Data Collection And Processing Problems in Automatic EEG Emotion Recognition

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Abstract. Research in the field of automatic recognition of emotions is quite important nowadays and can be used in a various field from military affairs (polygraphs) to medicine (psycho-correction) and entertainment. With the development of computer technology, it became possible to create a system that will automatically detect emotions in real time. However, many of the modern techniques of emotion detection strongly rely on a huge amount of valid and suitable data to process. Thus, the study of methods for obtaining data of sufficient quality is necessary. The article Is devoted to an analysis of the methods and problems of determining the emotional state of a person using electroencephalography. The problems of calling and evaluating emotions, as well as data processing when developing a software module for determining emotions, are considered. As a result of the analysis, recommendations for data collection were made, key features for machine learning algorithms were determined and a program of experiments for data collection was developed.

Keywords: Emotional state · Emotion recognition · Electroencephalography · Psycho-correction

1 Introduction

Undoubtedly, emotions play a big role in everyday life. Their influence extends to various aspects of human life, from communication and interaction with people to decision making. Information about the experienced emotions is widely used in various fields of society. For example, determining a response to a given stimulus can help correct a psycho-physiological state, allow an assessment of an attitude to the environment (workplace, equipment used) and draw appropriate conclusions, or contribute to improving the content recommendation system through more detailed feedback from users.

Thereby, automatic and accurate determination of an emotional state is important. With the development of information technology and the current availability of medical and computer equipment, research in this area is also becoming more accessible and attractive.

2 Subject area

Achievements in the field of neurophysiological studies of human brain activity are significantly lagging behind in depth and completeness of data from the same animal studies. Also, the need for the practical application of these methods (medicine, optimization of operator activity, the creation of neurocomputer interfaces) necessitates the continued of fundamental research on the human brain. Methods and technologies for determining emotions can be applied in various areas of society, from law enforcement agencies (various polygraphs) to entertainment field (environmental regulation in games based on current emotional state) and medical institutions (psychocorrection). However, the most relevant area of application of this study is the field of study of the functional state of a person.

Recognition of emotions can be carried out on the basis of audiovisual methods, such as recognition and analysis of facial expressions, speech, body language and others, but these methods do not always allow us to give a reliable assessment of a person's current emotional state. Facial expressions, speech, body movements, and other external physical characteristics can be easily altered if desired, and can also be misinterpreted according to the true emotion experienced. The mental state is more difficult for a person to control. Therefore, the determination of the emotional state by measuring the bioelectric activity of the brain is of great scientific and practical value.

The information theory of emotions by Simonov P.V. was chosen as the main theoretical base of this study. According to this theory, emotion is a reflection by the human or animal brain of any actual need (its quality and magnitude) and the likelihood (possibility) of its satisfaction, which the brain evaluates on the basis of genetic and previously acquired individual experience [1]. In general, the rule for the emergence of emotions can be represented in the formula:

$$E = f[N, (Ir - Ih), ...], \tag{1}$$

where E is emotion; N = strength and quality of an actual need; (Ir-Ih) - assessment of the ability to meet needs based on innate and ontogenetic experience, Ir - information about means required to achive the need; Ih - information about means to achive the goal that subject has at the current moment.

3 Problems of determining emotions using EEG

The main problems in the field of determining emotions using EEG are:

- The complexity of invoking a specific emotion

- The complexity of an objective and unambiguous assessment
- Data processing

EEG-based emotion recognition imposes certain restrictions on the available methods. Working with electrical signals involves invoking a specific emotion. In the case of facial recognition, emotion can be reproduced using Paul Ekkman's [FACS] system [3], however, such methods are not applicable here. In this case, to extract pure emotion, it is necessary to immerse a person in a situation where he can experience it, to make him feel the need for something that can cause emotion. For example, when displaying a video in which any injustice is shown, a person will be empathic for the events in the video and is likely to experience positive emotions if the injustice is eliminated, or negative emotions if the situation is not resolved well.

Before conducting experiments, it is recommended to conduct an initial diagnosis of the test subjects: to determine the interests, personal preferences and other psychological characteristics of the subjects. Based on this information, it will be possible to select the stimuli that are best suited for a particular subject. At this stage, you can also determine the temperament of the subject using the test, which can help in the future with training machine learning model. Some other parameters such as gender, age and dominant hand can also complete the feature set. The last parameter can greatly affect on the outcome result, since the work of the cerebral hemispheres is different for each right- and left-handed people.

To invoke a specific emotion, it is necessary to identify stimuli. It can be presented in various forms of media content (music, films, pictures, computer games), as well as in some actions with the test subject. For example, a compliment can cause embarrassment or joy, as well as offering the test subject a cup of tea. It is worth noting that different stimuli have different levels of immersion and have different effects on the emotional state. For example, a funny or sad music video can cause negative emotions instead of joy or sadness for the reason that the subject does not like this musical genre. Computer games provide the highest level of immersion, but may require the participation of the test person in them, and as a result, interference and artifacts on the EEG signal may occur. Video materials do not imply the active participation of the test subject, and involve only observation, and therefore are the most appropriate stimulus. An important point is also the entry barrier of the stimulus. Funny or disgusting pictures are more effective and productive for invoking emotion than a ten-minute video with some story.

The big problem is the correct assessment of experienced emotions. To train the machine learning model, manual control and markup of data according to the "presentation of the stimulus - assessment" model is assumed. Control can be carried out by various methods:

- Survey of the test subject (which of the following emotional states have you experienced? Rate the strength and sign of the experienced emotion on a scale of 1-10)

– Data on heart rate, HRV, ECG, etc. (subject claims he had experienced a sheer emotion, while his physical indicators tell otherwise - it is worth considering the correctness of the answer)
– Subject's face expressions (subject with an emotionless face claims he had experienced a sheer emotion, or states with obvious facial expressions that the stimulus did not cause him any emotions)

At this stage, it is necessary to reject possible incorrect reactions, and in some cases make a decision on the basis of subject's physical condition, rather than on the basis of his answers. An important role in determining the reaction is played by the fact that the subject knows about the conducting of the experiment and can change his answers willing to help the researcher or, vice versa, hide his emotions for some personal reasons.

During the tests, it is possible to oversaturate the subject's emotional state, worsen the emotional reaction and, as a result, receive incorrect data. This can happen with the continuous presentation of several stimuli of the same type in a row or with insufficient rest time of the subject. Thus, it is necessary to alternate stimuli of different types in random order, as well as give the subject time to "reboot" and relax. The recommended relaxation time is one minute, however, the time may vary depending on the state of the subject. Relaxation should occur with closed eyes and clean thoughts, however, this process is fully depends on the test subject.

4 Data collection and processing

When developing a software module for emotion recognition, the methods of data processing are important. The most popular processing method is building and training a machine learning model. Some researchers use K-nearest neighbours[6] and support vector machine methods[5]. Tools for data gathering are also important. So, for example, different EEG devices will have a different number of electrodes and different locations for it, which makes it difficult to develop a universal tool that can work with different types of equipment.

The feature selection is very important. First of all, it is necessary to choose those electrodes that are closest to the centers of emotion processing, namely: electrodes near the thalamus, hypothalamus, frontal and middle lobes of the brain. The selection of all available electrodes may be redundant and lead to retraining of the ML model, so the least important electrodes can be excluded. Of the additional features, you can take such parameters as a person's temperament. For this, the subjects will need to undergo appropriate testing in advance. Additional ECG electrodes, heart rate or HRV sensors are also can be selected as a features. However, this also imposes a limitation on the equipment used.

There are several models for classifying emotions that can be used in this study:

– There is a circumplex model that compares a qualitative assessment of emotion with its arousal and valence.

- There is a vector model, that consists of vectors that point in two directions, representing a "boomerang" shape. The model assumes that there is always an underlying arousal dimension, and that valence determines the direction in which a particular emotion lies.
- Positive activation - negative activation (PANA) model suggests that positive affect and negative affect are two separate systems. Similar to the vector model, states of higher arousal tend to be defined by their valence, and states of lower arousal tend to be more neutral in terms of valence in the PANA model, the vertical axis represents low to high positive affect and the horizontal axis represents low to high negative affect.

Lets take the circumplex model as example (shown in Fig 1). Arousal and Valence can be used as features for the ML model. Since Beta rhythms are associated with an activity, and alpha rhythms with a relaxed state, arousal state of the emotion can be characterized by a large activity of beta rhythms and low activity of alpha rhythms [2]. Thus, the ratio of beta / alpha rhythms can be an objective indicator of arousal. The calculation of the arousal parameter is presented in formula 2.

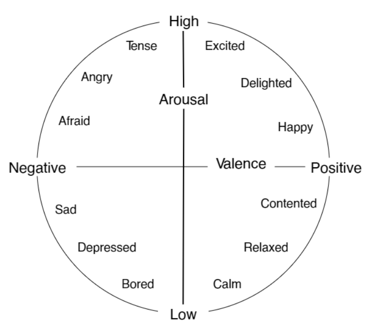

Fig. 1. Circumplex model

$$Arousal = \frac{sum(\beta)}{sum(\alpha)}, \qquad (2)$$

$$Valence = \frac{\alpha 4}{\beta 4} - \frac{\alpha 3}{\beta 3}, \qquad (3)$$

Studies by psychophysiologists also show that activity in the right and left hemispheres is associated with sensory and logical thinking, these types of thinking lead to appropriate behavior, and this is already associated with a feeling of positive and negative emotions, respectively[4]. By determining the ratio of beta / alpha rhythms, you can calculate the inactivity of the right hemisphere, and from it to subtract the inactivity of the left hemisphere, getting the value of valence in result. The calculation of the valence parameter is presented in formula 3.

Many factors influence the EEG data. So, for example, physical activity is more reflected on the EEG than mental and emotional ones, so the movement of a person (blinking, movement of the body and limbs, swallowing, etc.) during experiments can lead to artifacts in a certain time period, therefore, random unwanted movements on the part of the subject should be kept to a minimum. Internal defects in the EEG equipment and the electrical background from nearby third-party equipment (mobile phones, laptops) can also distort the signal, so the readings must additionally go through several stages of preliminary processing. For instance, the bioelectrical activity of the brain is defined in the range from 1 to 40 hertz among Delta, Theta, Alpha and Beta rhythms. Therefore, all signals that are not in this range can be taken as noise and artifacts and be excluded from the processing. It can be achieved by using low and highpass filters. Among the signal processing methods, some researchers use the Fast Fourier Transform and Discrete Wavelet Transform [5] to divide the signal to the specific bands. Additionally, these bands can be divided into a several sub-bands, and its summary power can be calculated and used as a feature.

Thus, to obtain the correct data set, it is necessary to take into account:

- Experiment program;
- Selection of subjects;
- Set of stimuls;
- Preliminary manual data evaluation;
- Feature selection;
- Processing interference and artifacts;

5 Experiment program

During the analysis, some key points for data collection and analysis were identified, and an experiment program and some requirements for its implementation were created. The experiment for a single subject is the following sequence of actions:

1. Connecting a test subject to an EEG device, connecting electrodes, checking equipment.
2. Recording background activity of the brain. The subject remains motionless with his eyes closed for several minutes.
3. Analysis of the condition and behavior of the subject. Needed to determine the most necessary emotional reactions at the moment.
4. Presentation of stimuli. It is carried out using the display of a computer/ laptop. The subject concentrates on the screen and prepares to perceive the information.
5. Assessment of the induced reaction.
6. Subject recovery, similar to pt.2.
7. Repeat paragraphs 3-6.

Thus, taking all notes into account, the correct data will be collected for training the machine learning model. After this, it is necessary to conduct an initial analysis of the data, to classify the results according to the responses of the researcher and the subjects.

6 Conclusion

The article identified and analyzed the main problems in determining emotion using EEG signals and an experiment program was created. Based on the information obtained during this study, it is planned to conduct experiments to collect data and develop a software module for determining emotions using EEG.

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