Effect of a Humorous Audio-Visual Stimulus on Autonomic Nervous System and Heart of Females

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***Abstract*— This study was an attempt to recognize the effect of a humorous audio-visual stimulus on the autonomic nervous system (ANS) and the heart physiology of females. Electrocardiogram (ECG) signals were acquired from eleven female volunteers under pre- and post-stimulus conditions. Heart rate variability (HRV) and time-domain ECG analyses were performed to non-invasively realize the effect of the humorous audio-visual stimulus on the ANS and heart physiology, respectively. HRV analysis suggested an increase in the parasympathetic activity during post-stimulus period. Time-domain analysis of ECG signals suggested a post-stimulus alteration in the electrical activity of the heart. Artificial neural network (ANN) classification resulted in an efficiency of ≥ 85% in both HRV and time-domain ECG analyses.**

Keywords— ECG; HRV; females; ANN; heart

I. Introduction

The Sinoatrial (SA) node, located in the upper region of the right atrium is a collection of self-exciting cells, responsible for rhythmic contraction of the heart. Because of this unique property, SA node is also known as the natural pacemaker of the heart. This pacemaking function is regulated by nerve innervations of the ANS into the SA node. Based on various external stimuli sensed by the sense organs and the internal conditions, ANS issues either excitatory or inhibitory signals to the SA node (through sympathetic or parasympathetic nerves) that helps in achieving the required alteration in the heart rate. This also results in the alteration of the duration of the consecutive cardiac cycles. The study of the deviation in the time intervals of the successive cardiac cycles is regarded as heart rate variability (HRV) [1]. Exposing an individual to stimuli like listening to music and viewing audio-visual clips has been reported to alter the ANS activity [2-4]. It has been well reported in the literature that HRV can be used as a non-invasive indicator of the ANS activity [5-6].

In this study, we report the effect of a humorous audio-visual clip on the ANS and heart physiology of females. In normal healthy females, the gonadotropic hormone levels undergo continuous change during the menstrual cycle. Change in levels of these hormones not only affects the reproductive organs but also influences the ANS [7]. To minimize the effect of hormonal changes, all the females involved in the study were exposed to the audio-visual stimulus when they were on the 1st day of phase-1 (i.e. follicular phase) of their menstrual cycle. HRV and time-domain features were extracted from the ECG signals acquired from the volunteers before and after watching the humorous audio-visual clip. Statistically important features were derived using linear and non-linear methods. Classification of pre- and post-stimulus conditions was attempted using ANN.

II. Requirements

DAQ USB-4704 multifunction USB module (Advantech Corporation, Taiwan), disposable ECG electrodes (BPL Medical Technologies Pvt. Ltd, India), ECG cables (Real Time Health Care, Bhubaneswar, India) and LabVIEW (V13, National Instruments, USA) were used for acquiring of ECG signals. The ECG signals were further processed using LabVIEW, and Statistica (trial version, V13.2, Dell Inc., USA).

III. Methods

A. Volunteers

Eleven female volunteers (in the age group of 20-24 years) were invited to take part the study. All of them were students in the Department of Biotechnology and Medical Engineering at NIT Rourkela. The volunteers were verbally informed about the study in detail. The volunteers were requested to sign an informed consent form after they agreed to take part in the study as per WHO guidelines. The ethical approval for acquiring the ECG signals was received from the Institute ethical clearance (IEC) committee of NIT Rourkela (Ref. No.: NITRKL/IEC/ FORM/2/25/4/11/001, Dated: 13/12/2013). The volunteers were advised to make a visit to the ECG recording station at the Department of Biotechnology and Medical Engineering, NIT Rourkela on the 1st day of phase-1 of their menstrual cycle. ECG signals were acquired in lead-1 configuration of Einthoven's triangle for 6 min after they sat comfortably on a chair. These ECG signals were categorized under Category-N. Then, they were made to watch a humorous audio-visual clip. ECG signals were again acquired in the post-stimulus condition for 6 min and were labeled under Category-S.

B. HRV Analysis

HRV analysis was performed on 5 min recordings of the acquired ECG signals using the biomedical Workbench toolkit of LabVIEW 2013. A band-pass filter (10-25 Hz) was used to detect the QRS complexes, which in turn, were further used to extract the RR intervals. The RR intervals were given as input to the HRV Analyzer Toolkit of LabVIEW and 29 HRV features were extracted. These HRV parameters were subjected to t-test and decision tree based statistical analyses, namely, classification and regression tree (CART), boosted tree (BT) and random forest (RF) using Statistica software for identifying the statistically important features (i.e., important predictors). The important predictors were compared to understand the ANS activity during the pre- and post-stimulus conditions and subsequently used as input to implement ANN classification. The conventional Multilayer Perceptron (MLP) and Radial Basis Function (RBF) networks were used as the ANN networks.

C. Time-Domain Analysis of ECG

A LabVIEW program was used to process the 6 minute ECG recordings for obtaining 5 sec ECG signals. Time-domain features, namely, energy density (ED), log energy (LE), Shannon entropy (SE), arithmetic mean (AM), standard deviation (SD), root mean square value (RMS), variance, kurtosis, skewness, summation (SUM), mode and median were calculated using a LabVIEW program . The important predictors among the features were estimated and classified subsequently using ANN.

IV. Results and Discussion

A. HRV Analysis

HRV can be defined as the quantification of the deviation in the time interval between successive cardiac cycles. It is a non-invasive method which provides an indication of the ANS activity [1]. A total of 29 HRV parameters were obtained using time-domain statistical analysis, frequency-domain power spectral analysis and non-linear Poincare analysis of the RR intervals. The time-domain statistical parameters included RR mean, RR standard deviation (RR SD), heart rate mean (HR mean), heart rate standard deviation (HR SD), RMSSD, NN50, pNN50, RR triangular index and TINN [8]. The parameters obtained from the frequency-domain power analysis were very-low-frequency (VLF) power, low-frequency (LF) power, high-frequency (HF) power, VLF%, LF%, HF%, LF norm, HF norm and LF/HF ratio [9]. The Poincare analysis provided two parameters, namely, SD1 and SD2. However, none of these HRV parameters were obtained as statistically important from t-test (with $p \leq 0.05$). The CART analysis suggested HR SD to be only important predictor (Table I). The BT and the RF analyses suggested VLF% and HF norm as the important predictors. The power spectrum of the short-term ECG signal consists of three different regions, i.e., VLF power, LF power and HF power [9]. The frequency range of VLF power, LF power and HF power has been reported to be 0.00-0.04 Hz, 0.04-0.15 Hz, and 0.15-0.40 Hz, respectively [9]. These power spectral components are also expressed as a percentage of the total power. For example, the ratio of VLF power to total power is expressed as VLF%. Apart from the above-mentioned representations, LF and HF powers are also expressed in normalized units (n.u.). For example, HF norm can be defined as the ratio of HF power to total power-VLF power as given in Equation 1 [9].

$$HF\ norm\,(n.u.) = \frac{HF\ Power\ (ms^2)}{Total\ Power\ (ms^2) - VLF\ Power\ (ms^2)} \ldots\ldots(1)$$

It has been reported that VLF power is a marker of the parasympathetic activity, since this can be suppressed by atropine administration [5]. In our study, a higher value of VLF% suggested a dominant parasympathetic activity in the post-stimulus condition. Kleiger *et al.* (2005) have reported that the normalized value of HF power, the normalized value of LF power and the LF/HF ratio can be used to obtain a better estimate of sympathetic activity (“ying-yang” model) [5]. In our study, HF norm (n.u.) was found to be less in the post-stimulus condition. However, both the LF norm and the LF/HF ratio (statistically insignificant; hence, not shown) also decreased in the post stimulus condition. This might be due to the reduction in the sympathetic activity [5].

In summary, the statistically important parameters suggested a parasympathetic dominance (associated with a reduction in the sympathetic activity) during the post-stimulus condition. ANN classification of the HRV data was performed using the statistically important predictors as the categorical inputs to MLP and RBF networks. Out of the total number of samples, 80% samples were used for training and 20% were used training during the ANN classification. The MLP (3-3-2) and RBF (3-10-2) networks resulted in the overall classification efficiencies of 95.00% and 86.36%, respectively. The classification summary of the MLP (3-3-2) and RBF (3-10-2) networks have been provided in Table II and III and their architectural details are summarized in Table IV.

B. Time-Domain Analysis of ECG

The calculated parameters were found to be statistically insignificant from t-test. But, the non-linear decision tree-based analyses (i.e., CART, BT and RF) indicated that AM, Kurtosis, SUM and Skewness were statistically important predictors with predictor importance ≥ 0.95 (Table V). This indicated that the ECG parameters can be classified in a non-linear space. Hence, it can be summarized that the audio-visual stimulus altered the cardiac activity. The MLP (4-13-2) and the RBF (4-14-2) ANN networks provided classification efficiencies of 95.45% and 90.91% respectively (Table VI and VII), for the pre- and post-stimulus ECG data, when AM, kurtosis, SUM and skewness were used as the categorical inputs. The architectural details of the networks are summarized in Table VIII. This further confirmed the alteration in the cardiac activity during post-stimulus stages.

TABLE I. STATISTICALLY IMPORTANT HRV PREDICTORS

Methods	HRV Features	Mean ± SD		Predictor Importance
		Category-N	Category-S	
CART	HR SD	39.39±47.61	41.19±51.56	1.00
BT	VLF (%)	11.46±6.95	15.84±7.33	1.00
RF	HF norm (n.u.)	43.51±12.04	39.94±13.98	1.00

TABLE II. CLASSIFICATION DETAILS OF MLP 3-3-2 NETWORK

	Category-N	Category-S	Overall
Total	11.00	11.00	22.00
Correct	11.00	10.00	21.00
Incorrect	0.00	1.00	1.00
Correct (%)	100.00	90.00	95.00
Incorrect (%)	0.00	10.00	5.00

TABLE III. CLASSIFICATION DETAILS OF RBF 3-10-2 NETWORK

	Category-N	Category-S	Overall
Total	11.00	11.00	22.00
Correct	10.00	9.00	19.00
Incorrect	1.00	2.00	3.00
Correct (%)	90.91	81.82	86.36
Incorrect (%)	9.09	18.18	13.64

TABLE IV. ARCHITECTURE DETAILS OF MLP AND RBF NETWORKS

Networks	Features used	Classification Accuracy	Training Performance	Test Performance	Algorithm	Error Function	Hidden Activation Function	Output Activation Function
MLP 3-3-2	HR SD, VLF% and HF norm (n.u.)	95.00%	94.44%	100.00%	BFGS 18	SOS	Exponential	Logistic
RBF 3-10-2	HR SD, VLF% and HF norm (n.u.)	86.36%	81.25%	100.00%	RBFT	Entropy	Gaussian	Softmax

TABLE V. STATISTICALLY IMPORTANT FEATURES OBTAINED FROM TIME-DOMAIN ANALYSIS OF ECG

Methods	Time Domain Features	Mean ± SD		Predictor Importance
		Category-N	Category-S	
CART	AM	-0.00033±0.000492	0.00002±0.000900	1.000000
	Kurtosis	11.88786±4.526302	12.45146±4.280840	0.964898
	SUM	-1.64354±2.458640	0.08824±4.498494	1.000000
BT	AM	-0.00033±0.000492	0.00002±0.000900	1.000000
	SUM	-1.64354±2.458640	0.08824±4.498494	1.000000
RF	Skewness	2.34245±0.806185	2.37037±0.732220	1.000000

TABLE VI. CLASSIFICATION DETAILS OF MLP 4-13-2 NETWORK

	Category-N	Category-S	Overall
Total	11.00	11.00	22.00
Correct	10.00	11.00	21.00
Incorrect	1.00	0.00	1.00
Correct (%)	90.91	100.00	95.45
Incorrect (%)	9.09	0.00	4.56

TABLE VII. CLASSIFICATION DETAILS OF RBF (4-14-2) NETWORK

	Category-N	Category-S	Overall
Total	11.00	11.00	22.00
Correct	10.00	10.00	20.00
Incorrect	1.00	1.00	2.00
Correct (%)	90.91	90.91	90.91
Incorrect (%)	9.09	9.09	9.09

TABLE VIII. ARCHITECTURE DETAILS OF MLP AND RBF NETWORKS

Networks	Features used	Classification Accuracy	Training Performance	Test Performance	Algorithm	Error Function	Hidden Activation Function	Output Activation Function
MLP 4-13-2	AM, SUM, Kurtosis, Skewness	95.45%	100.00%	100.00%	BFGS 63	SOS	Exponenti al	Logistic
RBF 4-14-2	AM, SUM, Kurtosis, Skewness	90.91%	100.00%	100.00%	RBFT	Entropy	Gaussian	Softmax

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V. CONCLUSION

In this study, we have tried to determine the alteration in the ANS and the heart activity of females when subjected to a humorous audio-visual stimulus. ECG signals were acquired from eleven female volunteers during pre- and post-stimulus stages. HRV analysis was performed to understand the ANS activity. An increase in the parasympathetic activity was observed in the post-stimulus condition from the HRV analysis. The mean heart rate was found to be statistically insignificant. Time-domain ECG analysis was performed to find out the existence of any alteration in the electrical activity of the heart in the post-stimulus condition. Some of the time-domain ECG features were found to differ significantly between the pre- and post-stimulus conditions, suggesting an altered cardiac activity in the post-stimulus condition. However, an in-depth analysis has to be performed to figure out the exact alteration in the electrical activity of the heart. The current study was preliminary in nature and provided encouraging results. As the size of the populations (i.e., Category-N and Category-S) involved in this study was small, effort will be made to involve a higher population size during future studies for proper validation of the results.

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