Mental Stress Assessment of ECG Signal using Statistical Analysis of Bio-Orthogonal Wavelet Coefficients

Vikas Malhotra[1], Mahendra Kumar Patil[2]

[1]MMU, Mullana, Haryana, India
[2]MMU, Mullana, Haryana, India

***Abstract:** It is observed that the stress level is function of various statistical parameters like standard deviation, entropy, energy,, mean, Co- variance and power of the ECG signals of two states i.e. normal state of mind and stressed state of mind. Further, it is observed that the features extracted are directly from the ECG in frequency domain using db4 wavelet. However, db4 introduces some error on account of db4 wavelet shape. This error in turn amplifies while measuring the features as mentioned above. In order to reduce this error, we propose a Bior 3.9 wavelet family to decompose the ECG signal. The decomposed ECG signal is now analyzed statistically to extract the above feature. Further, in the existing work, all the ECGs are taken by using the 12 leads method. This factor also adds some undue stress to the person under scanner. And this is time consuming too. Therefore, to reduce this complexity, we propose to analyze all above features by using a two lead ECG. Further, a back propagation neural network is trained using the above features as input neurons in order to classify the stress level.*

Keywords: ECG, Bior 3.9, Wavelet \decomposition, Entropy.

1. Introduction

Stress can be defined as any uncomfortable emotional experience accompanied by predictable biochemical, physiological and behavioral changes. Reaction of a person from a normal state to an exited state in order to preserve his/her integrity can also be defined as stress. An extreme amount of stress can produce extreme health issues and it can affect the cardiovascular and central nervous system .If stress occur continuing for a long time a leading risk factor for heart diseases, diabetes, asthma and depression.

Today's increased use of computer-based systems in the medical domain requires computer processing of Biomedical signals such as, ECG, EEG (electroencephalography), EMG (electromyography), heart rate etc. Biomedical signals obtaining from sensors, transducers, etc. have an abundance of information about their underlying Biological systems, most of it well hidden in the signal.

The physiological signal approach is more successful than other methods. Since, this method is non Invasive and stress impact of the body can be easily analyzed using physiological signals. A number of physiological markers of stress have been identified, including electro dermal activity (EDA), heart rate (HR), various indices of heart rate variability (HRV), blood pressure (BP), muscle tension, and respiration.

Among the several physiological signals, the HRV signal is frequently used as an efficient measure to identify the stress because stress reflects the changes in heart rates under stressful situation. Most of the researchers have investigated about the characteristic changes of high frequency (HF) and Low frequency (LF) bands from HRV signals for stress identification and its level measurements. Only very few Researchers have discussed the effect of stress in the ECG signals for stress assessment. Interestingly, recent studies are reported that ECG signal has been progressively used to identify the Autonomic Nervous Activity (ANS) of emotion and stress identification.

2. Related Works

The frequency variability of HRV and mental stress response are related. PTG also indicates changes in emotional response. PTG can easily be measured without body surface electrodes. This method is less invasive than ECG measurement. Wavelet analysis of the PTG is done to evaluate mental stress. PTG was measured in the resting and mental stress states, and wavelet transformed PTGs were compared. In nine out of ten subjects, the wavelet result for PTG revealed a decrease in the frequency band [1].

As we know ECG consists of various waveforms of electric signals of heat. Machine Learning methods such as the MLP classification have proven to perform well in ECG classification. In this paper, preprocessing was performed through wavelet transform, and in classification several characteristics were evaluated using BP algorithm that applied generalized delta rules to MLP. To evaluate the results above according to the learning method, learning iteration and learning rate of neural networks, various experiments were conducted and analyzed [2].

The artifacts of ECG signals include baseline wander (BW), muscle (EMG) artifact, electrode motion artifact and power line interference. In order to get the optimal and robust de-noising algorithm among the generally used de-noising methods based on stationary wavelet transform (SWT), they adjust the signal-to-noise ratio (SNR) of the noisy signal from 1db to 10db, and evaluate the results by means of SNR and visual inspection, then concluded using Symlet4, decomposition at level 5, and Hard shrinkage function with empirical Bayesian (EBayes) threshold can get consistently superior de-noising performance [3].

Through the analysis of ECG signal which is measured with wearable patch-style HAMS, the parameter highly related with mental stress were extracted from frequency and time domain. These parameters were certified as the meaningful factor after correlation analysis on the results from questionnaire and stress hormone test. It is proved in this paper that the availability of wearable patch-style heart monitoring system is efficient as health monitoring system in any places and occasion [4].

In this paper mental stress is detected using unobtrusive wearable sensors. This method relies on estimating the state of the autonomic nervous system from an analysis of heart rate variability. When PDM and spectral features are combined, the system discriminates stressful events with a success rate of 83% within subjects (69% between subjects) [5].

Physical Activity Monitoring is a device that can measure the human activity quantity quantitatively through Heart Rate detection in real time. R-Spike detection of ECG is required for this Heart Rate detection. Since Physical Activity Monitoring System is usually used during activity or exercise, however, signal measured in ECG System is contaminated by diverse noises. Diverse noises become the factors of failure in R-Spike detection. Such factors impede the exact HR detection. The sensitivity of R-Spike detection rate for noise was also additionally tested by gradually lowering SNR of NSTDB. Then, it was verified through ECG signal that was actually measured in physical activity monitoring [6].

This paper presents a signal pre-processing and feature extraction approach based on electrocardiogram (ECG) sensor signal. The extracted features are used to formulate cases in a case-based reasoning system to develop a personalized stress diagnosis system. The results obtained from the evaluation show a performance close to an expert in the domain in diagnosing stress using ECG sensor signal [7].

The activity of the autonomic nervous system is noninvasively studied by means of autoregressive (AR) frequency analysis of the heart-rate variability (HRV) signal. Spectral decomposition of the Heart Rate Variability during whole night recordings was obtained, in order to assess the characteristic fluctuations in the heart rate [8].

Advances in wireless communication technologies, such as wearable and implantable biosensors, along with recent developments in the embedded computing area are enabling the design, development, and implementation of body area networks [9].

The approach consists of 1) Recording the ECG signals, 2) Signal processing using wavelets, 3) Fuzzy evaluation techniques to provide robustness in ECG signal analysis, 4) Monitoring the function of ANS under different stress conditions. Our experiment involves 20 physically fit persons under different conditions. Fuzzy technique has been used to model the experimental data [10].

The Stroop color word test is used to induce stress and ECG signal was simultaneously acquired from the 10 female subjects in the age range of (20 - 25) years in non invasive manner. An acquired ECG signals are preprocessed using 4th order elliptic band pass filter. The High Frequency (HF) and Low Frequency (LF) bands of ECG signals were considered to extract the stress related features through discrete wavelet Transform (DWT) using "db4" wavelet function. The extracted features are mapped into two states such as stress and relax using a K Nearest Neighbor (KNN). The experimental results show the maximum average classification accuracy of 96.41% on classifying the stress and relax states from the ECG signals [11].

Continuous existence of negative emotions (disgust, anger, fear and sad) over a longer period of time induces emotional stress. This emotional stress can be analyzed through physiological signal characteristics such as Electrocardiogram (ECG), Electromyogram (EMG), etc. In this paper, they have proposed a customized protocol experiment to induce emotional stress through audio-visual stimuli (video clips) and simultaneously acquired ECG signals. ECG signals are preprocessed using Elliptic filter and Discrete Wavelet Transform (DWT). Heart Rate Variability (HRV) signals is derived from ECG signals through QRS detection algorithm [12].

Mental stress is one of the major risk factors for many diseases such as hypertension, coronary artery disease, heart attack, stroke, even sudden death. Conventionally, interviews, questionnaires or behavior observation are used to detect mental stress in an individual. The identification and prediction of stress levels using existing data processing methodologies are incompetent to predict the stress levels either in real time or laboratory based experiments. The main objectives of the this paper is to classify the stress levels using mental arithmetic task and appropriate signal processing methodology, (ii) to analyze the characteristics of Electrocardiogram (ECG) signal for different stress levels, and (iii) to derive the optimum features from a set of statistical features over different frequency bands [14].

The parameters like Heart rate, PR interval, QRS duration, QT interval and RR interval are compared. The result shows 99% accuracy in the data obtained by this method. The process of extraction of ECG data is also validated for Normal Sinus Rhythm/Arrhythmia from MIT-BIH database. The correlation obtained is nearly 98%. Thus the method is useful for automatic analysis of ECGs from ECG strips at rural areas also [15].

The variations in the feature signals with respect to the stress were expressed in terms of correlation coefficients and were tabulated. The analysis clearly showed the changes in the feature signals with respect to the stress of the driver. It showed a direct proportionate relation in the QRS power and the breathing rate with respect to the stress of the driver. The analysis also showed that QRS power signal is a better feature signal for analyzing the stress since it showed more correlation with the heart rate marker signal. The analysis points out the fact that the physiological signals can be used as a metric for monitoring the stress of a person [16].

Stress is a serious concern facing our world today, motivating the development of better objective understanding using non-intrusive means for stress recognition. The aim for the work was to use thermal imaging of facial regions to detect stress automatically. The work uses facial regions captured in videos in thermal (TS) and visible (VS) spectra and introduces our database ANU Stress DB [17].

3. Proposed Methodology

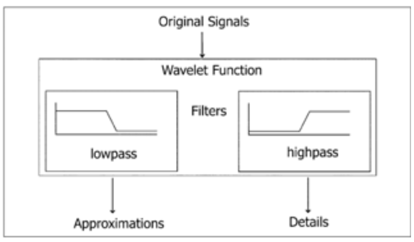
The proposed methodology is divided into following stages:

- Extraction of ECG using two leads method (including H/W and S/W – embedded system)
- Decomposition of ECG using (bio-orthogonal) bior 3,9 wavelet family
- Extraction of SD, mean, power, entropy, energy, covariance and homogeneity
- Analysis of the above features to measure the stress level
- Stress Level = f(SD, mean, power, entropy, energy, and covariance)

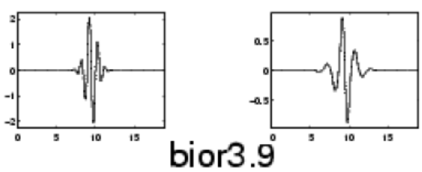
Further, a back propagation neural network is trained using the above features as input neurons in order to classify the stress level.

4. Decomposition of ECG Signal using BIOR3.9

The first step of wavelet decomposition is to select an appropriate wavelet for the signal to be analyzed. Appropriate wavelets should have a wave shape, which is close to the signal to be analyzed or filtered. Convolving the wavelet function with the original signal produces the equivalent of a high-pass filter (or a low-pass filter), resulting in the details (or the approximation) of the signal as shown in figure.

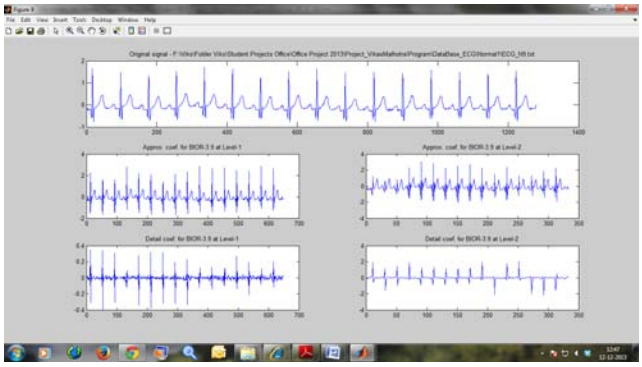


The wavelet 'bior3.9' was selected because of the similarity of its wave-form to ECG signals. This is shown in below fig.



This family of wavelets exhibits the property of linear phase, which is needed for signal and image reconstruction. By using two wavelets, one for decomposition (on the left side) and the other for reconstruction (on the right side) instead of the same single one, interesting properties are derived. The start of the QRS complex is defined as the beginning of the each beat.

Following fig. shows the decomposed ECG at different decomposition levels.



5. ECG Parameters Extraction

Following parameters from ECG signals are extracted using the MATLAB software.

5.1 Entropy (Ent)

The entropy of a signal is a measure of the randomness of the signal. In other words, it can be viewed as a measure of uncertainty. Entropy has been shown to be effective in dealing with complex biological signals. The entropy (Ent) is given by:

$$Entropy\ (Ent) = -\sum_{i=1}^{n} p(xi).\log_{10} p(xi)$$

Where, x = (x1, x2. . .xn) is a set of random phenomena of wavelet co-efficient, and p is a probability of random phenomenon of wavelet co-efficient.

5.2 Power (P)

Power is given by average square sum of wavelet coefficients and given by the following equation:

$$Power\ (P) = \frac{1}{n}\sum_{i=1}^{n} x_i^2$$

Where xi is the wavelet coefficient and n is the total no of wavelet coefficients

5.3 Energy (E)

Power is given by square sum of wavelet coefficients and given by the following equation:

$$Energy\ (E) = \sum_{i=1}^{n} x_i^2$$

Where xi is the wavelet coefficient and n is the total no of wavelet coefficients

5.4 Mean (μ)

Mean is given by average sum of wavelet coefficients and given by the following equation:

$$Mean\ (\mu) = \frac{1}{n}\sum_{i=1}^{n} x_i$$

Where xi is the wavelet coefficient and n is the total no of wavelet coefficients

5.5 Standard Deviation (SD)

Standard Deviation is given by:

$$SD = \frac{1}{n}\sum_{i=1}^{n} (x_i - \mu)^2$$

Where xi, μ and n are the wavelet coefficients, mean total no of wavelet coefficients respectively.

6. Results

The different features of normal state at three decomposition level of 10 subjects as given below

Sr. No.	Level-1						Level-2						Level-3					
	Power	Energy	Mean	St.d	Entropy	Co.var.	Power	Energy	Mean	St.d	Entropy	Co.var.	Power	Energy	Mean	St.d	Entropy	Co.var.
1	0.412,	13257.206,	0.639,	0.060,	5.695,	0.004,	0.825,	13298.812,	0.904,	0.086,	5.741,	0.007,	1.653,	13306.475,	1.279,	0.131,	0.048,	0.017,
2	0.418,	10075.100,	0.641,	0.082,	6.199,	0.007,	0.836,	10085.878,	0.907,	0.118,	5.628,	0.014,	1.675,	10119.015,	1.282,	0.176,	0.207,	0.031,
3	0.415,	16265.908,	0.639,	0.076,	5.699,	0.008,	0.830,	16287.251,	0.904,	0.110,	5.707,	0.012,	1.666,	16366.468,	1.279,	0.175,	0.083,	0.031,
4	0.424,	4630.614,	0.647,	0.074,	5.651,	0.005,	0.848,	4639.548,	0.915,	0.106,	5.578,	0.011,	1.697,	4657.786,	1.293,	0.154,	0.250,	0.024,
5	0.420,	13481.302,	0.641,	0.098,	6.238,	0.010,	0.841,	13502.465,	0.906,	0.142,	5.579,	0.020,	1.688,	13559.879,	1.282,	0.213,	0.595,	0.045,
6	0.417,	10183.711,	0.641,	0.079,	5.963,	0.006,	0.834,	10191.898,	0.906,	0.113,	5.842,	0.013,	1.672,	10209.552,	1.281,	0.175,	0.182,	0.031,
7	0.414,	8735.986,	0.640,	0.069,	6.066,	0.005,	0.829,	8749.331,	0.905,	0.100,	5.760,	0.010,	1.663,	8794.021,	1.280,	0.158,	0.072,	0.025,
8	0.418,	10098.462,	0.640,	0.095,	5.916,	0.009,	0.838,	10117.886,	0.906,	0.128,	5.447,	0.018,	1.683,	10160.658,	1.281,	0.207,	0.518,	0.040,
9	0.414,	12387.469,	0.640,	0.069,	6.056,	0.005,	0.828,	12396.954,	0.905,	0.099,	5.769,	0.010,	1.662,	12409.569,	1.280,	0.152,	0.104,	0.023,
10	0.432,	13338.152,	0.650,	0.099,	5.891,	0.010,	0.865,	13554.160,	0.918,	0.142,	5.112,	0.020,	1.735,	13613.445,	1.299,	0.218,	0.618,	0.046,

The different features of stressed state at three decomposition level of 10 subjects as given below;

Sr. No.	Level-1						Level-2						Level-3					
	Power	Energy	Mean	St.d	Entropy	Co.var.	Power	Energy	Mean	St.d	Entropy	Co.var.	Power	Energy	Mean	St.d	Entropy	Co.var.
1	0.417,	17045.233,	0.642,	0.073,	5.990,	0.005,	0.835,	17054.022,	0.908,	0.104,	5.663,	0.011,	1.671,	17086.407,	1.284,	0.154,	0.134,	0.024,
2	0.415,	37247.076,	0.640,	0.070,	6.015,	0.005,	0.830,	37262.499,	0.905,	0.099,	5.796,	0.010,	1.661,	37315.876,	1.281,	0.147,	0.143,	0.022,
3	0.423,	16581.690,	0.643,	0.096,	5.837,	0.009,	0.847,	16606.774,	0.910,	0.139,	5.736,	0.019,	1.701,	16697.777,	1.286,	0.216,	0.340,	0.046,
4	0.422,	17392.586,	0.643,	0.092,	6.183,	0.008,	0.844,	17401.755,	0.909,	0.130,	5.620,	0.017,	1.691,	17445.695,	1.286,	0.190,	0.277,	0.036,
5	0.421,	40059.545,	0.643,	0.086,	6.207,	0.007,	0.843,	40078.066,	0.910,	0.122,	5.662,	0.015,	1.688,	40158.618,	1.287,	0.180,	0.206,	0.033,
6	0.411,	38002.149,	0.639,	0.050,	5.504,	0.003,	0.822,	38019.611,	0.904,	0.073,	5.612,	0.005,	1.646,	38071.667,	1.278,	0.110,	0.071,	0.012,
7	0.417,	47804.951,	0.641,	0.083,	6.202,	0.007,	0.835,	47856.994,	0.906,	0.121,	5.787,	0.015,	1.676,	48039.646,	1.281,	0.187,	0.134,	0.035,
8	0.432,	18952.743,	0.649,	0.101,	6.147,	0.010,	0.864,	18976.916,	0.918,	0.146,	5.481,	0.021,	1.733,	19036.983,	1.298,	0.217,	0.452,	0.047,
9	0.417,	15740.229,	0.641,	0.072,	6.035,	0.005,	0.833,	15750.272,	0.907,	0.102,	5.790,	0.010,	1.670,	15801.320,	1.283,	0.157,	0.158,	0.025,
10	0.431,	16672.674,	0.649,	0.097,	5.875,	0.009,	0.862,	16682.286,	0.918,	0.138,	5.153,	0.019,	1.730,	16750.010,	1.299,	0.208,	0.560,	0.043,

7. Conclusion

Accurate discrimination between stressed and normal person was made possible by analyzing the different features extracted using the bior3.9 wavelet function. The presented work shows a fair accuracy in analyzing the stress and normal person based on ECG signal. Further, we have analyzed the results in order to increase the resolution between stressed levels. That is, stress levels may be further divided into level-1, level-2 and level-3. Analysis of signals from a database of 20 subjects with two different states (stressed and relaxed) shows that the proposed method is very well-suited for characterizing based on their stress level. More generally, the presented work analysis framework may be of valuable importance for the field of cardiovascular research, as it provides an innovative monitoring tool for the patients in coma, where they cannot respond visually; however their state of health or response could be monitored by using the proposed system.

References

[1] K. Yashima, T. Sasaki, Y.Kageyama, M. Odagaki, H. Hosaka 'Application of wavelet analysis to the plethysmogram for the evaluation of mental stress'.. 27th Annual International Conference of the Engineering in Medicine and Biology Society, 2005, vol., no., pp.2781, 2784, 17-18 Jan. 2006

[2] Man Sun Kim, HyungJeong Yang 'A Study of ECG Characteristics by Using Wavelet and Neural Networks'. International Conference on Computer Systems and Applications, 2007, AICCSA '07. IEEE/ACS, vol., no., pp.786, 790, 13-16 May 2007

[3] Suyi Li, Jun Lin 'The optimal de-noising algorithm for ECG using stationary wavelet transform' WRI World Congress on Computer Science and Information Engineering, 2009, vol.6, no., pp.469,473, March 31 2009-April 2 2009

[4] Heui-Kyung Yang*, Jeong-Whan Lee, Kang-Hwi Lee, Young-Jae Lee, Kyeong-Seop Kim, Hee-Jung Choi, Dong-Jun Kim 'Application for the Wearable Heart Activity Monitoring System: Analysis of the autonomic function of HRV''. 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2008, vol., no., pp.1258,1261, 20-25 Aug. 2008

[5] Jongyoon Choi and Ricardo Gutierrez-Osuna 'Using Heart Rate Monitors to Detect Mental Stress' Sixth International Workshop on Wearable and Implantable Body Sensor Networks, 2009. , vol., no., pp.219, 223, 3-5 June 2009

[6] Uk Jin. Yoon, YeonSik. Noh, Young Myeon. Han, Min Yong. Kim, Jae Hoon. Jung, In Seop. Hwang, Hyung Ro. Yoon, 'Electrocardiogram signal processing method for exact Heart Rate detection in physical activity monitoring system: Wavelet Approach' EMBS Conference on Biomedical Engineering and Sciences (IECBES), 2010 IEEE, vol., no., pp.232,235, Nov. 30 2010-Dec. 2 2010

[7] S. Begum, M. U. Ahmed and P. Funk 'ECG Sensor Signal Analysis to Represent Cases in a Case-based Stress Diagnosis System' 10th IEEE International Conference on Information Technology and Applications in Biomedicine (ITAB), 2010, vol., no., pp.1,5, 3-5 Nov. 2010

[8] G. Ranganathan, V. Bindhu, Dr. R. Rangarajan 'ECG Signal Processing using Dyadic wavelet for Mental Stress Assessment' 4th International Conference on

Bioinformatics and Biomedical Engineering (iCBBE), 2010, vol., no., pp.1,4, 18-20 June 2010

[9] Min Chen, Sergio Gonzalez, Athanasios Vasilakos, Huasong Cao, Victor C. M. Leung'Body Area Networks: A Survey (Mobile Networks and Applications)' The Journal of special issues on Mobility of Systems, Users, Data and Computing ISSN 1383-469X ,Volume 16, Number 2 ,2010

[10] G.RANGANATHAN, R.RANGARAJAN, V.BINDHU 'Evaluation of ECG Signals for Mental Stress Assessment using Fuzzy Technique'International Journal of Soft Computing and Engineering (IJSCE) ISSN: 2231-2307, Volume-1, Issue-4, September 2011

[11] P Karthikeyan, M Murugappan, S Yaacob 'ECG Signals Based Mental Stress AssessmentUsing Wavelet Transform' International Conference on Control System, Computing and Engineering (ICCSCE), 2011 IEEE , vol., no., pp.258,262, 25-27 Nov. 2011

[12] Bong Siao Zheng, M Murugappan, Sazali Yaacob 'Human Emotional Stress Assessment through Heart Rate Detection in a Customized Protocol Experiment' Symposium on Industrial Electronics and Applications (ISIEA), 2012 IEEE , vol., no., pp.293,298, 23-26 Sept. 2012

[13] HaritonCostin, CristianRotariu, AlexandruPasarica 'Mental Stress Detection using Heart Rate Variability and Morphologic Variability of ECG Signals' International Conference and Exposition on Electrical and Power Engineering (EPE), 2012 , vol., no., pp.591,596, 25-27 Oct. 2012

[14] P Karthikeyan, M Murugappan, S Yaacob'A Study on Mental Arithmetic Task based Human Stress Level Classification Using Discrete Wavelet Transform' IEEE Conference on Sustainable Utilization and Development in Engineering and Technology (STUDENT), 2012, vol., no., pp.77,81, 6-9 Oct. 2012

[15] Vikash Kumar, Jitu Sharma, Shahanaz Ayub, J. P. Saini 'Extracting Samples As Text From ECG Strips For ECG Analysis Purpose' Fourth International Conference on Computational Intelligence and Communication Networks (CICN), 2012, vol., no., pp.317,321, 3-5 Nov. 2012

[16] Karthik Soman, Varghese Alex, Chaithanya Srinivas 'Analysis of Physiological Signals in Response to Stress using ECG and Respiratory Signals of Automobile Drivers' International Multi-Conference on Automation, Computing, Communication, Control and Compressed Sensing (iMac4s), 2013, vol., no., pp.574,579, 22-23 March 2013

[17] Nandita Sharma, Abhinav Dhally, Tom Gedeony,Roland Goecke 'Modeling Stress Using Thermal Facial Patterns: A Spatio-Temporal Approach ACII 2013

[18] Po-Ching Chen, Steven Lee, and Cheng-Deng Kuo'Delineation of T-Wave in ECG by Wavelet Transform Using Multiscale Differential Operator'IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 53, NO. 7, JULY 2006

[19] M. Sifuzzaman1, M.R. Islam1 and M.Z. Ali 'Application of Wavelet Transform and its Advantages Compared to Fourier Transform' 'Journal of Physical Sciences, Vol. 13, 2009, 121-134

[20] Shahina Begum, Mobyen Uddin Ahmed, Peter Funk, ECG Sensor Signal Analysis to Represent Cases in a Case-based Stress Diagnosis System, 10th IEEE International Conference on Information Technology and Applications in Biomedicine (ITAB 2010), Corfu, Greece, p. 193-198, November, 2010

[21] Healey, J.A.; Picard, R.W., "Detecting stress during real-world driving tasks using physiological sensors," IEEE Transactions on Intelligent Transportation Systems, vol.6, no.2, pp.156, 166, June 2005

[22] Haet Bit Lee,Jung Soo Kim, Yun Seong Kim, Hyun Jae Baek, Myung Suk Ryu, Kwang-Suk Park, "The relationship between HRV parameters and stressful driving situation in the real road," 6th International Special Topic Conference on Information Technology Applications in Biomedicine, ITAB 2007 , vol., no., pp.198,200, 8-11 Nov. 2007

[23] Wanqing Wu, Jungtae Lee "Development of full-featured ECG system for visual stress induced heart rate variability (HRV) assessment, "IEEE International Symposium on Signal Processing and Information Technology (ISSPIT), vol., no., pp.144,149, 15-18 Dec. 2010

[24] Janusek, D., Kania, M., Zavala-Fernandez, H., Maniewski, R., Zaczek, R., Kobylecka, M., Opolski, G., Krolicki, L., "Evaluation of T-wave alternans in comparison with ECG stress test and scintigraphic examination in patients with coronary artery disease,", IEEE 12th International Conference on Bioinformatics & Bioengineering (BIBE), vol., no., pp.208,210, 11-13 Nov. 2012

[25] Bong Siao Zheng, Murugappan, M., Yaacob, S., "FCM clustering of emotional stress using ECG features," International Conference on Communications and Signal Processing (ICCSP) , vol., no., pp.305,309, 3-5 April 2013

[26] Jongyoon Choi, Ahmed, B., Gutierrez-Osuna, R., "Development and Evaluation of an Ambulatory Stress Monitor Based on Wearable Sensors," IEEE Transactions on Information Technology in Biomedicine, vol.16, no.2, pp.279,286, March 2012

Author Profile

Vikas Malhotra has received the B.Tech. Degree in ECE from SUSCET, Tangori, Mohali, Punjab in 2005 and pursuing his M.Tech in ECE from MMU, Mullana, Ambala, Haryana. His field of interest is in Bio medical based application system developments. Presently the author I working as Project Assistant – ETD in CDAC, Mohali.

Mahendra Kumar Patil is Assistant Professor in Electronics and Communication Engineering department at Maharishi Markandeshwar University, Mullana, Ambala, Haryana, India. He was born in 1986 in India. He obtained his Master degree in Signal Processing from Indian Institute of Technology Guwahati, Assam, India in 2011 and Bachelor of Engineering in Electronics and Communication Engineering from UIT RGPV (previously government Engineering College), Bhopal, MP, India, in 2008. His research area is speech processing, image processing and biomedical signal processing. He has significant publication in his short duration carrier.