Tracking Position and Orientation through Millimeter Wave Lens MIMO in 5G Systems

Arash Shahmansoori, Bernard Uguen, Member, IEEE, Giuseppe Destino, Member, IEEE, Gonzalo Seco-Granados, Senior Member, IEEE, and Henk Wymeersch, Member, IEEE

Abstract—Millimeter wave signals and large antenna arrays are considered enabling technologies for future 5G networks. Despite their benefits for achieving high data rate communications, their potential advantages for tracking of the location and rotation angle of the user terminals are not well investigated. A joint heuristic beam selection and user position and orientation tracking approach is proposed. First, the user location is tracked in the uplink by joint beam selection together with time-of-arrival (TOA) and angle-of-arrival (AOA) tracking at the base station (BS). Then, the user rotation angle is obtained using the location information by joint beam selection and tracking at the mobile station (MS). The beam selection, TOA and AOA tracking at the BS and MS are performed during the data transmission phase. Numerical results demonstrate that the proposed method performs close to the estimated position and rotation angle in the training phase with reduced complexity and reduced number of required pilots for the estimation.

Index Terms—5G networks, millimeter wave, lens arrays, position and orientation tracking, heuristic beam selection.

I. INTRODUCTION

MILLIMETER WAVE and massive multiple-input-multiple-output (MIMO) will likely be adopted technologies in fifth generation (5G) communication networks, thanks to a number of favorable properties. Particularly, by exploiting the carrier frequencies beyond 30 GHz and large available bandwidth, millimeter wave (mm-wave) can provide high data rate. This can be obtained through dense spatial multiplexing with large antennas [1], [2]. Despite the aforementioned properties that are desirable for 5G services, there are a number of challenges regarding mm-wave communications. One of the most important challenges is the severe path loss at high carrier frequencies. The loss in signal-to-noise ratio (SNR) is compensated through beamforming at the transmitter and/or receiver resulting in highly directional links [3]–[5].

Arash Shahmansoori and Bernard Uguen are with the Institute of Electronics and Telecommunications of Rennes, Université de Rennes 1, 35042 Rennes, France, emails: arash.mansoori65@gmail.com and Bernard.Uguen@univ-rennes1.fr. Gonzalo Seco-Granados is with the Department of Telecommunications and Systems Engineering, Universitat Autònoma de Barcelona, 08193 Barcelona, Spain, email: gonzalo.seco@uab.cat. Henk Wymeersch is with the Department of Electrical Engineering, Chalmers University of Technology, 412 96 Göteborg, Sweden, email: henkw@schalmers.se. Giuseppe Destino is with the center for wireless communications, University of Oulu, 90014 Oulu, Finland, and visiting fellow at King’s College London, email: giuseppe.destino@ee.oulu.fi. This work was financially supported by MSHESTIA (mmW Multi-user Massive MIMO Hybrid Equipment for Sounding, Transmissions and HW Implementation) project, the VINOVA COPPLAR project, funded under Strategic Vehicle Research and Innovation grant nr. 2015-04849, FALCON (Fundamental of simultaneous localization and communications) funded by the Academy of Finland, and R&D Projects of Spanish Ministry of Economy and Competitiveness TEC2017-89925-R. (Corresponding author: Arash Shahmansoori.)

A possible way for low-cost implementation of mm-wave MIMO is achieved by using switching circuits together with lens antenna arrays [6]–[12]. Position-based beamformer design requires the knowledge of propagation channel, e.g., user position, scatterer locations, and so on. The relative location of transmitter and receiver can be obtained using the estimated AOA/angle-of-departure (AOD) for the line-of-sight (LOS) condition [13]. To this end, position and orientation estimation was previously explored in [14]–[19] and in [17], [20], [21] for mm-wave and massive MIMO systems for static channels. To speed up initial access between nodes, a location-aided beamforming method was proposed in [22].

In the case of dynamic channels, a beam switching approach was suggested for tracking of AOA in [14]. A link by link mm-wave AOA/AOD and channel gain tracking was proposed in [23], while a tracking solution for all the links was investigated in [24]. In [25] and [26] different solutions were proposed mainly based on AOA tracking for mm-wave and Terahertz lens antenna arrays by Markov model and a temporal variation law of the physical direction, respectively. All of the aforementioned papers propose the solutions for static channels and AOA based tracking for time-varying channels. However, for tracking the user location and orientation it is essential to consider the combination of TOA and AOA.

In this letter, we propose a joint beam selection position and orientation tracking method using a lens antenna array with one BS. The proposed method tracks the channel parameters with a heuristic beam selection method based on the angular uncertainties provided by the extended Kalman filter (EKF) in the uplink followed by a downlink transmission. This enables tracking of the position and rotation angle of the user with reduced number of required beams within the observation time. From the simulation results, it is observed that the proposed algorithm provides position and rotation angle estimates during the data transmission phase with similar accuracy to those obtained during the training phase while involving a reduced complexity and number of pilot transmissions.

II. PROPOSED METHOD

In this section, a joint heuristic beam selection and tracking method is proposed for a mm-wave MIMO system with a lens antenna array. The mm-wave lens MIMO channel model in the uplink (UL) for the $n$-th subcarrier is obtained as [10], [27]

$$
\mathbf{H}_{UL}[n] = \sum_{k=0}^{K} \gamma_k(\tilde{h}_k, \tau_k) \mathbf{x}_{BS,k} \mathbf{x}_{MS,k}^T,
$$

(1)
where \( \gamma_k(h_k, \tau_k) \) is defined as \( \gamma_k = h_k e^{-2\pi n \tau_k/(NT_k)} \) in which \( \tau_k \) is the delay of the \( k \)-th path, \( K + 1 \) denotes the total number of paths of the LOS indexed by the subscript zero, \( N \) is the number of subcarriers, \( T_s = 1/B \) is the sampling period, and \( h_k = \sqrt{(N_{\text{BS}} N_{\text{MS}} \rho)} h_k \) in which \( \rho \) denotes the path loss with complex channel gain of \( h_k \). The term \( \chi_{\text{MS,k}} \) is an \( N_{\text{MS}} \times 1 \) vector denoting lens array with \( N_{\text{MS}} \) antenna elements and the entries \( \chi_{\text{MS,k}}(\phi_k - \pi \theta_{\text{OA}}^k) \) with \( \phi_k \) being the AOA in the downlink (DL) for \(- (N_{\text{MS}} - 1)/2 \leq i \leq (N_{\text{MS}} - 1)/2 \) where \( \chi_{\text{MS}}(\phi) = \sin(\pi \theta_{\text{OA}}^k) / (\sqrt{N_{\text{MS}} \sin(\pi \phi)}) \), and \( \chi_{\text{BS,k}} \) denotes an \( N_{\text{BS}} \times 1 \) lens array with \( N_{\text{BS}} \) antenna elements and defined similarly by replacing the subscript MS by BS and the downlink AOA (DL-AOA) \( \phi_k \) by AOA in the UL \( \theta_k \).

Using the information provided by the LOS path, the goal is to track the user position, \( p = q + \sigma^2 \cos(\theta_k) \theta_k \) where \( q \) denotes the location of the BS assumed to be known and \( \epsilon \) is the speed of light, and rotation angle \( \alpha = \pi - \theta_k - \theta_0 \) with reduced number of pilot transmissions. It is assumed that the BS does not move and tracks the location of the MS, and the MS tracks its rotation angle using the location information provided by the BS.

### A. Measurement and State Equations

A continuous white noise acceleration (CWNA) model defines the state evolution used for tracking DL-AOA/uplink AOA (UL-AOA), and TOA [28]. The state vector for the LOS path can be written as

\[
\psi_0^{[m]} = \left[ (\eta_0^{[m]})^T \ (\theta_0^{[m]})^T \right]^T,
\]

where \( \eta_0^{[m]} = \left[ \tau_0^{[m]} \theta_0^{[m]} \phi_0^{[m]} \right]^T \) and \( \theta_0^{[m]} = \left[ \tilde{\tau}_0^{[m]} \tilde{\phi}_0^{[m]} \tilde{\theta}_0^{[m]} \right]^T \). The terms \( \theta_0^{[m]} \) and \( \phi_0^{[m]} \) denote the UL-AOA and DL-AOA for the LOS path at the time instant \( m \), respectively. Similarly, \( \tilde{\tau}_0^{[m]} \) denotes the TOA for the LOS path. Finally, the parameters \( \tilde{\phi}_0^{[m]} \) and \( \tilde{\theta}_0^{[m]} \) denote the rate-of-change of the TOA, UL-AOA, and DL-AOA for the block duration \( T_B \), the time between two instants \( m \) and \( m + 1 \), respectively. Assuming CWNA model, the state evolution model can be written as

\[
\psi_0^{[m]} = \Phi \psi_0^{[m-1]} + u_0^{[m]},
\]

where \( u_0^{[m]} \) denotes the state noise with \( \mathbb{E}[u_0^{[m]}(u_0^{[m]})^T] = Q_{0}^{[m]} \). In general, the bi-azimuth generalized Von-Mises-Fisher (VMF) distribution for joint DL-AOA/UL-AOA or its approximation by a 2-D truncated Gaussian pdf can be applied for directional data [29], [30]. In this case, we apply the approximation with a 2-D truncated Gaussian pdf with \( \sigma_{\tilde{\theta}_0}, \sigma_{\tilde{\phi}_0}, \rho_{\tilde{\theta}_0\tilde{\phi}_0} \) denoting the direction spreads of the AOA, AO, and cross correlation for the LOS path, respectively. Moreover, the amount of noise would depend on \( T_B \). The state transition matrix \( \Phi \in \mathbb{R}^{6 \times 6} \) is defined as

\[
\Phi = \begin{bmatrix}
1 & T_B & 0 & 1 & 0 & 0 \\
0 & 1 & T_B & 0 & 1 & 0 \\
0 & 0 & 1 & T_B & 0 & 1 \\
\end{bmatrix}
\]

For \( m = 1 \), the entries of \( \psi_0^{[m-1]} \) in (3) are initialized as: \( \tau_0^{[1]} = \tilde{\tau}_0^{[0]} \), \( \phi_0^{[1]} = \tilde{\phi}_0^{[0]} \), and \( \theta_0^{[1]} = \tilde{\theta}_0^{[0]} \) where \( \tilde{\tau}_0^{[0]} \), \( \tilde{\phi}_0^{[0]} \), and \( \tilde{\theta}_0^{[0]} \) are obtained from the training phase. The rate-of-change terms are initialized by two consecutive estimates of \( \phi_0^{[1]} = \tau_0^{[1]} - \tau_0^{[0]} / T_B \); \( \phi_0^{[1]} = \phi_0^{[1]} / T_B \), and \( \phi_0^{[1]} = \phi_0^{[1]} / T_B \).

For tracking of the channel parameters, the EKF is applied with the state comprising the LOS delay, DL-AOA, UL-AOA, and their corresponding rates of changes, with the linear process model and nonlinear measurement equations in the downlink and the uplink. These parameters are initially available at the BS and the MS from the training/initial access phase [19]. The measurement equation in the uplink is obtained for the orthogonal frequency division multiplexing (OFDM) transmission as

\[
\tilde{y}_i^{[m]} = z_0^{[m]}(\tilde{\eta}_i^{[m]}; \tilde{\theta}_i^{[m]}) + \sum_{l=1}^{K} z_l^{[m]}(\tilde{\eta}_l^{[m]}; \tilde{\phi}_l^{[m]}) + \tilde{\eta}_i^{[m]},
\]

where \( \tilde{\eta}_l^{[m]} = [\tilde{\tau}_l^{[m]}, \tilde{\phi}_l^{[m]}, \tilde{\theta}_l^{[m]}] \), and \( \tilde{y}_i^{[m]} \) denotes the received signal vector of size \( N_{\text{MS}} \times 1 \) which \( M_{\text{BS}} \) is the number of received beams at the BS. In (5), the first term denotes the received signal from the LOS, and the second term denotes the superposition of all the other \( K \) non-line-of-sight (NLOS) paths acting as an added term to the Gaussian measurement noise vector \( \tilde{\eta}_i^{[m]} \) in \( \mathbb{C}^{NM_{\text{BS}}} \) with zero mean and variance \( N_{\text{BS}}/2 \) per real dimension.

The 3rd TOA-AREs are the parameters to be tracked for the block index \( m \) in the BS, and \( z_0^{[m]}(\tilde{\eta}_1^{[m]}; \tilde{\theta}_1^{[m]}) \) denotes

\[
z_0^{[m]}(\tilde{\eta}_1^{[m]}; \tilde{\theta}_1^{[m]}) = h_k^{[m]} \left( X_0^T (F_{\text{MS},0}^{-1/m-1})^T x_{\text{MS},k} \right) \otimes F_{\text{BS},0} x_{\text{BS},k}^{[m]},
\]

where \( X_0 = \left[ x^{[0]}(0), \ldots, x^{[0]}(N - 1) \right]^T \) denotes the pre-coded signal where \( x^{[0]}[n] \) is the \( M_{\text{BS}} \times 1 \) vector of simultaneously transmitted symbols for the \( m \)-th subcarrier for the LOS link. The delay vector is defined as \( a_{\text{bs}} = [1, \ldots, e^{-2\pi n (N - 1)/NTB}]^T \).

The term \( F_{\text{BS},0}^{[m]} \) denotes the uplink beam selection matrix, i.e., a matrix of zeros and ones with all-zero elements in each column except the index of the corresponding beam. The beam selection matrix \( F_{\text{BS},0}^{[m]} \) selects the corresponding beams to cover \( \phi_{0,1}^{[m]} \) with the uncertainty \( \sqrt{[P_{\phi_{0,1}^{[m-1]}]}]_{1,1} \). This angular uncertainty is obtained from the first diagonal element of the covariance estimation of \( \phi_{0,1}^{[m]} = \phi_{0,1}^{[m]} \) by the EKF. In the BS, the received beam selection matrix \( F_{\text{BS},0}^{[m]} \) is fixed and selects the corresponding beams to cover \( \theta_0 \) with the maximum uncertainty during the observation time \( T_{ob}^{[m]} \).
As in the top plot. However, this usually does not happen as the estimated channel parameters lead to power reduction without considering the uncertainty.

\[
\begin{align*}
\hat{\psi} & = \arg\min_{\psi} p[m] \left( \sum_{i=1}^{N} \left( \sin(\theta_i) - \hat{\theta}_i \right)^2 \right) \quad \text{subject to } -\pi \leq \psi \leq \pi, \\
\hat{\phi} & = \arg\min_{\phi} p[1] \left( \sum_{i=1}^{N} \left( \cos(\phi_i) - \hat{\phi}_i \right)^2 \right) \quad \text{subject to } -\pi \leq \phi \leq \pi.
\end{align*}
\]

where \( p[m] \) and \( p[1] \) denote the power of the received signal from the \( m \)-th and 1-th transmitter, respectively.

\[\eta_{ul}^{[m]} = \arg\min_{\eta} \left\| y_{ul}^{[m]} - z_{ul}^{[m]} (\eta^{[m]} ; \phi^{[m]}_{ul}) \right\|_2^2 + \left\| \eta^{[m]} - f_n (\eta^{[m-1]}_{ul}) \right\|_2^2,\]

where \( y_{ul}^{[m]} \) denotes the received signal, \( z_{ul}^{[m]} \) denotes the transmitted signal, \( \eta^{[m]} \) denotes the state vector, and \( f_n \) denotes the nonlinear function.

Algorithm 1: Heuristic Beam Selection and Position and Orientation Tracking

Input: Set \( m = 1 \), and \( T_{\text{ob}} \).

Output: Tracked position \( \hat{p}[m] \) and rotation angle \( \hat{\theta}[m] \) within \( T_{\text{ob}} \), with the corresponding uncertainties in (7) and (8), respectively.

repeat
1. Compute \( \hat{\tau}_0^{[0]} \) and \( \hat{\phi}_0^{[0]} \) in the BS, \( \hat{\phi}_0^{[m]} \) in the MS, and the corresponding values of \( \hat{p}[0] \) and \( \hat{\theta}[0] \) in the training;
2. Set the received beam selection matrix \( F_{\text{BS,0}} \) in the uplink, and \( F_{\text{MS,0}} \) in the downlink to cover \( \hat{\theta}_0^{[0]} \) and \( \hat{\phi}_0^{[0]} \), respectively, with the maximum uncertainty within \( T_{\text{ob}} \);
3. while \( m T_B \leq T_{\text{ob}} \) do
   4. Set the transmit beam selection matrix \( F_{\text{MS,0}}^{[m-1]} \) in the uplink to direct the beams towards \( \phi_0^{[m-1]} \) covering the angular uncertainty \( \sqrt{p[m-1]} \); 
   5. Compute \( \hat{\phi}_0^{[0]} \) and \( \hat{\phi}_0^{[m]} \) in the MS;
   6. Compute \( \hat{\phi}_0^{[0]} \) in the MS;
   7. Using \( \hat{p}[m] \) communicated from the BS to the MS and \( \hat{\phi}_0^{[m]} \), compute \( \hat{\theta}[m] \) in the MS;
   8. Compute \( \hat{\theta}[0] \) in the MS;
   9. Compute \( \hat{\phi}_0^{[0]} \) and \( \hat{\phi}_0^{[m]} \) in the MS;
   10. Set \( m = m + 1 \);
end
12. until the next observation time \( T_{\text{ob}} \);

6For the case of asynchronous networks, rather than considering the joint AOA-AOD tracking, the tracking is performed in the UL and DL. This way, it is possible to cancel clock bias by two-way TOA estimation.
corresponding process noise covariance. The operation \(\| \cdot \|_{M,2}\) stands for weighted vector norms, \(f_{n,0}(\cdot)\) is the dynamic function that is in the form of \(f_{n,0}([m-1]) = \tilde{f}_{n,0}([m-1]) + \text{const}\) for constant rate-of-change vector const. In step 7, the downlink beam selection matrix \(P_{BS}^{-1}\) selects the beams directed towards the previous uplink AOA, \(\hat{\phi}_{0}([m-1])\), covering the angular uncertainty \(\sqrt{\text{tr}[P_{\hat{\phi}_{0}}([m-1])]}\). In step 8, the MS tracks the AOA in the downlink in a similar way as explained in step 6. In step 9, the rotation angle is obtained using the location information that is fed back to the MS and the AOA in the downlink, and the block index is updated in step 10 until \(mT_{B} \leq T_{ob}\). Finally, the steps 2-11 are repeated for the next observation time \(T_{ob}\).

III. SIMULATION RESULTS

In this section, the performance of the proposed method for different parameters is investigated.

A. Simulation Setup and Results

We consider a scenario representative of outdoor localization based on METIS Madrid grid model [33]. We employ a ray tracing simulation tool in order to model the propagation of signals in the uplink and downlink for channel training and tracking [34]. We set \(f_{c}\) [GHz] = 60, \(B\) [MHz] = 200, \(c\) [m/ns] = 0.299792, and \(N = 40\). The number of antennas in the BS and MS are set to \(N_{BS} = 32\) and \(N_{MS} = 32\), respectively. The received SNR in the uplink/downlink is set to 10 dB. During the tracking, the MS moves with the velocity up to 50 km/h suggested for outdoor vehicular mobility [33]. The angular rates for the UL-AOA and DL-AOA are up to 0.5676 deg/\(T_{B}\) and 0.3410 deg/\(T_{B}\), respectively. The block duration and the observation time are on the order of \(T_{B}\) [ms] \(\approx\) 18 and \(T_{ob}\) [s] \(\approx\) 1, respectively. The maximum angular spreads are set to \(\sigma_{\theta_{0}}\) [deg] = \(\sigma_{\phi_{0}}\) [deg] = 20 centered around \(\hat{\theta}_{0}\) and \(\hat{\phi}_{0}\). During the tracking, the number of beams \(M_{BS}\) in the downlink and \(M_{US}\) in the uplink are set to guarantee the aforementioned maximum angular supports, e.g., \(M_{MS} = 7\) in the downlink and \(M_{BS} = 7\) in the uplink for \(N_{BS} = N_{MS} = 32\). The power of the process noise for the continuous-time state model is set to \(Q_{\theta} = \text{diag}(\sigma_{\theta_{0}}^{2}, \sigma_{\phi_{0}}^{2}, \sigma_{\phi_{0}}^{2})\), and \(Q_{\theta}^{[m]}\) is obtained by numerical discretization [36]. The value of \(\sigma_{\theta_{0}}\) is set to \(\sigma_{\theta_{0}}\) [ns] = 0.5 as it only affects the tracking of the position and does not influence the rotation angle tracking. The performance of the root-mean-square error (RMSE) was assessed from 100 Monte Carlo realizations.

Fig. 2 shows the performance of the training with refinement (i.e., \(m = 0\)) [19], and tracking algorithm (i.e., \(m > 0\)) using heuristic beam selection with respect to the power of the process noise for the aforementioned rate of changes. The components of the standard deviation of the UL-AOA and DL-AOA process noise for the continuous-time state model \(Q_{\theta}\) are set to \(\sigma_{\theta_{0}}\) [deg] = \(\sigma_{\phi_{0}}\) [deg] = \{5, 12.5\} during the

Although lower values of \(f_{c}\), e.g., 28 GHz, are commonly used in the outdoor scenarios; however, using higher values of \(f_{c}\), e.g., 60 GHz, is of great interest due to the increase in the demand of higher frequencies [35].

Fig. 2. The RMSE of the MS (top) rotation angle \(\hat{\alpha}[m]\) and (bottom) position \(\hat{\rho}[m]\) after training with refinement (block index 0) for the first 100 block indices with \(N_{MS} = N_{BS} = 32\) and SNR [dB] = 10.
REFERENCES


This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/LSP.2019.2925969, IEEE Signal Processing Letters