Physical Communication 26 (2018) 170–174

Contents lists available at ScienceDirect

Physical Communication

journal homepage: www.elsevier.com/locate/phycom

Full length article

FOMP algorithm for Direction of Arrival estimation

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ARTICLE INFO

Article history:
Received 14 September 2017
Received in revised form 5 December 2017
Accepted 19 December 2017
Available online 24 December 2017

Keywords:
Direction of Arrival
Focused Orthogonal Matching Pursuit
Adaptive antennas
Array processing

ABSTRACT

Adaptive antennas and antenna array processing are much significant issues for improving the performance of wireless communication systems. One of the most important applications of adaptive antenna systems is the Direction of Arrival (DOA) estimation. Recently, compressive sensing algorithms, including convex relaxation methods and greedy algorithms, have been recognized as a type of novel DOA estimation methods. The Orthogonal Matching Pursuit (OMP) is an example of compressive sensing methods. Using the OMP method for DOA estimation has many advantages in comparison to other algorithms. In spite of these advantages, the DOA estimation by OMP algorithm has a substantial challenge. The OMP algorithm cannot distinguish between two adjacent signal sources. In the DOA estimation by OMP algorithm, when there are two adjacent sources, the mutual coherent condition of the compressive sensing methods is violated. The situation gets worse when there are two sources from two adjacent DOAs. In this situation, the beam former has a single peak. In this paper, we propose the Focused Orthogonal Matching Pursuit (FOMP) algorithm for estimation of DOA. The FOMP algorithm is an improved version of the OMP algorithm. It can detect two signal sources exactly when they are very close and beam former has a single peak corresponding to a direction between right directions. Simulation results demonstrate the advantages of the proposed scheme. It can be observed the FOMP algorithm could detect very close signal sources with a negligible error.

1. Introduction

Recently, adaptive antennas and array processing have much significant effects to the efficiency of communication systems. In this paper, we peruse Direction of Arrival (DOA) estimation which is one of the most significant issues of adaptive antenna systems. The DOA estimation plays an important role in wireless communication systems [1], radar [2], sonar [3], medical diagnosis and treatment, radio astrology, electronic surveillance, seismic systems and other areas. Over the last several decades, DOA estimation has received a remarkable amount of attention due to its widespread applications and difficulty of designing an optimum estimator.

Several algorithms have been proposed for estimation DOA which can be classified into different categories. The beam scan algorithms form a conventional beam which scans an appropriate region and analyzes the magnitude of the output. MVDR [4], Root-MVDR [5] are two examples of this class of algorithms. Moreover, the data adaptive algorithms such as APES (Amplitude and Phase Estimation) [6] have been proposed.

Subspace algorithms exploit the orthogonality between the signal and noise subspaces. The key problem of eigen-subspace methods is the estimation of signal and noise subspaces, and then the parameters can be obtained by using the orthogonality of these subspaces. The subspace algorithms such as MUSIC [7], Root-MUSIC [8] and ESPRIT [9] are among the most efficient methods for estimation of direction of arrival. As a challenge for subspace algorithms, the strong correlation of the signals leads to serious performance degradation in these methods.

The maximum likelihood schemes such as the stochastic maximum likelihood and deterministic maximum likelihood methods are another category of DOA estimation methods [10]. Some statistical properties of the data, e.g., a covariance matrix are used by the methods of this category. Besides, there are some schemes without the need of obtaining the covariance matrix. They exploit learning techniques to derive the statistical properties, e.g., Support Vector Machines (SVM) [11] and Neural Networks (NN) [12]. For these methods, a sufficiently large number of snapshots are required to obtain the statistical properties.

Recently, compressive sensing methods have been introduced as a type of novel high resolution DOA estimation algorithms. They work based on the sparse property of the spatial spectrum when there are only a limited number of point sources [13]. Compressive sensing algorithms are still effective, even when there is only one snapshot. This property is totally different from the conventional DOA estimation algorithms. The existing references have shown

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https://doi.org/10.1016/j.phycom.2017.12.012
1874-4907/

the advantages of this type of methods from diverse viewpoints, e.g., Bayesian statistics [14] and convex optimization [15]. These algorithms are especially significant in the high-dynamic environments. In these situations, it is difficult to obtain sufficient snapshots. The representative compressive sensing algorithms contains the convex relaxation algorithms [16,17] and the greedy algorithms [18–20]. In comparison with the convex relaxation algorithms, the greedy algorithms are more computationally efficient; however, they suffer little performance degradation. Many works in the literature have already proven that the measurement matrix has to meet the incoherence condition [19]. In the DOA estimation problem, the columns of the measurement matrix are steering vectors according to different DOAs. All of the compressive sensing algorithms for DOA estimation should satisfy the incoherence condition [19]. Thus, almost all of these algorithms fail when the maximum pairwise coherence of the measurement matrix exceeds a constant value.

The DOA estimation problem by the compressive sensing algorithms can be described as a sparse representation problem over a redundant dictionary since the spatial spectrum is sparse when there are a small number of signal sources in far-field space. Thus, the aim of DOA algorithms is the sparsest representation of the received signal by exploiting a redundant dictionary involving steering vectors of DOAs. The sparse signal representation problem over a redundant dictionary is a Non-deterministic Polynomial-time hard (NP-hard) problem [18]. Several greedy algorithms have been offered for solving this problem such as Basis Selection (BS) algorithms. The Matching Pursuit (MP) [18], Orthogonal Matching Pursuit (OMP) [19] and Compressive Sampling Matching Pursuit (CSMP) [20] are examples of BS algorithms.

The BS algorithms are methods of selection of basis for signal decomposition by determining the smallest subset of vectors selected from a large redundant set of vectors to match the given data. This problem has diverse applications such as speech coding [21], time–frequency representations [18] and spectral estimation [22]. For the case of DOA, the set of vectors are modeled as possible outputs of the antenna array elements corresponding to different steering vectors. Hence, the problem of choosing correct linear combination of these vectors is equivalent to the problem of selecting correct direction of arrival.

Applying BS algorithms to a DOA problem enhances resolution and decreases complexity. Moreover, the knowledge of the number of signal sources is not required to know in these algorithms. In addition, they do not need any post-processing to converge to the ML solution since the output of these algorithms is straightly the DOAs. ML algorithm compares all feasible directions and then selects the most likely one. On the other hand, BS algorithms compare some of the angles and select them in a smart method. Hence, BS algorithms are much more computationally efficient in comparison to other algorithms of DOA estimation such as MUSIC and ESPRIT to approach to the ML solution. Moreover, BS algorithms converge to the ML solution when the value of SNR is low, whereas other approaches converge at high SNRs only. In addition, in other methods for DOA estimation, the number of estimated DOAs is limited by the number of antennas. The BS based DOA estimation methods can estimate more DOAs than the antennas number. Among BS methods, OMP algorithm provides slightly higher performance than MP algorithm with moderately higher computational complexity.

In spite of these advantages, the DOA estimation by OMP algorithm has an important challenge owning to the coherence condition [23]. It cannot resolve very close sources. Thus, it finds only a single direction for the composite signal. Hence, in this paper, we propose Focused Orthogonal Matching Pursuit (FOMP) algorithm as a solution to improve DOAs estimation. In this method, OMP algorithm is firstly used to obtain the initial estimated DOAs and then FOMP algorithm focuses around the initial estimations. Therefore, the main contributions of this paper can be summarized as follows:

- We propose FOMP algorithm which is an improved version of OMP algorithm which can distinguish between very close DOAs.
- We investigate on the capability of FOMP algorithm for distinguishing between adjacent DOAs by simulation results in diverse scenarios. Moreover, we analyze the effect of the interferences among different sources on the performance of FOMP algorithm.
- We compare the performance of FOMP algorithm with OMP and MUSIC algorithms for different values of SNR.

This paper is organized as follows. First, we present the system model in Section 2. Then, in Section 3, we discuss why OMP algorithm cannot distinguish between very close DOAs. Next, we propose FOMP algorithm in Section 4. Then, simulation results are presented in Section 5. Finally, we conclude this paper in Section 6.

2. System model

The baseband received signals for an antenna array by M elements are described as

$$x(t) = \left[s(t-\tau_1)e^{jw_c\tau_1}, \dots, s(t-\tau_M)e^{jw_c\tau_M}\right]^T. \tag{1}$$

The propagation delays are specified by the angle between the signal source direction and the antenna array. In a linear array, propagation delays can be written as

$$\tau_m = \tau_0 - \frac{d_m}{c}\sin\theta, \tag{2}$$

where τ_0 is the propagation delay between the signal source and a reference point on the antenna array, d_m is the distance of mth element of the array from the mentioned reference point, θ is the measured angle between the source direction and the line perpendicular to the array and c is the light velocity. Fig. 1 shows the structure of antenna array. Without loss of generality, we consider $\tau_0 = 0$. Therefore, in the rest of paper we assume

$$\tau_m = -\frac{d_m}{c}\sin\theta. \tag{3}$$

We consider D is the aperture of the array for wavelength λ and $D\frac{\lambda}{c} = \frac{D}{f_c}$ is the propagation time over the array, so that $\tau_m < \frac{D}{f_c}$. When bandwidth of the signal is B and $B \ll \frac{f_c}{D}$, thus we have $s(t-\tau_m) \approx s(t)$. This condition implies that $s(t)$ is narrowband. Hence, the received signal is described as

$$x(t) = s(t)\left[e^{jw_c\tau_1}, \dots, e^{jw_c\tau_M}\right]^T. \tag{4}$$

We define $a(\theta)$, the array response to a unit amplitude signal, i.e., $s(t) = 1$ as

$$a(\theta) = \left[\exp\left\{\frac{j2\pi d_1}{\lambda}\sin\theta\right\}, \dots, \exp\left\{\frac{j2\pi d_M}{\lambda}\sin\theta\right\}\right]^T. \tag{5}$$

Next, for achieving a comprehensive model for the narrowband received signal, we consider $s(t)$ is a unit power signal. Thus, we can write

$$y(t) = \sqrt{\mathrm{SNR}}\, s(t)a(\theta_0) + v(t), \tag{6}$$

where $v(t)$ is the noise vector that it contains independent Gaussian random variables with zero mean and unit-variance.

3. Challenge of OMP algorithm for direction of arrival

Basis Selection (BS) algorithms are described over $\mathbb{C}$ as follows. In these algorithms, we consider $Q = \{q_k\}_{k=1}^{M}$ is a highly redundant dictionary of vectors (i.e. $q_k \in \mathbb{C}^N$ and $N \ll M$ where $\mathbb{C}^N = \mathrm{Span}\,(Q)$).

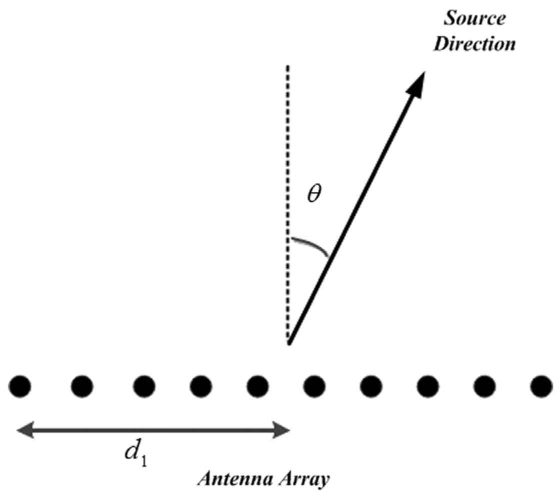

Fig. 1. The structure of antenna array when number of antennas is 10.

BS algorithms are described as obtaining the sparsest solution for a linear system of equations. More exactly, when we consider a matrix B which is composed from the columns of dictionary Q, $B = [b_1, b_2, \ldots, b_M]$, BS algorithms are expressed as obtaining an $\bar{x}$ that satisfies

$$\|B\bar{x} - x\| \leq \varepsilon, \tag{7}$$

with at most h non-zero entries such that for $\varepsilon \geq 0$ and $h > 1$. For the perfect representation case, i.e., $\varepsilon = 0$, BS algorithms decrease to solve the system $B\bar{x} = x$. Obtaining the sparsest solution for (7) in an over complete dictionary via exploiting an exhaustive search is impossible. Thus, suboptimal algorithms based on parallel and sequential basis selection are proposed to solve this problem. The sequential BS algorithms are more practical owing to high complexity of the parallel BS methods. OMP algorithm is one of the sequential BS algorithms.

The main idea of the DOA estimation by OMP algorithm is to derive DOAs via finding the maximum correlation between the residual and the steering vectors of different DOAs which are not included in the estimated DOA set. Besides, the residual is recomputed by subtracting the contributions of the estimated sources. In DOA estimation by OMP algorithm, a processing which is called delay-and-sum beam forming is used [24]. The beam forming is implemented by exploiting appropriate phase shifts. In the expression in (6), the received signal is represented by the array manifold, i.e., $a(\theta)$. In beam forming, combining the signals in phase is done by using the complex conjugate of the array manifold. Hence, we derive

$$F(\theta) = \left|a(\theta)^H a(\theta_0)\right|. \tag{8}$$

When the selected angle θ is equivalent to the real source direction, the largest value of $F(\theta)$ is achievable as

$$F(\theta_0) = \left|a(\theta_0)^H a(\theta_0)\right| = M. \tag{9}$$

On the other hand, if $\theta \neq \theta_0$, the signals are not added in phase and $F(\theta) < M$. Hence, in OMP algorithm for direction of arrival estimation, first $P(\theta)$ is calculated as

$$P(\theta) = \left|W(\theta)^H y\right|^2, \tag{10}$$

where

$$W(\theta) = \frac{a(\theta)}{|a(\theta)|}. \tag{11}$$

Finally, peak-picking process is performed by exploiting OMP algorithm to estimate the DOA [19]. We assume the signal model

$$y(t) = \alpha_0 a(\theta_0) + v(t), \tag{12}$$

that $y(t)$ is the output signals vector, α_0 is a complex scale factor which is assumed unknown ($\alpha_0 = \sqrt{\text{SNR}}\, s(t)$ in (6)), $a(\theta)$ is the array manifold, θ_0 is the unknown source angle, and $v(t)$ is the noise vector that it contains independent Gaussian random variables with zero mean and unit-variance. The ML estimation is derived via joint minimization of the following error over the unknowns θ_0 and α_0.

$$e(\theta_0) = |y - \alpha_0 a(\theta_0)|^2. \tag{13}$$

By minimizing first over α_0, we obtain

$$\alpha_0 = \frac{a^H(\theta_0)y}{a^H(\theta_0)a(\theta_0)}. \tag{14}$$

By inserting α_0 into (13), we obtain

$$e(\theta_0) = \left|y - \frac{a^H(\theta_0)y}{a^H(\theta_0)a(\theta_0)}\right|^2. \tag{15}$$

Minimizing $e(\theta_0)$ with respect to θ_0 is equivalent to maximizing

$$y^H \frac{a(\theta_0)a^H(\theta_0)y}{|a(\theta_0)|^2}, \tag{16}$$

and it can be written as $P(\theta) = \left|W^H(\theta_0)y\right|^2$. Thus, the estimation DOA which is obtained via beam forming analysis by maximizing $P(\theta)$ is equivalent to the generalized likelihood direction estimation.

In the practical scenarios, there are multiple co-channel signals which arrive from diverse sources or from a sole source via multiple traveling paths. Multiple co-channel signals, especially when their directions are close together, decrease the accuracy of the direction estimation schemes. According to the literature about DAS algorithm [23], the estimated DOA resolution of DAS algorithm depends on the Rayleigh limit. This means where the DOAs difference is less than Rayleigh limit, DAS algorithm cannot distinguish between two sources. In this situation, due to the strong correlation between the steering vectors of two DOAs, DAS algorithm find a single peak between two real DOAs. Hence, the two sources are recognized as only one source. Based on the same reason, OMP algorithm detect one DOA locating between two real DOAs. Therefore, the estimated directions which are derived by OMP method become biased.

It can be concluded by experimental results that OMP method can detect DOAs which are separated by more than a beam width. For analyzing this conclusion, we assume the scenario that two signals arrive the array from directions θ_0 and θ_1. The received signal is

$$y(t) = \sqrt{\text{SNR}_0} S_0(t) a(\theta_0) + \sqrt{\text{SNR}_1} S_1(t) a(\theta_1) + v(t), \tag{17}$$

where SNR_0 and SNR_1 are the signal to noise ratios of the sources locating at θ_0 and θ_1, respectively. The expected value of $P(\theta)$ can be derived as

$$E\{P(\theta)\} = \text{SNR}_0 \left|W(\theta)^H a(\theta_0)\right|^2 + \text{SNR}_1 \left|W(\theta)^H a(\theta_1)\right|^2 + 2\rho_{01}\sqrt{\text{SNR}_0}\sqrt{\text{SNR}_1}\,\text{Re}\{W(\theta)^H a(\theta_0)(W(\theta)a(\theta_1))^*\} + 1, \tag{18}$$

where $\rho_{01} = E\{s_0 {s_1}^*\}$, $E\left\{|s_0|^2\right\} = E\left\{|s_1|^2\right\} = 1$ and $Re\{.\}$ denotes the real part. Two signals can be assumed uncorrelated when they originate from two different sources or when they emanate from a single source and motion-induced Doppler is present. In

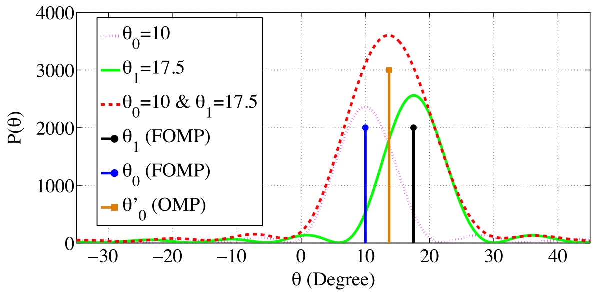

Fig. 2. The DOA estimation for OMP and FOMP algorithms when two signal sources are $BW/2 = 7.5°$ apart. In this scenario, we assume $\mathrm{SNR}_0 = 10$ dB and $\mathrm{SNR}_1 = 10$ dB.

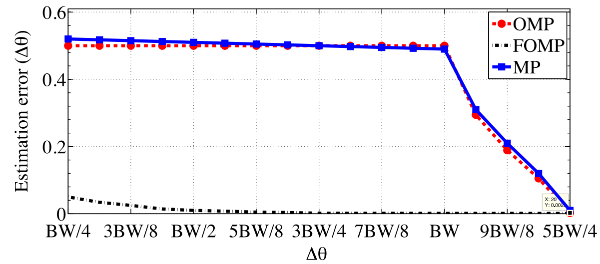

Fig. 3. The DOA estimation error as a proportion of $\Delta\theta$ for OMP, MP and FOMP algorithms versus different values of direction distances between sources ($\Delta\theta$).

our scenario, we assume two signals are uncorrelated. Thus, since $\rho_{01} = 0$, we have

$$E\{P(\theta)\} = \mathrm{SNR}_0 \left|W(\theta)^H a(\theta_0)\right|^2 + \mathrm{SNR}_1 \left|W(\theta)^H a(\theta_1)\right|^2 + 1. \tag{19}$$

Fig. 2 shows $P(\theta)$ when the beam width of the array is 15° since the 3 dB beam width of the array is defined as the difference between the lower and upper half-power points. We assume the signal directions are a half-beam width apart. It can be observed the beam forming analysis cannot distinguish between two signal sources, and thus, $P(\theta)$ has a sole peak corresponding to the composite signal. Hence, in OMP algorithm the peak location which is between θ_0 and θ_1, provides a biased estimation $\theta_0{}'$.

4. Focused Orthogonal Matching Pursuit

As stated before, theoretical results show that the mutual coherence limits the success of OMP algorithm. When there are two sources from two adjacent DOAs, the situation becomes worse. Then, OMP algorithm cannot distinguish between two sources. Therefore, in this section, we propose FOMP algorithm which can distinguish between two very close sources. In this method, OMP algorithm is firstly used to obtain the initial estimated DOAs; then, this process is utilized to improve DOAs estimation accuracy by minimizing the residual. We describe FOMP algorithm by 9 steps in the following.

- **Step 1:** We define a dictionary as $Q = \{P_n(\theta|\theta_k)\}_{\frac{-\pi}{2} \le \theta_k \le \frac{\pi}{2}}$ that each element of dictionary is defined as normalized $P(\theta|\theta_k)$.

$$P_n(\theta|\theta_k) = \frac{P(\theta|\theta_k)}{\sqrt{\frac{1}{\pi}\int_{\frac{-\pi}{2}}^{\frac{\pi}{2}} |P(\theta|\theta_k)|^2 d\theta}}. \tag{20}$$

- **Step 2:** Initialization:

$$e_0(\theta) = P(\theta), \quad i = 1. \tag{21}$$

- **Step 3:** Calculate the residual for all θ_k

$$e_i(\theta|\theta_k) = e_{i-1}(\theta) - a_{i-1}(\theta_k)P_n(\theta|\theta_k), \tag{22}$$

where $a_{i-1}(\theta_k)$ is the inner product of $e_{i-1}(\theta)$ and $P_n(\theta|\theta_k)$.

- **Step 4:** Select θ_i

$$\hat{\theta}_i = \arg\min_{\theta_k} \left(\sum |e_i(\theta|\theta_k)|^2\right). \tag{23}$$

- **Step 5:** Calculate the residual for all θ_{k1} and θ_{k2}

$$e_i{}'(\theta|\theta_{k1}, \theta_{k2}) = e_{i-1}(\theta) - a_{i-1}(\theta_{k1})P_n(\theta|\theta_{k1}) - a_{i-1}(\theta_{k2})P_n(\theta|\theta_{k2}),$$

where $\hat{\theta}_i - \frac{BW}{2} \le \theta_{k1}, \theta_{k2} \le \hat{\theta}_i + \frac{BW}{2}$ and BW is the beam width.

- **Step 6:** Select θ_{i1} and θ_{i2}

$$\left(\hat{\theta}_{i1}, \hat{\theta}_{i2}\right) = \arg\min_{\theta_{k1},\theta_{k2}} \left(\sum \left|e_i{}'(\theta|\theta_{k1}, \theta_{k2})\right|^2\right). \tag{24}$$

- **Step 7:** If $e_i{}'(\theta|\hat{\theta}_{i1}, \hat{\theta}_{i2}) \le e_i(\theta|\hat{\theta}_i)$ then $\hat{\theta}_i = \hat{\theta}_{i1}, \hat{\theta}_{i+1} = \hat{\theta}_{i2}$, $i = i + 2$ and

$$e_i(\theta) = e_{i-2}(\theta) - a_{i-2}(\hat{\theta}_{i1})P_n(\theta|\hat{\theta}_{i1}) - a_{i-2}(\hat{\theta}_{i2})P_n(\theta|\hat{\theta}_{i2}).$$

- **Step 8:** If $e_i{}'(\theta|\hat{\theta}_{i1}, \hat{\theta}_{i2}) > e_i(\theta|\hat{\theta}_i)$ then $\hat{\theta}_i = \hat{\theta}_i$, $i = i + 1$ and

$$e_i(\theta) = e_{i-1}(\theta) - a_{i-1}(\hat{\theta}_i)P_n(\theta|\hat{\theta}_i). \tag{25}$$

- **Step 9:** If

$$\frac{\int e_0{}^2(\theta)d\theta}{\int e_i{}^2(\theta)d\theta} < \delta, \tag{26}$$

return to Step 3, or else end the algorithm. In the expression in (26), δ is the stopping criterion.

5. Simulation results

In this section, we evaluate the performance of FOMP scheme for DOA estimation. First, we consider the scenario that there are a pair of very close sources in our simulation environment. We consider the receiver has an array antenna with 10 elements. We assume SNR = 10 dB in the input of all antenna elements. Moreover, we consider two signal sources in $\theta_0 = 10°$ and $\theta_1 = 17.5°$. We set $\delta = 0.01$ in OMP and FOMP algorithms. Fig. 2 shows the detected DOAs by OMP and FOMP algorithms. It shows that FOMP algorithm can distinguish between two sources exactly when $P(\theta)$ has a sole peak corresponding to a direction between θ_0 and θ_1 while OMP algorithm detects only a DOA corresponding to the peak of $P(\theta)$.

Fig. 3 shows the error of DOA estimation of OMP and FOMP algorithms for different direction distances between sources ($\Delta\theta$). It can be observed when $\Delta\theta < \frac{5BW}{4}$, FOMP algorithm can distinguish between two signal sources with a negligible error; however, MP and OMP algorithms estimate a single direction between real directions of sources with $\frac{\Delta\theta}{2}$ error, approximately. Then, when $\Delta\theta > \frac{5BW}{4}$, the estimation errors of MP and OMP algorithms reduce and these algorithms have the same efficiency.

Next, we consider the scenario that there are two pairs of adjacent sources in our simulation environment to analyze the effect of interferences among different sources on the performance of FOMP scheme for DOA estimation. Fig. 4 shows $P(\theta)$ when we consider two pairs of adjacent sources at $\theta_{11} = 20°$, $\theta_{12} = 30°$ and $\theta_{21} = -30°$, $\theta_{22} = -40°$. The detected directions by OMP algorithm are marked by two solid lines in Fig. 4. It can be observed that OMP algorithm estimates a single direction between real directions of each pair of sources with $\frac{\Delta\theta}{2}$ error. The detected directions by FOMP algorithm are marked by four dash lines in Fig. 4. We can conclude that FOMP algorithm can detect the directions of four signal sources with a negligible error.

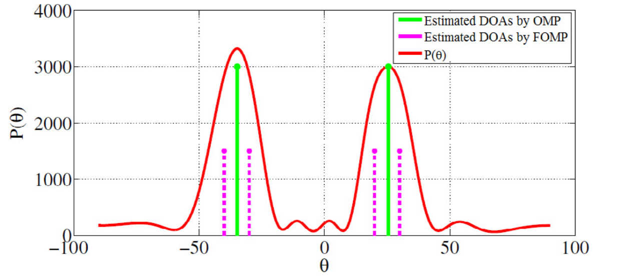

Fig. 4. The DOA estimation for OMP and FOMP algorithms when there are two pairs of adjacent signal sources in the simulation environment.

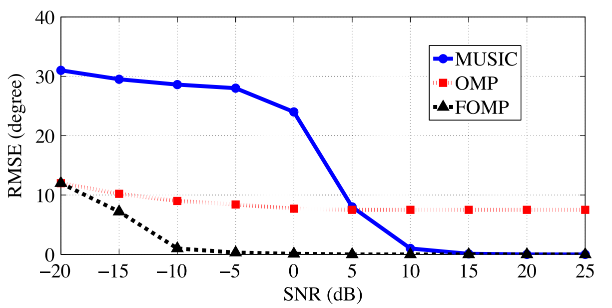

Fig. 5. Root mean square error for FOMP, OMP and MUSIC algorithms versus different values of SNR.

Fig. 5 compares FOMP algorithm with OMP and Music algorithms in terms of Root Mean Square Error (RMSE) for different values of SNR when we consider two very close sources in our scenario. We assume the number of snapshots is 100 for all methods. It can be observed FOMP algorithm outperforms OMP and MUSIC algorithms. By enhancing SNR, MUSIC method approaches to FOMP method in terms of RMSE. However, FOMP algorithm has a higher performance in comparison to OMP method for all values of SNR.

6. Conclusion

In this paper, we have proposed FOMP algorithm for estimation of DOA. We have expressed FOMP algorithm is an improved version of OMP algorithm. It could separate two signal sources exactly when beam former has a single peak corresponding to a direction between real directions of signal sources. Simulation results have shown when $\Delta\theta < \frac{5BW}{4}$, FOMP algorithm could detect two signal sources with a negligible error; however, OMP algorithm has estimated only a single direction between real directions of signal sources with $\frac{\Delta\theta}{2}$ error. Moreover, we have considered the scenario that there are two pairs of very close sources to analyze the effect of interferences among different sources on the performance of FOMP scheme for DOA estimation. Simulation results have shown that FOMP algorithm could detect the directions of the signal sources in this situation. In addition, we have compared FOMP algorithm with OMP and Music algorithms in terms of RMSE for different values of SNR when we have considered two very close sources in our scenario. It has been observed FOMP algorithm outperforms other methods.

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