ECG Signal Enhancement Using Wavelet Transform

Rajiv Ranjan[1], V.K. Giri[2]
[1]Associate Professor, Department of Electrical & Electronics Engineering
Dronacharya Group of Institutions, Greater Noida, INDIA
[2]Professor & HOD, Electrical Engineering Department
Madan Mohan Malaviya Engineering College, Gorakhpur, INDIA
[1]rajiv_ee_rex@yahoo.com
[2]girivkmmm@gmail.com

Abstract - **Electrocardiogram (ECG) signal has been widely used in cardiac pathology to detect heart disease. The ongoing trend of ECG monitoring techniques to become more ambulatory and less obtrusive generally comes at the expense of decreased signal quality. To enhance this quality, consecutive ECG complexes can be averaged triggered on the heartbeat, exploiting the quasi-periodicity of the ECG. However, this averaging constitutes a trade-off between improvement of the SNR and loss of clinically relevant physiological signal dynamics. Recent work has attempted to utilize wavelet techniques in the analysis of biomedical signals including ECG. In this paper Multi- Resolution Analysis property of wavelet transform is used to enhance ECG signal quality by denoising the signal using Daubechies 6 Wavelet as best suited mother wavelet at level 4.**

Keywords: **Electrocardiogram (ECG), Adaptive Wavelet Transform (AWT), Multi- Resolution Analysis (MRA), Signal to Noise Ratio (SNR), Daubechies 6 (db 6).**

I. INTRODUCTION

In ECG, during every heartbeat, P, Q, R, S, T, and U waves can be seen. These waveforms result from depolarization and repolarization of different parts of the heart muscle. The performance of ECG analyzing system depends mainly on the accurate and reliable detection of the QRS complex, as well as T and P waves. The P-wave represents the activation of the upper chambers of the heart, the atria, while the QRS complex and T-wave represent the excitation of the ventricles or the lower chamber of the heart. The detection of the QRS complex is the most important task in automatic ECG signal analysis. Once the QRS complex has been identified a more detailed examination of ECG signal including the heart rate, the ST segment etc. can be performed. In the normal sinus rhythm (normal state of the heart) the P-R interval is in the range of 0.12 to 0.2 seconds. The QRS interval is from 0.04 to 0.12 seconds. Normally, the frequency range of an ECG signal is of 0.05–100 Hz and its dynamic range of 1–10 mV.

The Q-T interval is less than 0.42 seconds and the normal rate of the heart is from 60 to 100 beats per minute. So, from the recorded shape of the ECG, we can say whether the heart activity is normal or abnormal. The electrocardiogram is a graphic recording or display of the time variant voltages produced by the myocardium during the cardiac cycle. The P, QRS and T-waves reflect the rhythmic electrical depolarization and repolarization of the myocardium associated with the contractions of the atria and ventricles. This ECG is used clinically in diagnosing various abnormalities and conditions associated with the heart. The normal value of heart beat lies in the range of 60 to 100 beats/minute. A slower rate than this is called bradycardia (slow heart rate) and a higher rate is called tachycardia (fast heart rate). If the cycles are not evenly spaced, an arrhythmia may be indicated. If the P-R interval is greater than 0.2 seconds, it may suggest blockage of the AV node. The horizontal segment of this waveform preceding the P-wave is designated as the baseline or the isopotential line. The P-wave represents depolarization of the atrial musculature. The QRS complex is the combined result of the repolarization of the atria and depolarization of the ventricles, which occur almost simultaneously. The T-wave is the wave of ventricular repolarization, where as the U-wave, if present is generally believed to be the result of after potentials in the ventricular muscle. So, the duration amplitude and morphology of the QRS complex is useful in diagnosing cardiac arrhythmias, conduction abnormalities, ventricular hypertrophy, myocardial infection and other disease states.

Monitoring and analysis of the ECG has long been used in clinical practice. In recent years, the application field of ECG monitoring is expanding to areas outside the clinic. An example of such an area is at-home monitoring of patients with sleep apnea [1]. Also within the clinic, a transition in ECG monitoring applications is taking place. With developments in sensor technology (e.g., textile electrodes and capacitive electrodes), sensors that are incorporated in garments or the mattress of an incubator [2] have become available. As a result of these new sensor technologies, the comfort of the patient is improving progressively. Whereas some years ago the patient had to

reconcile himself or herself with the discomforts of the only available technology, nowadays patients prefer the more comfortable ways of recording the ECG. However, in most cases, this increased comfort comes at the expense of signal quality. Electrodes that are incorporated in garments generally provide signals with a lower SNR and more artifacts than contact electrodes that are glued to the body [3]. Another example of ECG signals with a typically low SNR is fetal ECG signals, either recorded invasively after membrane rupture or noninvasively from the maternal abdomen [5]. Some of the SNR and artifact problems that arise during these recordings can be suppressed by simple, frequency-selective filtering [5]–[7]. However, due to the partial overlap of signal and noise bandwidths [8], [9], this frequency-selective filtering can only help to some extent. Further improvement of the ECG can be achieved by exploiting its (quasi-)periodicity. Consecutive ECG complexes resemble one another and are, moreover, in general uncorrelated with noise and artifacts. Hence, by averaging several consecutive ECG complexes, the SNR can be improved. For additive Gaussian noise, this improvement is directly related to the number of ECG complexes included in the average [10]. The drawback of averaging multiple consecutive ECG complexes is that, besides noise, also the physiological dynamics of the ECG are suppressed. That is, changes in the ECG that originate from physiological events for instance, changes in the ST segment that might be associated to metabolic acidosis are suppressed in the averaging, complicating clinical diagnosis. From this, it is clear that the averaging of ECG complexes entails a trade off between the pursued increase in SNR and the time scale at which physiologically relevant changes in ECG morphology are expected to occur.

Wavelet transform (WT) is a very promising technique for time frequency analysis. By decomposing signals into elementary building blocks that are well localized both in time and frequency, the WT can characterize the local regularity of signals [4]. This feature can be used to distinguish ECG waves from serious noise, artifacts and baseline drift. Using aBayesian framework a sequential averaging filter is developed that, in essence, adaptively varies the number of complexes included in the averaging based on the characteristics of the ECG signal. The filter has the form of an adaptive Kalman filter. The adaptive estimation of the process and measurement noise co-variances is performed by maximizing the Bayesian evidence function of the sequential ECG estimation and by exploiting the spatial correlation between several simultaneously recorded ECG signals, respectively [13]. In this paper, we have used Multi Resolution Analysis (MRA) technique of WT to denoise ECG signal and enhance signal quality by increasing SNR.

II. WAVELET TRANSFORM

A. Continuous Wavelet Transform (CWT)

Let $x(t)$ be a signal defined in $L^2(R)$ space, which denotes a vector space for finite energy signals. R is a real continuous number system. Such signals satisfy:

$$\int_{-\infty}^{+\infty} |x(t)|^2 dt \le 0$$

The Wavelet Transform or Continuous Wavelet Transform (CWT) of a continuous time domain signal $x(t)$ is given by $X(a,\tau)$ which is defined as :

Forward CWT:

$$X(a,\tau) = \int_{-\infty}^{+\infty} x(t).\frac{1}{|a|^{1/2}}\psi^*\left(\frac{t-\tau}{a}\right)dt \qquad (1)$$

Inverse CWT:

$$x(t) = \frac{1}{c}\int_{\tau=-\infty}^{\infty}\int_{a=-\infty}^{\infty} X(a,\tau).\frac{1}{|a|^{5/2}}\psi\left(\frac{t-\tau}{a}\right)da.d\tau \qquad (2)$$

The analyzing wavelet $\Psi(t)$ term can be written as -

$$\psi_{a,\tau}(t) = \frac{1}{|a|^{1/2}}.\psi\left(\frac{t-\tau}{a}\right) \qquad (3)$$

Notice that $\psi_{1,0}(t) = (t)\,\psi$

Then above equations can be written as:
Forward CWT:

$$X(a,\tau) = \int_{-\infty}^{\infty} x(t)\psi_{a,\tau}{}^*(t)dt \qquad (4)$$

Inverse CWT:

$$x(t) = \frac{1}{c}\int_{\tau=-\infty}^{\infty}\int_{a=-\infty}^{\infty} X(a,\tau).\frac{1}{a^2}\psi_{a,\tau}(t)da.d\tau \qquad (5)$$

Where a , $\tau \in R$ and $a \neq 0$ and 'c' is a constant($0 < c < \infty$) that depends on the wavelet used. The success of the reconstruction depends on this constant called admissibility constant, to satisfy the following admissibility condition

$$c = \int \frac{|\psi(\omega)|^2}{|\omega|} d\omega$$

Where $\Psi(\omega)$ is the Fourier transform and $\Psi^*(t)$ is the complex conjugate of the mother wavelet $\Psi(t)$, $x(t)$ the signal to be transformed, a and τ the *dilations* (scaling) and *translations* (time-shift) parameters, respectively. With a suitable choice of the mother wavelet, the scale parameter is proportional to the reciprocal of frequency; the translation parameter stands for time [12].

A. Discrete Wavelet Transform (DWT)

The corresponding discrete wavelet transform (DWT) of a time domain signal $x(t)$ is given by $X(j,k)$ which is defined as

$$X(j,k) = \int_{-\infty}^{+\infty} x(t).\frac{1}{|a_0|^{j/2}}\psi^*\left(\frac{t-k\tau_0 a_0^{\,j}}{a_0^{\,j}}\right)dt \qquad (6)$$

The analyzing wavelet $\Psi(t)$ term can be written as

$$\psi_{j,k}(t) = \frac{1}{|a_0|^{j/2}}.\psi\left(\frac{t-k\tau_0 a_0^{\,j}}{a_0^{\,j}}\right) \qquad (7)$$

Then the expression of Eq. (6) can be written as:

$$X(j,k) = \int_{-\infty}^{+\infty} x(t).\frac{1}{|a_0|^{j/2}}\psi^*_{j,k}(t)dt \qquad (8)$$

We can define the DWT of a signal x(t) to be the set of analysis coefficients:

$$\text{Analysis: } c_{j,k} = \int_{-\infty}^{\infty} x(t)\psi_{j,k}(t)dt \qquad (9)$$

From these we can recover the signal as:

$$\text{Synthesis: } x(t) = \sum_j\sum_k c_{j,k}\psi_{j,k}(t) \qquad (10)$$

Assuming existence of a scaling function, $\varphi(t)$ we can modify this definition as follows:

Since the spaces are getting larger and larger as j goes to $+\infty$ we can approximate any signal $x(t)$ closely by choosing a large enough value of $j = J$ and projecting the signal into V_j using the basis

$$cA_0(m) = \int_{-\infty}^{\infty} x(t)\phi_{J,m}(t)dt \qquad (11)$$

From these we can approximately recover the signal as:

$$x(t) \approx \sum_m^n cA_0(m)\phi_{J,m}(t) \qquad (12)$$

In effect, we replace the signal x(t) by the approximate signal given by the projection coefficients, cA0(m). From Eq. (10), (11) and (12), we can write

$$x(t) = \sum_m cA_0(m).\phi_{J,m}(t)$$

$$= \sum_k cA_1(k).\phi_{J-1,k}(k) + \sum_k cD_1(k).\psi_{J-1,k}(t)$$

$$= A_1(t) + D_1(t) \qquad (13)$$

As before, we call the signals $A_1(t)$ and $D_1(t)$ the approximation and the detail at level-1. We call the coefficients $cA_1(k)$ and $cD_1(k)$ the approximation-coefficients and the detail-coefficient at level-1.

We can further decompose $A_1(t)$ to get:

$$x(t) = A_1(t) + D_1(t)$$

$$= \sum_k cA_2(k)\phi_{j-2,k}(t) + \sum_k cD_2(k).\psi_{j-2,k}(t)$$

$$+ \sum_k cD_1(k).\psi_{j-1,k}(t)$$

$$= A_2(t) + D_2(t) + D_1(t) \qquad (14)$$

We call the signals $A_2(t)$ and $D_2(t)$ the approximation and the detail at level-2. We call the coefficients $cA_2(k)$ and $cD_2(k)$ the approximation-coefficients and the detail-coefficients at level-2 [12].

C. Multi-resolution Analysis

Define W_j to be set of all signals x(t), which can be synthesized from the daughter wavelets $\psi_{j,k}(t)$,

$$x(t) = \sum_{j=-\infty}^{\infty} x_j(t) \qquad (15)$$

$$\text{where } x_j(t) = \sum_{k=-\infty}^{\infty} c_{j,k}\psi_{j,k}(t)$$

This leads to various decompositions:

$$x(t) = A_1(t) + D_1(t)$$

$$= A_2(t) + D_2(t) + D_1(t)$$

$$= A_3(t) + D_3(t) + D_2(t) + D_1(t)$$

$$= A_4(t) + D_4(t) + D_3(t) + D_2(t) + D_1(t)$$

where $D_i(t)$, in W_i, is called the detail at level i and $A_i(t)$, is called the approximation at level i.

The approximate coefficients can be computed as below: $cA_1(k) = \langle x(t), \phi_{j-1,k}(t)\rangle$

$$= \left\langle \sum_n cA_0(n)\phi_{j,n}(t), \phi_{j-1,k}(t) \right\rangle$$

$$= \sum_n cA_0(n) \left\langle \phi_{j,n}(t), \phi_{j-1,k}(t) \right\rangle \quad (16)$$

To complete this calculation we have to compute the inner product:

$$\left\langle \phi_{j,n}(t), \phi_{j-1,k}(t) \right\rangle = \int_{-\infty}^{\infty} \sqrt{2^j}\phi(2^j t - n)\sqrt{2^{j-1}}\phi(2^{j-1}t - k)dt$$

$$= \int_{-\infty}^{\infty} \sqrt{2^{2j-1}}\phi(2^j t - n)\phi(2^{j-1}t - k)dt$$

(substitute $= 2^{j-1}t - k$)

$$= \int_{-\infty}^{\infty} \sqrt{2}\,\phi(2s + 2k - n)\phi(s)ds$$

(Use the 2-scale equation for $\phi(s)$)

$$= \int_{-\infty}^{\infty} \sqrt{2}\phi(2s + 2k - n) \sum_m h_0(m)\sqrt{2}\phi(2s - m)ds$$

$$= \sum_m h_0(m) \int_{-\infty}^{\infty} \phi(2s + 2k - n)\phi(2s - m)2ds$$

(integral is 0 unless m=n-2k)

$$= h_0(n-2k)$$

The detail coefficients can be computed similarly [12] as

$$cD_1(k) = \left\langle x(t), \psi_{j-1,k}(t) \right\rangle$$

$$= \left\langle \sum_n cA_0(n)\phi_{j,n}(t), \psi_{j-1,k}(t) \right\rangle$$

$$= \sum_n cA_0(n) \left\langle \phi_{j,n}(t), \psi_{j-1,k}(t) \right\rangle \quad (17)$$

The Equations (16) and (17) are used for decomposing the signal into approximation and detailed coefficients.

III DATA ACQUISITION AND DEMARCATION OF INDIVIDUAL ECG COMPLEXES

To evaluate the used technique AWT, a diversity of arrhythmic ECG signals is used. The signals are obtained from the Massachusetts Institute of Technology–Beth Israel Hospital [11]. To map the AWT's performance as a function of the SNR of the recorded signals as well, the ECG signals are corrupted with additive Gaussian noise of various amplitudes, yielding ECG signals with SNRs ranging from −3 to 24 dB. The TWA signals comprise a rather ideal dataset for evaluating the performance of the AWT. They exhibit relatively high SNR values that can be made smaller by additive Gaussian noise, and that moreover facilitate quantitative assessment of the processed ECG signals. Before defining the individual ECG complexes, the QRS complexes need to be detected. To facilitate this detection, the SNR of the ECG signals is a priori enhanced by linearly combing the signals in such a way as to maximize the variance. The linear combination with maximum variance is referred to as the principal component. The QRS complexes are subsequently detected in the principal component as local extrema that exceed an adaptive threshold. This adaptive threshold is updated continuously by means of an AWT and depends on the SNR of the ECG signals complexes in the principal component, when the SNR changes, the threshold is adapted to prevent noise from exceeding it, in the mean time ensuring that the QRS complexes still exceed the threshold.

IV. RESULTS AND DISCUSSIONS

Noisy signal is shown in figure (1) which is analysed with Daubechies 6 Wavelet as best suited mother wavelet at level 4 with the help of Wavelet tool of MATLAB R2012a. Figure 2 shows approximation signal having lower frequency and figure (3) to figure (6) depicts detailed signal d_4, d_3, d_2, and d_1 which contains higher frequency component of the signal. From the waveform shown in figure 3 it is clear that detailed coefficient d1 is having higher frequency than that of d_2, detailed coefficient d_2 is having higher frequency than that of d_3 and detailed coefficient d_3 is having higher frequency than that of d_4. Signal is denoised with Wavelet transform and denoised signal is plotted which is shown in figure 7. For analysis many mother wavelet like Haar, Coiflet, Symlet, Morlet, Mexican Hat, Daubechies 2, Daubechies 4, Daubechies 6 and Daubechies 8 have been tried but Daubechies 6 (db- 6) provides high SNR.

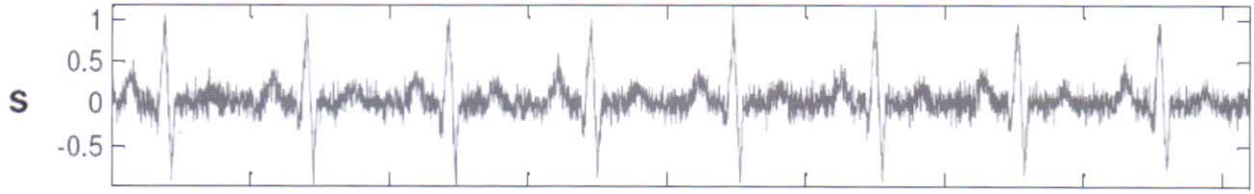

Figure 1

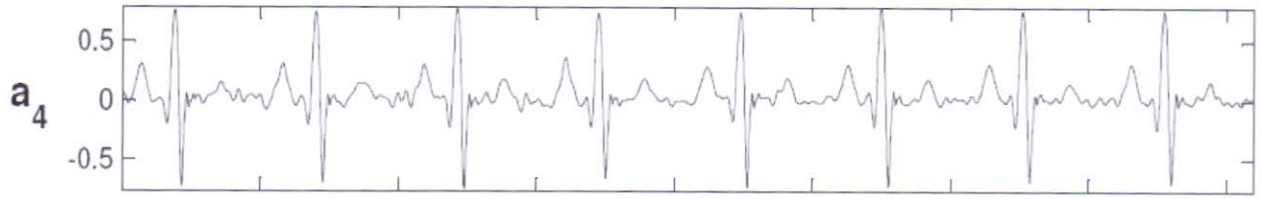

Figure 2

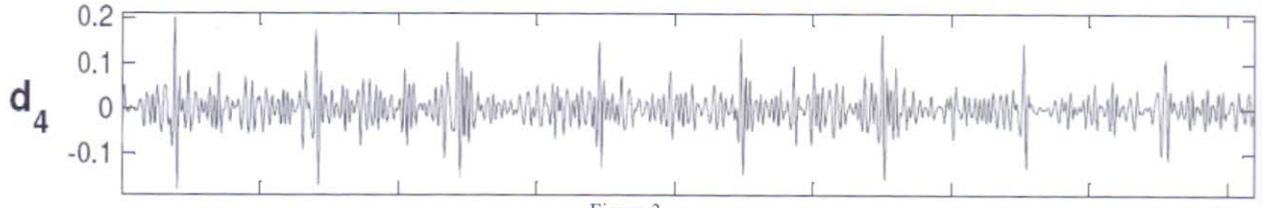

Figure 3

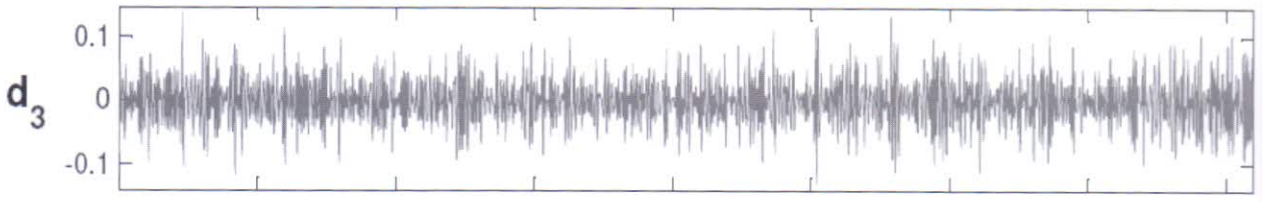

Figure 4

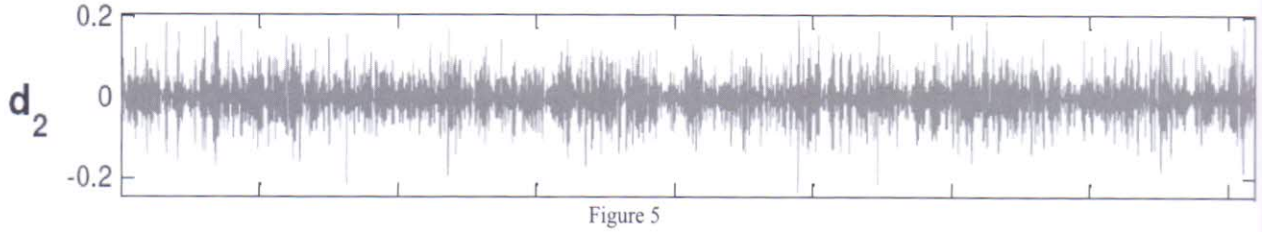

Figure 5

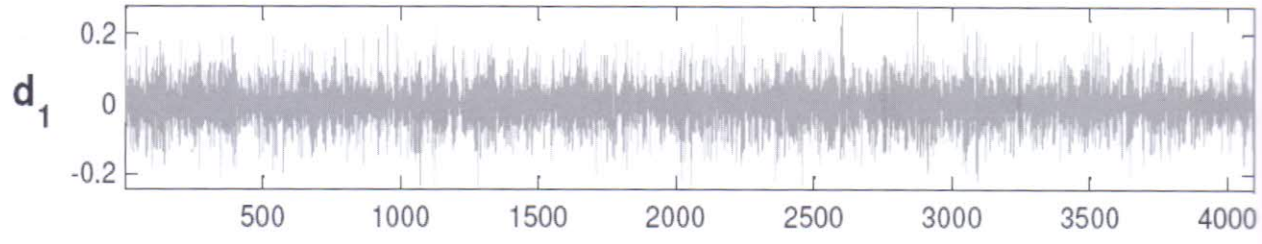

Figure 6

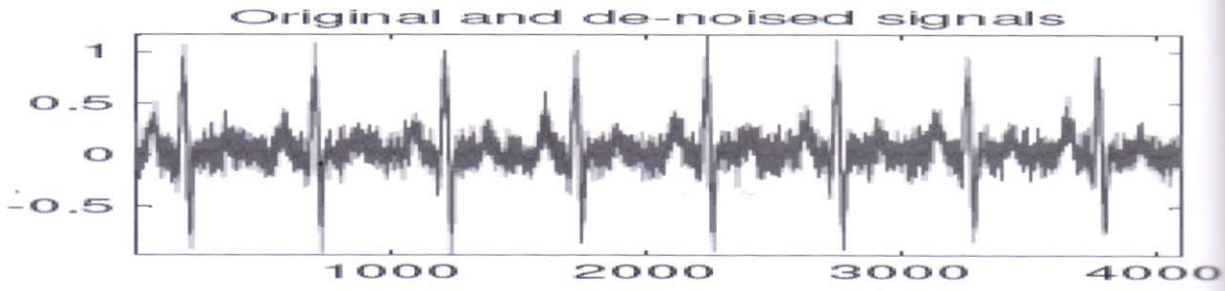

Figure 7

V. CONCLUSIONS

An approach to study ECG signal based on adaptive wavelet transform is investigated in this paper. Computer simulation results show this approach is promising for ECG signal noise reduction and signal enhancement. More tests will be conducted to investigate further its performance in the future.

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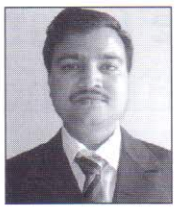
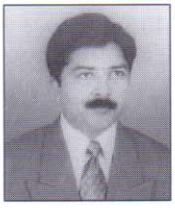


Rajiv Ranjan received his B.E. Degree in Electrical Engineering in 2002 from Regional Engineering College (Now, National Institute of Technology), Silchar, Assam, M.Tech. (Electrical) degree from Uttar Pradesh Technical University, Lucknow, and pursuing Ph.D. since 2009 from G.B. Technical University, Lucknow, India. Currently, he is working as an Associate Professor in Department of Electrical and Electronics Engineering Department at Dronacharya Group of Institutions, Greater Noida, U.P., India. His area of interests include Biomedical Instrumentation, Digital Signal Processing, Power System, Electrical Machines and Instrumentation & Control.



V K Giri obtained his B.E. (Electrical) Degree from REC, Surat (Gujarat) in 1988, M.E. (Measurement and Instrumentation) Hons degree from University of Roorkee, Roorkee in 1997 and Ph.D. degree from Indian Institute of Technology Roorkee, Roorkee in 2003. He joined the Electrical Engineering Department of M.M.M Engineering College, Gorakhpur (UP) in 1989 as lecturer. Presently, he holds the position of Professor & HOD in the same department. He has published more than 20 research papers, guided 6 PG students; and supervising 3 Ph.D. theses. He has received many awards including the best paper awards of the Institution of Engineers (India) in 23rd Indian Engineering Congress in year 2008. He was elected as Fellow of the Institution of Engineers (I), Institution of Electronics and Telecommunication Engineers, and is a member of many professional bodies such as life member ISTE, member IEE and member CSI. He has also undertaken large number of consultancy, testing & sponsored projects from industries and government departments. His research interests include Digital Signal Processing, Measurement and Instrumentation, Biomedical Instrumentation, Data Compression and Telemedicine.