Applied Acoustics 141 (2018) 125–135

Contents lists available at ScienceDirect

Applied Acoustics

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

Blind speech intelligiblility enhancement by a new dual modified predator-prey particle swarm optimization algorithm

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ARTICLE INFO

Keywords:
Acoustic noise cancellation
Particle swarm optimization
Predator-prey PSO
Output signal-to-noise ratio (SNR)
System mismatch (SM)

ABSTRACT

This paper addresses the problem of acoustic noise cancellation by adaptive filtering algorithms. To deal with acoustic noise reduction and speech enhancement problems, we propose to use the modified predator-prey particle swarm optimization (MPPPSO) to design a new dual adaptive noise canceller based on swarm intelligence heuristic search. The proposed dual MPPPSO algorithm improves the single-channel PPPSO algorithm convergence speed behavior when a large filter length is used. Also, the proposed algorithm leads to a low steady-state error in comparison with the single-channel PPPSO algorithm behavior which fails with large filters length and non-stationary input. The proposed dual MPPPSO algorithm shows significant improvement in the system mismatch (SM) and Output signal-to-noise ratio (SNR) values. We present the simulation results of the proposed dual MPPPSO algorithm that confirm its superiority and good performances in comparison with the single-channel PPPSO and the two-channel normalized least mean square (2C-FNLMS) algorithm.

1. Introduction

Acoustic noise cancelling refers to the improvement in the quality of degradation of speech signal caused by different types of noise. Several methods were proposed to resolve the problem of adaptive noise cancellation (ANC) [1], by the use of adaptive filtering algorithms. The most used adaptive filtering algorithm is the least mean square (LMS) [2], and others ones based on stochastic and *meta*-heuristic optimization techniques such as artificial bee colony algorithm (ABC) [3], genetic algorithm (GA) [4,5], and particle swarm optimization (PSO) [5].

The LMS-based algorithms which are widely used due to their simplicity in implementation and computation suffer from local minima problem and the global minima are seldom reached. In order to overcome this problem, the stochastic and *meta*-heuristic optimization algorithms are able to avoid local minima problem. Various *meta*-heuristic approaches were adopted to solve the ANC problem. In [7,8], the authors suggested to use adaptive genetic algorithm, standard particle swarm optimization and its derived version, gravitational search algorithm (GSA) and bat algorithm (BA) to be applied in speech enhancement and acoustic noise reduction application.

In this paper, we propose a new dual modified predator-prey particle swarm optimization (MPPPSO) that can be used as a blind speech signal enhancer (we only suppose the knowledge of noisy observations that are, in our paper, generated by a convolutive mixing model [9]). The proposed MPPPSO algorithm is based on the combination between the single-channel predator-prey particle swarm optimization (PPPSO) [10,11], and the forward blind source separation (FBSS) structure.

This paper is organized as follows, in Section 2, we present the convolutive mixing model that generates the noisy observations, and we focus on the forward blind source separation (FBSS) structure. Section 3 describes the two-channel normalized least mean square (2C-FNLMS) and the two-channel variable step size forward algorithm (2C-VSSF). Then our proposed algorithm is presented in Section 4, and then Section 5 is reserved to the simulation results and discussions. Finally, we conclude our work in Section 6.

2. Problem statement

2.1. Simplified convolutive mixing model

In this paper, we consider the simplified convolutive mixing model proposed in [9]. In Fig. 1, the input signals $s(n)$ and $b(n)$ are the speech signal, and the punctual noise respectively.

According to Fig. 1, two microphones placed at the output of the mixing signal provide two noisy observations $p_1(n)$ and $p_2(n)$. The parameters $h_{12}(n)$ and $h_{21}(n)$ represent the cross-FIR filters between the two channels. We suppose that the speech and the noise signals are statistically independent. The two noisy observations are given by:

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https://doi.org/10.1016/j.apacoust.2018.07.006
Received 21 February 2018; Received in revised form 10 June 2018; Accepted 5 July 2018

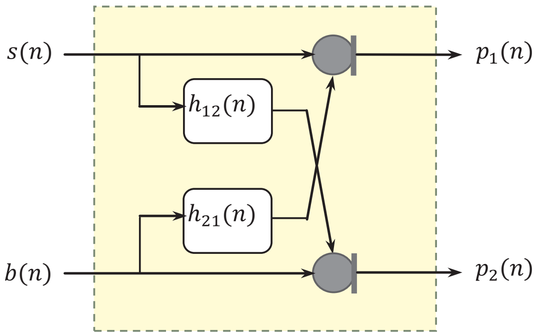

Fig. 1. Two-microphone mixing model with two cross-FIR filters.

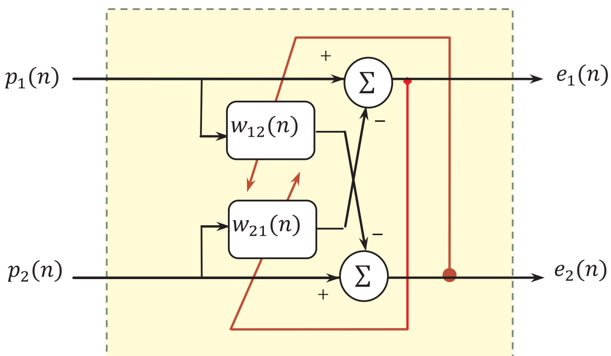

Fig. 2. Two-channel forward blind source separation FBSS structure.

$$p_1(n) = s(n) + b(n)*h_{21}(n) \quad (1)$$

$$p_2(n) = b(n) + s(n)*h_{12}(n) \quad (2)$$

where $(*)$ represents the convolution operator.

2.2. Acoustic noise cancelling by forward blind source separation (FBSS) structurer

In this paper, we consider the forward blind source separation (FBSS) structure shown by Fig. 2 [9,13,14], the observed signals $p_1(n)$ and $p_2(n)$ are the inputs of the adaptive FIR filters $w_{12}(n)$ and $w_{21}(n)$ respectively, The output signals, $e_1(n)$ and $e_2(n)$, of the FBSS structure are given by:

$$e_1(n) = p_1(n) - p_2(n)*w_{21}(n) \quad (3)$$

$$e_2(n) = p_2(n) - p_1(n)*w_{12} \quad (4)$$

The estimations of the speech and noise signal are obtained when these solutions are got, i.e. $w_{21}(n) = h_{21}(n)$, $w_{12}(n) = h_{12}(n)$ and we can write $e_1(n) = \hat{s}(n)$, and $e_2(n) = \hat{b}(n)$, where $\hat{s}(n)$ and $\hat{b}(n)$ are given as follows:

$$\hat{s}(n) = \mathrm{s}(n)*[\delta(n) - h_{12}(n)*h_{21} \quad (5)$$

$$\hat{b}(n) = \mathrm{b}(n)*[\delta(n) - h_{12}(n)*h_{21} \quad (6)$$

In addition, the filter coefficients are updated by the adaptation algorithm using the error signals $e_1(n)$and$e_2(n)$, a selected algorithm updates the coefficient of the adaptive filter whose output gives the estimated noise. Furthermore, the selected algorithm still minimizing

Table 1
Two-channel normalized least mean square (2C-FNLMS) [13].

Computation details	Variables
1. Initialize $w_{12}(-1) = 0$, $w_{21}(-1) = 0$ 2. $for n = 1: k$ **do** Estimation of the output signals: 3. $e_1(n) = p_1(n) - \mathbf{w}_{21}^T(n-1)\mathbf{p}_2(n)$ 4. $e_2(n) = p_2(n) - \mathbf{w}_{12}^T(n-1)\mathbf{p}_1(n)$ Filters coefficient adaptation: 5. $\mathbf{w}_{12}(n) = \mathbf{w}_{12}(n-1) + \mu_{12}e_2(n)(\frac{\mathbf{p}_1(n)}{\xi + \mathbf{p}_1(n)^2})$ 6. $\mathbf{w}_{21}(n) = \mathbf{w}_{21}(n-1) + \mu_{21}e_1(n)(\frac{\mathbf{p}_2(n)}{\xi + \mathbf{p}_2(n)^2})$ 7. $n = n + 1$ 8. end for	L: adaptive filter length.k: number of iteration.$\mathbf{w}_{12}$:The adaptive FIR filters: $\mathbf{w}_{12}(n) = [w_{12,0}(n), w_{12,1}(n), ..., w_{12,L-1}(n)]^T$$\mathbf{w}_{21}$:The adaptive FIR filters: $\mathbf{w}_{21}(n) = [w_{21,0}(n), w_{21,1}(n), ..., w_{21,L-1}(n)]^T$ $\mathbf{p}_1(n) = [p_1(n), p_1(n-1), ..., p_1(n-L+1)]^T$ $\mathbf{p}_2(n) = [p_2(n), p_2(n-1), ..., p_2(n-L+1)]^T$ μ_{12}: First fixed step-size: $0 < \mu_{12} < 2$$\mu_{21}$: Second fixed step-size$0 < \mu_{21} < 2$$\xi$: Small positive constants that avoids division by zeros.

Table 2
Two-channel variable step size forward algorithm (2C-VSSF) [14].

Computation details	Variables
1. Initialize $w_{12}(-1)$= 0, $w_{21}(-1)$= 0, $g_{12}(-1)$= 0, $g_{21}(-1)$= 0 2. $for n = 1: k$ **do** Estimation of the output signals: 3. $e_1(n) = p_1(n) - \mathbf{w}_{21}^T(n-1)\mathbf{p}_2(n)$ 4. $e_2(n) = p_2(n) - \mathbf{w}_{12}^T(n-1)\mathbf{p}_1(n)$ Filters adaptation: 5. $\mathbf{w}_{12}(n) = \mathbf{w}_{12}(n-1) + \mu_{12}(n)e_2(n)(\frac{\mathbf{p}_1(n)}{\xi + \mathbf{p}_1(n)^2})$ 6. $\mathbf{w}_{21}(n) = \mathbf{w}_{21}(n-1) + \mu_{21}(n)e_1(n)(\frac{\mathbf{p}_2(n)}{\xi + \mathbf{p}_2(n)^2})$ Step-sizes adaptation: 7. $\mu_{12}(n) = \mu_{12,max}\frac{\mathbf{g}_{12}(n)^2}{\mathbf{g}_{12}(n)^2 + \delta}$ 8. $\mu_{21}(n) = \mu_{21,max}\frac{\mathbf{g}_{21}(n)^2}{\mathbf{g}_{21}(n)^2 + \delta}$ 9. $\mathbf{g}_{12}(n) = \alpha_1\mathbf{g}_{12}(n-1) + (1-\alpha_1)\frac{e_2(n)\mathbf{e}_1(n-m)}{\mathbf{p}_1(n)^2 + \gamma}$ 10. $\mathbf{g}_{21}(n) = \alpha_2\mathbf{g}_{21}(n-1) + (1-\alpha_2)\frac{e_1(n)\mathbf{e}_2(n-m)}{\mathbf{p}_2(n)^2 + \gamma}$ 11. $n = n + 1$ 12. end for	L: adaptive filter length.k: number of iteration.$\mathbf{w}_{12}$:The adaptive FIR filters: $\mathbf{w}_{12}(n) = [w_{12,0}(n), w_{12,1}(n), ..., w_{12,L-1}(n)]^T$$\mathbf{w}_{21}$:The adaptive FIR filters: $\mathbf{w}_{21}(n) = [w_{21,0}(n), w_{21,1}(n), ..., w_{21,L-1}(n)]^T$ $\mathbf{p}_1(n) = [p_1(n), p_1(n-1), ..., p_1(n-L+1)]^T$ $\mathbf{p}_2(n) = [p_2(n), p_2(n-1), ..., p_2(n-L+1)]^T$$\mu_{12}(n)$: First variable-step-size: $0 < \mu_{12}(n) < \mu_{12,max} < 2$$\mu_{21}(n)$: Second variable-step-size$0 < \mu_{21}(n) < \mu_{21,max} < 2$$\alpha_1$, α_2:Small positive constants defined between 0 and 1.ξ, γ: Small positive constants .δ: Positive constants to control the variation of $\mu_{12}(n)$ and $\mu_{21}(n)$ .m: Delay index, $m = 0, 1, 2, ..., L-1$.$\mathbf{g}_{12}(n) = [g_{12,0}(n), g_{12,1}(n), ..., g_{12,L-1}(n)]^T$ $\mathbf{g}_{21}(n) = [g_{21,0}(n), g_{21,1}(n), ..., g_{21,L-1}(n)]^T$