Performance Assessment for Distributed Broadband Radio Localization

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***Abstract*—Various emerging technologies, such as autonomous vehicles and fully autonomous flying, require precision positioning. This work presents a localization and tracking method based on joint direction of arrival (DOA), time delay, and range estimation using the SAGE algorithm. The proposed method does not rely on external sources of information such as global navigation satellite systems (GNSS). The method is opportunistic and does not require any location-based data exchange. A set of numerical simulations is presented to assess the performance of the proposed method.**

***Index Terms*—Localization, Antenna Arrays**

I. Introduction

Recent advances in technologies such as autonomous flying and driving, with promising applications such as platooning [1], have called for accurate and reliable positioning methods. Furthermore, modern wireless communication standards, such as 5G, demand precise and low latency positioning methods.

Indoor positioning has also recently become the focus of research [2]. Satellite-based positioning systems such as GPS and infrastructure based systems such as 5G positioning are not capable of providing precise positioning for users located in indoor environments. Thus, new technologies and algorithms are necessary to enable reliable and accurate indoor positioning.

Modern communication standards, such as 5G, call for the usage of multiple-input multiple-output (MIMO) systems. MIMO systems allow for better spectral efficiency, faster data rates, and more robust communication, being an integral part of such modern standards. MIMO usage for vehicular network scenarios has also been proposed [3], [4]. This work leverages the presence of multiple antennas for accurate position estimation of a radio transmitter. Furthermore, massive MIMO base station antennas with very large apertures experience spherical wave fronts at reception [5]. This work leverages this property for positioning.

This work proposes the usage of a variant of the space alternating generalized expectation maximization (SAGE) [6], [7], [8] algorithm for position estimation. The proposed approach takes advantage of radio signals transmitted by network users to estimate their relative position with respect to the receiving massive MIMO array. The proposed method does not require localization specific messages.

The remainder of this work is divided into five sections. Section II details the data model assumed for this work while section III details the proposed method. The performance of the proposed method is assessed in section V. Finally, conclusions are drawn in section VI.

II. Data Model

We assume that L wavefronts are impinging onto an uniform linear array (ULA) composed of M antenna elements. The signal is assumed to be transmitted using an orthogonal frequency-division multiplexing (OFDM) scheme composed of K subcarriers. This model takes into account the curvature of the spherical wavefront [5]. Using the Fresnel approximation, after removing the cyclic prefix and taking the discrete Fourier transform (DFT) of the received signal the space-frequency response of the k-th subcarrier received at antenna m during time snapshot t can be written as

$$x_{m,k,t} = \sum_{l=1}^{L} s_{l,k,t}\alpha_{m,l,k}\, e^{\omega_l(m-1)+\psi_l(m-1)^2}\, e^{j2\pi k\Delta_f\tau_l} + n_{m,k,t}, \tag{1}$$

where

$$\omega_l = -\frac{2\pi\Delta_m \sin(\theta_l)}{\lambda}, \tag{2}$$

and

$$\psi_l = \frac{\pi\Delta_m^2\cos^2(\theta_l)}{\lambda r_l}, \tag{3}$$

where $s_{l,k,t}$ is the symbol transmitted by the l-th source at time instant t, $\alpha_{m,l,k}$ is the complex channel gain coefficient, Δ_m is the separation between antenna elements of the array, θ_l is the DOA of the l-th signal, r_l is the range of the l-th source, λ is the wavelength of the carrier frequency, Δ_f is the frequency separation between the subcarriers of the OFDM signal, τ_l is the propagation delay of the l-th received signal, and $n_{m,k,t}$ is additive complex white Gaussian noise.

The model can be rewritten in matrix form as

$$\mathbf{Y} = \mathbf{D}(\mathbf{A} \diamond \mathbf{Z})\mathbf{S} + \mathbf{N} \in \mathbb{C}^{MK\times T}, \tag{4}$$

where $\diamond$ is the Khatri-Rao product, T is the number of signal snapshots available, $\mathbf{D}$ is a diagonal matrix containing the channel gain coefficients, $\mathbf{S} \in \mathbb{C}^{L\times T}$ contains the symbols transmitted by the L sources for all T snapshots, $\mathbf{N} \in \mathbb{C}^{MK\times T}$ is the noise matrix with its entries drawn from $\mathcal{CN}(0, \sigma_n^2)$,

$$\mathbf{A} = [\mathbf{a}(\theta_1, r_1), \mathbf{a}(\theta_2, r_2), ..., \mathbf{a}(\theta_L, r_L)] \in \mathbb{C}^{M\times L}, \tag{5}$$

$$\mathbf{Z} = [\mathbf{z}(\tau_1), \mathbf{z}(\tau_2), ..., \mathbf{z}(\tau_L)] \in \mathbb{C}^{K \times L}, \tag{6}$$

and

$$\mathbf{a}(\theta_l, r_l) = \left[1, e^{\omega_l + \psi_l}, \ldots, e^{\omega_l (M-1) + \psi_l (M-1)^2}\right]^{\mathrm{T}} \in \mathbb{C}^{M \times 1}, \tag{7}$$

$$\mathbf{z}(\tau_l) = \left[e^{j2\pi 1 \Delta_f \tau_l}, e^{j2\pi 2 \Delta_f \tau_l}, \ldots, e^{j2\pi K \Delta_f \tau_l}\right]^{\mathrm{T}} \in \mathbb{C}^{K \times 1}, \tag{8}$$

being the space and frequency steering vectors of the l-th received signal, respectively.

III. Scenario Description

In this work we assume that a receiving base station is equipped with a linear massive MIMO antenna array with a large span. This allows for the curvature of the received spherical wavefront to be measurable. The proposed approach is also applicable to the scenario where two separate arrays are present and located far enough away from each other. However, in this case, it is necessary that both arrays be synchronized in order to perform coherent reception. Figure 1 depicts an example of a massive MIMO array with two subarrays separated by a large distance. Alternatively, these arrays can be independent (separated by a larger distance) from each other as long as they can perform synchronous measurements.

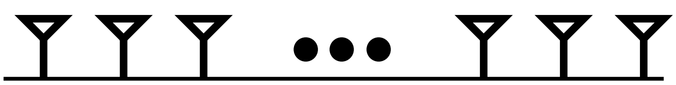

Fig. 1: Scenario description

IV. Array Processing Localization

The proposed method consists of iteratively performing individual estimations at each subarray and using the estimates of each subarray to update the SAGE estimates of the other one.

Given that the data available is the set of superimposed signals received at the antenna arrays, the expectation step can be given as

$$\hat{\mathbf{X}}_l^k = \mathbf{Y}^k - \sum_{\substack{l'=1 \\ l' \neq l}}^{L} \left(\hat{\mathbf{h}}\left(\mathbf{p}_{l'}^k\right) \hat{\mathbf{s}}_{l'}\right), \tag{9}$$

where $\mathbf{Y}^k \in \mathbb{C}^{MK \times T}$ is the received data of the k-th subarray, with $k \in [1, 2]$, following the signal model given in (4), $\hat{\mathbf{X}}_l^k$ is the estimate for the signal received from the l-th source at the k-th subarray and $\mathbf{p}$ is the parameter vector

$$\mathbf{p}_l^k = \left[\hat{\theta}_l^k, \hat{r}_l^k, \hat{\tau}_l^k\right], \tag{10}$$

where $\hat{\theta}_l^k$, $\hat{\tau}_l^k$, and $\hat{r}_l^k$ are the azimuth, delay, and range estimates for the l-th source at the k-th subarray, respectively. $\hat{\mathbf{s}}_l$ is a vector with the estimates of the symbols transmitted by the l-th source. Furthermore, $\hat{\mathbf{h}}$ is the current estimate of $\mathbf{h}$, which is defined as

$$\mathbf{h}\left(\mathbf{p}_l^k\right) = \left[\ \mathbf{a}\left(\hat{\theta}_l^k, \hat{r}_l^k\right) \otimes \mathbf{z}\left(\hat{\tau}_l^k\right)\ \right] \in \mathbb{C}^{MK \times 1}, \tag{11}$$

where $\otimes$ denotes the Kronecker product.

Following the expectation step, the maximization step transforms a D-dimensional estimation problem into D one-dimensional estimation problems by fixing all except one of the parameters during the estimation. Let the cost function d be defined as

$$d\left(\mathbf{p}_l^k, \mathbf{Y}^k\right) = ||\mathbf{h}^{\mathrm{H}}\left(\mathbf{p}_l^k\right) \mathbf{Y}^k||_2^2. \tag{12}$$

To obtain a complete estimate of $\mathbf{p}$ the algorithm will solve the D one-dimensional optimization problems

$$\hat{\theta}_l^k = \underset{\theta_l^k}{\operatorname{argmax}}\, d\left(\mathbf{p}_l^k, \hat{\mathbf{X}}_l^k\right), \tag{13}$$

$$\hat{r}_l^k = \underset{r_l^k}{\operatorname{argmax}}\, d\left(\mathbf{p}_l^k, \hat{\mathbf{X}}_l^k\right), \tag{14}$$

$$\hat{\tau}_l^k = \underset{\tau_l^k}{\operatorname{argmax}}\, d\left(\mathbf{p}_l^k, \hat{\mathbf{X}}_l^k\right). \tag{15}$$

To estimate each parameter, a different set of parameters is fixed, and a one-dimensional search is performed over the parameter that is currently being estimated. This process is iteratively performed until the estimates of all parameters of all wavefronts converge.

Once the range and DOA have been estimated for one of the subarrays, an estimate of the position of the transmitter can be obtained. Assuming that the center of a line crossing the car and both wing mirrors to be the origin of the reference coordinate system, denoted as O. It is necessary to obtain the angle ϕ_l^k, which, as shown in Figure 1, is a complementary angle to θ_l^k. Thus, the relationship between ϕ_l^k and θ_l^k is given as

$$\phi_l^k = \begin{cases} -(\frac{\pi}{2} + \hat{\theta}_l^k) & \text{if } \hat{\theta}_l^k < 0 \\ (\frac{\pi}{2} - \hat{\theta}_l^k) & \text{if } \hat{\theta}_l^k > 0 \end{cases} \tag{16}$$

With this parameter at hand and following the coordinate system shown in Figure 1, an estimate of the position of the l-th transmitter with respect to the signal received at the k-th subarray Rx_k is given by

$$x_l^k = \hat{r}_l^k \cos(\phi_l^k) + x_{\mathrm{Rx_k}} \tag{17}$$

and

$$y_l^k = \hat{r}_l^k \sin(\phi_l^k), \tag{18}$$

where x_l^k and y_l^k are the estimated coordinates for the position of the l-th transmitter and $x_{\mathrm{Rx_k}}$ is the position of the center of the k-th subarray on the X axis as illustrated in Figure 1.

A position estimated with respect to one of the subarrays can be mapped then into a DOA and range estimation to the other subarray. Thus, once the full set of the parameters from one of the subarrays has been estimated after a SAGE iteration, the position estimate extracted from such parameters can be used to update the current estimates for the remaining subarray before its next SAGE iteration. This can improve the rate of convergence for the SAGE algorithms as well as prevent the search of one of the SAGE algorithms from running into a local maximum and converging to an imprecise estimate. Figure 2 presents a block diagram illustrating the flow of the proposed method called flip-flop.

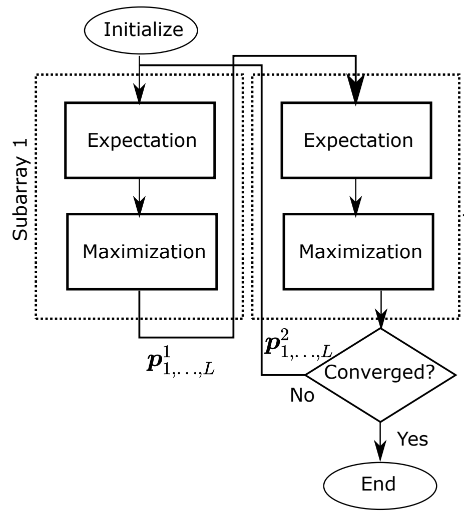

Fig. 2: Block diagram for the proposed flip-flop method

Ideally, after the SAGE algorithm has converged for both subarrays, the transmitter would be detected at the same point concerning both subarrays, that is, $\hat{x}_l^1 = \hat{x}_l^2$ and $\hat{y}_l^1 = \hat{y}_l^2$. However, due to the noise present in the antenna measurements and possible numerical errors induced during the estimation of the position of the transmitter with respect to the two subarrays, they will be different; i.e. $\hat{x}_l^1 \neq \hat{x}_l^2$ and $\hat{y}_l^1 \neq \hat{y}_l^2$. To solve this, the final estimation can be given as a function of the estimates for each of the subarrays as

$$\hat{x}_l = \frac{\gamma \hat{x}_l^1 + \nu \hat{x}_l^2}{\gamma + \nu} \tag{19}$$

and

$$\hat{y}_l = \frac{\gamma \hat{y}_l^1 + \nu \hat{y}_l^2}{\gamma + \nu}, \tag{20}$$

where γ and ν are weighting coefficients that represent how reliable are the position estimates of each subarray. These weights can be set, for instance, as a function of the received signal strength at each of the subarrays. In this case γ and ν are given by

$$\gamma = \frac{\left(\mathbf{a}(\hat{\theta}_l^1, \hat{r}_l^1) \otimes \mathbf{z}\left(\hat{\tau}_l^1\right)\right)^{\mathrm{H}} \mathbf{Y}^1 \ \mathbf{Y}^{1\ \mathrm{H}} \left(\mathbf{a}(\hat{\theta}_l^1, \hat{r}_l^1) \otimes \mathbf{z}\left(\hat{\tau}_l^1\right)\right)}{\left(\mathbf{a}(\hat{\theta}_l^1, \hat{r}_l^1) \otimes \mathbf{z}\left(\hat{\tau}_l^1\right)\right)^{\mathrm{H}} \left(\mathbf{a}(\hat{\theta}_l^1, \hat{r}_l^1) \otimes \mathbf{z}\left(\hat{\tau}_l^1\right)\right) \mathrm{tr}\left(\mathbf{Y}^1 \ \mathbf{Y}^{1\ \mathrm{H}}\right)}, \tag{21}$$

and

$$\nu = \frac{\left(\mathbf{a}(\hat{\theta}_l^2, \hat{r}_l^2) \otimes \mathbf{z}\left(\hat{\tau}_l^2\right)\right)^{\mathrm{H}} \mathbf{Y}^2 \ \mathbf{Y}^{2\ \mathrm{H}} \left(\mathbf{a}(\hat{\theta}_l^2, \hat{r}_l^2) \otimes \mathbf{z}\left(\hat{\tau}_l^2\right)\right)}{\left(\mathbf{a}(\hat{\theta}_l^2, \hat{r}_l^2) \otimes \mathbf{z}\left(\hat{\tau}_l^2\right)\right)^{\mathrm{H}} \left(\mathbf{a}(\hat{\theta}_l^2, \hat{r}_l^2) \otimes \mathbf{z}\left(\hat{\tau}_l^2\right)\right) \mathrm{tr}\left(\mathbf{Y}^2 \ \mathbf{Y}^{2\ \mathrm{H}}\right)}. \tag{22}$$

V. Simulation Results

The performance of the proposed method is assessed by a set of numerical simulations. The simulation assumes two antenna subarrays separated from each other by two meters; these are considered to be ULAs composed of $M = 8$ antennas with an inter-element spacing of $\Delta_m = \frac{\lambda}{2}$. For the simulations, this work assumes the transmitter is using the LTE standard, with the maximum fast Fourier transform size of 2048, of which 1200 are effective subcarriers and 15 kHz subcarrier spacing. We assume that $T = 100$ OFDM symbols have been received with a normal cyclic prefix. Frequency correlation is introduced following the method proposed in [9]. The signal is assumed to have a bandwidth of 20 MHz. The simulations consider 5 multipath components arriving form scatters randomly located between the transmitter and the receiving array. The root mean squared error (RMSE) is derived based on 1000 Monte Carlo runs and is calculated as

$$\mathrm{RMSE} = \sqrt{(\hat{x} - x)^2 + (\hat{y} - y)^2}. \tag{23}$$

The first set of simulations assesses the performance of the proposed methods for different SNR. For this set of simulations the distance between the receiving array and the transmitter is kept fixed at 30 m and the SNR varies from -5 to 25 dB. Figure 3 presents the performance of the proposed method. The results show that even for moderately low SNRs the proposed method is capable of accurate positioning.

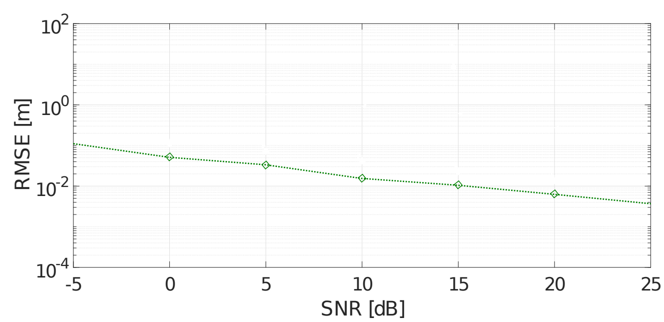

Fig. 3: Position estimation error vs SNR

The second set of simulations studies the performance of the proposed methods dependence on the distance from the transmitter. For this set of simulations, the SNR is kept fixed at 15 dB, and the distance between the receiving array and transmitter varies from 5 to 50 meters. The results in Figure 4 show that the accuracy is degraded as the distance from the transmitter increases. Despite the performance degradation, the proposed method is still capable of sub-meter performance for distances up to the 35 m from the transmitter.

The next set of simulations presented in Figure 5 studies the performance of the proposed algorithms as the number of multipath components (MPCs) increases while the K-factor is kept fixed at 3 dB. For this simulation, the SNR is kept fixed at 15 dB, and the distance from the transmitter to the receiver is fixed at 20 m. The results show that the number of MPCs has only a moderate impact on the performance of

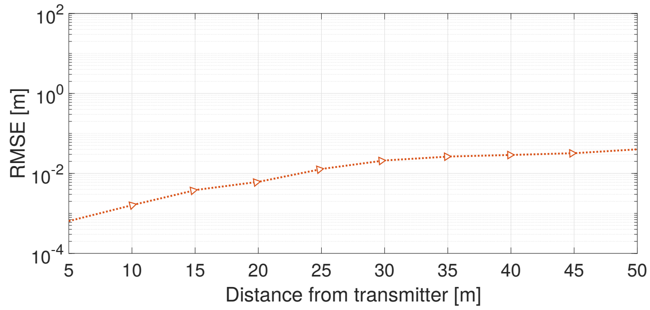

Fig. 4: Position estimation error vs distance from source

the proposed method if the K-factor is reasonable. As the number of MPCs increases, the probability of closely spaced sources increases and the probability of MPCs with similar DOAs and delays increases, leading to a possible higher spatial correlation and frequency correlation. The increased spatial correlation is especially harmful as it can make an MPC non-separable from the LOS component by SAGE. The results also show that, in the unlikely scenario where only the LOS component is present, the performance of the proposed methods is significantly improved.

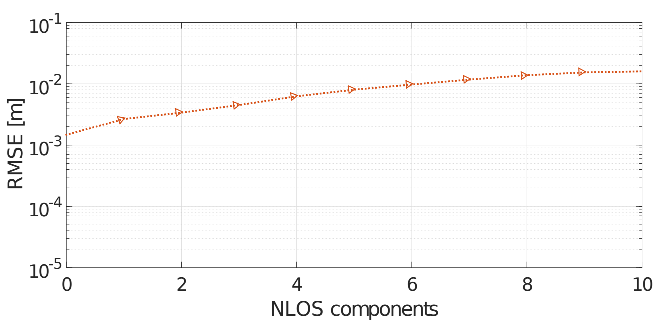

Fig. 5: Position estimation error vs number of NLOS components

Next, to assess the effect of the K-factor on the proposed methods, the number of MPCs is kept fixed at 6 and the K-factor is varied. Figure 6 shows that the performance is significantly improved in the case of high K-factors.

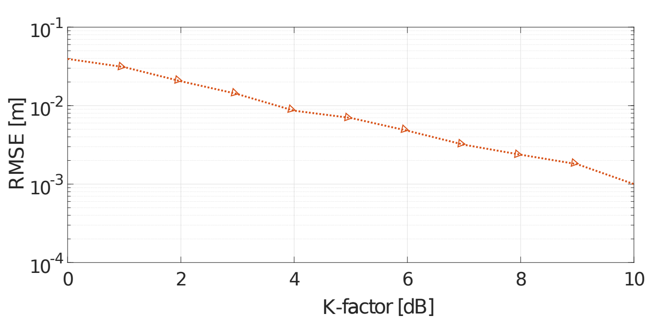

Fig. 6: Position estimation error vs K-factor

VI. Conclusion

This work presented novel methods for position estimation for vehicular network systems. The proposed methods rely on using a spherical wave model and the SAGE algorithm to provide position estimates. The presented method estimates the DOA and range of the received signals and the respective transmitter at two subarrays separately and uses the results of one array to update the problem on the remaining one. This method has fast convergence time and high accuracy.

The proposed method can be used as a stand-alone localization estimation method when MIMO systems are used at the receiving side of any wireless communication. Furthermore, it may be used for spoofing detection and mitigation, as they rely solely on estimating parameters from the physical layer. Such parameters are extremely hard to fake with hardware available today.

The proposed method can be used to complement and enable technologies such as autonomous driving or flying, allow for better indoor positioning and facilitate safer methods for instrument landing systems.

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