**Final submitted version**

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

# ECG Sensor Signal Analysis to Represent Cases in a Case-based Stress Diagnosis System

S. Begum, M. U. Ahmed and P. Funk

***Abstract*—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.**

## I. INTRODUCTION

TODAY's increased use of computer-based systems in the medical domain requires computer processing of biomedical signals such as, ECG, EEG (electro-encephalography), 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 [1]. Clinicians often make a diagnosis by carefully inspecting or continuously monitoring signal data. But the level of complexity associated with manual analysis and interpretation of these biomedical signals is great even for experienced clinicians. Going beyond threshold alarms and moving towards more elaborate and "intelligent" data processing of signals to extract clinically significant information from these biomedical signals is feasible today with increased processing power in computers and new methods and techniques. For example, in [2] Nilsson et al. have explored classification of Respiratory Sinus Arrhythmia using case-based reasoning approach. Authors in [6], [16] deal with temporal abstraction by key sequences representing a pattern of signal changes in the medical domain. Ölmeza and Dokur have applied artificial neural networks to classify heart sounds [3]. Wavelet transformation is used in [4], [5] to characterize ECG signals. In [18], the author has described a process for extracting features from finger temperature sensor data for a case-based classification scheme.

Heart Rate Variability (HRV) depicts the activity of the autonomous nervous system and is thereby commonly used as a quantitative indicator of stress [8]. ECG sensor signal reflects changes in electrical potential over time. HRV features can be extracted from ECG signals by detecting the QRS complex. QRS of the ECG represents the electrical activity in the heart during the ventricular contraction. The time period between consecutive heart beats (or RR intervals) can be detected from the QRS complex which helps to determine the measurement of HRV analysis. Therefore, it is important to detect QRS complex, in particular, RR interval as correctly as possible to get reliable HRV features.

This paper presents a computer system capable of receiving analogue ECG signal and produces heartbeat in QRS complex waveform to calculate the inter-beat-interval (IBI). HRV features extracted from this calculated IBI values are then employed in a CBR system to diagnose stress. The features are extracted by considering a combination of time and frequency domain features. The original IBI signal is presented in time domain. Features are extracted from the time domain signal and transferred into the frequency domain using Fast Fourier Transform (FFT) to extract frequency domain features.

The rest of the paper is organized as follows. Section II describes the related work. Section III explains the choice of the methods and materials. Section IV presents the detailed analysis of feature extraction and section V contains the implementation. Evaluation results are discussed in section VI. Finally, section VII presents the concluding remark.

## II. RELATED WORK

The authors in [10] use a mobile ECG sensor for diagnosing stress using HRV. McCraty et al. [11] determine the power spectrum density (PSD) of HRV to investigate relationship between the PSD and human emotional state. It shows that during anger there is a significant increase in low frequency power (LF) with no changes in higher frequency power (HF) and as a result it provides an increase in the LF/HF ratio. During appreciation there is an increase in both LF and HF power so that the ratio remains approximately unchanged. In [12], Fuzzy c-means clustering algorithm is applied to determine continuous stress curve. They have collected data from drivers during a stress recognition test. Different biomedical signals e.g., electrocardiograph, electromyography, skin conductance of feet and hands, heart rate signal and respiration signal of the drivers while they were experiencing driving in various levels are used in this

Manuscript received July 15, 2010. Accepted August 12, 2010.

S. Begum is with the School of Innovation, Design and Engineering, Mälardalen University, PO Box 883 SE-721 23, Västerås, Sweden, (phone: +46 21 10 14 53; fax: +46 21 10 14 60; e-mail: shahina.begum@ mdh.se).

M.U. Ahmed is with the School of Innovation, Design and Engineering, Mälardalen University, PO Box 883 SE-721 23, Västerås, Sweden, (e-mail: mobyen.ahmed@ mdh.se).

P. Funk is with the School of Innovation, Design and Engineering, Mälardalen University, PO Box 883 SE-721 23, Västerås, Sweden, (e-mail: peter.funk@ mdh.se).

**Final submitted version**

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

study. The authors in [13] use ECG signal to measure and analyze HRV and also discuss the relationship of HRV and stress. CBR has been applied in the psycho-physiological domain in several studies. For example, a procedure using CBR for diagnosing stress-related disorder was put forwarded by Nilsson et al. [14] where stress-related disorders were diagnosed by classifying the heart rate patterns. A CBR system was outlined in [15], [17], [7] where cases are formulated using finger temperature sensor signal for diagnosing stress in the psycho-physiological domain, however it is not sufficient to depend only on finger temperature for classifying individual sensitivity to stress. Therefore, in this proposed system we have introduced another physiological parameter i.e. heart rate variability as a reference of our previous work described in [15]. Moreover, some of the discussed research works e.g., [11] uses only frequency domain HRV features while a combination of frequency and time domain features are used in our CBR system is diagnosing stress.

## III. Materials and Methods

### A. Data Collection

ECG is a standard way to measure heartbeat and still it is the best and widely used approach. It records electrical activity of heartbeat and presents it in a continuous time period captured by attached electrodes in the skin. The three standard limb leads are used to obtain the ECG signal. Data were collected following a fifteen minutes protocol [9]. Fig. 1 shows the phases that were followed during the data collection.

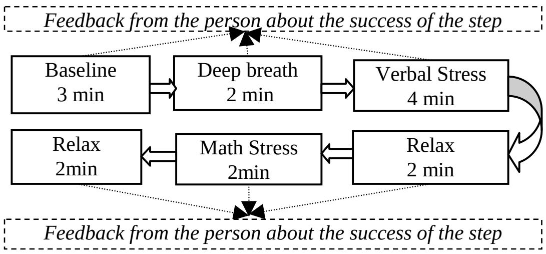



Fig. 1. Measurement procedure used to create an individual stress profile

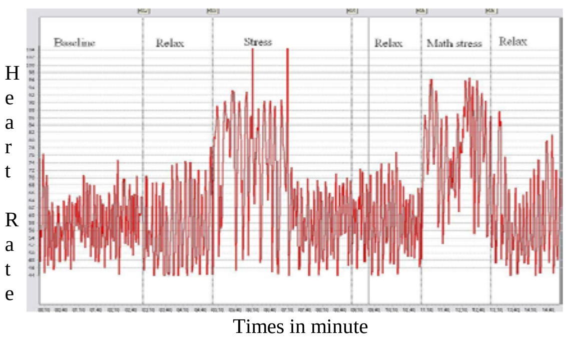



Fig. 2. Variations of HR signal during different test conditions

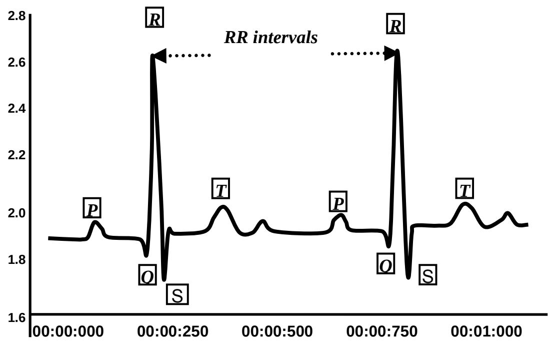
The measurements were collected from 22 subjects. Both male and female within the age range of 39±14 were participated in the study. An example shown in Fig. 2 is demonstrating the variations on heart rate during the different test phases. After completing each calibration step a visual analogue scale (VAS) was used to collect subject's feedback about the success of each step. The scale was ranged from 0-10 (10 is the maximum success rate) and used to verify the measurements. As the physicians during stress diagnosis are not only considering the physiological parameters but also other subjective parameters, subjects were also asked to complete a stress questionnaire [21]. This helps to measure job-related, environment and health-related stress. Finally, combinations of all these measurements are used to classify whether a subject is stressed or healthy.

### B. Case-based Reasoning

Case-based reasoning (CBR) is a problem solving technique that reuses past cases and experiences to find a solution to a current case [20]. CBR is especially suitable for domains with a weak domain theory, i.e. when the domain is difficult to formalize and is empirical such as, stress domain. The advantages of CBR in medical domain have been identified in several research works i.e. in [22- 23]. In CBR, a case represents a piece of knowledge as experience and plays an important role in the reasoning process. It comprises unique features to describe a problem. In the case retrieval, a major phase of CBR, matching between features of two cases plays a vital role. Cases with hidden key features may affect the retrieval performance in a CBR system. Therefore, extraction of features potential to represent cases is highly recommended in developing a CBR system. A critical issue is to identify relevant features to represent a case in domains where data is coming from sensor signals or images or in a form of time series or free text format.

## IV. ECG Signal Analysis and Feature Extraction

The proposed feature extraction in this stress diagnosis system includes, 1) develop a computer interface to collect analogue ECG measurement in real time and calculate the RR interval or IBI. 2) remove outlier using a filter at the pre-processing stage, 3) feature detection and calculation 4) problem case formulation using extracted features 5) enter the new problem case into the CBR cycle.



**Final submitted version**

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

Fig. 3. R peaks of an ECG signal and corresponding RR Interval

*Inter-beat-interval:* In Fig. 3, the ECG signal is plotted against time, where X axis represents the time in milliseconds and Y axis represents the amplitude. Here, the R peak, which is the highest amplitude value, is above 2.6. Each R wave comes after a certain amount of time and the time difference between two R waves is the rate of the RR interval or inter-beat interval (IBI). So, the time difference between R and R waves in Fig. 3 is around 750 ms.

The number of R waves occur in a minute is used to calculate HR and the standard unit is beat per minute (bpm). To compute HR in real time, the time required to produce a total ECG signal is considered, which is further calculated in minute to find the number of beats per minute. For example, if one beat (from R to R) requires 750 ms then in one minute i.e. 60*1000=60000ms, (60000/750=80bpm) 80 beats can be achieved. This 80bpm is the heart rate against the time. Subjective random noise in the IBI signal is a major problem since they could deficiently influence the corresponding extracted feature values. It was observed that the normal range of IBI signal is 0.4 to 1.1 second. However, some IBI values can be higher than the range if the data contain any artefact.

*Feature extraction for the CBR system:* HRV reflects the status of autonomous nervous system and is well establish to diagnose stress. A combination of both time and frequency domain HRV features are used in the CBR system. The time domain features include mean RR interval, mean heart rate, difference between maximum and minimum heart rate, square root of variance i.e. standard deviation of NN interval (SDNN), etc. The frequency domain analysis is the spectral analysis of HRV. The transformation of HRV into power spectral density helps to determine the balance between sympathetic and parasympathetic nervous system [19]. The HRV spectrum is divided into high frequency component ranging from 0.18 to 0.4 Hz which is generally considered to be an index of cardiac vagal control [11]. The low frequency component ranges from 0.04 to 0.15 Hz appears generally due to both the vagus and cardiac sympathetic nerves. Therefore, it is the ratio of the low to high frequency spectra which can be used as an index of cardiac sympathovagal balance. The Fast Fourier Transformation (FFT) is one of the important methods practiced commonly in calculating the PSD. Here, the PSD is calculated using the FFT. However, this calculation can be affected due to distortion in the IBI signal. So, the filtration of the IBI signal is important.

The time domain and frequency domain features are extracted based on the IBI values. The list of extracted features and their description are presented in Table 1. Except the baseline, the features are calculated for the step2 to step6. In the table, the first three features are the frequency domain features and next three are the time domain features. These time and frequency domain features are used to formulate a new problem case. In CBR, the new problem case is matched against all the cases in the case library to retrieve the most similar cases. The most similar cases are then displayed in a sorted list depending on their similarity values. Finally, a clinician is revising (if needed an adaptation can be done by the clinician) the cases and confirm a solution to reuse and restore the new case. To measure similarity of new case with the previous cases, the weighted Euclidian distance is applied. Weight reflects the relative importance of each feature and here it is defined by the domain expert.

TABLE I
LIST OF FEATURES AND THEIR DESCRIPTION

| No | Features | Description |
|---|---|---|
| 1 | Step2_LF | Low frequency for step2 |
| 2 | Step2_HF | High frequency for step2 |
| | Step2_ LF/HF | Power density spectrum for step2 |
| 4 | Step2_pNN50 | The fraction of NN intervals that differ by more than 50 ms from the previous NN interval in step2 |
| 5 | Step2_SDNN | standard deviation of NN intervals for step2 |
| 6 | Step2_RMSDD | root-mean-square of successive differences of NN intervals for step2 |
| . | . | . |
| . | . | . |
| 25 | Step6_LF | Low frequency for step6 |
| 26 | Step6_HF | High frequency for step6 |
| 27 | Step6_ LF/HF | Power density spectrum for step6 |
| 28 | Step6_pNN50 | The fraction of NN intervals that differ by more than 50 ms from the previous NN interval for step6 |
| 29 | Step6_SDNN | standard deviation of NN intervals for step6 |
| 30 | Step6_RMSDD | root-mean-square of successive differences of NN intervals for step6 |

The k-Nearest Neighbour (kNN) algorithm is applied for the retrieval of similar cases. The system provides the adaptation using an interactive interface where the expert has the permission to adapt the retrieved case. The system can provide matching outcomes in a sorted list of best matching cases according to their similarity values in three circumstances: when a new problem case is matched with all the solved cases in a case library (between subject and class), within a class where the class information is provided by the user and also within a subject.

## V. IMPLEMENTATION

The ECG sensor system is implemented mainly using Java programming language but the framework depends on a third party solution. Fig. 4 illustrates the different parts of the system using a block diagram.

*Sensors*: the first part of the system is the sensors attached to the human skin. Two electrodes placed in the left arm and one in the right arm. The electrodes transformed a physical signal from the body into an electrical signal. Then the signal is transmitted to an amplifier.

**Final submitted version**

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

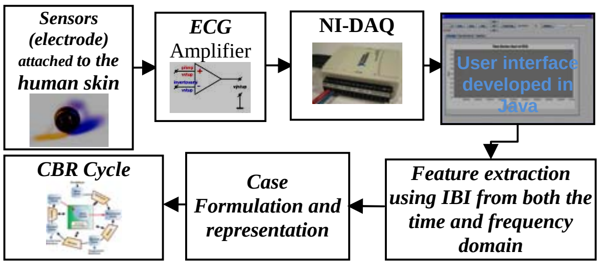



Fig. 4. Block diagram of the proposed system

*ECG amplifier*: the amplifier takes analogue signal (voltage) as an input. The amplification of the signal can be tuned manually in the hardware device. The amplified output from the amplifier is then sent to the National instruments- data acquisition (NI-DAQ) device.

*NI-DAQ*: the data acquisition device from the national instruments (NI) mainly takes the amplified analogue signal and sends it to the computer through USB. It has 8 analogue inputs as single-ended channels in 14 bits resolution. It can also work as 4 differential channels and 2 analogue outputs in 12 bits resolution. The driver of the device provided by the NI is available for Windows XP. The sampling rate is possible to change using the editable C program which helps to read data from the USB.

*User interface*: the user interface is developed in Java using Netbeans editor. The raw data are captured using C programming code provided by the NI, the code is further edited and formed as a .dll file. This .dll file is then used in Java using the Java Native Interface (JNI). In Java, the user interface is developed using java multithread programming where one thread is only for receiving the data and the other is for the calculation, logic and display information. The R peaks, IBI calculation and outlier removal on IBI values are implemented following the steps described below:

1. Threshold detection: the computer receives 1000 samples in one second. However, not all the samples contain the highest amplitude. To save the computational time a threshold value is generated. The system will start to scan when it receives the threshold value in order to find the highest amplitude. The procedure to detect the threshold is as follows: a) first it receives samples for 3 seconds and identifies maximum and mean amplitudes. B) from this range (Mean to Maximum), 2$^{nd}$ mean amplitude is calculated. This 2$^{nd}$ mean value is treated as a threshold.

2. R peak detection: initially the threshold value is considered as the peak value which further replaced with the higher amplitude, if any exists. When the sample value becomes lower than the peak, the system determines the amplitude value as the R peak.

3. IBI calculation: each time the system detects the R peak, it saves the time. Let assume that the system saves the time according to the R peak ($t_0, t_1$, …., $t_n$), so the IBI value for $t_1$ will be the time difference from $t_1$ to $t_0$. i.e. $IBI_{t_1} = t_1 - t_0$

4. Outlier removal: the algorithm for outlier removal works in two steps: 1) outlier detection and 2) re-sampling the signal. For the outlier detection, first the signal is divided into a number of windows (winH) horizontally in every 30 sec and each horizontal window is again divided vertically in a number of windows (winV). Now, the frequency and mean for the each window (winV) are calculated. Then the mean of the lowest frequency window (winV) is compared with the normal range (0.4 to 1.1 sec). If the mean value is not within the normal range then all the sample data are considered as outliers. These steps are continued until the program reaches the last window (winH) and determines all the outliers. After the outliers' detection, the programs also identify length of the outliers for each window (winH) and have marked the entire original sample in that length as artefact. This length of samples is then replaced by the same length of usual data received just before or after the artefact. The usual data is defined by the highest frequency window (winV).

*Feature extraction and case representation*: The IBI values are first represented in the time domain and the time domain's features namely pNN50, SDNN and RMSDD are excreted. The IBI values are then transferred into the frequency domain by means of FFT and then the frequency domain features i.e. low power spectrum/low frequency (LF), high power spectrum/high frequency (HF) and their ratio (LF/HF) are extracted. Afterwards both the extracted features are combined to formulate a case for the CBR cycle. Finally, a case is represented with 30 features as described in Table I.

*CBR Cycle*: This part of the system is implemented using JAVA programming language and MySQL database. The initial case library is constructed in MySQL database with 22 classified cases where rational database management system (RDMS) approach is considered. The retrieve, reuse and retrain part of the CBR cycle are developed in JAVA programming language and Netbeans editor. For the retrieval, traditional k-Nearest Neighbour (kNN) algorithm is implemented and for the reuse, the top most case (k=1) is selected.

## VI. Experimental Work

A preliminary evaluation had been conducted with 22 subjects where, 5 women and 17 men, (age ranges between 25 and 53) were participated in the study. All the cases were classified by one expert and one senior clinician. For the evaluation purpose, the measurements were collected using more than one parameter (Finger temperature, skin conductance, respiration rate, CO2/ETCO2) together with ECG signal. So, the expert and the senior clinician had classified the cases using all the above parameters during the clinical trials as a reference purpose. The cases are classified as *healthy* or *stressed*.

**Final submitted version**

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

The sensitivity and specificity test was carried out on these 22 cases. One case was taken out from the case library at a time and then the case was matched against the remaining cases. Here, kNN (k=1) was applied to retrieve similar cases, i.e. for the evaluation purpose, the top most similar case is considered. Several indices were used to evaluate the system performance and presented in Table II. In Table II, the 2nd column presents the value while considering the expert's classifications and 3rd column presents the value considering the senior clinician's classifications. According to the expert, out of 22 cases, 12 cases are classified as *stressed* and 10 are classified as *healthy*. Among the 12 *stressed* cases, 10 are correctly diagnosed as *stressed* (i.e. true positive) and only 2 are incorrectly identified as *healthy* (i.e. false negative) by the system. Similarly, among the 10 h*ealthy* cases, 8 are correctly classified as *healthy* (i.e. true negative) and 2 are incorrectly classified as *stressed* (i.e. false positive) by the system. So, the sensitivity and specificity obtains 83% and 80%. The overall accuracy obtained is 81%.

TABLE II
SENSITIVITY AND SPECIFICITY ANALYSIS

| Criteria/Indices | Values (expert) | Values (senior clinician) |
|---|---|---|
| Total cases | 22 | 22 |
| Cases belong to *Stressed* group (P) | 12 | 10 |
| Cases belong to *Healthy* group (N) | 10 | 12 |
| True positive (TP): | 10 | 9 |
| False positive (FP): | 2 | 1 |
| True negative (TN): | 8 | 10 |
| False negative (FN): | 2 | 2 |
| Sensitivity = TP / (TP + FN) | ≈ 0.83 | ≈ 0.81 |
| Specificity = TN / (FP + TN) | ≈ 0.80 | ≈ 0.90 |
| Accuracy = (TP+TN)/(P+N) | ≈ 0.81 | ≈ 0.86 |

According to the senior clinician, out of 22 cases, 10 cases are classified as *stressed* and 12 are classified as *healthy*. Note that, some cases are grouped into the same classes both by the expert and senior clinician whereas some are classified into dissimilar classes. Among the 10 *stressed* cases, 9 are correctly diagnosed as *stressed* (i.e. true positive) and only 1 is incorrectly identified as *healthy* (i.e. false negative) by the system. Similarly, among the 12 h*ealthy* cases, 10 are correctly classified as *healthy* (i.e. true negative) and 2 are incorrectly classified as *stressed* (i.e. false positive) by the system. So, the sensitivity and specificity obtained are 81% and 90%. The overall accuracy achieved is 86%.

## VII. CONCLUSIONS

Characteristic of a sensor signal can be expressed and analyzed by identifying the key features in a CBR approach. This paper presents a feature extraction approach from ECG sensor signals to classify individual sensitivity to stress in a CBR system. The approach combines features both from the time and frequency domain to formulate a case. These features along with the CBR system help the clinicians to reduce complexity of manual analysis, interpretation and characterization of the information contained in the ECG signal. The evaluation using the extracted features shows that the CBR system can diagnoses stress (considering both the expert and senior clinician) 82±1% accurately in terms of sensitivity and 85±5% in terms of specificity. The initial result of the evaluation is acceptable by the clinician and the roadmap is to evaluate the system in a larger scale.

## REFERENCES

[1] R. B. Northrop, *Signals and systems in biomedical engineering*, CRC press, New York. 2003

[2] M. Nilsson, and P. Funk, "A case-based classification of respiratory sinus arrhythmia." *7th European Conference on Case-Based Reasoning*, Springer, Madrid, 2004, pp 673-685

[3] T. Ölmeza and Z. Dokur. "Classification of heart sounds using an artificial neural network." *Pattern Recognition Letters*. Volume 24, Issues 1-3, January 2003, Pages 617-629

[4] J.S. Sahambi, S.N.Tandon and R.K.P. Bhatt. "Using wavelet transforms for ECG characterization. An on-line digital signal processing system". *Engineering in Medicine and Biology Magazine, IEEE. Publication*. 1997. volume: 16, Issue: 1. pp 77-83

[5] T. Kalayci, and O. Ozdamar. "Wavelet preprocessing for automated neural network detection of EEGspikes." *Engineering in Medicine and Biology Magazine, IEEE*.1995. Issue: 2. pp 160-166

[6] P. Funk, N. Xiong, "Case-based reasoning and knowledge discovery in medical applications with time series", *Computational Intelligence*, Vol. 22, 2006, pp. 238-253.

[7] M.U. Ahmed, S. Begum, P. Funk, N. Xiong, B.V. Schéele, "A Multi-Module Case Based Biofeedback System for Stress Treatment", *Artificial Intelligence in Medicine*, vol In press, ELSEVIER, 2010.

[8] L. Bernardi, J. Wdowczyk-Szulc, C. Valenti, S. Castoldi, C. Passino, G. Spadacini, and P. Sleight. "Effects of Controlled Breathing, Mental Activity, and Mental Stress with or without Verbalization on Heart Rate Variability". *Journal of the American College of Cardiology*, May 2000, Vol. 35, No. 6, pp. 1462-1469.

[9] S. Begum, M.U. Ahmed, P. Funk, N. Xiong and B.V. Scheele. "Using Calibration and Fuzzification of Cases for Improved Diagnosis and Treatment of Stress", In *the Proceedings of the 8th European Workshop on Case-based Reasoning*, 2006, 113-122

[10] L. Salahuddin and D. Kim, "Detection of Acute Stress by Heart Rate Variability Using a Prototype Mobile ECG Sensor.", In *the Proceedings of the International Conference on Hybrid Information Technology*. pp. 2006, 453-459. ISBN:0-7695-2674-8

[11] R. McCraty, M. Atkinson, A.W. Tiller, G. Rein, and A. D. Watkins, "The Effects of Emotions on Short-Term Power Spectrum Analysis of Heart Rate Variability", *American Journal of Cardiology*, 1995, 76(14): 1089-1093

[12] M. Jiang, and Z. Wang, "A Method for Stress Detection Based on FCM Algorithm", *International Congress on Image and Signal Processing*. pp.1-5, 2009.

[13] D. Bansal, M. Khan, A.K. Salhan, "A Review of Measurement and Analysis of Heart Rate Variability", *International Conference on Computer and Automation Engineering*, IEEE, 2009.

[14] M. Nilsson, P. Funk, E. M. G. Olsson, B. V. Schéele, N. Xiong, "Clinical decision-support for diagnosing stress-related disorders by applying psychophysiological medical knowledge to an instance-based learning system", *Journal of Artificial Intelligence in Medicine*, vol 36, nr 2, p156-176, Elsevier, 2005

[15] S. Begum, M.U. Ahmed, P. Funk, N. Xiong, B.V. Schéele, "A case-based decision support system for individual stress diagnosis using fuzzy similarity matching", In *Computational Intelligence (CI)*, vol 25, nr 3, Blackwell, (2009), p180-195(16).

[16] S. Montani. "Exploring new roles for case-based reasoning in heterogeneous AI systems for medical decision support", *Applied Intelligence*. Springer, Volume 28, Number 3 / June, 2008

[17] M.U. Ahmed, S. Begum, P. Funk, N. Xiong, and B. V. Schéele, "Case-based Reasoning for Diagnosis of Stress using Enhanced Cosine and Fuzzy Similarity," *Transactions on Case-Based Reasoning on Multimedia Data*, vol Volume 1, nr Number 1, IBaI Publishing, 2008a, ISSN: 1864-9734

**Final submitted version**

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

[18] S. Begum, "Sensor signal processing to extract features from finger temperature in a case-based stress classification scheme", *6th IEEE International Symposium on Intelligent Signal Processing (Special Session on Signal Processing in Bioengineering),* Budapest, Hungary, August, 2009.

[19] S. Akselrod, D. Gordon, F.A. Ubel, D.C. Shannon, A.C. Berger, and R.J. Cohen, "Power spectrum analysis of heart rate fluctuation: a quantitative probe of beat-to-beat cardiovascular control". *Science*, 1981, Vol. 213. no. 4504, pp. 220 – 222

[20] I. Watson, *Applying Case-Based Reasoning: Techniques for Enterprise Systems*. Morgan Kaufmann Publishers CA 94104, USA, 1997.

[21] S. Begum, M. U. Ahmed, B. V. Schéele, E. Olsson, P. Funk, "Development of a Stress Questionnaire: A Tool for Diagnosing Mental Stress", Technical Report, MRTC, June, 2010

[22] I. Bichindaritz, and C. Marling, "Case-based reasoning in the health sciences: what's next? " In *Artificial Intelligence in Medicine*. 36(2), 2006, pp 127-135

[23] S. Begum, M.U. Ahmed, P. Funk, N. Xiong and M. Folke, "Case-Based Reasoning Systems in the Health Sciences: A Survey on Recent Trends and Developments", Accepted in *IEEE Transactions on Systems, Man, and Cybernetics--Part C: Applications and Reviews* 2010.