

## PAPER DETAILS

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## Particle Swarm Intelligence Based Univariate Parameter Tuning of Recursive Least Square Algorithm for Optimal Heart Sound Signal Filtering

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### Highlights

- For diagnosis of heart related diseases, the lung sound is considered as noisy component.
- Suppression of lung sound signal from heart sound signal using Recursive least square algorithm.
- The forgetting factor of the RLS algorithm is tuned using DNL-PSO algorithm.
- The performance of RLS algorithm is compared with Least Mean Square (LMS) adaptive algorithm.

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### Abstract

Heart Sound Signal (HSS) is considered as one of the important bio-signals. It carries vital information about the heart functions. For bio-acoustic observations, the HSS is diagnosed and recorded with auscultatory procedures. During auscultation, the noisy components gets added along with the reading. The physician's individual diagnostic experience, ecological noise and the intersection of heart and lung sound signal (LSS) are considered as the major noisy components in HSS diagnosis. Suppression of LSS from the HSS is a challenging task. Due to its quasi stationary nature, adaptive filtering techniques are used for the noise removal. In this paper, Recursive Least Square (RLS) adaptive algorithm is proposed to obtain the HSS from the noisy mixture. Faster convergence is a benefit in selecting RLS algorithm over other adaptive algorithms. The forgetting factor is one of the important parameters of RLS which defines the convergence. The RLS performance is improved by choosing an optimal forgetting factor. A Particle Swarm Optimization (PSO) based search algorithms are deployed for optimization. To enhance the implementation time, a Dynamic Neighbourhood Learning Particle Swarm Optimizer (DNL-PSO) is analysed. In DNL-PSO, each particle studies from its knowledge in dynamically varying neighbourhood that prevents early convergence. The normal HSS with different LSS interference is taken to assess the RLS filter performance. In this paper, the RLS algorithm performance is compared with Least Mean Square (LMS) adaptive algorithms. Various metrics are used to compare the performance of both RLS and optimization algorithms.

## 1. INTRODUCTION

The noise cancellation technique has been applied in the field of image processing, echo cancellation, signal processing and speech enhancement [1,2]. During signal acquisition, noise from the nearby surroundings reduces the signal quality. Suppression of noise improves the signal quality. In medical field, the heart sounds are recorded to take necessary actions upon the heart related diseases [3,4]. Recording heart sounds using stethoscope is simple and cost effective. During auscultation, the LSS and the HSS are overlapped. A continuous wavelet transform technique [5] was used to analyse this signal. Phonocardiograph (PCG) is a technique used to record the HSS [6,7]. Noises such as the sounds of internal organs, environmental noises are also mixed with the heart sound. Here the LSS is considered as one of the major noise since its frequency range lies between 20 Hz to 100 Hz [8,9]. The major components of HSS also lie within this range. For diagnosing heart diseases, separating the HSS and LSS become a challenging task.

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The separation of LSS and HSS suffer from unpredicted fluctuation due to the spectral overlap. Using non adaptive filters these signals cannot be separated. The filter should be chosen in such a way that it should get adapted to adjust the coefficients to handle the fluctuations of the input signals [10]. The Adaptive Noise Canceller (ANC) that suppress the noise from the corrupted signal by means of adaptive filters was first presented by Widrow [11]. The classic digital filters does not have self- learning ability but the adaptive filters have [12,13]. The adaptive filters fine-tune their impulse response, to filter out the correlated input signal. For non-stationary environments like LSS mixed HSS, the convergence of noise gets slows down, because of the high spectral dynamic nature of the environment [14]. To overwhelm this situation several adaptive algorithms have been projected. The Recursive-Least-Square (RLS) algorithm was proposed to attain the performance of adaptive filters [15]. The Least Mean Square (LMS) algorithm is most commonly used for its robustness and simplicity [16,17]. Algorithms such as adaptive filtering [18-20], wavelet denoising [21], spectrogram independent component analysis [22], time-frequency filtering [23] are also used to separate HSS and LSS. A Hybrid Nelder Mead algorithm [24] was implemented to reduce the unpredicted corrupted signal. Different filtering methods are reviewed for separating heart sounds from the lung sounds [25]. The independent component analysis method [26] was suggested to identify the heart sounds. A modulation filtering method [27] was proposed to remove the transient noise. An enhanced thresholding method for wavelet multi threshold technique was designed to cancel the noises from HSS [28]. The reduction of noise from HSS was attained in joint cycle frequency time frequency domain [29]. A spectro-temporal clustering method was proposed to extract the heart sound signals [30]. An adaptive noise cancellation technique is also used in [31] for the separation of HSS and LSS. Adaptive filtering techniques for heart and lung sound separation are reviewed and concluded that the accuracy of the filtered signal can be improved by modifying the step size value of Least Mean Square (LMS) algorithm [32].

In this paper, a stable RLS adaptive filter is used for the separation of HSS and LSS. The forgetting factor parameter of RLS filter is considered and it is optimized using an improved particle swarm optimization technique to improve accuracy and stability. Particle Swarm Optimization (PSO) algorithm uses the knowledge gained by each particle in the swarm to solve many optimization problems [33]. Though the PSO implementation is simple, it has drawbacks like slow convergence rate, reduced search, getting stuck in local best [34,35]. So a Dynamic Neighbourhood Learning Based Particle Swarm Optimizer (DNL-PSO) was suggested that overcomes the drawbacks of PSO [36]. The LMS based filter is also used for comparison. In LMS filter the step size optimization is done using DNL-PSO algorithm with two different initial conditions. The main purpose of this paper is to study and analyse the stability of RLS and to give good accuracy output by comparing PSO and DNL-PSO on various bio acoustic signals and to extract the noise free heart sound signal from the corrupted input signals.

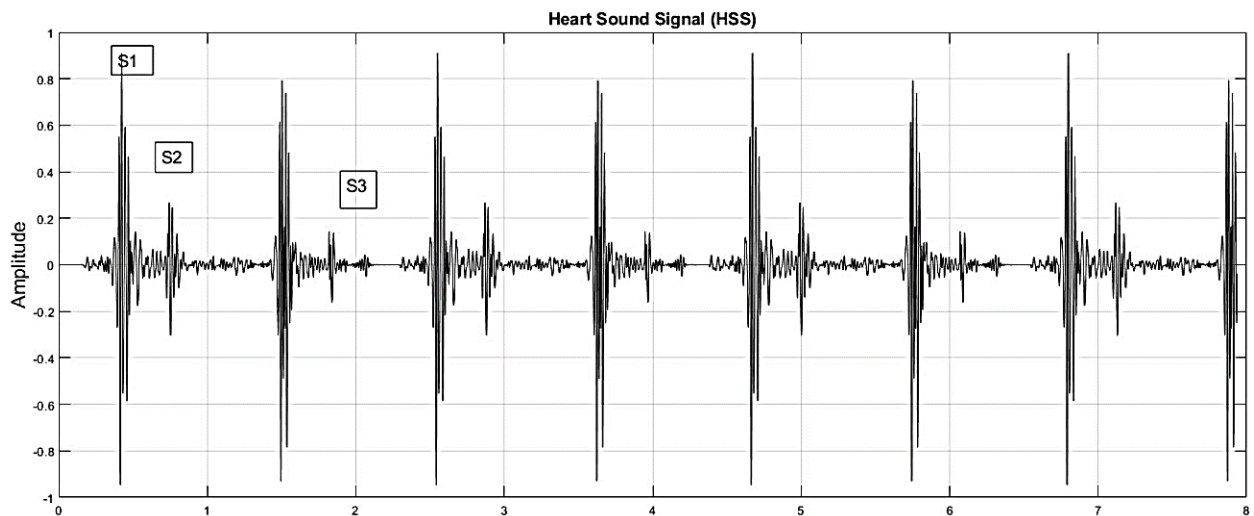
This paper is organised as follows: section 2 discuss about the inputs. The methodology is described in section 3. Section 4 presents the results analysis and discussion with tables and figures. Finally the conclusion is determined in section 5.

## 2. INPUTS

In this paper, normal heart sound signal is considered to study the accuracy of the filter. These normal HSS is corrupted with the various lung sound signals and the corrupted signals are used as input for the filter. The sound data are collected from reliable online sources [37].

### 2.1. Normal Heart Sounds

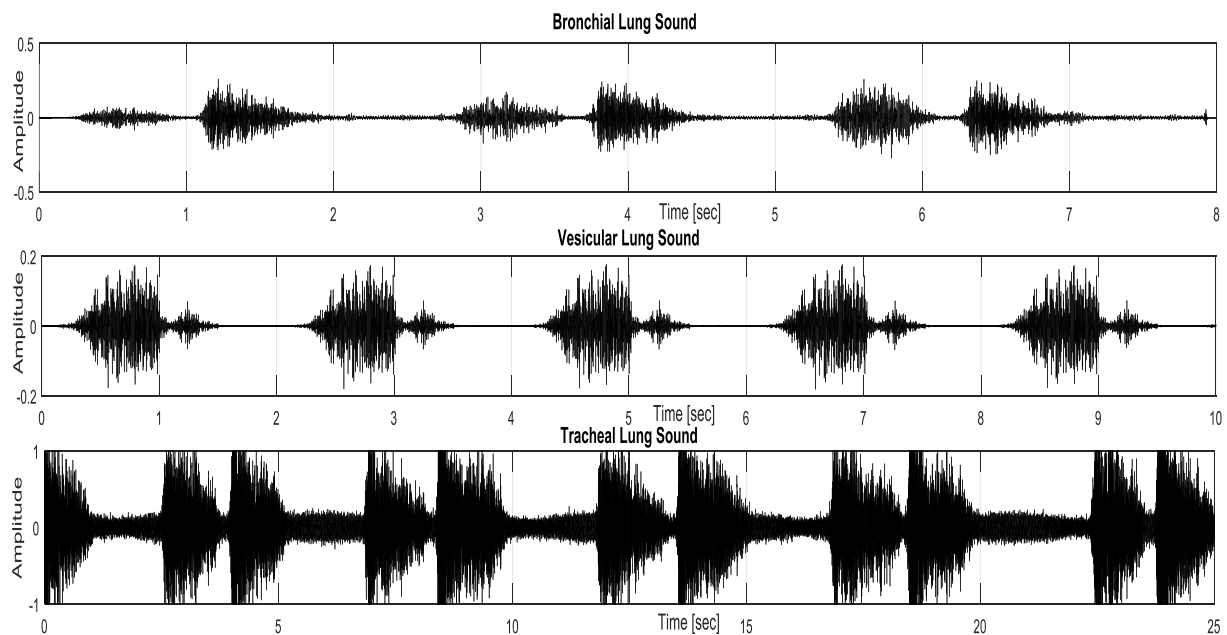
The heart sounds are produced mainly due to blood turbulence that occurs when the heart valves opens and closes. A heart cycle consists of four components: the first heart sound (S1), the second heart sound (S2), the third heart sound (S3) and the murmurs as shown in Figure 1.



**Figure 1.** Heart Sound Signal

## 2.2. Lung Sounds

The Lung sounds are produced when air flows through the passage of trachea and bronchi. The lung sounds are characterised as bronchial, vesicular and tracheal sounds as shown in Figure 2. The Bronchial lung sound occurs as the air traverses along the pulmonary airways with high pitch when compared to vesicular lung sound. Normally, this sound is heard over the trachea and the larynx. These sounds overlay with heart sounds and it is considered as noise. Vesicular lung sound is the normal lung sound which is heard clearly during inhalation. The frequency components of lung sound mostly range up to 1000 Hz [38,39]. In the range <100 Hz, more chances are there to get overlap with the heart sounds and therefore these components of lung sounds are considered as noise. The tracheal lung sound can be listened over the trachea with a deep and harsh breath sound. The frequency range is up to 5000 Hz. These noises should be suppressed while auscultating heart sound.



**Figure 2.** Various Lung Sound Signals



### 3. METHODOLOGY

The adaptive filters are in the form of transversal filter using RLS algorithm or LMS algorithm. An adaptive filter requires an adaptive algorithm with faster convergence with better filtered output.

#### 3.1. LMS Algorithm

For noise cancellation, Widrow and Hoff developed the LMS adaptive algorithm that uses a gradient descent to evaluate a time varying signal [12]. LMS is used for signal enhancement. The step size parameter in the LMS algorithm is used to determine the convergence rate [40]. But the selection of step size value will consume more time. The LMS filter coefficient update is defined in Equation (1)

$$w(n+1) = w(n) + 2\mu e(n)x(n), \quad (1)$$

$$y(n) = w(n).x^T(n). \quad (2)$$

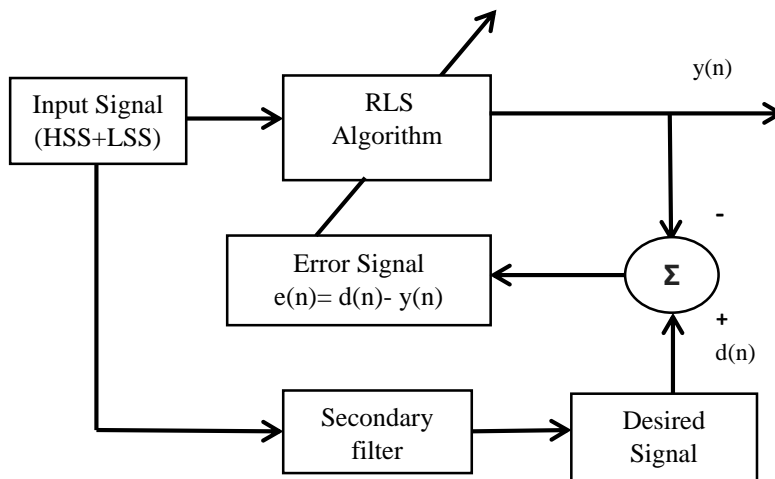
The error signal  $e(n)$  is calculated using the Equation (3)

$$e(n) = d(n) - y(n), \quad (3)$$

where  $x(n)$  is the mixed signal which is given as input with the weight vector  $w(n)$  at time  $n$ , and the pure heart sound is obtained from the output  $y(n)$ . The  $d(n)$  is the desired signal. The step size is termed as  $\mu$ .

#### 3.2. RLS Algorithm

The Recursive Least Square (RLS) algorithm is one of the effective linear adaptive filters used for noise cancellation. Compared to digital filters, the adaptive filters have self-learning capability [11]. One of the main advantages of this adaptive filter is that the rate of convergence is faster. The block diagram of RLS is given in Figure 3.



**Figure 3.** Block Diagram of the RLS algorithm [19]

The filtered output  $y(n)$  of RLS algorithm is computed using the Equation (2) and the error signal  $e(n)$  is computed using Equation (3). A secondary recursive filter is used to determine the reference signal  $d(n)$ . If the value of the error signal  $e(n)$  is minimum, it means that  $y(n)$  is very near to the reference signal  $d(n)$ . It can be achieved by optimizing the forgetting factor  $\lambda$  present in the cost function  $\varepsilon(n)$  which is defined in Equation (4)

$$\varepsilon(n) = \sum_{i=1}^n \lambda^{n-i} |e(i)|^2. \quad (4)$$

The RLS filter consists of parameters like; observable filter length, forgetting factor or weighing factor and the reference signal. The same input is used as the input for the secondary filter to generate reference signal  $d(n)$  which is the main advantage of the proposed scheme. The forgetting factor lies between the range 0 and 1. If the forgetting factor  $\lambda$  value is close to 1, the algorithm shows poor tracking. On the other hand if the  $\lambda$  reduces, the tracking is improved but it affects the stability. So to obtain the best optimal  $\lambda$  value, a suitable optimization algorithm should be used.

### 3.3. Optimization Algorithms

The optimization algorithm gives the best solution that provides an enhanced performance. In this paper Dynamic Neighbourhood Learning based PSO (DNL-PSO) algorithm is used to find the optimal forgetting factor for RLS algorithm.

#### 3.3.1. Particle swarm optimization (PSO)

Particle swarm optimization (PSO) is an intelligent optimization technique. It randomly search and escape from local minima and detects a good estimation to the global minima [41]. PSO algorithm mimics the navigation of school of fish. When compared to genetic algorithm, PSO algorithm is simpler to implement.

In swarm intelligence, an intelligent behaviour is created by means of agents like birds, fish, ants etc. PSO contains a population of candidate solutions termed as swarm. PSO involves communications between the swarm of agents within their location [42]. The Agents interaction are controlled using some protocols. Every particle is a candidate solution to the optimization problem. Each particle has the position in the search space of the optimization problem. The search space is the set of all probable solutions for optimization problem and the best solution is recognised from these probable solutions in the search space.

- For a particle  $i$ , the position of the particle is denoted by  $\vec{x}_i$  and it is the member of search space  $X$ .  $\vec{x}_i(t) \in X$ , where  $i$  is the index of particle and  $t$  is the no. of iteration. (5)
- The velocity  $\vec{V}_i$  is described as the movement of the particle  $i$  with respect to direction and distance.
- In addition to position  $\vec{x}_i(t)$  and velocity  $\vec{V}_i(t)$ , every particle has a memory of its own best position and it is denoted as personal best  $\vec{p}_i(t)$  and a common best experience belong to members of swarm known as global best  $g(t)$ .

In the every iteration of PSO, the position and velocity of each particle is updated. The new position  $\vec{x}_i(t + 1)$  is created according to the previous velocity, personal best and the global best. It is considered as the better solution. Based on this, every particle in the swarm collaborates to provide a best solution in search space.

In PSO the particle motion can be given as,

$$V_i(t + 1) = wV_i(t) + c_1(p_i(t) - x_i(t)) + c_2(g(t) - x_i(t)), \quad (6)$$

$$x_i(t + 1) = x_i(t) + V_i(t + 1), \quad (7)$$

where,  $c_1, c_2, w \rightarrow$  real value coefficients.

The equation for updating the velocity is given in Equation (8)

$$V_{ij}(t + 1) = wV_{ij}(t) + r_1c_1(p_{ij}(t) - x_{ij}(t)) + r_2c_2(g_{ij}(t) - x_{ij}(t)), \quad (8)$$

where,  $r_1, r_2 \rightarrow$  uniformly distributed random number that range from (0-1)

$$x_{ij}(t + 1) = x_{ij}(t) + V_{ij}(t + 1). \quad (9)$$

This equation is used to create new velocity vector and this new velocity vector translates the position to a new position in search space.

### 3.3.2. Dynamic neighbourhood learning based PSO (DNL-PSO)

Dynamic neighbourhood learning based Particle Swarm Optimizer (DNL-PSO) is a powerful single independent optimisation algorithm. The DNL-PSO updates the velocity by selecting the best from its neighbourhood. It chooses the optimal position from its neighbourhood by motivating each and every particle to learn from different other particles on different dimensions. In this technique to create a neighbourhood for a particle in the swarm, a topological like structure is formed. The topology can be of any type like ring, pyramid, square etc. The neighbourhood length can be fixed. Accordingly the entire swarm is divided into subgroups. A particle from this subgroup randomly learns from its neighbourhood. After some time interval the neighbourhood gets changed so that the information is exchanged to other particles. In such a way this technique achieves a best searching behaviour.

In DNL-PSO, the velocity is updated using the Equation (10)

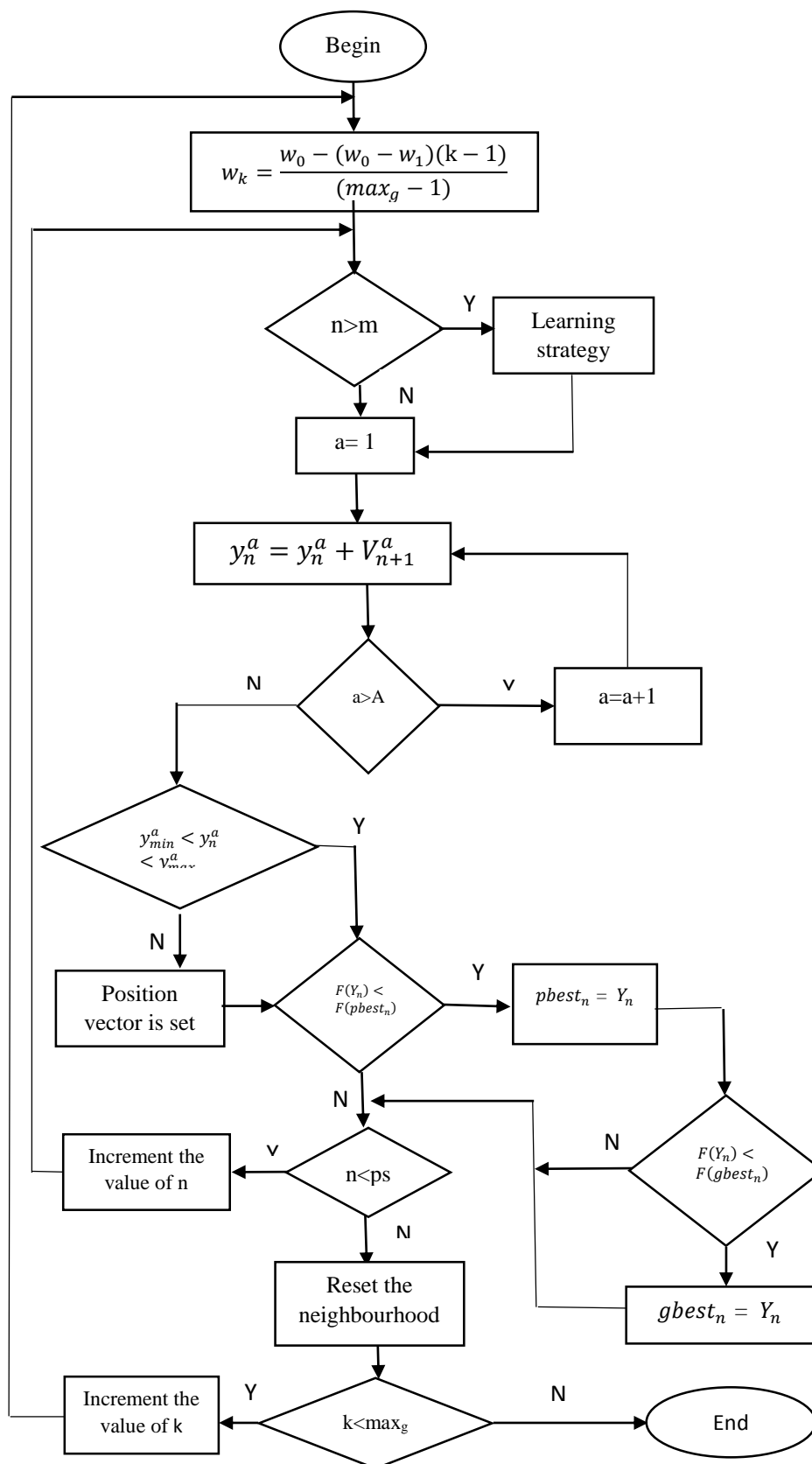
$$v_{n+1}^a = w * v_n^a + l_1 * r_1 * (pbest_{f_n^a}^a - y_n^a) + l_2 * r_2 * (gbest^a - y_n^a), \quad (10)$$

$$f_n = [f_n^1, f_n^2, \dots, f_n^A], \quad (11)$$

where  $f_n$  = best local position,  $v_{n+1}^a$  is the modified velocity,  $v_n^a$  is the velocity before updation,  $pbest_{f_n^a}^a$  is the best particle of  $f_n$ . The  $f_n$  may be the particle itself or any other particle from the group. The coefficients  $l_1, l_2$  are the accelerating parameters that makes each particle pull to the pbest and the gbest locations. The updated position is calculated by using the Equation (12)

$$y_n^a = y_n^a + V_{n+1}^a, \quad (12)$$

where  $y_n^a$  is the position vector in 'a' dimension for 'n' particles.



**Figure 4.** Functional Flowchart of DNL-PSO Algorithm

The DNL-PSO is used in this paper because it optimizes the forgetting factor ( $\lambda$ ) in which it led to improve the overall convergence speed. The working of the DNL-PSO algorithm is shown in a flowchart given in Figure 4.

The description of the flowchart is given as follows;

- Initialize the default value for the coefficients  $l_1$  and  $l_2$ . The generation counter  $k$  is set as 1. The  $k^{\text{th}}$  inertia weight is calculated as  $w_k = \frac{w_0 - (w_0 - w_1)(k-1)}{(max_{gen} - 1)}$ . The learning strategy of the DNL-PSO will be done only if the pbest fitness does not increase for a certain number of iterations repeatedly. Otherwise the vector  $f_i$  remains unchanged.
- The velocity is updated using  $v_{n+1}^a$  and the position is updated using  $y_n^a$ .
- If the dimension in the solution space 'a' is lesser than A then increase 'a' by 1 and repeat the previous step. If A is greater, then find out its neighbourhood particles in such a way its minimum position  $y_{min}^a$  and its maximum position  $y_{max}^a$  is also set. Now the vector  $f_n$  is constructed in which a particles pbest particle 'n' would learn.
- If the random number generated is less than the probability learning then the particle must learn from other particle pbest and its neighbourhood is identified.

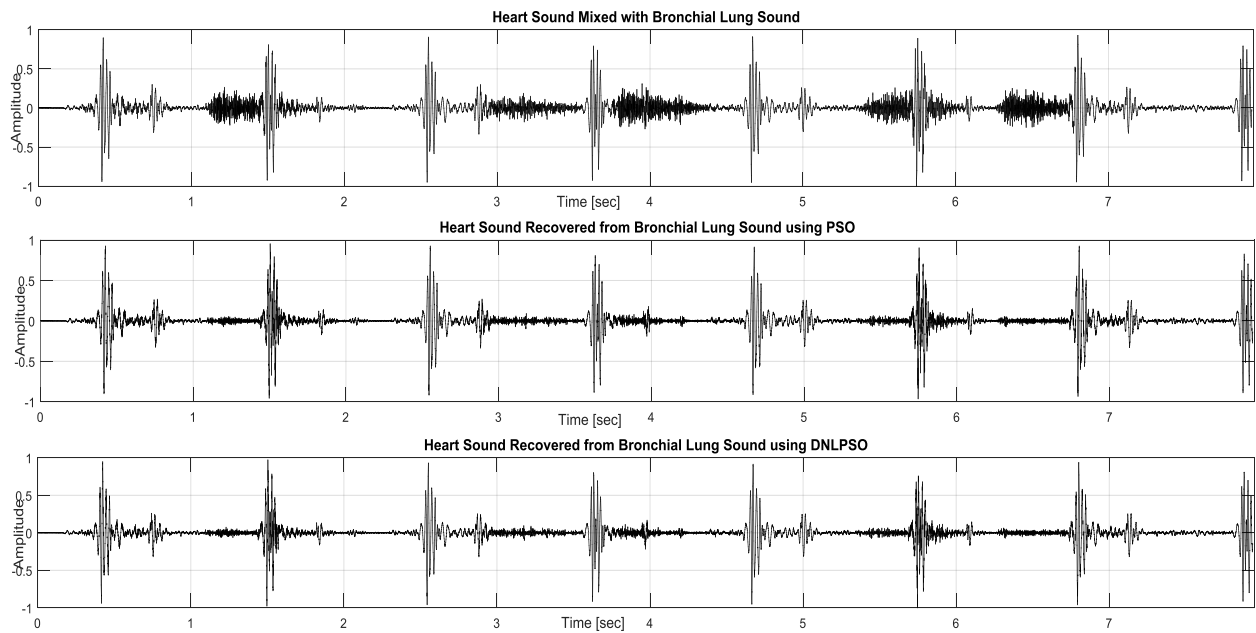
In DNL-PSO each and every particle studies from its knowledge in a dynamically varying neighbourhood that prevents early convergence. In such a way the best position is reached from the neighbourhood [43]. For standard PSO, the average execution time depends on its stopping conditions that is after reaching certain number of iterations [44]. In DNL-PSO the position updation and particle velocity is achieved dimension wise and the number of basic operations is relative to the number of iterations in the algorithm. So it is proved that when compared to classical PSO, the DNL-PSO algorithm is computationally efficient [36].

## 4. RESULTS AND DISCUSSION

The noise free Heart Sound Signal is mixed with different LSS such as Bronchial, Vesicular, and Tracheal Lung sound. An additive noise signal is generated by this procedure. The RLS algorithm with the fixed forgetting factor is used (the forgetting factor should be in the range of  $0 < \lambda < 1$ ). So three different  $\lambda$  values are considered they are; 0.1, 0.5 and 0.9 low, middle and higher ranges of forgetting factors respectively. A swarm based intelligence optimizing approaches such as PSO and DNL-PSO are implemented to derive an optimal  $\lambda$  ( $\lambda_{opt}$ ) value and the generated filter output is compared with the  $\lambda_{opt}$  based RLS algorithm.

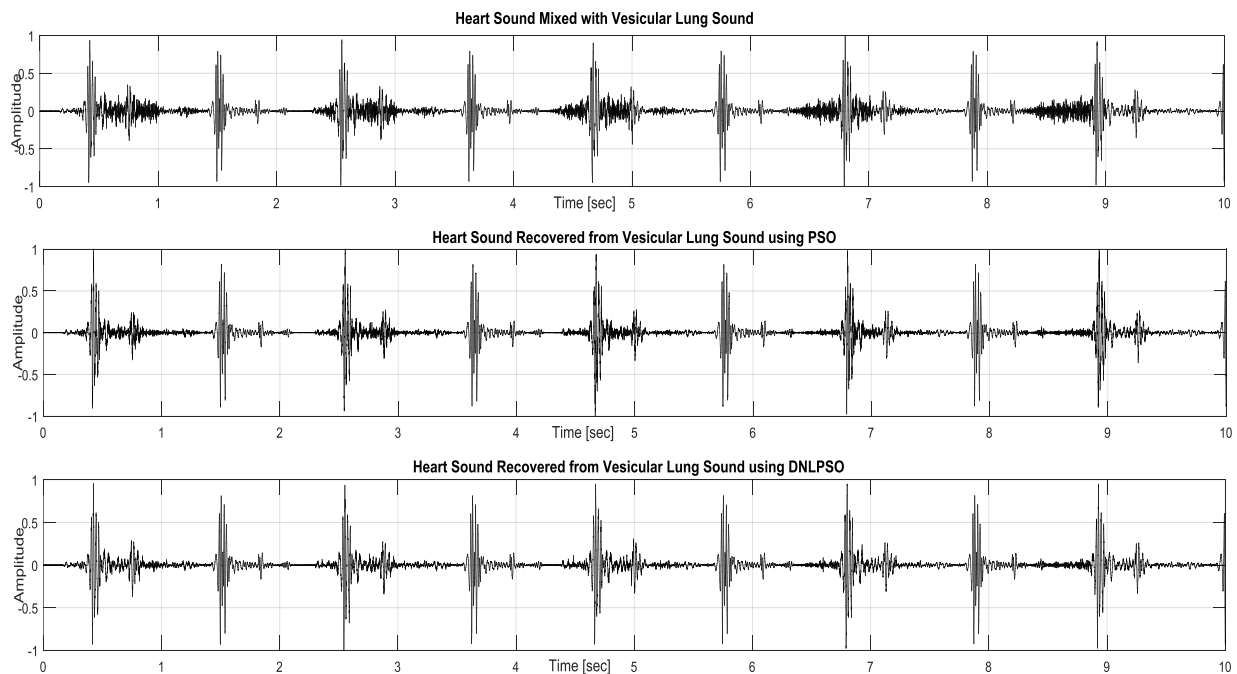
### 4.1. Results

The entire algorithm is implemented using MATLAB and the graphs are plotted using it. The results of HSS separated from different LSS mixture are shown in the following figures.



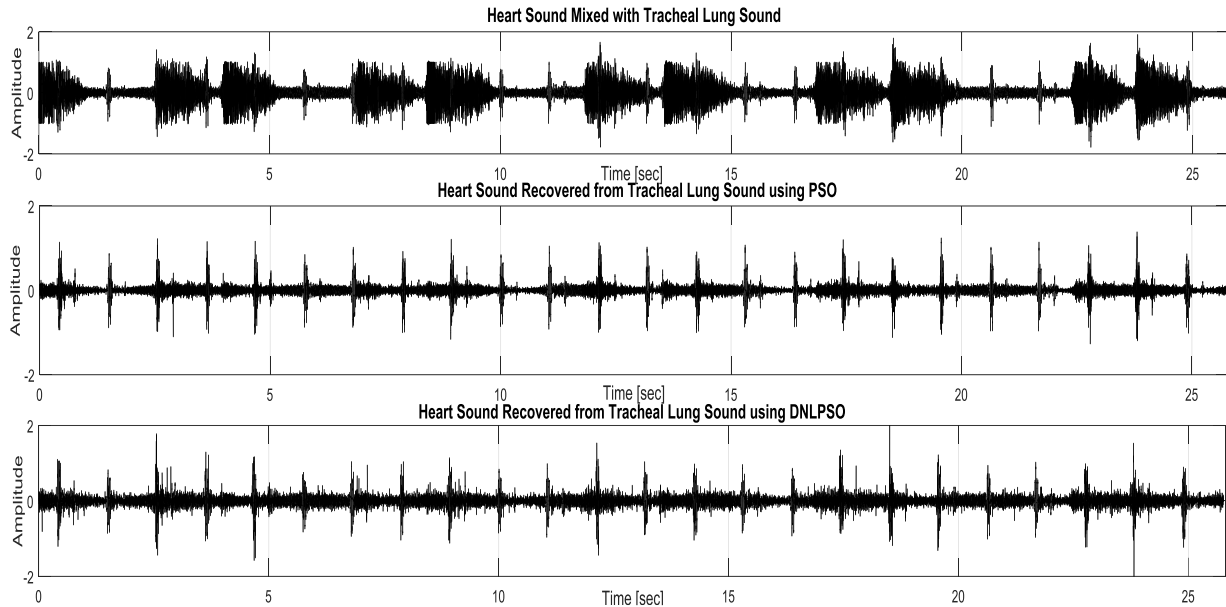
**Figure 5.** (a) Mixed Heart Sound and Bronchial Lung Sound signals; (b) Bronchial Lung Sound Interference Cancelled Heart Sound using PSO; (c) Bronchial Lung Sound Interference Cancelled Heart Sound using DNL-PSO

Figure 5(a) shows the Heart sound mixed with Bronchial Lung Sound, Figure 5(b) shows the recovered HSS from the bronchial mixture using PSO based on RLS algorithm and Figure 5(c) shows the recovered HSS from the bronchial mixture using DNL-PSO based on RLS algorithm.



**Figure 6.** (a) Mixed Heart Sound and Vesicular Lung Sound signals; (b) Vesicular Lung Sound Interference Cancelled Heart Sound using PSO; (c) Vesicular Lung Sound Interference Cancelled Heart Sound using DNL-PSO

Figure 6(a) displays the Heart sound mixed with Vesicular Lung Sound, Figure 6(b) shows the recovered HSS from the vesicular mixture using PSO based on RLS algorithm and Figure 6(c) shows the recovered HSS from the vesicular mixture using DNL-PSO based on RLS algorithm.



**Figure 7.** (a) Mixed Heart Sound and Tracheal Lung Sound signals; (b) Tracheal Lung Sound Interference Cancelled Heart Sound using PSO; (c) Tracheal Lung Sound Interference Cancelled Heart Sound using DNL-PSO

Figure 7(a) displays the Heart sound mixed with Tracheal Lung Sound, Figure 7(b) shows the recovered HSS from the Tracheal mixture using PSO based on RLS algorithm and Figure 7(c) shows the recovered HSS from the Tracheal mixture using DNL-PSO based on RLS algorithm.

#### 4.2. Discussion

For adaptive noise cancellation the popular algorithms are LMS and RLS. The LMS filter is used with the range of step size is being given as the initial values to the DNL-PSO. The ranges are 0.1- 0.9 and 0.01- 0.09. The result is given in Table 1.

**Table 1.** Correlation Coefficient for set of  $\mu$  values of LMS

Signals	Correlation for set of $\mu$ values of LMS	
	0.1 - 0.9	0.01- 0.09
HSS with Bronchial Lung sound	Do not Converge	Do not Converge
HSS with Vesicular Lung sound	Do not Converge	Do not Converge
HSS with Tracheal Lung sound	Do not Converge	Do not Converge

The LMS filter convergence greatly depends on the step size. Choosing the optimal step size plays an important role. In the given application, the LMS filter step size was tried to optimize using DNL PSO in two different ranges. But the filter does not converge (nearly zero correlation coefficient) on both the ranges. So even though the LMS filters are simple and easy to implement, we need computationally complex optimization algorithms to find the optimal step size of the LMS filter. So we have chosen RLS filter which is easily optimizable and stable at all the forgetting factors.

From the above Figures 5, 6, & 7, it is evident that the proposed algorithm gives better separation which is required for the accurate diagnostic procedure. The trade-off between the RLS with default forgetting factors and the RLS with  $\lambda_{opt}$  is quantified using the correlation coefficient between the uncorrupted heart sound signal and the filtered HSS, which is given in the Tables 2 and 4.

**Table 2.** Comparison of default  $\lambda$  with respect to Correlation Coefficient

Signals	Correlation Coefficient (%) - Default $\lambda$		
	0.1	0.5	0.9
HSS with Bronchial Lung Sound	No correlation	85	85
HSS with Vesicular Lung Sound	No correlation	88	88.1
HSS with Tracheal Lung Sound	No correlation	34	<b>80</b>

Table 2 shows that the correlation coefficient of 85% is achieved for HSS recovered from Bronchial LSS with default forgetting factor 0.5 and 0.9. The lower range forgetting factor 0.1 does not produce any convergence at all. And the lower values of forgetting factor do not give any result in this signal. The correlation coefficient attained for the HSS recovered from the vesicular LSS with default forgetting factors 0.5 and 0.9, are 88% and 88.1% respectively. The correlation coefficient for the HSS recovered from the tracheal LSS is 34% and 80% for the non-optimized default forgetting factor 0.5 and 0.9. So finding the optimal value of  $\lambda$  between 0.5 and 0.9 is the whole objective of this research. Table 3 shows the length of the signal and original power value of HSS in different length based on the LSS.

**Table 3.** Original Power Spectrum of different LSS

Signals	Signal Length (sec)	Original Power (mW)
HSS with Bronchial Lung Sound	8	0.0018
HSS with Vesicular Lung Sound	10	0.001
HSS with Tracheal Lung Sound	25	0.72

To find the optimal value of the forgetting factor and to enhance the performance of the algorithm, particle swarm intelligence is used. The forgetting factor parameter is tuned using PSO and DNL-PSO algorithms to recover HSS and it is compared. The effectiveness of the algorithm is evaluated using the power of the recovered signal; correlation coefficient and execution time of the algorithm.

#### 4.2.1. Correlation coefficient (c)

Correlation coefficient measures the likeness of two signals. The correlation coefficient is calculated as;

$$c = \left\{ \frac{E[(HSS - HSS_{avg})(y - y_{avg})]}{\sigma_{HSS} \cdot \sigma_y} \right\}. \quad (13)$$

#### 4.2.2. Power spectral density (PSD)

Welch's method is used to calculate the spectral density. A stationary random process is characterized by using power spectral density in the frequency domain. In various frequencies the signal power is compared in PSD  $S_{xx}(v)$ . The PSD is defined as;

$$S_{xx}(v) = \frac{1}{K} \sum_{k=1}^K P_k(v), \quad (14)$$

$$P_k(v) = \lim_{T \rightarrow \infty} \frac{1}{2T} \int_{-T}^T |x_k(v)|^2 dt, \quad (15)$$

K - Number of Segments;

$P_k$  - Power of  $x_k(v)$ ;

$v$  - Frequency;

T - Time.

Table 4 shows the comparative study of swarm optimization based parameter tuning of RLS algorithm.



**Table 4.** Comparative analysis of swarm optimization Based Parameter Tuning of RLS Algorithm for the recovery of HSS from LSS

HSS with various LSS	Optimal Forgetting factor		Power of recovered HSS		Correlation Coefficient (%)		Execution time (Sec)	
	PSO	DNL-PSO	PSO	DNL-PSO	PSO	DNL-PSO	PSO	DNL-PSO
HSS with Bronchial Lung sound	0.99	0.9736	0.0166	<b>0.0167</b>	86.19	85.7	1569	<b>823.07</b>
HSS with Vesicular Lung sound	0.99	0.7727	0.0163	<b>0.0173</b>	88.52	88.16	1822	<b>806.27</b>
HSS with Tracheal Lung sound	0.99	0.8666	0.0153	<b>0.195</b>	80.16	80.07	4786	<b>2097</b>

Figure 8(a) shows the iteration graph for HSS with bronchial LSS using PSO and Figure 8(b) illustrates the convergence of the cost function for HSS with Bronchial LSS using DNL-PSO.

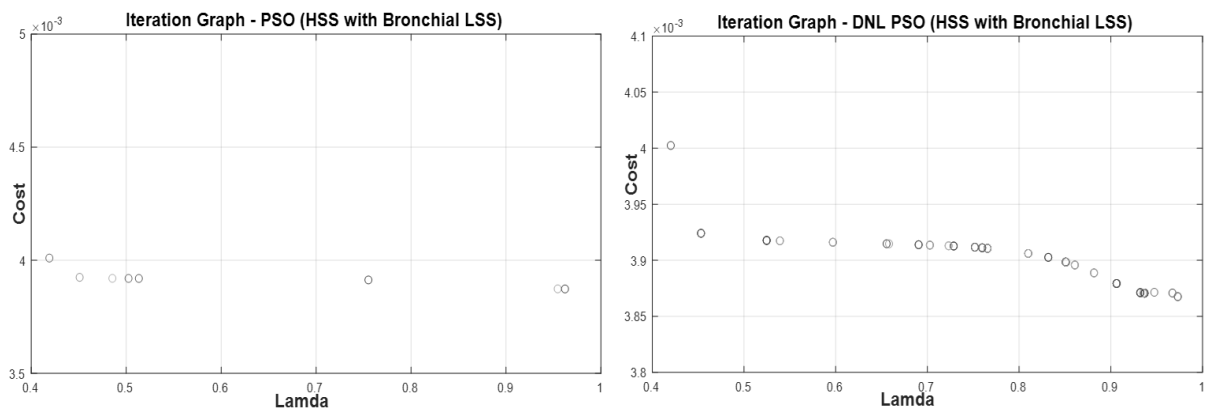
**Figure 8.** (a) Iteration Graph for HSS with Bronchial LSS using PSO; (b) Iteration Graph for HSS with Bronchial LSS using DNL-PSO

Figure 9(a) shows the iteration graph for HSS with vesicular LSS using PSO and Figure 9(b) illustrates the convergence of the cost function for HSS with vesicular LSS using DNL-PSO.

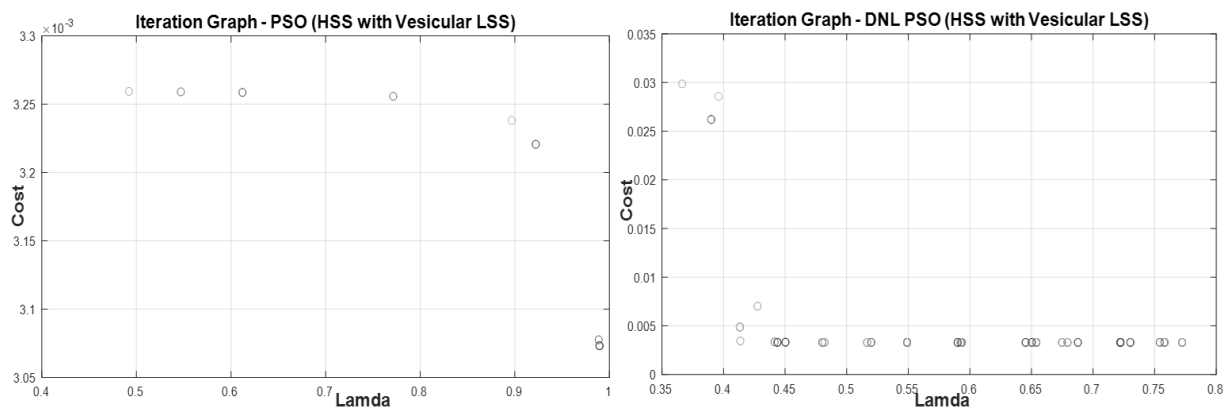
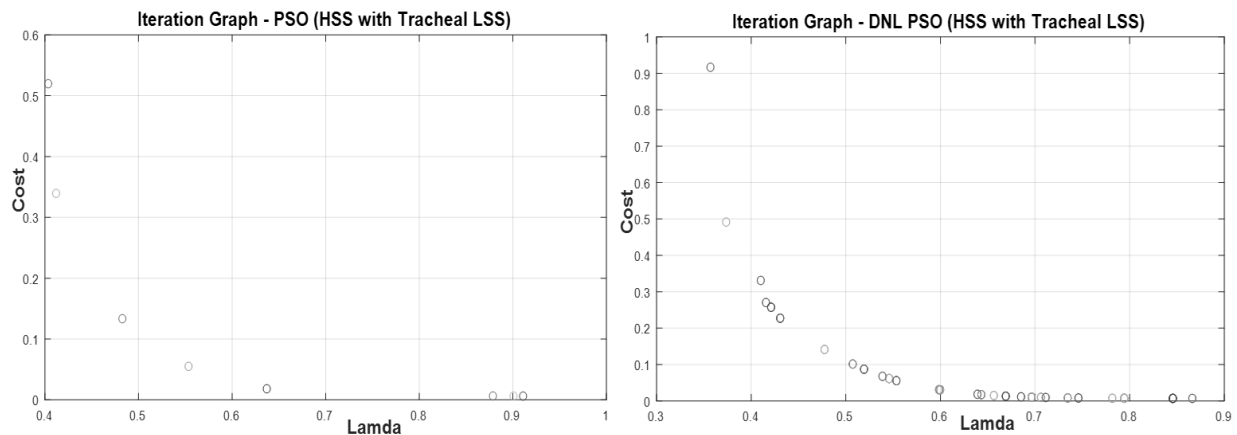
**Figure 9.** (a) Iteration Graph for HSS with Vesicular LSS using PSO; (b) Iteration Graph for HSS with Vesicular LSS using DNL-PSO

Figure 10(a) shows the iteration graph for HSS with tracheal LSS using PSO and Figure 10(b) illustrates the convergence of the cost function for HSS with tracheal LSS using DNL-PSO.



**Figure 10.** (a) Iteration Graph for HSS with Tracheal LSS using PSO; (b) Iteration Graph for HSS with Tracheal LSS using DNL-PSO

From the Figures 8,9 and 10, it is clear that DNL-PSO algorithm converges faster than the PSO algorithm except for the tracheal mixed HSS input signal. More over the PSO algorithm always converges to the maximum limit. Table 4, gives the power of the recovered signal; correlation coefficient and execution time value of the different input signal. The RLS filter with  $\lambda_{opt}$  gives 85.7% of correlation for the HSS recovered from Bronchial LSS. For HSS recovered from the vesicular LSS, the average correlation coefficient attained for the optimal forgetting factors is 88.5%. The correlation coefficient for the HSS recovered from the tracheal LSS for the optimized value is 80.1%. From Table 2 and 4, it is evident that optimizing the parameters of RLS algorithm produces better results.

## 5. CONCLUSION

The diagnosis and analysis of heart valve abnormalities with the help of heart sound signals are possible only if the signal is captured and studied without noise. But the heart sound signal recording is noisy due to many reasons. Lung Sound signals are the major contributor of the noises, since both the sounds occurs in the same thoracic region. To recover the HSS from various noise sources, effective noise cancellation algorithms are required. For the mentioned noise removal, an adaptive filtering is required. Least Mean Square (LMS) algorithm and RLS algorithm are compared and the RLS algorithm is chosen based on the performace and faster convergence over LMS.

In RLS, the weightage of the error signal is determined by the forgetting factor, which exponentially decreases the weight for past error signals. By selecting the optimal forgetting factor the RLS algorithm performance is improved. Swarm based search algorithm is used to adjust the parameter to obtain an optimized forgetting factor. The Dynamic Neighbourhood Learning Particle Swarm Optimizer is used in this paper to improve the execution time and reduce the computational complexity. HSS recovered from the tracheal LSS gives only 80% of correlation for both PSO and DNL-PSO, because the tracheal LSS are the harse and high pitch lung sound compared with other lung sounds. Though the correlation is approximately closer for PSO and DNL-PSO, the PSO consumes more time for execution compared to DNL-PSO. So based on the execution time DNL-PSO outperforms the conventional PSO, Since DNL-PSO searches in the neighbourhood. And also optimizing other parameters like length of the filter may give more accurate results.

## CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

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