Acoustic Noise Cancellation Using an Adaptive Algorithm Based on Correntropy Criterion and Zero Norm Regularization

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Received: 25/May/2015 Revised: 14/Jul/2015 Accepted: 26/Jul/2015

Abstract

The least mean square (LMS) adaptive algorithm is widely used in acoustic noise cancellation (ANC) scenario. In a noise cancellation scenario, speech signals usually have high amplitude and sudden variations that are modeled by impulsive noises. When the additive noise process is nonGaussian or impulsive, LMS algorithm has a very poor performance. On the other hand, it is well-known that the acoustic channels usually have sparse impulse responses. When the impulse response of system changes from a non-sparse to a highly sparse one, conventional algorithms like the LMS based adaptive filters can not make use of the priori knowledge of system sparsity and thus, fail to improve their performance both in terms of transient and steady state. Impulsive noise and sparsity are two important features in the ANC scenario that have paid special attention, recently. Due to the poor performance of the LMS algorithm in the presence of impulsive noise and sparse systems, this paper presents a novel adaptive algorithm that can overcomes these two features. In order to eliminate impulsive disturbances from speech signal, the information theoretic criterion, that is named correntropy, is used in the proposed cost function and the zero norm is also employed to deal with the sparsity feature of the acoustic channel impulse response. Simulation results indicate the superiority of the proposed algorithm in presence of impulsive noise along with sparse acoustic channel.

Keywords: Adaptive Filter; LMS Algorithm; Sparse Acoustic Channel; Zero Norm; Impulsive Noise; Correntropy.

1. Introduction

Adaptive Filters are used in large applications to endow a system with learning and tracking abilities, especially when the signal statistics are unknown and are expected to vary with time. Over the last several years, a wide range of adaptive algorithms has been developed for diverse demands such as channel equalization, spectral estimation, target localization, system identification and noise cancellation. One group of the basic adaptive algorithms is gradient-based algorithms such as the LMS algorithm. The well-known LMS algorithm is perhaps one of the most familiar and widely used algorithms because of its good performance in many circumstances and its simplicity of implementation [1],[2].

In many scenarios such as speech echo cancellation, parameters of the acoustic channel impulse response can be assumed to be sparse [3]-[5]. When the system changes from a non-sparse to a highly sparse one, conventional algorithms like the LMS based adaptive filters can not make use of the priori knowledge of system sparsity and thus, fail to improve their performance both in terms of transient and steady state. Using such prior information about the sparsity of acoustic channel can be helpful to improve LMS

Algorithm performance. In the past years, several algorithms have been proposed for sparse adaptive filtering using LMS, which was motivated by recent progress in compressive sensing [6]. The basic idea of these techniques is to introduce a penalty into the cost function of the standard LMS to exploit the sparsity of the system impulse response and achieve a better performance [7].

Many approaches for signal processing problems have been studied when the additive noise process is modeled with Gaussian distribution. However, for many real-life situations, the additive noise of the system is found to be dominantly nonGaussian and impulsive. One example of nonGaussian environments is the acoustic noise in speech processing applications [8]-[10]. When the additive noise process is nonGaussian or impulsive, LMS algorithm has a very poor performance [11]. In [12],[13] it was shown that for some environments with nonGaussian noise, maximum correntropy criterion (MCC) algorithm outperforms LMS algorithm.

In order to modify LMS algorithm performance in sparse conditions and nonGaussian noises, Wentao Ma, proposed a hybrid algorithm in [14] based on MCC and correntropy induced metric (CIM), for robust channel estimation problem. Specifically, MCC is utilized to mitigate the impulsive noise while CIM is adopted to exploit the channel sparsity.

Based on ANC recent works, it is clear that in this field of research, we need to deal with two important features, sparse acoustic channels [3]-[5] and nonGaussian acoustic noises [8]-[10]. Thus, in order to address this problem, we propose a novel adaptive algorithm in this paper which is mathematically different

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with [14] in order to exploit sparsity. The proposed algorithm is obtained by combination of maximum correntropy criterion and zero norm regularization. The zero norm is utilized in the cost function to deal with sparsity feature of acoustic channel and the correntropy criterion is used to eliminate nonGaussian noises from speech signal. Computer simulation results show that the proposed adaptive algorithm achieves better performance compared to the conventional adaptive LMS algorithm.

This paper is organized as follows. After the introduction, adaptive noise cancellation configuration is expressed in section II. In order to cancelling nonGaussian noise from speech signal, a novel adaptive sparse MCC algorithm is developed in section III. Finally, simulation and comparison results are given in section IV, followed by conclusions in section V.

2. Adaptive Noise Cancellation

An important application of adaptive filters is in acoustic noise cancellation [15]. Fig. 1 shows the configuration of a noise cancellation system. Assume that signal x(n) is the acoustic noise which passes through an acoustic channel, with impulse response:

$$h(n) = \sum_{i=0}^{N-1} w_i \delta(n-i) \quad (1)$$

By sorting the channel coefficients w_i into a column vector, the acoustic channel impulse response can be expressed as follows,

$$W^o = [w_0, w_1, \dots, w_{N-1}]^T \quad (2)$$

that $(.)^T$ represents the transpose operator. An observation of the desired signal which is sensed by the first microphone is denoted by,

$$d(n) = X(n)^T W^o + s(n) \quad (3)$$

where $s(n)$ is the speech signal (speaker, music or etc) and $X(n) = [x(n), x(n-1), \dots, x(n-N+1)]^T$ denotes a vector of delayed input signal which is sensed by the second microphone. Given a desired signal $d(n)$ and acoustic noise $X(n)$, adaptive filter tries to replicate colored noise by exactly modeling the sparse acoustic channel between the noise source and the desired signal. The difference between the desired signal $d(n)$ and the output of adaptive filter $y(n)$ is in fact the noise-free signal (cleaned speech).

The objective of an adaptive algorithm is to identify the sparse channel W^o using the signals $X(n)$ and $d(n)$. Let $W^o = [w_0, w_1, \dots, w_{N-1}]^T$ be the estimated vector of the adaptive filter at iteration n. In the standard LMS, the cost function $J_{MSE}(n)$ is defined as

$$J_{MSE}(n) = e^2(n) \quad (4)$$

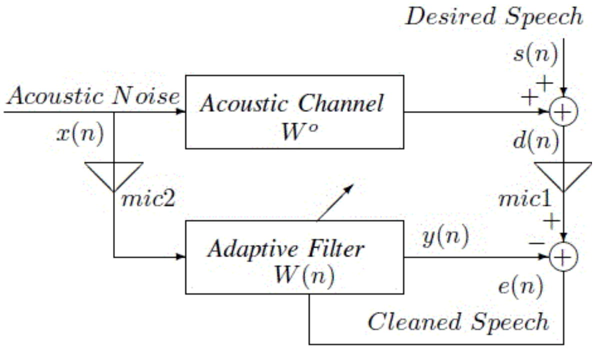

Fig. 1. The block diagram of a noise cancellation system.

where $e(n)$ is the instantaneous error determined as

$$e(n) = d(n) - y(n) \quad (5)$$

in which $y(n)$ is the output of adaptive filter and it is equal to $X(n)^T W(n)$. The filter coefficients vector is then updated by stochastic gradient descent equation [1]:

$$W(n+1) = W(n) - \mu \nabla J_{MSE}(n) \quad (6)$$

in which ∇ represents gradient and can be calculated by,

$$\nabla J(n) = \left[\frac{\partial J(n)}{\partial w_0}, \frac{\partial J(n)}{\partial w_1}, \dots, \frac{\partial J(n)}{\partial w_{N-1}}\right] \quad (7)$$

According to the equations (4), (6) and (7), the LMS algorithm is obtained,

$$W(n+1) = W(n) - \mu \nabla J_{MSE}(n)$$
$$= W(n) + 2\mu e(n) X(n) \quad (8)$$

where μ is the step size and controls the convergence rate and steady state error.

More recently, there have been concerns about the effects of nonGaussian noise on adaptive algorithms [11]–[14]. This has led a number of authors to investigate adaptive algorithms which reduce the bad effects of nonGaussian noise. On the other hand, the sparse nature of such an impulse response causes standard adaptive algorithms like LMS to perform poorly [5].

In this work, we design a novel adaptive algorithm based on maximum correntropy criterion and zero norm regularization, in order to improve LMS weak performance in ANC application, in which the acoustic channel is sparse and the system noise is nonGaussian and impulsive. The next section developes the proposed algorithm that aim to give improved performance when these two important features exist in speech data.

3. Adaptive l_0 MCC Algorithm

The Mean Square Error (MSE) criterion may perform poorly in nonlinear and nonGaussian situations, especially when the data are disturbed by impulsive noises. To improve the performance in these situations, the maximum correntropy criterion (MCC), which is a robust criterion for non-Gaussian signal processing, has recently been successfully applied in adaptive filtering [12],[13]. The correntropy is a nonlinear measure of similarity between two random variables. Given two random variables X and Y, the correntropy is:

$$V(X,Y) = E[k_\sigma(x-y)] \quad (9)$$

where $k_\sigma(x-y)$ is a positive definite kernel with the kernel width σ. The MCC has recently been applied to adaptive filtering algorithm to improve the tracking performance in impulsive interference [12], while MSE-based algorithms perform poorly [11]. The most widely used kernel in correntropy is the Gaussian kernel:

$$k_\sigma(x-y) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-y)^2}{2\sigma^2}} \quad (10)$$

By using a Taylor series expansion of the exponential function in the Gaussian kernel,

$$V(X,Y) = E\left[\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-y)^2}{2\sigma^2}}\right]$$
$$= \frac{1}{\sigma\sqrt{2\pi}} \sum_{n=0}^{\infty} \frac{(-1)^n}{n!\,2^n\sigma^{2n}} E[(x-y)^{2n}] \quad (11)$$

it can be seen that the correntropy criterion involves all the higher even order statistical moments of the error random variable $(x-y)$ .On the other hand, mean square error (MSE) criterion just contain the second order statistical moment. Thus the MCC included more information of the error random variable $(x-y)$ and it should be very useful for cases when the measurement noise is nonzero mean, non-Gaussian, with large outliers.

Under the MCC criterion, the optimal weight vector of the adaptive filter can be obtained by maximizing:

$$J_{MCC}(n) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{e^2(n)}{2\sigma^2}} \quad (12)$$

A stochastic gradient ascent based adaptive algorithm, namely the MCC algorithm can be easily derived [12],

$$W(n+1) = W(n) + \mu\nabla J_{MCC}(n)$$
$$= W(n) + \mu\nabla\left[\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{e^2(n)}{2\sigma^2}}\right]$$
$$= W(n) + \mu_{MCC} e^{-\frac{e^2(n)}{2\sigma^2}} e(n)X(n) \quad (13)$$

in which μ_{MCC} is equal to $\frac{\mu}{\sigma^3\sqrt{2\pi}}$. By choosing the kernel width so large, the MCC algorithm will simplify to the LMS algorithm:

$$\sigma \to \infty \quad => \quad e^{-\frac{e^2(n)}{2\sigma^2}} \to 1$$
$$W(n+1) = W(n) + \mu_{MCC} e^{-\frac{e^2(n)}{2\sigma^2}} e(n)X(n)$$
$$W(n+1) = W(n) + \mu_{MCC} e(n)X(n) \quad (14)$$

Comparing the MCC (13) with the LMS (8) weight update rule, we see that the weight update equation at each iteration in (13) just contains an extra scaling factor which is an exponential function of the instantaneous error $e(n)$. This factor rejects the impulsive and nonGuassian noise. As $\to \infty$, the exponential function goes to zero and therefore, processing of nonGaussian signal will be neglected. According to the above discussion, adaptation of weights using MCC filter is more stable when the desired signal has strong outliers or impulsive characteristics. By contrast, whenever a high amplitude outlier is encountered in the desired signal or in the error, $e(n) = d(n) - y(n)$, the LMS weight update rule (8) is forced to make a large increment, which takes the weights away from the optimal values.

By minimizing the zero norm of the filter coefficients vector in cost function of LMS algorithm, the sparsity of parameters has been exploited [6],[7]. In order to apply the zero norm in the MCC algorithm, the negative sign of zero norm should be inserted in the maximum correntropy cost function (12). By combining the correntropy criterion with the zero norm regularization, a new cost function is proposed in this paper,

$$J_{new}(n) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{e^2(n)}{2\sigma^2}} - \gamma\|W(n)\|_0 \quad (15)$$

where γ is a regularization parameter, which represents a trade off between estimation error and sparsity of the parameters. Operator $\|W(n)\|_0$ denotes zero norm, which counts the number of nonzero coefficients of vector $W(n)$. Because solving differentiation of zero norm is not possible, the zero norm is generally approximated by a continuous function [7]:

$$\|W(n)\|_0 \approx \sum_{i=0}^{N-1}\left(1 - e^{-\beta|w_i(n)|}\right) \quad (16)$$

when some elements of vector $W(n)$ are near zero, we have:

$$|w_i(n)| \approx 0 \quad => \quad \left(1 - e^{-\beta|w_i(n)|}\right) = 0 \quad (17)$$

On the other hand, when some elements of vector $W(n)$ are not zero, and also β is chosen as a large number, then we have:

$$|w_i(n)| \neq 0 \;, \beta\uparrow \quad => \quad \left(1 - e^{-\beta|w_i(n)|}\right) = 1 \quad (18)$$

According to (17), (18) it can be seen that equation (16) is a general approximation of the zero norm function and the number of nonzero coefficients of vector $W(n)$ is counted. By this general approximation, the gradient of zero norm can be calculated,

$$\nabla\|W(n)\|_0 = \left[\frac{\partial\|W(n)\|_0}{\partial w_0(n)}, \frac{\partial\|W(n)\|_0}{\partial w_1(n)}, \dots, \frac{\partial\|W(n)\|_0}{\partial w_{N-1}(n)}\right]$$
$$=\beta\left[sgn(w_0(n))e^{-\beta|w_0(n)|}, \dots, sgn(w_{N-1}(n))e^{-\beta|w_{N-1}(n)|}\right]$$
$$=\beta\begin{bmatrix} e^{-\beta|w_0(n)|} & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & \cdots & e^{-\beta|w_{N-1}(n)|}\end{bmatrix} sgn(W(n))$$
$$= \beta\, diag\left[e^{-\beta|w_0(n)|}, \dots, e^{-\beta|w_{N-1}(n)|}\right] sgn(W(n)) \quad (19)$$

in which $diag[.]$ represents a diagonal matrix. By inserting the proposed cost function (15) in a gradient ascent updating, the proposed filter update is obtained as:

$$W(n+1) = W(n) + \mu\nabla J_{new}(n)$$
$$= W(n) + \mu\nabla\left(\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{e^2(n)}{2\sigma^2}} - \gamma\|W(n)\|_0\right)$$
$$= W(n) + \mu\nabla\left(\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{e^2(n)}{2\sigma^2}}\right) - \mu\gamma\nabla\|W(n)\|_0$$
$$= W(n) + \frac{\mu}{\sigma^3\sqrt{2\pi}} e^{-\frac{e^2(n)}{2\sigma^2}} e(n)X(n) - \mu\gamma\nabla\|W(n)\|_0 \quad (20)$$

By exerting sparse penalty to the MCC cost function, the solution will be sparse and the gradient ascent recursion will improve the performance of near-zero coefficients in the sparse acoustic channel. By inserting (19) in (20), the proposed algorithm can be rewritten as follows:

$$W(n+1) = W(n) + \frac{\mu}{\sigma^3\sqrt{2\pi}} e^{-\frac{e^2(n)}{2\sigma^2}} e(n)X(n)$$
$$-\mu\gamma\beta \; diag\left[e^{-\beta|w_0(n)|}, \dots, e^{-\beta|w_{N-1}(n)|}\right] sgn\big(W(n)\big) \quad (21)$$

In the next section, the proposed algorithm is simulated for sparse acoustic channel along with impulsive and shot noise, like in ANC application. The robustness of the proposed method against channel sparsity and impulsive noise is verified by detailed simulation studies.

4. Simulations

In this section, we have tried to simulate a real life conditions as closely as possible. The speech signal $s(n)$ that has been used is shown in Fig. 2(a). The nonGaussian noise is generated from mixture of multiple Gaussian distributions. After adding the noise to the speech signal, its non stationary characteristics can be seen in Fig. 2(b).

The sparse acoustic channel is that of a typical closed room environment [5], shown in Fig. 3. We use 21 taps to model the sparse acoustic channel path as follows,

$$W^o = [0,0.9,0,0,1,0,0,0,0,0,0.5,0,0,0,0,0,0,0,0,0,0]^T \quad (22)$$

The sparsity ratio of W^o is equal to 3/21 which means vector W^o containing only 3 large coefficients and others are near zero. The impulsive and nonGaussian observation noise is often modeled by a two component Gaussian mixture [11] with the following probability density function (pdf),

$$f_Z(z) = 0.6N(0,0.1) + 0.4N(0,10) \quad (23)$$

in which $N(0,10)$ denotes a Gaussian distribution with mean 0 and variance 10. Clearly, in this pdf, the second Gaussian distribution with variance 10 creates strong outliers as shown in Fig. 4. The kernel width σ for the MCC cost function is set to 2 in this case. According to various experiments and similar to references, other parameters such as step size μ, regularization parameter γ and sparsity parameter β were chosen to be 0.01, 0.001 and 8, respectively.

For comparing the error performance of the algorithms described in the previous section, the Mean Square Deviation (MSD) is defined as,

$$MSD(n) = E[\|W^o - W(n)\|^2] \quad (24)$$

Fig. 5, shows the MSD performances of the presented algorithms in the presence of impulsive noise (23) along with sparse acoustic channel (22). The sudden and high amplitude bursts of samples which occur in speech signals can easily disturb the LMS weight updating. However, MCC algorithm (13) places exponentially decreasing weights on samples that are distant and impulsive. In order to handle the case of channel sparsity, the MCC algorithm was modified further to a novel proposed algorithm (21). In this algorithm, each coefficient is updated with an independent step size that is made proportional to the magnitude of the particular filter coefficient, resulting in better performance for sparse systems. As seen in Fig. 5, the proposed l0-MCC algorithm has a superior performance in a noise cancellation scenario of highly impulsive speech signal.

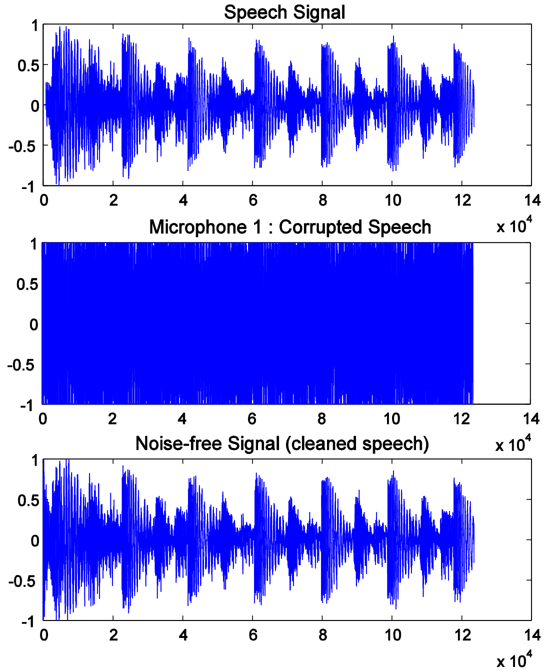

Fig. 2. (a) Original speech signal, (b) corrupted speech signal by implusive noise, (c) cleaned speech signal using proposed algorithm

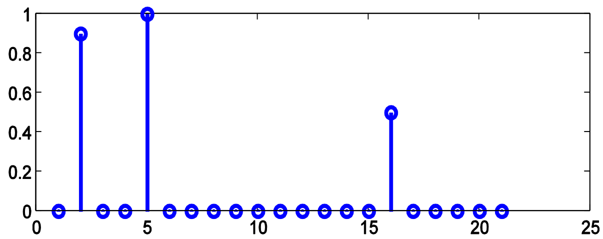

Fig. 3. A typical sparse acoustic channel (22)

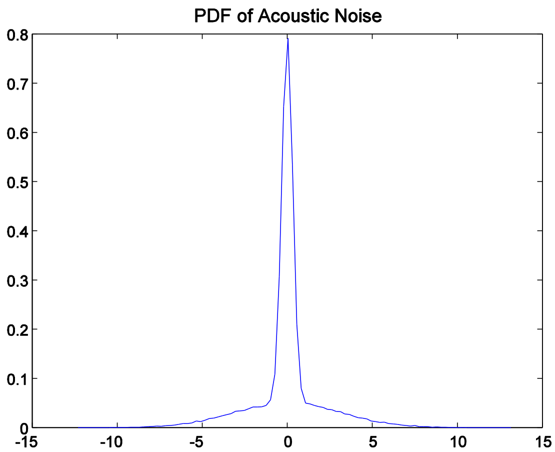

Fig. 4. Impulsive noise pdf (23), containing a two Gaussian components with identical zero means and different variances.

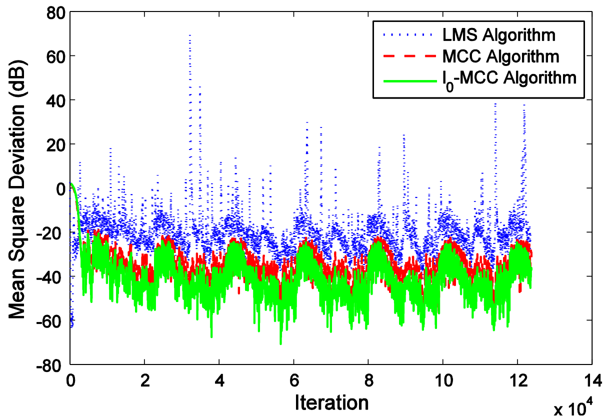

Fig. 5. MSD performance comparison in presence of impulsive noise (23) along with sparse acoustic channel (22) with a real speech signal s(n).

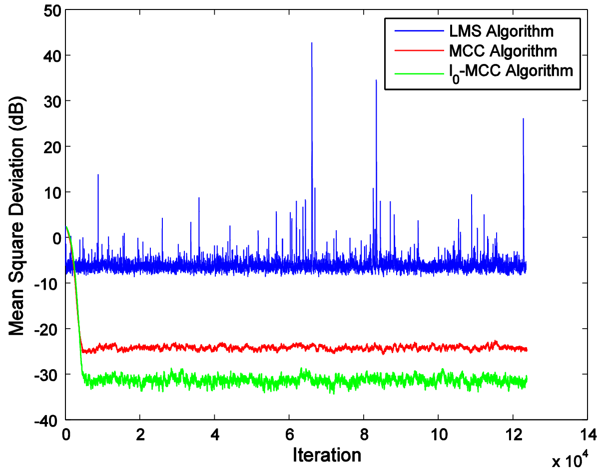

Fig. 6. MSD performance comparison in presence of impulsive noise (23) along with sparse acoustic channel (22) with a white normal signal s(n).

The performance of the described algorithms is also evaluated with a white normal input and is shown in Fig. 6. As seen, the proposed algorithm has superior performance in comparison with LMS (8) and MCC (13) algorithms.

The robustness of the proposed algorithm for diverse conditions of channel sparsity and nonGaussian noises is demonstrated by various simulation studies. Another experiment is utilized to show the superiority of the proposed algorithm in a different noise cancellation scenario. In this experiment, the acoustic channel W^o is assumed to be

$$[0,0.9,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]^T \quad (25)$$

Here, we use an acoustic channel with sparsity ratio of 2/30 as shown in Fig. 7. The nonGaussian noise is modeled by a three component Gaussian mixture with the following pdf,

$$f_Z(z) = 0.2N(-3,0.1) + 0.6N(0,0.1) + 0.2N(3,0.1) \quad (26)$$

as shown in Fig. 8. For comparison purposes, the MSD performances of this experiment are plotted in Fig. 9, by averaging over 20 independent runs. From various simulation studies, it is evident that the proposed filter achieves a 25 dB decrement of steady-state error, when the channel is sparse and the noise is nonGaussian or impulsive.

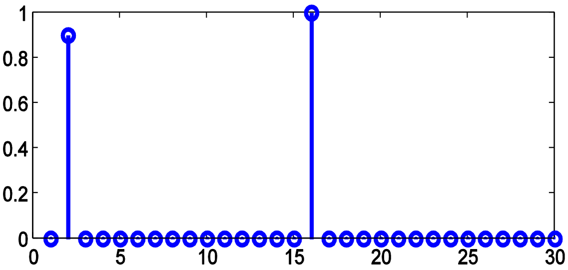

Fig. 7. Another sparse acoustic channel for second experiment (25).

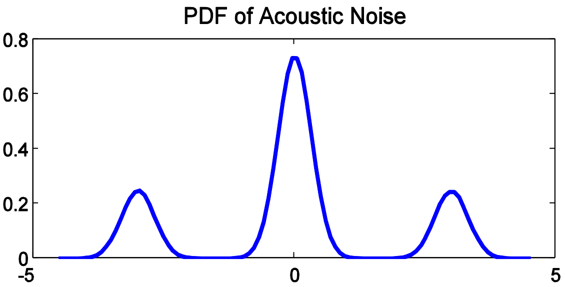

Fig. 8. Gaussian mixture noise pdf (26), containing three Gaussian components with different means and same variances

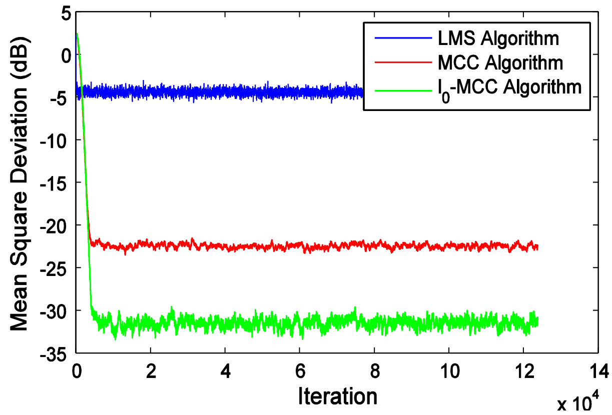

Fig. 9. MSD performance comparison for noise pdf (26) along with sparse acoustic channel (25) and a white normal signal s(n).

In the last experiment, the acoustic channel W^o is assumed to be

$$[0,0.8,0,0.8,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0.8,0,0.8,0]^T \quad (27)$$

with sparsity ratio of 4/30 as shown in Fig. 10. The nonGaussian noise is modeled by two component Gaussian mixture with the following pdf,

$$f_Z(z) = 0.5N(-2,0.1) + 0.5N(2,0.1) \quad (28)$$

as shown in Fig. 11. The MSD performances of the last experiment are plotted in Fig. 12. From various simulation studies, it is evident that the proposed filter achieves better performance, when the channel is sparse and the noise is nonGaussian type.

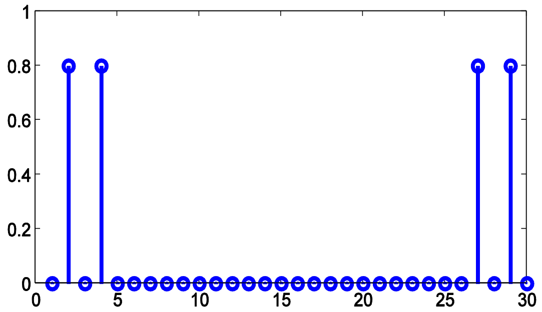

Fig. 10. Typical sparse acoustic channel for third experiment (27).

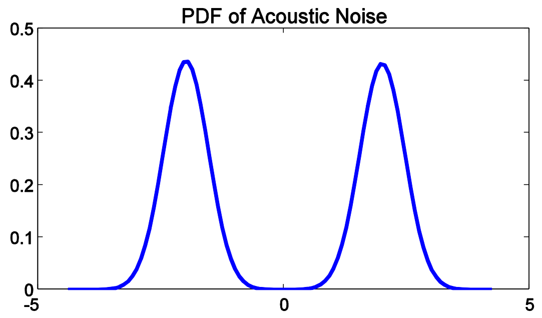

Fig. 11. Gaussian mixture noise pdf (28), containing two Gaussian components with different means and same variances.

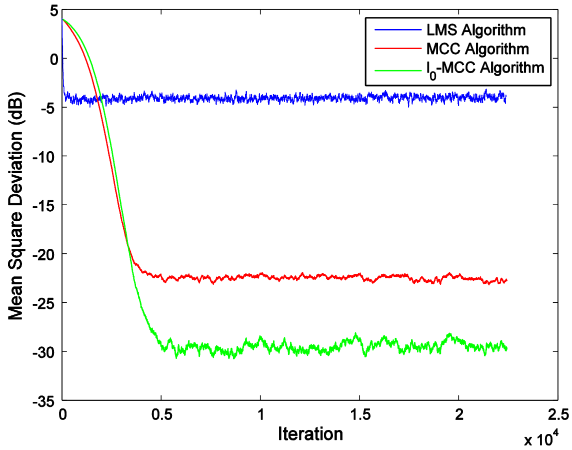

Fig. 12. MSD performance comparison for noise pdf (28) along with sparse acoustic channel (27) and a white normal signal s(n).

5. Conclusions

In a noise cancellation scenario, speech signals usually have high amplitude and sudden variations that are modeled by impulsive disturbances. In this paper, a novel adaptive algorithm has been proposed to improve LMS algorithm performance in impulsive disturbances and sparse acoustic channels. In order to provide robustness against impulsive noise, the cost function is derived by maximizing the correntropy. Additionally, an accurate approximation of zero norm is also utilized to further improve the performance in sparse acoustic channels. Simulation results show that the proposed algorithm achieves a better performance in terms of steady-state error as compared with the LMS and MCC algorithms.

Acknowledgments

The author would like to thank his superviser, Dr. Hossein Zamiri-Jafarian, whose valuable comments and kind evaluations improved the idea and presentation of this paper.

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