Robust and Low Complexity Beam Tracking with Monopulse Signal for UAV communication

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Abstract—UAV communications based on an antenna array entail a beam tracking issue for reliable link acquisition. Unlike conventional cellular communication, beam tracking in UAV communication addresses new issues such as mobility and abrupt channel disconnection from UAV’s perturbation. To deal with these issues, we propose a beam tracking scheme based on extended Kalman filter (EKF) using a monopulse signal, which can provide (1) higher robustness by offering a reliable link in the estimated spatial direction and (2) lower complexity compared with the existing codebook based beamforming scheme. We point out the limitations of using a beamformed signal as a measurement model for a Kalman filter (KF) based scheme and instead utilize the monopulse signal as a more plausible model. For the performance evaluation, we derive the upper bound of the mean square error for spatial angle estimation of the UAV and confirm that our proposed scheme is stable with a certain bounded error. We also show from our simulations that our proposed scheme can efficiently track UAV and detect beam disconnection every time frame using a beamformed signal.

Index Terms—Beam Tracking, UAV communication, Beamforming, Kalman filter, Extended Kalman filter, Monopulse signal

I. INTRODUCTION

With the increasing demands for applications of unmanned aerial vehicle (UAV) communications as an element technology of 5G or B5G, the critical issue is to have a reliable link between the ground node and a UAV or UAV-to-UAV [1]–[3]. UAV communication assisted link can be efficiently established by aligning the beam toward the UAV because the line of sight (LOS) is mainly considered in the aerial network [4]. Note that the beam alignment between a transmitter and a receiver and an accurate direction parameter estimation are two prerequisites for a beam tracking [5]–[7].

One of the main beam tracking schemes is based on Kalman filter (KF) [5], [8]–[12]. It is widely known that two KF based algorithms, extended Kalman filter (EKF) [13] and unscented Kalman filter (UKF) [14], can be applied to the nonlinear model. Most studies of KF based beam tracking have established the beamformed signal as a measurement model [8]–[12]. They focus on the beamformed received signal which is described as adaptive beamforming [9]–[11] or codebook based beamforming [8], [12]. However, it is not suitable for a KF based scheme, which provides an optimal solution in a linear system, because the nonlinearity of the beamformed signal is strong. The considered measurements such as real and imaginary terms of the received signal follow a concave function of spatial angle $x$, which lies within the main lobe beamwidth. Therefore, it should be noted that the performance of EKF and UKF based beam tracking schemes with the measured beamformed signal may be limited since such schemes require linear approximation.

More importantly, their measurement models are affected by the parameters of the beamforming weight, $\phi$, as well as the angular parameters of the channel, $\phi$. When it comes to adaptive beamforming deriving the beam toward a particular direction as $\phi$, the KF based scheme can be a viable solution only if the derived beam targets the main lobe of beam pattern corresponding to the actual channel. Thus, determining the beam direction is not practical toward the main lobe of the beam pattern without the actual channel state information. [9]–[11]. In [9], [11], authors tackle additional optimization methods to compensate for the performance loss of EKF, but this does not resolve the underlying problem of designing the beamforming weight parameter, $\phi$. The codebook based beamforming scheme [8], [12] shows a more stable performance than the former, but steering the entire codebook every time index is not practical. Moreover, the dimension of the measurement model becomes very large, which requires $O(n^3)$ complexity to calculate the innovation covariance matrix or Kalman gain, where $n$ is the length of the codebook. In [12], they employ the UKF and conduct extra optimization to reduce the size of codebook, but it also raises overhead to find a suboptimal beamforming matrix. Besides them, there are sensor based beam tracking researches [5], [13], and the authors apply UKF on estimating UAV’s position information with sensor measurements such as global positioning system (GPS) and flight controller.

This paper focuses on three main contributions to UAV communications. 1) We propose a beam tracking scheme based on EKF using the monopulse signal, which is a more plausible measurement model of KF for lower complexity compared to beamformed signal based KF algorithms. 2) It is observed that our proposed scheme can efficiently track the UAV and detect error and beam misalignment over time frame. 3) To evaluate the performance, we derive the upper bound of mean square error (MSE) and verify that the proposed scheme is stable under the bounded estimation error over time while UAV keeps flying. Simulation results show that the proposed scheme outperforms the conventional schemes [8], [12] under planar array and LOS channel.

The rest of paper is organized as follows. Section II presents the system and channel models under consideration. In Section III we propose the robust EKF based beam tracking algorithm with monopulse signal measurement and in Section IV we...
present the error detection for the stable beam connection. In Section V, we analyze the performance in terms of bounded mean square error for tracking and then we present some selected results in Section VI. Section VII summarizes our proposed scheme.

II. SYSTEM AND CHANNEL MODELS

We consider beam tracking system as depicted in Fig.1. At each frame, ground station (GS) estimates the channel parameter based on the monopulse signal, and then GS transmits information-bearing signal data to the target UAV. Here, we assume that the channel is invariant during $T$ period of a frame. The system is composed of two phases such as 1) channel estimation phase and 2) data transmission phase. In the channel estimation phase, we estimate the spatial angle and align the beam to the estimated parameter. We transmit the information data to the target and detect beam alignment with beamformed signal in the transmission phase. If the beam misalignment over a certain error threshold is continuously detected, we implement a mechanical alignment and initialize the process.

We consider a GS with $N = N_x \times N_y$ uniform planar array and target UAV, which is tracked by GS, has a single antenna. Note that our scheme can be easily extended to multiple antenna structure of UAV by considering the angle of departure of transmitted signals of the array of UAV. Moreover, the LOS channel link is mainly assumed in the high altitude air network that the majority of the signals are transmitted by the LOS path with a high probability [5]. [9]. Then, we have a time-varying channel at the $k$th frame between GS and UAV with distance $D_k$, which can be represented as

$$H_k = \frac{\rho_k \alpha_k}{D_k^\beta} a_x(u_k)a_y(v_k)^H,$$

where $(\cdot)_k$ denotes the corresponding value of the $k$th frame. In (1), $\rho_k$ denotes the path-loss gain embracing the antenna gain and transmitted power, and $\alpha_k$ and $\beta_k$ are the channel gain and path-loss exponent, respectively. We also denote $u_k$ and $v_k$ for spatial direction parameter of UAV’s transmitted signal for $x$-axis and $y$-axis, respectively. The array response vector for $x$-axis and $y$-axis, $a_x$ and $a_y$, in (1) can be expressed as

$$a_x(u_k) = \left[ 1 \ e^{-j\varpi u_k} \ldots e^{-j(N_x-1)\varpi u_k} \right]^T,$$

$$a_y(v_k) = \left[ 1 \ e^{-j\varpi v_k} \ldots e^{-j(N_y-1)\varpi v_k} \right]^T,$$

respectively, where $u_k$ and $v_k$ denote the spatial angle as $\frac{2\pi d}{\lambda} \sin \theta_k$ and $\frac{2\pi d}{\lambda} \sin \theta_k$ with $d$ of antenna spacing, and $\lambda$ of the wavelength of the incident signal. Considering UAV flying the sky at the constant altitude for particular missions [14], we can set up the state model for spatial angle as

$$x_{k+1} = \begin{bmatrix} u_{k+1} \\ v_{k+1} \end{bmatrix} = \begin{bmatrix} \cos \psi & -\sin \psi \\ \sin \psi & \cos \psi \end{bmatrix} \begin{bmatrix} u_k \\ v_k \end{bmatrix} + \begin{bmatrix} w_{u,k} \\ w_{v,k} \end{bmatrix},$$

where $w_{u,k}$ and $w_{v,k}$ are the process noise with variances $\sigma_u^2$ and $\sigma_v^2$, respectively, and $\psi$ is the angle of rotation of the UAV every time frame. We first propose the state evolution model for a practical UAV’s movement and the obtained state can be is directly employed to designing the beamforming weight. Moreover, the channel gain $\alpha_k$ is given by the first-order Gaussian-Markov model [10]

$$\alpha_{k+1} = \rho \alpha_k + \epsilon_k,$$

where $\rho$ is the correlation coefficient and $\epsilon_k \sim CN(0,(1-\rho^2)/2))$. Then we can write the received signal in matrix form as

$$Y_k = H_k s_k + N_k,$$

where $s_k$ denotes the transmitted pilot signal. The beamformed signal in the transmission phase of the $k$th frame can be represented by

$$y_k = w^H(\hat{x}_k)h_k s_k + w^H(\hat{x}_k)n_k,$$

where $\hat{x}_k$ denotes the estimated angle of the target and, $h$, $w$ and $n$ are the channel, beamforming, and noise in vector form, respectively. The beamforming weight vector $w(\hat{x}_k)$ generates the beam for the desired direction and can be written as

$$w(\hat{x}_k) = \text{vec}\left( w_x(\hat{u}_k)w_y(\hat{v}_k)^H \right),$$

where vec$(\cdot)$ represents transformation from matrix to vector and the beamforming weight vector for $x$-axis and $y$-axis can be defined, respectively, as

$$w_x(\hat{u}_k) = \frac{1}{\sqrt{N_x}} \begin{bmatrix} 1 \\ e^{-j\hat{u}_k} \\ \vdots \\ e^{-j(N_x-1)\hat{u}_k} \end{bmatrix},$$

$$w_y(\hat{v}_k) = \frac{1}{\sqrt{N_y}} \begin{bmatrix} 1 \\ e^{-j\hat{v}_k} \\ \vdots \\ e^{-j(N_y-1)\hat{v}_k} \end{bmatrix}.$$

III. PROPOSED BEAM TRACKING BASED ON EKF WITH MONOPULSE SIGNAL

The KF generally assumes the Gaussian distribution for both a linear state transition and measurement models, $p(x_k|x_{k-1}) = N(x_k|F x_{k-1}, Q_{p,k-1})$ and $p(y_k|x_k) = N(y_k|G x_k, Q_{n,k})$ [15], where $G$ is a measurement model, and $Q_{p,k}$ and $Q_{n,k}$ are the process noise and the measurement noise at the $k$th frame, respectively. Thus, KF in a linear system has an optimal
The monopulse signal is defined as the ratio of sum and difference of the received signals in two adjacent antennas \( n \). We can calculate the phase difference between the received signals in two adjacent antennas as \( \tan^{-1}(\frac{\sum_{m} x_{m} - \sum_{n} x_{n}}{\sum_{n} x_{n} + \sum_{m} x_{m}}) \), where \( x_{m} \) and \( x_{n} \) are the received signals in the \( m \)th and \( n \)th antenna, respectively. Given the simplest case, when the monopulse signal is defined as \( R = \frac{1}{1 - e^{-j/2}} = \frac{\sin \frac{u}{2}}{\cos \frac{u}{2}} = j \tan \frac{u}{2} \), the monopulse signal \( R \) can be expressed as

\[
R = 1 - e^{-j/2} = \frac{\sin \frac{u}{2}}{\cos \frac{u}{2}} = j \tan \frac{u}{2}.
\]

Then, we can obtain the phase difference \( u \) from \( \arctan(\Im \{R\}) \), in which \( \Im \) denotes imaginary term of the corresponding complex value. In our proposed system with a planar array, we extend (11) to the monopulse signals on the \( n \)th frame, whose measurement model with monopulse signal can be set up as

\[
\hat{r}_{k} = r_{k} - g(\hat{x}_{k}) = g(x_{k}) + n_{k} - g(\hat{x}_{k}),
\]

where \( g(\hat{x}_{k}^{-}) \) denotes predicted measurement value for the predicted state, \( G \) is the Jacobian matrix as \( \frac{\partial g(x_{k})}{\partial x_{k}} \mid_{\hat{x}_{k}} = 0.5 I_{2} \), where \( I_{2} \) is the \( 2 \times 2 \) identity matrix, and \( n_{k} \) is measurement noise vector in (14). Then, the innovation covariance of \( r_{k} \) can be expressed as \( S_{k} = GP_{k}G^{T} + Q_{n,k} \), Here, since the measurement dimension of this scheme is 2 regardless of the number of antenna elements, the proposed scheme can significantly reduce the complexity related to the size of antenna array. Finally, the updated state and error covariance is obtained by

\[
\hat{x}_{k} = \hat{x}_{k}^{-} + K_{k} r_{k},
\]

\[
P_{k} = P_{k}^{-} - K_{k} S_{k} K_{k}^{T},
\]

where the Kalman gain \( K_{k} \) can be defined as \( P_{k}^{-} G^{T} S_{k}^{-1} \), minimizing the MSE for estimation. EKF repeats the prediction and the update-correction steps in every estimation phase, which is presented in Fig. 2. As such, the system can establish a reliable communication link with 3D beamforming gain for the updated state, which will be shown in the following sections.

### IV. Beam Misalignment Detection

We consider two procedures for the beam alignment such as 1) coarse alignment and 2) fine alignment for UAV communications. Note that the mechanical approach is often adopted for coarse alignment while the electrical beamforming approach is employed for fine alignment. The mechanical approach adjusts the normal vector of the planar array toward the antenna of the UAV, that is, employing the incident angle to be within a certain range as \( [-\theta_{a}, \theta_{a}] \) for an example. When the incident angle deviates from the normal vector of the planar array, the beamforming performance declines, and the linearity error of the monopulse signal increases, resulting the performance degradation of the estimation. Therefore, we can expect a stable tracking performance by estimating the
In the proposed scheme, we estimate real-time errors and detect the beam misalignment with the received power in the transmission phase. When the estimated error exceeds a certain threshold, the scheme declares the beam misalignment and executes the mechanical alignment. Note that in this paper, we do not mention the method for an initial estimation and mechanical beam alignment [2], but we only consider the method for estimating errors and detecting beam misalignment.

The received power can be expressed as a value on the 3-D beam pattern model [19] as

\[
P_r = \frac{1}{N^2} \left( \frac{\sin \left( \frac{N_x}{2} (u - \hat{u}) \right)}{\sin \left( \frac{\pi}{2} (u - \hat{u}) \right)} \right)^2 \left( \frac{\sin \left( \frac{N_y}{2} (v - \hat{v}) \right)}{\sin \left( \frac{\pi}{2} (v - \hat{v}) \right)} \right)^2. \tag{19}
\]

In this section, we ignore the subscript of time index \( k \) for notational simplicity. By exploiting an approximation of the main lobe of the beam pattern model [20], (19) can be written as

\[
P_r \approx \cos \left( \frac{N_x}{4} (u - \hat{u}) \right)^2 \cos \left( \frac{N_y}{4} (v - \hat{v}) \right)^2, \tag{20}
\]

which is validated in the main lobe. Here, we can estimate the error vector as \( \xi = x - \hat{x} \). Arranging (20) with \( \xi \), we can obtain

\[
P_r \approx \cos \left( \frac{N_x}{4} \xi_1 \right)^2 \cos \left( \frac{N_y}{4} \xi_2 \right)^2, \quad |\xi_1| < \frac{2\pi}{N_x}, \quad |\xi_2| < \frac{2\pi}{N_y}. \tag{21}
\]

where \( \xi_i \) denotes the \( i \)-th element of the corresponding vector, and \( \frac{2\pi}{N_x} \) and \( \frac{2\pi}{N_y} \) are the corresponding null-to-null beamwidth of the main lobe, respectively. To find the error norm for the square array, we reformulate (21) as

\[
P_r \approx \cos \left( \frac{N_x}{4} ||\xi|| \right)^2 \cos \left( \frac{N_y}{4} ||\xi|| \right)^2 \quad \text{where} \quad ||\xi|| < \frac{2\pi}{N_x}, \tag{22}
\]

where the three-dimensional beam pattern model has the same magnitude at a location with the same radius from the center, \((0,0)\), then, we can re-express (21) as (22) using the norm of error, \( ||\xi|| \). Under this approximation, the problem of finding the estimation error can be written as

\[
||\hat{\xi}|| = \arg \min_{||\xi|| \in E} |P_r - f(||\xi||)|^2, \tag{23}
\]

where \( f(||\xi||) \) is defined as \( \cos \left( \frac{N_x}{4} ||\xi|| \right)^2 \). We can solve (23) by an exhausted search over the feasible range of \( ||\xi|| \). Note that the feasible region, \( E \) of \( ||\xi|| \) is confined on the line of \( E = \{ y = x, 0 \leq x \leq \gamma \} \), in which \( \gamma \) is below the value of \( \frac{2\pi}{\sqrt{c}} \), which is a null point. The Euclidean distance from \( x \) to \( \hat{x} \) is equal to \( ||\xi|| \), and we search the nearest point on grid line, \((y,y), 0 \leq y \leq \gamma\), with the corresponding radius of \( ||\xi|| \). With the grid search in the range of \( E = \{0 : \Delta : \gamma\} \), we can estimate the estimation error in real-time and detect the beam misalignment when the estimated error is over the threshold such as 3dB beamwidth, \( \frac{0.895\pi}{N_x} \). Moreover, in a rectangular array, we can obtain the estimated error with the same method by extending the corresponding feasible region as \((x,y)\) of \( 0 \leq x, y \leq \gamma \).

V. MEAN SQUARED ERROR BOUND ANALYSIS

In this section, we analyze the stability of the proposed scheme by showing that the MSE of the proposed scheme is upper bounded. One of the methods for analyzing the stability of the system is to calculate the estimated error or boundary of the Lyapunov function [21], and we herein use the estimated error dynamics to confirm stability.

Let us define the estimation error of the spatial direction of UAV’s transmitted signal as

\[
\xi_k = x_k - \hat{x}_k, \tag{24}
\]

in here, and then by substituting (17) and (18) into (24), then (24) can be represented as

\[
\xi_k = (I - K_k G) (x_k - \hat{x}_k) - K_k n_k - K_k \chi (x_k - \hat{x}_k), \tag{25}
\]

where \( \chi (x_k - \hat{x}_k) \) denotes remainder terms of Taylor expansion in (17), which is negligible in high SNR channel. Arranging (25) with (4) and (15), (25) can be written in recursive form as

\[
\xi_k \approx (I - K_k G) (F \xi_{k-1} + w_{k-1}) - K_k n_k. \tag{26}
\]

Then, we can derive the approximated MSE as

\[
\mathbb{E} \left[ ||\xi_k||^2 \right] = \mathbb{E} \left[ \xi_k^T \xi_k \right],
\]

\[
\approx \mathbb{E} \left[ \xi_{k-1}^T A_k \xi_{k-1} + w_{k-1}^T B_k \xi_{k-1} + n_k^T K_k^T K_k n_k \right], \tag{27}
\]

where \( A_k \) denotes \( (I - K_k G) F \) and \( B_k \) is \( (I - K_k G) \). Using linearity of the trace operator, (27) can be rearranged as

\[
\mathbb{E} \left[ ||\xi_k||^2 \right] \approx \text{Tr} \left( \mathbb{E} \left( A_k P_{k-1} A_k^T \right) \right) + \text{Tr} \left( \mathbb{E} \left( B_k Q_{p,k-1} B_k^T \right) \right) + \text{Tr} \left( \mathbb{E} \left( K_k Q_{n,k} K_k^T \right) \right). \tag{28}
\]

Note that we herein only consider the stable situation to evaluate the accuracy of estimation, thus we assume that process noise and measurement noise are constant over time while UAV moves. Moreover, the process noise variance are known and determined parameters as \( \sigma_n^2 \) and \( \sigma_p^2 \), but the measurement noise variance of \( n_k \) in (25) is unknown, which is a variance of the monopulse signal [23]. Consequently, we can show that (28) is upper bounded as

\[
\mathbb{E} \left[ ||\xi_k||^2 \right] < \text{Tr} \left( \mathbb{E} \left( A_k P_{k-1} A_k^T \right) \right) + \text{Tr} \left( \mathbb{E} \left( B_k Q_{p,k-1} B_k^T \right) \right) + \text{Tr} \left( \mathbb{E} \left( K_k Q_{n,k} K_k^T \right) \right), \tag{29}
\]

where \( Q_n \) is defined as relaxed assumption of \( Q_n \) as \( Q_n > Q_n \).

VI. SIMULATION RESULTS

In this section, we verify from the simulations that the proposed scheme is robust in terms of MSE for UAV beam tracking compared to the codebook based beamforming scheme. We have a GS of which height \( h \) is eight times the radius \( R_o \) of flying with an \( 8 \times 8 \) planar array for an example. Thus, the fixed elevation angle is 0.1244 radian by assuming height is 8 times of the radius, which is an stable alignment situation. The azimuth angle is randomly distributed from \([-30, 30]\) degrees considering the mechanical baseline.
we consider the codebook-based beamforming scheme where the number of beamforming vectors across 2-D beam space is 169 \([8], [14]\). The process noise matrix \(Q_p\) is assumed as

\[
Q_p = \begin{bmatrix}
\sigma_u^2 & 0 \\
0 & \sigma_v^2
\end{bmatrix},
\]

and the measurement noise matrix \(Q_n\) is assumed as \(\sigma_n^2 I\).

Fig. 3 shows tracking performance in real-time compared to the codebook based beamforming scheme. It is observed that the proposed scheme can track perturbations of the spatial directions more accurately while the codebook based beamforming is not capable of tracking the abrupt beam changes rapidly from the measurement.

With respect to the complexity of the codebook based beamforming and the proposed schemes, the codebook based beamforming scheme has \(O(n^3)\) for inversion of innovation covariance, in which \(n\) is the codebook length, that is, 169 in this example, and it has a measurement vector of 338 sizes because EKF can be employed with real and imaginary terms, respectively. On the other hand, the proposed algorithm has a measurement vector of size 2 in \([14]\), thus the computational load is much lower.

In Fig. 4 we show the trends of beamforming gain over time for the proposed scheme and codebook based beamforming scheme. In data transmission phase, the GS receives data from the UAV with directional 3D beamforming. Fig. 4 presents the normalized beamforming gain to show a beam alignment accuracy. Our scheme achieves an consistent gain based on the robust estimation, while the codebook based beamforming scheme shows larger fluctuations over time.

The results in Fig. 5 are provided with the error trend. We set the value of SNR as 30dB, and the process noise standard deviation as \(\sigma_u, \sigma_v = 0.05\) for an example. The assumed variation in here is large compared to the assumptions considered in \([8]–[10]\), thus it can detect the fluctuations in general navigations. Moreover, we also set the height as the three times of the navigation radius as \(h = 2 \times R_o\), which is a misalignment situation with the UAV deviating from the normal vector of the planar array. At each frame, the system checks the beam alignment with beamforming power. In Fig. 5 as we can see that the estimation performance degrades from the 45th time index. At the 48th time index, the estimated error exceeds the 3dB beamwidth, then the scheme declares the misalignment. As a result, the scheme adjusts the beam with the mechanical alignment and can track the UAV with stable performance. After the mechanical alignment, we can see that the spatial angle \(u, v\) become small values around 0.

We can evaluate the tracking performance in terms of MSE in Fig. 6. We have simulation results assuming the height as \(h = 8 \times R_o\), the channel variation as \(\sigma_u, \sigma_v = 0.005\),

\[
\begin{align*}
Q_p &= \begin{bmatrix}
\sigma_u^2 & 0 \\
0 & \sigma_v^2
\end{bmatrix} \\
Q_n &= \sigma_n^2 I
\end{align*}
\]
and the initial variation as \( \sigma_y = 0.00005 \). To deal with a numerical MSE upper bound, we establish the measurement noise matrix \( Q_n \) with \( \sigma_n^2 = 10^{-4} \) in the simulation. It should be noted that the exact variance of the monopulse signal may not be available, thus the exploited value of \( \sigma_n^2 = 10^{-4} \) is the relaxed assumption. It is clearly seen that the proposed scheme outperforms the codebook based beamforming scheme with lower complexity. Moreover, we can verify that our proposed system is stable over time with the obtained MSE upper bound.

VII. CONCLUSIONS

In this study, we proposed a robust beam tracking scheme with EKF for UAV-based air-network. First, we presented the limitations of conventional beam tracking studies and designed a more plausible framework to solve this problem. Simulation results showed that the proposed scheme accurately tracks the perturbation of beam direction of UAV using the monopulse signal with low complexity and estimates the error to detect beam misalignment in real-time. Moreover, we derived the numerical MSE upper bound to analyze the performance and then demonstrated that our scheme is stable over time while UAV keeps moving and outperforms conventional one.

VIII. ACKNOWLEDGE

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