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Speech Enhancement Based on Adaptive Noise Cancellation and Particle Swarm Optimization

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Abstract: Speech enhancement is used in almost all modern communication systems. This is due to the quality of speech being degraded by environmental interference factors, such as: Acoustic additive noise, acoustic reverberation or white Gaussian noise. This paper, explores the potential of different benchmark optimization techniques for enhancing the speech signal. This is accomplished by fine tuning filter coefficients using a diverse set of adaptive filters for noise suppression in speech signals. We consider the Particle Swarm Optimization (PSO) and its variants in conjunction with the Adaptive Noise Cancellation (ANC) approach, for delivering dual speech enhancement. Comparative simulation results demonstrate the potential of an optimized coefficient ANC over a fixed one. Experiments are performed at different signal to noise ratios (SNRs), using two benchmark datasets: the NOIZEUS and Arabic dataset. The performance of the proposed algorithms is evaluated by maximising the perceptual evaluation of speech quality (PESQ) and comparing to the audio-only Wiener Filter (AW) and the Adaptive PSO for dual channel (APSOforDual) algorithms.

Keywords: Speech Enhancement, Adaptive Noise Cancellation, Adaptive Filters, Meta-Heuristic Algorithms, Particle Swarm Optimization

Introduction

Many researchers have worked on the problem of noise cancellation over the past several decades (Aggarwal *et al*., 2016; Fisli *et al*., 2018a; Mahbub *et al*., 2010). Speech enhancement and noise cancellation have involved extensive applications in speech bandwidth compression, speaker verification and speech recognition (Gorriz *et al*., 2009; Lin, 2003). For speech recognition and speaker identification, signal enhancement techniques improve the quality of the audio signal, which in itself is a fundamental step towards achieving correct classification. If single channel applications are considered, spectral subtraction methods are most commonly used after noise estimation (Lin, 2003; Lu and Loizou, 2008). In practical scenarios, however, these techniques have their own share of limitations. They can result in musical noise that might distort the signal in the process. Furthermore, such techniques are hugely dependent on properties of the noise signal as, they only work best when the additional noise is assumed to be constant or stationary. These assumptions, however, do not hold true in actual operational situations where the properties and amplitudes of additional noise signals are varying, along with external factors, such as traffic noise, factory sounds and cafeteria babble. To deal with such problems, we make use of the ANC approach. In The conventional ANC comprises two channels:the first captures the reference noise signal and the second captures the desired or primary signal source (with noise). This enables the ANC device to sense variations in the noise amplitude easily. A number of different algorithms have been proposed for ANC using such a dual channel set-up, (Kunche and Reddy, 2016a). The most commonly used methods are least mean-squares (LMS) and normalized LMS (NLMS) (Widrow and Stearns, 1985; Gorriz *et al*., 2009; Mohammed, 2007; Bai and Yin, 2010). However, these methods are not ideal for a multimodal error surface as they have a tendency to get stuck in local optima (Ji *et al*., 2008).

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Stochastic optimization algorithms have matured quite rapidly over the past few decades and one possible application is for solving challenging noise reduction problems Stochastic approaches in fact, are far superior to (Gentle *et al*., 2012). In general, there are two types of stochastic algorithms, namely, heuristics and meta-heuristics based. Heuristic means to find or to discover, whilst meta-heuristic is associated with (Yang, 2011).

Popular meta-heuristic optimization techniques include: Particle Swarm Optimization (PSO), Accelerated Particle Swarm Optimization (APSO) and Gaussian Particle Swarm Optimization (GPSO). In particular, the PSO, a hugely popular optimization technique, has been applied in a growing range of applications. The use of PSO is not restricted to a simple function optimization, but applied in many challenging applications such as control systems and pattern classification systems (Geravanchizadeh and Asl, 2010). PSO and its variants are known for their quick convergence, robust global search and ease of implementation (Bai, 2010).

Mahbub *et al*. (2010) considered the variation in the total number of considered particles in different acoustic environments. They conducted research on different kinds of noise and voices and also under varied operating conditions. They compared the results of PSO with other adaptive algorithms, namely LMS and NLMS. Their experiments showed that PSO outperforms other techniques with respect to SNR improvement and demonstrated a satisfactory convergence rate under different acoustic conditions. Asl and Nezhad (2010) proposed a Modified PSO (MPSO) and compared it with PSO when used for adaptive filtering in the enhancement of speech signals. Their experimental results showed that MPSO is capable of a much faster search speed when finding an optimal solution. Moreover, MPSO improves SNR to a greater extent than the simple PSO. This improvement is more pronounced in the construction of higher order filters. (Krohling, 2004) proposed a slightly modified MPSO technique, based on Gaussian probability distribution. It is termed Gaussian PSO or GPSO. In the standard PSO, a number of parameters, such as accelerating constants, inertia weight, maximum velocity and the number of particles, need to be initially defined, which the GPSO does not require. The sole variable that needs to be initially defined is the total number of swarm particles. Comparative simulation results showed the superiority of GPSO over the standard PSO for the data that was considered. To the best of our knowledge, GPSO has never been used before for speech enhancement problems.

Selvi and Suresh (2016) employed a hybridization of spectral filtering and an optimization algorithm for speech enhancement, by combining MMSE and PSO. Their proposed method yielded better evaluation results compared to Bayesian Non Negative Matrix Factorization (BNMF) (Schmidt *et al*., 2009) and MMSE approaches (Ephraim and Malah, 1984).

A Modified Predator-Prey Particle Swarm optimization (MPPPSO) for noise cancellation has been recently proposed by (Fisli *et al*., 2018b), (Fisli and Djendi, 2018). The proposed algorithm showed good results compared to other methods such as the Predator-Prey Particle Swarm Optimization (PPPSO) and other methods in the literature.

The main drawback of using standard PSO is that in some cases, its convergence speed becomes very low. Its search space is also fairly limited (Kunche and Reddy, 2016b). Yang (2010) however, the authors provided a solution to these limitations by proposing another modified form of PSO, termed the Accelerated PSO(APSO). This was shown to have a comparatively simpler implementation and a much faster convergence speed. APSO was used for speech enhancement in 2014 by (Prajna *et al*., 2014). The authors conducted study on dual channel speech enhancement and compared the results of APSO with PSO. For evaluation purposes they used objective measures of: speech intelligibility (FAI), Perceptual Evaluation of Speech Quality (PESQ) and Signal to Noise Ratio (SNR). The noise types they considered were babble and factory noise, for which APSO proved to be far superior to PSO in terms of improved speech signal quality and intelligibility.

The key contribution of this research is to formulate an ANC system based on Butterworth and Elliptic filters, in the form of an optimization task. Three meta-heuristic optimization techniques (PSO, APSO, GPSO) are used to find the optimal filters coefficients, that optimize the perceptual evaluation of speech quality (*PESQ*), signal distortion (C_sig), signal overall quality (C_ovrl) and Likelihood Ratio (LLR,) for the noise-free audio signal and the filtered signal.

The rest of this paper is organized as follows: Section 2 presents the background and related work. Section 2 introduces the proposed optimized speech enhancement system. Comparative results and a discussion of the experimental set-up is presented in Section 4. Finally, some concluding remarks and future work suggestions are presented in Section 5.

Background and Related Work

Swarm systems consist of nature-based computational methods (Kennedy and Eberhart, 2001) that are based on the behavior of a group of birds. Swarm systems can solve complex problems with considerable efficiency (Poli, 2008). When a group of birds solves some given problem, it is said to be due to swarm intelligence. Other common examples are from colonies of social insects, such as bees, termites or ants. This section will present a review of popular meta-heuristic algorithms, namely classical PSO and APSO and Gaussian PSO.

Particle Swarm Optimization and its Variants

PSO is an artificial intelligence technique, quite commonly used for optimization purposes. It models the social behavior of a group of birds (a swarm) (Lee and Lee, 2013). PSO provides an approximate solution for a given optimization problem, using a population of candidate solutions (the particles are termed birds in this case). These birds then fly throughout the search space in accordance with mathematical models determining their velocity and position. One of its main advantages is that it can handle very large search spaces with little or no assumptions about the problem at hand and does not require the problem to be differentiable. Hence it is robust enough to deal with problems that have some factors changing over time (Lee and Lee, 2013).

PSO has the ability to carry out a global search by adjusting the positions of particles (Subha and Himavathi, 2016). The position of each particle is determined by the current global best position and the personal best position.

If x_i^t and x_i^t represent the current position and velocity vector respectively for particle *i*, the subsequent velocity vector and the position of the particle are determined by the following equations:

$$v_i^{t+1} = wv_i^t + \alpha\varepsilon_1\left(G_{best} - x_i^t\right) + \beta\varepsilon_2\left(P_{best} - x_i^t\right) \tag{1}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{2}$$

where, ε_1 and ε_2 are random numbers less than 1, α and β are the acceleration constants and w is the inertia weight. Although it has numerous advantages, PSO nevertheless has the tendency to get trapped in local minima, in some cases, converging to solutions that are far from ideal (Farooq *et al*., 2017).

The PSO algorithm has several parameters that are required to be appropriately set, in order to deliver a good solution. The choice of these fixed parameters is known to have a considerable effect on the quality of optimization. Much research has been conducted to find appropriate methods which can assist in finding a suitable set of these parameters. According to (Lee and Lee, 2013). GPSO, which is based on Gaussian distribution instead of a random distribution, enhances the convergence quality of PSO without the need for any kind of parameter adjustment.

Algorithm 1 Finding optimal solution by using PSO

```
For each particle in the population initializes positions
and velocities in the search space
while end criteria not reached do
    for each particle i do
        Calculate velocity of the particle using Equation 1
        Update the position of the particle using Equation 2
        Evaluate the fitness of each particle as in Equation 7
        if fitness is better than its pBest in the history then
            set current value as the new pBest
        end if
        if fitness is better than its gBest then
            set current value as the new gBest
        end if
    end for
end while
```

Hence, the velocity equation is defined as follows (Wan *et al*., 2011):

$$v_i^{t+1} = v_i^t + \beta_1\left(G_{best} - x_i^t\right) + \beta_2\left(P_{best} - x_i^t\right) \tag{3}$$

where, β_1 and β_2 are positive random number generated by a normal Gaussian distribution $N(0, 1)$.

The standard PSO uses both the global best and personal best position of the particles (Subha and Himavathi, 2016). The accelerated particle swarm optimization (APSO) algorithm is a simpler version of the PSO algorithm, which uses the global best only. Thus, in the APSO, the velocity vector is generated by the following simpler formula:

$$v_i^{t+1} = v_i^t + \alpha\varepsilon + \beta\left(G_{best} - x_i^t\right) \tag{4}$$

where, the value of e is a random number between 0 and 1. The position of the particles can then be updated using Equation 2. The next position of the particle is computed by combining Equations 2 and 4:

$$x_i^{t+1} = (1-\beta)x_i^t + \beta G_{best} + \alpha\varepsilon \tag{5}$$

Therefore, APSO is much simpler and results in faster convergence.

Noise Cancellation using Adaptive Filters

The concept of ANC was first introduced by (Widrow *et al*., 1975). It requires a minimum of two microphones and was developed on the basis of finding orientation channel(s) that can detect features of associated samples or references to the polluted noise. An estimate of the noise is produced with the help of an adaptive filter by utilizing the reference microphone output. Its output is then deducted from the primary microphone output (signal + noise). The output of the canceler is used to regulate the tap weights in the adaptive filter. With the help of an adaptation algorithm, ANC minimizes the mean square error value of the output. It generates an output which is the best approximation of the anticipated signal in the sense of being the minimum mean square error (Taha *et al*., 2018). ANC removes or suppresses a noisy signal by using Adaptive-Filters and adjusting their parameters according to an optimization algorithm, as in Fig. 1. Many works are reported in the literature use Adaptive filters for noise reduction and cancellation (Akhaee *et al*., 2005), (Kalamani *et al*., 2014).

Conventional adaptive-filters include classical Butterworth-filters, Chebyshev-filters and Elliptic-filters. A Butterworth filter provides the maximum flat response and its calculations are comparatively simpler than other forms of filters. This factor, combined with the fact that it produces impressive performance for most applications, has made it a popular choice in the field of electronics-RF as well as with audio active filters (Adrio, 2015).

An Elliptic filter (also called a Cauer filter) has ripple in the pass-band and in the stop-band (Adrio, 2013). Ripple levels in the pass-band and stop-band are independently adjustable during the design phase, as followes:

- When a ripple in the stop band approaches zero, then the filter becomes a Chebyshev type I
- When a ripple in pass band approaches zero, then the filter becomes a Chebyshev type II
- When a ripple in both, the stop and the pass-bands approaches zero, then the filter becomes a Butterworth type

In this paper, we aim to formulate the ANC problem in the form of an optimization task. Specifically, we optimize Butterworth and Elliptic adaptive filters for noise cancellation. Next, we outline our proposed speech enhancement system, employing ANC based on optimisation algorithms.

Proposed Speech Enhancement System

The aim of this research is to compare the performance of PSO, APSO and GPSO algorithms for tuning coefficients of an adaptive filter, in order to remove the noise from speech signals. This is realized by determining the optimal set of filter parameters that optimize (*PESQ*), (*C_sig*), (*C_ovrl*) and (LLR) for noise-free audio signal and filtered signal.

PESQ is a popular speech objective measure, it was recommended by ITU-T recommendation P.862 (Recommendation, 2001), that compares the clean signal to the degraded signal. It returns a score value ranging between -0.5 to 4.5, the higher the value the better quality of the speech.

Hu and Loizou (2008) a composite measure is introduced by combining different objective measures, to determine the overall speech quality. The composite measure is obtained by combining PESQ, Weighted Spectral Slope (WSS) and (LLR) in one measure C_{ovrl}, where:

$$C_{ovrl} = 1.594 + 0.805 \cdot PESQ - 0.512 \cdot LLR - 0.007 \cdot WSS \tag{6}$$

Hence, we formulate the objective function as:

$$C = \min \frac{1}{PESQ} + \frac{2}{C\_Ovrl} + \frac{1}{C\_Sig} + LLR \tag{7}$$

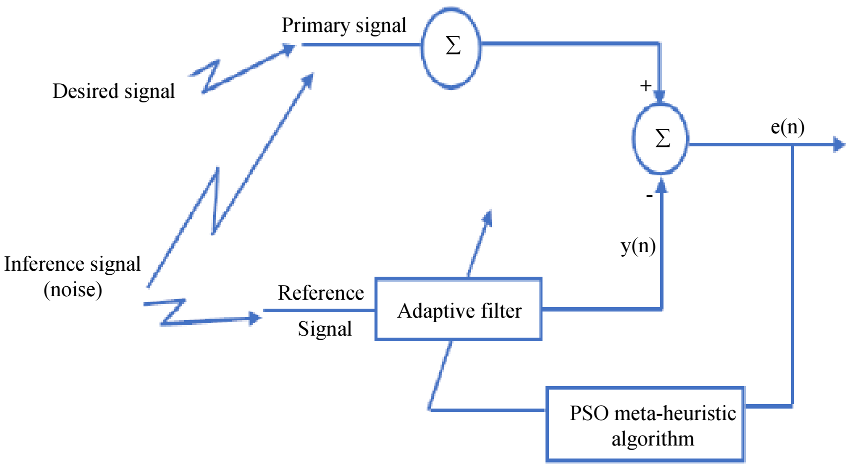

Fig. 1: Adaptive optimised filter

Figure 2 explains the overall structure of the proposed speech enhancement system. Here, the standard PSO and GPSO are utilized to obtain the optimum solution. The APSO can be obtained in the figure by ignoring the particle best (using the global best only).

Dataset

Two different databases are used to evaluate results:

- A noisy speech corpus for the evaluation of a speech enhancement algorithm dataset (NOIZEUS) which is a freely available database (Hu and Loizou, 2007). It has a total of 30 IEEE speech sentences (Rothauser, 1969), which were spoken by three females and three males
- The second speech corpus used for experimenting for a proposed system was an Arabic speech corpus (Halabi, 2016). It is a Modern Standard Arabic (MSA) speech corpus for speech synthesis and was recorded in South Levantine Arabic (with a Damascan accent) using a professional studio. It contains 1813 wav files containing spoken utterances
- The Babble noise is chosen from the Signal Processing Information Base (SPIB) (SPIB, 2013) and added to these clean signals at different SNRs for both datasets

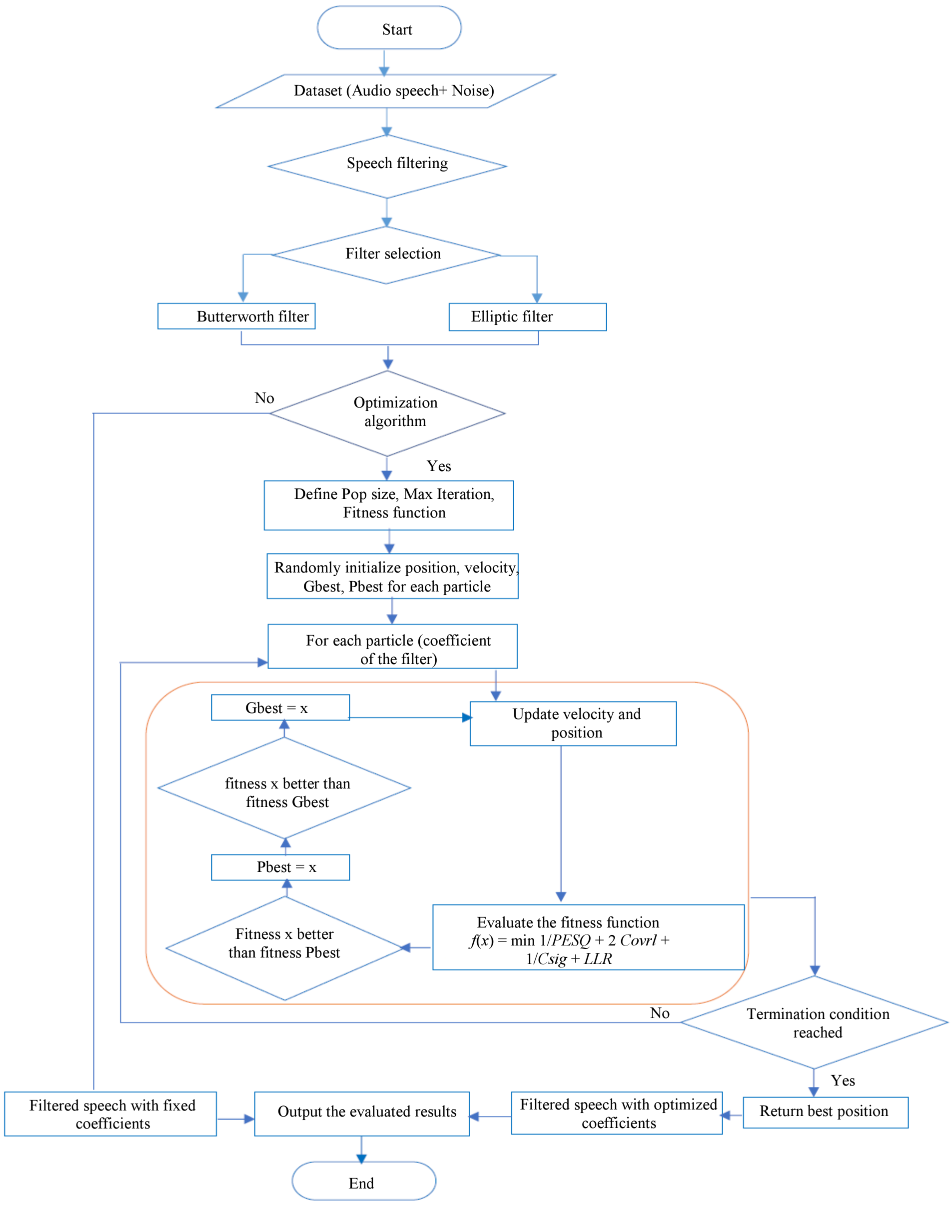

Fig. 2: The overall structure of the proposed speech enhancement system

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Adaptive Noise Cancellation based on Optimization Algorithms

Each particle in the search space is considered a possible solution representing the coefficients of the filter. The proposed optimized speech enhancement is carried out as follows:

1. Initialize positions and velocities randomly for each particle in the search space
2. Evaluate the fitness function for each particle using Equation 7
3. Find the personal best and the global best (for PSO; the global best is only for APSO)
4. Update the velocity and the position of each article for PSO (using Equations 1 and 2), for APSO (using Equations 4, 5) and for GPSO (using Equation 3)
5. Repeat steps 2-4 until the stop criteria are met (the maximum no of iteration is reached or the optimal solution is found)

In order to find the optimized filter co-efficients, the following parameters are calculated. In the case of the Butterworth-filter:

- The cut-off frequency

And in the case of the Elliptic filter:

- The filter order
- Peak-to-peak ripple in decibels
- Minimum stop band attenuation
- Passband edge frequency

The noisy signal is filtered using these optimized coefficients.

Finally, a comparison of the speech enhancement results with and without the use of optimized coefficients is carried out.

The noisy signal is filtered using fixed filter coefficients with following values of parameters:

In the case of Butterworth:

- Cut-off-frequency = 0.5 Hertz.

And in the case of the Elliptic filter:

- Filter order = 2
- Peak-to-peak ripple = 0.5
- Stop-band attenuation = 20
- The passband edge frequency 0.99

Evaluation Measurement

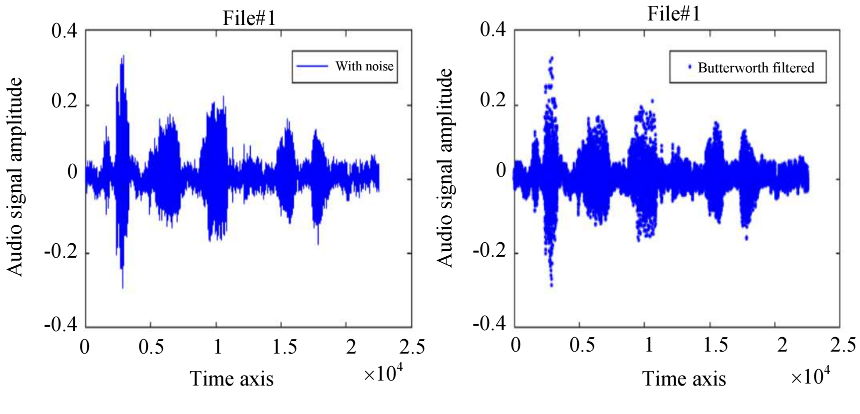
To evaluate the proposed enhancement system, the objective PESQ measurement is used. PESQ is a popular and widely used objective speech measure; recommended by ITU-T recommendations P.862 (Recommendation, 2001). It compares the clean signal to the degraded signal and returns a score value ranging from -0.5 to 4.5; the higher the value, the better the quality of the speech.

Results and Discussion

The performance of the proposed system was examined for different SNR values at (-10 db, 0 db, 5 db), both benchmark datasets. Further, it was compared to that of the state-of-the-art audio only and dual channel speech enhancement algorithms, namely the audio only Wiener Filter (AW) (Scalart *et al*., 1996) and the dual speech enhancement approach based on APSO (APSOforDual) (Prajna *et al*., 2014). Matlab implementations of the audio only Wiener method were used from (Loizou, 2013).

The simulation conditions for all the three algorithms were as follows: the population size was set to 20, total iterations set to 50 and other parameters set as follows: $\alpha = 1.5$; $\beta = 2$ and $\alpha = 0.3$; $\beta = 0.5$ for PSO and APSO respectively.

The resulting waveforms of PSO and GPSO are presented in Figs. 3 and 4 where an improved sound is seen to be produced when using both Butterworth and Elliptic filters with optimized coefficients. The audio signal is corrupted by babble noise at 5 db SNR only. Files were chosen randomly from the NOIZEUS dataset.



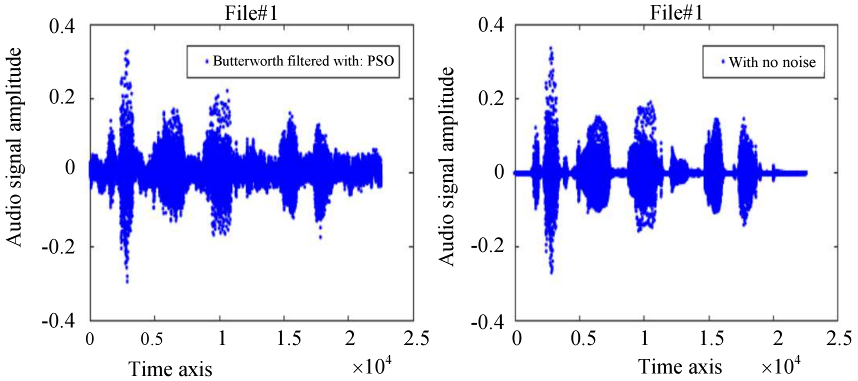


Fig. 3: Audio signal filtered by a PSO optimized Butterworth coefficients

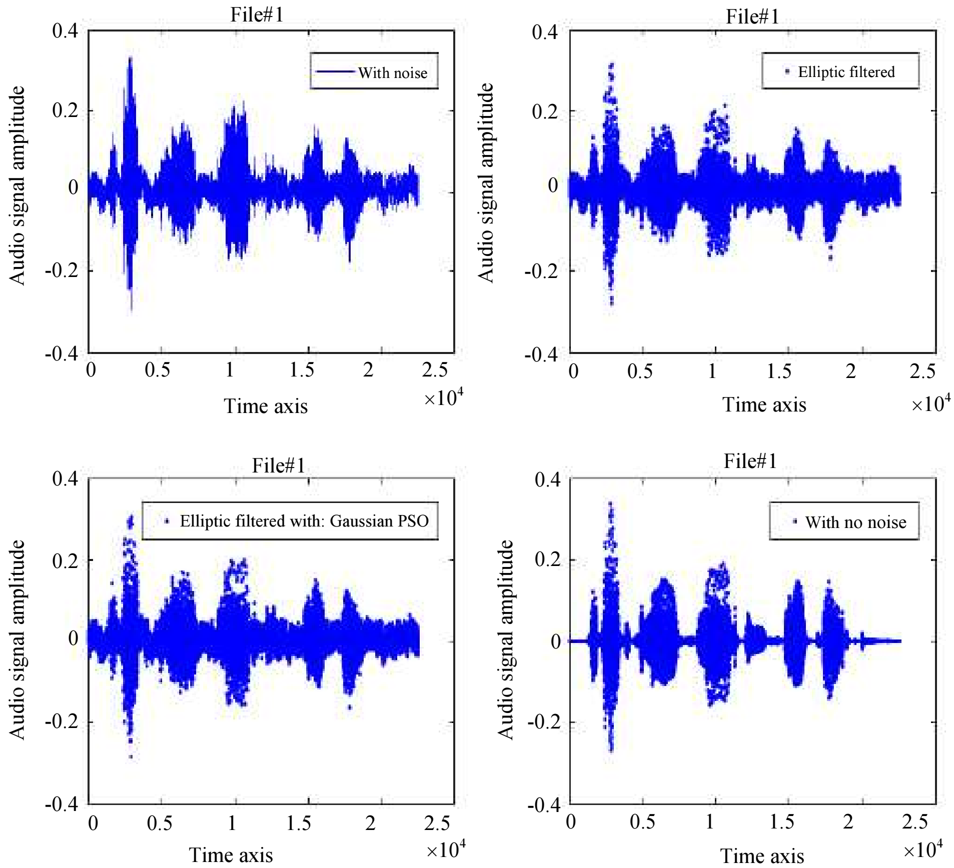


Fig. 4: Audio signal filtered by a GPSO optimized Elliptic coefficients

Table 1 shows the results of experiments conducted with the NOIZUS dataset. An optimized Butterworth filter with PSO, APSO and GPSO is applied at 5db, 0db and-10db SNRS. The averaged PESQ scores were computed for all six speech enhancement methods. The three optimized algorithms are seen to improve the PESQ score and outperform the audio-only Winer filter and the Dual APSO speech enhancement algorithms. Equal scores are obtained for PSO and APSO at SNRs of 5db, 0db and-10db.This trend does not remain the same for GPSO, which performs the worst at -10db among all the methods. On the other hand, the fixed coefficient filter performs better than the Audio-only Wiener Filter and the Dual APSO and slightly worse than the optimized filter by PSO, APSO and GPSO.

For Table 2 when the Elliptic filter is applied, the PSO outperforms all the other methods at all SNRs of 5db, 0db and -10db. Yet the optimized filter yields higher PESQ values compared to the audio-only Wiener filter and the Dual APSO speech enhancement algorithms.

We carried out experiments for the Arabic speech corpus. The results are shown in Tables 3 and 4 for different SNRs of 5db, 0db and -10db, for the case of both Butterworth and Elliptic Filters. The APSO performs the best, compared to PSO and GPSO, at 0db and -10db in Table 3, when applying the Elliptic filter. The APSO is also seen to outperform both the PSO and APSO, at 0db and 5db.

Overall, applying optimized adaptive filter coefficients was found to enhance the results, compared to those achieved by applying a fixed adaptive coefficient filer and state-of-the-art algorithms.

Statistical Analysis using the t_Test

To investigate whether there are any significant differences between the means of the clean speech signal, the filter with a fixed coefficient and the filter with an optimized coefficient, the authors applied the t tests to the results, at 0:05 level of significance. The null and alternatet hypothesis is tested for the case of the filter with a fixed coefficient as follows:

H_0: the clean signal did not make any difference to the signal obtained when applying a filter to it, thereby providing evidence against the alternate hypothesis
H_a: there is a significant difference between the clean signal and the application of a filter with a fixed coefficient

For the case of a filter with an optimized coefficient, the null and alternate hypotheses are as follows:

H_0: the clean signal did not make any difference to the signal obtained when applying a filter, thereby providing evidence against the alternate hypothesis.
Ha: there is a significant difference between the clean signal and a filter with an optimized coefficient.

The t_test result shown in Table 5 attests the significance of the optimized filters, compared to the non-optimized ones and the noisy signal.

Conclusion and Future Work

This paper presents noise cancellation techniques with adaptive filter coefficients optimised using three meta-heuristic optimization techniques, namely PSO, APSO and GPSO.

The objective function is formulated such that the PESQ, Signal distortion (Csig) and overall speech quality (Covrl) measures are maximized and the Log-Likelihood Ration (LLR) is minimized. The algorithm searches for optimal particles over different iterations, until the optimum solution is reached or the number of iterations is exceeded.

The proposed algorithms were tested under various levels of SNR (5db, 0db,-10db). Benchmark NOIZUS and Arabic datasets were used to evaluate the proposed techniques using PESQ as a standard evaluation metric. The proposed methods were also compared with two state-of-the-art algorithms: the audio-only Wiener Filter and the APSO for dual-speech enhancement algorithm.

For the NOIZUS dataset and for the case of both Butterworth and Elliptic filters, results in Tables 1-2, show that the PSO and APSO generally perform better than GPSO at all levels of SNR. Furthermore, the three proposed algorithms outperform the audio-only Wiener filter and the APSO for dual-channel speech enhancement algorithms, except at SNR of 5db, for the case of GPSO, which performs the worst among all methods. Similarly, for the ARABIC dataset, for the case of both Butterworth and Elliptic filters, Tables 3 and 4 show that the performance of PSO and APSO is better than the other methods in comparison with GPSO at different SNRs. However, at 5db SNR, for the case of PSO and APSO, it performs the worst among all methods.

Furthermore, a statistical analysis was carried on the means of a clean speech signal, a filter with a fixed coefficient and a filter with an optimized coefficient respectively and on the scores collected at each SNR level. The results showed there was no statistically significant difference at (p_0.05) amongst the enhancement methods and the clean speech.

For future experiments, we plan to utilize other optimization algorithms to optimize ANC coefficients, such as the Bat optimization algorithm and Artificial immune systems. Intelligibility tests will also be carried out using additional benchmark datasets.

Table 1: PESQ Comparing Filters with a fixed coefficient (Coeff), a PSO optimized coeff, an APSO optimized coeff, a GPSO optimized coeff, Audio only Wiener Filter (AW) and APSO for Dual. The Butterworth filter is applied to an audio signal at SNRs of 5db,0db and -10 db in Babble noise

SNR level	Fixed coeff	PSO	APSO	GPSO	AW	APSOforDual
5db	2.5657	2.6852	2.6852	2.7900	2.2714	2.0611
0db	2.3089	2.4194	2.4194	2.1722	1.9581	2.2785
-10db	1.7656	1.7890	1.7890	0.3118	1.2835	1.6641

Table 2: PESQ Comparing Filters with a fixed coeff, a PSO optimized coeff, an APSO optimized coeff, a GPSO optimized coeff, Audio only Wiener Filter (AW) and APSO for Dual. The Elliptic filter is applied to an audio signal at SNRs of 5db,0db and -10 db in Babble noise

SNR level	Fixed coeff	PSO	APSO	GPSO	AW	APSOforDual
5 db	2.5160	2.6015	2.5793	2.5142	2.2714	2.0611
0 db	2.2537	2.3144	2.2853	2.2537	1.9581	2.2785
-10 db	1.7018	1.8625	1.8477	1.8116	1.2835	1.6641

Table 3: PESQ Comparing Filters with a fixed coeff, a PSO optimized coeff, an APSO optimized coeff, a GPSO optimized coeff, Audio only Wiener Filter (AW) and APSO fo rDual. The Butterworth filter is applied to an audio signal at SNRs of 5db,0db and -10 db in Babble noise, for Arabic Speech Corpus

SNR level	Fixed Coeff	PSO	APSO	GPSO	AW	APSOforDual
5db	1.3305	1.9657	1.9697	1.2004	0.5169	2.0611
0db	1.9401	2.7671	3.0092	2.0620	0.5417	2.2785
-10db	2.7967	2.4837	3.0899	2.8533	0.5155	1.6641

Table 4: PESQ Comparing Filters with a fixed coeff, a PSO optimized coeff, an APSO optimized coeff, a GPSO optimized coeff, Audio only Wiener Filter (AW) and APSO for Dual. The Elliptic filter is applied to an audio signal at SNRs of 5db,0db and -10 db in Babble noise, for Arabic Speech Corpus

SNR level	Fixed Coeff	PSO	APSO	GPSO	AW	APSOforDual
5db	1.2641	2.0975	2.3168	1.5805	0.5169	2.0611
0db	1.8351	2.9864	2.9945	2.4303	0.5417	2.2785
-10db	2.6339	3.6165	3.6001	2.8998	0.5155	1.6441

Table 5: The result of t_test of at the 0.05 level of significance

Dataset		Alternate Hypothesis H_1	p value	t value	Null hypothesis H_0
	PSO	$H_a : \mu_C - \mu_{Opt} \neq 0$	0.2690	-1.1054	Accept H_0
		$H_a : \mu_C - \mu_{Fix} \neq 0$	0.3799	-0.8780	Accept H_0
	APSO	$H_a : \mu_C - \mu_{Opt} \neq 0$	0.2690	-1.1054	Accept H_0
NOIZEUS Dataset		$H_a : \mu_C - \mu_{Fix} \neq 0$	0.3799	-0.8780	Accept H_0
	GPSO	$H_a : \mu_C - \mu_{Opt} \neq 0$	0.3242	-0.9858	Accept H_0
		$H_a : \mu_C - \mu_{Fix} \neq 0$	0.3799	-0.8780	Accept H_0
	PSO	$H_a : \mu_C - \mu_{Opt} \neq 0$	0.4982	-0.6773	Accept H_0
		$H_a : \mu_C - \mu_{fix} \neq 0$	0.5038	-0.6684	Accept H_0
	APSO	$H_a : \mu_C - \mu_{Opt} \neq 0$	0.4982	-0.6773	Accept H_0
Arabic Corpus		$H_a : \mu_C - \mu_{Fix} \neq 0$	0.5038	-0.6684	Accept H_0
	GPSO	$H_a : \mu_C - \mu_{Opt} \neq 0$	0.4955	-0.6814	Accept H_0
		$H_a : \mu_C - \mu_{fix} \neq 0$	0.5038	-0.6684	Accept H_0

Author's Contributions

Tayseer M.F Taha: Collected the data, carried out the experiments, performed the data-analysis and writing of the manuscript, along with designing and organizing the study.

Summrina Kanwal: Designed and organized the paper, advised on the design the figures, provided critical feedback and revised the manuscript.

Amir Hussain: Conceived the original idea and contributed to the design and implementation of the research, along with supervision of the research.

Ethics

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