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# A Study of Physiological Signals-based Emotion Recognition Systems

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## ABSTRACT

The use of physiological signals is relatively recent development in human emotion recognition. Interest in this field has been motivated by the unbiased nature of such signals, which are generated autonomously from the central nervous system. Generally, these signals can be collected from the cardiovascular system, respiratory system, electrodermal activities, muscular system and brain activities. This paper presents an overview of emotion recognition using physiological signals. The main components of a physiological signals-based emotion recognition system are explained, including discussion regarding the concepts and problems about the various stages involved in its framework.

## Indexing terms/Keywords

Classification; Emotion Recognition; Feature Extraction; Physiological Signals

## Academic Discipline And Sub-Disciplines

Computer Science

## SUBJECT CLASSIFICATION

Physiological Signals Processing

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## INTRODUCTION

Emotion is dynamic and and highly subjective. It arises spontaneously with short-lived affective states and is often accompanied by physiological changes in evoking human reactions and expressions. Emotion is also important to convey how one actually feels as it is sometimes difficult to do so using the limited set of verbal resources alone. Lately, including emotion for the enrichment of user-computer experience has become a focus in the area of Human Computer Interaction (HCI).

Emotion oriented computing is intrinsically complex as it consists of multiple components that represent different aspects of emotions. These components are cognitive appraisal, action tendencies, motor expression, physiological symptoms and subjective feelings [1] [2]. All of these components need to be interdependent and concurrent in order to evoke the emotions [3].

Emotion recognition through facial expressions, speech recognition and gesture movements have been proposed over the last decade where satisfactory results have been reported for specific applications [4]. However, the performances for the approaches such as facial expression recognition system are relying on the performance capture [5]. Besides that, such behavioral modalities might be easily triggered by intentional control or human social masking. For example, anger can masked by the happy face of a person possessing high emotional quotient (EQ). Thus, to obtain a promise result in emotion recognition, an insight into human feelings has to be considered [6]. In affective computing, physiological signals have become a robust emotional channel to combat the artifacts created by human social masking [4].

This paper aims to study the methods used in recognizing emotion using physiological signals. The rest of the paper is structured as follows. Section II discusses the widely used emotional models, followed by an evaluation of the commonly utilized emotion recognition physiological measures in Section III. Section IV outlines the general framework for physiological signals-based emotion recognition systems. Finally, Section V concludes the paper.

## EMOTION REPRESENTATION

Due to individual differences, various ways are used to express certain emotions. Generally, emotion can be represented using the discrete approach by Ekman [7], or the dimensional approach by Lang [8].

The discrete approach claims that the core emotions, which include happiness, sadness, surprise, anger, disgust fear, curiousity and acceptance, evolved from other emotions. For example, disappointment is derived from sadness and surprise [9].

The dimensional approach is derived from cognitive theories, which map the emotions into a two-dimensional bipolar model of arousal and valence [10]. Valence, which ranges from negative to positive, is used to represent the pleasantness of the stimuli. Arousal, on the other hand is the activation level that ranges from calm to excited [4]. For example, sadness has negative valence and low arousal, whereas anger has negative valence but high arousal.

Both the discrete and dimensional approaches are widely used due to their simplicity and integrability. The different emotional labels can be plotted by mapping the discrete core emotions in the dimensional approach as shown in Figure 1.

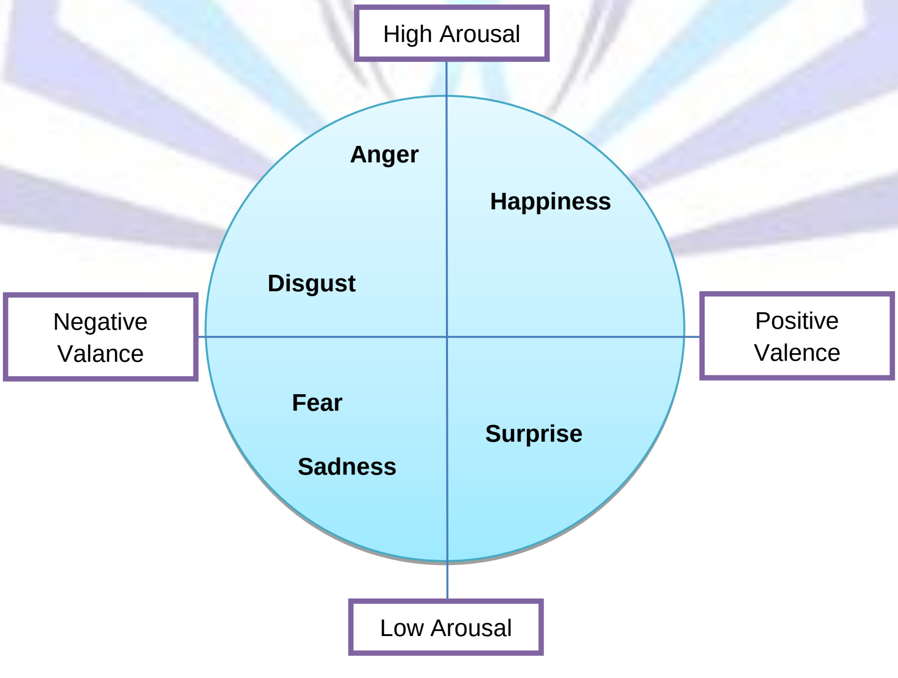


**Figure 1: Discrete Arousal-Valence Model**

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## PHYSIOLOGICAL MEASURES IN EMOTION RECOGNITION

Physiological signals are originating from autonomic and central nervous system. According to [6] and [11], five physiological measures are commonly adopted in HCI: cardiovascular system, electrodermal activity, respiratory system, muscular system and brain activity.

### Cardiovascular System

The human cardiovascular system is a closed circulatory system powered by the heart, where the left and right ventricles provide adequate oxygenated blood to the body. Electrocardiogram (ECG) is used to measure the electrical activity associated with the muscular contraction and relaxation of the heart by placing an array of electrodes on the body's surface.

Generally, the ECG traces the sequence of depolarization and repolarization of the atria and the ventricles of the heart. The ECG signal is composed of the P wave, the QRS Complex (ventricular depolarization) and the T wave (ventricular repolarization), as shown in Figure 2. The readings from the ECG wave is then utilized to derive the heart rate (HR), heart rate variability (HRV), blood volume pressure (BVP) and other measurements. The HR can be obtained by measuring the time duration between successive R waves. On the other hand, the BVP can be calculated from the HR and HRV measurements.

In emotion recognition, ECG can be reliably used to classify negative and positive emotions such as stress and happiness [4]. Besides that, ECG signals can be obtained relatively easily through wearable sensors.

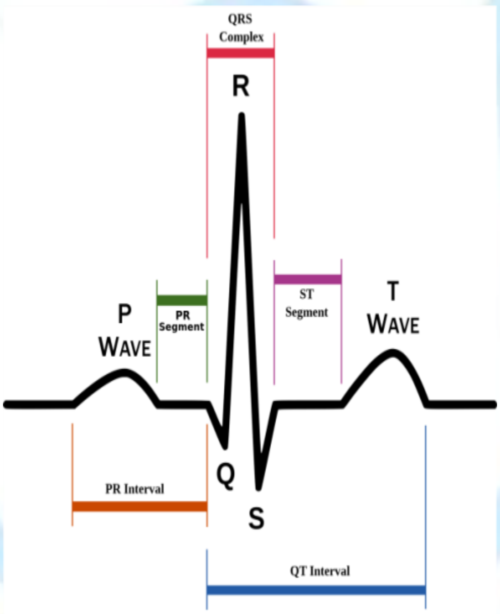


**Figure 2: ECG Wave**

### Electrodermal Activity

Electrodermal activity (EDA) or sometimes referred to as Galvanic skin response (GSR) is another indicator that prompts emotion to reflect the sympathetic nervous activity. In the past, many studies have shown that EDA signals have good potential in exploring emotions such as attention, arousal difference, anxiety and excitement [12].

EDA describes the ability of the human skin in handling electricity [13]. EDA sensors are usually placed on the fingers to measure the skin's current conduction or resistance property after applying a fixed small voltage to the skin. Electrical changes in the skin are caused by the activity of the sweat glands, which are present throughout the human body. When there is an increase in arousal or cognitive workload, the sweat gland activity increases, thereby increasing the level of skin conductance.

EDA signals are one of the most robust physiological signals in emotion recognition as they indicate sympathetic-centered response whereby the emotion is easily evoked during stimuli presentation [12]. However, EDA signal measurement may be confounded by environmental conditions, different types of physical activities and placement of the sensors. Although controlled experimental conditions can be applied, there is still room for improvement to reduce these artifacts.

### Respiratory System

Respiration (RSP), another form of autonomic control, may change in response to the increase in heart rate and sweating activity [13]. RSP measurements refer to the respiration rate (RF) and the relative breath amplitude (RA) or depth of the breath.

Generally, the respiratory measures can be recorded by wearing elastic stretch sensors placed on the upper chest and the lower abdomen. The amount of the stretch (chest expansion) is recorded and is used for RF and RA calculations. Previous studies in [4][13][14] have shown that RSP patterns highly rely on an individual's emotional state changes. RF generally decreases during relaxation and bliss, but increase during anger and anxiety. Besides that, irregular RSP patterns are detectable when dealing with negative valence. To obtain a complimentary result in emotion recognition, comprehensive assessment of ECG, EDA and RSP is suggested.

## Muscular System

Muscle activity is a common observation used to recognize the correlation between emotion and physiological signals [4]. An electrical current is transmitted from motor neurons to drive muscles to contract and relax; and these activities are captured using an Electromyogram (EMG) [15]. On one hand, EMG is used to capture the electrical activity of muscles. On the other hand, EMG is used to measure the conducting function of the nerves.

In general, surface EMG is more practical compared to intramuscular EMG to collect signals for emotion recognition. Surface EMG signals can be collected by placing the sensors on the surface of the face, arm or leg, while intramuscular EMG involves inserting a needle electrode into the muscle. The frequency (speed) and amplitude (strength) of the surface EMG signals travelling between the sensor points are then measured. In most cases, the amplitude changes in EMG signals are directly proportional to muscle activity

## Brain Activity

Brain is the center of the nervous system responsible to coordinate the activity of the peripheral nervous system [14]. The electroencephalogram (EEG) is used to measure the brain's spontaneous electrical activity along the surface of the scalp.

Today, EEG-based emotion recognition has received significant attention in HCI, which is partly due to the development of wearable EEG sensors. EEG signals data collection process is faster, easier and less invasive compared to other methods such as via functional Magnetic Resonance Imaging (FMRI) [16].

The performance of EEG-based emotion recognition relatively depends on the spatial location, response time and frequency structure of the brain waves [14]. Besides that, EEG signals usually require more than 3 electrodes consists of Fp1, Fp2 and Fpz as illustrated in Figure 3, mounted on the forehead to collect the measurements. This setup can be cumbersome for feature extraction and also prone to noise, compared to other physiological signals with less electrodes.

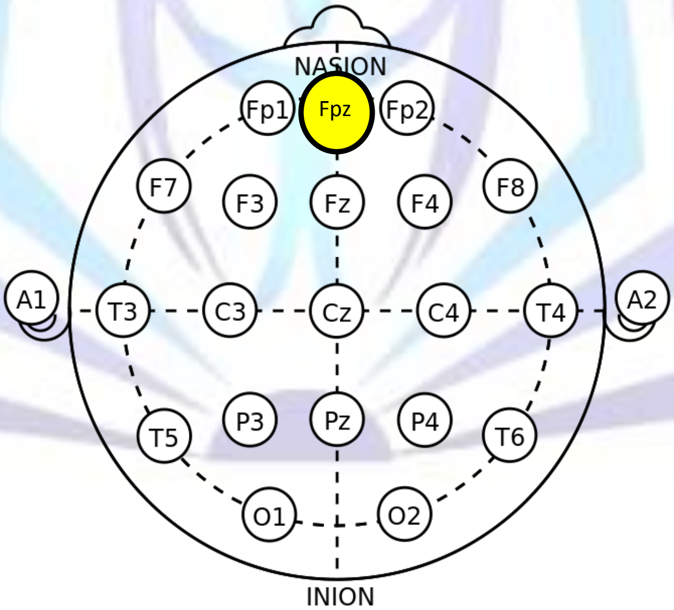


**Figure 3: 10-20 system of electrode placement**

# PHYSIOLOGICAL SIGNAL BASED EMOTION RECOGNITION FRAMEWORK

Different physiological measures are used for different states of emotions. To recognize happiness for instance, ECG and RESP are adequate measurements to attain high accuracy, whereas EDA alone is sufficient to recognize anxiety. Generally, the processing steps involved to recognize emotions are similar regardless of the different types of physiological signals used.

The overall framework for a physiological signals-based emotion recognition is illustrated in Figure 4. Brief descriptions for each stage are presented below.

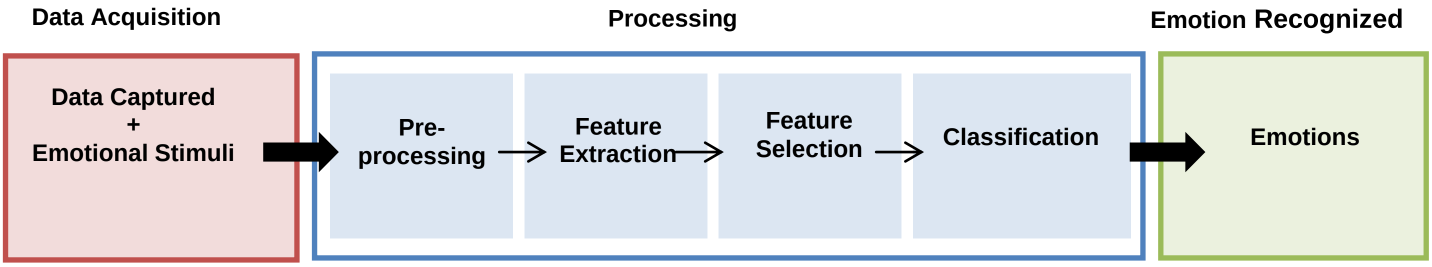


**Figure 4: Overview of the Physiological Signals based Emotion Recognition Framework**

## Data Acquisition – Emotional Stimuli

Emotional stimuli are important to evoke the respective emotion during the data acquisition stage. There are generally two ways to evoke emotions: personal imagery from previous experiences or audio-visual material shown to the participants [17]. Most of the experiments prefer to use audio visual stimuli because the experiences from memory are difficult to spontaneously call up to evoke the targeted emotion.

International Affective Digitized Sounds (IADS)[18] and International Affective Picture System (IAPS)[19] are two non-profit libraries providing emotional annotated sounds and images for research purposes. The study done by [20] claims that films achieve better results in evoking the target emotions. However, the same stimuli might not evoke the same emotional states to all participants [21]. A funeral scene may easily evoke sadness for a female, but not for a male. A comedy may evoke happiness but not excitement for an adult. Thus, selecting well suited stimuli is important to gather the quality data.

## Preprocessing

Readings from sensors might be inaccurate due to body movement during data acquisition. To avoid such noises and artifacts, a preprocessing stage is needed. Some technique can be used such as a low pass and smoothing filter. These filters may vary for different types of physiological measurements. ECG and facial EMG signals best adapt to the low pass filter at 100Hz and 500Hz. The moving average filter is used to preprocess RSP and EDA signals [22]. During EMG signal collection, the muscle contraction frequency for each sensor point may vary. Thus, extra preprocessing is required for EMG signals. In [4], an adaptive bandpass filter is used to remove the noise and artifacts from the EMG signal generated by the heartbeat and RSP.

Compared to other physiological measurements, EEG signals generate more noise and artifacts due to the large number of electrodes and its sensitivity to the face movement such as eye blinks or eyebrow raises. Bos et al. [17] used a bandpass filter provided by EEGLab for Matlab to remove the noises and artifacts of EEG signals. At first, Fourier frequency analysis [23] is adapted to split up the raw EEG signals. The detected noise is then removed using the bandpass filter. After noise filtering, the targeted frequencies are retransformed to be used for further processing.

Apart from noise filtering, certain physiological signals will be segmented into different samples and normalized by its mean and standard deviation before proceeds to the next stage.

## Feature Extraction

Feature extraction in physiological signals processing involves the extraction of statistical features in the time domain, frequency domain, time-frequency domain and other domains from the preprocessed physiological signals. As the input channels are different for each physiological measurements, feature extraction is generally performed separately. The time domain statistical feature (root-mean-square) is extracted from EMG signals. This feature describes the power of the signal, which can determine the level of strength or fatigue of a muscle. The feature extracted from ECG signals is from the frequency domain, namely the power spectrum that identifies the mental state changes from relaxation to stress.

To transform time domain features to frequency domain features, certain techniques are applied such as wavelet transform (WT), fast Fourier transform (FFT), Hilbert Huang transform (HHT) and principal component analysis (PCA). However, physiological signals are non-stationary (the signals hardly remain constant over time). Thus, it is crucial to select the best suited technique for feature extraction. Compared to the other previously mentioned techniques, the wavelet transform is particularly useful in extracting features from aperiodic and non-stationary signals [24].

S.Koelstra et al. [25] extracted a total of 106 features: time frequency, zero crossing rate, silence and others from six physiological signals namely, GSR, RSP, EMG, blood volume pressure(BVP), skin temperature(SKT) and EEG . On the other hand, Zong and Chetouani [26] extracted 28 features by using the proposed fission and fusion approaches based on the HHT from four physiological signals (ECG, RSP, EMG and GSR) to recognize joy, anger, sadness and pleasure. C.Maaoui et al. [27] acquired 30 features from each five physiological signals (BVP, EMG, SC, SKT and RSP) using six different affective states (amusement, contentment, disgust, fear, neutrality and sadness) by using the IAPS as stimuli.

From this information, it is noted that the number of features extracted depends on the type of physiological signal. For example, more features are required when dealing with EEG (Table 1). In addition, the number of emotions to be recognized will affect the number of extracted features. For instance, 28 features may perform well to recognize four different emotional states, but might not work well for six emotional states.

**Table 1: Features extracted from different physiological measures**

| Type of Signal | Features |
|---|---|
| **ECG** | Mean amplitude rate, Average and Standard Deviation of HR, Mean of absolute values of first differences, Mean Frequency, Median Frequency |
| **EDA** | Mean amplitude rate, Conductance responses, Rate of skin conductance, Mean of absolute values of first differences, Mean rise duration of skin |
| **RSP** | Mean amplitude rate, Respiration rate, Average respiration signal, Mean of absolute values of first differences, Average peak to peak time, Median peak to peak time |
| **EMG** | Mean Value, Root Mean Value, Standard deviation |
| **EEG** | Fpz alpha band, Fpz beta band , F3/F4 alpha band, Fpz beta frequency , F3/F4 beta power or power ratio, Fpz alpha and beta band power, F3/F4 alpha and beta band power |

## Feature Selection

The ultimate goal of feature selection is to select the most relevant features from the extracted features in order to differentiate each emotional state. Removal of redundant and irrelevant features can decrease the computational time and avoid classifier over-fitting.

Several feature selection techniques have been proposed by the research community, such as sequential forward selection (SFS), sequential backward selection (SBS), sequential floating forward selection (SFFS), margin based feature selection and Fischer projection. Among these, SFS and SBS are frequently adopted in emotion recognition. SFS starts with an empty set where the best fit feature is inserted in every step. In contrast to SFS, SBS reduces the worst features from a full set of features [28]. J. Kim et al. [4] used SBS and pseudo inverse linear discriminant analysis (pLDA) classifier to obtain average recognition accuracy ranging from 87 to 98 percent for arousal, valence and four emotional classes.

In order to obtain promising results, the criterion to employ the appropriate feature selection technique can depend on the classifier. Most feature selection techniques run in offline mode. Thus, there is still room for improvement to run feature selection in real-time as the demand for HCI to imply the real time response increased relatively [6].

## Classification

In the context of this framework, classification involves categorizing the set of feature measurements into its respective emotional state. This is normally done using machine learning techniques such as supervised learning, unsupervised learning and/or semi-supervised learning. In the supervised case, the label for the training data, along with their respective class label, are prepared. The learning process then generates a hypothesis that generalizes future unseen patterns into the supposed class. In contrast to unsupervised learning, input patterns are unlabeled. The algorithm has to seek out similarites between the data to define groups or clusters that a particular pattern might belong to. Semi-supervised learning uses both labeled and unlabeled data for training [6][29].

Recently, various techniques and approaches have been proposed in order to pursue high accuracy in classification. Picard [30] attained 81% classification accuracy for eight emotional classes from four physiological signals using Maximum a Posteriori (MAP). A hybrid SFFS with Fisher Projection feature selection method is proposed by them to select the relevant features before MAP classification. Arroyo [31] and his team developed a bio-affective computer interface that can recognize four emotional states using three physiological signals. A probabilistic neural network (PNN) was used as the classifier, which managed to obtain a classification accuracy of 84.46%. Jang et al. [32] used a support vector machine (SVM) to classify three different emotions (boredom, pain and surprise).

Several other classifiers were also used in emotion recognition such as AdaBoost (AB), nearest neighbor(NN) and Naive Bayes (NB). Each has its own strength to work with the given data set. The classification accuracy seems to depend on the number of physiological signals being measured. However, it remains a challenge to compare different classification algorithms as the emotion recognition systems are tested on different data sets.

## CONCLUSION

The implementation of a physiological signals-based emotion recognition system involves several stages: physiological signal data acquisition, preprocessing, feature extraction, feature selection and classification. Each stage has been discussed and summarized in this paper. It is noted that the performance of each stage of the emotion recognition system is interdependent. If the raw signal noise artifacts do not undergo preprocessing, the number of irrelevant features extracted can increase causing lengthy computational time. Besides that, various techniques and methods can be employed in the feature extraction (WT, FFT, HHT), feature selection (SFS, SBS, SFFS ) and classification (PNN, SVM). Selecting the most suitable techniques and methods for each stage is important as it will affect the recognition accuracy.

Emotion recognition from physiological signals still posses a number of challenges. Since physiological reactions are sensitive to motion artefacts, mapping the physiological patterns onto specific emotional states, especially in real-time, becomes increasingly difficult. Besides that, most of the current emotion recognition systems work with core emotions and smaller subsets of emotions such as depression, boredom and frustration. Fine-grained emotions such as hopelessness and hopefulness are rarely being studied as these emotions are hard to detect. Integrating other emotion recognition modalities such as face recognition, speech recognition or gesture recognition with physiological signals has shown promising results in recognizing emotional states [14]. However, there is a tradeoff between accuracy and computational time, which remains a worthy issues to be explored.

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