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Acoustics Recognition with Expert Intelligent System

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Abstract

In this article, we present a creative scheme for improving the noisy voice speech signal within a multi-channel voice improving and enhancement system. A hybrid optimization algorithm is a new approach using the mix of traditional fuzzy-PSO and hybrid fuzzy PSO (HFPSO) methodology. The F-PSO algorithm considered to have higher efficiency in optimization than regular PSO. It proposed that the F-PSO algorithm increases the variety of particles of a swarm by choosing a particular value for the specified parameters to more improve the performance of the conventional PSO. The suggested speech enhancement process called FHPSO is a hybrid strategy that combines both F-PSO and HPSO to optimize the benefits of both algorithms. The new FHPSO algorithm is shown to be very successful in obtaining global convergence for adaptive filters and resulting in a powerful funnel of noise from the input voice signal. The findings of the experimental simulation show in terms of convergence rate and SNR-amelioration the current algorithm goes beyond the conventional PSO, F-PSO, and HFPSO.

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1 Introduction

Speech amplification is a difficult challenge when it comes to learning speech synthesis that aims to restore a clear voice distorted voice. To date, numerous kinds of gradient-based algorithms introduced in speech improvement, which utilizes various schemas to regulate the filter weights depending on particular parameters. The Least-Mean-Squares (LMS), [1] contain several popular algorithms. Structure variants Standardized LMS [NLMS] and Recursive-Least-Squares (RLS) [2] are available. However, if the surface of the errors is multimodal, gradient descent algorithms are not suitable for IIR filters which function well for FIR adapted filters. Another drawback of differential descent strategies is that they will stick to a limited domestic approach. Small changes to respectable gradient algorithms can achieve improved efficiency, such as annexing noise to gradient computation to make it more feasible to emerge from a minimum in-house or using the error adaptation function to turn the layer of the error into uni-modal.

A generalized stochastic, error space quest for interface configuration is an alternative to gradient-based lineage approaches, as the uncalculated gradient and parameter changes are not specifically affected by an adaptive filter architecture apart from error calculation, [3].

Because of this property, technically, these kinds of techniques can optimize every type of adaptive filter architectures or topical functions globally [4]. Stochastic methods of optimization, like PSO, are tested for utilizing in adaptive recursive filtering troubles, where the average surface (MSE) is unconditional, [5-7].

Even though a regular PSO seeks successful solutions for quicker from another stochastic algorithm [6-8], but premature convergence still suffered when complicated issues streamlined, and the need to more develops that is required to prevent clogging in a local optimum. Many propose the traditional PSO algorithm's modifications, and their changes to increase overall efficiency, [8-10].

This article suggested a novel algorithm to connect the fuzzy with PSO to fine-tune the PSO parameters to solve the above-mentioned problem and provide effective stable speech recognition to improve the voice and cancel the noise effect.

The document is organized as: Section 2 explains the schematic system for the voice double-channel amplification system along for regular PSO, some-PSO, and F-PSO techniques. Section 3 introduces the presented algorithm for the capability-FHPSO. Section 4 discusses the effects of applying the suggested approach to voice enhancement., also finally, the concluding remarks in Section 5.

2 Problem Formulation

2.1 *Dual –Channel Speech Modelling*

The block scheme for the two-channel general improvement device seen in Figure 1, [9]. It assumed that the cleaner speech signal s(n) was stored in a single circuit that is then corrupted by the ambient noise b(n) to create the noisy speech signal d(n). For the reference noise, the new channel possesses the signal r(n). a dynamic filter, W(z), seeks to form P(z), [11-12], the transfer function.

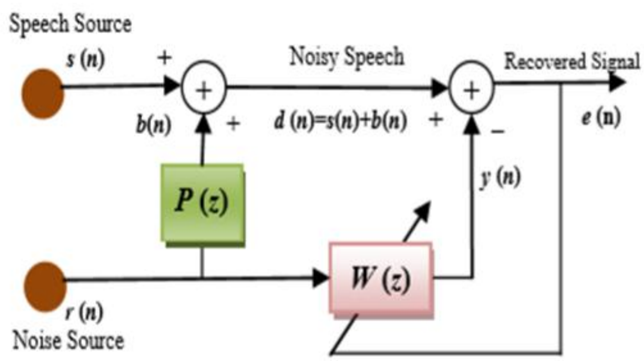

Figure 1: Adaptive filter configuration for voice recognition.

The filter performance y(n) is, thus, just the estimate of the noise present in d(n). Finally, a performance from structure e(n) would be the approximation for a pure signal s(n). assume we would like to guess the unknown device P(z) is defined by:

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

Where a_i, b_i Are undefined parameters which must be calculated dynamically. Unidentified system variables calculated by Mean-Square Error (MSE) efficiency, by means of the noisy d(n) voice and an adaptive filter y(n). A predicted y(n) noise that achieves the best signal by subtracting from the warped d(n) expression. Signal changed.

2.2 PSO Modelling of PSO

A Particle Swarm Optimization (PSO) discovered by Kennedy and Eberhart in 1995[10], this optimization method, inspired by animal social behaviour (e.g. fish schooling and bird flocking), is commonly used in many fields [11]. A regular PSO algorithm [12] starts with the initialization of the random swarm for M particles to maximize every with unknown R parameters. Every particle's fitness calculated at each time according to its suitability function. An algorithm saves, slowly substitutes the best prior place of every particle (Pbesti, i=1,2, ..., M). And one particle strongest (gbest) as seen in fig. 2.

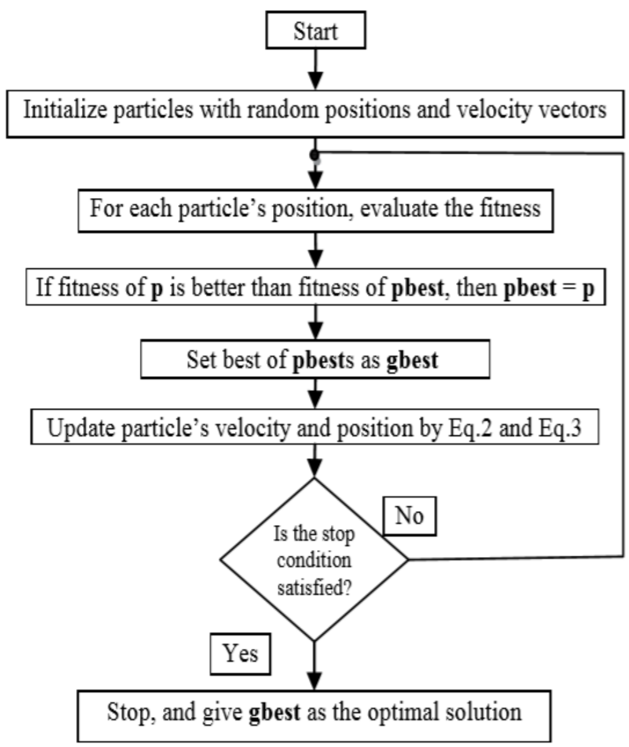

Figure 2: Schematic flowchart of PSO.

At each epoch (k) the variables are modified according to the:

$$x_p(new) = x_p(old) + V_p(new) \tag{2}$$

Where x_p (new) is the new value of the adaptive parameters for the adaptive filter, x_p (old) is the old value, V_p (new) is defined as:

$$V_p(new) = \mathrm{w}V_p(old) + c_1R_1\left(P_{pbest} - x_p(old)\right) + c_1R_1\left(P_{gbest} - x_p(old)\right) \quad (3)$$

Where particle vector i is involved, both R_1, R_2 are indeterministic numbers at random distributed in intervals (0,2), c_1 and c_2 (their value from 0 to 4) are cognitive and public coefficients are gbest (i) and pbest (i), and w is inertia weight, respectively, [11]. Here Fuzzy set is one approach for sequential updating of the above parameters.

2.3 Fuzzy Rules Modelling

The learning variables c_1 and c_2, influence the total velocity of an object, [12]. The logical aspect (c1) points out the dependability of the particle, and the public dimension (c2) defines confidence for the particle in neighbours.

The definition consists of two inputs: The number of deviations (No.) although the equilibrium condition does not change and the true inertia weight value of (w) Two outputs: the variation in momentum weight (w) and the variance in training factors (c1 and c2).

Three membership functions to every output and input at a fuzzy inference scheme: shown in Fig.3, set as LOW, MEDIUM, and HIGH and performed as a left triangle, mid triangle, and right triangle, respectively.

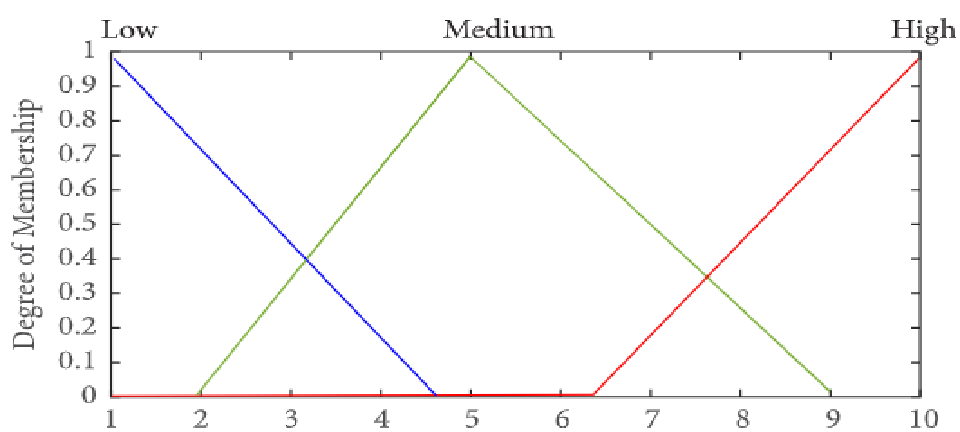

Figure 3: Fuzzy member ship function.

Fig.4 displays the blurry method configuration for two inputs (number of repetitions where maximum suitability is not transformed (No.) and real momentum weight (w)) and three outputs (increase inertia weight (w) and training variables (c1) and (c2)).

In the fuzzy inference process, nine fuzzy rules used to extract the new others, c_1, and c_2 values. An instance of one Blurry law is as follows:

If No. is MEDIUM, and w is HIGH

Then c1 is HIGH, c2 is HIGH, and Δw is LOW.

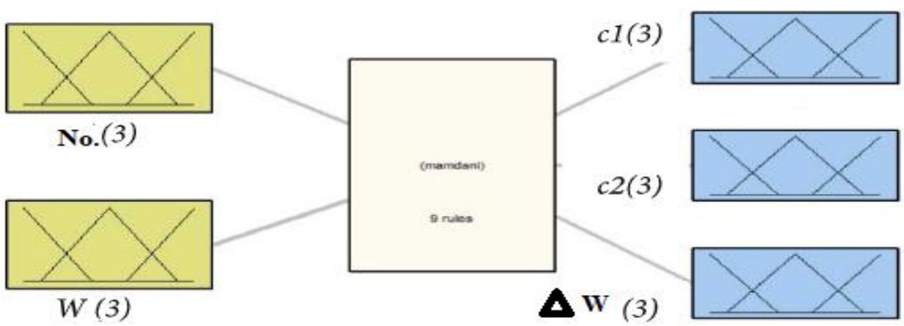

Figure 4: Parameters fuzzification system.

The simulation results chose to be No. [0,50]. Where the value of $0.2<w<2$, the values of $c1>1$, $c2<2$. The rules acquired by experimental scientific experience and are seen in Table 1.

Table 1: Fuzzy rule of Δw, c1, c2, respectively.

Rule No.	input		output		
	No.	w	Δw	c_1	c_2
1	1	1	3	1.5	1

The initial PSO parameters that set up in this simulation listed in Table 2.

Table 2: Initial value setup parameters for PSO algorithm.

Parameters	Value
C1	1
C2	1
Wmin	0.6
Wmax	0.9
Number of particle(n)	5
Number of iterations (itr)	25

3 Fuzzy-PSO Algorithm

Fig. 1 has dual-channel speech amplification features. Signal entries found in the archives. We want to learn the cost function to determine the suitability of a particle in the optimization-based stochastic speech enhancement. As for cost function, using the average error between the noisy speech signal, d(n), in-frame, and the noise signal expected, the cost function of particulate fitters has a lower value. The Specific Cost function is given as, [13-15]:

$$F_i = \frac{1}{N}\sum_{j=0}^{N}(d_i(j) - y_i(j))^2 \tag{4}$$

Where N is the numeral of samples in every frame part, and where y(k) is the output response of G(z) established process. If Ji is minimal, consequently, parameters of G(z) constitute the best approximation of an unbeknown structure of P(z). The location for every particle in a swarm is the candidate of adaptive filter coefficients in speech amplification based on PSO optimization, [16-17].

The maximal adaptive filter G(z), determined after a predefined number of iterations, according to the posture vector of the strongest (global) particle in a swarm (gbest), Therefore, y(n) calculated using changing a noise relation r(n) with an adaptive filter G(z). Subtract y(n) from d(n) essentially gives the container a boost, [18].

Twenty-five variables are grouped into three groups to structure the functions of each of the Fuzzy logic outputs. The speech enhancement fuzzy-PSO executes the following steps (as shown in fig. 5):

1- Initialize PSO function.
2- To create a population of particles randomly.
3- Change the flippant rational law.

4-Test fitness function.
5- Test the optimum solution for all particles, plus the current version.

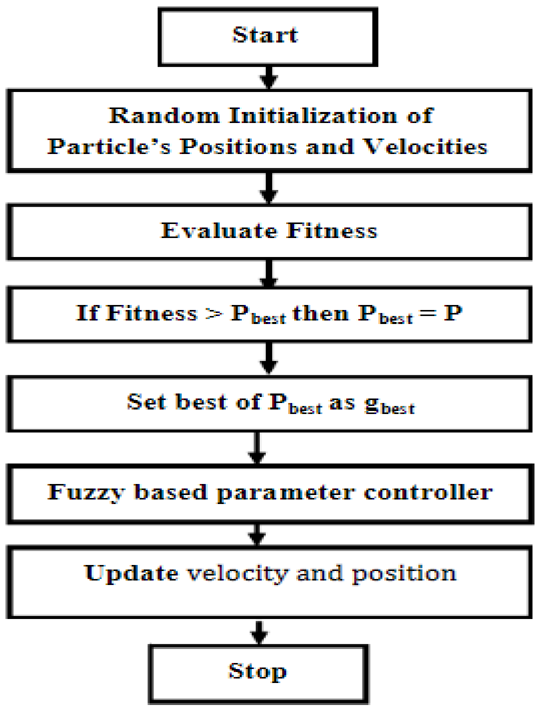

Figure 5 Adaptive fuzzy PSO schematic diagram.

4 Result and Discussion

In our simulations, we produce a speech signal, which distorted with noise. The loud speech got using applying the clear voice signal to the noise relationship adjusted using the P(z) transfer function. We have considered the following P(z) filter as the acoustic direction in the simulations setup as an example:

$$P(z) = \frac{100z^2}{z^2 - 120z + 36} \tag{5}$$

The adaptive filter G(z) deemed of the particle position index (i) in the simulations setup is given as [17-19], corresponding to the selected filter P(z) (acoustic path):

$$G^i(z) = \frac{z^2 {p_1}^i}{z^2 + z{p_2}^i + {p_3}^i} \quad (6)$$

Figure (6) Displays the time-waveforms of the PSO's messy, orderly, and improved expression, respectively, the FPSO algorithms.

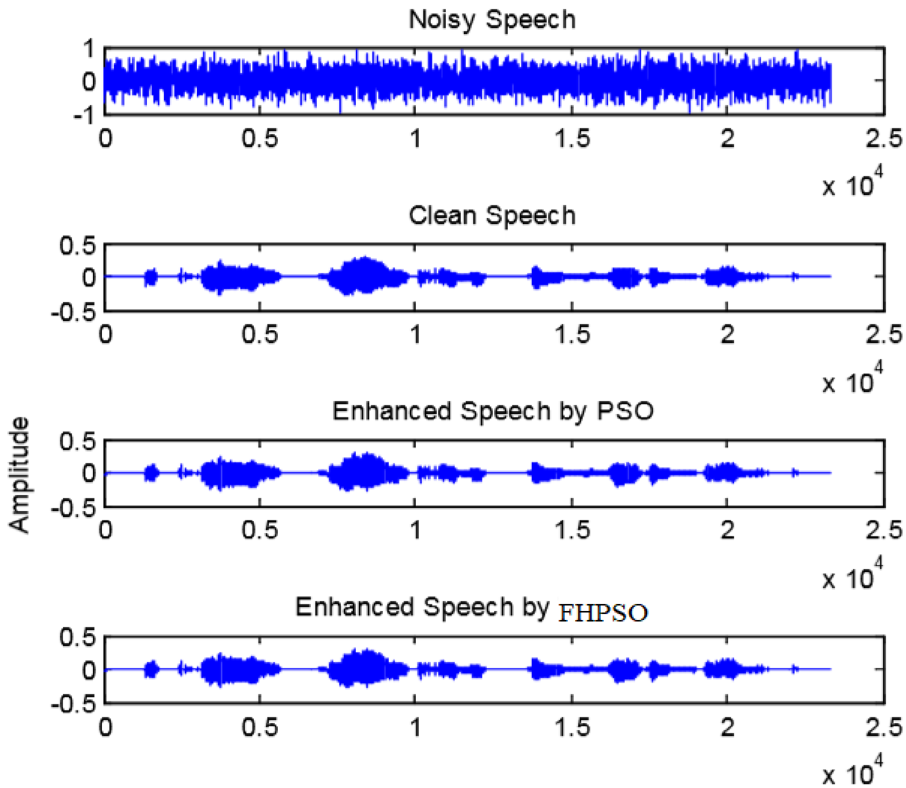

Figure 6 Simulation results: original and clean signal.

Input noise signal SNR set at -10, 0, and 5 dB for a generator, babble, and white noise types, respectively. The tests of each algorithm run on an average of over 20 trials. The SNR-improvement for each algorithm shown in Table 3. From this table, it will demonstrate that the FHPSO algorithm outperforms other algorithms from an SNR growth perspective.

Table 3 Simulation results, improvements of different algorithms, different level noises.

Algorithms	Improvement SNR (dB)		
	SNR with range of -10 dB(noise generated by engine)	SNR of 0 dB (babble noise)	SNR of 5 dB (white noise)
PSO scheme	20.23	9.3	3.7
FHPSO scheme	21.2	9.82	3.78

Figure 6 displays the MSE (cost function) of the best particle in the population through the repetitions (i.e., gbest) for PSO, FH-PSO. From the figure, our presented method can seem to be outperforming a stochastic-based simulated convergence rate meaning method and a constant-state error.

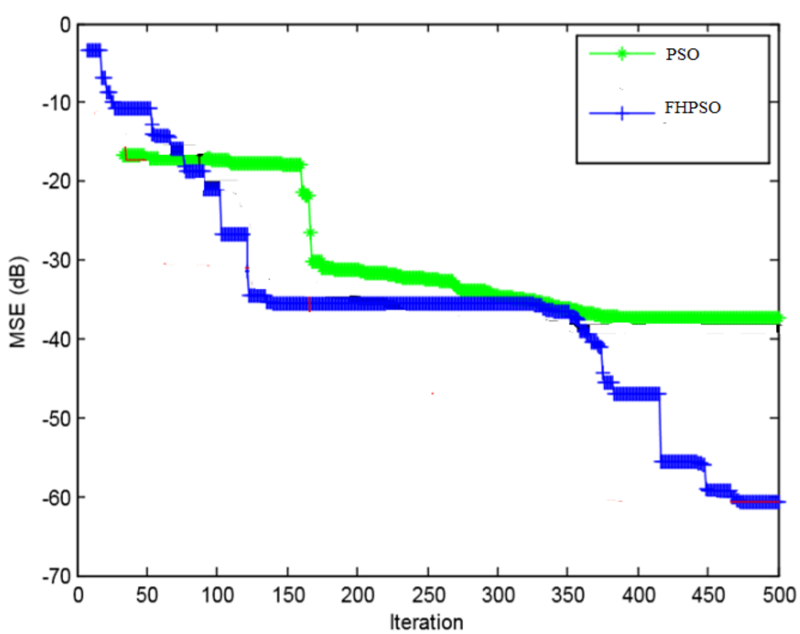

Figure 7: MSE for PSO and FHPSO.

5 Conclusion and Future Works

We are analyzing the MSE pattern, SNR-improvements as unbiased evaluation. It can see from the MSE plot that some-FHPSO converges more easily of the PSO algorithm. After taking into account the findings of SNR, we infer the algorithm FHPSO statistically outperforms other approaches. Our proposed optimization algorithm has the highest output of improved signals transmitted via all other methods. It can conclude from the studies performed that the current approach of optimization (i.e., FHPSO) has the highest results in terms of speech amplification relative to other algorithms applied. This is worth implementing this new technique at different applications that include optimization at a heart for the process, after understanding the benefits of the existing optimization approach.

The FHPSO algorithm will advance further by using other adapted PSO-based algorithms as works in the future, instead of the conventional PSO approach Where the sticky rules could grow from three to five.

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