Automatic Emotion Detection through Biosignals and Standardized Emotional Stimuli

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Abstract. Monitoring physiological signals using biomedical devices has experienced significant growth due to its wide range of applications in various fields, such as Health and Education. This work reports on implementation of a physiological data acquisition system based on the Mehrabian and Russell model, associating emotional dimensions with specific parameters: valence (heart rate), activation (skin conductance), and dominance (temperature). System allows interpretation of human emotional states, including happiness, anger, fear, and sadness, using standardized stimulations from International Affective Picture System (IAPS) and Digital Affective Sounds (IADS).

Keywords: Emotion Detection, Conductance, Temperature, Heart Rate, IAPS, IADS.

1 Introduction

Biosignal monitoring has traditionally been focused on diagnosis and follow-up of physical diseases, overlooking its potential in evaluating and understanding mental health. Relative lack of technologies that effectively integrate these parameters, allowing assessment of relationship between specific physiological responses and emotional states, limits practical application of scientific advances in this field. Different emotional states manifest themselves in different physiological ways. By studying biosignals of subjects in whom a research protocol has been used to induce a specific emotional state, it is possible to analyze these signals in a general way better to understand physiological responses to a subjective situation. By better understanding how a person thinks, feels, and acts, it is possible to improve educational, work, and business systems, among many others.

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1.1 Study of Emotions

Traditionally, study of emotions has been restricted to subjective methods, such as questionnaires and self-assessments, which have limitations regarding accuracy and reproducibility. Therefore, development of innovative biomedical devices that allow accurate interpretation of emotional states improves monitoring in this field and contributes to closing gap between scientific research and its application in everyday life.
For this purpose, present work deals with design and implementation of an automatic emotion detection system using biosignals and standardized emotional stimulations based on acquisition of physiological data such as skin conductance, body temperature, and heart rate, capable of identifying human emotional states (happiness, anger, fear, sadness).

1.2 Justification

This automatic detection system is designed for use in various sectors., including mental health professionals, who can benefit from continuous monitoring of their patient's emotional states; educators, who could adapt their teaching methods according to students' emotional responses; and researchers interested in exploring relationship between physiological responses and emotions, in developing more effective approaches to treatments of emotional disorders or gain more precise insights into the relationship between emotional system and people's physiological state.
System processes and classifies these signals using machine learning techniques, allowing identification of four basic emotional states. This technology aims to reduce reliance on subjective methods, facilitate integration of scientific advances into everyday life, and promote a more accurate approach to understanding and managing emotions.

1.3 Hypothesis

- Biosignals such as skin conductance, body temperature and heart rate can be used to objectively and accurately identify different emotional states.
- Machine learning techniques like neuronal networks are most effective in classifying emotional states from biomedical data.
- Accuracy and reproducibility of automatic detection system is more reliable compared with traditional methods of emotional assessment based on self-reports and questionnaires.

1.4 Literature overview

Several studies have addressed identifying and analyzing emotions from biosignals, exploring methodologies and technologies that integrate machine learning, biomedical sensors, and advanced computational models. Among them, García Manzo's thesis [1] analyses the possibility of detecting emotions using biosignals such as skin conductance, body temperature, and heart rate in combination with virtual reality environments. His methodology involves recording, processing, and classifying physiological signals through machine learning models, using standardized emotional stimuli such as International Affective Picture System (IAPS) and the International Affective Digitized Sound System (IADS) to induce and evaluate emotional responses.

In affective neuroscience, Dalgleish [2] examines involvement of brain structures such as amygdala, hippocampus, and prefrontal cortex in emotional processing. In addition, he analyses their interaction with autonomic nervous system, providing a fundamental framework for understanding physiological mechanisms underlying changes in parameters such as skin conductance, temperature, and heart rate, which are essential in biosignal-based emotion detection.

On the other hand, Aqajari et al. [3] have developed an open-source tool for analyzing galvanic skin response (GSR) as an indicator of stress. Their model employs deep learning algorithms and statistical methods to extract meaningful features from GSR, achieving 92% accuracy in detecting stress levels. Since emotional arousal is reflected in skin conductance, this study is highly relevant for automatic biosignal emotion detection.

Similarly, Gao [4] has developed an electronic skin capable of continuously monitoring nine physiological biomarkers associated with stress response. This device, which incorporates advanced sensors to measure skin conductance and temperature, represents a significant advance in real-time physiological monitoring, with direct applications in detecting and analyzing emotional states.

Another relevant work is Spanish adaptation of International Affective Picture System (IAPS) [5], which provides a standardized set of visual stimuli used in emotion research. Validating this system in different populations is crucial to ensuring its effectiveness in inducing emotional states in experimental studies.

Finally, Ean-Gyu et al. [6] propose a real-time emotion recognition method based on photoplethysmographic (PPG) and electromyographic (EMG) signals using convolutional neural networks (CVCNN). Their approach, which achieved an accuracy of over 80%, demonstrates potential of integrating cardiac signal processing with machine learning models to identify emotional states accurately.

Several authors have explored quantification of emotional states from physiological signals. Works such as Koelstra et al. [7] and Chanel et al. [8] have demonstrated feasibility of these methods for assessing emotional responses using biomedical signals. In this work, we have proposed a protocol that is as controlled as possible, with homogeneous stimulations as much as possible, to avoid introducing biases in interpretation of results and, based on references we have, to improve this type of analysis.

Unlike other approaches, experimental protocol incorporated in this work is highly standardized. It is based on IAPS and IADS systems, ensuring all participants are exposed to same audiovisual input with a homogeneous design. In addition, a three-dimensional model of emotions, according to Mehrabian and Russell, is employed, allowing for a more complete quantification of affective states regarding valence, activation, and dominance. This approach, coupled with simultaneous integration of multiple biomedical sensors and rigorous control of experimental conditions, *represents a significant advance* over previous studies in the field.

2 Metodology

2.1 How to cuantify an emotion?

An emotion is a multi-component response to an emotionally potent antecedent event, causing changes in subjective quality of feeling, expressive behavior, and physiological activation [9]. In analysis of emotions, the function of the autonomic nervous system is known, which, from interactions with neurotransmitters (chemicals that transmit information to neurons from a synapse), produces involuntary reactions [10]. Under influence of emotions, autonomic nervous system produces quantifiable physiological and behavioral manifestations [1].

Based on the above, selection of four base emotions considered in this project is based on identifying quantifiable manifestations, specifically on activation, valence, and Dominance levels. **Valence** refers to how pleasant or unpleasant an experience is and is directly related to Heart Rate; Arousal reflects state of agitation or calmness as measured by galvanic skin response (GSR), while **Dominance** indicates how much control one has over emotion as represented by peripheral temperature.

García Manzo [1] uses Mehrabian and Russell's three-dimensional model to represent emotions through these three fundamental parameters as it is based on discrete emotions. In this approach, each emotion is situated within a three-dimensional space defined by these levels, allowing for a more accurate characterization of emotional responses.

This model is incredibly convenient when implementing Machine Learning Techniques because it allows for better accuracy in emotion classification compared to label-based models. As shown in **Table 1**, spatial coordinates of emotions are represented on valence, activation, and dominance axes.

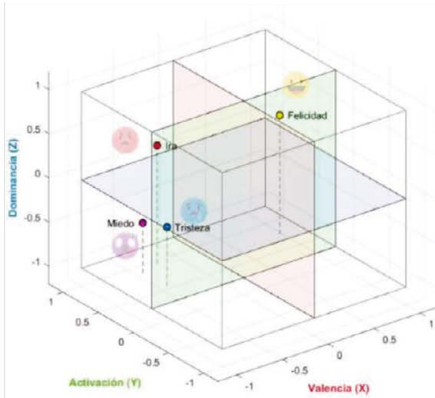

Fig. 1. Representation of Mehrabian and Russell's three-dimensional model [1].

Table 1. Spatial coordinates of emotions

Emotion	Valence (X)	Arousal (Y)	Dominance(Z)
Happiness	0.76	0.48	0.35
Anger	-0.43	0.67	0.34
Fear	-0.64	0.6	-0.43
Sadness	-0.63	0.27	-0.33

2.2 Stimulus

Experimental study of emotion requires stimulation that reliably evokes psychological and physiological reactions. Over the last few years, stimulus batteries have been developed that cover different sensory modalities and can generate different emotional states, such as International Affective Picture System (IAPS) and International Affective Digitized Sound (IADS) [10].

IAPS was developed to provide a set of normative emotional stimuli for experimental emotion research. It includes various images in (*.jpg*) format that can be classified within three dimensions (valence, activation, and dominance). It includes stimuli of humans, animals, landscapes, and objects that vary in complexity, color, and composition. IADS was developed for same purpose, using auditory rather than visual stimuli, including audio files in *.wav* format.

For stimulation of emotions, videos were produced by selecting images and audio that presented valence, dominance, and activation levels most consistent with each emotion, according to values shown in Table 1.

2.3 Circuit and sensors for biosignal acquisition

For data acquisition during emotional stimulus session, evoked by IAPS and IADS databanks, three primary sensors were used: a galvanic skin response sensor (GSR from Seeed Studio), a temperature sensor (LM335), and a heart rate sensor based on photoplethysmography, which incorporates amplification by a TL084 integrated circuit and an optical pair. Each sensor is operated in a specific way according to its characteristics and efficiency in relation to project's objectives.

- **Galvanic skin resistance sensor** (GSR Grove - Seed Studio). Galvanic skin response (GSR) sensor measures electrodermal activity or skin resistivity, directly related to sympathetic nervous system activation and, thus, emotional responses [11]. Variations in skin resistivity are detected as a function of sweat gland activity. Among main characteristics of sensor provided by the manufacturer, we can find that it has a measurement range of 10 kΩ to 4.5 MΩ; its supply voltage is 3.3-5 V; it has a high sensitivity, with immediate response to changes in sweating and communication with acquisition cards is through an analog output, which allows easy integration with microcontrollers [12]. GSR is widely used in psychophysiological studies to measure emotional arousal, especially in response to affective stimuli such as IAPS images and IADS sounds. Previous research has shown that GSR is a reliable biomarker differentiating between high and low emotional arousal states [3] [4].

- **Temperature sensor (LM335)**. LM335 is a high-precision semiconductor-based temperature sensor that provides a linear output proportional to absolute temperature in degrees Kelvin. This sensor has been integrated into project's emotion detection system because of close relationship between skin temperature and emotional states. It has been observed that emotions such as stress or excitement can cause detectable thermal changes in peripheral areas of body, such as skin of fingers, making it possible to use this variable as an indicator for emotional assessment. For main characteristics of sensor, a measurement range of -40° C to 100° C, an accuracy of ±1° C, an operating voltage of 2 - 20 V, and a linearity of 10 mV/°K are recorded in its datasheet [13]. When discussing its efficiency in detecting emotions, it has been shown that peripheral temperature decreases in states such as anxiety or stress and increases in relaxation conditions [2]. Its integration with other sensors improves classification of emotional states.

- **Heart Rate Sensor** - Photoplethysmography with TL084. Circuit shown in Fig. 2 uses an optical pair consisting of an infrared LED and a receiver photodiode (optical pair), which allows changes in light absorption caused by blood flow in capillaries to be captured. Signal obtained is amplified by a TL084 operational amplifier, which includes two stages to improve signal quality.

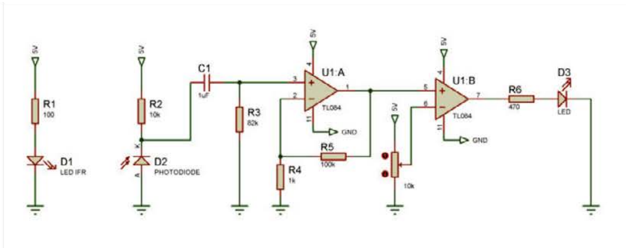

Fig. 2. Diagram of the proposed circuit for heart rate detection (photoplethysmography).

Heart rate is a key indicator of emotional response. Accelerations of pulse may be associated with emotions such as fear or excitement, while a decrease may indicate relaxation or sadness [14].

This photoplethysmography method has an analog signal output picked up by acquisition board. The proposed circuit consists of 4 stages: an acquisition stage with optical pair, then filtering with a cut-off frequency of 2 Hz using a passive filter; signal is then passed to an amplification stage with a TL084 operational amplifier configured in a non-inverting way; gain of proposed circuit is about a factor of 100, so signal coming out of this stage is easier to handle and depending on 5 V supply. Last stage is not vital for data acquisition of the project as it is only a display stage that uses a variable resistor to visualize heartbeat with an LED to ensure that circuit works correctly without need to connect it to a computer to visualize data on display.

Power supply for the whole circuit was covered by using an Arduino UNO board (5V). A USB-6000 DAQ acquisition board was used for data acquisition; the choice of this acquisition board was based on its ability to provide a stable and sufficient sampling frequency (fs) for capturing biomedical signals. Sampling frequency is critical to ensure proper signal processing, especially when working with physiological signals of low amplitude and high temporal variability. An fs of 100 Hz was selected to accurately capture dynamic variations of signals without risk of aliasing, ensuring that information contained in time domain is reliably represented. USB interface and compatibility with programming environments such as Matlab facilitated the integration of hardware with acquisition software to perform process efficiently and synchronized, ensuring that database construction stage was robust, accurate, and reproducible.

2.4 Data adquisition protocol.

In order to guarantee the best possible quality in acquisition of signals required to create database and, above all, to guarantee safety of test subjects at all times, an acquisition protocol was designed to ensure that information worked with follows same standard, homogeneity, and quality necessary to achieve best possible accuracy in results, minimizing external factors that may influence physiological measurements.

Before participation, a form was provided to assess subjects' eligibility. Main inclusion criteria were:

- To be over 18 years of age.
- No history of epilepsy or heart disease.
- No photosensitivity or severe discomfort when viewing or listening to audiovisual content.
- Not to be under effect of substances or medications that can modify mood (anxiolytics, antidepressants, among others).
- If you have nail polish or false nails, remove them before procedure to avoid interference in acquiring photoplethysmographic signal.

In addition, complementary data such as regular sugar consumption, menstrual cycle phase, and recent emotionally significant events were recorded. Although these were not exclusion criteria, they were considered for future analysis of results.

Efforts have been made to maintain a gender balance, with an equal distribution of 50% men and 50% women (9 men and nine women in total, as shown in **Table 2**). This helps to minimize possible biases arising from physiological differences in emotional expression. In addition, average age of subjects is 21 years, which allows for greater homogeneity in sample.

Table 2. Test subjets

Subject	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Age	22	22	23	23	21	24	22	18	21	22	21	22	21	21	19	19	22	21
Gender	F	M	M	M	M	M	M	F	F	F	F	F	M	M	M	F	F	F

Upon arrival at the study area, the research team welcomed each test subject and gave a brief presentation of study, explaining its objectives and experimental procedure. Subsequently, they were asked to sign an informed consent form detailing the experiment's conditions, guaranteeing the methodology's non-invasive nature, confidentiality of data, and freedom to discontinue participation at any time.

Once consent form has been signed, test subjects are asked to remove metallic objects such as bracelets, rings, watches, mobile phones, and other accessories that may interfere with data acquisition. They then proceed with placement of sensors according to an established standard:

- Photoplethysmography (PPG): Sensor placed on left hand's ring finger.
- Skin conductance (GSR): Sensor electrodes placed on middle and ring fingers of right hand.
- Skin temperature: Sensor placed on index finger of right hand.

Headband headphones were also placed to isolate external noise and improve immersion in auditory stimuli. It was indicated to maintain a comfortable posture to fix eyes on monitor and thus reduce involuntary hand movements, minimizing noise in physiological signal.

Before starting formal data acquisition, brief training sessions of 10 seconds each were carried out to familiarize participant with task and verify correct functioning of sensors. These sessions allowed for detection of possible artifacts in signal and for making necessary adjustments before proceeding with leading acquisition.

Each experimental session consisted of presentation of 4 videoseach one associated with a specific emotion: fear, happiness, sadness, and anger; order in which each of videos was presented was determined taking into account quantification of parameters of activation, valence, and dominance of each of four emotions concerning values shown in **Table 1**, thus separating as much as possible emotions with very similar values in one or more parameters in order to achieve a better distinction in results. Each video contains seven IAPS images displayed for 30 seconds, interspersed with 10-second intervals of blank screen. In addition, three IADS sounds synchronized with images 2, 4, and 6 and having coherence with displayed image have been presented; sounds used in each case respected activation, valence, and dominance values for each emotion, shown in **Table 1**.

Each subject generated four text files, one per-video, with a total recording time of 4:40 minutes per file, sampled at an fs of 100 Hz. During acquisition, research team monitored process in real-time and noted any relevant occurrences.

Fig. 3. Test subject during the biosignal acquisition protocol.

At the end of each video, each participant was given a short break for comfort and to interrupt immersion in previous emission. This allowed participant to evaluate quality of acquisition and to make annotations on possible noise or artifacts. If significant noise was detected in data, corrective strategies were implemented before continuing with next video.

Finally, after five videos are acquired, each participant is provided with a general explanation of subsequent use of collected data, thanked for his or her collaboration, and session is cordially concluded.

3 Neural Network

3.1 Data Pre-processing

All physiological signals were processed to remove noise and any potential artifacts that could affect the information they contain.
For galvanic skin resistance and temperature signals, a degree twenty polynomial filter was applied to preserve the overall trend of these biosignals.
Additionally, the heartbeats were transformed into a tachogram signal. This involved calculating the interval between beats and then deriving the inverse of this period to capture variations in heart rate over time (tachogram). This signal was also conditioned using a degree twenty polynomial filter to create a version that reflects general variations in heart rate.

3.2 Neural Network Setup

In this study, "raw" acquired data are used as inputs for an artificial neural network implemented in Matlab, which has been designed to classify emotional states into four distinct categories. Architecture of network comprises an input layer with four neurons, responsible for receiving physiological signals processed, a hidden layer of 10 neurons that allows extraction of complex patterns in data, and an output layer consisting of 2 neurons, whose combination enables prediction of emotional state experienced by subject. Choice of this structure responds to need to find a balance between model's ability to capture nonlinear relationships in data and prevention of overfitting, ensuring that network can generalize adequately when processing samples.

Activation's function used in this study was sigmoid for both hide and output layer. Sigmoid activation function was chosen for hidden layer due to its ability to introduce non-linearity and constrain outputs between 0 and 1, which aligns with normalized input data. Network's output layer consists of two neurons, with each neuron using a sigmoid activation function to produce outputs between 0 and 1. This configuration requires a binary encoding scheme to represent four emotions, such as:

- Happiness: (1,0)
- Anger: (0,1)
- Fear: (1,1)
- Sadness: (0,0)

This encoding approach allows network to differentiate between emotions based on combination of activations from two output neurons.

Richness of database is a key aspect of efficiency of neural network since an extensive and balanced training set improves model's ability to identify patterns in physiological activity associated with different emotional states. By integrating multiple recordings per subject and emotion, model's generalization is favored, reducing risk of overfitting and improving its performance in classifying new samples. Furthermore, acquisition of data in individual sessions using an appropriate sampling frequency and calibrated measurement devices strengthens consistency of dataset, ensuring that neural network can extract meaningful features from obtained signals. In this sense, standardization of acquisition protocol and th efficiency of recorded data play a determining role in accuracy of predictive model, not remaining a simple technical requirement but being an essential element for correct implementation of machine learning models in study of physiological activity linked to human emotions.

4 Results

The intra-subject multi-class classification results indicate that a simple neural network model can accurately classify four emotional states: happiness, anger, fear, and sadness. Table 3 presents the accuracy rates for each emotion and the overall accuracy for all 18 subjects, with an average accuracy of 92% within subjects. The model's accuracy varied between 0.78 and 0.99 depending on the participant.

The results indicate that the neural network achieved high classification performance, with most subjects reaching accuracy values above 0.90. The best-performing subject was Participant 16, attaining an accuracy of 0.99, indicating that the model correctly classified nearly all evaluated instances. In contrast, the lowest accuracy was observed for Participant 3, with a value of 0.78, suggesting more incredible difficulty in identifying consistent patterns in this individual's physiological data. This outcome may be attributed to inter-individual variations in physiological responses to emotional stimuli, signal noise, or preprocessing quality.

It is important to note that the selection of input features is crucial for a neural network to perform classification effectively. In this study, galvanic skin resistance, temperature, and photoplethysmography sensors provided the network with sufficient relevant information for the multi-class classification task. Additionally, the choice of emotional stimuli plays a crucial role in eliciting distinct physiological responses. While subjective factors can influence emotions, standardized materials such as the International Affective Picture System (IAPS) and International Affective Digital Series (IADS) have been shown to reliably induce targeted emotional states.

Regarding the network's ability to differentiate between emotions, anger and fear exhibited the highest average accuracy, ranging from 0.89 to 1.00 depending on the subject, suggesting that the physiological patterns associated with these emotions are more distinct. On the other hand, happiness and sadness, while still achieving high accuracy, showed slightly lower values for some subjects, possibly due to reduced variability in their physiological parameters or more significant overlap in their physiological characteristics.

From a methodological perspective, the Levenberg-Marquardt algorithm facilitated rapid convergence and minimized training error, contributing to model stability. However, inter-subject variability in accuracy highlights the need for additional optimization strategies, such as implementing more robust data normalization techniques or dynamically adjusting hyperparameters based on signal quality.

Table 3. Results of intra subject multiclass classification.

Subject	1	2	3	4	5	6	7	8	9
Accuracy model	**0.95**	**0.89**	**0.78**	**0.92**	**0.97**	**0.98**	**0.89**	**0.97**	**0.94**
Hapiness	0.99	0.96	0.89	0.95	0.98	1.00	0.93	0.98	0.96
Anger	0.97	0.92	0.86	0.97	0.98	0.99	0.96	0.98	0.99
Fear	0.97	0.96	0.92	0.96	0.98	0.99	0.92	0.98	0.97
Sadness	0.96	0.93	0.88	0.97	0.99	0.98	0.96	0.98	0.95
Subject	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
Accuracy model	**0.87**	**0.93**	**0.96**	**0.96**	**0.94**	**0.84**	**0.99**	**0.93**	**0.84**
Hapiness	0.95	0.97	0.98	0.99	0.96	0.92	0.99	0.96	0.91
Anger	0.90	0.99	0.98	0.99	0.99	0.89	1.00	0.96	0.93
Fear	0.97	0.94	0.98	0.97	0.95	0.94	1.00	0.97	0.94
Sadness	0.91	0.95	0.97	0.97	0.98	0.94	0.99	0.97	0.89

5 Conclusions

Results obtained in this study confirm that biosignals such as skin conductance, body temperature, and heart rate can be used to objectively and accurately identify different emotional states, thus validating the first hypothesis. Implemented neural network achieved a mean accuracy of 92% (intra-subject), supporting the second hypothesis that machine learning techniques, specifically neural networks, are effective for classifying emotional states from biomedical data.

Furthermore, system demonstrated superior accuracy and reproducibility when compared to traditional methods based on self-reports and questionnaires, affirming the third hypothesis. This outcome reinforces project's justification, as automatic detection system effectively reduces reliance on subjective evaluations, promoting a more accurate and objective approach to understanding and managing emotions.

Standardizing experimental protocol, using validated emotional stimuli (IAPS and IADS), and structured acquisition of physiological signals ensured robustness and consistency of results. These findings highlight potential of this system to be applied in mental health, education, and research, enabling continuous monitoring of emotional states and facilitating more personalized approaches in these fields.

In conclusion, successful implementation of this project demonstrates how biosignal-based emotion detection systems can bridge gap between scientific advancements and their practical application in everyday life.

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