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A New Shuffled Sub-swarm Particle Swarm Optimization Algorithm for Speech Enhancement

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Abstract - **In this paper, we propose a novel algorithm to enhance the noisy speech in the framework of dual-channel speech enhancement. The new method is a hybrid optimization algorithm, which employs the combination of the conventional θ-PSO and the shuffled sub-swarms particle optimization (SSPSO) technique. It is known that the θ-PSO algorithm has better optimization performance than standard PSO algorithm, when dealing with some simple benchmark functions. To improve further the performance of the conventional PSO, the SSPSO algorithm has been suggested to increase the diversity of particles in the swarm. The proposed speech enhancement method, called θ-SSPSO, is a hybrid technique, which incorporates both θ-PSO and SSPSO, with the goal of exploiting the advantages of both algorithms. It is shown that the new θ-SSPSO algorithm is quite effective in achieving global convergence for adaptive filters, which results in a better suppression of noise from input speech signal. Experimental results indicate that the new algorithm outperforms the standard PSO, θ-PSO, and SSPSO in a sense of convergence rate and SNR-improvement .**

Index Terms - **Adaptive filtering, Particle Swarm Optimization, Shuffled Sub-Swarm, Speech Enhancement, θ-PSO.**

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I. INTRODUCTION

Speech enhancement is a challenging problem in speech processing research, which aims at recovering clean speech from noisy speech. So far many types of gradient-based algorithms have been proposed in speech enhancement, which employ different schemes to adjust the filter weights based on different criteria. Some of the common algorithms are the Least-Mean-Squares (LMS) [1], the normalized version of LMS [NLMS], and Recursive-Least-Squares (RLS) [2]. However, when the error surface is multimodal, gradient descent algorithms that work well for FIR adaptive filters, are not suitable for IIR filters. A further drawback of gradient descent techniques is that they are likely to get trapped in a local minimum solution. A few modifications to gradient decent algorithms exist that can improve the performance, such as adding noise to the gradient calculation to make it more likely to escape from a local minima, or using the equation error adaptation to transform the error surface to unimodal [3].

An alternative to gradient descent-based techniques is a structured stochastic search of error space. These types of global search methods are independent from system structure, because a gradient is not calculated and the adaptive filter structure, aside from error computation, does not directly influence parameter updates. Due to this property, these types of techniques are potentially capable of globally optimizing any class of adaptive filter structures or objective functions [4]. Stochastic optimization algorithms, such as PSO, have been studied for use in adaptive filtering problems, where the Mean-Square-Error (MSE) surface is ill-conditioned [5].

Although the standard PSO finds good

solutions much faster than other stochastic algorithms [6], is still suffers from premature convergence, when complicated problems are optimized, and needs further improvements to avoid entrapping in local optima. Some suggest modifications and variations of the standard PSO algorithm to improve the overall efficiency [7-8].

In this paper, we propose a novel algorithm, called θ-shuffled sub-swarms particle optimization (θ-SSPSO) technique to solve the above mentioned problems and compare the results with the standard PSO, θ-PSO, and SSPSO algorithms for speech enhancement.

The paper is organized as follows. Section II describes the structure of a dual-channel speech enhancement system, together with the techniques of standard PSO, θ-PSO, and SSPSO. Section III introduces the proposed θ-SSPSO algorithm. The results of applying the proposed method to speech enhancement are presented in Section IV. Concluding remarks are given in Section V.

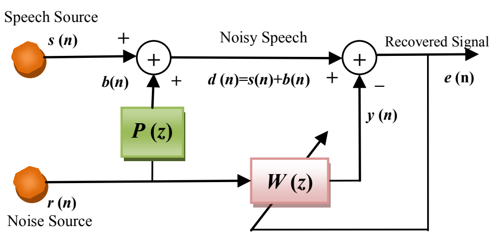

Figure1. Dual-channel speech enhancement

II. BACKGROUND

1. Dual-channel Speech Enhancement

Figure 1 shows the block diagram for a general two-channel enhancement system [9]. The clean speech signal *s(n)* is assumed to be present in only one channel, which is then corrupted by the background noise *b(n)* to generate the noisy speech signal *d(n)*. The second channel has the reference noise signal *r(n)*. The adaptive filter, *W(z)*, tries to model the transfer function *P(z)*. As a result, the filter output *y(n)* becomes an estimate of only the noise present in *d(n)*.

Finally, the output of the structure *e(n)* will be an estimate of the clean signal *s(n)*.

Suppose that the unknown system *P(z)*, which we want to estimate, is described by

$$y(n) = \sum_{i=0}^{L} a_i x(n-i) - \sum_{i=1}^{M} b_i y(n-i). \tag{1}$$

where a_i , b_i are the unknown parameters, which should be determined in an iterative way.

The parameters of the unknown system *P(z)* are estimated by minimizing the Mean-Square Error (MSE) between the noisy speech *d(n)* and the output of the adaptive filter *y(n)*.

The enhanced signal is obtained by subtracting the estimated noise *y(n)* from the noisy speech *d(n)*.

2. Standard PSO Algorithm

Particle swarm optimization (PSO) was introduced by Kennedy and Eberhart in 1995 [10]. This optimization technique, which is inspired by the social behavior of animals (e.g., fish schooling and bird flocking) has already come to be widely used in many areas [11].

The conventional PSO algorithm [12] begins by initializing a random swarm of *M* particles, each having *R* unknown parameters to be optimized. At each epoch, the fitness of each particle is evaluated according to the fitness function. The algorithm stores and progressively replaces the best previous position of each particle (**pbest**$_i$, i =1,2,...,M)”. as well as a single best particle (**gbest**).

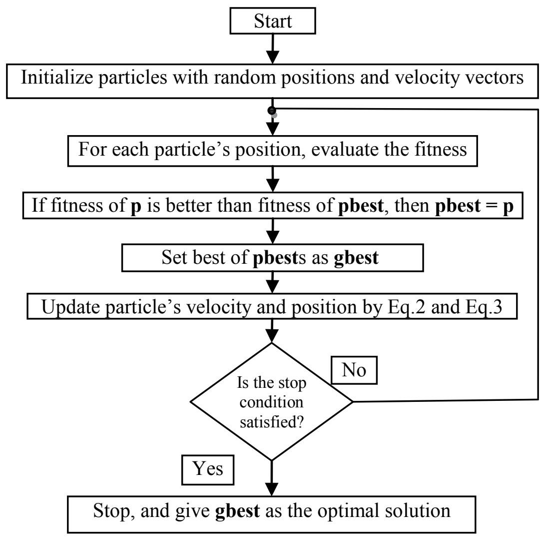

Figure2. Flowchart of the standard PSO algorithm

The parameters are updated at each epoch *(k)* according to

$$x_{id}(k+1) = x_{id}(k) + vel_{id}(k+1) \tag{2}$$

$$vel_{id}(k+1) = wv_{id}(k) + c_1 r_1 \left(p_{pbestd} - x_{id}(k)\right) + c_2 r_2 \left(p_{gbestd} - x_{id}(k)\right), \tag{3}$$

where $\mathbf{vel}_i$ is the velocity vector of the particle i, r_1, r_2 are random numbers uniformly distributed in the interval (0,1), c_1 and c_2 are the cognitive and social coefficients toward **gbest** and $\mathbf{pbest}_i$, respectively, and w is the inertia weight.

Inertia weight is updated as follow:

$$w = \left(w_{ini} - w_{end}\right)\frac{(T-t)}{T} + w_{end}, \tag{4}$$

where T is the maximum number of iterations. w_{ini} and w_{end} are initial and final values of the inertia weight, respectively. Through the run of PSO, the inertia weight decreases from a relatively large value to a small value. Using this technique, in early stages of the algorithm, the particles search the space globally. As the process goes on, their velocity decreases gradually, where at some point the particles begin to search the solution space locally [13].

Figure 2 represents flowchart of the standard PSO algorithm.

3. Standard θ-PSO Algorithm

Here, we introduce the θ-PSO algorithm to improve the performance of the standard PSO algorithm, which appears to be a promising approach of function optimization. In θ-PSO, the velocity and position of each particle are replaced by phase and phase increment using a mapping function [8]. The standard θ-PSO can be described in vector notation as follow

$$\begin{aligned}\Delta\boldsymbol{\theta}_i(t+1) = w\Delta\boldsymbol{\theta}_i(t) + c_1 r_1(t)\times\left(\boldsymbol{\theta}_{pbesti}(t) - \boldsymbol{\theta}_i(t)\right) + \\ c_2 r_2(t)\times\left(\boldsymbol{\theta}_{gbest}(t) - \boldsymbol{\theta}_i(t)\right)\end{aligned} \tag{5}$$

$$\boldsymbol{\theta}_i(t+1) = \boldsymbol{\theta}_i(t) + \Delta\boldsymbol{\theta}_i(t+1) \tag{6}$$

$$\mathbf{x}_i(t) = f^{-1}\left(\boldsymbol{\theta}_i(t)\right) \tag{7}$$

$$F_i(t) = \text{fitness}\left(\mathbf{x}_i(t)\right), \tag{8}$$

with $\theta_{ij} \in (\theta_{\min}, \theta_{\max})$, $\Delta\theta_{ij} \in (\Delta\theta_{\min}, \Delta\theta_{\max})$,

$x_{ij} \in \left(x_{\min}, x_{\max}\right)$ for *i-th* (i = 0,…, s) particle the *j-th* (j = 1,…,n) component, t is an index of time (iteration), f is a monotonic mapping function, c_1 and c_2 are cognitive and social coefficients, respectively, w is the inertia weight, and $r_1(t)$ and $r_2(t)$ are random numbers uniformly distributed in the interval (0,1). $x_i(t)$ is the particle position vector, decided by the mapping function f^{-1}, $\boldsymbol{\theta}_i(t)$ is the phase angle, $\Delta\boldsymbol{\theta}_i(t)$ is the increment of phase angle, $\boldsymbol{\theta}_{ip}(t)$ is the phase angle of best solution (***pbest**$_i$*), $\boldsymbol{\theta}_g(t)$ is the phase angle of global best (***gbest***), and $F_i(t)$ is the fitness value. In this paper, we define the mapping function as

$$f(\theta_{ij}) = \frac{x_{\max} - x_{\min}}{2}\sin(\theta_{ij}) + \frac{x_{\max} + x_{\min}}{2}, \tag{9}$$

where

$$\theta_{ij} \in \left(-\frac{\pi}{2}, \frac{\pi}{2}\right),\ \Delta\theta_{ij} \in \left(-\frac{\pi}{2}, \frac{\pi}{2}\right).$$

4. SSPSO Algorithm

In SSPSO (Shuffled Sub-swarms Particle Swarm Optimizer) [7], the swarm is partitioned equally into sub-swarms to increase the diversity of particles. The division of sub-swarms is not done randomly, but is based on the fitness of particles. Within each sub-swarm, the individual particles hold ideas (i.e., information) of searching for the destination that can be influenced by ideas of other particles. The particles of each sub-swarm evolve through a process of standard PSO algorithm. After a predefined number of generations, all sub-swarms are shuffled to produce a new swarm, during which the ideas are passed among sub-swarms. If the stop condition of the optimization process is not satisfied, the new swarm will be again partitioned into several new sub-swarms, and the computations are resumed. This process will be continued until the stop condition is satisfied. The division procedure for particle swarm in the SSPSO algorithm is shown as in Figure 3.

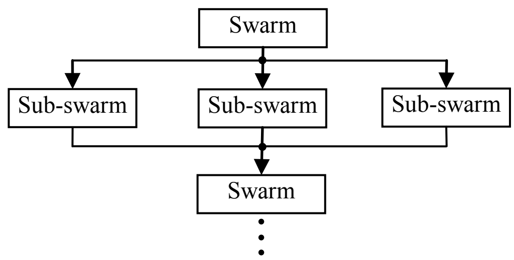

Figure3. The division and shuffle of sub-swarm mode

III. PROPOSED METHOD FOR SPEECH ENHANCEMENT

In this part, we propose a hybrid method, called θ-SSPSO as a new optimization method to improve further the performance of previously discussed algorithms, and apply it to dual-channel speech enhancement.

ALGORITHM 1: SUMMARY OF Θ-SSPSO ALGORITHM

1- Initialization:

angle $\in \left[-\frac{\pi}{2}, \frac{\pi}{2}\right]$, phase increament $\in \left[-\frac{\pi}{2}, \frac{\pi}{2}\right]$, **p-best**, **gbest**,

w_{init}=0.9, w_{end}=0.4, c_1=1.5, c_2=1.2, $x_{min}=-100$, x_{max}=100

2- Loop n =0,1,2,…

$$\text{position}(n,j)=\frac{x_{max}-x_{min}}{2}\sin(\theta_{nj})+\frac{x_{max}+x_{min}}{2},$$

2.1- Compute cost function value for each particle.

2.2- Rank particles by their corresponding fitness values.

The minimum cost takes the first rank.

2.3- Divide particles to sub-swarms based on their ranks.

3- Update particles in each sub-swarm.

Loop i=1,2,3,…

3.1- If i^{th}-particle's cost function < (fittness value of **pbest**)

Cost of **pbest** = i^{th}-particle's fittness value;

pbest = **angle**(i);

endif

3.2- If i^{th} –particle's fittness value < **gbest** fittness value

gbest fittness value = i^{th} –particle's fittness value

gbest vector = **angle**(i);

endif

3.3- Update angle and phase increment by Eq.5, Eq.6

End loop

4- Shuffle sub-swarms and generate one swarm.

End loop

1. θ-SSPSO Algorithm

In this paper, we propose a new optimization algorithm by combining the θ-PSO and SSPSO algorithms.

As discussed above, θ-PSO has better convergence behavior than standard PSO. So, it seems reasonable to combine the θ-PSO algorithm with the shuffled sub-swarms procedure to obtain a robust optimization algorithm. The resulting hybrid θ-SSPSO algorithm enhances the diversity of particles, which leads to decrease the possibility of entrapping in local minima.

The θ-SSPSO method can be described as follows:

Step1. Initialize randomly the positions and velocities of all particles. Set m = "number of sub-swarms" and n = "number of particles in each sub-swarm".

Step2. Compute the fitness of each particle.

Step3. Rank particles by their fitnesses.

Step4. Partition particles into sub-swarms according to their fitness. For example, for the number of sub-swarm m=3, rank 1 goes to the first sub-swarm, rank 2 goes to the second sub-swarm, rank 3 goes to the third sub-swarm, rank 4 goes to the first sub-swarm, and so on.

Step5. Update the phase angle and phase angle increment of particles based on Eq. (5) and Eq. (6) in each sub-swarm.

Step6. Shuffle sub-swarms to produce a new swarm after a predefined number of iterations and rank particles according to their fitness.

Step7. Go to Step 4, if the stop condition is not satisfied. Otherwise, stop and obtain the results from the global best position (gbest) and the global best fitness.

Algorithm 1 shows pseudo code of our proposed method.

2.θ-SSPSO Algorithm for Speech Enhancement

The structure of a dual-channel speech enhancement is shown in Figure 1. The input signals are processed in frames. In the stochastic optimization-based speech enhancement, we need to define the cost function to evaluate the fitness of each particle. The average error between the noisy speech signal, d(n), and the estimated noise signal in each frame is used as the cost function. Fitter particles have less cost function values. The cost function of the i-th particle is given as:

$$J_i=\frac{1}{N+1}\sum_{k=0}^{N}\left[d(k)-y_i(k)\right]^2, \qquad (10)$$

where N is the number of samples in each frame, and *y(k)* is the output of *W(z)* designed by the algorithm. When *Ji* is minimum, then the parameters of *W(z)* represent the best estimation of the unknown system *P(z)*.

In PSO-based optimization speech enhancement, the position of each particle in the swarm is a candidate for the coefficients of the adaptive filter. After a predefined number of iterations, the optimal adaptive filter *W(z)* is calculated according to the position vector of the best (global) particle in the swarm (**gbest**). Then, *y(n)* is determined by modifying the noise reference *r(n)* by the adaptive filter *W(z)*. Finally, the enhanced frame is obtained by subtracting *y(n)* from *d(n)*.

IV. SIMULATION RESULTS

For our simulations, we use speech signal from the NOIZEUS database [14]. As the noise references, we take noises from the NOISEX-92 database [15].

The noisy speech is obtained by adding the clean speech signal to the noise reference modified by the transfer function *P(z)*. As example, we have used the following filter *P(z)* as acoustic path in our simulations:

$$P(z^{-1}) = \frac{1}{1-1.2z^{-1}+0.36z^{-2}} \qquad (11)$$

Corresponding to the selected (acoustic path) filter *P(z)*, the adaptive filter *W(z)* considered for the particle *i* in the simulations is given as [5]:

$$W^i(z^{-1}) = \frac{p_1^i}{1+p_2^i z^{-1}+p_3^i z^{-2}}, \qquad (12)$$

where p_j^i is the *j-th* dimension of the *i-th* particle in swarm.

As objective evaluation of our proposed method, we use the segmental SNR (SNR_{seg}) and PESQ [16] tests.

For the computation of SNR_{seg}, speech signals are first segmented into frames. Then, SNR in each frame is computed as signal-to-noise power ratio. Finally, the computed SNR values are averaged over all frames. The overall process of obtaining SNR_{seg} can be given as:

$$SNR_{seg} = \frac{1}{T}\sum_{m=0}^{T-1} 10\log\left(\frac{\frac{1}{N}\sum_{n=0}^{N-1} s^2[n+Nm]}{\frac{1}{N}\sum_{n=0}^{N-1}\left(s[n+Nm]-s'[n+Nm]\right)^2}\right). \qquad (13)$$

where $s[n+Nm]$ and $s'[n+Nm]$ are the n^{th} sample of the m^{th} frame of the clean and the enhanced speech signals, respectively, N is the number of samples in each frame, and T is the number of frames.

The perceptual evaluation of speech quality (PESQ) measure is an alternative objective measure which is able to predict subjective quality of speech signals. This objective measure is based on models of human auditory speech perception which is selected as the ITU-T recommendations P.862 [17].

The range of the PESQ score is 0.5 to 4.5, although for most cases the output range will be a MOS-like score, i.e., a score between 1.0 and 4.5.

The PESQ score is computed as a linear combination of the average disturbance value d_{sym} and the average asymmetrical disturbance value d_{asym} as follows:

$$PESQ = 4.5 - 0.1.d_{\mathrm{sym}} - 0.0309.d_{asym} \qquad (14)$$

where d_{sym} and d_{asym} are computed as:

$$d_{sym} = \left(\frac{\sum_k (D_k^{'''} t_k)^2}{\sum_k (t_k)^2}\right)^{1/2} \qquad (15)$$

$$d_{asym} = \left(\frac{\sum_k (DA_k^{'''} t_k)^2}{\sum_k (t_k)^2}\right)^{1/2}. \qquad (16)$$

Here, $D_k^{'''}$ and $DA_k^{'''}$ are the averaged frame disturbance values as described in [17]. The summation over k is performed over the speech-active intervals, and t_k are weights applied to the frame disturbances and depend on the length of the signal.

Four stochastic optimization techniques (i.e., PSO, θ-PSO, SSPSO, and θ-SSPSO) are used to assess our proposed method. The experimental conditions for these algorithms are shown in Table I.

The SNR of the input noisy signal for engine, babble, and white noise types is set at -10, 0, and 5 dB, respectively. The results of each algorithm are averaged over 20 trial runs. Table III shows the SNR-improvement for each algorithm. It can be seen from this table that the θ-SSPSO algorithm outperforms other algorithms in a sense of SNR-improvement.

Table IV shows PESQ-improvement for each algorithm. The results of this evaluation show clearly that the θ-SSPSO algorithm outperforms other algorithms.

The time waveforms of the noisy, clean, and enhanced speech obtained by the PSO, θ-PSO, SSPSO, and θ-SSPSO algorithms, respectively, are illustrated in Figure 4.

The MSE (cost function) of the best particle in the population during the iterations (i.e.,**gbest**) are shown in Figure 5 for PSO, θ-PSO, SSPSO and θ-SSPSO. It can be seen from the figure that our proposed method outperforms simulated stochastic-based algorithms in a sense of convergence rate and steady state error.

TABLEI. EXPERIMENTAL CONDITIONS FOR THE PSO, Θ-PSO, SSPSO, Θ -SSPSO ALGORITHMS

Algorithms	Parameters	Range of Values
PSO, θ-PSO, SSPSO, and θ-SSPSO	inertia weight	linearly decreasing from 0.9 to 0.4
	c_1	1.5
	c_2	1.2
	population size	32
	iteration	500
	frame overlap	50%
	frame length (in samples)	240
SSPSO, θ-SSPSO	sub-swarm number	4

TABLEII. THE EXPERIMENTAL RESULTS OF PSO-BASED ALGORITHMS FOR DIFFERENT BENCHMARK FUNCTIONS

	Benchmarks	Sphere Function	Rastrigin Function
Experimental Conditions	Formula	$f(x)=\sum_{i=1}^{40} x_i^2$	$f(x)=\sum_{i=1}^{10}\left(x_i^2-10\cos\left(2\pi x_i\right)+10\right)$
	Solution space	[-100,100]	[-30,30]
	Iteration	2000	1000
	Actual minimum	0	0
Optimization results	Standard PSO	0.0104	7.9597
	θ-PSO	0.0037	7.5617
	SSPSO	1.3412×10^{-16}	6.9647
	θ-SSPSO	3.0082×10^{-17}	4.2783

TABLEIII. SNR-IMPROVEMNET OF DIFFERENT ALGORITHMS FOR DIFFERENT NOISY INPUT CONDITIONS

Algorithms	SNR-Improvement (dB)		
	Engine noise SNR of -10 dB	Babble noise SNR of 0 dB	White noise SNR of 5 dB
Standard PSO	20.6810	9.4010	3.8101
θ-PSO	21.0420	9.7440	3.8706
SSPSO	23.0313	10.1913	4.3730
θ-SSPSO	23.7804	10.3241	4.5181

As subjective measure, we use the MUlti Stimulus test with Hidden Reference and Anchor (MUSHRA) which is a ITU-R Recommendation BS.1534-1 [18] as implemented in [19]. The subjects are provided with test utterances plus one reference and one hidden anchor, and are asked to rate the different signals on a scale of 0 to 100, where 100 is the best score. The listeners are permitted to listen to each sentence several times and always have access to the clean signal reference. The test signals are the same as those, which are used for the objective evaluation. Three types of noise (i.e., white noise, destroyer engine noise, and babble noise) are used in our listening tests. A total of 10 listeners (2 females, 8 males between the ages of 18 to 30) have participated in these tests. Table V shows the subjective results of each algorithm for different noise types.

As an alternative way of evaluating the performance of our proposed hybrid optimization algorithm, we use two famous benchmarks, which are composed of Sphere and Rastrigin functions. The optimization results of each algorithm in each benchmark are shown in Table II.

TABLE IV. PESQ-IMPROVEMNET OF DIFFERENT ALGORITHMS FOR DIFFERENT NOISY INPUT CONDITIONS

Algorithms	PESQ-Improvement		
	Engine noise SNR of -10 dB	Babble noise SNR of 0 dB	White noise SNR of 5 dB
Standard PSO	1.5898	0.5395	0.2890
θ-PSO	1.6240	0.5652	0.2903
SSPSO	1.6614	0.6548	0.3203
θ-SSPSO	1.6781	0.7104	0.3410

TABLE V. THE RESULTS OF MUSHRA COMPARATIVE LISTENING TEST FOR THE STANDARD PSO, θ-PSO, SSPSO, AND θ-SSPSO ALGORITHMS FOR DIFFERENT NOISY INPUTS AND DIFFERENT SNR VALUES

Noise type	Speech Signals				
	Noisy speech	Standard PSO	θ-PSO	SSPSO	θ-SSPSO
Engine noise SNR of -10 dB	12.6	53.7	55	58.2	60
Babble noise SNR of 0 dB	16.4	46.5	47	50.1	52.6
White noise SNR of 5 dB	18.2	44.2	44	46.1	46.8

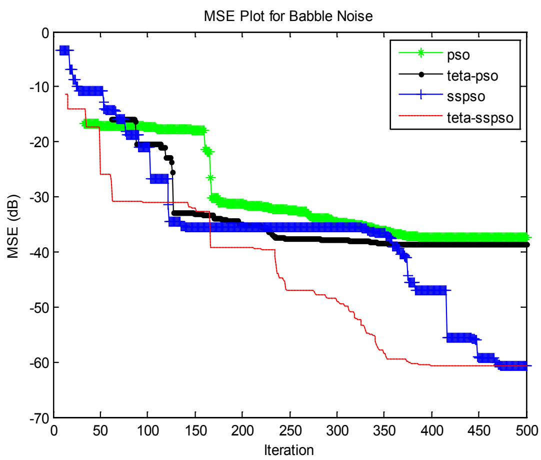

Figure 4. Mean-Square-Error plot for PSO, PSO, θ-PSO, SSPSO, and θ-SSPSO algorithms.

V. CONCLUSION

In Section II, we presented θ-PSO and SSPSO as two optimizations techniques. The major drawback of θ-PSO is that it may easily stick in local minima, when handling some complex or multi-mode functions. On the other hand, SSPSO has the advantage that it increases the diversity of particles in the search space. This in turn avoids entrapping the optimization algorithm in local optima.

The proposed hybrid θ-SSPSO algorithm combines the standard θ-PSO algorithm with shuffling sub-swarm idea. In order to evaluate our proposed method, we test our new method in some famous benchmarks. As the results show, the θ-SSPSO algorithm has the least final fitness value. In order to assess our proposed method in the framework of speech enhancement, we examine the quality of the enhanced speech both subjectively and objectively.

As objective assessment, we investigate the MSE plot, SNR-improvements, and PESQ-improvements. From the MSE plot, it can be obviously seen that θ-SSPSO converges faster than other algorithms. By considering the results of SNR and PESQ, we conclude that the θ-SSPSO algorithm outperforms other methods objectively.

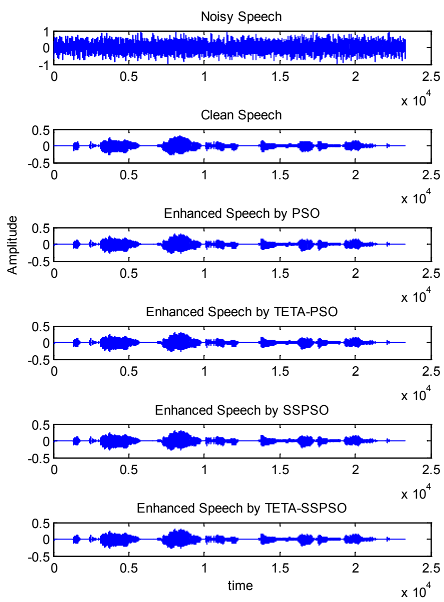

Figure 5. From the top, time waveforms of the noisy, the clean, and the recovered signals with PSO, θ-PSO, SSPSO, and θ-SSPSO algorithms, respectively

The quality of the enhanced speech is evaluated subjectively by listening tests. Listening tests show once again that the speech enhanced by our proposed optimization method has the best quality among the enhanced signals processed by all other methods.

In general, it can be inferred from the conducted experiments that the new optimization method (i.e., θ-SSPSO) has the best performance in the framework of speech enhancement as compared with other implemented algorithms. By considering the advantages of the new optimization method, it is worthwhile to utilize this new method in other applications which incorporate optimization in the heart of their work.

As future works, the SSPSO algorithm can further be improved by employing other modified PSO-based algorithms instead of the standard PSO technique.

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