. 185–195, 2016.

[37] B. Allotta, A. Caiiti, R. Costanzi, F. Fanelli, D. Fenucci, E. Meli, and A. Ridolfi, “A new AUV navigation system exploiting unscented Kalman filter,” *Ocean Engineering*, vol. 113, pp. 121–132, 2016.

[38] Y. Meng, S. Gao, Y. Zhong, G. Hu, and A. Subic, “Covariance matching based adaptive unscented Kalman filter for direct filtering in INS/GNSS integration,” *Acta Astronautica*, vol. 120, pp. 171–181, 2016.

[39] A. Kallapur, M. Samal, V. Puttige, S. Anavatti, and M. Garratt, “A UKF-NN framework for system identification of small unmanned aerial vehicles,” in *2008 11th International IEEE Conference on Intelligent Transportation Systems*. IEEE, 2008, pp. 1021–1026.

[40] H. Zhang, G. Dai, J. Sun, and Y. Zhao, “Unscented Kalman filter and its nonlinear application for tracking a moving target,” *Optik*, vol. 124, no. 20, pp. 4468–4471, Oct 2013.

[41] S. G. Larew and D. J. Love, “Adaptive beam tracking with the unscented Kalman filter for millimeter wave communication,” *IEEE Signal Processing Letters*, vol. 26, no. 11, pp. 1658–1662, 2019.

[42] E. A. Wan and R. Van Der Merwe, “The unscented Kalman filter for nonlinear estimation,” in *Proc. IEEE Adaptive Systems for Signal Processing, Communications, and Control Symposium*. IEEE, 2000, pp. 153–158.

[43] N. Gordon, B. Ristic, and S. Arulampalam, “Beyond the Kalman filter: Particle filters for tracking applications,” *Artech House, London*, vol. 830, no. 5, pp. 1–4, 2004.

[44] S. Han, I. Chih-Lin, Z. Xu, and C. Rowell, “Large-scale antenna systems with hybrid analog and digital beamforming for millimeter wave 5G,” *IEEE Communications Magazine*, vol. 53, no. 1, pp. 186–194, 2015.