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Heart Sound Signal Separation From Lung Sound Signal At Real Time Using Radial Basis Function Network

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Abstract

During lung sound recordings, an incessant noise source occurs due to heart sounds. The heart sound interference on lung sounds is significant especially at low flow rates. This paper presents a technique for separation of heart sound signal (HSS) from lung sound signal (LSS) using Radial Basis Function Network (RBF) with real time recorded sound signal. Here two signals are used in RBF network noise separation scheme. The two signals are raw signal and reference heart signal. The raw signal is given as input signal to R.BF network and reference heart signal is used as target signal. The proposed system is applied and the results show the error rate of the desired sound signal (DSS), signal to noise ratio (SNR) and execution time.

Keywords: Heart Sound Signal, Lung Sound Signal, Radial Basis Function Network.

Introduction

Usually, all LSSs create from airways during inspiration - expiration cycles [1]. The LSS propagates through lung tissues in the parenchyma and can be heard over the chest wall using a sound transducer. The tissue act as a frequency filter-like structure whose characteristics differ according to pathological and indeed physiological changes [1, 2]. In addition the fact that normal and abnormal lung sounds are mixed in the air ways and as a result, a problem of classification of respiratory diseases, semi-periodic HSS from heart beat activity invariably interfere with the LSS and therefore mask or inhibit clinical interpretation of LSS mainly over low frequency components. The main frequency components of HSS are in the range 20−100Hz. This is the range in which LSS has major components [3]. Therefore, since HSS and LSS overlap in frequency and, are somewhat non-stationary, the major problem being faced in separating HSS from LSS is, doing so without tempering with the main characteristic features of the LSS. This has been of interest to many researchers in the field of biomedical signal processing. Traditional bandpass filtering with arbitrary cut off frequencies of between 70 and 100 Hz [4], results in an inefficient performance since LSS has major components around this region especially at low flow rates. In [3], the authors have used adaptive filtering with a pre-processing stage comprising a variable amplifier gain. Others used an adaptive filter based on least mean square (LMS) algorithm to remove HS interferences [5]. In both cases mentioned above, they used HSS recorded from the patients' heart location as the reference signal for the adaptive system, which themselves are not free of the LSS. Along the same line, authors in [6, 7] have used an adaptive system with the ECG signal information as the reference signal. The discrepancy with this line of tactic is the significantly high number of filter coefficients which results in a long adaptation gain. In [8], the authorsrecommended to use a reduced order Kalman filtering technique (ROKF) for separation of signals based on the mainstatement that HSS and LSS are mutually uncorrelated - These sounds may not be assumed uncorrelated since they stem from the same human physiological and metabolic changes. Also The ROKF is computationally expensive [8]. Efforts have been made to remove the use of a reference signal when performing adaptive filtering. In Wide-band signal [9], a single recording based on the modified version of the adaptive LMS algorithm was suggested. Here, a lowpass filter with a cut off frequency of 250Hz was added in the error signal path. More recently, in [10], a recursive least squares (RLS)-based adaptive noise cancellation (ANC) filtering method is suggested to separate or reduce the HSS from LSS. Here, a bandpass filtered version of the recorded LSS was used as the reference signal. Even though experimental results are favorable, the method however, suffers from high computational load. Time-Frequency (TF) filtering methods have also been suggested for HSS reduction in LSS [11], [12], and [13]. It must be stated that the technique employed in [12] is found computationally effective. To eliminate the interferences we use the reference signal when performing adaptive filtering. Adaptive line enhancer (ALE) with normalized least mean square (NLMS) algorithm which is used to obtain the desired sound signal from real time sound signal and the linear predictive FIR filter are used to detect the other sound signals and the interferences is presented in [14]. This paper presents a technique for separation of heart sound signal (HSS) from lung sound signal (LSS) using RBF Network with real time recorded sound signal obtained using digital stethoscope and its details are given in Appendix. The results show the error rate of the desired sound signal (DSS), signal to noise ratio (SNR) and execution time are computed with different hidden layers of RBF network.

Implementation of RBF Network To Separate HSS From LSS

The idea is to separate heart sound signal from raw signal (heart and lung) recorded from different age groups of male and female using stethoscope.

The proposed block diagram of RBF network noise cancellation scheme is shown in fig 1.

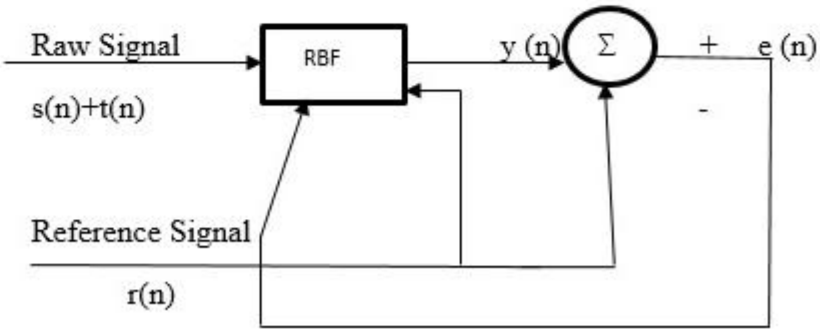

Figure 1: Block Diagram of Proposed Approach

Where s(n) is lung sound signal, t(n) is heart sound signal, r(n) is heart sound reference signal, y(n) is RBF network output and e(n) is error signal. There are 2 signals used in RBF network noise separation scheme. They are raw signal and reference heart signal. The raw signal is given as input signal to RBF network and reference heart signal is used as target signal.

The RBF network has a feed forward structure having a single hidden layer of *J* locally tuned units, which are completelyinterrelated to an output layer of *L* linear units. All hidden units at the same time receive the *n*-dimensional real valued input vector *X*. The main difference from that of MLP is the absence of hidden-layer weights. The hidden-unit outputs are not calculated using the weighted-sum mechanism/sigmoid activation; rather each hidden-unit output Z_j is obtained by closeness of the input *X* to an *n*-dimensional parameter vector $\mu_j$related with the j^{th} hidden unit.

The response characteristics of the j^{th} hidden unit. ($j = 1, 2, \ldots, J$) is assumed as,

$$Z_j = K\left(\frac{\|X-\mu_j\|}{\sigma_j^2}\right) \tag{1}$$

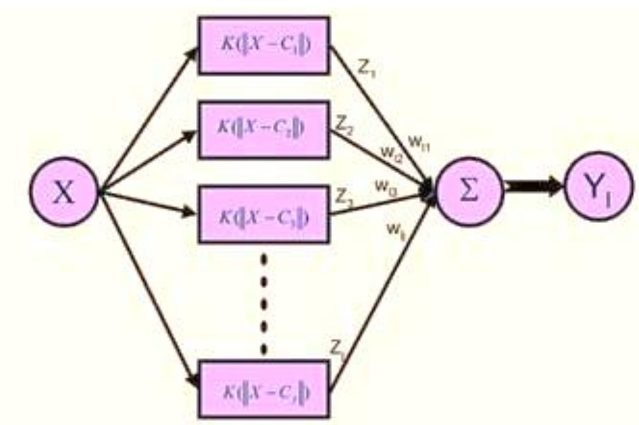

Figure 2: Radial Basis Function Neural Network

where$K$ is a strictly positive radially symmetric function (kernel) with a unique maximum at its 'center' μ_j and which drops off rapidly to zero away from the center. The parameter σ_j is the width of the receptive field in the input space from unit j. This indicates that Z_j has an appreciable value only when the distance $\left\| X - \mu_j \right\|$ is smaller than the width σ_j. Given an input vector X, the output of the RBF network is the L-dimensional activity vector Y, whose l^{th} component (l = 1, 2 …L) is given by,

$$Y_l(X) = \sum_{j=1}^{J} w_{lj} Z_j\,(X) \qquad (2)$$

For l = 1, mapping of eq. (1) is similar to a polynomial threshold gate. However, in the RBF network, a choice is made to use radially symmetric kernels as 'hidden units'.

RBF networks are best fitted for approximating continuous or piecewise continuous real-valued mapping $f : R^n \rightarrow R^L$, where n is sufficiently small. These approximation problems contain classification problems as a special case. From eqs (1) and (2), the RBF network can be noticed as approximating a desired function $f(X)$ by superposition of non-orthogonal, bell-shaped basis functions. The degree of exactness of these RBF networks can be organized by three parameters: the number of basic functions used, their location and their width.

Results and Discussion

The diagnosing the lung sound through auscultation is subjective and is mainly depends on the hearing ability and skill of physician. But, the proposed approach is an attempt to make a model for adaptively filtering heart sound signal from lung sound signal. The real time heart and lung sound signals are obtained from different age groups of male and female. The entire architecture design are simulated using MATLAB.

The fig.3 shows the real time recorded sound signal. It contains both heart and lung sound signal with the sources of interferences.

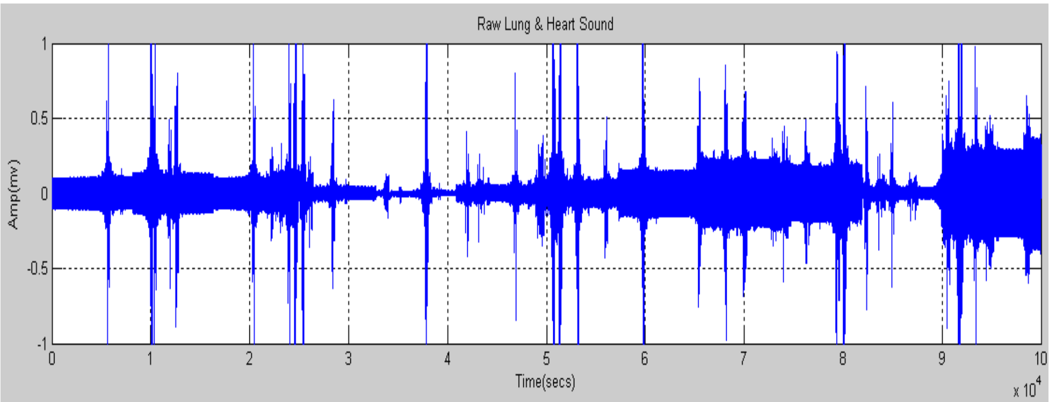

Figure 3: Real Time Recorded Sound Signal

The input signal to the RBF network is heart sound signal corrupted by lung sound signal. The reference heart signal is set as target. The output of the RBF network is lung sound recovered heart sound signal.

The simulation study is carried out with full sample data values on RBF network. For evaluating performance of the developed model the following parameters are evaluated. They are,

1. Mean Square Error (MSE)
2. Signal to Noise Ratio (SNR)

The evaluated values of MSE and SNR with full sample data are given in Table 1.

Algorithm	N	No of epoch	MSE	SNR	Execution Time
LMS	4	6	0.01	810.9047	56.916201
LMS	8	12	0.0098	3.54E+03	131.24762
LMS	16	21	0.0099	1.41E+04	308.20369
NLMS	4	2	0.0062	92.5035	52.5945
NLMS	8	2	0.0056	103.6592	35.068992
NLMS	16	2	0.0053	107.239	34.48902

The optimum values, that is low MSE are acquired using LMS algorithm at N=8 and using NLMS algorithm at N=16. The output HSS and error signal using LMS algorithm are plotted in Figure 4 and 5 respectively. And the output HSS and error signal using NLMS algorithm are plotted in Figure 6 and 7 respectively.

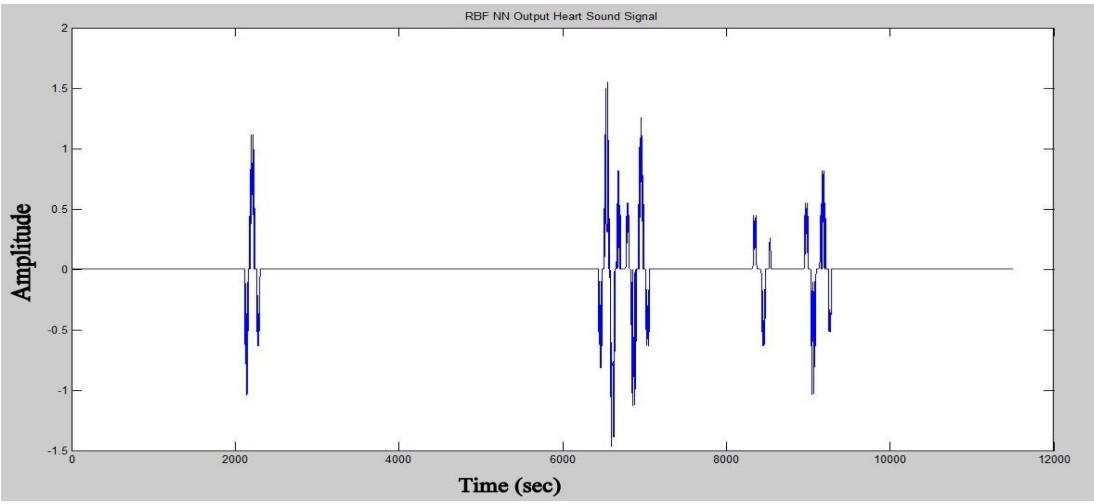

Figure 4: Output HSS using LMS algorithm at N=8

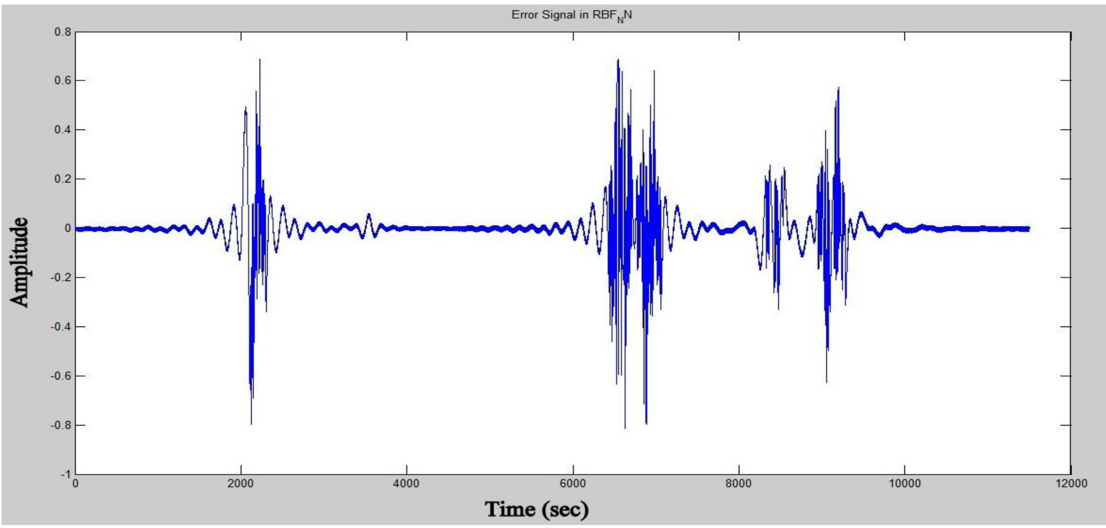

Figure 5: Error signal using LMS algorithm at N=8

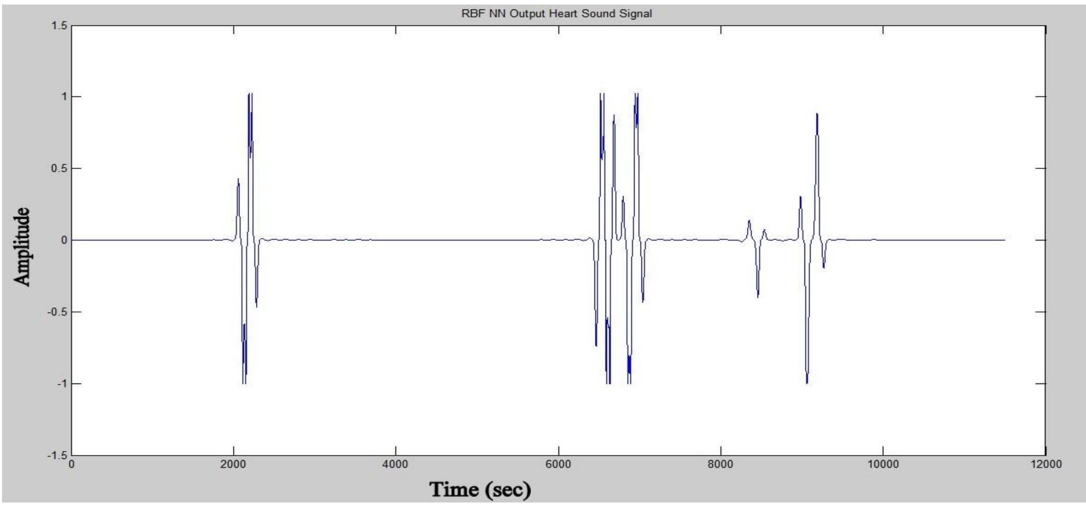

Figure 6: Output HSS using NLMS algorithm at N=16

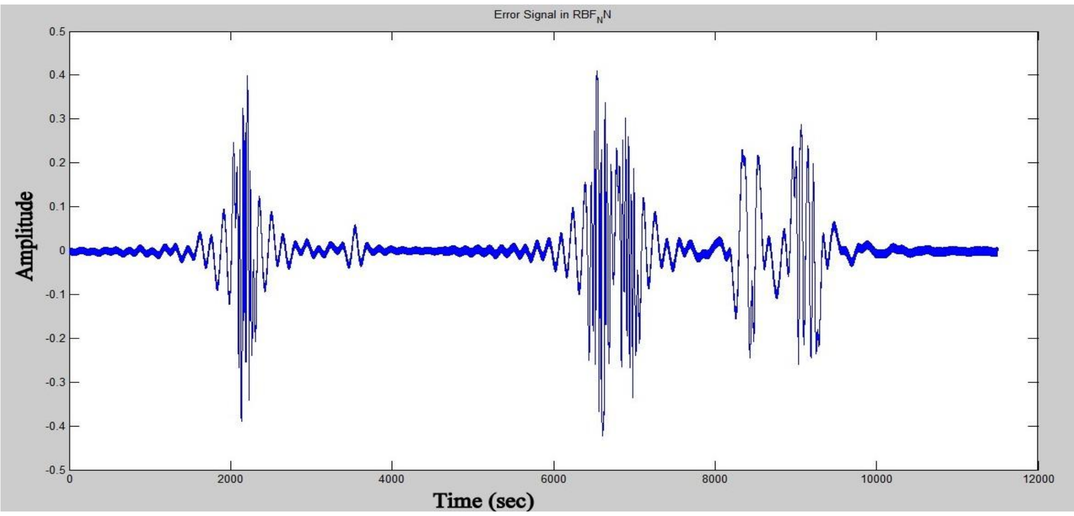

Figure 7: Error signal using NLMS algorithm at N=16

Conclusion

In this paper real time heart sound signals are extracted from lung sound signals using RBF network. The performance of RBF network is evaluated based on Signal to Noise ratio and Mean square Error. The real time signals are taken from the digital stethoscope from different age group. The proposed RBF Network Architecture provides the desired output Heart Sound Signal (HSS). The RBF Network has been developed with different hidden layer in order to find suitable effective architecture for separating Heart Sound Signal (HSS) from Lung Sound Signal (LSS). From the analysis of RBF network for separation of HSS signal from LSS the RBF network using LMS algorithm at N=8 and NLMS algorithm at N=16 provide more efficient output compared to other RBF network.

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Appendix

Digital stethoscope details
Hardware used - digital stethoscope
Sampling frequency used - 44.1 kHz
Open source software used -Think labs phonocardiography.