

Detection Number of Sources Based on Hybrid Technique in Sensor Networks

Taqwa Oday Fahad¹, Jehan Zuhair Abid Dixon², Ali Hussein Mary³

¹Biomedical Engineering Department, University of Technology- Iraq, taqwa.o.fahad@uotechnology.edu.iq

²Information Technology Department, Basrah Oil Company, Iraq, jehan.zuhairo5@gmail.com

³Mechatronics Engineering Department, Al-Khwarizmy College, Baghdad University, Iraq, Alimary76@kecbu.uobaghdad.edu.iq

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ABSTRACT

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Estimating number of sources in sensor networks is a well investigated problem. A common method for solving this problem is to use a Minimum Description Length technique (MDL). The performance of MDL degrades with noise conditions. This paper is concern with the development and application of adaptive noise canceller technique for enhancement the response of MDL. A new system is proposed to estimate number of sources by applying MDL to the outputs of adaptive noise canceller based ANFIS. Simulation outcomes of the offered system demonstrate well, effectiveness, and accurate determination of the number of sources.

Keywords: Detection Number of Sources, Minimum Description Length, Adaptive Noise cancellation, LMS, ANFIS.

INTRODUCTION

The use of adaptive signal processing in sensor network is prevalent due to its capacity to assess the total sources number [1,3]. The Minimum Description Length (MDL) is a publicly available approach for assessing the sources number that state in numerous sensors [4-5]. The performance of MDL degrades with noise conditions.

Adaptive filtering noise cancellation is a significant subfield of digital signal processing having important in wireless sensor network applications. It has high consideration and represents a principle model to remove the noise mixed with the original signal]. The LMS is effective method for calculating the coefficients of adaptive noise cancellation and it is significant in wireless sensor networks, the LMS is suffer performance degrade with slow convergence [6].

On the other hand, the Adaptive Neuron Fuzzy Inference System (ANFIS) facilitates Takagi-Sugeno fuzzy inference utilizing the network principle. It has the usefulness of neural networks with fuzzy systems; which achieves the input variable fuzzification besides fuzzy inference processes, whereas neural networks achieve the consequent portion of Takagi-Sugeno fuzzy inference. Moreover, the ANFIS has proven it's useful in various applications, such as adaptive noise cancellation, identification of system, adaptive image processing, due to its ability to process nonlinear functions, in addition to its rapid convergence rate with minimal convergence error. [7-8].

In the light of above, a new model is provided in the current paper considering Adaptive noise cancellation and ANFIS network in order to specify the total sources number using MDL. For the response evaluation, our proposal is compared to classical algorithms by computer simulations.

METHODS

MINIMUM DESCRIPTION LENGTH

The array sensor has k elements, every one collects m received samples from p sources according to the following specified model [9]:

$$Y = AS + Z \quad (1)$$

In which $Y \in R^{k \times m}$ represents the received samples matrix, while $A \in R^{k \times p}$ represents the steering (mixing) matrix, and $S \in R^{p \times m}$ represents the matrix of the source signal, furthermore $Z \in R^{p \times m}$ represents the nontrivial temporal and spatial covariance matrix with additive Gaussian noise component. It will be presumed that $p \leq k$ or the sensors number k is greater than the emitting sources number p . The data vector (Y)'s covariance matrices would thus be [10-11]:

$$R = E[YY^\dagger] \quad (2)$$

Due to the limited number of snapshots available in practice, it is not possible to get precise covariance matrices; instead, we can only obtain an estimate \hat{R} of the real R thru

$$\begin{aligned} \hat{R} &= \frac{1}{m} Y Y^\dagger \\ &= \sum_{j=1}^k \hat{\lambda}_j \hat{u}_j \hat{u}_j^H \end{aligned} \quad (3)$$

Where \dagger signifies complex conjugate with transpose, while $\hat{u}_j, j = 1, \dots, k$ represent relating eigenvectors,

wherease $\hat{\lambda}_j, j = 1, \dots, k$ represent the eigenvalues. Descendant eigenvalues are arranged by means of:

$\hat{\lambda}_1 \geq \hat{\lambda}_2 \geq \dots \geq \hat{\lambda}_p \geq \hat{\lambda}_{p+1} = \dots = \hat{\lambda}_k$ In which; $\hat{\lambda}_1, \hat{\lambda}_2, \dots, \hat{\lambda}_p$ represent the eigenvalues related to sources, whereas $\hat{\lambda}_{p+1}, \dots, \hat{\lambda}_k$ represent the eigenvalues that related to noise [12,14].

If the estimated eigenvalues are provided, the MDL approach makes use of the earlier statistical derivations to identify number of sources, the estimated function of MDL will be given as follows [15]:

$$\begin{aligned} MDL(j) &= -m \ln \left(\frac{\prod_{i=1+j}^k \lambda_i}{\frac{1}{k-i} \sum_{j=1}^k \lambda_i} \right) + \frac{1}{2} j(2k-j) \ln(m) \\ &\text{for } j = 0, 1, 2, \dots, k-1 \end{aligned} \quad (4)$$

In which; λ_i signify the \hat{R} eigenvalues, and j represents the sources number value, that reduces the cost function in the given function.

THE ADAPTIVE NOISE CANCELLING

Generally, noisy signal is presented via equation

$$x(n) = s(n) + y(n) \quad (5)$$

where $s(n)$ and $v(n)$ denote the clean with noise signals, respectively. Adaptive Noise Canceller system was utilized for eliminate noise from signal. This is advantageous technicality when signal is mixed with noise [16,117]. The method of utilized the adaptive filter to solve the adaptive noise Canceller case is shown at Fig. 1. The source signal $x(n)$ mixed by corrupted noise $y(n)$ that produced from other noise source $v(n)$ via an unknown nonlinear channel. The noise $v(n)$ is Gaussian noise. The objective of this system is to generate an anti-signal which has magnitude is quite the same as that of the unwanted noise and which has phase is quite opposite. The prime input source receives the desired signal $s(n)$ with corrupting noise $y(n)$. The corrupting noise $y(n)$ is produced via the noise signal $v(n)$. The received signal of primary input is given in equation (1). The noise $v(n)$ is correlated with the corrupting noise $y(n)$. The $v(n)$ is utilized by the system to produce output $y(n)$ that a copy of $y(n)$. The output is subsequently subtracted from $x(n)$ signal to recover the desired signal $s(n)$.

The LMS is common algorithm utilized by adaptive noise canceller. The input signal $x(n)$ was assumed in order to adjust the coefficients of adaptive noise canceller as follows [18]:

$$W(n+1) = W(n) + 2\mu e(n)x(n) \quad (6)$$

where n is the iteration index, the $e(n)$ is given via:

$$e(n) = d(n) - x^T(n)W(n) \quad (7)$$

where $d(n)$ is the desired signal. LMS method is the most common adaptive algorithm due to its simplicity. Generally, the LMS method suffers performance degrades and slow convergence rate

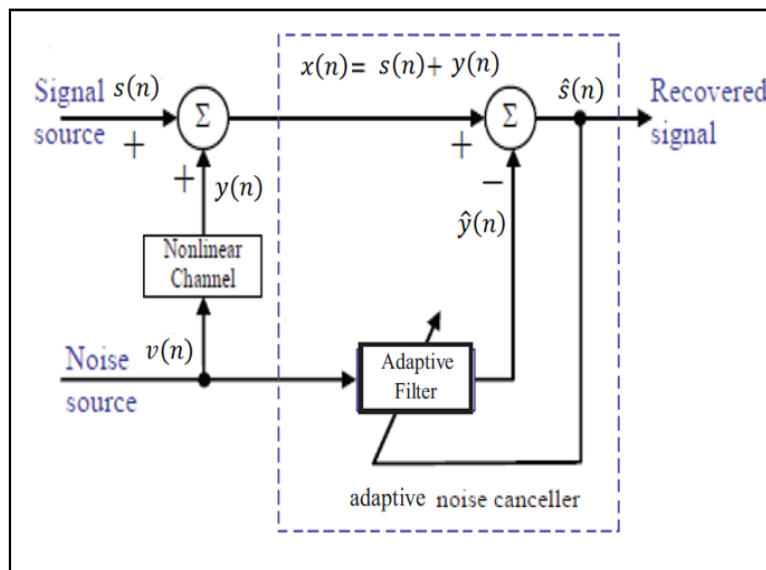


Figure 1. Adaptive noise canceller model

PROPOSED MODEL

The proposed model incorporates the adaptive noise cancellation with ANFIS algorithms for MDL technique in order to estimate the number of sources as displayed at Figure (2a).

The system's primary procedure can be described as follows. First, the signals are received by sensors. Next, these signals are denoising by the adaptive noise canceller with ANFIS algorithms as shown in figure (2b). Then, the output of adaptive noise cancellation is used to compute its covariance matrix. Finally MDL is calculated to estimate the numbers of sources.

The main process of the algorithm at figure (2b) is defined as follows:

1. Generate white Gaussian noise $v(n)$
2. Generate noise $y(n)$ via $v(n)$ through non-linear channel.
3. The signal $x(n)$ is mixed of source signal $s(n)$ with noise $y(n)$.
4. Noise $v(n)$ process via the ANFIS adaptive filter to yield output $\hat{y}(k)$
5. Estimation $\hat{y}(n)$ via ANFIS after training, $\hat{y}(n)$ is replica of $y(n)$
6. Estimation desired signal via proposed model by $\hat{s}(n) = s(n) + y(n) - \hat{y}(n)$

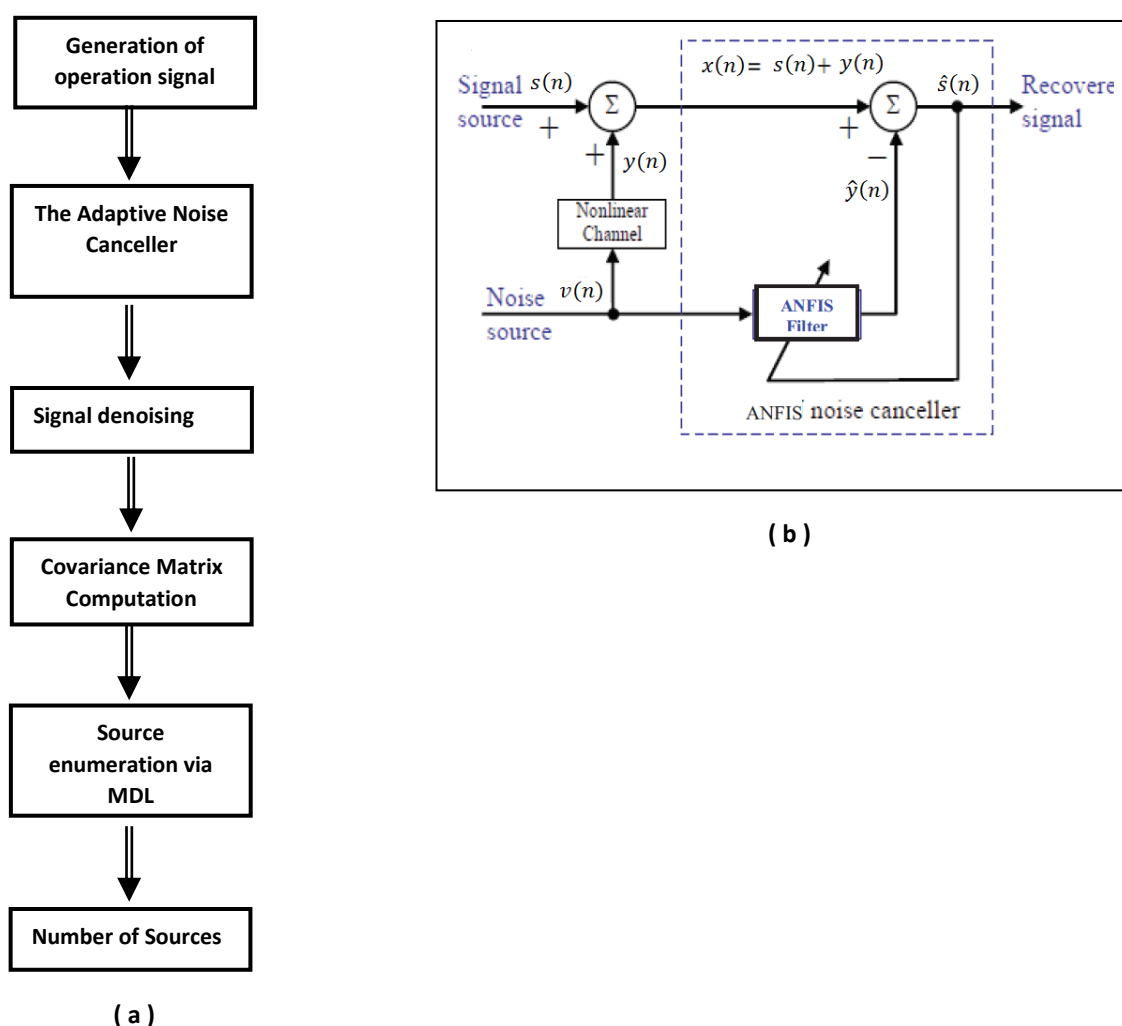


Figure 2. a) Diagrammatic Representation for the Proposed Model b) The Adaptive Noise Cancellation

SIMULATION EXPERIMENTS AND RESULTS

Simulation tests were conducted utilizing MATLAB 2023 to assess the effectiveness of the suggested approach. The response of the proposed model, which involves estimating sources using a combination of adaptive noise cancellation with ANFIS for the MDL technique are compared with two other models. The first model uses only the MDL method, while the second model involves estimating sources using a combination of adaptive noise cancellation with LMS for the Minimum Description Length (LMS-MDL).

We take into consideration a uniform linear array that uses $m=100$ snapshots and has $k=14$ sensors. Furthermore, Parameters sets for ANFIS include a training epoch number of ten, a triangular membership function with a total of four membership functions for each input. 0.1 is taken for initial step size, and 1.1 for step size increase rate, and a step size decrease rate of 0.9 is considered. In addition, a hybrid learning algorithm was utilized. Two situations were examined; each contains different number of sources: two sources are used in the first scenario, while three sources are taken into consideration in the second.

The initial experiment utilizes two sources ($p=2$) with a signal-to-noise ratio (SNR) of -4dB. The first source is positioned at an angle of 60° degrees, while the subsequent source is located at an angle of 64° degrees. It is evident that both the proposed and (LMS-MDL) models achieve correct sources enumeration of two, whereas the MDL system produces an incorrect total of one source. However, the iteration convergence speed of proposed model is quicker compared to the (LMS-MDL) model, which is shown in Figure 3.

In the second scenario, three sources with a number ($p=3$) have an SNR of -4dB. The first one of them is located at 60° , while the second one is at 64° , and the final source is at 68° . The suggested system in this scenario can accurately obtain a total of three sources, whereas the (LMS-MDL) system and MDL system produces an incorrect total of two sources. Figures 4-6 display the likelihood of detecting for the comparison systems. These figures demonstrate that the suggested system yields a detection probability, convergence rate and identification accuracy better than the (LMS-MDL) and MDL models.

CONCLUSIONS

This research presents an effective approach to figure out number of sources in sensor networks. The underlying technique utilizes Minimum Description Length technique applied to the output of adaptive noise cancellation with ANFIS algorithms. The suggested approach could produce an accurate estimate of number of sources. In addition, the suggested model demonstrates rapid convergence speed compare with LMS and high effectiveness through computer simulation.

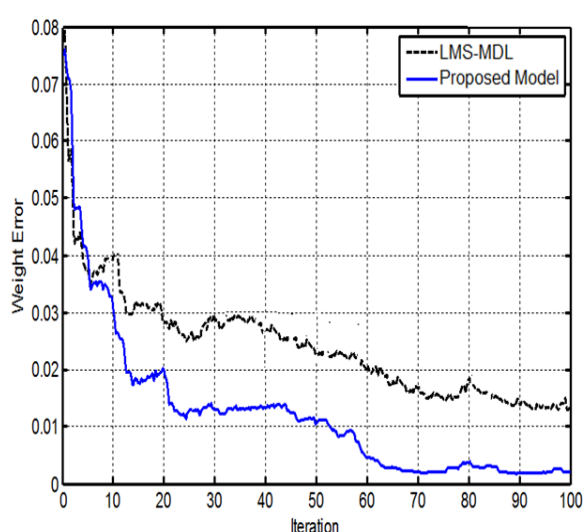


Figure 3. Weight error Curves per iteration for Proposed and Comparative

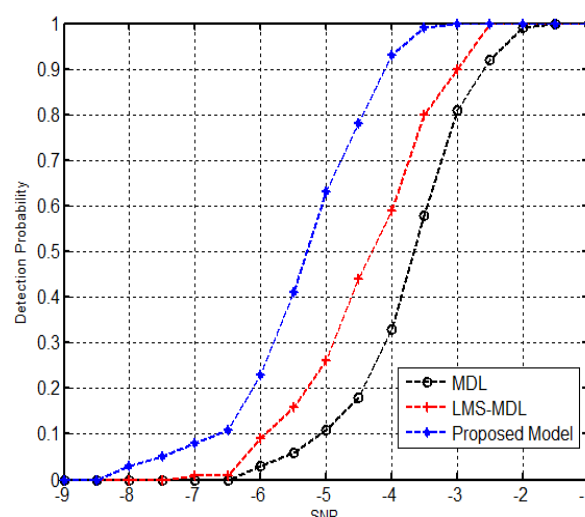


Figure 4. Detection Probability vs. SNR for Proposed and Comparative methods

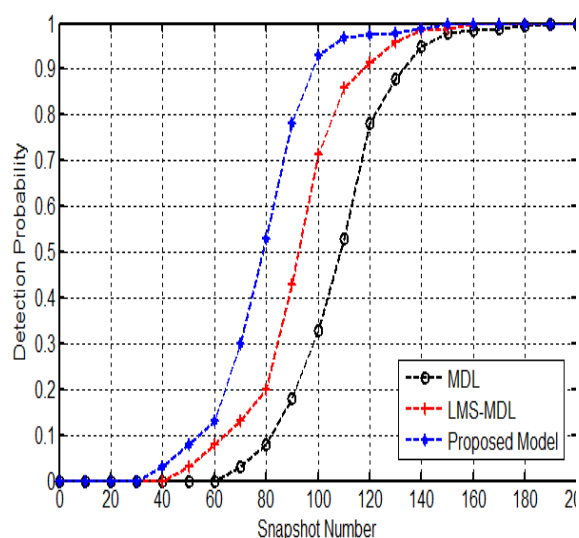


Figure 5. Detection Probability vs. snapshot number (m) for Proposed and Comparative

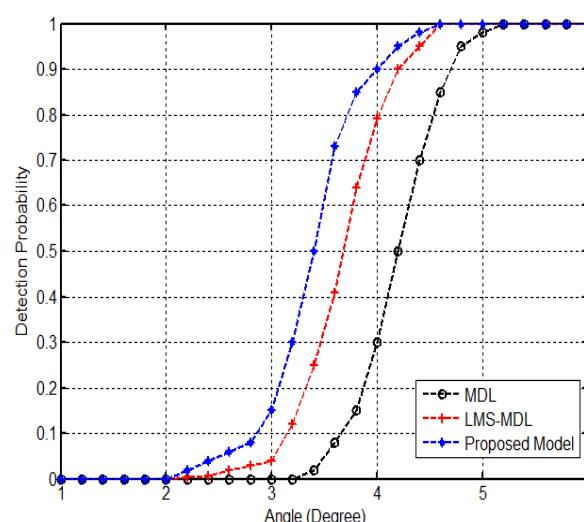


Figure 6. Detection Probability vs. angle separation for Proposed and Comparative

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