

# Narrowband Signal Localization Based on Enhanced LAD Method

Ke Xin Jia and Zi Shu He

**Abstract:** In this paper, an enhanced localization algorithm based on double thresholds (LAD) is proposed for localizing narrowband signals in the frequency domain. A simplified LAD method is first studied to reduce the computational complexity of the original LAD method without performance loss. The upper and lower thresholds of the simplified LAD method are directly calculated by running the forward consecutive mean excision algorithm only once. By combining the simplified LAD method and binary morphological operators, the enhanced LAD method is then proposed and its performance is simply discussed. The simulation results verify the correctness of discussion and show that the enhanced LAD method is superior to the LAD with adjacent cluster combining method, especially at low signal-to-noise ratio.

**Index Terms:** Forward consecutive mean excision (FCME), localization algorithm based on double thresholds (LAD), narrowband (NB) signal.

## I. INTRODUCTION

In spectrum monitoring, narrowband (NB) signal localization is indispensable for blindly detecting and separating NB signals as well as estimating their characteristics at low signal-to-noise ratio (SNR). The outputs of NB signal localization include the number of separable signals and their localizations in the frequency domain, which are valuable in spectrum monitoring. According to these signal characteristics, spectrum monitoring system can control an independent bank of NB filters to extract these separable signals and perform further processing on them, such as modulation identification, demodulation as well as decoding.

There are a large number of NB signal localization algorithms that are based on a threshold [1]–[4]. In these algorithms, threshold setting is a critical task since the performance of localization algorithm heavily depends on it. Even though the threshold is set properly, there exists the following problem. NB signal energy at certain frequencies within the frequency band of the NB signal may temporarily drop below the threshold. This causes needless separation of the NB signal into two (or more) parts. Also, the noise may temporarily yield to threshold crossing and cause falsely detected NB signals.

Several methods have been proposed for reducing problems mentioned above, e.g., [5]–[7]. However, many of these methods either need some priori knowledge or have high computational complexity. The original localization algorithm based on double thresholds (LAD) method has been proposed in [8] and

[9]. It does not need a priori knowledge about the signal to be detected or the noise level and its computational complexity is relatively low. The original LAD method uses not one but two thresholds, upper and lower. The lower threshold is used to avoid signal separation and the upper threshold helps to avoid false detections. However, the two LAD thresholds are calculated by performing the forward consecutive mean excision (FCME) algorithm twice [10]–[12]. Additionally, the lower threshold has a limited capacity for avoiding separating a signal into two or more signals. This causes the performance degradation of the original LAD method when estimating the correct number of signals.

In order to further reduce the computational complexity of the original LAD method, the LAD with normalized thresholds (NT) method has been proposed in [10]. The LAD NT method calculates only one threshold using the FCME algorithm and constitutes the corresponding upper and lower thresholds by multiplying the calculated threshold with two different fixed coefficients. However, those fixed coefficients must be selected by extensive computer simulation. This limits the flexibility of the LAD NT method. In this paper, a simplified LAD method is proposed and its upper and lower thresholds are directly calculated by running the FCME algorithm only once. The simplified LAD method is more flexible than the LAD NT method at the expense of increasing a slight computational complexity.

Moreover, by using LAD with adjacent cluster combining (ACC) method as recently proposed in [10] and [12], errors in the estimation of the number of signals can be reduced. Therein, an extra condition is added after the original LAD method: If two accepted clusters are separated by  $n$  or less samples, the accepted clusters are jointed together including the samples between the two accepted clusters. In this paper, by combining the simplified LAD method and binary morphological operators, the enhanced LAD method is proposed. Compared with the LAD ACC method, the proposed method has relatively low computational complexity and gives better performance, especially at low SNR.

This paper is organized as follows. In Section II, the system model is first described. The original LAD and LAD NT methods are discussed in Section III. According to the characteristics of the FCME algorithm, the simplified LAD method is proposed in Section IV. By combining the simplified LAD method and binary morphological operators, the enhanced LAD method is investigated in Section V. Simulation results are presented in Section VI. Finally, Section VII gives the conclusion.

## II. SYSTEM MODEL

The received discrete-time signal samples  $x(n)$  are assumed to have the basic form

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K. X. Jia is with the Department of Electronic Engineering, University of Electronic Science and Technology of China, China, email: jiakexin@sina.com.cn.

Z. S. He is with the Department of Electronic Engineering, University of Electronic Science and Technology of China, China, email: zshe@uestc.edu.cn.

$$x(n) = \sum_{k=1}^M s_k(n) + v(n) \quad (1)$$

where  $M$  is the number of unknown NB signals and  $s_k(n)$  is the  $k$ th NB signal.  $v(n)$  is a zeros-mean complex additive white Gaussian noise (AWGN) with total variance  $2\sigma^2$ . The noise variance is assumed to be unknown. The considered NB signals are binary phase shift keying (BPSK) communication signals. The signals are assumed to be independent of each other. Although only BPSK signals are considered, corresponding results can be achieved when using other NB signals that have similar-type spectra, for example, quadrature phase shift keying (QPSK) or 16-quadrature amplitude modulation (QAM) signals.

### III. ORIGINAL LAD AND LAD NT METHODS

#### A. Original LAD Method

The original LAD is an adaptive two-threshold based NB signal localization method. The usage of two thresholds provides NB signal separation and localization. Usually, the upper and lower thresholds are calculated using the FCME algorithm [13]–[15].

The FCME algorithm performs the threshold calculation iteratively. The magnitude squared frequency domain samples are first sorted in an ascending order. Denote these samples with  $z_{(i)}$ , where  $i = 1, 2, \dots, D$ ,  $D$  is the number of samples. Let  $I$  denote the initial set size, which is assumed to be clean from signal samples. If the initial set is too large, the probability of having a clean initial set decreases, if the initial set is not clean, the performance is degraded. Typically, the size of the initial set is around 10% of the number of samples.

In the first iteration, the following test is performed with  $k = I$ .

$$z_{(k+1)} \geq T_{\text{CME}} \frac{1}{k} \sum_{i=1}^k z_{(i)} \quad (2)$$

where  $T_{\text{CME}}$  is the FCME threshold multiplier which defines the operation performance of the FCME algorithm. The threshold multiplier depends on the distribution of the noise, and in this exponential case it is  $T_{\text{CME}} = -\ln(P_{\text{FA,DEC}})$ , where  $P_{\text{FA,DEC}}$  is the desired clean sample rejection ratio (DCRR). If the test is true, the algorithm stops and the remaining samples are decided to be signals. Otherwise, the sample below the current threshold is added to the clean set and the test is performed again with  $k$  incremented 1. This is continued until the test is true for some value of  $k$  or  $k = D$  which means that all the samples are decided to be clean of signals.

For the original LAD method, the FCME algorithm is run twice with two different threshold multipliers  $T_{\text{CME}}$ , which are called the upper ( $T_1$ ) and lower ( $T_2$ ) threshold multipliers,  $T_2 \leq T_1$ , to get the upper ( $T_U$ ) and lower ( $T_L$ ) thresholds. After the thresholds have been calculated, the original LAD method groups the adjacent samples above the lower threshold  $T_L$  into the same group, a cluster. The cluster is accepted to be a narrowband signal if at least the sample with the largest energy is also above the upper threshold  $T_U$ . Hence, one accepted cluster corresponds to one detected signal.

#### B. LAD NT Method

To simplify the complexity of threshold calculation of the original LAD method, the LAD NT method has been proposed in [10]. Firstly, threshold  $T_{\text{new}}$  is calculated by running the FCME algorithm once with a threshold multiplier  $T_x$ , and after that, the following expressions are used to get the required upper and lower thresholds.

$$T_U = T_{\text{new}} P_{\text{up}}, \quad (3)$$

$$T_L = T_{\text{new}} P_{\text{lo}} \quad (4)$$

where  $P_{\text{up}} = (T_1/T_x)a$ ,  $P_{\text{lo}} = (T_2/T_x)b$ , and  $a$  and  $b$  are fixed coefficients which are selected by extensive computer simulations.

### IV. SIMPLIFIED LAD METHOD

In this section, the simplified LAD method is discussed. The original LAD and simplified LAD methods have the same detection performance. The only difference between them is the way of calculating thresholds. For the simplified LAD method, the algorithm of calculating the two different thresholds is as follows.

The lower threshold is obtained by performing the following iteration.

$$z_{(k+1)} \geq T_2 \frac{1}{k} \sum_{i=1}^k z_{(i)}. \quad (5)$$

If the FCME algorithm stops at  $k = D$  which means that all the samples are decided to be clean of signals, the upper and lower thresholds are given by

$$T_U = T_1 \frac{1}{D} \sum_{i=1}^D z_{(i)}, \quad (6)$$

$$T_L = T_2 \frac{1}{D} \sum_{i=1}^D z_{(i)}. \quad (7)$$

If it stops at  $k = K_L < D$ , the following expression is obtained

$$z_{(K_L+1)} \geq T_2 \frac{1}{K_L} \sum_{i=1}^{K_L} z_{(i)}. \quad (8)$$

The corresponding lower threshold is expressed as

$$T_L = T_2 \frac{1}{K_L} \sum_{i=1}^{K_L} z_{(i)}. \quad (9)$$

According to the principle of FCME algorithm, it is easily shown that

$$z_{(K_L)} < T_2 \frac{1}{K_L - 1} \sum_{i=1}^{K_L-1} z_{(i)}. \quad (10)$$

For  $T_2 < T_1$ , the following result is immediately verified

$$z_{(K_L)} < T_1 \frac{1}{K_L - 1} \sum_{i=1}^{K_L-1} z_{(i)}. \quad (11)$$

The above expression implies that when computing the upper threshold, the initial set is not  $\{z_{(i)}, i = 1, 2, \dots, I\}$  but  $\{z_{(i)}, i = 1, 2, \dots, K_U\}$ . The iteration (5) is continued by replacing  $T_2$  with  $T_1$  until the test is true for some value of  $k = K_U < D$  or  $k = D$ . If the iteration stops at  $k = D$ , the upper threshold is given by

$$T_U = T_1 \frac{1}{D} \sum_{i=1}^D z_{(i)}. \quad (12)$$

If it stops at  $k = K_U < D$ , the upper threshold can be written as

$$T_U = T_1 \frac{1}{K_U} \sum_{i=1}^{K_U} z_{(i)}. \quad (13)$$

From above discussion, we can see that the complexity of calculating upper and lower thresholds with two different threshold multipliers,  $T_1$  and  $T_2$ , in the simplified LAD method is equivalent to that of calculating upper threshold with a threshold multiplier  $T_1$  in the original LAD method.

As to the LAD NT method, the complexity depends on the selection of threshold multiplier  $T_x$ . if  $T_x \leq T_1$ , the complexity is not higher than that of the simplified LAD method. However, the LAD NT method has a deficiency: Its fixed coefficients must be selected through simulations, which limits the flexibility of its usage in practice. In contrast, the simplified LAD method is more flexible at the expense of increasing a slight computational complexity.

## V. ENHANCED LAD METHOD

The problem with the original LAD is that the lower threshold has a limited capacity for avoiding separating a signal into two or more signals. This problem can be radically reduced by using the LAD ACC method proposed in [10] and [12]. Therein, an extra condition is added after the original LAD method: If two accepted clusters are separated by  $n$  or less samples, the accepted clusters are jointed together including the samples between the two accepted clusters. In this section, an enhanced LAD method is proposed. As discussed in Section IV, the simplified LAD method has lower computational complexity than the original LAD method. Hence, compared with the LAD ACC method, the proposed method has relatively low computational complexity.

### A. Enhanced LAD Method

By combining the simplified LAD method and binary morphological operators, the enhanced LAD method can be summarized as follows.

Step 1: The upper ( $T_U$ ) and lower ( $T_L$ ) thresholds are calculated by the simplified LAD method.

Step 2: Two different binary vectors,  $z_L = \{z_L^i, i = 1, 2, \dots, D\}$  and  $z_U = \{z_U^i, i = 1, 2, \dots, D\}$ , are constructed by the following expressions.

$$z_U^i = \begin{cases} 1, & z_i \geq T_U \\ 0, & z_i < T_U \end{cases}, \quad z_L^i = \begin{cases} 1, & z_i \geq T_L \\ 0, & z_i < T_L \end{cases} \quad (14)$$

where  $z_i$ ,  $i = 1, 2, \dots, D$  are the frequency samples and  $z_U \subset z_L$ .

Step 3: For  $z_L = \{z_L^i, i = 1, 2, \dots, D\}$ , a binary morphological close operator is used to identify the two adjacent connected components separated by  $n$  or less samples as a connected component. The result is denoted as  $z_C$ , which is also a binary vector with the same length as  $z_L$ . As stated in literature [16], [17], the binary morphological close operator is an extensive transformation. Therefore,  $z_C$  and  $z_L$  satisfy the following ordering relationship:  $z_L \subseteq z_C$ .

Step 4: let  $z_U$  denote a marker vector and  $z_C$  a mask vector ( $z_U \subset z_C$ ). A binary morphological reconstruction operator, denoted by  $R_{z_C}(z_U)$ , is performed by iterating elementary geodesic dilation of  $z_U$  inside  $z_C$  until stability. In other words,

$$R_{z_C}(z_U) = \delta_{z_C}^{(i)}(z_U) \quad (15)$$

where  $i$  is such that

$$\delta_{z_C}^{(i)}(z_U) = \delta_{z_C}^{(i+1)}(z_U). \quad (16)$$

$\delta_{z_C}^{(i)}(z_U)$  denotes the geodesic dilation of size  $i$  of the marker vector  $z_U$  with respect to the mask vector  $z_C$ . It can be obtained by performing  $i$  successive geodesic dilations of  $z_U$  with respect to  $z_C$ :

$$\delta_{z_C}^{(i)}(z_U) = \delta_{z_C}^{(1)}[\delta_{z_C}^{(i-1)}(z_U)]. \quad (17)$$

The initialized conditions of the above successive geodesic dilations are given by

$$\delta_{z_C}^{(1)}(z_U) = \delta^{(1)}(z_U) \cap z_C, \quad (18)$$

$$\delta_{z_C}^{(0)}(z_U) = z_U \quad (19)$$

where  $\delta^{(1)}(z_U)$  is a basic elementary dilation operator and  $\cap$  a point-wise intersection operator.

The goal of the above processing is to extract connected components from  $z_C$  marked by  $z_U$ . The result of binary morphological reconstruction operator,  $R_{z_C}(z_U)$ , is denoted as  $z_R$ . Hence, each connected components in  $z_R$  is accepted as a NB signal.

In practice, two different signals can be separated by the enhanced LAD method if there is at least  $n + 1$  adjacent samples between the corresponding connected components that are below the lower threshold. Herein, we select  $n = 2$ . This choice improves the performance significantly, with only marginal degradation in the separation ability. More generally, the optimal value of  $n$  depends on the used scenario and its requirements.

### B. Discussion

From above discussion, it can be seen that after detecting by the lower threshold  $T_L$  in step 2, the frequency samples are grouped into several clusters which are correspond with the connected components included in the binary vector  $z_L$ . There may present several adjacent clusters that are separated by  $n$  or less samples. The binary morphological close and reconstruction operators in steps 3 and 4 achieve the following operation: If the largest frequency sample in these adjacent clusters exceeds the upper threshold, the enhanced LAD method identifies these clusters as a cluster. For the LAD ACC method, proposed in [10]

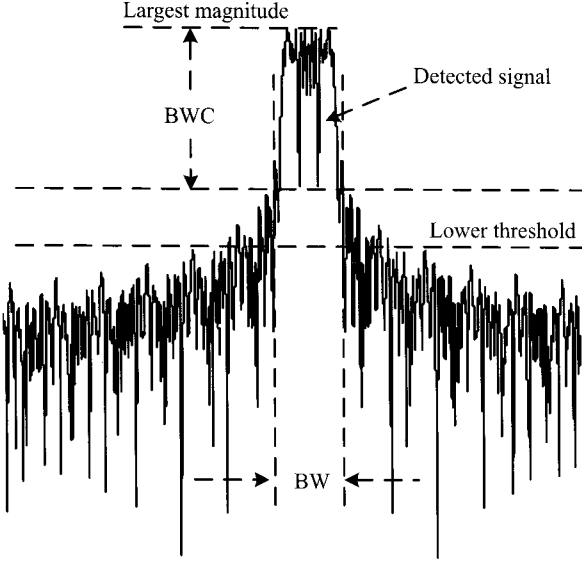


Fig. 1. Method of estimating BW with a BWC.

and [12], it requires that all largest samples in each of these clusters are above the upper threshold.

In the case of detecting correct number of signals, the two methods have similar performance at high SNR. However, at low SNR, the probability that a signal is separated into two or more adjacent clusters increases, but the probability that each cluster exceeds the upper threshold decreases. This indicates that the enhanced LAD method has better performance at low SNR.

When estimating bandwidth (BW), the length of a cluster accepted as a signal is taken into account. The enhanced LAD method has better accuracy at low SNR. This is because the binary morphological close operator combines adjacent clusters as much as possible. However, at high SNR, when the rising side lobes exceed the lower threshold, some of them as well as the main lobes may be identified as the same cluster by the binary morphological close operator if they are separated by  $n$  or less samples. Hence, compared with the LAD ACC method, the enhanced LAD method widens the estimated BW. This problem can be overcome by the following method.

Given a BW criterion (BWC)  $T_{BWC}$ , if the difference between the lower threshold and the largest sample of a cluster accepted as a NB signal is larger than  $T_{BWC}$ , The method of estimating BW is considered in Fig. 1. Otherwise the length of this cluster is used as an estimated BW. In this paper,  $T_{BWC} = 20$  dB. This choice significantly improves the performance of estimating BW at high SNR. More generally, the optimal value of  $T_{BWC}$  depends on the used scenario.

At last, the ratio of falsely detecting the number of signals (FDR) is discussed when only noise is presented. The above LAD methods, discussed in this paper, have the same FDR, which is due to the fact that the FDR only depends on the upper threshold and all the methods have the same upper threshold. If no frequency sample exceeded the upper threshold, the FDR would equal to zero. Assume that the frequency samples,  $z_i, i = 1, 2, \dots, D$ , are statistically independent, the FDR

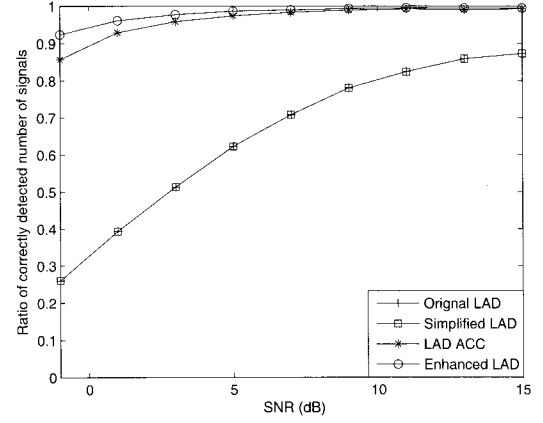


Fig. 2. Ratio of correctly detected number of signals vs. SNR. Two RC-BPSK signal, BWs 2%.

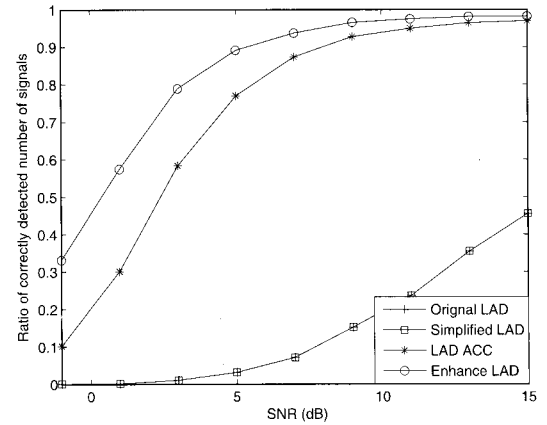


Fig. 3. Ratio of correctly detected number of signals vs. SNR. Two RC-BPSK signal, BWs 5%.

can be expressed as

$$P_{FDR} = 1 - (1 - P_1)^D \quad (20)$$

where  $P_1$  denotes the corresponding DCRR of the upper threshold.

## VI. SIMULATION RESULTS

In the Monte Carlo computer simulation, the original LAD, simplified LAD, LAD ACC, and enhanced LAD methods are studied in the frequency domain. There are complex AWGN channel and 2–3 BPSK signals with relative BWs of 2–7% of the system bandwidth. The BPSK signals are band-limited by a root raised cosine (RC) with a roll-off factor of 0.22. The frequency domain samples are calculated with the windowed 1024-point fast Fourier transformation (FFT). A 4-term Blackman-Harris window is used to reduce the spectrum leakage. It should be noticed that the windowing loss caused by this window is about 3 dB [18]. The LAD method multipliers are  $T_1 = 13.81$  (upper,  $P_{FA,DEC} = 10^{-6}$ ) and  $T_2 = 4.61$  (lower,  $P_{FA,DEC} = 10^{-2}$ ). 10000 tests are included in each Monte Carlo simulation.

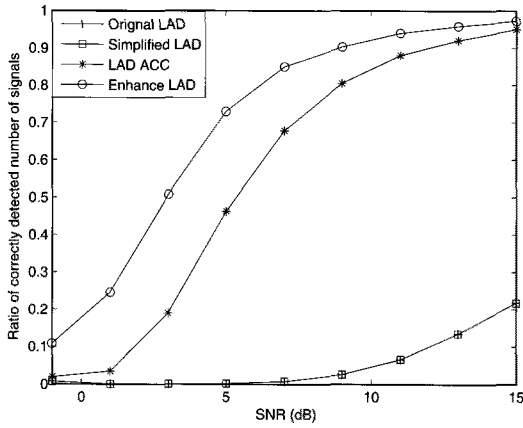


Fig. 4. Ratio of correctly detected number of signals vs. SNR. Two RC-BPSK signal, BWs 7%.

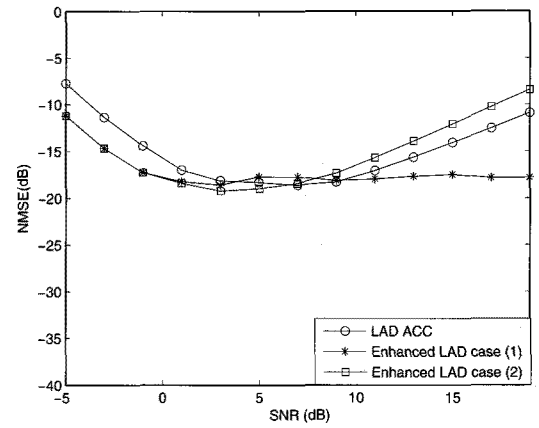


Fig. 6. NMSE of BW estimation vs. SNR. LAD ACC and enhanced LAD methods, BW 2%.

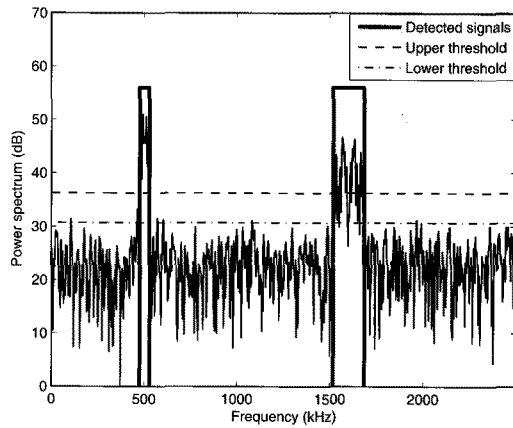


Fig. 5. Two RC-BPSK signals with SNR values 5 dB, enhanced LAD method. Actual BWs 2%, 7%, estimated BWs 2.051%, 6.74%, Actual CFs 500, 1600, estimated CFs 501.71, 1601.

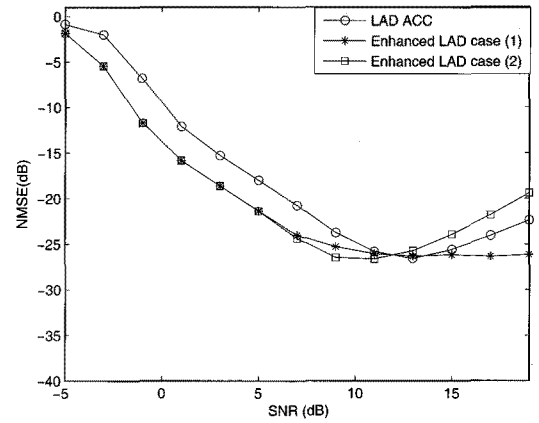


Fig. 7. NMSE of BW estimation vs. SNR. LAD ACC and enhanced LAD methods. BW 7%.

Figs. 2, 3, and 4 presents the ratio of detecting correct number of signals. It presents how often the methods are able to find the correct number of signals. For example, if the ratio of detecting correct number of signals is 0.6, it means that in 60% of the cases the method estimates the number of signals correctly. It can be seen that the original LAD and simplified LAD methods have the same performance. The performance of the enhanced LAD method is better than that of the LAD ACC method at low SNR. This is consistent with the discussion in Section V. Moreover, as the relative bandwidths of BPSK signals gradually increase, the performance of the above methods degrades. The enhanced LAD method has the slowest speed of performance degradation.

When there are two simultaneous BPSK signals, a 'snapshot' of center frequency (CF) and BW estimations is presented in Fig. 5. It is assumed that the number of signals is detected correctly, i.e., the number of detected signals is two. In Figs. 6 and 7, the normalized mean square error (NMSE) [11] is used to measure the correctness of the estimated BWs. The BW estimation results are presented only for the enhanced LAD

Table 1. The FDRS of four different LAD methods.  $10^6$  tests, theoretical FDR 0.001.

METHOD	FDR
Original LAD	0.000902
Simplified LAD	0.000902
LAD ACC	0.000902
Enhanced LAD	0.000902

and LAD ACC methods. In the LAD ACC method, the length of a cluster accepted as a NB signal is used as the estimated BW [10]. For the enhanced LAD method, two different cases are investigated. In case (1), the BWC based method, proposed in Section V, is used to estimate BW. In case (2), the length of a cluster accepted as a signal is used. It can be seen from Figs. 6 and 7 that at low SNR, the enhanced method has better estimation accuracy. At high SNR, the BW estimated by the enhanced LAD case (2) method is wider than that by the LAD ACC method. The enhanced LAD case (1) method achieves relatively good BW estimates.

When no signal is presented, the FDRs of four different LAD

methods are simulated with  $10^6$  tests. The simulated results are listed in Table 1. It can be seen that the discussed LAD methods in this section offer the same FDR. The theoretical FDR is computed through equation (20) with  $P_1 = 10^{-6}$  and  $D = 1024$ . The simulated results are very close to the theoretical FDR. The enhanced LAD method does improve the performance but not increase the FDR.

## VII. CONCLUSION

To reduce the computational complexity of the original LAD method, the simplified LAD method is investigated. By combining binary morphological operators and the simplified LAD method, the enhanced LAD method is proposed. Compared with the LAD ACC method, the enhanced LAD method has relatively low computational complexity and gives good performance, especially at low SNR. However, all these LAD methods discussed in this paper are not always capable to separate two adjacent signals and they are not able to localize weak signals accurately. These problems will be studied in the future work.

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**Ke Xin Jia** was born in Shandong, China, on September 12, 1982. He received the B.Sc. degree in Electronic Information Science and Technology from Yantai Normal University in 2004 and the M.Sc. degree in Signal and Information processing from University of Electronic Science and Technology in 2007. Presently, he is studying for D.Sc. degree in University of Electronic Science and Technology. His major interests are in communication signal interception and identification.



**Zi Shu He** was born in Sichuan, China, in 1962. He received the M.Sc. and D.Sc. degree from University of Electronics Science and Technology of China, in 1988 and 2000, respectively. He is currently a Professor in the Department of Electronic Engineering, University of Electronics Science and Technology of China. His research interests include MIMO systems, signal processing of radar, techniques of digital array radar, and so on.