Comparison of Electrocardiogram Signals in Men and Women during Creativity with Classification Approaches

Sahar ZAKERI, Ataollah ABBASI[*], Ateke GOSHVARPOUR

Computational Neuroscience Laboratory, Department of Biomedical Engineering, Faculty of Electrical Engineering, Sahand University of Technology, Tabriz, PO. BOX 51335/1996, Iran
E-mails: s_zakeri@sut.ac.ir, ata.abbasi@sut.ac.ir, ak_goshvarpour@sut.ac.ir

[*] Author to whom correspondence should be addressed; Tel.: +98 4133459356; Fax: +98 4133444322

Abstract
Electrocardiogram (ECG) analysis is mostly used as a valuable tool in the evaluation of cognitive tasks. By taking and analyzing measurements in vast quantities, researchers are working toward a better understanding of how human physiological systems work. For the first time, this study investigated the function of the cardiovascular system during creative thinking. In addition, the difference between male/female and normal/creativity states from ECG signals was investigated. Overall, the purpose of this paper was to illustrate the heart working during the creativity, and discover the creative men or women subjects. For these goals, six nonlinear features of the ECG signal were extracted to detect creativity states. During the three tasks of the Torrance Tests of Creative Thinking (TTCT- Figural B), ECG signals were recorded from 52 participants (26 men and 26 women). Then, the proficiency of two kinds of classification approaches was evaluated: Artificial Neural Network (ANN) and Support Vector Machine (SVM). The results indicated the high accuracy rate of discriminations between male/female (96.09%) and normal/creativity states (95.84%) using ANN classifier. Therefore, the proposed method can be useful to detect the creativity states.

Keywords: Creativity; Artificial Neural Network; Electrocardiogram; Gender; Nonlinear Features; Support Vector Machine

Introduction

Research on human ingenuity is increasing and many studies are designed to explore talent and creativity [1]. There is no agreement about the definition of creativity and several theories have been proposed to explain it [2]. Other researchers, such as Torrance Harrington [3, 4], believed that creativity is a means to affect personal factors such as motivation, emotions, feelings, experiences and personal learning. Some researchers, such as Guilford [3] proposed that creativity and cognitive dimension depend on higher mental processes such as thinking, intelligence, imagination, and associated information processing. Sternberg [5] showed that creativity is a multivariate phenomenon. This means that factors such as community, family, personality and cognitive abilities impact on creativity, simultaneously. In general, the selection of applicable test to measure the level of creativity is important. Dr. Paul Torrance designed a creativity test that it includes of four factors: flexibility, fluency, originality, elaboration. The

development of the Torrance Test of Creative Thinking (TTCT) was known in 1966 [5], which have been translated into more than 35 languages. In this research, this test was used in Persian Language. One of the most common forms of TTCT is figural (Form B), which has three separate tasks (see figure 1). Each task is scored by four parameters:

- Originality: Stretching or shifting the mind to generate a variety of categories
- Elaboration: Many responses within a category
- Flexibility: Unique ideas that are relevant, but not obvious
- Fluency: Adding details for interest or clarity [4]
- For ideas that have been seen in more than 5% of the participants, zero points are given, between 4-4.99% of participants ideas, 1 points, between 3-3.99%, 2 points, between 2-2.99%, 3 points, between 1-1.99%, 4 points and for less than 1%, 5 point are given [4].
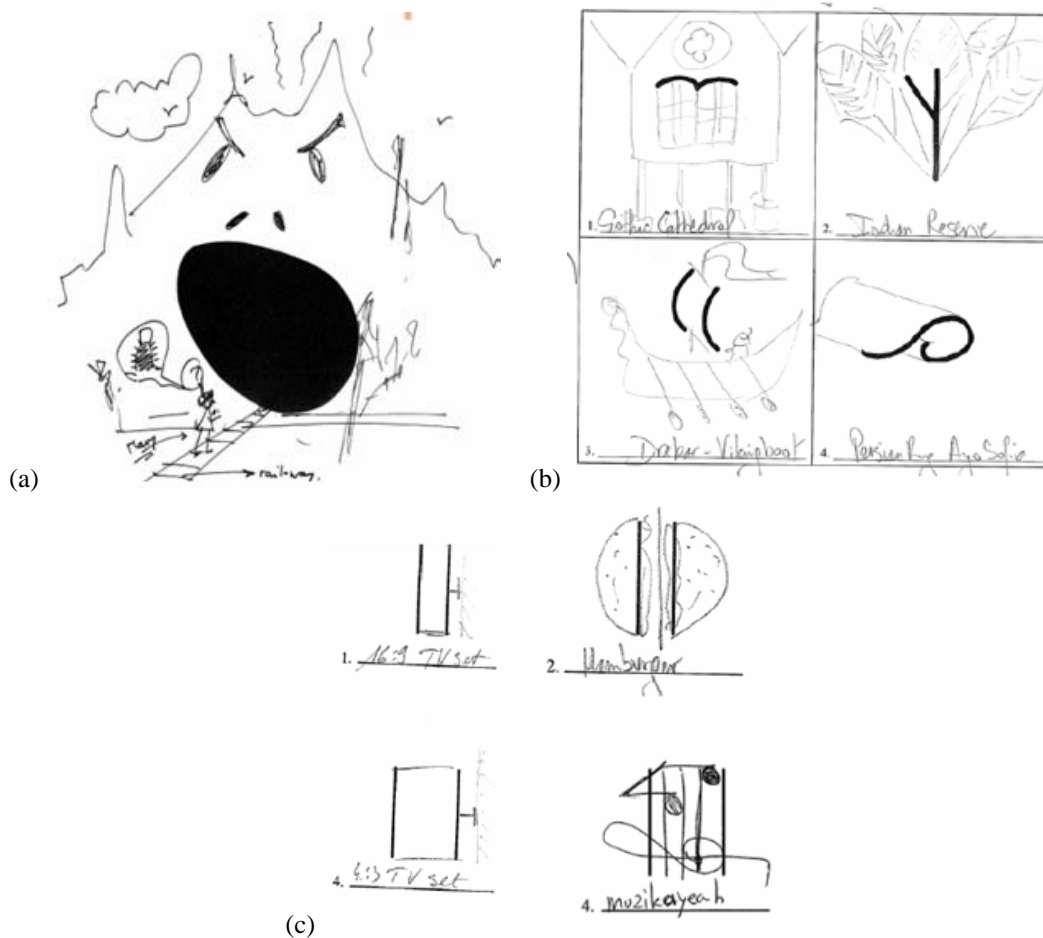

Figure 1. A completed example of three tasks of the Torrance Tests of Creative Thinking (TTCT) by one participant, (a) Task 1: picture construction, the bold black area was supplemented with mountain and other details, (b) Task 2: picture completion, bold black lines were supplemented with house, leaves and etc., (c) Task 3: lines, bold black lines were supplemented similarly too [6].

In accordance with the results of cognition research about the interaction of creativity in creative spaces, neuroscientific studies have shown these abilities correlated with the structure of intelligence, such as analysis and evaluation, those abilities associated with creativity such as the mix of complex, original and creative treatment, all have their foundation in the prefrontal

cortex [7]. Nowadays, many investigations on electrocardiogram (ECG) are progressing. The electrical activity of the heart could be recorded from digital signals [8]. The Myogenic rhythm of the heart works with the ability to beat orderly, that activity is regulated by the central nervous system [9, 10]. Researches use ECG signals to detect many types of heart arrhythmia [11, 12], such as non-ectopic beats, supra-ventricular ectopic beats, ventricular ectopic beats, fusion beats and unclassifiable, Atrial Fibrillation [13] Bradycardia and Tachycardia [14]; as well as prediction of cardiovascular death [15]. The heartbeat shows dynamic, nonlinear and nonstationary behavior [16-18]. Linear analysis of cardiac function involves delicate and detailed interactions between regulatory mechanisms [19]. So, nonlinear methods have been proposed. In previous studies, the role of this signal is confirmed in the cognitive tasks, but the dynamic analysis of the creative modes of normal signal has not been investigated. Many researches have done with morphological features, such as the QT interval to detect the type of arrhythmia [14, 15]. Others have examined linear and nonlinear features achieved from the ECG signal [12, 13]. Elhaj et al. [11] found that compared with linear features, nonlinear features characterize the ECG signal more effectively sense and extract hidden information in the signal. Also, these features achieve good efficiency under noisy conditions [11].

Formerly, Electroencephalography (EEG) signals were used in the detection of creativity levels [20]. Most of these studies have been done statistically and detailed analysis based on feature extraction methods has not been performed. In addition, the role of physiological signals such as ECG has not been studied. The registration of ECG signals is easy and it is less affected by noise. Although the EEG has important features such as phase, power and synchronization [21-23], the most important objection to it is the limited spatial resolution in the nervous processes. Furthermore, because of the EEG recording limitations and its sensitivity, researchers are forced to choose specified creativity tests which cause the least motion artifacts. Previously, the scientist investigated effects of age and gender on the creativity. They have found that females generally had a better performance in creative tasks than males. Originality and flexibility were stronger in men and women in adding details [24]. Also, the creative ability of older people and adolescents were less likely than that of the younger people [25]. Applying physiological tests and studying EEG or MRI, some scientists have shown that women are more creative [26-30], although totally [27-30]. In the current study, we used ECG signals and applied its features to separate creative subjects based on their gender. In many situations, the ECG is recorded during disease [17] and cognitive behavior [19] conditions such that the signal is corrupted by different types of noise, sometimes originating from the other physiological processes of the body. Hence, noise reduction represents another important objective of the ECG signal analysis. Once the information produced by the basic set of algorithms is available, a wide range of ECG applications exists that researchers can use them to signal processing for quantifying heart rhythm and beat morphological properties. Up to now, there is no study for the classification of creativity levels of female/male applying nonlinear features of the ECG signal. In this paper, we study the effect of creativity on ECG signal using six nonlinear features to separate creativity steps and also female from male. In our previous studies, linear features such as: RMSD (root mean square deviation), mean, median, variance, maximum, minimum, energy, power, Normal to Normal 50ms were verified to detect creativity tasks. The results showed the significant difference between task 1 and 2 [31]. Moreover, the power spectral density, ultra-low frequency (ULF), very low frequency (VLF), low frequency (LF) and high frequency (HF) were also checked. These features are the good pointers of sympathetic and parasympathetic function, where sympathetic nerve activity is determined in the HF band and LF shows sympathetic and parasympathetic modulation of the heartbeat. The findings indicated that ECG signal's power decreases at VLF and LF rather than HF, in the later stages of the creativity test [6].

The aim of this article was evaluated the creativity level of participants using physiological signal analysis. To this end, ANN and SVM in combination with nonlinear features extraction approaches were applied to ECG signals. The proposed methodology has been examined physiological of male/female separately.

Material and Methods

In Figure 2, the study process has been shown. After ECG recording and preprocessing, nonlinear features were extracted and data matrix is attributed to classifiers. Then, each of the normal and creativity states was separated. As such, the differences between two groups of male and female were shown. The resulted six features vector is fed to Artificial Neural Network (ANN) and Support Vector Machine (SVM) system for classification. On the basis of performance, the fit classifiers were chosen to detect creative group.
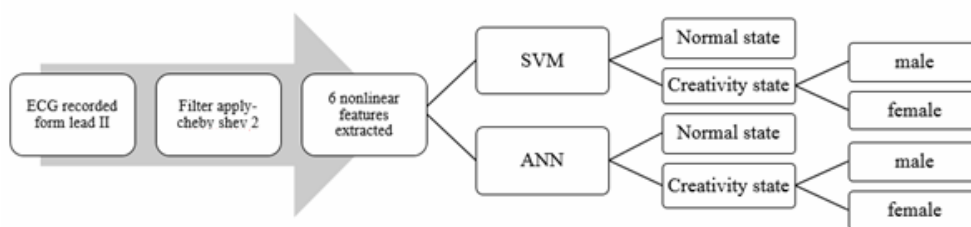

Figure 2. The block diagram of classification process

ECG Recording

In this article, the ECG signal was collected from 52 students (biomedical engineering, material engineering and control engineering, 26 female and 26 male). The subjects were asked not to drink coffee for 5 hours before the experiment and have enough sleep to not feel tired and reach accurate signals. First, all tasks were explained. They sat on a comfortable chair and ECG electrodes were connected to their wrist. Participants presented in the lab about an hour earlier. The supervisor spoke with the subjects to feel relaxed. The ECG signals recorded from lead II, 2-minutes of rest states and 30-minutes during the TTCT. Sample frequency of ECG signals was 1000 Hertz. The signals were filtered between 0.4 Hz and 250 Hertz with Chebyshev 2 (filter order 4). An additional 50 Hertz notch filter was applied to eliminate power line contamination. Electrode impedances were below 5 kΩ. The window length considered 5sec with no overlap. All signals were recorded in the Computational Neuroscience Laboratory of Sahand University of Technology.

Table 1 shows mathematics of two filters that were applied to ECG signals for noise reduction.

Table 1. Mathematics of Chebyshev 2 and notch filters

The transfer function of Chebyshev 2 (filter order 4, band pass 0.4-250Hz)#	Notch filter (cutoff frequency 50Hz): band-stop filter with a narrow stop band (high Q factor)
$$\| H(j\Omega) \|^2 = \frac{1}{1 + \varepsilon^2 T_N^2 \left(\frac{\varpi}{\varpi 0} \right)}$$ where ε is a ripple factor, $\omega 0$ is the cutoff frequency and T_n is a Chebyshev polynomial of the nth order. A ripple amplitude of 3dB results	$$f_{notch} = \frac{1}{2\pi RC}$$ $$\frac{V_{out}}{V_{in}} = \frac{Z}{Z+R}, \ Z = j\varpi L - \frac{j}{\varpi C}$$ $$Q = 2\pi L f_{notch}$$

from $\varepsilon = 1$.

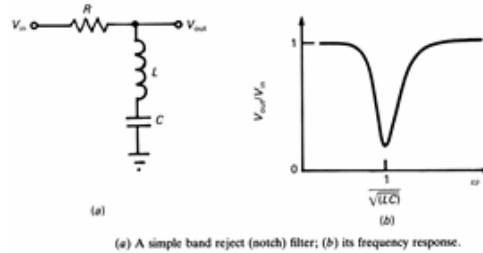*(a)* A simple band reject (notch) filter; *(b)* its frequency response.

Figure 3, displays one of the participants ECG signals before and after applying filters. According to this figure, power line noise in 50Hz has been eliminated (figure 3 a, b) and environmental and motion artifacts have been reduced in ECG signal (Figure 3 c, d).
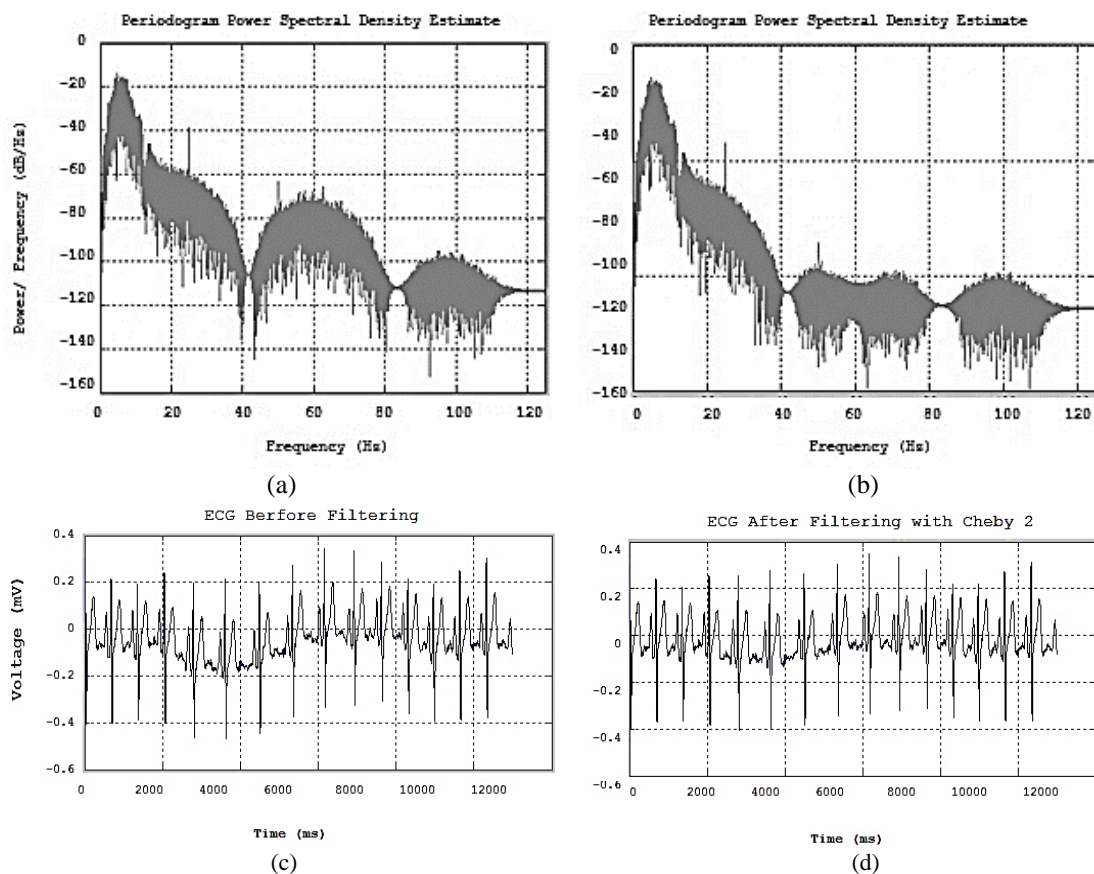

(a)

(b)

(c)

(d)

Figure 3. (a) power spectral density of ECG signal before applying a notch filter, (b) power spectral density of ECG signal after applying a notch filter, (c) ECG signal before applying Chebyshev 2, (d) ECG signal after applying Chebyshev 2.

Feature Extraction

Nonlinear methods have proven to be more useful for the analysis of nonstationary and nonlinear methods. They can capture subtle changes in the signals. Hence, we have used nonlinear methods to extract the features in the ECG signals. In this part, the nonlinear features (four kinds of Entropy, Fractal Dimension (FD) and Detrended Fluctuation Analysis (DFA)) extracted for further analysis are explained.

Fractal Dimension. The FD of a signal represents a strong tool for transient detection. This feature has been used to analyze ECG and distinguish specific conditions of physiological functions. There are several algorithms to define the FD of the waveform [32]. Amongst the others algorithms, Higuchi and Katz algorithm were chosen [29]. According to this method, the FD can be defined as:

$$D^{katz} = \frac{log(L)}{log(d)} \tag{1}$$

where L is the length of the wave, and d is the diameter approximation as the distance between the first point of the trail and the most distant points of the trail, d can be expressed as:

$$d = max\|x(1) - x(i)\| \tag{2}$$

where $X(1)$ is the first sample and $x(i)$ represents the ith sample of the ECG signal. The FD compares the actual number of units that compose a curve with the minimum number of units required to reproduce a pattern of the same spatial extent. FDs computed in this fashion depend upon the measurement units used. If the units are different, then so are the FDs. Katz algorithm solves this problem by creating a general unit: the average distance between successive points, a. Normalizing the distances, D^{katz} is given by:

$$FD = \frac{log(L/a)}{log(d/a)} \tag{3}$$

Detrended Fluctuation Analysis (DFA). Detrended fluctuation analysis (DFA) is used to quantify the fractal measurement properties of short interval. This technique is a correction of root mean square (RMS) analysis of random steps applied to nonstationary waves. The RMS fluctuation of an integrated and detrended time series is measured at different observation windows and plotted on a log-log scale. In this research, Pan-Tompkins algorithm was used to detect R peaks from ECG. First, the *RR* interval time series x is integrated as follows:

$$y(k) = \sum_{i=1}^{k} \left[x(i) - x_{average} \right] \tag{4}$$

where $y(k)$ is the kth value of the integrated series, $x(i)$ is the ith RR interval and x average is the mean of the RR intervals over the whole series. Then, the conjunct time series is divided into windows of equal length n. The root-mean-square fluctuation of this conjunct and detrended series is calculated using the equation:

$$root\ mean\ square\ fluctuation : F(n) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} \left(y(k) - y_n(k) \right)^2} \tag{5}$$

This calculation is repeated over all time scales to obtain the relationship between $F(n)$ and the window size n (the number of points, here RR intervals, in the window of observation) [33].

Entropy. Entropy shows signal regularity, randomness and allows signals to be quantified by the rate of information loss or generation [34]. It is defined as:

$$H_a(p_1, p_2, p_3, ..., p_n) = -\frac{1}{1-a} \ln \sum_{i=1}^{n} p_i^n \tag{6}$$

where a>0

"p_i" is the probability of a symbol. The entropy provides a lower limit for the compression that can be acceded by the data coding compression walks. Entropy displays the amount of

"disorder" of a signal [35]. The specific regions of the hypothalamus coordinated by control of sympathetic and parasympathetic activities, such as temperature regulation, the reproductive cycle, emotional expression and behavior. The heartbeat is influencing the parasympathetic nerves. So, if ECG was studied, results can investigate the brain function during the TTCT.

All the nonlinear features discuss about complexity and chaos of ECG signals, and we can use this information to determine what happens during the creative thinking, then we can detect male from female whom are more creative.

Classifier

Support Vector Machine. Support Vector Machine (SVM) classification was applied to the ECG signals [36]. Since the SVM is known to have the advantage of offering a solid performance of classification with even smaller learning data. The SVM classification with "RBF" Kernel function [37], "SMO" methods, sigma=0.2 and box constraint=2.5 were used in this research to classify the ECG signal data in which C parameters were optimized. Three parameters, namely accuracy, sensitivity and specificity were used to determine the performance of the SVM classifier. The value of the accuracy shows the overall detection accuracy, sensitivity is defined as the ability of the classifier to accurately recognize a true case and specificity would indicate the classifier's ability not to generate a false negative (normal subject to creative case). These parameters are defined:

$$Accuracy = 100*(TP+TN)/n \tag{7}$$

$$Sensitivity = 100*TP/(TP+FN) \tag{8}$$

$$Specificity = 100* TN/(TN+FP) \tag{9}$$

where n is the number of input samples, TP is the number of positive correctly identified, TN is the number of correct negatives identified, FP is the number of false recognition with positive label and FN is the number of false recognition with a negative label.

Artificial Neural Network (ANN). An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex by computer techniques. This ability to learn by example makes them very flexible and powerful [38].

Results and Discussion

Gender

The first task of TTCT has two parameters to score; originality and elaboration, while second and third tasks have four parameters to score; originality, elaboration, flexibility and fluency. After the extraction of TTCT scores, z transform and normalization is applied to range these scores. Therefore, all scores placed on the range of zero to 100 points. Comparisons between males and females signals indicated that the level of women creation is higher than that of men in all four TTCT's scales (see Table 2). Although, previous studies in the psychology field showed girls are more creative than boys in a TTCT, but in this paper for the first time to the identification and separation, intelligent algorithms were evaluated from the perspective of biomedical engineering [24].

Table 2. The mean score (standard deviation of the three tasks of TTCT for men and women

	Originality	Elaboration	Flexibility	Fluency
Women	53.44±30.90	54.16±24.64	52.96±22.60	56.30±24.12
Men	46.03±21.54	42.21±25.78	46.23±16.82	46.02±22.77

Alterations in nonlinear features are shown in Table 3. Significant differences between the male/female groups were displayed by the Wilcoxon test ($p < 0.05$). According to Table 2, FD, DFA and wavelet norm entropy have significant differences between men and women in task 1 of TTCT, but other features do not have. Also, significant differences have not been observed in other tasks.

Table 3. P value of nonlinear features in task 1 of TTCT

Features	FD	DFA	Renyi entropy	Wavelet Shannon entropy	Wavelet norm entropy	Wavelet log entropy
Male vs. Female	<0.0001[*]	<0.0001[*]	0.3928	0.0804	0.0014[*]	0.3951

In this article, six parameters (DFA, FD, Renyi Entropy, Wavelet Shannon Entropy, Wavelet Norm Entropy and Wavelet Log Entropy) were used. It can be seen in Figure 4 that the DFA, Renyi entropy and wavelet Norm entropy values are increased during the task 1, but FD and wavelet entropy log are decreased. Most features have less value in the female subjects compared to the male. After all tasks, the value of each feature is less than the initial value. In contrast, the wavelet Shannon and wavelet Log entropy features have increased.

SVM Classifier Results

The best results are achieved with kernel functions and radial basis function (RBF). The maximum performance of the SVM classifier reached from task 1. Respectively, its accuracy, sensitivity and specificity were 91.74%, 91.69% and 91.75% between two groups of gender. Other tasks didn't have optimal results and to avoid prolonging the report, their results were not reported. Three classes are defined to compare extracted features from ECG signals in task 1 with the normal state and other TTCT tasks: class A (normal vs. task 1), class B (task 1 vs. task 2) and class C (task 1 vs. task 3). Table 4, shows SVM results of creativity states in three different classes and a maximum accuracy with SVM classifier was observed in group "A".

Table 4. SVM classification results with nonlinear parameters between normal and creativity states

	Accuracy (%)	Sensitivity (%)	Specificity (%)	Error (%)
A	**91.36**	**90.00**	**92.71**	**0.9**
B	85.41	88.22	82.72	0.15
C	86.55	89.32	84.27	0.14

ANN Classifier Results

All features applied on Artificial Neural Network with 50 hidden layers. Levenberg-Marquardt back propagation algorithm was chosen to train ANN. Table 5 shows Mean square error (MSE) as output of the ANN between two groups of male and female in task 1 of TTCT.
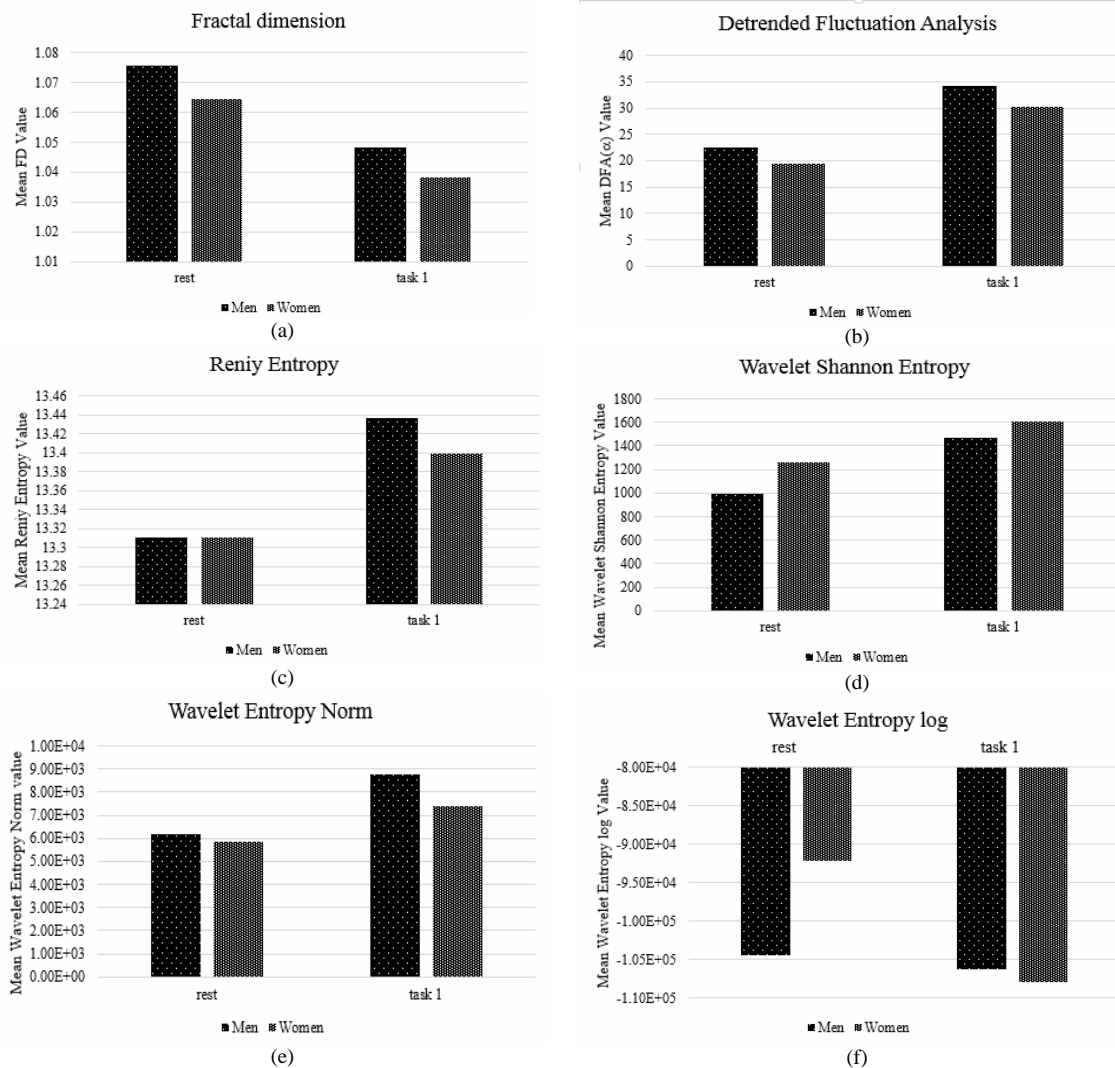
Figure 4. Nonlinear parameters distribution diagram for creating tasks and normal states. a) FD, (b) DFA, (c) Renyi entropy, (d) Wavelet Shannon entropy, (e) Wavelet norm entropy, (f) Wavelet log entropy.

Table 5. MSE on NN classification results using nonlinear parameters between male-female

	Layer	5	10	15	20	50
Task 1	MSE	0.125	0.0934	0.0768	0.0701	**0.0391**
	Epoch	28	46	50	45	53

The error of the ANN was lower for task 1 with 50 layers and 53 epochs than other tasks between two groups, as shown in Table 5. Table 6 shows MSE in ANN between task 1 and other TTCT tasks. Table 6, indicates less error happened with 50 layers and of these class lower error (0.04) belonging to class "A". In figure 5, the error of two classifiers was compared. It reports the summary of accuracy percentage classification of these classifiers on men and women's groups using ECG signals. In Figure 5, the error diversity of structural classifiers including SVM and ANN classifier is demonstrated that ANN error was less than the SVM. So, the ANN's performance is better than the other network to separate two creative groups of men and women.

Table 6. MSE of ANN classification results using nonlinear parameters creativity states and normal

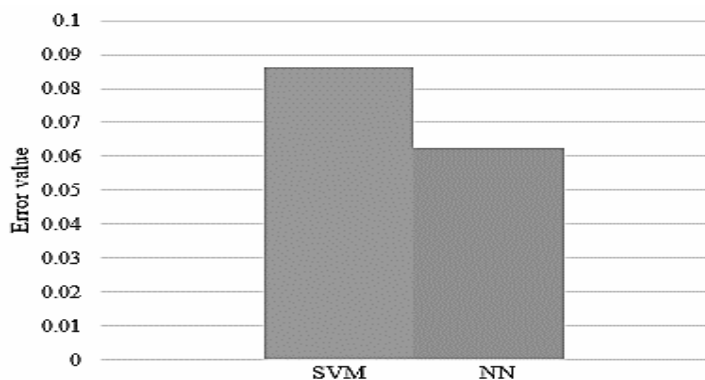|		5	10	15	20	50
	Layer	5	10	15	20	50
A	MSE	0.123	0.109	0.0824	0.0604	**0.0623**
	epoch	304	61	49	114	49
B	MSE	0.155	0.136	0.134	0.124	0.101
	epoch	43	34	22	43	41
C	MSE	0.158	0.131	0.126	0.0938	0.0873
	epoch	32	38	24	55	41

Figure 5. The error diversity of two structural classifiers including SVM and ANN classifier in task 1 among men and women

For the first time, TTCT effects on ECG signals were studied using six nonlinear features. Since, no study has been done in this field; the results cannot be compared with the work of others. Originally, many studies are done on EEG and heart rate (HR) signals during the other creativity tests [19]. These researchers showed that power of alpha band in EEG signals increases during the creative thinking. Some other researches worked on fMRI data [39]. The study from fMRI showed activation in the frontal lobe of creative people and those with low levels of creativity is clearly recognizable.

Previously, ECG analysis focused on the diagnosis of heart disease [10, 34]. But now it could show cognitive treatment like anxiety, nervousness and anguish from ECG signals [16, 17, 40, 41]. In our initial studies, by extracting linear features from the ECG signals, the significant difference between task 1 and 2 with the Wilcoxon tests [30] has been revealed, as well as decrement in VLF and LF rather than HF power, in the later stages of creativity test [6]. Also, our previous study indicated that heart rate variability (HRV) fluctuates during the TTCT activity [42]. Using frequency power analysis, significant differences in the originality, flexibility and elaboration scales between two groups with high and low creative [42] have been indicated.

Conclusion

According to the article, ECG signals are useful for detection of this type of cognitive behavior. Many studies on ECG signals using nonlinear parameter method will greatly aid in the understanding of the inner dynamics of the system. Already, Classification of creativity/normal states and male/female groups with ECG signals is not done, but now it is done in this paper for the first time.

This paper indicates that mostly extracted features have less value in the female rather than male during the creativity states. Finally, the proposed feature set achieved an accuracy of

96.09% with ANN, the accuracy of 91.74%, the sensitivity of 91.69% and the specificity of 91.75% with SVM network in task 1 of TTCT. In this research, we present a new solution to deal with the shortcomings of creative classification of the ECG signal. It shows that the proposed *ANN* performs better than SVM classifier. The average classification accuracy on the subset using *ANN* is higher than the other network.

Acknowledgements

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