A Review of Emotion Recognition Using ECG Signal based on Biological Signs

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ABSTRACT

Use of facial expressions to recognize an emotion is suitable for healthcare system because this technique recognizes emotions from a natural user interface: the face. Recognizing emotions from only facial expressions might fail to correctly classify human emotions, since humans sometimes hide their emotions from their appearance. Emotion recognition using biological signals: analyzes and recognizes human emotional states from such biological signals as electroencephalography (EEG), electrocardiography (ECG). Since, recognizing emotions by biological signals can solve this issue. Compared to other biosensors, ECG is the most widely used biosensor because ECG signals are less noisy and they contain emotion related information. Due to its un-mask able nature, compared to facial emotion recognition and speech analysis, bio-signal based methods provide highly accurate results.

Keywords: Electrocardiogram, Electromyogram, Galvanic Skin Response, Stochastic Gradient Descent, Deep Neural Network, Restricted Boltzmann Machine, Deep Boltzmann Machine

1. INTRODUCTION

Emotions, which affect both human physiological and psychological status, play a very important role in human life. Positive emotions help improve human health and work efficiency, while negative emotions may cause health problems. Long term accumulations of negative emotions are predisposing factors for depression, which might lead to suicide in the worst cases [4].

Emotion recognition has been applied in many areas such as safe driving, health care especially mental health monitoring, social security, and so on. In general, emotion recognition methods could be classified into two major categories. One is using human physical signals such as facial expression, speech, gesture, posture, etc., which has the advantage of easy collection and have been studied for years. However, the reliability can't be guaranteed, as it's relatively easy for people to control the physical signals like facial expression or speech to hide their real emotions especially during social communications. For example, people might smile in a formal social occasion even if he is in a negative emotion state [2]. The other category is using the internal signals—the physiological signals, which include the electroencephalogram (EEG), temperature (T), electrocardiogram (ECG), electromyogram (EMG), galvanic skin response (GSR), respiration (RSP), etc. [4].

1.2 ECG Signal

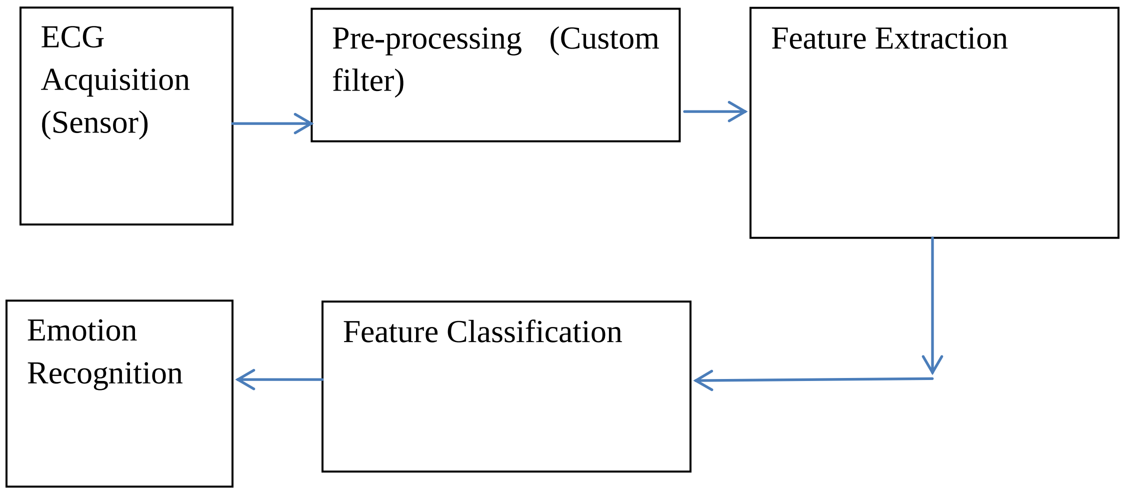

Figure 1: General Block Diagram of Emotion Recognition System

Signal Acquisition: Signals can be acquired by placing electrodes on skin (ECG)

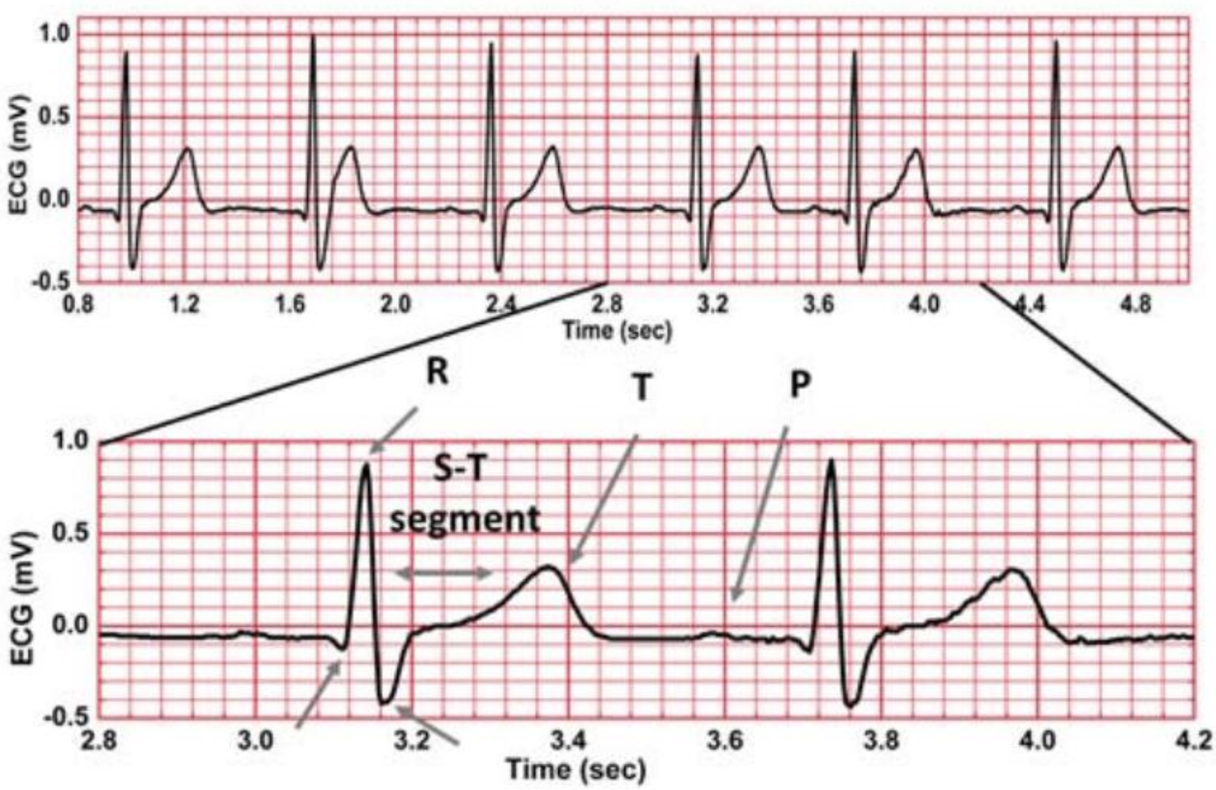

Figure 2: ECG Signal Waveform

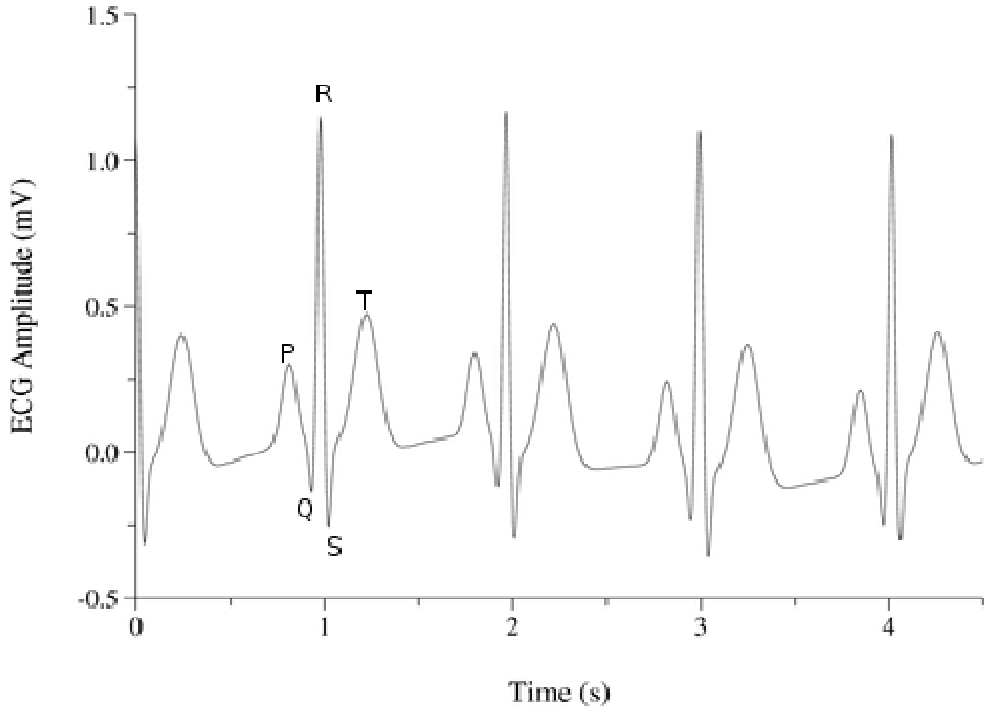

Figure 3: A waveform of PQRST-complex cycle generated by ECG signal

Pre-Processing: Since an ECG signal contains various noises, custom filters are used to remove power-line and narrow band noises caused by ECG sensor or user motion artifact based on specification of ECG sensor.

Feature Extraction:

When location of each wave on ECGs is located, several parameters that indicate each part of heart's activity can be calculated (RR-interval or HR, PR, QRS, ST, QT intervals, PR, and ST segments.

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Emotions Classification: Classifier is first trained with sample data of emotions and after training classifier recognises the emotions of human. For classification deep convolutional neural network (DCNN) architecture which ensures promising robustness-related results for both subject-dependent and subject-independent human emotion recognition are widely used.

1.3 Deep Learning

Deep learning can be generally considered to be sub-field of machine learning. ŒThe typical defining essence of deep learning is that it learns deep representations, i.e., learning multiple levels of representations and abstractions from data. For practical reasons, we consider any neural differentiable architecture as ‘deep learning‘as long as it optimizes a differentiable objective function using a variant of stochastic gradient descent (SGD). Neural architectures have demonstrated tremendous success in both supervised and unsupervised learning tasks [10] [11].

Basic terminologies of deep learning

- **Restricted Boltzmann machine (RBM):**A special BM consisting of a layer of visible units and a layer of hidden units with no visible-visible or hidden-hidden connections.
- **Deep Boltzmann machine (DBM):**A special BM where the hidden units are organized in a deep layered manner, only adjacent layers are connected, and there are no visible-visible or hidden-hidden connections within the same layer.
- **Deep neural network (DNN):**A multilayer network with many hidden layers, whose weights are fully connected and are often initialized (pre-trained) using stacked Restricted Boltzmann machine (RBM) or Deep Boltzmann machine DBN [11].

2. LITERATURE REVIEW

C.-H. Lin et al. [1] presented review of nonlinear features such as approximate entropy (APEN), largest Lyapunov exponent (LLE), correlation dimension (CD), Hurst exponent (H) and non-linear prediction error.

KanlayaRattanyu and Makoto Mizukawa [2] focused on emotion recognition for service robots in the living space based on Electrocardiogram (ECG). The authors applied a diagnosis method that uses both interbeat and within-beat features of ECG.**R.-N. Duan et al. [3]** reported that researchers are working on a number of physiological signals such as electroencephalogram (EEG), electrocardiogram (ECG), electromyogram (EMG), galvanic skin response (GSR) andblood volume pulse (BVP) to understand the underlying and true emotional state of the person.**Jerritta S et al. [4]** identified the six basic emotional states (Happiness, sadness, fear, surprise, disgust and neutral) from the QRS complex of electrocardiogram (ECG) signals. The author focused specifically on the nonlinear feature ‘Hurst exponent’ computed using two methods namely rescaled range statistics (RRS) and finite variance scaling (FVS).**SiaoZheng Bong et al. [5]** proposed methodology for feature extraction Time domain features: heart rate

(HR), mean R peak amplitude (MRAmp), and mean R-R intervals (MRRI) from ECG signals and mapped into emotional stress classification using K-nearest neighbor (KNN) and Support Vector Machine (SVM).**A. Mikuckas et al. [6]** proposed recognition by means of the heart rate variability (HRV) analysis, because it is a noninvasive method. The emotional state should be identified in the situations which correspond to real life at home: a person sits, walks, and changes his/her posture over time. The impact of the emotional state and the posture impact on heart rate variability are examined. Time domain, frequency domain and nonlinear parameters are calculated.**Tivatansakul et al. [7]** designed a healthcare system that focuses on emotional aspects to cope with negative emotions in daily life. Emotional healthcare system proposed by author integrates emotion recognition based on facial expressions and ECG signals to identify user emotions to provide appropriate services. The author adapted the local binary pattern (LBP) and local ternary pattern (LTP) which are favorable local pattern description methods for emotion recognition by facial expressions.**Christopher et al. [8]** reported that emotional intelligence is widely used to develop emotionally-aware healthcare monitoring systems, computer games and entertainment systems and safe driving systems. In computer games, emotional intelligence can be used to evaluate the player's active state for dynamic game content generation.**Ayata et al. [9]** developed an emotion recognition model to classify arousal and valence using galvanic skin response. The mentioned model incorporates features from empirical mode decomposition and statistical analysis methods.**Granados et al. [10]** applied the deep learning approach using a Deep Convolutional Neural Network (DCNN), on a dataset of physiological signals (Electrocardiogram -ECG and Galvanic Skin Response -GSR-), in this case, the AMIGOS dataset. The detection of emotions is done by correlating these physiological signals with the data of arousal and valence of this dataset, to classify the affective state of a person.**Lin Shu et al. [11]** presented a comprehensive review on physiological signal-based emotion recognition, including emotion models, emotion elicitation methods, the published emotional physiological datasets, features, classifiers, and the whole framework for emotion recognition based on the physiological signals.**Dissanayake et al. [12]** proposed a novel method using machine learning procedure of this investigation evaluated the performance of a set of well-known ensemble learners for emotion classification and further improved the classification results using feature selection as a prior step to ensemble model training. The model developed by author outperforms most of the multiple biosensor based emotion recognition models with a significantly higher classification accuracy gain.**Xiefeng et al. [13]** proposed two emotion evaluation indicators HRV of heart sounds (difference between successive heartbeats) and DSV of heart sounds (the ratio of diastolic to systolic duration variability). Then, the author extracted linear and nonlinear features from two emotion evaluation indicators to recognize four kinds of emotions.

Table 1: Findings of Emotion Recognition Approaches

Author	Year	Technique/Signal/Classifier	Accuracy(%)	Findings
KanlayaRattanyuand Makoto Mizukawa	2011	Diagnosis method based on interbeat and within-beat features of ECG.	61.44	Proposed approach reduced the amount of raw data by using analyzed value of ECG signals and statistical data in emotion recognition.
Jerritta S	2013	Nonlinear feature 'Hurst exponent' computed using two methods Rescaled Range Statistics (RRS) and Finite Variance Scaling (FVS) from ECG data.	70.23	Hurst computed FVS based method performs well on categorizing emotional states for the individual age groups.
SiaoZheng Bong	2014	ECG signals,K-nearest neighbor (KNN) and Support Vector Machine (SVM).	77.69, 61.48	Proposed QRS detection algorithm gives lower R peak error detection rate compared to our earlier work.

A. Mikuckas	2014	Heart Rate Variability (HRV) Analysis, ECG signals.	71	It was found that HRV parameters depend not only on the emotional state, but also on the human posture. The posture changes influence HRV parameters more than the changes in the emotional state.
Tivatansakul	2016	Local Binary Pattern (LBP) and Local Ternary Pattern (LTP), ECG signals, K-nearest neighbor (KNN).	84.17, 87.92	LBP and LTP effectively extracted ECG emotional features and produced high accuracy.
Granados	2018	ECG signals, Deep Convolutional Neural Network (DCNN).	76	The convolutional networks in comparison with the classic algorithms of machine learning demonstrated a better performance in the emotion detection in physiological signals.

Dissanayake	2019	Four feature extraction methods with machine learning procedure, ECG signals.	80.0	Combined features and the selected ensemble learners provide better performance compared to single learner models.
Xiefeng	2019	HRV of heart sounds (difference between successive heartbeats)and DSV of heart sounds (the ratio of diastolic to systolic duration variability), ECG signals.	96.87	Average accuracy rate for the HS DSV was lower than that for the HS HRV, when combining the features of HRV and DSV together to recognize emotions.

3. CONCLUSION AND FUTURE SCOPE

A number of studies have examined the use of ECG signals for emotion recognition. Most of the studies have used different analysis methods to extract features from ECG signals. An ECG based method is an adequate solution due to four important reasons. Firstly, the ECG signal is a result of activities in the heart that has nerve endings from the autonomic nervous system that governs the behavior of each emotion. Secondly, ECG sensors can be used as a wearable device. Thirdly, it is convenient to use because ECG signals can be captured from different parts of the body. Finally, it has high amplitude compared to other biosensors.

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