ARTICLE IN PRESS

Engineering Science and Technology, an International Journal xxx (2017) xxx–xxx

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Engineering Science and Technology, an International Journal

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

Full Length Article

Hybrid Nelder-Mead search based optimal Least Mean Square algorithms for heart and lung sound separation

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A R T I C L E I N F O

Article history:
Received 7 September 2016
Revised 9 February 2017
Accepted 21 February 2017
Available online xxxx

Keywords:
Heart sound separation
Nelder-Mead search
Least Mean Square algorithm
Adaptive noise cancellation
Biologically inspired optimization algorithms
Biological signals

A B S T R A C T

Algorithms for separation of heart sounds from background lung sound noises are vital for accurate diagnosis of heart diseases. In this paper, an improved adaptive noise cancellation technique based on the Least Mean Square (LMS) algorithm is used to separate heart sounds from lung sounds. The step size parameter in the LMS algorithm is optimally chosen using a hybrid Nelder-Mead (H-NM) optimization algorithm. The NM algorithm is initialized with a good initial solution by using computationally cheap random search to compute a rough estimate of the global minimum. Initialization of the NM algorithm with a good initial guess avoided convergence to shallow local minima and improved the quality of the final solution. The effects of using two state-of-the-arts biologically inspired heuristic optimization algorithms instead of the H-NM algorithm and three variants of the standard LMS algorithm are investigated. The correlation coefficient between the ideal and filtered heart sound signal and running time-complexity of different algorithms are taken as the metric for comparison of different heart sound separation approaches. Simulation results indicate that the approach presented in this paper performs significantly better than a variety of alternate approaches on heart sound separation problems.

1. Introduction

Methods for effective separation of the Heart Sound Signal (HSS) from background lung sound noise are of great importance in the diagnosis of cardiac diseases. The separated noise free HSS is used in real time diagnostic applications like feature segmentation and analysis, the study of a second heart sound (S2) split [1] and sleep parameter assessment [2]. The separated lung sound is also used as an indicative tool for anesthetic management during surgical procedures [3,4]. In this paper, a novel optimal Least Mean Square (LMS) algorithm based approach for accurate separation of the heart sound is proposed and compared with a variety of existing approaches.

Auscultation refers to the action of listening to the sounds produced by internal organs traditionally with a stethoscope [5]. Physicians use auscultation as a non-invasive method to get functional information relating to internal organs like the heart, the lung, and the gastrointestinal system. In auscultation of the heart, besides the sounds produced from the flow of blood into and out of the heart, and the breath sounds, there are artifacts in the form of murmurs, gallops, and environmental noises. The HSS is the sound produced by the flow of blood, in and out of the cardiac structure and the movement of the cardiac structure itself. The HSS is basically composed of two major sounds S1 and S2. S1 is caused by ventricular contraction during the closure of the atrioventricular valves. S1 is the longest and loudest of the heart sounds. S2 is due to the closure of the semilunar valves at the end of ventricular systole. Lung Sound Signal (LSS) is produced by turbulent air flow during respiration. Major frequency components of the LSS lie in the range of 20 to 100 Hz [5,6]. This is also the range in which the HSS has its main frequency components [7]. The spectral overlap of the heart and Lung sounds makes the HSS separation problem challenging. Moreover, HSS and LSS are random signals and can suffer unexpected fluctuations, and also due to the spectral overlap, the separation of the two signals cannot be performed using any non-adaptive or time invariant linear filter. So, the filter used should be able to adapt with such inconsistencies. The word “adapt” means to adjust the filter coefficients to cope with the fluctuations of the input signals [8]. Adaptive filters have a self-learning ability where as traditional digital filters do not have [9].

Yang-sheng Lu et al. [7] used adaptive filters for accurate separation of heart and lung sounds. Hans pasterkamp et al. [10] discussed the problem of recording LSS using a stethoscope and also

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Peer review under responsibility of Karabuk University.

http://dx.doi.org/10.1016/j.jestch.2017.02.005
2215-0986/© 2017 Karabuk University. Publishing services by Elsevier B.V.

Please cite this article in press as: R. Nersisson, M.M. Noel, Hybrid Nelder-Mead search based optimal Least Mean Square algorithms for heart and lung sound separation, Eng. Sci. Tech., Int. J. (2017), http://dx.doi.org/10.1016/j.jestch.2017.02.005

suggested active noise cancellation techniques for operation in noisy environments. Yip et al. [11] proved the reduction of heart sound artifacts using the adaptive noise cancellation algorithms with automatic gain control technique using experimental results. Thato Tsalaile et al. [12] considered the separation of HSS from colored noise using the Adaptive Line Enhancement (ALE) LMS algorithm. This paper also addresses the issues relevant to the optimal selection of ALE algorithm parameters. M. T Pourazad et al. [13] proposed a time-frequency filtering technique for separation of HSS and LSS. January Gnitecki et al. [14] presented a detailed study of various adaptive noise cancellation algorithms for HSS and LSS separation and indicated the importance of properly selecting adaptive filter parameters such as filter order and the convergence rates. Foad Ghaderi et al. [15] proposed a separation approach based on the singular spectral analysis. Muhammad Sukrisno Mardiyanto et al. [16] analyzed the frequency spectrum of the LSS for diagnostic applications. Ruban et al. [17] reviewed a variety of algorithms for HSS separation and concluded that adaptive filters with some modification in the step size could improve the quality of the separated signals. Mostafa Guda et al. [18] explored a variety of LMS algorithm improvements for denoising Electro Cardio Graph (ECG) signals. An adaptive noise cancellation technique, where the step size is updating based on the power of the input signal is reported by Yüksel Özbay et al. [19].

This paper is organized as follows: firstly HSS, LSS, mixed signal and adaptive noise cancellation based schemes for separation are discussed, secondly, an improved adaptive noise cancellation scheme where the step size is optimally chosen using a hybrid Nelder-Mead algorithm is proposed and finally the proposed approach is compared with a variety of alternate approaches.

2. Heart and lung sounds

2.1. Recording sounds produced by internal organs

HSS is recorded with electronic stethoscopes and suitable data acquisition systems. HSS is usually digitally stored in .mp3 or .wav formats [10]. The prime location for the HSS recording is right and left sternal margin between second and fifth intercostal spaces.

The lung sound auscultation is mostly done on upper anterior region of the chest, mid axillary region and on the posterior basal side [20]. The HSS is recorded near the mid-axillary line to minimize LSS noise.

2.2. Heart sounds

The heart sound has multiple components such as first heart sound (S1), second heart sound (S2), third heart sound (S3) and murmurs Fig. 1.

2.3. Lung sounds

Breathing consists of two phases – inspiration and expiration. Lung sounds are created when air moves through the airways (trachea and bronchi). The nature of heart and lung sounds is determined by the movement of the body structures. These sounds can be classified as tracheal, bronchial, broncho-vesicular, vesicular and adventitious sounds [20]. The types of lung sounds considered in this paper are described in Fig. 2.

a. **Bronchial sounds:** The bronchial sounds are mainly present and detected over the large airways in the anterior chest near the second and third intercostal spaces and are thus heard above the sternum. So these sounds mostly overlap with the HSS. These sounds are not as harsh and coarse as tracheal breath sounds but are loud and high in pitch.
b. **Vesicular breath sounds:** These sounds are heard over most of the lung region. There is a significant overlap between the vesicular breath sound and HSS. These sounds are high pitched in the inspiration cycle and low pitched in the expiration cycle without a gap between inspiration and expiration cycles [20].
c. **Adventitious lung sounds:** These sounds include crackles, pleural sounds and wheezes. Wheezing is the major sound present with lung sounds of patients suffering from breathing related problems, so the breath sound recorded with wheezing is also considered as one of the noise signal.

In this paper four different corrupted signals are used to test the performance of different HSS separation algorithms. Fig. 3 shows the heart sounds contaminated with different lung sound noises.

3. Methodology

In the following section, the standard LMS algorithm and its popular improved variants are reviewed. The design procedure for filter parameters and the values are presented.

3.1. Adaptive algorithms

The process of active noise cancellation uses an adaptive Finite Impulse Response (FIR) filter. The filtering is performed in two parts – the adaptive algorithm and the digital filter.

3.1.1. The LMS algorithm

The LMS algorithm [21,22] is used to adapt the coefficients of a FIR (Finite Impulse Response) filter based on a suitably defined error signal to achieve noise separation from the input signals. To obtain the pure heart sound output y(n) from the noisy input, an estimate of the noise (lung sound) is computed using an adaptive FIR filter. The LMS filter coefficient update rule is given in Eq. (1).

$$w(n+1) = w(n) + 2\mu e(n)x(n) \tag{1}$$

$$y(n) = w(n).x^T(n) \tag{2}$$

The error signal e(n) is defined as follows:

$$e(n) = d(n) - y(n) \tag{3}$$

where

x(n) → contaminated heart sound signal
w(n) → vector of filter coefficients
y(n) → filtered heart sound
d(n) → desired signal
μ → step size

The convergence rate of the LMS algorithm depends critically on the step size parameter μ [23]. The overall scheme for separation of the heart sound signal using the LMS algorithm is shown in Fig. 4.

3.1.2. Normalized LMS

In the conventional LMS algorithm, the noise level varies based on the value of the step size (μ), since the step size is calculated by the Eigen value of the input vector. To solve this problem, another approach is used in which the step size is calculated by the autocorrelation of the input vector [24]. The filter coefficient vector w(n) is normalized [24–27] based on the input vector in each iteration.

The step size is given by [24];

$$\mu(n) = \mu_0\left[\frac{1}{N}\sum_{i=0}^{N-1}x^2(n-i)\right]^{-1} = \frac{N\mu_0}{X^T(n).X(n)} \tag{4}$$

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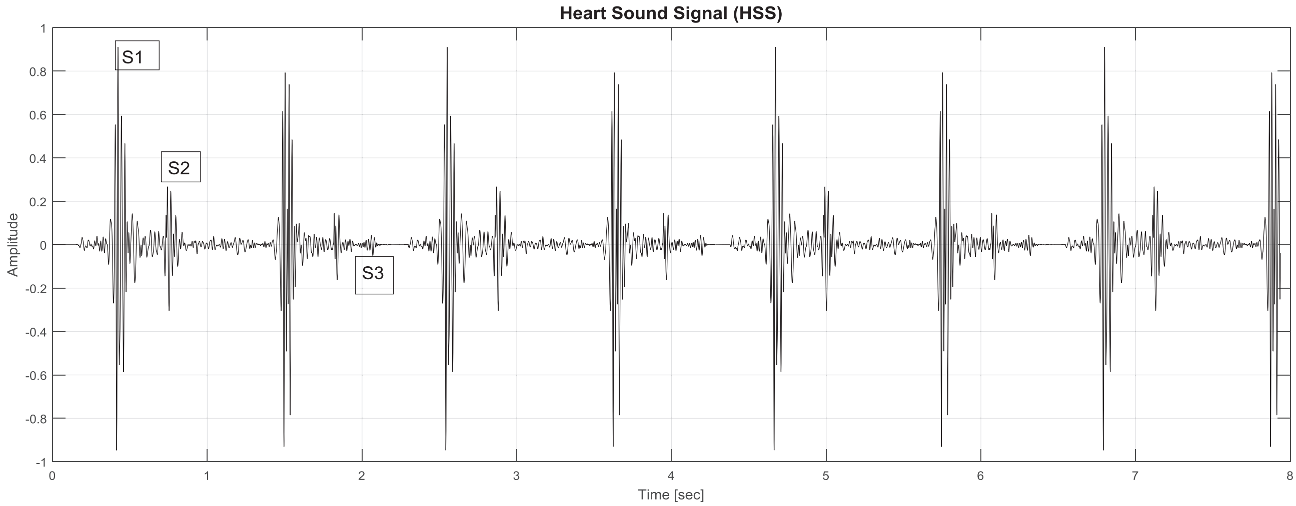

Fig. 1. Ideal HSS signal with its components.

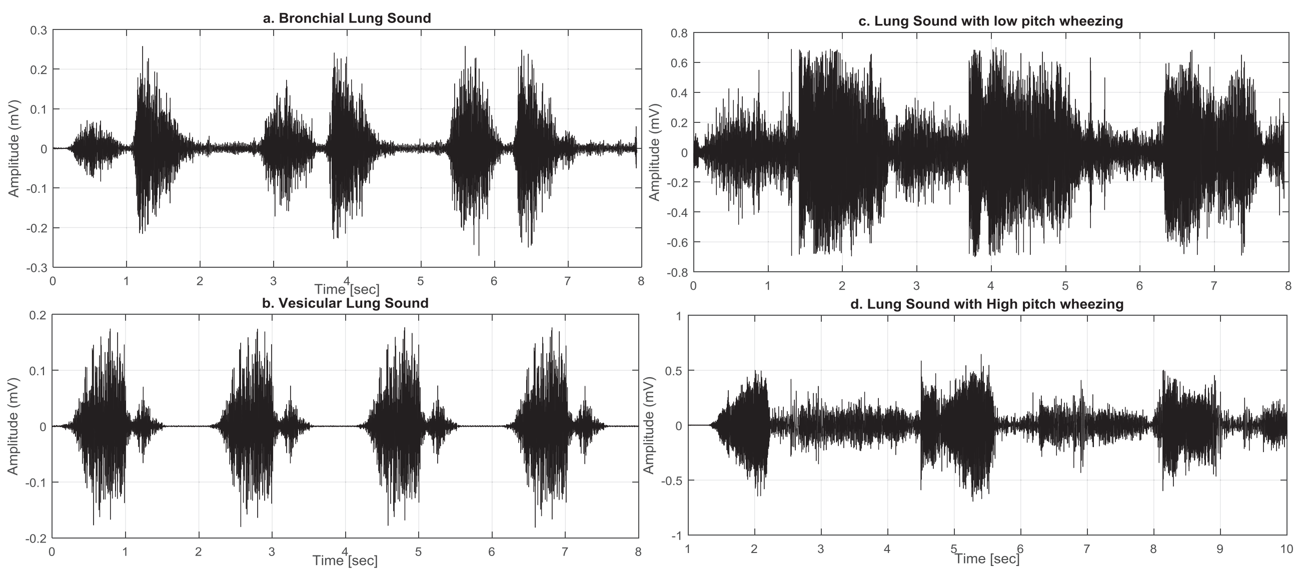

Fig. 2. a. Bronchial lung sound; b. Vesicular lung sound; c. Lung sound with low pitch wheezing; d. Lung sound with high pitch wheezing.

N → number of data sample

The adaptive filter weight w(n + 1) is given by [28];

$$w(n+1) = \left\{1 - N\mu_0 \left[\frac{X(n).X^T(n)}{X^T(n).X(n)}\right]\right\} w(n) + N\mu_0 \left[\frac{d(n).X(n)}{X^T(n).X(n)}\right] \quad (5)$$

Once the weight is updated then the Eqs. (2) and (3) are used to find the filtered output.

3.1.3. Block LMS

In this algorithm, the input signal is divided into equal sized blocks and the filter coefficient is updated for every block [29,30]. The input is analyzed blockwise (the block size needs to be specified). The gradient vector is also calculated based on the input data block set of the current block.

$$w(k+1) = w(k) + \mu_B \frac{\sum_{i=0}^{L-1} e(kL+i)X(kL+i)}{L} \quad (6)$$

The output and error vector are calculated based on the kth block;

$$\sum_{i=0}^{L-1} y(kL+i) = \sum_{i=0}^{L-1} \{w(k).x^T(kL+i)\} \quad (7)$$

$$e(kL+i) = d(kL+i) - y(kL+i) \quad (8)$$

L → length of the block

k → block index

3.2. Design parameters

The Adaptive filter parameters are:

(i) Adaptive filter length L: The order of the filter (Filter length L) is considered to be 300 for all the LMS schemes and this value is considered based on the length of the input signal.

(ii) The step size parameter μ: The step size is calculated by the Eigen value of the input vector given in Eq. (10).

(iii) Desired signal d(n).

(iv) Block size (only for BLMS): The block size is chosen to be close to the length of the filter [29], the larger length makes the converging faster but the adaptation efficiency goes down.

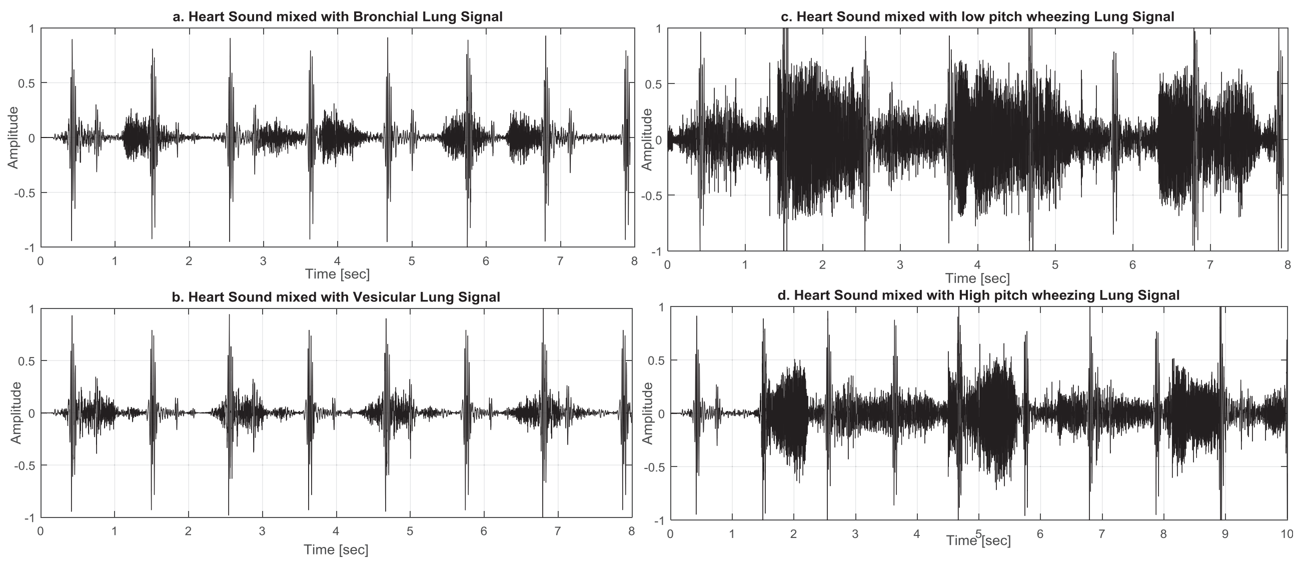

Fig. 3. HSS mixed with various LSS; a. HSS mixed with bronchial lung sound; b. HSS mixed with vesicular lung sound; c. HSS mixed with low pitch wheezing; d. HSS mixed with high pitch wheezing.

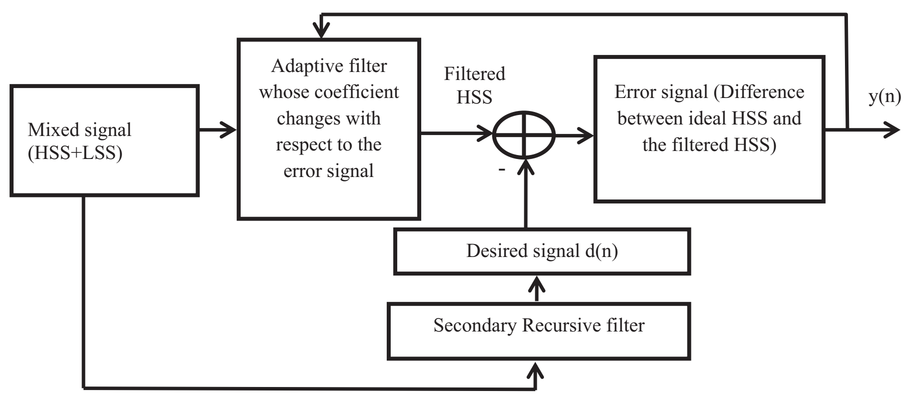

Fig. 4. Block diagram: adaptive noise cancellation algorithm.

3.2.1. Selection of step size

The following guidelines are considered while choosing the step size for the adaptive filter [31].

- Small step size to ensure a small steady state error. However, a small step size also decreases the convergence speed of the resulting adaptive filter.
- Larger step size to improve the convergence speed of the resulting adaptive filter. However, a large step size might cause the adaptive filter to become unstable.
- The larger step sizes affect the coefficients causing them to fluctuate and eventually lead to instability of the filter [21].

The μ is chosen for a stable filter by the following bound [21]

$$0 < \mu < \frac{2}{\lambda_{max}} \tag{9}$$

The default step size is calculated using [21];

$$\mu = \left|\frac{2}{\lambda_{max} + \lambda_{min}}\right| \tag{10}$$

where λ_{max}, and λ_{min} are maximum and minimum Eigen values of the autocorrelation (A_{cor}) of input vector respectively.

$$A_{cor} = E[x(n).x^T(n)] \tag{11}$$

The step size can be a fixed value, in that case, μ will be a small positive integer value and also the μ can be time-varying with iteration.

3.2.2. Filter parameter for the desired signal d(n)

A recursive bandpass filter is designed to get the desired signal from the mixed input signal [32]. The filter length (order) is calculated by the scopeFIR software for the required signal noise reduction based on the input signal characteristics. The frequency parameter, like the normalized cut-off frequency ranges are considered based on the frequency spectrum by taking Fast Fourier Transform (FFT) analysis of the input signals [6].

4. Optimization algorithms

In this section, the theoretical back ground and the mathematical representation of proposed algorithm for the step size optimization of LMS filters and two other biologically inspired optimization algorithms which are used for the comparative study are presented.

4.1. Hybrid Nelder-Mead algorithm (H-NM)

The efficiency of LMS filter in bio signal separation from the noise depends highly on selection of optimal step size value. So an optimization algorithm based on Nelder-Mead (NM) search

[33–35] is designed for the purpose. The NM algorithm needs an initial set of population, which is generated by the random search algorithm [36]. Thus a hybrid NM-based approach is derived (Fig. 5). It runs in two stages, stage one is the random search, which will find out the close approximation (μ_{opt}). Using the μ_{opt} as initial population, the second stage proceeds and the best possible step size is examined. The cost function in the designed algorithm seeks to minimize the difference in the correlation coefficient. The algorithm for H-NM is given below and the Table 1 gives the nomenclature for the algorithm.

Algorithm
Stage 1: Random Search:

(i) Generate 'N' random value in the interval [0.0009, 0.1];
(ii) For $k \leftarrow 1$ to N;
Perform the adaptive filtration process on the input signal,
$y(k)$ is derived using the Eqn. 2 and 7 for the different adaptive algorithms.

$$MSE\ (k) = \frac{1}{m}\sum_{k=1}^{N}|HSS - y(k)|^2 \tag{12}$$

$m \rightarrow$ length of the signal

(iii) $$k_{best} = \underbrace{argmin}_{k}\ MSE(k) \tag{13}$$

(iv) $\mu_{opt} \leftarrow \mu(k_{best})$

Stage 2: Nelder –Mead Search

Stage 2.a:

Initialize $x_0 \leftarrow \mu_{opt}$
(i) For $i \leftarrow 1$ to $n+1$;

$$x_0 = x_c = \frac{\sum_{i=1}^{n} x_i}{n} \tag{14}$$

(ii) Using Eqn. 14, x_i vertices are formed,
(iii) The function 'f' is evaluated for each x_i to get $f(x_i)$.

$$f(x)\ = min\left(1 - \left\{\frac{E[(HSS - HSS_{avg})(y - y_{avg})]}{\sigma_{HSS}.\sigma_y}\right\}\right) + DC \tag{15}$$

(iv) **Sort:** The function values are sorted such that;

$f(x_1) < f(x_2) < f(x_3) < \ldots\ldots\ldots..f(x_n) < f(x_{n+1})$.
$x_1 = x_{low} \rightarrow f(x_{low})$
$x_n = x_{high} \rightarrow f(x_{high})$
$x_{n+1} = x_{worst} \rightarrow f(x_{n+1})$.

Reflection:

$$x_{refl} = (1+\alpha)\ x_c - \alpha\ x_{high} \tag{16}$$

(i) If $f(x_{low}) \leq f(x_{refl}) \leq f(x_{high})$ Then

$x_{worst} \leftarrow x_{refl}$ Then
go to Sort operation
Else, go to Expansion

Expansion:

(i) If $f(x_{refl}) < f(x_{low})$ Then

$$x_{exp} = \gamma.\ x_{refl} + (1-\gamma)x_c, \tag{17}$$

If $f(x_{exp}) < f(x_{refl})$ Then
$x_{worst} \leftarrow x_{exp}$, Then
go to sort operation
Elseif $f(x_{refl}) < f(x_{exp})$, Then
$x_{worst} \leftarrow x_{refl}$, Then
go to sort operation
Else, go to Contraction

Contraction:

If $f(x_{refl}) \geq f(x_{high})$

Case (i):

If $f(x_{high}) < f(x_{refl}) < f(x_{n+1})$, Then

$$x_{Cout} = \beta\ x_{ref} + (1-\beta)x_c, \tag{18}$$

If $f(x_{Cout}) < f(x_{high})$ Then
$x_{high} \leftarrow x_{Cout}$
Else, go to shrink operation

Case (ii):

If $f(x_{n+1}) < f(x_{refl})$, Then

$$x_{Cin} = \beta\ x_{n+1} + (1-\beta)x_c, \tag{19}$$

If $f(x_{Cin}) < f(x_{n+1})$, Then
$x_{n+1} \leftarrow x_{Cin}$
Else, go to shrink operation

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Shrink:

If $f(x_{Cout}) > f(x_{high})$ or $f(x_{Cin}) > f(x_{n+1})$, then the simplex need to be shrink with new test points except x_{low}.

For i ← 2 to n+1;

$$S_i = \varepsilon\, x_i + (1+\varepsilon)\, x_{low} \tag{20}$$

new test points → x_{low} , S_i

And the search will restart with new test points, it will continue until the best possible 'x' is reached or the maximum number iteration is reached.

Stage 2.b

To make the search engine more focused towards the optimal solution, a deviation coefficient (DC) is introduced. And it is calculated based on the cor;

$$cor = \min\left(1 - \left\{\frac{E[(HSS - HSS_{avg})(y - y_{avg})]}{\sigma_{HSS}.\sigma_y}\right\}\right) \tag{21}$$

Case (i) For Heart sound mixed with normal lung sounds,
If (cor) < 0.15, Then
DC ← 0
Else
*DC ← DC+ (cor*1000)*
Case (ii) For Heart sound mixed with adventitious lung sounds,
If (cor)< 0.25, Then
Then DC ← 0
Else
*DC ← DC+ (cor*1000)*

This DC is added to the cost function so that deviation value gets added up and the function value will get rejected from the population.

Table 1
Nomenclature.

Variable	Description	Standard values [34,35]
N	*Number of random test points*	*100*
MSE	*Mean Square Error*	
μ_{opt}	*Best possible solution for random search*	
n	*Number of variables*	
x_c	*Centroid point*	
x_0	*Initial vertex ($x_c \leftarrow x_0 \leftarrow \mu_{opt}$)*	
f	*Cost function*	
DC	*Deviation Coefficient*	
x_{refl}	*Reflected x value*	
α	*Reflection coefficient (Positive number)*	**1**
x_{exp}	*Expanded x value*	
γ	*Expansion coefficient (greater than unity)*	**2**
x_{Cout}	*Contracted x value (outside)*	
x_{Cin}	*Contracted x value (inside)*	
β	*Contraction coefficient (lies between 0 and 1)*	**0.5**
S	*New test points after shrink operation*	
ε	*Shrink coefficient (lies between 0 and 1)*	**0.5**
cor	*Condition function for DC*	
σ	*Standard deviation*	

4.2. Genetic algorithm (GA)

Genetic algorithm (GA) is a search algorithm based on natural selection and natural genetics. A simple GA consists of three operators [37];

Reproduction: It is the process in which individual strings are copied according to their objective function values. The effect of reproduction is computed by,

$$m(H, t+1) = m(H, t)\frac{f(H)}{\bar{f}} \tag{22}$$

H → Schemata (similarity templates)
m → Number of copies of a schema H
t → time

The average fitness of the strings representing schema is given by;

$$f(H) = \frac{\sum\limits_{S_i \in H} f(s_i)}{m(H, t)} \tag{23}$$

The average fitness of the entire population (A) is given by;

$$\bar{f} = \sum f_i / u \tag{24}$$

u → number of strings in the population

Crossover: In this process, the newly copied strings are mated and each pair of strings will undergo crossing over at the uniformly selected crossing site.

Mutation: It is the process of random alteration of the value of a string position.

By considering all these three operators, the next generation copies of a particular schema H is given by the following equation,

$$m(H, t+1) \geqslant m(H, t).\frac{f(H)}{\bar{f}}\left[1 - p_c\frac{\delta(H)}{l-1} - o(H)p_m\right] \tag{25}$$

δ(H) → Defining length of a schema
o(H) → order of a schema
P_c, P_m → cross over and mutation probabilities
l → length of the string

4.3. Particle swarm optimization (PSO)

It is a population based metaheuristic approach. In PSO, the particle which is a potential solution used to move in the problem space with the help of its own historical best experiences and with the overall best experiences of the swarm [38].

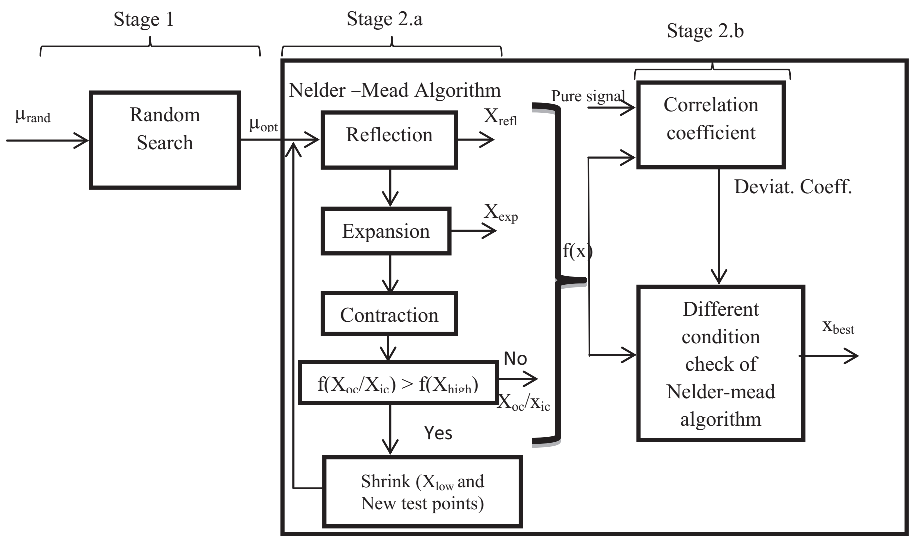

Fig. 5. Block diagram: H-NM algorithm.

Table 2
Parameter settings.

	GA	DNL-PSO	H-NM
Dimension	1	1	1
Population size	10	10	–
Number of iteration	–	–	10
Inertia factor (w)	–	0.4–0.9	–
Crossover fraction	0.8	–	–
Acceleration parameter C_1 & C_2	–	2	–
Stopping criteria	Maximum No. Generation (20)	Maximum No. Generation (20)	Maximum No. Generation (20)

4.3.1. Dynamic neighborhood learning based particle swarm optimizer (DNL-PSO)

It is a powerful variant of PSO; it is a single- objective optimization problem. In which the best particle is selected from the defined neighborhood only.

Velocity updating equation of DNL-PSO is given by [39];

$$V_i^d = w * V_i^d + C_1 * r_1 * \left(pbest_{f_i^d}^d - X_i^d\right) + C_2 * r_2 * (gbest^d - X_i^d) \tag{26}$$

The position will updated by the new velocity vector using the below equation;

$$X_i^d = X_i^d + V_i^d \tag{27}$$

V_i → Velocity vector of the ith particle
d → Dimension of the problem
X_i → position vector
$pbest_i$ → personal best of the ith particle
gbest → best position of all the particle
w → inertia factor
r_1 & r_2 → random numbers [0 to 1]
C_1 & C_2 → acceleration parameter (approximately 2)
f_i → local best of a particle which will be followed by ith particle

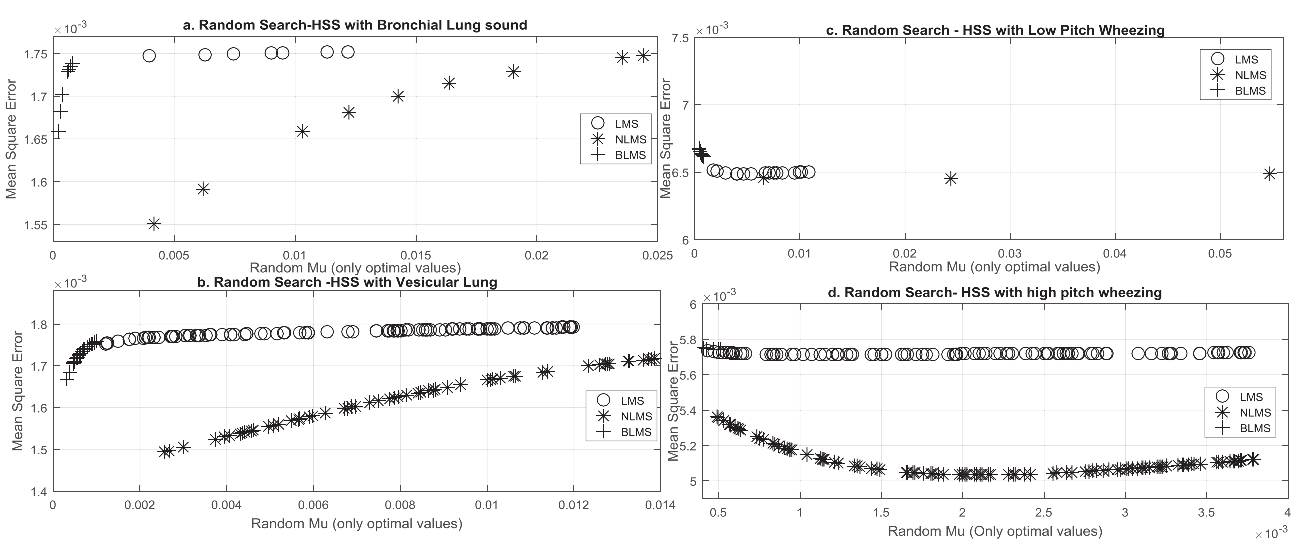

Fig. 6. Random search results for three different algorithms (only selected values are plotted), a. HSS mixed with bronchial Lung sound; b. HSS mixed with Vesicular lung sound; c. HSS mixed with low pitch wheezing; d. HSS mixed with high pitch wheezing.

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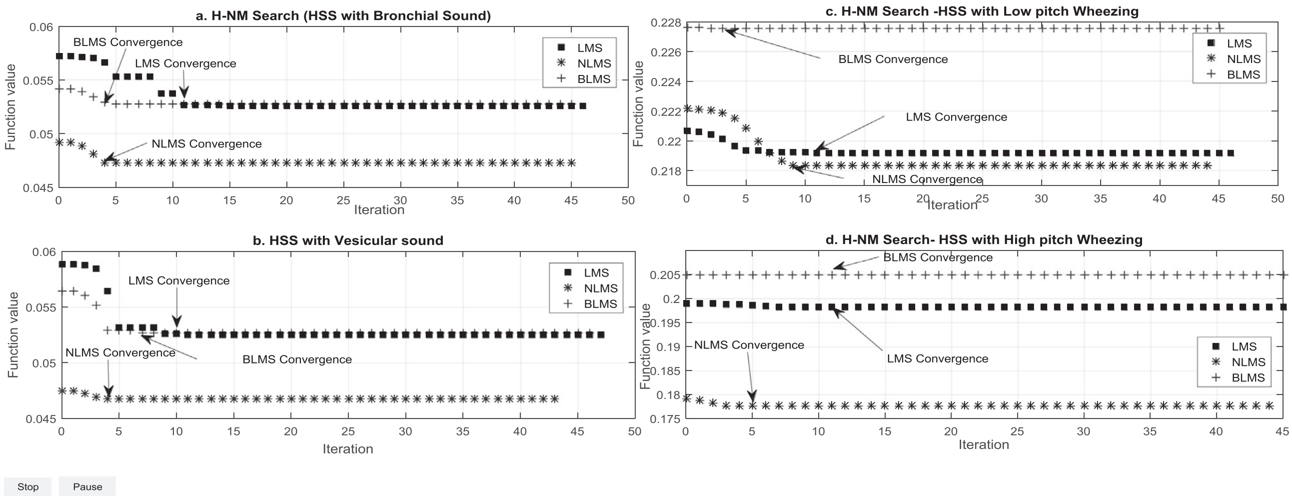

Fig. 7. The function evaluation graph for the proposed H-NM search of different algorithms, a. HSS mixed with bronchial lung sound; b. HSS mixed with vesicular lung sound; c. HSS mixed with low pitch wheezing; d. HSS mixed with high pitch wheezing.

Table 3
Convergence of the H-NM algorithm.

	Algorithm	Number of Iterations for Convergence (H-NM search)
HSS with Bronchial LSS	LMS	11
	NLMS	**4**
	BLMS	**4**
HSS with Vesicular LSS	LMS	10
	NLMS	**4**
	BLMS	7
HSS with adventitious LSS (Low pitch Wheezing)	LMS	11
	NLMS	9
	BLMS	**3**
HSS with adventitious LSS (High pitch Wheezing)	LMS	11
	NLMS	**5**
	BLMS	11

The bold value is the lowest number of iteration in all the three algorithms.

The fitness function for the GA and DNL-PSO is given in the Eq. (28). And the fitness function for the H-NM is given in Eq. (15). The parameter selection for GA, DNL-PSO and H-NM are given in Table 2.

$$f(x) = \min\left(1 - \left\{\frac{E[(HSS - HSS_{avg})(y - y_{avg})]}{\sigma_{HSS}.\sigma_y}\right\}\right) \tag{28}$$

5. Results and discussion

Fig. 1 shows the ideal HSS recorded without LSS interference. The mixed signal is a combination of the HSS and the LSS as shown in Fig. 3. The filtered outputs with the step size optimally chosen using random search, basic NM search, and H-NM search for the three different LMS algorithms are presented. H-NM search results are compared with two other biologically inspired algorithms. In the following section, the metrics of different algorithms are com-

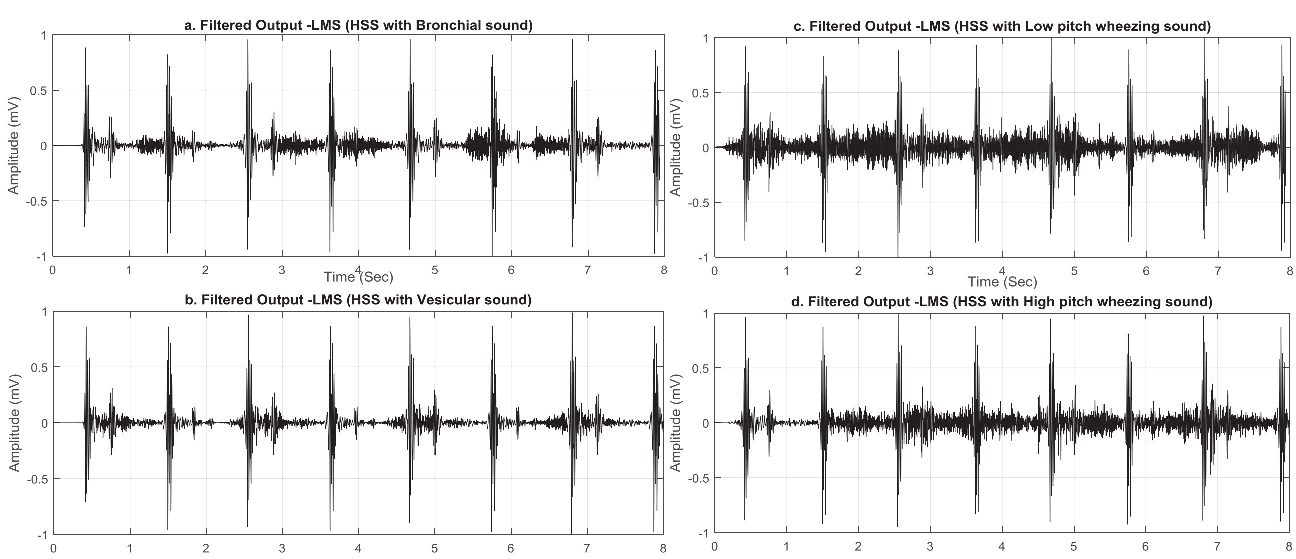

Fig. 8. The filtered output using LMS algorithm with the optimized step size (μ); a. HSS retrieved from bronchial lung sound; b. HSS retrieved from vesicular lung sound; c. HSS retrieved from low pitch wheezing; d. HSS retrieved from high pitch wheezing.

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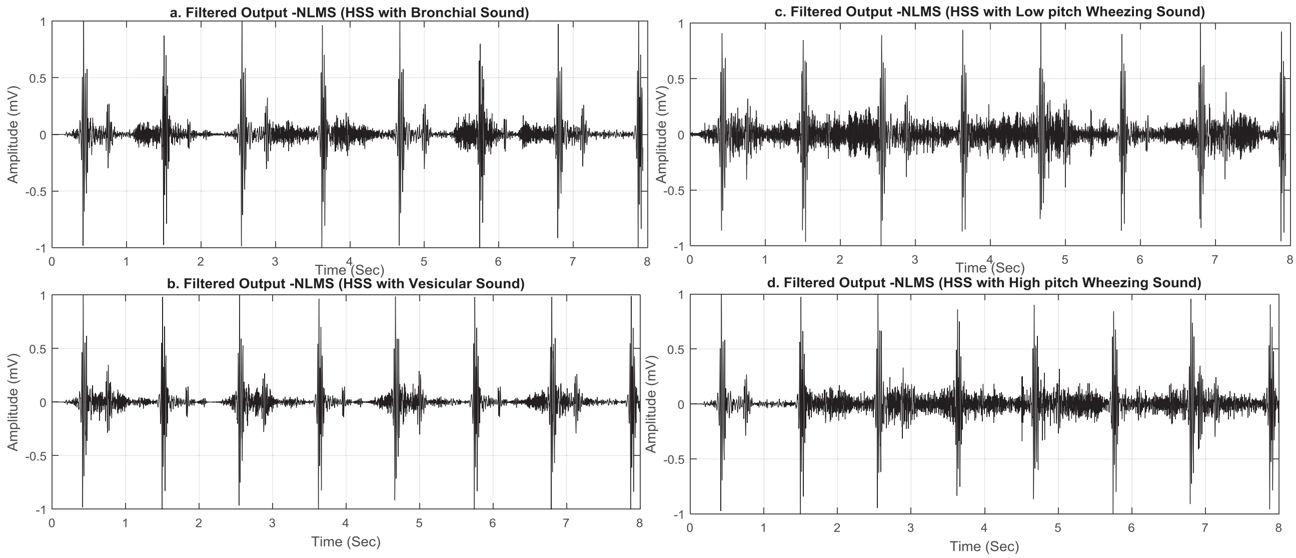

Fig. 9. The filtered output using NLMS algorithm with the optimized step size (μ); a. HSS retrieved from bronchial lung sound; b. HSS retrieved from vesicular lung sound; c. HSS retrieved from low pitch wheezing; d. HSS retrieved from high pitch wheezing.

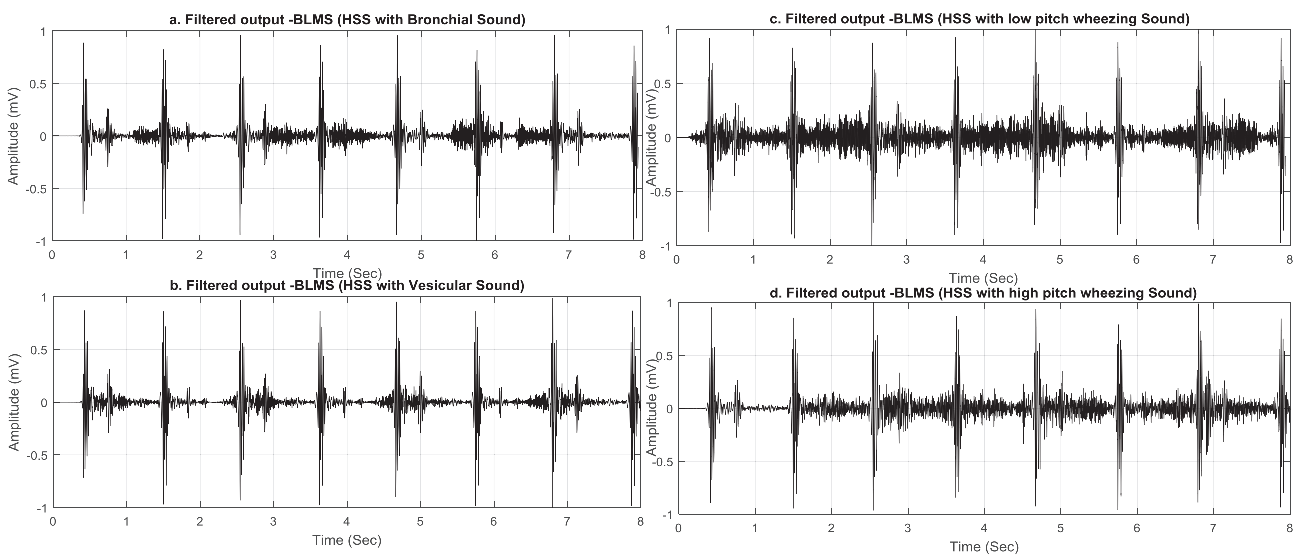

Fig. 10. The filtered output using BLMS algorithm with the optimized step size (μ); a. HSS retrieved from bronchial lung sound; b. HSS retrieved from vesicular lung sound; c. HSS retrieved from low pitch wheezing; d. HSS retrieved from high pitch wheezing.

Table 4
Filter performance assessed with correlation coefficient for NM search initialized with the default μ.

	Algorithm	Initial μ (Approximated)	No. of iteration for convergence	Correlation coefficient (%)
HSS with Bronchial LSS	LMS	0.0758	Not converging	No correlation
	NLMS	0.0758	14	95.27
	BLMS	0.0758	Not converging	No correlation
HSS with Vesicular LSS	LMS	0.126	15	94.7
	NLMS	0.126	7	95.32
	BLMS	0.126	Not converging	No correlation
HSS with adventitious LSS (Low pitch Wheezing)	LMS	0.4315	Not converging	No correlation
	NLMS	0.4315	5	78.17
	BLMS	0.4315	Not converging	No correlation
HSS with adventitious LSS (High pitch Wheezing)	LMS	0.216	Not converging	No correlation
	NLMS	0.216	13	82
	BLMS	0.216	Not converging	No correlation

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Table 5
Filter performance assessed with correlation coefficient using default step size and the step size computed with different optimization algorithms including the proposed algorithm.

	Algorithm	Default		GA	DNL-PSO	H-NM algorithm	
		Default μ	Correlation coefficient (%)	Correlation coefficient (%)	Correlation coefficient (%)	Optimal μ	Correlation coefficient (%)
HSS with Bronchial LSS	LMS	0.0758	No correlation	94.7	94.38	8.4e-05	**94.74**
	NLMS	0.0758	94	95.27	95.27	0.00134	**95.27**
	BLMS	0.0758	No correlation	94.7	94.7	8.79e-05	**94.7**
HSS with Vesicular LSS	LMS	0.126	No correlation	94.75	94.18	6.9e-05	**94.75**
	NLMS	0.126	93	95.3	95.32	0.0012	**95.32**
	BLMS	0.126	No correlation	94.7	94.73	6.9e-05	**94.74**
HSS with adventitious LSS (Low pitch Wheezing)	LMS	0.4315	No correlation	78.02	77.9	0.0109	**78.1**
	NLMS	0.4315	78	78.1	76.65	0.6848	**78.17**
	BLMS	0.4315	No correlation	77.2	77.24	8.12e-04	**77.24**
HSS with adventitious LSS (High pitch Wheezing)	LMS	0.216	No correlation	79.64	79.62	0.0068	**80.2**
	NLMS	0.216	79	82.04	81.52	0.003	**82.23**
	BLMS	0.216	No correlation	79.51	79.5	5.34e-04	**80.5**

The bold values are the best possible correlation coefficient by the proposed algorithm.

Table 6
Time complexity analysis of the three algorithms.

	Algorithm	GA		DNL-PSO		H-NM algorithm	
		Converging time (Sec)		Converging time (Sec)		Converging time (Sec)	
		Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
HSS with Bronchial LSS	LMS	118.04	6.02	363.69	11.44	**37.22**	**0.53**
	NLMS	134.41	2.88	349.45	23.4	**41.3**	**1.56**
	BLMS	75.5	1.37	168.73	7.755	**22.09**	**0.41**
HSS with Vesicular LSS	LMS	159.19	6.39	360.14	36.1	**46.6**	**1.43**
	NLMS	173.1	8.11	411.47	17.25	**52.46**	**1.6**
	BLMS	92.04	2.58	211.42	18.66	**26.81**	**0.45**
HSS with adventitious LSS (Low pitch Wheezing)	LMS	131.06	9.91	455.23	12.25	**35.13**	**0.7**
	NLMS	131.25	5.68	490.82	26.28	**46.16**	**3.13**
	BLMS	71.28	1.17	165.32	4.03	**25.13**	**2.08**
HSS with adventitious LSS (High pitch Wheezing)	LMS	143.06	11.03	474.28	13.91	**39.24**	**0.63**
	NLMS	144.98	2.59	454.72	49.3	**45.75**	**0.91**
	BLMS	77.58	1.09	202.98	9.73	**22.85**	**0.21**

The bold values denote the lowest meantime and standard deviation among the three optimization algorithm.

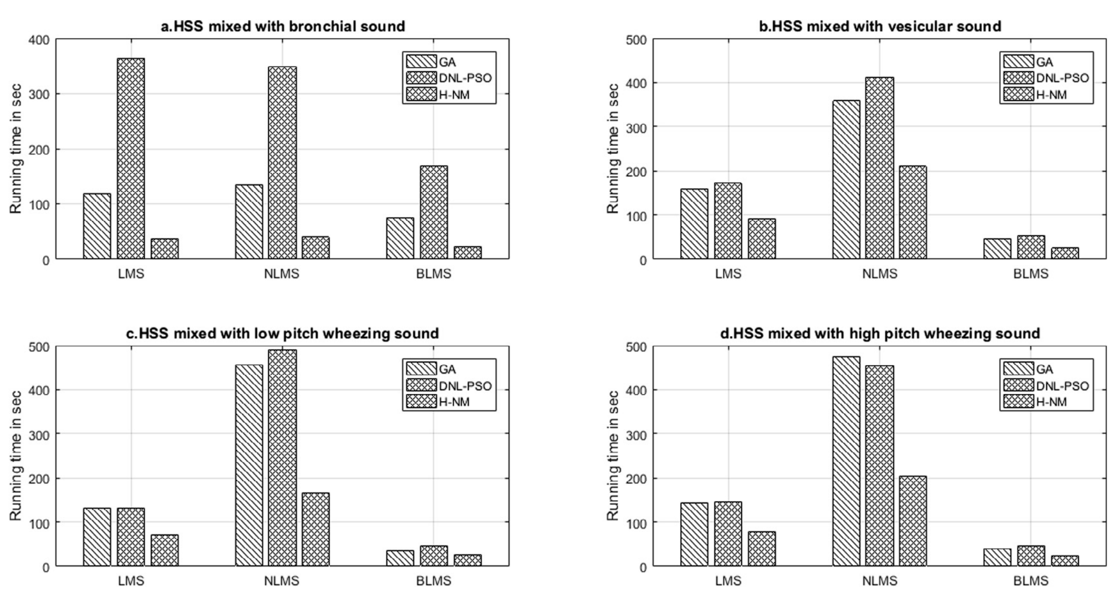

Fig. 11. The running time comparison of different optimization algorithms; a. HSS mixed with bronchial lung sound; b. HSS mixed with vesicular lung sound; c. HSS mixed with low pitch wheezing; d. HSS mixed with high pitch wheezing.

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pared based on the correlation coefficient and average running time complexity.

5.1. Filter performance with random search

Fig. 6 depicts the performance of all the three LMS algorithms with the random search for step size. The graph is plotted between Random μ to the MSE values for all the four input signals. The step size (Mu or μ) which results in lowest MSE is considered to be the optimal choice (μ_{opt}).

5.2. Filtering performance with step size computed by H-NM search

The Fig. 7 depicts the function evaluation graph of the H-NM search algorithm, where graph is plotted between the iteration number and cost function values. The convergence of each algorithm is marked in the graph. From the plot it is clear that NLMS algorithm converges quickly than the other two algorithms.

Table 3 shows the convergence rate of each algorithm for different input classes. It is observed from the Table 3 that; the LMS, NLMS and BLMS algorithms converge at 11th, 4th, and 7th iterations respectively. There after the convergence reaches a stable condition in all the three algorithms.

5.3. Filtered output using LMS, NLMS and BLSM algorithms

LMS: The filtered heart sound signal (HSS) extracted from the corrupted signal (HSS with different Lung sounds) using LMS algorithm with optimal step size identified by the proposed scheme is shown in Fig. 8. The graph is plotted between time and amplitude. The correlation values are given in Table 5.

NLMS: The filtered heart sound signal extracted from the corrupted signal (HSS with different Lung sounds) using NLMS adaptive algorithms is shown in Fig. 9. The graph is plotted between time and amplitude. The correlation values are given in Table 5.

BLMS: The filtered heart sound signal extracted from the corrupted signal (HSS with Normal and Adventitious LSS) using BLMS with the optimal step size is shown in Fig. 10. The graph is plotted between time and amplitude. The correlation values are given in Table 5.

5.4. Discussion

The performance of different LMS filter variants on benchmark heart sound separation problems is summarized in Tables 4 and 5. Table 4 presents the performance of LMS filter variants with step size computed by NM search initialized with default step size. The results indicate that the filter does not converge for LMS and BLMS algorithms with the NM (default step size) choice.

In Table 5 the correlation coefficients are given for four cases; default μ (without optimization), optimized μ with GA, DNL-PSO and H-NM.

Both the biologically inspired algorithms converge close to the proposed algorithm, and the correlation coefficient is also similar with negligible difference, but the computational complexity is more in the case of GA and DNL-PSO which increases the time complexity of the algorithm (Table 6 & Fig. 11).

Table 6 shows the average running time complexity of different optimization algorithms. The mean and standard deviation for over 10 independent trials are presented. Table 6 indicates that the average running time for GA is approximately 3 times, and DNL-PSO is approximately 9 times that of the proposed H-NM algorithm. The standard deviation is large in the case of DNL-PSO. Thus the LMS filter with step size computed with the H-NM algorithm presented in this paper performs significantly better in terms of correlation coefficient with less running time compared to other biologically inspired algorithms. This is because, optimizing the step size parameter of LMS algorithm is a simple one dimensional problem for which computationally expensive multidimensional optimization algorithms are inappropriate.

The Table 6 values are graphically indicated in the bar chart given Fig. 11.

The correlation values depicted in Table 5 shows that the recovered HSS from the mixed Bronchial and Vesicular LSS using the proposed approach has an average correlation coefficient of **94.9**%. Also the HSS recovered from the adventitious LSS has an average correlation coefficient of **79.4**%. Thus the approach proposed in this paper significantly improves the quality of heart sounds recovered from lung sounds and will enable more effective diagnosis of heart issues.

6. Conclusion

This paper presented an effective method for separation of the HSS from background lung sound noise using an improved LMS algorithm. The step size parameter in the improved LMS algorithm was optimally chosen using a combination of the Nelder-Mead simplex algorithm and random search. Use of random search to provide a good initial solution to the NM algorithm avoided convergence to the nearest local minima and resulted in significant improvement in filter performance. Simulation results indicate that the approach presented in this paper significantly outperforms other heart sound separation approaches in terms of correlation with the ideal filtered output. The effect of replacing the NM algorithm with more sophisticated biologically inspired algorithms was explored. Two popular variants of the standard LMS algorithm were also considered. The Normalized LMS algorithm with step size optimized using the NM algorithm initialized with random search provided the best performance among the approaches considered in terms of filtering accuracy and running time complexity. Future work might apply the approach presented in this work for the filtering of other biological signals.

Acknowledgement

The authors would like to extend their gratitude to VIT University, Vellore, India for providing all the required resources for carrying out this research.

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