ECG-based Emotion Recognition: Overview of Methods and Applications

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Abstract*—*This paper presents an overview of recent methods for recognition of human emotions based on Electrocardiogram (ECG) signals and related applications. The major challenges in emotion modeling (affective computing) from ECG data are finding representations that are invariant to inter- and intra-subject differences, as well as the inherent noise associated with the ECG data recordings. The most common invariant features (in frequency and time domain) extracted from the raw ECG signals are outlined. The reviewed studies reveal the great potential of ECG to decode basic human emotional states such as joy, sadness, anger, fear in combination with other physiological signals and facial expression. Major application areas cover patient monitoring, marketing, car driving.

Keywords*— *ECG, emotion recognition, machine learning, neural networks, human–machine interface, Cyber Physical Systems with Human in the Loop

I. Introduction

The heart is one of the most critical organs in the human body, and electrocardiography (ECG) is considered to be one of the most powerful diagnostic tools in medicine that is routinely used for the assessment of the functionality of the heart. ECG being a physiological signal is used as the conventional method for noninvasive interpretation of the electrical activity of the heart in real time. But is usefulness not only in analyzing the heart's activity it can be also used for emotion recognition. Some of the physiological signals are highly used for classifying the human emotional state are: electroencephalogram (EEG), electrocardiogram (ECG), electromyogram (EMG), electrooculogram (EoG), skin conductive resistance (SCR), skin temperature (ST), and respiration rate (RR). Among these physiological signals, ECG and EMG play a vital role in developing portable, non-intrusive, reliable, and computationally efficient emotion recognition systems. Understanding human emotions using physiological signals is one of the active research areas on developing intelligent human–machine interface (HMI) systems and Cyber Physical Systems with Human in the Loop. One of the advantages of recognizing emotions and feelings using physiological signals is that these are unconscious responses of the human body, and therefore are very difficult to conceal.

The electrical cardiac signals are recorded by an external device, by attaching electrodes to the outer surface of the skin of the patient's thorax. These currents stimulate the cardiac muscle and cause the contractions and relaxations of the heart

The electrical signals travel through the electrodes to the ECG device, which records them as characteristic waves. Different waves reflect the activity of different areas of the heart which generate the respective flowing electrical currents.[1] On Fig 1. Is illustrated a schematic representation of a normal ECG and its various waves, where P-waves represent atrial depolarization, T-wave represents ventricular repolarization, the first deflection in the complex, if it is negative, is called a Q wave, the first positive deflection in the complex is called an R wave, a negative deflection after an R wave is called an S wave and finally U waves are thought to represent repolarization of the Purkinje fibers [2].

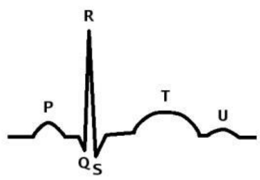

Figure 1. Normal ECG with the relevant waves
Source: https://upload.wikimedia.org/wikipedia/commons/a/ae/Qrs.png

Emotion recognition from ECG signal has become an important research topic in the field of affective computing. The future of facial expression recognition is the multimodal emotion sensing. An accurate and real-time emotion recognition system cannot be based only on images and video. It is important to use all the available modalities: voice, touch, physiological signals etc.

Potential application of emotion recognition based on physiological signals can be in the areas of marketing, intelligent gaming, health care and Ambient Assisted Living (AAL) [3]. One can only imagine the possibilities for health care such as analysis of emotions or detection of changes in mood as the disease progresses or as therapies kick in.

Marketing specialist could better gauge how viewers respond to their products and ads by following the changes in the heart rate. Smart cars might alter directions and stop if they perceive that driver is upset, confused or angry.

In this paper, we introduce recent advances in research on emotion recognition based on ECG signals. We examine the state-of-the-art results that have not been reviewed in previous survey papers. The rest of this paper is organized as follows. Section 2 describes the related scientific papers in the field. Section 3 provides a detailed review of practical scenarios and applications. Section 4 discusses some of the challenges and opportunities in this field and identifies potential future directions.

II. Overview of ECG-based Emotions Recognition Methods

In this section we discuss the most successful recent methods used to distinguish emotions extracted from the ECG signals. Detecting emotions through ECG signal is beneficial because the heart responses are involuntary and if we could hide our emotions behind the face, it is difficult to mask spontaneous heart reactions caused by emotions.

Emotion recognition procedure using ECG data undergoes a number of steps as illustrated in Fig. 2. Appropriate selection and combination of different machine learning methods applied at step 3 and step 4 define the recognition success. The addition step of feature selection (step 3.1) often is crucial for the correct emotional recognition. The following review is focused on steps 3, 3.1 and 4 as they have crucial implication on the correctness of the recognition.

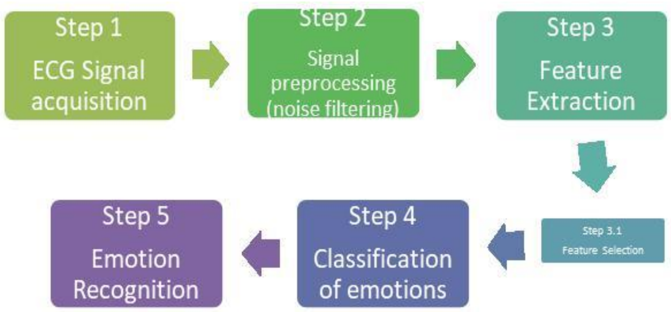

Fig. 2 ECG-based Emotion recognition process

Many affective computing methods are focused into binary classification of two emotions - Joy and Sadness. Most typically frequency domain features are extracted. Continuously Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT) are used in [4, 5, 6] for feature extraction. Afterwards feature selection methods were applied in order to select the best correlated features for the emotion recognition. Binary Particle Swarm Optimization (BPSO) and Hybrid Particle Swarm Optimization (HPSO) were combined with Genetic Algorithm (GA) in [7] for achieving best accuracy results of 92.10% for Joy, 100% for Sadness and 92.60% for Joy and Sadness in combination with HPSO.

Improved Binary Particle Swarm Optimization (IBPSO) and Improved Genetic Algorithm (IGA) were applied in [8] and K-Nearest Neighbor (KNN) and Fisher classifier have been used to distinguish between Joy, Sadness and both emotions, as the best performance is showed by the Fisher classifier with 88.90%, 88.70% and 88.89% respectively.

Automatic location of P-QRS-T wave and Discrete Wavelet Transform (DWT) defines the feature set in [9]. Tabu Search Algorithm (TS) has chosen the best features combinations to perform higher classification results. A Combination of Fisher and KNN classifiers has been used for distinguishing emotions, as well as to compare the performance between KNN and Fisher-KNN classifiers. Obtained results in distinguishing the two emotions Joy and Sandiness with 81.29% and 90.63% recognition rate respectively. Fisher-KNN classifier performed better recognition rate of 85.78% than KNN classifier (75.85%).

A combination of time and frequency domain features has been studied in [10]. Feature extraction was done by applying non-linear transformation on the 1st derivative of ECG (automatic location of QRS Complex) for feature extraction. Frequency domain features were extracted by the Fast Fourier Transform (FFT) of R-R, T-T and P-P heart rates. The best feature combinations have been selected by the means of Tabu search. Fisher Projection Classifier has been chosen to classify the recognized emotions.

For distinguishing between three emotional states Joy, Anger and Sadness, Local Pattern Description (LPD) methods are the preferred method in many recent papers. Local Binary Pattern (LBP) and Local Ternary Pattern (LTP) are used in [11] for feature extraction from the ECG Signal. To test and verify the performance a 10-fold cross validation for KNN is applied. Using LTP combined with KNN obtained better recognition accuracy (Joy – 85.75%; Anger – 82.75%; Sadness – 95.25%), than the other combination LBP with KNN (Joy – 85.75%; Anger – 77.50%; Sadness – 89.25%). The combination of 10-fold cross validation with LPD methods has been studied to evaluate the real-time emotion recognition from ECG using LTP. It validates how much the real-time emotion recognition can accurately detect user-experience emotions in real time process.

The authors of [13] aim to assess five different human emotions (happiness, disgust, fear, sadness, and neutral) using heart rate variability (HRV) signals derived from an electrocardiogram (ECG). The emotions were induced via video clips on the 20 healthy students with age of 23 years old. ECG signals were acquired using 3 electrodes and were preprocessed using a Butterworth 3rd order filter to remove noise and baseline wander. The Pan-Tompkins algorithm was used to derive the HRV signals from ECG. Discrete wavelet transform (DWT) was used to extract statistical features from the HRV signals using four wavelet functions: Daubechies6 (db6), Daubechies7 (db7), Symmlet8 (sym8), and Coiflet5 (coif5). The k-nearest neighbor (KNN) and linear discriminant analysis (LDA) were used to map the statistical features into corresponding emotions. KNN provided the maximum average emotion classification rate compared to LDA for five emotions (sadness − 50.28%; happiness − 79.03%; fear − 77.78%; disgust − 88.69%; and neutral − 78.34%).

The non-linear approach proposed in [14] distinguishes six emotions - happiness, sadness, fear, disgust, surprise and neutral induced by audio visual stimuli. The Hurst feature is computed using Rescaled Range Statistics (RRS) and Finite Variance Scaling (FVS) methods. Then new ones are proposed as a combination of existing RRS and FVS with Higher Order statistics (HOS). The Emotional State classification is made through Bayesian Classifier, Regression Tree, KNN and Fuzzy K-nearest neighbor. The results showed that RRS and FVS methods have similar classification accuracy, while the features obtained by combination of FVS and HOS performed better for classifying the six emotional states using random and subject independent validation respectively.

The ECG signals are also used in combination with other physiological signals such as skin conductance (SC), abdomen expansion, blood volume pulse (BVP) and skin temperature in the context of collaboration with a partner [14]. During the communication people tend to react to the partner's emotion through mechanisms of empathy and emotion contagion.

A combination of ECG and Galvanic Skin Responses (GSR) were collected and analyzed in [15] through three dictionaries, including Coiflets wavelet (Coif5) at level 14, Daubechies wavelet (db4) at level 8, and discrete cosine transform (DCT). Matching pursuit coefficients were calculated from the normalized GSR and ECG signals and Principal Component Analysis (PCA), Linear Discriminant Analysis, and Kernel PCA were applied for dimensionality reduction and feature selection. Probabilistic Neural Network (PNN) was applied, in subject dependent and subject independent modes, to classify emotional states in two-dimensional (valence-arousal) emotion space.

An automated emotion recognition approach based on different bio signals is proposed in [16]. EMG, ECG, RR, and electro dermal activity (EDA) are processed and evaluated. In this case Support Vector machine (SVM) and Adaptive Neuro-Fuzzy Inference System (ANFIS) have been used for classification of four emotional states – high stress, low stress, disappointment and euphoria. The overall classification rates achieved by using 10-fold cross validation are 79.3% and 76.7% for the SVM and the ANFIS, respectively.

In [17] the authors use ECG and EEG for analysis of emotional properties in this case passive valence /arousal model. They propose s solution based on the short Fourier transform for the recognition of dynamically developing emotion patterns on ECG and EEG. Features extractions that are used in this paper are Kernel Density Estimation (KDE) and Mel-frequency cepstral coefficients (MFCC). The classifier employed in this work is Multi-layer Perceptron (MLP), classification features are based on the valence and arousal. The results show that the ECG signal has direct relationship with the arousal factor rather than the valence factor.

A very recent research paper [18] deals with detection of emotions from ECG and EDA signals. The raw signals are directly fed into deep neural networks that perform the so-called end-to-end learning of the emotion. The motivation behind this idea is that, the network learns an intermediate representation of the raw input that better suits the task at hand, and hence leads to improved performance as the authors prove by comparing the results with the challenging REmote COLlaborative and Affective database.

Table 1 summarizes the most common methods used for emotions recognition. Note that the feature selection step reduces the complexity and the processing time of the classification step.

TABLE I. OVERWVIEW OF METHODS OF ECG-BASED EMOTIONS RECOGNITION

Feature extraction	Feature selection	Classifier
Continuously Wavelet Transform	Binary Particle Swarm Optimization (BPSO)	Genetic Algorithm -
	Hybrid Particle Swarm Optimization (HPSO)	k-Nearest Neighbor (KNN)
	Improved Binary Particle Swarm Optimization (IBPSO)	Fisher classifier
	Improved Genetic Algorithm (IGA)	
Discrete Wavelet Transform (DWT)	Daubechies6 (db6) Daubechies7 (db7), Symmlet8 (sym8) Coiflet5 (coif5). Tabu Search Algorithm (TS)	k-Nearest Neighbor (KNN) Linear Discriminant Analysis (LDA) Combination of KNN and Fisher
Local Patern Description (LPD) methods	Local Binary Pattern (LBP)	k-Nearest Neighbor (KNN)
	Local Ternary Pattern (LTP)	10-fold Cross-validation and KNN
Hurst	Rescaled Range Statistics (RRS) Finite Variance Scaling (FVS) Higher Order statistics (HOS)	Bayesian Classifier Regression Tree K- Nearest Neighbor Fuzzy K-nearest neighbor
Fast Fourier Transform (FFT) Non-linear Transformation on the 1st derivative of ECG	Tabu search (TS)	Fisher Projection Classifier
Statistical features		Adaptive Neuro-Fuzzy Inference System (ANFIS) Support Vector Machine (SVM)
Raw signal		Convolutional Neural Network, Recurrent Neural Network, Fully Connected Layer
Discrete Cosine Transform (DCT)	Principal Component Analysis (PCA) Linear Discriminant Analysis (LDA) Kernel PCA	Probabilistic Neural Network (PNN)

III. ECG based Emotion recognition Applications

Emotion modeling and recognition has drawn extensive attention from disciplines such as psychology, cognitive science, and, lately, engineering. Emotion recognition is part of the Affective computing - a domain that focuses on user emotions while interacting with computers and applications [19] The methods summarized in Table 1 are subject to diverse applications. In this section are discussed the most underlying approaches.

There are alternative ways to identify human emotional states, however the ECG signal is known to provide more realistic results. Fig. 3 represents the applications of emotions recognition together with their core sources.

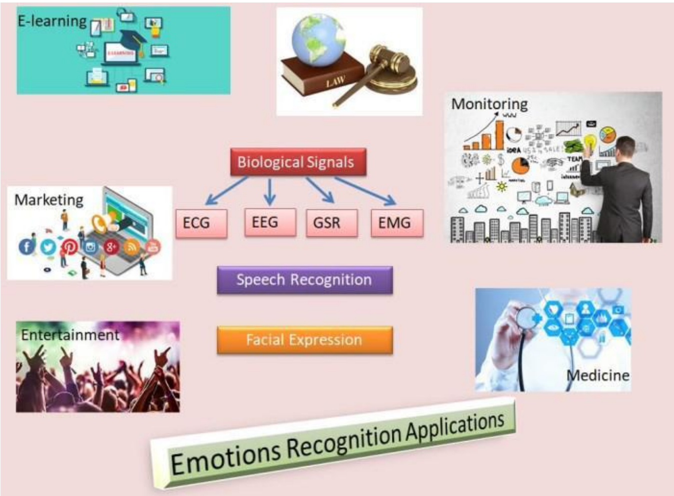

Fig. 3 Emotion Recognition applications

Most applications use a combination of different data sources. The most common combinations are biological signals and facial expression. Powerful machine learning algorithms are able to achieve very high recognition rates both in subject dependent [20] and in subject independent emotion recognizer's cases, [21]. In this section are considered major application areas and more specifically the ones that use ECG signal as a main source of data for emotions recognition.

A. Monitoring

Real time ECG data processing can be used during car races. The emotions and psychological situation generally affect the driver's behavior and reactions, which can lead to accidents. The authors of [16] make a study on the car's setting and development, based not only on subjective questionnaires filled by the driver but also on the driver's emotional state which may affect the car's performance. The car performance have an impact on the driver's emotional state, therefore the observer can give additional advice and guidance.

The proposed system can be also used in specific medical applications. It can support clinical diagnosis related to cases when the patient's capability to feel and express emotions is limited or totally absent. In some clinical treatments, such as Parkinson's disease, Huntington's disease, cortical lesion, stroke, doctors need to know the psychological condition of the patients. The goal is to evaluate the emotional state of the patient. However, the use of specific drugs temporarily normalizes or even decreases the facial muscular activity. Using the proposed system, the response of the patient to the specific drugs, adjusting and optimizing the dosages prescribed, can be achieved.

B. Medicine

The ECG-based human emotion recognition is helpful in applications involving patients with autism and other intellectual disabilities and human computer interaction. It is useful due to the fact that ECG signals are an activity of the autonomic nervous system (ANS) and reflect the underlying true emotional state of a person [11].

The goal in [22] is to recognize emotion states at each moment and not to detect several prototypic emotions. The authors make a conclusion that the present work still cannot meet the real life needs because we exhibit non-basic, subtle and rather complex emotional states, which cannot be fully expressed by one category emotion label [23].

The health care system proposed in [21] focuses on emotional aspects and integrates facial expression with ECG signals for identifying users' emotions and providing appropriate services. The authors' study showed that the real-time emotion recognition from ECG signal is beneficial and effective for detection and analysis of negative emotions and providing immediate assistance.

C. Marketing

A web-based system to support the users in different workspaces can provide access by web browsers and recognize the user's emotion. In [8] is presented a system that can suggest taking a break if the emotions, detected by the webcam and ECG sensors, are classified as negative.

The authors of [24] focus on two areas of application in software engineering: usability testing and development process improvement. Usability testing is defined through four testing steps: 1) impression test which aims to differentiate the user's interest from boredom; 2) task-based approach dedicated to help the users performing specific tasks and its purpose is to differentiate frustration from empowerment; 3) interaction test is based on free interaction with application, which is supposed to evaluate overall user experience and its objective is the distinction of engagement from discouragement. 4) Comparative test combines the previous tests. Development process improvement tried to verify the hypothesis that emotions have significant impact on software quality and developers' productivity.

IV. Conclusions

The reviewed studies reveal the great potential of ECG to decode basic human emotional states such as joy, sadness, anger, fear, etc. However, the current state of the art in affective computing reveals also that further research is required in order to achieve realistic recognition of complex human emotions.

Major application domains are in medicine, monitoring and marketing. Yet, the combination of ECG with other physiological signals and facial expression is far more promising approach to follow.

Understanding the non-verbal cues from people to infer the emotional states of others is central to our daily social interactions from very early in life [25]. We as humans are capable to distinguish happiness and stress as early as babies and we get better with age to recognize sadness, surprise, anger and disgust. For the machines to understand human emotion is totally different task. It is difficult to describe an emotion with quantitative characteristics. As a result of improvements in wearable sensor technologies and artificial intelligence techniques, machines are poised to take a big leap in their ability to understand humans from their facial expressions, physiological signals, gestures, gait and posture.

In [26] the authors give a very accurate description of the issues for the future of emotion recognition such as the multimodal emotion sensing. Emotion recognition cannot be based only on images and video it is important to use all the available modalities: voice, touch, bio signals etc. One of the main goals of this paper is to understand the challenges in emotion recognition based on ECG signals in real life contexts and continue the research in this direction.

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