Separation of Lung Sound from PCG Signals Using Wavelet Transform

Abhishek Misal[1], G. R. Sinha[2]

Electronics &Telecommunication, Faculty of Engineering and Technology, C.S.V.T.U. Bhilai
Chhatrapati Shivaji Institute of Technology, Durg, Chhattisgarh, India

Shri Shankaracharya Technical Campus, Bhilai Chhattisgarh, India

[1]misal_abhi@rediffmail.com; [2]drgrsinha@ieee.org

Abstract- **The Auscultation of the heart sound is a most common method to obtain all the useful information to detect various diseases of cardiovascular system. However one of the main problems of PCG (phonocardiogram) signal analysis is interference of different sound. These sounds may be external or internal. The external sound is avoided by using sound proof room or other method etc. but internal sound like lung sound, vessel sound and muscle contraction sound is unavoidable during the recording of PCG signal. Wavelet is a most successful method for denoising the PCG signal. We have implemented a wavelet based denoising method for separation of lung sound from heart sound. In the wavelet transform (WT) based filter it has been shown that the multiresolution representation of the lung sound signal in the WT domain combined with soft-thresholding can separate the input signal (lung sound) from the nonstationary one (heart sound). The study investigates the different parameter of PCG signal before and after the wavelet based filtering. In this paper we separated the PCG signal from lung sound by different wavelets and found the wavelet which gives the appropriate PCG signal.**

Keywords- Lung Sound; Normalized Root Mean Square Error (NMRSE); Peak Signal to Noise Ratio (PSNR); PCG(Phonocardiogram) Signal; Signal to Noise Ratio(SNR); Wavelet Transform

I. INTRODUCTION

As we know that the heart and lung are very important parts of human body, the two important parts are in almost the same position of the body. When we record the heart sound the lung sound is interfering the heart sound. It means that the lung sound is unavoidable source of noise that overlaps with heart sound components within the frequency band of interest. Because of considerable overlap in frequency spectra of two signals, it is more difficult to reduce the interfering sound from the heart without significantly disturbing the lung sound that are of interest [1]. The main frequency components of the heart sound are in the range of 20-150 Hz. Adaptive-based approaches may be the most suitable methods to reduce intelligently the undesired heart sound. However, they have been partially successful, as their performance generally depends on accurate time alignment of the reference and primary signal [2]. Here, we propose a method which separates the lung sound from noisy heart sound without reference signal in our method .The wavelet is a new transform technique for denoising signals called wavelet, transform (WT) based filtering. In WT based filter an adaptive separation of desired signal from unwanted signal can be achieved through an iterative wavelet decomposition-reconstruction process based on soft thresholding [3, 4].

II. RELATED RESEARCH

There are several research papers reported in the literatureon separation of lung sound using wavelet transform but only could address the separation of lung sound from phonocardiogram signals. Irina Hossain et al. (2003) proposed that adaptive denoising technique has been proposed for heart sound reduction from lung sound. Results show that the WT based filtering reduces the lung sound average power greatly over the whole frequency range. These results in pronounced change in the spectrum of the original signal that are of interest [1]. E. Saatci et al. (2005) suggested that Adaptive Filtering is an accepted method to intelligently remove the heart sound from the lung sounds. In this work an effective and easy method based on Spectrogram is presented to automatically generate a reference signal from the lung sound signal. Adaptive Noise Cancelation with Recursive Least Square (RLS-ANC) method is used to filter out the heart sound from lung sound [2]. P. Vkady et. Al. (2001) presented a novel wavelet-based denoising method using two-channel signal recording and an adaptive cross-channel coefficient thresholding technique. The qualitative evaluation of the denoising performance has shown that the proposed method cancels noises more effectively than the other examined techniques [3].

L. J. Hadjileontiadis et al. (1997) proposed that separation of pathological discontinuous adventitious sounds (DAS) from vesicular sounds (VS) is of great importance to the analysis of lung sounds, since DAS are related to certain pulmonary pathologies. The proposed algorithm combines multiresolution analysis with hard thresholding in order to compose a wavelet transform-based stationary-nonstationary filter (WTST-NST) [4]. Bai fang-fang et al. (2010) proposed a generalized mathematical morphology in handling the signal which contains noise. High-frequency and low-frequency noise could be eliminated by a combination of opening-closing and closing-opening generalized mathematical morphological filter, opening-closing and closing-opening generated through cascade of the structural elements of different sizes. Based on mathematical mor-phology we combine threshold and removing interference peaks methods to improve the method of denoising [5]. Yip et al. (2001) proposed an integrated platform including an electronic stethoscope, automated gain control (AGC), and an adaptive algorithm, to process the signal in real time. The AGC algorithm allows amplifying the LECG signal in different scales to solve the problem of detecting relatively weak LECG signals at the right chest [6]. Kovacs et al. (2000) proposed an algorithm which was implemented in a low-power portable electronic instrument to enable long-term surveillance. A large number of clinical tests have shown the very good performance of the phonocardiographic method in comparison with FHR curves simultaneously recorded with ultrasound cardiotocography [7]. Zhi-dong zhao et al. (2005) suggested a generalized threshold function which is derived computationally exact formulas of bias variance. On the basis of this, the relations between bias variance risk of generalized threshold function and threshold values wavelet coefficients are compared. The Stein Unbiased Risk Estimate (SURE) threshold value of generalized threshold function is derived [8]. Abhishek misal et al. (2012) presented a method for single channel noise reduction of heart sound recordings. Multiple noise sources, such as lung sounds, muscle contraction and background noise can contaminate the heart sound collection making subsequent analysis difficult. This method uses a “decision-directed” approach to estimate the noise without the need for a separate reference signal. The wavelet de-noising method based on three thresholding functions is used for heart sound signals de-noising; soft-thresholding and hard-thresholding functions are traditional and an improved novel thresholding function with double variables parameters is novel [9]. Abhishek misal et al (2012) addressed the PCG signals (Phonocardiogram) and their De-noising techniques. The PCG as a kind of weak biological signal under the background of strong noise is easily subject to interference from noise of various sources. Denoising of PCG signal therefore, forms the primary basis for achieving non-invasive diagnosis of coronary heart disease. There are various methods available for De-noising the PCG signal but the method most effective for the PCG signal is very much important [10]. Akay et al. (1997) presented a technique in which the compatibility with non-stationary random processes, wavelet transforms are particularly powerful when it comes to analyzing biomedical signals. The applications of wavelet are detecting coronary artery disease, and heart sounds related to turbulent blood flow analysis [11]. Jun Zhao et al. (2008) proposed a quasi real-time Wavelet denoising algorithm used to improve the online denoising effect based on wavelet transform, which is realized on the DSP embedded platform. The simulation and analysis, compared with off-line wavelet algorithm, were discussed [12]. Sheila R. Messer et al (2001) presented that Phonocardiograms (PCGs) had many advantages over traditional auscultation (listening to the heart) because PCGs may be replayed by frequencies inaudible to the human ear. However, various sources of noise may pollute a PCG including lung sounds, environmental noise and noise generated from contact between the recording device and the skin [13]. Michael unser et al. (1996) proposed the statistical properties of the wavelet transform (WT) and discussed some recent examples of applications in medicine and biology. The redundant forms of the transform (continuous wavelet transform (CWT) and wavelet frames) are well suited for detection tasks (e.g., spikes in EEG, or micro calcification in mammagrams) [14]. M. Kolinova et al (1998) summarized basic adaptive methods based upon the application of artificial neural networks simplified in many cases to an adaptive linear element only. Signals are compared with those obtained by noise rejection in wavelet transform domain either based upon signal decomposition and reconstruction using properly chosen threshold levels for signal modification or incorporating adaptive FIR filtering [15]. V Nigam et al. (2004) proposed a method such as time segmentation of the heart sound into, for example, the SI and S2 sounds, or spectral segmentation into frequency sounds produced by individual cardiac structures. Without any prior knowledge of PCG properties, they give a method to separate the PCG into sounds produced by individual parts of the heart. The Cardiac Sound Separator (CSS), which is intended be used like an electronic stethoscope, gives, in real-time, the individual sounds that contribute to the composite heart sound [16].

III. METHODS

Here we introduced a wavelet transform based filter for separation of lung sound. The wavelet transform (WT) based filter was first proposed. We know the fact that “nonstationary” part of a signal in time domain produce large wavelet transforms (WT) coefficients over many wavelet scales whereas for the “stationary” part the coefficients die out quickly with increasing scale. Therefore, it is possible to characterize the WT coefficients with respect to their amplitude; most significant coefficients at each scale with amplitude above some threshold correspond to nonstationary signal in time domain and the rest corresponds to stationary part of the signal. Consequently, a wavelet domain separation of WT coefficients corresponds to time domain separation of stationary and nonstationary part of a signal. In this way, the nonstationary part of the input signal is separated from the stationary one [4]. Here we use all wavelets from morlet family.

A. Wavelet Transform

A wavelet allows one to do multi-resolution analysis, which helps to achieve both time and frequency localization. Wavelet algorithms process data at different scales or resolutions [5].

The wavelet basis’s translation and companding capability enables the wavelet to possess flexible and variable time frequency windows that narrow down at high frequencies and broaden at low frequencies, making it available to focalize on any detail of the analytical object and perfectly suitable to analyze unstable heart sound signals. Nowadays, wavelet analysis has successful applications in bio-medical engineering, intelligent signal processing, image pro-cessing, voice and image coding, speech recognition and synthesis, multi-scale edge detection and reconstruction, fractal and digital television, and other fields [5]. In this paper we take four types of heart sound signal [6] which are: normal heart sound, aortic insufficiency, atrial septal defect and patent ductus arterio-sus. In these sounds we add the four lung sound as a noise and check the effect of lung sound before and after the denoising process. The wave form of normal heart sound and bronchovesicular are shown in Fig. 1 and Fig. 2. These figures show the characteristics of both sounds.

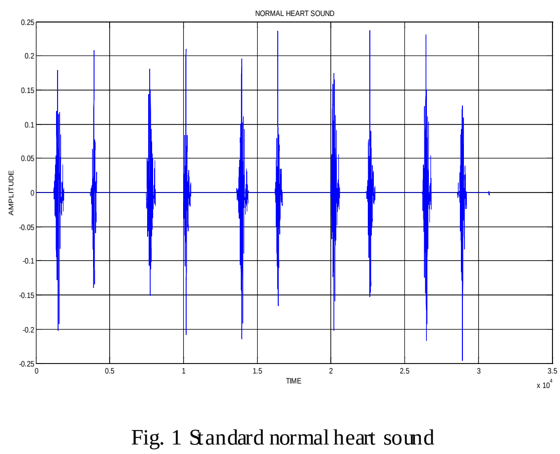

Fig. 1 Standard normal heart sound

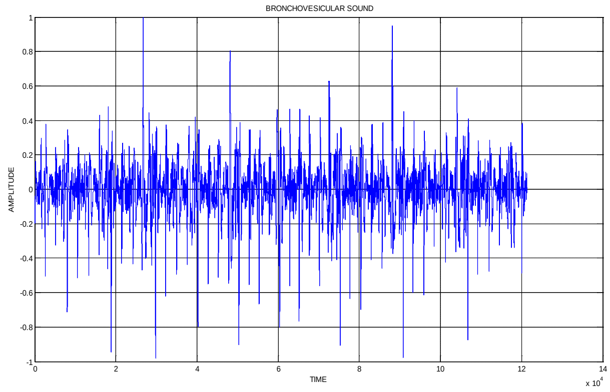

Fig. 2 Bronchovesicular sound

B. Signal Decomposition Using Wavelet Transform

The scaling function and wavelet functions can be implemented using pair of simple low pass and high pass filters. If the filters are interpreted with their impulse responses as {H(n), n€N} for a low pass filter and {G(n), n€N} for a high pass filter, then the decompo-sition of a signal using DWT will be shown in Fig. 3. This de-composition is also called as dyadic decomposition. First stage divides the frequency spectrum into two equal parts (low pass and high pass). The second stage then divides the low pass band into another low pass and high pass band .The second stage divides the lower half into quarter and so on [7].The Stein Unbiased Risk Estimate (SURE) threshold value of generalized threshold function is used in our method [8].

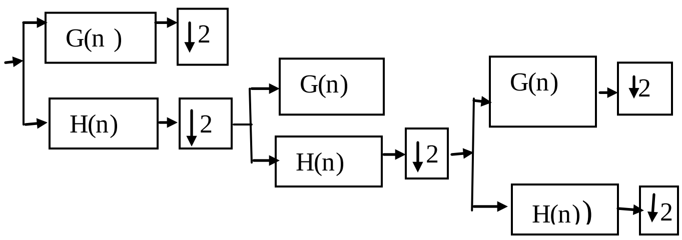

Fig. 3 Signal decomposition using DWT

Where H (n) = impulse response of low pass filter, A-approximate coefficient s, G (n) =impulse response of high –pass filter, D-Detail coefficients, 2-down sampling by factor 2

We have developed a function in MATLAB 7(2009) which adds the heart and lung sound. The lung sound is treated as a noise sound and denoised by different wavelet in different level [9]. After denoising the heart sound we calculate the different parameters of denoised heart sound with respect to the standard signal. From the parameters we find the wavelet gives the maximum or nearest to the maximum values in all wavelets [10]. These values are shown in Table I and III.

IV. RESULT

The separation of n independent sources requires the simultaneous recordings of at least m composite mixtures that are each made up of these independent sources. Here we mix the both standard heart and lung sound, then decompose the noisy PCG signals into six levels. Here we use all the wavelet of morlet families for denoising [11]. For measuring the performance of wavelet we use the three parameters which are signal to noise ratio (SNR), peak signal to noise ratio (PSNR) and normalized root mean square error (NRMSE) [12]. We calculate all the values for denoised PCG signal in different level and find best wavelet which gives the maximum performance; the output is shown below in Fig. 4.

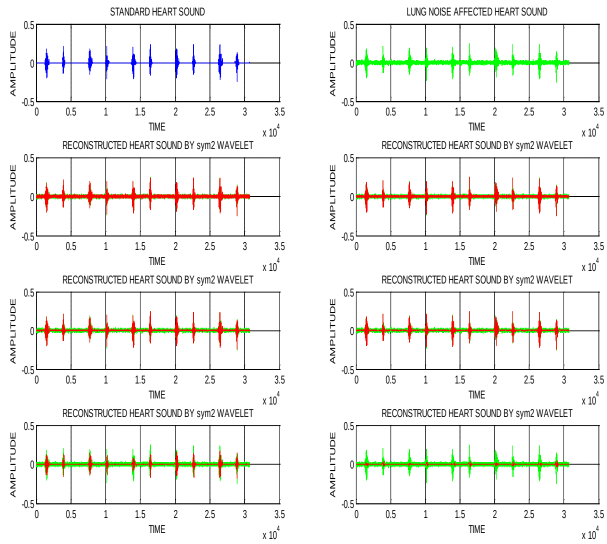

Fig. 4 The graph of the sym2 wavelet which contains ideal heart sound, noisy heart sound and different level of wavelet

Similarly we add the other types of lung sound and check the performance, here we add the four types of lung sound which are Tracel, Bronchial, Vesicular, and Bronchovesicular. In all types of lung sound, sym2 gives the maximum value of SNR, PSNR and minimum value of PSNR the value are shown in Table III. This table shows the comparisons of automatic denoising method for the heart sound [13].

TABLE I BEST SNR OF DIFFERENT WAVELETS, WITH DIFFERENT TYPES OF LUNG SOUND

SNR for Level 6 Decomposition for Normal Sound Heart Sound Affected by Four Different Lung Sound				
Level / ***Wavelets***	***Bronch Vesicular (4)***	***Tracel (4)***	***Bronchial (4)***	***Vesicular (4)***
Db2	1.4997	-16.7102	-21.1294	-20.2246
Db4	3.1736	3.1736	3.1736	3.1736
Db6	2.3879	2.3879	2.3879	2.3879
Haar	1.7355	1.7355	1.7355	1.7355
Sym2	12.1663	12.1663	12.1663	12.1663
Sym4	2.3165	2.3165	2.3165	2.3165
Sym6	2.4247	2.4247	2.4247	2.4247
Coif1	2.1294	2.1294	2.1294	2.1294
Coif3	3.4929	3.4929	3.4929	3.4929
Coif5	3.1078	3.1078	3.1078	3.1078
Dmey	3.2530	3.2530	3.2530	3.2530
Bior 1.1	1.7251	1.7251	1.7251	1.7251
Boir 2.4	2.0970	2.0970	2.0970	2.0970
Boir 3.3	2.9997	2.9997	2.9997	2.9997
Rbio1.1	1.7232	1.7232	1.7232	1.7232
Rbio2.4	1.4670	1.4670	1.4670	1.4670
Rbio3.3	-0.5183	-0.5183	-0.5183	-0.5183
Rbio4.4	1.7324	1.7324	1.7324	1.7324

TABLE II BEST SNR OF DIFFERENT WAVELETS, WITH DIFFERENT TYPES OF LUNG SOUND

PSNR for Level 6 Decomposition for Normal Sound Heart Sound Affected by Four Different Lung Sound				
Level / Wavelets	*Bronch Vesicular (4)*	*Tracel (4)*	*Bronchial (4)*	*Vesicular (4)*
Db2	12.9332	11.6608	10.4184	9.6147
Db4	12.1759	12.1759	12.1759	12.1759
Db6	9.6568	9.6568	9.6568	9.6568
Haar	1.4034	1.4034	1.4034	1.4034
Sym2	27.8152	27.8152	27.8152	27.8152
Sym4	10.6757	10.6757	10.6757	10.6757
Sym6	9.1177	9.1177	9.1177	9.1177
Coif1	16.4006	16.4006	16.4006	16.4006
Coif3	13.1966	13.1966	13.1966	13.1966
Coif5	12.9544	12.9544	12.9544	12.9544
Dmey	12.9500	12.9500	12.9500	12.9500
Bior 1.1	1.2332	1.2332	1.2332	1.2332
Boir 2.4	11.3099	11.3099	11.3099	11.3099
Boir 3.3	13.1259	13.1259	13.1259	13.1259
Rbio1.1	1.7378	1.7378	1.7378	1.7378
Rbio2.4	12.6863	12.6863	12.6863	12.6863
Rbio3.3	11.5010	11.5010	11.5010	11.5010
Rbio4.4	12.2667	12.2667	12.2667	12.2667

TABLE III NRMSE OF DIFFERENT WAVELETS, WITH DIFFERENT TYPES OF LUNG SOUND

PSNR for Level 6 Decomposition for Normal Sound Heart Sound Affected by Four Different Lung Sound				
Level / Wavelets	*Bronch Vesicular (4)*	*Tracel (4)*	*Bronchial (4)*	*Vesicular (4)*
Db2	0.6839	6.8122	11.3750	10.2444
Db4	0.3470	0.3470	0.3470	0.3470
Db6	0.4158	0.4158	0.4158	0.4158
Haar	0.6056	0.6056	0.6056	0.6056
Sym2	0.1069	0.1069	0.1069	0.1069
Sym4	0.4232	0.4232	0.4232	0.4232
Sym6	0.4157	0.4157	0.4157	0.4157
Coif1	0.4197	0.4197	0.4197	0.4197
Coif3	0.3220	0.3220	0.3220	0.3220
Coif5	0.3458	0.3458	0.3458	0.3458
Dmey	0.3330	0.3330	0.3330	0.3330
Bior 1.1	0.6065	0.6065	0.6065	\0.6065
Boir 2.4	0.4394	0.4394	0.4394	0.4394
Boir 3.3	0.3643	0.3643	0.3643	0.3643
Rbio1.1	0.6063	0.6063	0.6063	0.6063
Rbio2.4	0.4940	0.4940	0.4940	0.4940
Rbio3.3	0.7625	0.7625	0.7625	0.7625
Rbio4.4	0.4674	0.4674	0.4674	0.4674

The wavelet analysis experiments with symlet filters of different lengths (sym2 to sym12) and with soft thresholding showed that the use of sym2 filter with soft thresholding performed best for separating the stationary and nonstationary part of the lung sound signal as in [l]. It was found that the performance of the WT based filter was very much dependent on the threshold adjusting parameter. All the values are almost the same for all types of lung sounds.

V. CONCLUSIONS

In order to reduce the lung noise from heart sound we conclude that wavelet is most successful and useful technique for denoising any kind of noise. It simply disregards the parts of the lung sound that include heart sound. We have found that the sym2 wavelet gives the maximum value for all different types lung sound for normal heart sound which means that sym2 wavelet is the best wavelet for denoising the biomedical sound. In general, in denoising problems the noise is assumed to be gaussian white noise. The signal energy is concentrated in a small number of wavelet coefficients and the coefficients values are relatively large compared to the noise that has its energy spread over a large number of coefficients. This allows clipping, thresholding and shrinking of the amplitude of the coefficients to remove noise. In case of separating heart sounds from lung sounds, the problem is more complicated, because both the lung sounds and heart sounds have most of their energy in the same frequency band below 150 hz and heart sounds are not a gaussian white noise. Therefore, it needs more investigations to apply wavelet denoising technique to remove heart sounds from lung sounds. In the case of other advanced techniques like artificial neural networks and wavelet neural networks and wavelet transforms, features are extracted from the heart sound, and then these features are used to train a neural network in order to differentiate between pathological and physiological sounds.

REFERENCES

[1] Irina Hossain, Zahra Moussavi, "An overview of heart-noise reduction of lung sound using wavelet transform based filter", proceedings of the 25th annual International conference of the ieee embs cancun, mexico, pp. 458 – 461, september 17 – 21, 2003.

[2] E. Saatci and A. Akan "Heart sound reduction in lung sounds by spectrogram" The 3rd European Medical and Biological Engineering Conference November 20 – 25, 2005.

[3] P. Vkady, "Wavelet-based adaptive denoising of phonocardiographic riecords", Proceedings of the 23rd Annual EMBS International Conference, pp. 1846 – 1849, October 25 – 28, 2001.

[4] Hadjileontiadis LJ, Panas SM, "Separation of discontinuous adventitious sounds from vesicular sounds using a wavelet-based filter", IEEE Trans Biomed Eng. Vol 44 (12) pp. 1269 – 81, Dec, 1997.

[5] Bai Fang-fang, "Studying on denoising algorithm of heart sound signal based on the generalized mathematical morphology", Signal Processing (ICSP), 2010 IEEE 10th International Conference pp. 1797 – 1800, 24-28 Oct. 2010.

[6] L. Yip, Y & T. Zhang, "Reduction of heart sounds from lung sound recordings by automated gain control and adaptive filtering techniques", Proceedings of 23th Conference on Engineering in Medicine and Biology Society, EMBC01, pp. 21544 – 2156, 1997.

[7] F. KovBcs, M. Torok, I. Habermajer, "A rule-based phonocardiographic method for long-term fetal heart rate monitoring", IEEE Trans. of Biomedical Engg., Vol. 47, pp. 124 – 130, January 2000.

[8] Zhi-Dong Zhao, "Wavelet shrinkage denoising by generalized threshold function" Proceedings of the Fourth International Conference on Machine Learning and Cybernetics, Guangzhou, 18-21 pp. 5501 – 5506.

[9] Abhishek Misal and G.R.Sinha, " denoising of pcg signal by using wavelet transforms", Advances in Computational Research, 2012, Volume 4, Issue 1, pp. 46 – 49, August 2005.

[10] Abhishek Misal, G.R.Sinha, R. M. Potdar and M. K. Kowar "Comparison of wavelet transforms for denoising and analysis of pcg signal", i-manager's Journal on Communication Engineering and Systems, November, Vol. 11 pp. 48 – 52, 2011 January 2012.

[11] M. Akay, "Wavelet applications in medicine", IEEE Spectrum Magazine, pp. 50 – 56, May. 1997.

[12] Jun Zhao and Weiguo Liu "On signal denoising using quasi real-time wavelet algorithm in dsp embedded system" ICSP2008 Proceedings, pp. 46 – 51, 2008.

[13] Sheila R. Messer, John Agzarian and Derek Abbott, "Comparison of automatic denoising methods for phonocardiograms with extraction of signal parameters via the Hilbert Transform", Proc. SPIE 4304, Vol. No 46, 2001.

[14] Michael unser, "Wavelets, statistics, and biomedical applications", IEEE Transactions, pp. 244 – 249, April 1996.

[15] M. KolinovA, A. Prochiizka, and M. Mudrovii, "Adaptive fir filter use For signal noise cancelling ", IEEE transaction pp. 596 – 605, 1998.

[16] V Nigam, R Priemer, "Cardiac sound separation", Computers in Cardiology, Vol .31, pp. 497 – 500, 2004.

[17] J. Padhye, V. Firoiu, and D. Towsley, "A stochastic model of TCP Reno congestion avoidance and control," Univ. of Massachusetts, Amherst, MA, CMPSCI Tech. Rep. 99 – 02, 2008.

[18] J. Breckling, Ed., The Analysis of Directional Time Series: Applications to Wind Speed and Direction, ser. Lecture Notes in Statistics. Berlin, Germany: Springer, 2008, vol. 61.

Abhishek Misal was born on 18 June 1982 in Durg (C.G). He received M.Tech (Honours) from C.S.V.T.U .Bhilai. He is working as an Assitant professor at csit durg. He is a member of ISTE and IETE. He has presented 6 papers in national conferences. He published 2 international journals and 1 book on the topic of "Pcg Signal Denoising and Analysis Using Wavelet Transform".

Dr. G.R. Sinha is currently working as an (Electronics & Tele.) associate director in Faculty of Engineering and Technologyof Shri Shankaracharya Group of Institutions (Technical Campus) Bhilai, India. He obtained his B.E. (Electronics) and M.Tech (Computer Technology) from Govt. Engineering College (now is National old Medal forobtaining first position in University. He received his Ph.D. in Electronics & Telecommunication from Chhattisgarh Swami Vivekanand Technical University, India.Institute of Technology, Raipur).