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An Effective Sources Enumeration Approach for Single Channel Signal at Low SNR

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ABSTRACT In order to address the problem of achieving the poor performance of a single-channel receiver operated at a low signal-to-noise ratio (SNR) based on the existing source number estimation method, an effective source enumeration approach for the single-channel receiver operated at a low SNR is proposed in this paper. The proposed method is based on the empirical mode decomposition (EMD) with the auto-correlation coefficient matrix (ACCM) and the jackknifing method. First, the received single-channel signal is decomposed into several intrinsic mode functions and a residue via the EMD. Both the components and the original signal are employed to simulate the signals obtained from a pseudo-uniform linear array (ULA). After applying the multiple jackknifing methods to the signals obtained from the pseudo-ULA without complete overlap, we acquire a series of subsample datasets. Consequently, the ACCM instead of the conventional auto-covariance matrix is constructed for each subsample. After performing the eigenvalue decomposition of all the ACCMs, we acquire several sets of eigenvalues. For each set of eigenvalues, either moving increment criterion or moving standard deviation criterion is employed to determine the source number. Since more than one ACCM is employed because of using the multiple jackknifing methods, we have the statistics for the estimation of each ACCM. Then, we take the one that occurs the most frequently as the final result of source enumeration. The experiments validate the proposed method and show the excellent performance of our proposed algorithm. Finally, we also present the optimal scheme for selecting the important parameters, such as the jackknifing ratio and the jackknifing times in the approach.

INDEX TERMS Source enumeration for single channel receiver, empirical mode decomposition (EMD), jackknifing, auto correlation coefficient matrix, moving increment criterion, moving standard deviation criterion.

I. INTRODUCTION

It is well known that estimation of source number and direction of arrival (DOA) [1] are two syntrophic challenges in the array signal processing. Some algorithms such as the high resolution direction estimation such as the multiple signal classification (MUSIC) algorithm [2] and the signal parameter estimation algorithm via rotational invariance techniques (ESPRIT) [3] are widely applied to the signal processing in the fields for radar, sonar, communication and so on in the past decades. However, the implementations of the direction estimation algorithms are based on the priori knowledge of the total source number. The performance of the DOA algorithms will be greatly deteriorated if the source number estimation is inaccurate. So the source enumeration plays a critical role in the DOA procedure.

For the source number estimation, the classical types of signal source estimators include the Akaike information criterion (AIC) based estimator [4], the minimum description length (MDL) based estimator [5], the Bayesian information criterion (BIC) [6] based estimator as well as the improved ones based on the above estimators [7]–[10]. In general, there are two functions as the likelihood function and the penalty function in these above estimators. More precisely, the eigenvalues of the ACM of the received signal [11] by the array antennas are employed to perform the source number estimation through the estimators mentioned above.

Here, it assumes that the minimal and almost equal eigenvalues stands by the eigenvalues in the noise subspace, and the results of the source number estimation are acquired by the dimension of the ACM of the samples of the ACM minus the number of the noise eigenvalues in the sample of the ACM of the samples. That is to say, all the algorithms mentioned above are relevant to the eigenvalues of the ACM of the received signal samples. However, it is necessary to set an appropriate threshold in these methods. Besides, the eigenvectors of the sample ACM are also used in the source enumeration [12]–[14]. More precisely, the number of the sources is detected by combining the blind beamforming technique and the peak to average power ratio based on the frequency estimation algorithm [12]. Zhang *et al.* [13] took the advantage of the orthogonality between the signal subspace and the noise subspace. The bootstrap technique was combined with the Capon minimum power estimator based the DOA method to calculate the weighted inner product vectors. Then, the mean of the weighed inner product vectors after the above procedure iteration was employed to conduct the signal source enumeration through a clustering algorithm. Zhang *et al.* [14] presented a source number estimation approach based on the square of the Euclidean norm between the vectors, which were the inner product of the steering matrix and the left singular vectors of the Hankel matrix. But there is a common point of all the methods mentioned above that their performing are based on the assumption of multichannel received signals, which denotes multiple received antennas. Nevertheless, if we only consider the extreme case of utilizing the observed signals from single channel to finish source number estimation, the methods mentioned above seem to be helpless. Thus, it is very necessary for the received signals from single channel to virtually extend to higher dimensions.

Compared with the multiple channels, the single channel only needs one sensor. In addition to this, the single channel enjoys a number of benefits such as a simple construction, a low cost implementation, avoiding the interferences among the sensors, etc. In the past few years, the single channel model is widely used in a lot of fields such as in the speech signal processing [15], the biomedical signal processing [16], signal processing for the mechanical vibration [17], signal processing for communications [18], blind source separations [19], [20], etc. An accurate source enumeration via the received signals of a single channel plays an important role for the subsequent signal processing. For performing the source enumeration of the received signal of a single channel, the conventional methods are based on combining the dimension extension method by increasing the array elements and the existing source number estimation methods. A matching pursuit algorithm [21] based on the genetic algorithm method is used to select the optimal Gabor atoms in the complete dictionary. Then, the singular signal is described by the weighted sum of the selected atoms to create the pseudo multiple channels signals. In [22], Kouchaki *et al.* adopt the singular spectrum analysis (SSA) to construct a delay matrix and perform the EVD of the delay covariance matrix to obtain a set of eigenvalues and eigenvectors. Then, a series of projections and signal reconstructions are employed to perform the dimension extension of the single channel signals. Unfortunately, most of the computations are on the above two algorithms. Shao *et al.* [23] decomposed the signal of the single channel into that of the pseudo multiple channels by performing the wavelet transform. Then, a fast independent component analysis (ICA) is employed to perform the source signal separation in order to determine the number of the signal sources. However, it is the difficulty to choose an appropriate wavelet basis for performing the decomposition. In [24], the data of the single channel is converted into that of the multiple channels through a delay processing. The algorithms based on the information criterion are employed to estimate the number of signal sources subsequently. The experiment results show that it can achieve an excellent performance of the source enumeration with a huge number of snapshots. Barbedo *et al.* [25] developed a two stage algorithm by the single channel signal to estimate the number of sources. Here, one stage is harmonically related to the number of sources and another one is not closely harmonically related to the number of sources. The final estimated number of sources is the sum of the estimated numbers of sources in these two stages. However, the average detection accuracy of this approach is only about 80%.

Besides, the algorithms of the dimension extension mentioned above such as the EMD [26] are also capable of decomposing the signal of a single channel into several IMFs. Furthermore, as it is an adaptive decomposition method without any predefined function, EMD is widely used in the blind source separation for the signal of the single channel [27], [28]. In [29], the observed signal of single channel is decomposed into several IMFs, which are regarded as the signals received by pseudo multiple channels. Then, either AIC or MDL is employed to detect signal source number. A method of source enumeration based on diagonal loading to the ACM eigenvalues [30] is proposed for smoothing the eigenvalues in order to eliminate the inequality of noise eigenvalues. With the diagonal loading method being introduced in [29], the source enumeration performance is improved. However, the more excellent performance of source number detection acquired will partially scarify the SNR. The thought of resampling by multiple sampling without an overlap is employed to enhance the accuracy of estimation [31]. This method was invented by Quenouille in 1949 to construct the sub-sample datasets. Since the approach of resampling is not only subject to the assumption of the signal model, it also can effectively eliminate the estimated deviation of the sub-sample datasets. For the sake of its stronger robustness, it is widely applied in a lot of fields [32]–[34]. The method of resampling, which is also called jackknifing, is utilized to improve the source number estimation performance in the case of low SNR [24], [33]. However, the drawback of the method in [24] needs a great amount of snapshots to perform the time delay processing before jackknifing. By the way, the delay processing is important to dimension extension for the single channel signal. Besides, the approach in [33] is only applied to multiple channels signal. Salman *et al.* [35] presented a source enumeration algorithm, which took the advantage of the eigenvalues after the EVD of the ACCM rather than the conventional ACM to make the difference between the signal eigenvalues and the noise eigenvalues more accentuated. In this paper, an effective sources enumeration approach is presented. The new algorithm combines with the merits of EMD, jackknifing and ACCM, such as the self-adaptivity of EMD [26], to achieve the stronger robustness in jackknifing leading to the improvement on the source number estimation performance at low SNR [24], [33] and the greater discrimination between the signal eigenvalues and the noise eigenvalues from the ACCM [35]. The observed signal received by a single channel is decomposed into a series of IMF components and a residual component by EMD. The pseudo multiple channel signals are simulated by the combination of both the original signal and the components. After performing the jackknifing on the signals from the pseudo multiple channels without the overlap, we acquire a series of subsample datasets. Then, we use each subsample dataset to construct the corresponding ACCM. The eigenvalues of the ACCM acquired by the EVD processing, are made up of the signal eigenvalues and the noise eigenvalues. Subsequently, either MIC or MSTDC is utilized to detect the source number. Since more than one ACCM are obtained because of performing the jackknifing without the overlap, we have the statistics of the detection source number of each ACCM and regard the one that occurs the most frequently as the final result of source enumeration.

The rest of the paper is organized as follows. In Section II, the related theoretical basis such as the single channel signal model, the EMD algorithm and the jackknifing processing are introduced simply. In Section III, the construction of both the conventional ACM and the ACCM of a subsample dataset are presented. Then, the comparison between the performance of the ACM and that of the ACCM in source enumeration through a concrete example analysis is presented to verify the outperformance of the ACCM. Both the MIC and the MSTDC for source number detection are also introduced. In Section IV, our proposed algorithm will be demonstrated in details. Section V will present the computer numerical simulations as well as the corresponding analysis. Finally, Section VI concludes the paper.

II. RELATED THEORETICAL BACKGROUND

In this section, the related theoretical basis will be introduced including single channel signal model, EMD processing which can converts the single channel signal into the signals from a pseudo ULA, and the processing of jackknifing which is a general data-resampling method.

A. SINGLE CHANNEL SIGNAL MODEL

Suppose that there are p independent far field narrow band signal sources impinging on an antenna at the time instant t with the incident angle θ_i for $i = 1, 2, \ldots, p$. The sources are described as $S(t) = [s_1(t), s_2(t), \ldots, s_p(t)]^T$. Hence, the received single channel signal $x(t)$ is expressed as

$$x(t) = AS(t) + n(t), \tag{1}$$

where $A = [a(\theta_1), a(\theta_2), \ldots, a(\theta_p)] \in R^{1\times p}$ is a steering matrix and $n(t)$ is the Gaussian white noise with the zero mean and the variance σ^2. It is impossible for us to directly estimate the source number by the observed single channel signal especially in the case of $p \geq 1$. This is because it is actually an underdetermined problem. Thus, it is necessary to convert the observed single channel signal into pseudo multiple channel signals for the subsequent processing of source number detection.

B. EMD ALGORITHM

EMD, as an adaptive decomposition method being applied to both nonlinear and non-stationary signal, is capable to decompose the original signal into several IMF components and a residual component. All the components have the obvious physical meanings of characteristic time scales. For each IMF component, it has to meet the following two conditions: 1) The number of extreme points is equal to the number of zero crossing points. 2) The average value of the upper envelope and the lower envelope that defined by the maximum and the minimum, respectively, is zero. For an observed single channel signal $x(t)$, let $r(t) = x(t)$, $i = 1$ and $k = 0$, where i and k being the index of the IMF and the time index of iteration during one IMF decomposition, respectively. Hence, the process of EMD can be shown as follows:

1) Search for all the local maxima and minima and use cubic spline interpolation to get the upper envelope $e_{\max}(t)$ and the lower envelope $e_{\min}(t)$, respectively. Then, compute the mean described as $m(t)$ via

$$m(t) = \frac{e_{\max}(t) + e_{\min}(t)}{2}. \tag{2}$$

2) Let

$$h_{ik}(t) = r(t) - m(t), \tag{3}$$

where $h_{ik}(t)$ is defined as the proto-mode function after the k^{th} iteration in the process of the generation of $c_i(t)$, and let $r(t) = h_{ik}(t)$.

3) Repeat Step 1) and 2) until $h_{ik}(t)$ becomes an IMF, which means that it meets the two conditions mentioned in the above. Hence, $c_i(t) = h_{ik}(t)$ is acquired.

4) Let $r(t) = r(t) - c_i(t)$. If the number of the local extremum values in $r(t)$ is more than three, then let $i = i + 1$, $k = 0$ and go to Step 1). Else, the process of EMD is over and $r(t)$ is defined as a residual component.

Hence, the original signal $x(t)$ can be expressed as the sum of all the components in (4) as follows:

$$x(t) = \sum_{i=1}^{n-1} c_i(t) + r(t). \tag{4}$$

That is to say, the single channel signal is also treated as the signals from a ULA containing $n+1$ pseudo elements by EMD. The pseudo multiple channel signals is described as $y(t) = [y_1(t), y_2(t), \ldots, y_{n+1}(t)]^T$, where $y_i(t)$ is the signal of the i^{th} pseudo channel for $i = 1, 2, \ldots, n+1$, and $y_1(t) = x(t), y_2(t) = c_1(t), \ldots, y_n(t) = c_{n-1}(t), y_{n+1}(t) = r(t)$.

C. JACKKNIFING PROCESSING

Jackknifing, as a general data-resampling method used in statistical analysis, performs repeated computation for the statistical data, in order to make full use of the limited information in the original signal as much as possible [33]. Through the leaving out one or more observations at a time from the sample set, a newly subsample dataset is constructed. A series of subsample datasets generated from the jackknifing processing instead of directly utilizing the whole sample dataset is performed, because of the elimination of the estimated deviation of the subsample datasets. And the resultant stronger robustness in source enumeration is also desired. In fact, the jackknifing processing has been shown to be a novel data extraction strategy for sources number detection [33].

Supposing there are L snapshots in the single channel signal $x(t)$, and the sample dataset $\mathscr{X}$ is defined as

$$\mathscr{X} = \{x_l\} \quad (l = 1, 2, \ldots, L), \tag{5}$$

where x_l is the sampled data at the l^{th} snapshot in $x(t)$. Therefore, we also acquire L observations in the corresponding pseudo multiple channels signals $y(t)$ to construct the other sample dataset $\mathscr{Y}$ defined as

$$\mathscr{Y} = \{y_{il}\} \quad (i = 1, 2, \ldots, n+1 \;\; l = 1, 2, \ldots L), \tag{6}$$

where y_{il} is the sampled data of $y_i(t)$ at the l^{th} snapshot. Subsequently, L_r snapshots in each pseudo channel are randomly picked up from $\mathscr{Y}$, where $L_r = [r \times L]$ and r is a jackknifing ratio satisfying $0.5 < r < 1$, and [.] represents round numbers. After performing the jackknifing at the z^{th} time, the corresponding z^{th} subsample dataset $\mathscr{Y}_r^z$ is obtained as

$$\mathscr{Y}_r^z = \{y_{ij}^z\} \quad (i = 1, 2, \ldots, n+1 \;\; j = 1, 2, \ldots, L_r), \tag{7}$$

where $y_{ij}^z \in \mathscr{Y}$ and $\mathscr{Y}_r^z \subset \mathscr{Y}$. With the performing jackknifing of the data in the sample dataset $\mathscr{Y}$ without completely overlap for the total Z times, a sequence of subsample datasets expressed as $\mathscr{Y}_r^1, \mathscr{Y}_r^2, \ldots, \mathscr{Y}_r^Z$ is acquired. It means that there are Z subsample datasets being constructed. In the next section, how to take the advantage of the data in the constructed subsample datasets to detect sources number is introduced, including the ACCM construction with data of the subsample datasets as well as the two subsequent source enumeration criterions of the ACCM eigenvalues.

III. AUTO-CORRELATION COEFFICIENT MATRIX CONSTRUCTION AND TWO SOURCE ENUMERATION CRITERIONS

The greatest difference between our proposed algorithm and the other conventional algorithms is the type of matrix with the observed signal, where the ACCM rather than the ACM of the data in the sample dataset is constructed. In this section, the performance of the ACCM is compared with that of the ACM through a specific instance analysis. It is worth noting that both the ACCM and the ACM are constructed with the same data in the pseudo multiple channels sample dataset transformed from the same single signal by EMD. On the other side, the same conventional estimation criterions are utilized for the eigenvalues of both the ACCM and ACM. That is to say, both the performances of the ACCM and ACM are compared in the same case to reveal the superiority of the ACCM. Based on the analysis, it was found that the performance of the source detection is still unsatisfied, when the conventional criterions such as AIC and MDL are adopted for the ACCM eigenvalues. Thus, the two source enumeration criterions named MIC and MSTDC are introduced here.

A. CONVENTIONAL AUTO COVARIANCE MATRIX CONSTRUCTION AND ANALYSIS

Suppose $\mathscr{Y}$ is a sample dataset from the observed pseudo multiple channels signal $y(t)$. According to equation (6), there are total L snapshots in $\mathscr{Y}$. So the conventional ACM of the sample dataset $\mathscr{Y}$ is expressed as

$$R = E(\mathscr{Y} \times \mathscr{Y}^H), \tag{8}$$

where R is the ACM of the data of the sample dataset $\mathscr{Y}$ for $R \in C^{(n+1)\times(n+1)}$ and $(.)^H$ is the conjugate transpose transformation. Perform the EVD of R as

$$R = U \Lambda U^T, \tag{9}$$

where Λ is a diagonal matrix, in which the diagonal elements being λ_i, and U is defined as a matrix composed of the eigenvectors of R. Then, a set of eigenvalues expressed as λ_i is acquired, for $i = 1, 2, \ldots, n+1$, and rearrange the eigenvalues in descending order as

$$\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_p \geq \ldots \geq \lambda_n \geq \lambda_{n+1}. \tag{10}$$

There are total $n+1$ eigenvalues for R as the number of the pseudo multiple channels is $n+1$. In general, the former p eigenvalues in (10) mean signal eigenvalues and the others denote noise eigenvalues. Subsequently, either the AIC [4] or the MDL [5] is utilized to detect the source number, which are expressed by (11) and (12), respectively.

$$\begin{aligned} p_{\text{AIC}} &= \underset{k}{\operatorname{argmin}}\, 2L(n+1-k)\log f(k) \\ &\quad + 2k(2k(2(n+1)-k), \end{aligned} \tag{11}$$

$$\begin{aligned} p_{\text{MDL}} &= \underset{k}{\operatorname{argmin}}\, L(n+1-k)\log f(k) \\ &\quad + \frac{1}{2}k(2(n+1)-k)\log L, \end{aligned} \tag{12}$$

TABLE 1. Eigenvalues λ_i of auto covariance matrix R of single channel signal for varying with SNR.

	-15dB	-10dB	-5dB	0dB	5dB	10dB	15dB
λ_1	2.6929	2.8736	3.0508	4.4485	20.7824	181.3219	1.788e+13
λ_2	0.5517	0.5582	0.6469	1.0165	6.2636	54.4521	549.8975
λ_3	0.2409	0.2479	0.2819	0.4954	1.7497	12.9305	136.9919
λ_4	0.1260	0.1735	0.1470	0.1641	0.3319	1.7619	18.4897
λ_5	0.0754	0.0517	0.1041	0.0706	0.1062	0.1124	0.7659
λ_6	0.0371	0.0290	0.0483	0.0304	0.0473	0.0790	0.5653
λ_7	0.0255	0.0224	0.0347	0.0178	0.0218	0.0573	0.3525
λ_8	0.0135	0.0176	0.0217	0.0117	0.0140	0.0184	0.1246
λ_9	4.6399e-17	0.0133	0.0011	0.0101	0.0078	4.8667e-15	2.2662e-15

where p_{AIC} and p_{MDL} are the detection results by the AIC and the MDL respectively for $k = 1, 2, \ldots, n+1$ and $f(k)$ is a maximum likelihood function described as

$$f(k) = \frac{\frac{1}{n+1-k}\sum_{i=k+1}^{n+1}\lambda_i}{(\prod_{i=k+1}^{n+1}\lambda_i)^{\frac{1}{n+1-k}}}. \tag{13}$$

Unfortunately, neither the AIC nor the MDL can correctly detect the source number [28]. Because both the AIC and the MDL are applied to the case of the number of the received antennas being more than that of the detected sources [4], [5], while the signal discussed in this paper is physically only from a single received antenna, even though it is decomposed into pseudo multiple channels signals by EMD. For example, it supposes a scenario of three difference far field Gaussian signals impinging on a received antenna with the incident angles of $\theta_1 = 10°$, $\theta_2 = 20°$, $\theta_3 = 30°$ for simplicity and without loss of generality. The SNR value varies from -15dB to 15dB with the step of 5dB. After the EMD processing to get seven IMF components and a residual component, the sampling processing with $L = 500$ and the EVD processing, it acquires the nine eigenvalues in different SNR shown in Table.1. So both the AIC and the MDL fail to detect the three sources in the all SNR scales in Table.1 and it should be consistent with the conclusion in [28]. From the eigenvalues in each SNR scale in Table.1, according to (10) the former three eigenvalues are corresponding to the signal and the other eigenvalues mean the noise. The multiplicity of the smallest eigenvalues is only one, which means the detection number being eight, even though in the cases of SNR $=$ 10dB and SNR $=$ 15dB. In conclusion, the misjudgment on sources number resulting from the physical single channel signal leads to the mutual interference among signals [28].

The method of diagonal loading [29] is proposed to smooth the eigenvalues in the ACM in order to improve the performance of sources number detection for the subsequent processing of the AIC or the MDL in some cases. Thus, the diagonal loading is introduced before the performing of the AIC or the MDL to reduce the risk of misjudgment of the source number for the single channel signal. The procedure of the diagonal loading can be described as (14) and (15)

$$\lambda_{\mathrm{DL}} = \sqrt{\sum_{i=1}^{n+1}\lambda_i}, \tag{14}$$

$$\widetilde{\lambda_i} = \lambda_i + \lambda_{\mathrm{DL}}, \tag{15}$$

where λ_{DL} is the value of the heaped capacity and $\widetilde{\lambda_i}$ denotes the modified eigenvalue after the diagonal loading. Then all the modified eigenvalues in different SNR are shown in Table 2. Both the AIC and the MDL are employed to determine the sources number as

$$\widetilde{p_{\mathrm{AIC}}} = \arg\min_k 2L(n+1-k) \times \log\tilde{f}(k) + 2k(2(n+1)-k), \tag{16}$$

$$\widetilde{p_{\mathrm{MDL}}} = \arg\min_k L(n+1-k) \times \log\tilde{f}(k) + \frac{1}{2}k(2(n+1)-k)\log L, \tag{17}$$

where $\widetilde{p_{\mathrm{AIC}}}$ and $\widetilde{p_{\mathrm{MDL}}}$ are the detection result of the AIC and the MDL respectively, and $\tilde{f}(k)$ is a maximum likelihood function described as

$$\tilde{f}(k) = \frac{\frac{1}{n+1-k}\sum_{i=k+1}^{n+1}\widetilde{\lambda_i}}{(\prod_{i=k+1}^{n+1}\widetilde{\lambda_i})^{\frac{1}{n+1-k}}}. \tag{18}$$

Both the AIC and the MDL are capable to correctly detect the three sources only in the cases of both SNR $=$ 10dB and SNR $=$ 15dB. When the SNR scale decreases to 5dB or less, both the AIC and the MDL are failure. Although the technique of diagonal loading can improve the source enumeration performance for either the AIC or the MDL in some cases [28], the result implies that the ACM of the sample dataset is not applied to the source number detection for the single

TABLE 2. Eigenvalues $\widetilde{\lambda_i}$ of modified auto covariance matrix *R* of single channel signal for varying with SNR.

	-15dB	-10dB	-5dB	0dB	5dB	10dB	15dB
$\widetilde{\lambda_1}$	4.6423	5.1333	4.8665	6.9515	26.1976	197.1565	1.838e+13
$\widetilde{\lambda_2}$	2.5011	2.7293	2.5485	3.5195	11.6788	70.2867	599.8570
$\widetilde{\lambda_3}$	2.1973	2.3644	2.2312	2.9984	7.1649	28.7650	186.9513
$\widetilde{\lambda_4}$	2.1229	2.2295	2.1163	2.6671	5.7471	17.5965	68.4492
$\widetilde{\lambda_5}$	2.0011	2.1865	2.0656	2.5736	5.5214	15.9469	50.7254
$\widetilde{\lambda_6}$	1.9784	2.1307	2.0273	2.5334	5.4625	15.9136	50.5247
$\widetilde{\lambda_7}$	1.9718	2.1171	2.0157	2.5208	5.4370	15.8919	50.3120
$\widetilde{\lambda_8}$	1.9670	2.1042	2.0037	2.5147	5.4292	15.8530	50.0840
$\widetilde{\lambda_9}$	1.9627	2.0835	1.9958	2.5131	5.4230	15.8346	49.9595

channel signal especially in the case of low SNR. Thus, it is necessary for us to continue to exploit other more suitable type of sample dataset matrix for the single channel signal.

B. AUTO CORRELATION COEFFICIENT MATRIX CONSTRUCTION AND ANALYSIS

It still supposes $\mathscr{Y}$ as a sample dataset from the observed pseudo multiple channels signal $y(t)$. In the same way, there are total L snapshots in Y. Then the ACCM, $\hat{R}$, of the data of the sample dataset $\mathscr{Y}$ is defined by

$$\hat{R} = (\text{diag}(V))^{-\frac{1}{2}} \times V \times (\text{diag}(V))^{-\frac{1}{2}}, \quad (19)$$

where $\hat{R} \in C^{(n+1)\times(n+1)}$ and V is a covariance matrix of Y, and V is described as

$$V = E[(\mathscr{Y} - \mu)(\mathscr{Y} - \mu)^H], \quad (20)$$

for $\mu = E(\mathscr{Y})$ and diag(v) is a diagonal matrix. Both diag(v) and V have the same diagonal elements. The EVD of $\hat{R}$ is performed as

$$\hat{R} = \hat{U}\hat{\Lambda}\hat{U}^H, \quad (21)$$

where $\hat{\Lambda} = \text{diag}(\widehat{\lambda_1}, \widehat{\lambda_2}, \ldots, \widehat{\lambda_{n+1}})$ is a diagonal matrix composed of the eigenvalues of $\hat{R}$, and $\hat{U}$ denotes a matrix composed of the eigenvectors of $\hat{R}$. Thus, a series of eigenvalues $\widehat{\lambda_i}$ of the ACCM is acquired. All the eigenvalues are rearranged in descending order as

$$\widehat{\lambda_1} \geq \widehat{\lambda_2} \geq \ldots \geq \widehat{\lambda_p} \geq \ldots \geq \widehat{\lambda_n} \geq \widehat{\lambda_{n+1}}. \quad (22)$$

In (22), the former p eigenvalues mean signal eigenvalues and the others denote noise eigenvalues. Then both the AIC and the MDL are employed to determine the source number as

$$\begin{aligned} \widehat{p_{\text{AIC}}} &= \underset{k}{\text{argmin}}\, 2L(n+1-k)\log\hat{f}(k) \\ &\quad + 2k(2(n+1)-k), \quad (23) \\ \widehat{p_{\text{MDL}}} &= \underset{k}{\text{argmin}}\, L(n+1-k)\log\hat{f}(k) \\ &\quad + \frac{1}{2}k(2(n+1)-k)\log L, \quad (24) \end{aligned}$$

where $\widehat{p_{\text{AIC}}}$ and $\widehat{p_{\text{MDL}}}$ are the detection result of the AIC and the MDL respectively, and $\hat{f}(k)$ is a maximum likelihood function described as

$$\hat{f}(k) = \frac{\frac{1}{n+1-k}\sum_{i=k+1}^{n+1}\widehat{\lambda_i}}{(\prod_{i=k+1}^{n+1}\widehat{\lambda_i})^{\frac{1}{n+1-k}}}. \quad (25)$$

For the scenario mentioned above and in the same way, the nine eigenvalues of the ACCM can be easily obtained. All the eigenvalues in the different SNR are shown in Table. 3. According to (23) or (24), the source number can be calculated. It finds that both the AIC and the MDL are capable to correctly detect the three sources in the cases of SNR = 5dB, SNR = 10dB and SNR = 15dB. It is obvious that using the ACCM can bring about the correctly sources number detection in the case of lower SNR compared with that of the ACM in this instance. It should be noting that the comparison between the ACCM and the ACM is under the same condition. On the other side, it also finds that the difference between the signal eigenvalues and the noise eigenvalue is more distinct, and the multiplicities of the smallest eigenvalues in the right three columns are obviously six. It implies that the utilizing of the ACCM of the data of the sample dataset leads to the improvement on the source enumeration for the single channel signal in the lower SNR. However, when the SNR scale decreases to 0dB or less, it is difficult for both the AIC and the MDL to correctly detect the source number. Thus, it is necessary for us to continue to find the other source enumeration criterions to further improve on the performance of the source number detection in lower SNR. In the following, the two sources enumeration criterions called MIC and MSTDC [35] for the ACCM eigenvalues are introduced.

TABLE 3. Eigenvalues $\hat{\lambda}_i$ of the ACCM $\hat{R}$ of single channel signal for varying with SNR.

	-15dB	-10dB	-5dB	0dB	5dB	10dB	15dB
$\widehat{\lambda_1}$	1.2251	1.2285	1.2385	1.4049	2.8440	3.2437	3.5504
$\widehat{\lambda_2}$	1.1788	1.1784	1.2023	1.2742	2.4299	2.7101	2.9181
$\widehat{\lambda_3}$	1.0982	1.1003	1.0976	1.1841	2.0930	2.4632	2.6852
$\widehat{\lambda_4}$	1.0213	1.0191	1.0447	0.9572	0.3492	0.1098	0.0466
$\widehat{\lambda_5}$	0.9933	0.9924	0.9834	0.9405	0.3369	0.1065	0.0446
$\widehat{\lambda_6}$	0.9377	0.9344	0.9316	0.8960	0.3279	0.1040	0.0436
$\widehat{\lambda_7}$	0.9054	0.9068	0.8882	0.8325	0.2888	0.0942	0.0389
$\widehat{\lambda_8}$	0.8467	0.8479	0.8415	0.7668	0.2733	0.0894	0.0377
$\widehat{\lambda_9}$	0.7935	0.7922	0.8022	0.7238	0.2570	0.0791	0.0348

C. MOVING INCREMENT CRITERION FOR EIGENVALUES

A series of eigenvalues $\widehat{\lambda_i}$ of the ACCM $\hat{R}$ is acquired through (21). The eigenvalues are rearranged ascendingly as

$$\widehat{\lambda_1} \leq \widehat{\lambda_2} \leq \ldots \leq \widehat{\lambda_n} \leq \widehat{\lambda_{n+1}}. \tag{26}$$

Denote the increment between the two neighbor eigenvalues in (26) as δ_i

$$\delta_i = \widehat{\lambda_i} - \widehat{\lambda_{i-1}} \quad (i = 2, \ldots, n+1). \tag{27}$$

The value of δ_i should reach the maximum, when $\widehat{\lambda_i}$ and $\widehat{\lambda_{i-1}}$ are the signal eigenvalue and the noise eigenvalue, respectively. So I_{MIC} denoting the subscript of the maximal δ_i is easily obtained by

$$I_{\text{MIC}} = \underset{i}{\operatorname{argmax}}\, \delta_i. \tag{28}$$

Then the signal sources number p_{MIC} detection is described as

$$p_{\text{MIC}} = (n+1) - I_{\text{MIC}} + 1. \tag{29}$$

D. MOVING STANDARD DEVIATION METHOD FOR EIGENVALUES

The MSTDC for the ACCM eigenvalues is another signal sources detection criterion, which is parallel to the MIC. And it also utilizes the eigenvalues $\widehat{\lambda_i}$ from the ACCM $\hat{R}$. Supposing the bias standard deviation of two neighbor eigenvalues is done by

$$\text{STD}_i = \sqrt{\left(\widehat{\lambda_i} - u_i\right)^2 + \left(\widehat{\lambda_{i-1}} - u_i\right)^2} \quad (i = 2, 3, \ldots, n+1), \tag{30}$$

where u_i is the average of the two neighbor eigenvalues as

$$u_i = \frac{\widehat{\lambda_i} + \widehat{\lambda_{i-1}}}{2}, \tag{31}$$

so the increment of eigenvalues deviation α_i is described as

$$\alpha_i = \text{STD}_i - \text{STD}_{i-1} \quad (i = 3, 4, \ldots, n+1). \tag{32}$$

When $\widehat{\lambda_i}$ and $\widehat{\lambda_{i-1}}$ are the signal eigenvalue and the noise eigenvalue respectively, the value of α_i reaches the maximum. I_{MSTDC}, which is the subscript of the maximal α_i can be computed by

$$I_{\text{MSTDC}} = \underset{i}{\operatorname{argmax}}\, \alpha_i \tag{33}$$

Then the signal sources number estimation is described as

$$p_{\text{MSTDC}} = (n+1) - I_{\text{MSTDC}} + 1 \tag{34}$$

E. COMPARISON OF FOUR SOURCE ENUMERATION CRITERIONS

Compared with the conventional criterions of the AIC or the MDL, both the MIC and the MSTDC are unnecessary to construct the penalty function and the log-likelihood function of eigenvalues, which needs the greater computational cost. Besides, it is more important that the difference between the signal eigenvalues and the noise eigenvalues becomes more obvious after performing the EVD to the ACCM especially in the lower SNR. In addition, in Table 3, both the MIC and the MSTDC can accurately detect the three sources, when the SNR scale decreases to 0dB.

IV. THE PROPOSED SOURCE ENUMERATION ALGORITHM

In this Section, our complete source enumeration algorithm based on EMD, jackknifing, ACCM and MIC or MSTDC will be introduced, whose flowchart is shown in Fig. 1.

An observed single channel signal is decomposed into a series of IMFs and a residual component at first, which converts the single channel signal into the pseudo multiple channels signals. Performing the jackknifing on the observed signal of the pseudo multiple channels, a sequence of subsample datasets to eliminate the deviation of source enumeration

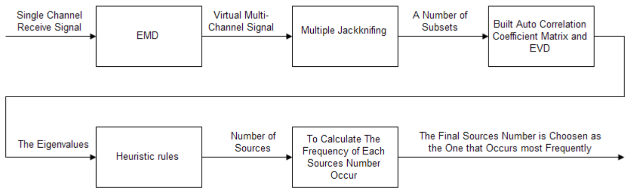

FIGURE 1. Overview of the proposed algorithm for single channel source enumeration.

is acquired. Then, for each subsample dataset, the ACCM of the data is constructed. After performing the EVD to the ACCM, it acquires a series of eigenvalues. Subsequently, either the MIC or the MSTDC for the ACCM eigenvalues is employed to detect the source number for the subsample dataset. Since there is a series of subsample datasets based on the jackknifing processing, it has to take all the subsample dataset to perform the source number detection, which implies that the number of the detection results is the same as the jackknifing times. Finally, the statistics of the detection of each ACCM is obtained and then take the one that occurring the most frequently as the final result of source enumeration.

V. COMPUTER NUMERICAL SIMULATION RESULTS

In this section, a lot of computer numerical simulations are presented to validate and demonstrate the estimation performance of our proposed algorithm. The source enumeration performance of our approach which combined with EMD, jackknifing, ACCM and MIC (EJAMIC) or EMD, Jackknifing, ACCM and MSTDC (EJAMSTDC) is compared with that obtained by the algorithms of the combination of EMD and conventional AIC (EAIC) [29], the combination of EMD and the conventional MDL (EMDL) [29], the combination of EMD and the eigenvalues diagonal loading AIC (EDLAIC) [29], the combination of EMD and the eigenvalues diagonal loading MDL (EDLMDL) [29], MDL after dimension extension based on delay processing (DMDL) [24] and the eigenvalues diagonal loading DMDL (DDLMDL) [24]. It is worth noting that the experimental single channel signal converts into the pseudo multiple channels signal by EMD as well as EAIC, EMDL, EDLAIC and EDLMDL in [29], while the method of delay processing is utilized for dimension extension in both DMDL and DLDMDL in [24]. Compared to other algorithms, the main difference is that the ACCM is utilized in our proposed approach while the ACM is adopted in the other compared algorithms.

There are five experiments in this section. In the former two experiments, the three independent narrow-band far field signals are impinging on an antenna with the incident angles of 20°, 30° and 45° respectively for simplicity and without loss of generality. The SNR of the signal varies from -15dB to 15dB with the step size of 1dB and $L = 500$. In order to validate the processing of EMD, the curves of the observed single channel signal, the IMF components and the residual component are shown in Fig. 2 in the case of SNR $= 5$dB and $L = 500$.

Algorithm 1: The EJAMIC and EJAMSTDC methods

Step 1: Acquire an observed single channel signal $x(t)$.

Step 2: Decompose $x(t)$ into a series of IMFs described as $c_i(t)$ for $i = 1, 2, \ldots, n-1$ and a residual component defined as $r(t)$ by EMD in terms of (4). Then construct signals of multiple channels $y(t)$ denoted by $y(t) = [y_1(t), y_2(t), \ldots, y_{n+1}(t)]^T$ for $y_1(t) = x(t)$, $y_2(t) = c_1(t), \ldots, y_n(t) = c_{n-1}(t)$ and $y_{n+1}(t) = r(t)$. Therefore, $y(t)$ are the resulting pseudo multiple channel signals.

Step 3: Suppose there are L snapshots in $x(t)$, and the sample dataset $\mathscr{Y}$ in the corresponding pseudo multiple channels signal is acquired by (5) and (6).

Step 4: The random L_r data picked up from the sample dataset $\mathscr{Y}$ is treated as a jackknifing processing. After the jackknifing of the sample dataset $\mathscr{Y}$ for Z times without completely overlap, we obtain a sequence of subsample datasets $\mathscr{Y}_r^z$ defined by (7) for $z = 1, 2, \ldots, Z$, which contains Z subsample datasets, and the subsample dataset produced at the z^{th} jackknifing is $\mathscr{Y}_r^z$.

Step 5: For each subsample dataset $\mathscr{Y}_r^z$ in the sequence of subsample datasets expressed as $\mathscr{Y}_r^1, \mathscr{Y}_r^2, \ldots, \mathscr{Y}_r^Z$, the ACCM $\widehat{R_r^z}$ of the data in $\mathscr{Y}_r^z$ is constructed by (19) and (20), where $\mathscr{Y}$ changes into $\mathscr{Y}_r^z$ and $\hat{R}$ changes into $\widehat{R_r^z}$. Perform the EVD to $\widehat{R_r^z}$ through (21), a series of eigenvalues described as $\widehat{\lambda_{ri}^z}$ for $i = 1, 2, \ldots, n+1$ is acquired, and in (22), $\widehat{\lambda_i}$ substitutes into $\widehat{\lambda_{ri}^z}$.

Step 6: Resort the eigenvalues $\widehat{\lambda_{ri}^z}$ ascendingly as (26), then utilize MIC by (27) to (29) or MSTDC by (24) to (28) to obtain the signal sources estimation result expressed as $p_{r(\text{MIC})}^z$ or $p_{r(\text{MSTDC})}^z$ respectively for the sub-sample dataset $\mathscr{Y}_r^z$, where δ_i, I_{MIC}, p_{MIC}, STD_i, u_i, α_i, I_{MSTDC} and p_{MSTDC} are replaced by δ_{ri}^z, $I_{r(\text{MIC})}^z$, $p_{r(\text{MIC})}^z$, STD_{ri}^z, u_{ri}^z, α_{ri}^z, $I_{r(\text{MSTDC})}^z$ and $p_{r(\text{MSTDC})}^z$ respectively.

Step 7: Statistics the values of $p_{r(\text{MIC})}^z$ (or $p_{r(\text{MSTDC})}^z$) for $z = 1, 2, \ldots, Z$ to find the one that occurs the most frequently. Then, regard it as the final sources enumeration result.

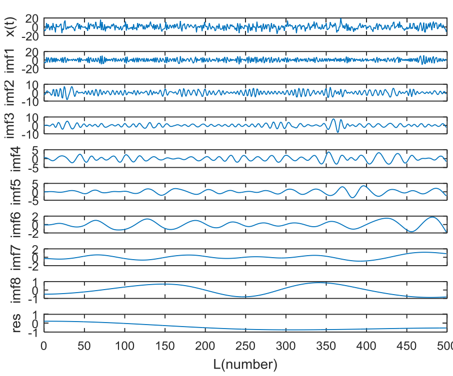

FIGURE 2. Decomposition result of an observed single channel data when three independent narrow band far field signals impinging on an antenna. (SNR = 5dB).

In experiment A, the jackknifing, as one of the most important parts of our proposed method, is eliminated in order to

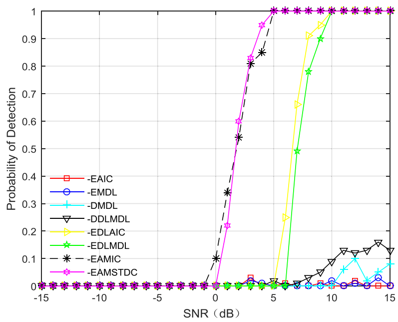

FIGURE 3. **Probability of detection against SNR obtained by our proposed algorithm without jackknifing (EAMIC and EAMSTDC), EAIC, EMDL, EDLAIC, EDLMDL, DMDL and DDLMDL.**

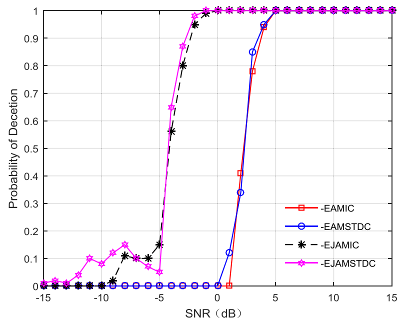

FIGURE 4. **Probability of detection against SNR obtained by our proposed algorithm without jackknifing (EAMIC and EAMSTDC) and our whole proposed algorithm (EJAMIC and EJAMSTDC).**

independently further verify the validation of the ACCM in signals source enumeration. And our method without jackknifing is shortened as EAMIC or EAMSTDC. Experiment B firstly presents the performances of the algorithms of EJAMIC, EJAMSTDC, EAMIC and EAMSTDC in order to verify the improvement on our proposed method of jackknifing performing especially in the case of low SNR. Then the experiment also demonstrates the performance comparison of our proposed algorithms including EJAMIC and EJAMSTDC and the other algorithms such as EAIC, EMDL, EDLAIC, EDLMDL, DMDL and DLDMDL. In experiment C, with the number of narrow band far field signals increasing, the number estimation performances of our proposed approaches including both EJAMIC and EJASTDC which are expressed by probability of detection under different SNR is presented to find the maximal detection signal numbers by our proposed approach. Experiment D focuses on the optimum of resampling ratio r in the case of general scenario to improve the performance of both EJAMIC and EJASTDC. Finally, experiment E exhibits the optimal jackknifing times Z of our proposed scheme in different SNR under the condition of white noise. All of the following experiments take 100 times Monte-Carlo simulations and the probability of detection is defined by

$$p = \frac{F_k}{F}, \tag{35}$$

where F means the times of Monte-Carlo simulations and F_k denotes the times of the correct detection.

A. SIMULATION ON AUTO COVARIANCE COEFFICIENT MATRIX VALIDATION OF SOURCES ENUMERATION

In this experiment, it only focuses on whether the ACCM can be employed to estimate signal source number or not. Jackknifing, as an important step to enhance the probability detection in our proposed algorithm, is eliminated in order to individually verify the validation of the ACCM in the source enumeration, while the other comparison algorithms utilize the ACM to detect signal source number. The performance of the algorithms including our proposed methods without jackknifing are shown in Fig. 3

It can be seen from Fig. 3 that EAIC, EMDL, DMDL and DDLMDL are almost invalid, while EDLAIC, EDLMDL and our proposed algorithm (both EAMIC and EAMSTDC) achieve better performance of the source enumeration. When the SNR reaches 10dB, the probability of detection obtained by both EDLAIC and EDLMDL is nearly 100%. By contrast, our proposed algorithm including EAMIC and EAMSTDC is able to acquire the same excellent performance in the case of SNR = 5dB even without jackknifing. Even in the case of SNR = 3dB, our approach can still acquire the detection probability of more than 80%. It implies that the ACCM is not only valid but also more suitable than the conventional ACM for the source enumeration. However, the case of SNR = 3dB should not mean the low SNR. So maybe it can further improve the performance of sources enumeration with the combination of the jackknifing operation.

B. SIMULATION ON JACKKNIFING OF SOURCE ENUMERATION

This experiment presents the contrast effect between our whole algorithm (EJAMIC and EJAMSTDC) and our algorithm without jackknifing (EAMIC and EAMSTDC) to reveal the improvement with the participation of jackknifing. The experimental environment is the same as that in experiment A. The comparison results are shown in Fig.4.

It is obvious that our proposed whole algorithm (EJAMIC and EJAMSTDC) acquires more excellent performance of sources estimation than our proposed algorithm without jackknifing (EAMIC and EAMSTDC). From Fig. 4, the probability detection of both EJAMIC and EJAMSTDC reaches more than 90% even in the case of SNR = −2dB, while the probability detection of both EAMIC and EAMSTDC reaches 90% in the case of SNR ≈ 4dB. In conclusion, with the jackknifing introduction, the performance of probability detection in low SNR is greatly improved. Combined Fig. 3 with Fig. 4, the probability of detection against SNR obtained by our proposed algorithm (EJAMIC and EJAMSTDC) and the other comparison approaches are shown in Fig. 5.

As shown in Fig. 5, compared to other algorithms, for example, the probability of detection of EDLAIC, which has the best performance in the state of the art, reaches to more

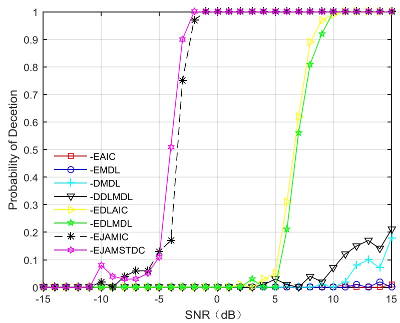

FIGURE 5. Probability of detection against SNR obtained by our proposed algorithm (EJAMIC and EJAMSTDC), EDLAIC, EDLMDL, DMDL and DDLMDL.

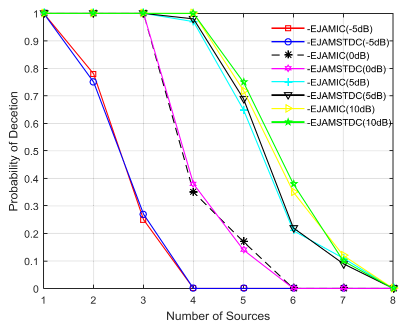

FIGURE 6. Probability of detection against number of sources in different SNR obtained by our proposed algorithm (EJAMIC and EJAMSTDC).

than 90% only in the case of SNR $=$ 8dB. It implies that it processes source enumeration by single channel in underdetermined case in low SNR, when our proposed approach is utilized.

C. SIMULATION ON THE MAXIMUM DETECTION NUMBER BY SINGLE CHANNEL

In the previous experiments, it shows that it can easily estimate sources number accurately by single channel in underdetermined and low SNR case, when the proposed algorithm (EJAMIC and EJAMSTDC) is employed. So it is necessary for us to know the specific maximum of the correctly detection number by our proposed algorithm. In this experiment, there are eight independent narrow-band far field signals, which are impinging on an antenna with the incident angles of 10°, 20°, 30°, 40°, 50°, 60°, 70° and 80° respectively for simplicity and without loss of generality. The SNR of signals vary from −5dB to 10dB with the step size of 5dB and $L =$ 500. Then there are p selected sources in the eight sources at random, which are impinging on an antenna simultaneously for $p = 1, 2, \ldots, 8$. So the probability of detection against number of sources by our proposed algorithm in the case of different SNR is described in Fig. 6.

In Fig. 6, one source can be accurately detected in all of the SNR from −5dB to 10dB. In the case of SNR = −5dB, neither EJAMIC nor EJAMSTDC can correctly source enumeration in underdetermined case. With the scale of SNR being 0dB, both EJAMIC and EJAMSTDC can correctly detect three signal sources at most. However, when the sources number rises to 4, the probability of detection of both EJAMIC and EJAMSTDC rapidly descends to less than 40%, which means its failure in source enumeration. While with the SNR increasing, the detection of the sources number rises to 4. For example, when SNR $=$ 5dB and SNR $=$ 10dB, the probability of detection is nearly 100% in the case of $p = 4$. However, if five narrow band far field signals were impinging on the antenna, the probability of detection declines to 70%, which means nearly failure. It also seems that the curves in the case of SNR $=$ 5dB is nearly the same as the curves in the case of SNR $=$ 10dB. It implies that with the value of SNR continues to increase, the curve of probability against number of sources only have little change. So it concludes that four signal sources at most can be detected successfully with single channel signal by our proposed method (EJAMIC and EJAMSTDC), when SNR $\geq$ 5dB. If SNR $=$ 0dB, our proposed algorithm can only correctly detect 3 sources number at most, which is in accordance with the conclusion in experiment B.

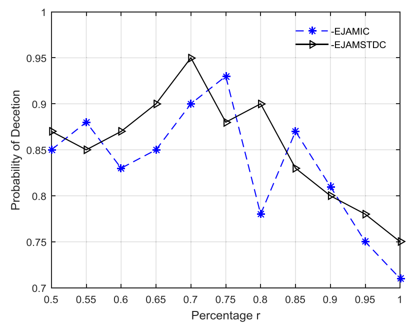

FIGURE 7. Probability of detection against jackknifing ratio *r* by obtained by our proposed algorithm (EJAMIC and EJAMSTDC).

D. SIMULATION ON PROBABILITY OF DETECTION INFLUENCED BY JACKKNIFING RATIO

In this experiment, the influence to the performance of our proposed algorithm by the jackknifing ratio is studied. It also supposed three narrow-band far field signals were impinging on a received antenna with the incident angles of 10°, 35° and 50° in white noise for simplicity and without loss of generality, for SNR $= -2$dB and $L = 500$. The time of jackknifing is 20 and the jackknifing ratio r varies from 0.5 to 1 with the step of 0.05. So the probability of detection against the jackknifing ratio r is shown in Fig. 7.

It can be seen from Fig. 7 that the detection probability is influenced by the jackknifing time. In the environment of the experiment, the probability of detection is in the state of fluctuation with r varying from 0.5 to 1. In summary, too big or too small value of r causes the probability of detection declines in our proposed algorithm including both EJAMIC and EJAMSTDC. An appropriate r has to be selected to ensure the more excellent performance of our method. In this experiment, the optimal values of r are 0.75 and 0.7 in

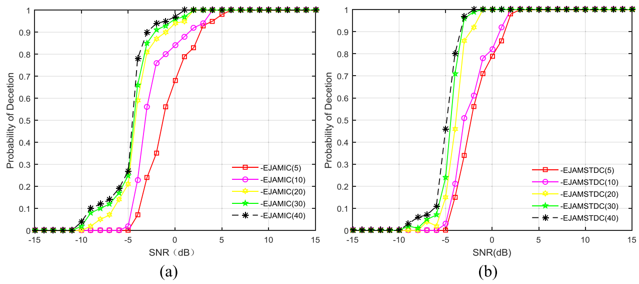

FIGURE 8. **Probability of detection against SNR in different jackknifing times *Z* by our proposed algorithm (EJAMIC and EJAMSTDC). (a) EJAMIC. (b) EJAMSTDC.**

TABLE 4. **(a) Optimal *r* and its corresponding maximal probability of detection by EJAMIC in different snapshots *L*. (b) Optimal *r* and its corresponding maximal probability of detection by EJAMSTDC in different snapshots *L*.**

(a)

Snapshots L	500	600	700	800	900	1000	1500
Optimal r	0.75	0.7	0.65	0.65	0.6	0.55	0.5
Maximal probability of detection	93%	95%	95%	96%	95%	96%	96%

(b)

Snapshots L	500	600	700	800	900	1000	1500
Optimal r	0.7	0.7	0.65	0.6	0.6	0.55	0.5
Maximal probability of detection	95%	95%	97%	97%	96%	98%	97%

EJAMIC and EJAMSTDC respectively. On the other hand, the number of snapshots L also influences the selection of r. The relationship between the number of snapshots and the optimal r by JAMIC and JAMSTDC are shown in Table 4(a) and Table 4(b) respectively. With the number of snapshots increasing, the value of the optimal jackknifing ration is decreasing.

E. SIMULATION ON PROBABILITY OF DETECTION INFLUENCED BY TIME OF JACKKNIFING

The performance of our proposed algorithm being influenced by time of jackknifing is also studied in the experiment. It is well known that the enhancement of jackknifing times should improve the performance of our algorithm in the probability of detection because of taking full advantage of the limited information. On the other hand, too many times of jacking also cause too much computational expense. So it is necessary for us to select an optimal jackknifing times Z. In this experiment, it also supposes three narrow-band far field signals were impinging on a received antenna with the incident angles of 40°, 55° and 70° in white noise for simplicity and without loss of generality, for SNR $= -2$dB, $L = 500$, $r = 0.8$ and the value of SNR varying from -15dB to 15dB with the step of 1dB.

TABLE 5. **(a) Optimal *Z* by EJAMIC in different snapshots *L*. (b) Optimal *Z* by EJAMSTDC in different snapshots *L*.**

(a)

Snapshots L	500	600	700	800	900	1000	1500
Optimal Z	20	20	18	18	18	18	18

(b)

Snapshots L	500	600	700	800	900	1000	1500
Optimal Z	30	25	25	24	24	24	20

Then the curves of probability of detection against SNR in different Z are shown in Fig. 8. There are five curves of probability of detection against SNR in the case of $Z = 5$, $Z = 10$, $Z = 20$, $Z = 30$ and $Z = 40$ respectively in Fig. 8. It is obvious that with the jackknifing times Z increasing, the performance of our algorithm is improved. However, when the value of Z is more than 20, the performance improvement is no longer inconspicuous. Considering the compromise between the performance improvement and the time expense cost, $Z = 20$ is selected to be the optimum.

On the other hand, the number of snapshots L also influences the selection of Z. The relationship between the number of snapshots and the optimal Z by EJAMIC and EJAMSTDC are shown in Table 5(a) and Table 5(b) respectively. With the number of snapshots increasing, the value of the optimal jackknifing times is decreasing.

VI. CONCLUSIONS

This paper proposed an effective sources enumeration algorithm based on EMD, jackknifing and ACCM, in order to improve the signal sources estimation by single channel in case of low SNR. The received single channel signal is decomposed into a series of IMFs and a residual component to construct a pseudo multiple channels signal at first for the dimension extension. Secondly, a multiple jackknifing to the signals in the pseudo ULA without completely overlap to acquire a series of sub-sample datasets is proposed. Consequently, the ACCM of the data in each subsample dataset is calculated. After the performing EVD of ACCM, a series of eigenvalues is obtained. Then, either MIC or MSTDC of ACCM eigenvalues is utilized to detect the sources number. Finally, it is necessary for us to regard the one that occurs the most frequently as the final sources enumeration result. Computer numerical simulations verify the validation and even more excellent performance of our proposed algorithm. The major important of this work is to allow using single channel signal to sources enumeration under low SNR. The experiments shows that we are able to accurately detect three narrow-band far field signals in the case of SNR $= -2$dB, when our proposed algorithm is employed. With respect to the jackknifing ratio and the jackknifing times, which are the most important parameters in resampling and are influenced by the number of snapshots, it also presents the scheme of the optimum in the case of SNR $= -2$dB.

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