Gaussian-Mixture-Model Based Clutter Suppression in Perceptive Mobile Networks

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***Abstract*—Suppression of undesired non-information bearing multipaths, aka clutter, from received signals is a key process for sensing parameter estimation in the perceptive mobile network, a next generation mobile network that integrates radar sensing into communications. In this correspondence, we propose a novel clutter suppression method based on the Gaussian mixture model (GMM) and expectation maximization (EM) estimation, which can achieve fast and effective clutter estimation requiring only a small number of samples. We then apply a one-dimension (1D) compressive sensing (CS) based sensing algorithm to extract useful channel information after removing the estimated clutter. Simulation results are provided for the proposed solution and existing techniques, and validate the effectiveness of the proposed scheme.**

***Index Terms*—Joint communication and radar sensing (JCAS), dual-functional radar-communication, compressive sensing, clutter suppression, Gaussian mixture model.**

I. Introduction

IN the recently proposed *perceptive mobile networks* based on joint communication and radar sensing (JCAS) techniques [1], [2], aka, dual-functional radar-communication [3], the single transmitted signals are used for both mobile communications and sensing. In a typical environment, base-stations (BSs) receive many multipath signals that are originated from permanent or long-period static objects. These signals are useful for communications, but are generally not of the interest for sensing and are known as *clutter* in the traditional radar literature. Clutter is better to be removed before sensing in perceptive mobile networks as it can significantly increase the number of sensing parameters to be estimated and make sensing algorithms failure [4].

In traditional radar, clutter is typically returned from ground, sea, rain, and atmospheric turbulence, and generally has distinct features from useful reflections [5], [6]. Most known algorithms in radar, such as space-time adaptive processing (STAP) [5], independent component analysis (ICA) [6] and singular value decomposition (SVD) [7] are adapted to such scenarios. In contrast, in perceptive mobile networks, clutter can be from the same types of objects with the ones of interest, and from complicated propagation environment with dense multipath. Moreover, most of the existing clutter reduction techniques used in radar is applied after radar sensing and thus unable to reduce multipath from the input to the sensing process in JCAS. So, traditional clutter suppression methods for radars may not directly work here.

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Recently, a limited number of clutter suppression techniques that are closely related to modern mobile networks were reported in [4]. In [4], maximum-likelihood based amplitude estimation was proposed for clutter estimation in JCAS. The sample averaging evaluation presented in this work uses a simplistic clutter model. However, under more complicated clutter models, the clutter cancellation residual will be larger and may adversely affects both communications and radar performance. Clutter reduction in JCAS can also be based on matched filtering [4], and differential or recursive background subtraction techniques [8]. Generally, background subtraction algorithms are of three types [8], such as background subtraction implemented by averaging or filtering, fuzzy model (a form of filtering) and Gaussian mixture model. For example, the results of using filtering based differential and recursive background subtraction methods for clutter suppression in the perceptive mobile network are reported in [9] and [1], respectively. These techniques typically require a large number of samples over a long period, and cannot adapt to fast channel variation. It was shown that the sample symbols need to be sufficiently separated in time and collected over a long period, to allow sufficient discrimination of signals with different Doppler frequencies. Moreover, it is hard for these methods to extract parameters containing information of slow moving objects. Their performance also highly depends on the effectiveness of the assumption that signal phases are unchanged across packets which may not always be met in practice. Hence more reliable clutter suppression algorithms need to be developed for the perceptive mobile network.

This correspondence proposes a novel clutter estimation (CE) and suppression method, called *GMM-EM-CE*, based on the Gaussian mixture model (GMM) and expectation maximization (EM) for perceptive mobile networks. GMM has been widely used in analyzing and separating moving objects from the background in image and video analysis, target identification and classification in radar system, image processing and positioning solutions [8], [10]. The statistical learning of the GMM model with respect to the mean and variance in background subtraction is used to determine the state of each pixel whether a pixel is background or foreground. It has also been applied recently to extract static channel state information from channel measurement in [10], using estimated signal parameters. Different from GMM in the image or video analysis where background and foreground cover each other, clutter and multipath of interest in perceptive mobile networks are additive and can coexist. Therefore, placing of foreground and background into two different sets by classical clustering approaches, which is applied in image and video signal processing is not feasible in the case of GMM based clutter separation from dynamic signals in radio sensing.

Our proposed method in this correspondence can achieve faster and more accurate clutter estimation, leading to more effective sensing parameter estimation. We first propose a GMM model for modelling dynamic and clutter multipaths that are added up the received signal. We highlight the factors that differentiate the usage of GMM in radio signal processing for clutter estimation in comparison with background and foreground separation in image processing. We then propose a method for estimating clutter signals from that received signal by discovering the distinctive phenomenon of dynamic and static paths in the radio propagation channel, using the EM algorithm. Different from the work in [10], we apply GMM to complicated modern mobile signals and directly to the received signals rather than to the estimated channel parameters. For the first time, we demonstrate how to apply GMM and EM to complicated communication signals with multi-user multiple-input-multiple-output (MIMO) and orthogonal frequency division multiple access (OFDMA) modulations. We also show how to perform clutter-free radio sensing from extracted dynamic signals. Simulation results are provided for the proposed method, as well as existing clutter estimation methods based on averaging [1] and maximum likelihood estimation [4]. The comparing results between our proposed GMM-EM-CE and the existing clutter estimation methods demonstrate that GMM-EM-CE can achieve clutter estimation faster and effectively.

The rest of this correspondence is organized as follows: In section II, the problem is formulated. Section III describes the proposed *GMM-EM-CE* method and clutter-free 1D radio sensing. Section IV presents simulation results, and Section V concludes the paper.

II. Signal Models and Problem Formulation

Here we only briefly summarize the signal and channel models to make this paper self-contained. For more details, the readers are referred to [1], [2].

We consider 5G-compatible demodulation reference signals (DMRS) [11] for sensing, which are comb-type training signals at non-equally-spaced interleaved subcarriers. The values and indices of interleaved DMRS subcarriers of received signals are known to the BS when doing sensing from the received signals. Let N denote the number of total subcarriers and B be the total bandwidth. Then the subcarrier interval is $f_0 = B/N$ and OFDM symbol period is $T_s = N/B + T_p$ where T_p is the period of cyclic prefix.

Consider uniform linear antenna arrays (ULA) with M_T and M antennas at the transmitter and receiver, respectively. The array response vector a size-M ULA is

$$\mathbf{a}(M,\theta) = [1, e^{j\pi\sin(\theta)}, \cdots, e^{j\pi(M-1)\sin(\theta)}]^H, \tag{1}$$

where θ is either an angle of arrival (AoA) or angle of departure (AoD).

After removing the DMRS signals, the estimated frequency-domain channel matrix at the n-th subcarrier in the t-th OFDM block between the $k-th$ transmitter and the BS receiver is given by

$$\hat{\mathbf{H}}_{n,k,t}(f) = \mathbf{H}_{n,k,t} + \mathbf{\Delta}_{n,k,t}, \tag{2}$$

where $\mathbf{H}_{n,k,t}$ is the true channel matrix, and $\mathbf{\Delta}_{n,k,t}$ is the channel estimation error and is approximated as AWGN. The signal to interference ratio (SIR) between the mean power of the channel coefficients and AWGN is denoted by Υ.

The true channel matrix can be represented as,

$$\mathbf{H}_{n,k,t} = \sum_{\ell=1}^{L} b_{k,t,\ell} e^{-j2\pi n \tau_{k,t,\ell} f_0} e^{j2\pi t f_{D,k,t,\ell} T_s} \cdot \mathbf{a}(M,\phi_{k,t,\ell})\mathbf{a}^T(M_T,\theta_{k,t,\ell}). \tag{3}$$

where for the ℓ-th out of total L multipath signals, θ_ℓ, ϕ_ℓ, b_ℓ, τ_ℓ and $f_{D,\ell}$ are the AoD, AoA, amplitude, propagation delay, and Doppler frequency, respectively.

In this paper, we consider clutter as propagation paths with near-zero Doppler-frequencies. Relatively, we call other echoes with nonzero Doppler frequencies as dynamic multipath or multipath of interests. So, $\mathbf{H}_{n,k,t}$ of (2) written as,

$$\mathbf{H}_{n,k,t} = \mathbf{H}^{dy}_{n,k,t} + \mathbf{H}^{st}_{n,k,t}, \tag{4}$$

where $\mathbf{H}^{st}_{n,k,t}$ and $\mathbf{H}^{dy}_{n,k,t}$ refer to (static) clutter matrix and dynamic channel matrix, respectively. Both $\mathbf{H}^{st}_{n,k,t}$ and $\mathbf{H}^{dy}_{n,k,t}$ have a size of $M \times M_T$.

Note, $L = L_1 + L_2$, where L_1 is the number of paths from moving scatters with nonzero $f_{D,\ell}$ and L_2 is the number of paths from static scatters with $f_{D,\ell}$ set to be near-zero values.

Our clutter reduction method focuses on separating $\mathbf{H}^{st}_{n,k,t}$ from $\mathbf{H}_{n,k,t}$. Once the clutter $\mathbf{H}^{st}_{n,k,t}$ is estimated, it can be removed from $\mathbf{H}_{n,k,t}$ to reduce the unknown parameters to be estimated and improve the accuracy of target sensing parameter estimation.

III. Proposed GMM-EM-CE Method

Fig.1 highlights the major process in the GMM-EM-CE method. Firstly, the estimated channel matrix is obtained from the received signal and then GMM-EM is used to estimate the clutter. The clutter estimate is then subtracted from the channel estimate to obtain the dynamic channel, and one-dimension (1D) compressive sensing (CS) technique is finally applied to accomplish radio sensing.

A. Signal Modelling Using GMM

Wireless channels can be modeled and estimated by a mixture of Gaussian distributions since each density represents multipaths in the channel [12]. Static and dynamic paths can be represented by Gaussian distributions with very different parameters over the time domain. This is because over a short time period, $\mathbf{H}^{st}_{n,k,t}$ changes little and $\mathbf{H}^{dy}_{n,k,t}$ could vary significantly. It is also quite common that static paths typically have larger mean power than dynamic ones. Hence, their distributions at least have very different variance values: static paths have near-zero variances, which is much smaller than those of the dynamic ones. Therefore, by learning the mean

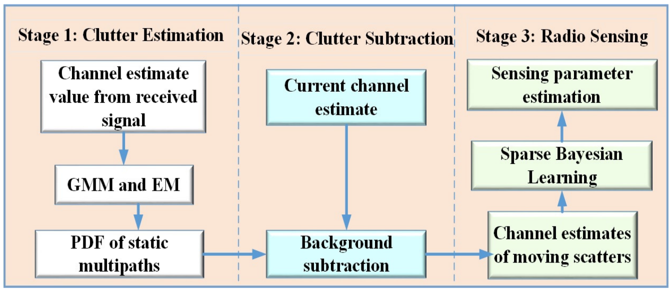

Fig. 1: Process of the proposed GMM-EM-CE method.

values of the distribution, static paths can be identified and separated via comparing the variance. GMM on the repeated prior received channel distribution of (2) for each user can provide the approximate distribution of the static multipaths with the EM principle.

We define ρ as a measure of clutter to dynamic signal ratio for all users K at the t-th OFDM block, which is given by

$$\rho = \frac{1}{NMK}\sum^{N}\sum^{M}\sum^{K}\left|\frac{\mathbf{H}^{st}_{n,k,t}}{\mathbf{H}^{dy}_{n,k,t}}\right|. \tag{5}$$

The GMM consists of L multivariate Gaussian distributions known as mixture components [10]. The probability density function (PDF) of multipath channel is obtained based on the estimated channel data, $\hat{\mathbf{H}}_{n,k,t}$ in (2). The PDF for GMM for the estimated channel is expressed as,

$$P(\mathbf{\Theta}_{t_h}) = \sum_{l=1}^{L}\omega_l.\eta(\mathbf{\Theta}_{t_h}|\mu_l,\Sigma_l). \tag{6}$$

where $\eta(\mathbf{\Theta}_{t_h}|\mu_l,\Sigma_l)$, each component of the multivariate Gaussian mixture $l = 1,..,L$ has its mean value μ_l, co-variance matrix Σ_l and non-negative mixing weight ω_l. Here the value of $\mathbf{\Theta}_{t_h}$ in (6) is taken the same as $\hat{\mathbf{H}}_{n,k,t}$ in (2) for over a time t_h and d is the dimension of $\hat{\mathbf{H}}_{n,k,t}$.

We assume moving scatters move a short distance over the period of t_h and the individual Gaussian distribution $\eta(\mathbf{\Theta}_{t_h}|\mu_l,\Sigma_l)$ is given by

$$\eta(\mathbf{\Theta}_{t_h}|\mu_l,\Sigma_l) = \frac{1}{(2\pi)^{\frac{d}{2}}\,|\Sigma_l|^{\frac{1}{2}}}e^{-\frac{1}{2}(\hat{\mathbf{H}}_{n,k,t}-\mu_l)^T\Sigma_l^{-1}(\hat{\mathbf{H}}_{n,k,t}-\mu_l)}. \tag{7}$$

B. The Expectation Maximization Algorithm

Here, we estimate ω_l,μ_l,Σ_l to maximize the log-likelihood function $\sum_{i=1}^{N_s}P((\mathbf{\Theta}_{t_h})_i)$, where $(\mathbf{\Theta}_{t_h})$ denotes the set of samples and $(\mathbf{\Theta}_{t_h})_i$ denotes its $i-th$ element. Note, N_s is the number of samples taken within the period of t_h. EM starts from some initial estimate of ω_l,μ_l,Σ_l and then proceeds to iteratively updating them until convergence is detected. The detailed operations in each EM iteration are described next.

In the *expectation* step, we estimate the probability matrix of $(\mathbf{\Theta}_{t_h})_i$ generated by the l^{th} Gaussian mixture component from dividing the weighted probabilities by the sum of weighted probabilities as

$$\Omega(i,l) = \frac{\omega_l.\eta((\mathbf{\Theta}_{t_h})_i|\mu_l,\Sigma_l)}{\sum_{j=1}^{L}\omega_j.\eta((\mathbf{\Theta}_{t_h})_i|\mu_j,\Sigma_j)}. \tag{8}$$

We take initial mean μ_l as a randomly selected data point from the set $(\mathbf{\Theta}_{t_h})$. We use the overall co-variance of the dataset $(\mathbf{\Theta}_{t_h})$ as the initial variance Σ_l and assign unit prior probability as initial mixing weight ω_l. EM algorithm is then used to derive the parameters of the GMM.

In the *maximization* step, we estimate the updated ω_l,μ_l,Σ_l. The updating equations are given by

$$\mu_l = \frac{1}{N_l}\sum_{i=1}^{N_s}\Omega(i,l)(\mathbf{\Theta}_{t_h})_i. \tag{9a}$$

$$\Sigma_l = \frac{1}{N_l}\sum_{i=1}^{N_s}\Omega(i,l)((\mathbf{\Theta}_{t_h})_i-\mu_l)((\mathbf{\Theta}_{t_h})_i-\mu_l)^T. \tag{9b}$$

$$\omega_l = \frac{N_l}{N_s}. \tag{9c}$$

where $N_l = \sum_{i=1}^{N_s}\Omega(i,l)$. The final $\{\omega_l,\mu_l,\Sigma_l\}$ are obtained when the results either converge or the maximal number of iterations N_m is reached. Then we obtain the clutter estimate as $\hat{\mathbf{H}}^{st}_{n,k,t}$ from the finalized values of $\{\omega_l,\mu_l,\Sigma_l\}$. That means, clutter estimate is actually taken as the estimate of the mean when the covariance matrix is near zero.

After subtracting the clutter estimate from the current channel estimate, we can obtain dynamic multipath signals with different non-zero Doppler frequencies. Most sensing parameter estimation algorithms can achieve better performance when the number of unknown parameters is smaller. Therefore, we can further separate multipath signals with different ranges of non-zero Doppler frequencies into different groups, enabling refined identification of different objects, such as pedestrian, slow moving vehicles and fast moving vehicles for future 5G networks and obviously in 5G/6G based vehicular solutions. This remains as one of the interesting future works.

C. Clutter Free Sensing Parameter Estimation

Now, we get the clutter-free channel estimate, $\hat{\mathbf{H}}^{dy}_{n,k,t}$, as

$$\hat{\mathbf{H}}^{dy}_{n,k,t} = \hat{\mathbf{H}}_{n,k,t} - \hat{\mathbf{H}}^{st}_{n,k,t}, \tag{10}$$

Referring to (3), we consider delay-on-grid signal model where the delays $\tau_\ell f_0$ are quantized as q_ℓ/N' with q_ℓ being an integer and $N' = gN$. Therefore $e^{-j2\pi n\tau_\ell f_0} \approx e^{-j2\pi nq_\ell/N'}$. Then, the dynamic channel matrix part of (4) can be written as,

$$\mathbf{H}^{dy}_{n,k,t} = \sum_{\ell=1}^{L_1} b_\ell e^{-j2\pi nq_\ell/N'}e^{j2\pi tf_{D,\ell}T_s}.$$
$$\mathbf{a}(M,\phi_\ell)\mathbf{a}^T(M_T,\theta_\ell) = \mathbf{A}_R\mathbf{D}\mathbf{C}_n\mathbf{A}_T^T, \tag{11}$$

where the ℓ-th column in $\mathbf{A}_R$ (or $\mathbf{A}_T$) is $\mathbf{a}(M,\phi_\ell)$ (or $\mathbf{a}(M_T,\theta_\ell)$), $\mathbf{D}$ and $\mathbf{C}_n$ are diagonal matrices with the ℓ-th diagonal element as $b_\ell e^{j2\pi tf_{D,\ell}T_s}$ and $e^{-j2\pi nq_\ell/N'}$, respectively.

By stacking similarly formulated row vectors for all usable subcarriers together, we obtain

$$\hat{\mathbf{H}}^{dy}_{n,k,t} = \mathbf{W}\underbrace{\mathbf{D}\mathbf{A}_R^T\mathbf{A}_T^T}_{\boldsymbol{G}}, \tag{12}$$

where the ℓ-th column of the $N_u \times L$ matrix $\mathbf{W}$ is $\{e^{-j2\pi nq_\ell/N'}\}$.

Now, we do sensing parameter estimation for each user using $\hat{\mathbf{H}}^{dy}_{n,k,t}$ of (12) by the same indirect method developed in [1] by extending 1D CS algorithms [13]. Here we consider only one multipath signal stays within each quantized delay bin for each user.

Treating (12) as an on-grid multi-measurement vector (MMV) CS problem, we can get the estimate for $\boldsymbol{G}$. Once the delays and $\boldsymbol{G}$ are estimated, we get the AoA estimates through calculating the cross-correlation between columns from $\boldsymbol{G}$ on the indexes obtained from a given threshold as below,

$$\hat{\phi}_\ell \approx \frac{1}{\pi}\angle(\underbrace{\sum_{p=1}^{M-1}((\boldsymbol{G})_{\cdot,p})^*(\boldsymbol{G})_{\cdot,p+1}}_{\varepsilon_\ell}), \tag{13}$$

where $(\boldsymbol{G})_{\cdot,p}$ denote the p-th column of $\boldsymbol{G}$.

The value of $|b_\ell|^2$ can also be obtained easily during the process of computing AoA, being $|\varepsilon_\ell|^2$. The estimates of $|b_\ell|^2$ can be used to find the effective multipath delay bins in noisy channels from the MMV CS estimation output by using a threshold of $\gamma \cdot \max(\mathrm{abs}(\varepsilon_\ell))$ determined, e.g., as a fractional scalar of the maximum power of multipath signals.

IV. Simulation Results

We consider a system with 4 SDMA users, each with a single antenna, and a BS with a 4 antenna uniform linear array. The signal bandwidth is assumed to be 100 MHz and the carrier frequency is 2.35 GHz. Propagation channels are generated based on clustered channel models following a complex Gaussian distribution. In each cluster, multipath signals for each RRU/MS are generated randomly by mimicking reflected/scattered signals from objects, similar to those in [1], [2]. The total number of channel paths in each cluster is generated following a uniform distribution over $[5, 10]$. Random continuous values are generated within given ranges for AoAs, AoDs, Doppler shift, delay, and amplitude. We use a pathloss model with pathloss factor 40 for downlink and 20 for uplink sensing. As in [1], the transmission power of the RRU and MS is 30 dBm and 25 dBm respectively. The total thermal noise in the receiver is $-174 + 10\log(10^8) = -94$ dBm.

The noise is assumed to be AWGN with variance determined from the product of the basic thermal noise power spectrum density and the bandwidth. While the transmission power is fixed, the multipath signals reflected from objects at different distances to the transceiver will lead to different SIRs for estimating the sensing parameters. For the simulated sensing range, the received SIR range could be from 0 dB to 30 dB, due to the pathloss factor of 40 and 20 for downlink and uplink sensing, respectively.

A. Performance Evaluation of GMM-EM-CE

GMM-EM is applied to obtain the clutter channel estimation, $\hat{\mathbf{H}}^{dy}_{n,k.t}$. Then we calculate root mean square error (RMSE) of clutter estimation as

$$RMSE = \sqrt{\frac{1}{(\Psi * NMK)}\sum_{j=1}^{\Psi}\left|\hat{\mathbf{H}}^{st}_{n,k,t} - \mathbf{H}^{st}_{n,k,t}\right|^2}. \tag{14}$$

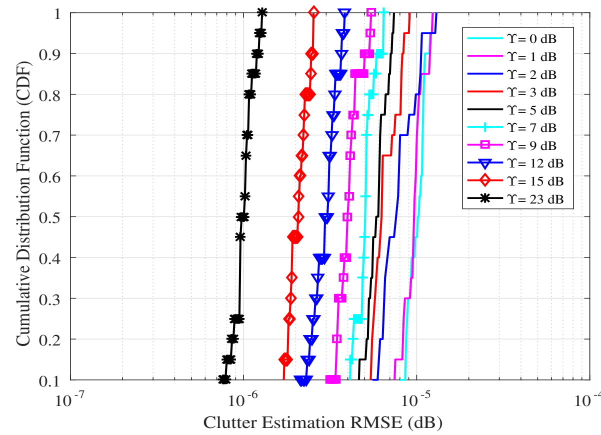

Fig. 2: CDF of RMSE at different Υ values.

We take histogram-based PDF from the correct window of 40 bins while $\Psi = 20$. Then, interpolated cumulative distribution functions (CDF) are derived from the PDFs of RMSE to present clutter estimation results.

Fig. 2 provides CDF results for RMSE of clutter estimation obtained at different values of SIR, Υ with $N_m = 10$. The figure shows that the RMSE is quite small at a high probability and it also decreases with Υ increases.

B. Comparison of GMM-EM-CE with Recursive Averaging and Maximum Likelihood Amplitude Estimation

Next we compare GMM-EM-CE with the simple recursive moving average (RMA) method [1] and maximum likelihood amplitude estimation (MLAE) method [4]. RMA estimates the clutter via averaging over channels at different measurements using a forgetting factor. The RMA is applied to the channel coefficient at each subcarrier for each user. From the refined channel matrix estimates, we pick up estimates at an interval of T_h seconds, and denote them as, $\cdots, \mathbf{H}(i-1), \mathbf{H}(i), \mathbf{H}(i+1), \cdots$, where the expression of $\mathbf{H}(i)$ is similar to $\hat{\mathbf{H}}_{n,k,t}$ of (2), but $\mathbf{H}(i_1)$ and $\mathbf{H}(i_2)$, $i_1 \neq i_2$ may have different sensing parameters. We use the following recursive equation with learning rate α for estimating the clutter matrix $\bar{\mathbf{H}}$,

$$\bar{\mathbf{H}}(i) = \alpha\bar{\mathbf{H}}(i-1) + (1-\alpha)\mathbf{H}(i), \tag{15}$$

where the initial one $\bar{\mathbf{H}}(1)$ can be either 0 or computed as the average of several initial $\mathbf{H}(i)$s after r recursions. For MLAE, we introduce it to (2) in the way similarly to that being implemented in [4], since the clutter is static over a certain period.

Fig. 3 provides clutter estimation RMSE results vs Υ values obtained at high and low ranges of ρ for GMM-EM-CE, RMA and MLAE. The RMSE of clutter estimation with GMM-EM-CE is obtained at $N_m = 10$. We perform MLAE over $r = 10$ realizations of $\hat{\mathbf{H}}_{n,k,t}$ to get the RMSE of clutter estimation. Whereas, the RMSE of RMA is obtained with the forgetting factor of 0.95 over both $r = 10$ and 150 iterations. For both cases of $\rho = 1$ and 100, the GMM-EM-CE method with $N_m = 10$ outperforms MLAE with $r = 10$ and RMA with both $r = 10$ and 150 iterations, achieving significant lower

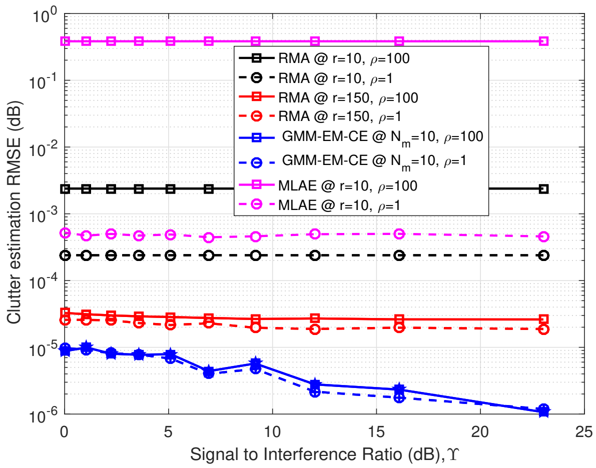

Fig. 3: Clutter estimation RMSE vs Υ at high and low values of ρ for the GMM-EM-CE, RMA and MLAE method.

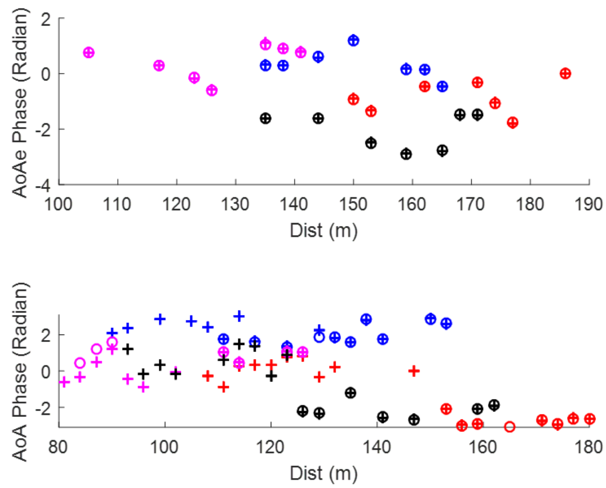

Fig. 4: Uplink sensing at $\gamma = 0.25$, $\Upsilon = 12\ dB$, $\rho = 1$, after clutter suppression by (top) GMM-EM-CE with $N_m = 10$ at $t_h = 30\ ms$ and by (bottom) RMA with $r = 10$. The estimated values for AoA are shown in star and the actual AoAs are shown in circle. Different colours correspond to different users.

RMSE for clutter estimation. Noticeably the impact of noise is predominant with the RMA and MLAE, causing hardly varying RMSE with the SIR compared to GMM-EM-CE.

C. Radio Sensing Results after Clutter Reduction

Fig. 4 demonstrates the results of AoA estimation in the uplink sensing, for the cases with (in the top plot) GMM-EM-CE and with (in the bottom plot) RMA. A total of $N_u = 128$ interleaved subcarriers are used. The estimates with clutter reduction by GMM-EM-CE with $N_m = 10$ are shown to be much more accurate compared to those by RMA with the same 10 iterations. Moreover, different from the bottom plot, the top plot results show no presence of residual clutter in AoA estimation. Note that, with the increment of iterations r and simulation complexity, the RMA method can also provide more accurate AoA estimation with complete clutter removal as shown in [1]. Hence, GMM-EM-CE indicates its usefulness by providing more accurate results at much lower complexity and iterations in comparison with the RMA method.

V. Conclusion

We presented a Gaussian mixture model based clutter estimation method for joint communication and sensing, and provided 1D compressive sensing based cluster channel parameter estimator based on estimated dynamic channels. For the first time, we utilized the GMM approach in clutter suppression for achieving effective sensing applications in modern mobile communication systems. We presented the GMM modeling for complicated communication signals, proposed the EM method for clutter estimation, and 1D compressive sensing for sensing parameter estimation. Simulation results demonstrate that our proposed method can achieve fast and effective clutter estimation, leading to accurate sensing parameter estimation. The proposed techniques can also be applied to (MIMO)-OFDM radar systems. Our scheme can be further improved by incorporating more accurate statistical information of the multipath signals into the GMM model, and by developing lower-complexity algorithms than EM for clutter estimation.

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