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Emotion Recognition using EEG Signals with Relative Power Values and Bayesian Network

Kwang-Eun Ko, Hyun-Chang Yang, and Kwee-Bo Sim*

Abstract: Many researchers use electroencephalograms (EEGs) to study brain activity in the context of seizures, epilepsy, and lie detection. It is desirable to eliminate EEG artifacts to improve signal collection. In this paper, we propose an emotion recognition system for human brain signals using EEG signals. We measure EEG signals relating to emotion, divide them into five frequency ranges on the basis of power spectrum density, and eliminate low frequencies from 0 to 4 Hz to eliminate EEG artifacts. The resulting calculations of the frequency ranges are based on the percentage of the selected range relative to the total range. The calculated values are then compared to standard values from a Bayesian network, calculated from databases. Finally, we show the emotion results as a human face avatar.

Keywords: Bayesian network, electroencephalogram (EEG), emotion recognition, relative power value.

1. INTRODUCTION

People communicate and exchange information with each other using language and nonverbal communication. In addition to human-to-human communication, communication between humans and machines or computer agents has become more common [1]. Emotion recognition in humans is an increasingly important research subject in this area. EEG signals are well known in the measurement of brain activity [2], and have been studied for various purposes. Hojjat Adeli described seizure detection and prediction from EEG analysis [3]. Anna Caterina studied EEG features extracted from wavelet transformations to investigate the feasibility of deception detection [4]. Junko Murakami extracted EEG signals to classify some human conditions [5]. Sebastien Marcel used EEG signals for authentication purposes [6].

In this paper, we propose an emotion recognition method using electroencephalogram (EEG) signals. First, we measured EEG signals and analyzed them using a power spectrum analysis method. This method is based on the fast Fourier transform (FFT). Each EEG signal was decomposed into five EEG sub-bands: *delta* (0-4 Hz), *theta* (4-8 Hz), *alpha* (8-13 Hz), *beta* (13-30 Hz), and *gamma* (30-50 Hz). We removed the *delta* band to eliminate noise such as pulses, neck movement, and eye blinking. Along this line, Wakako Nakamura proposed the application of independent component analysis (ICA) together with the post processing of high-pass filtering to remove ballistocardiogram artifacts [7].

Also, we calculated each EEG signal using a relation power value equation that selects the EEG sub-band over the total EEG band. We then compared the calculated EEG signals with EEG databases. To accomplish this, EEG signals were needed for analysis using Bayesian networks. Along this line, Shiliang Sun proposed a new approach, based on Bayesian networks, for traffic flow forecasting [8]. Yan Sun [9] and Naruhoko Shiratori [10] used Bayesian networks to aid in the early diagnosis of Alzheimer's Disease and to study anesthetic practice. Also, Rui Zhang used wavelet analysis and a Bayesian network for the classification of auditory brainstem responses [11].

In this study, we recognized human emotion using an EEG signal with relative power values and a Bayesian network. Our results are shown using text and a human face avatar representing human emotion.

The organization of this paper is as follows: Section 2 introduces the concepts of relative power values and Bayesian networks. Section 3 describes the experimental data acquisition process. Section 4 shows our experimental results and the performance of the proposed approach. In Section 5, we present conclusions and suggest future work.

2. RELATIVE POWER VALUES AND BAYESIAN NETWORKS

2.1. Relative power values

Relative power value analysis uses an EEG signal data analysis method to obtain correct values. In our first analysis, measured EEG signals were transformed into a power spectrum using fast Fourier transforms (FFTs). The transformed EEG signals were divided into five

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parts (δ, θ, α, β, γ) which were displayed in different colors. Fig. 1 shows a power spectrum of EEG signals measuring the human emotion of anger.

We can easily identify the different power rates at each frequency band as emotion. We analyzed human brainwaves to measure this difference. Divided EEG signals at low frequencies (0 to 4 Hz) were removed because they included many EEG artifacts. Each selected frequency range (δ, θ, α, β, γ) were calculated with related power values function.

$$\textit{Relative power value}(\%) = \frac{\sum \textit{Selecting range}}{\sum \textit{Total range}(4 \sim 50 Hz)} \tag{1}$$

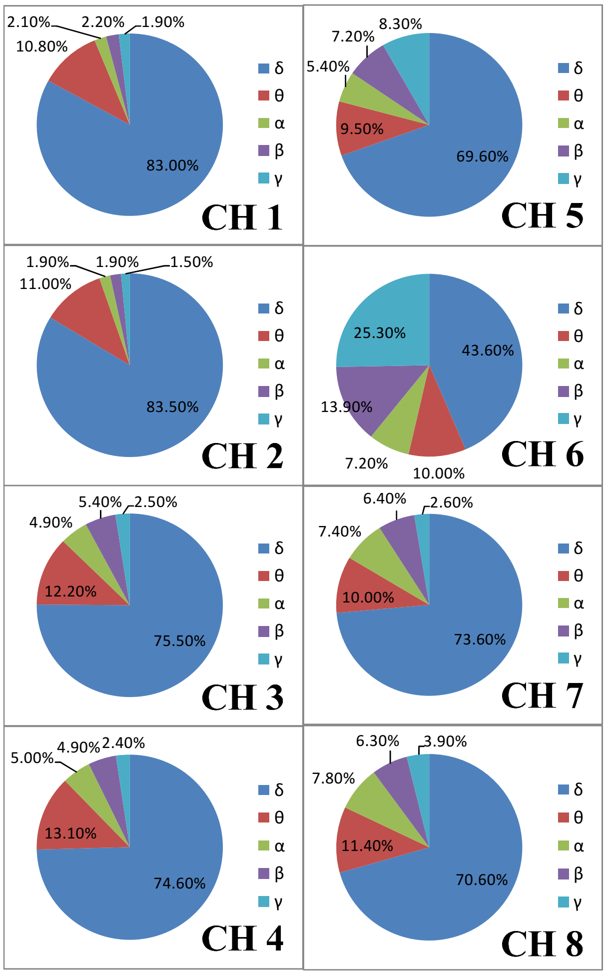


Fig. 1. Power spectrum of EEG signals measuring human emotion (anger).

2.2. Bayesian network

Bayesian networks are widely accepted as powerful tools for representation and reasoning under conditions of uncertainty in decision-support systems. A Bayesian network is a concise model of a joint probability distribution given a set of stochastic variables. The network consists of a directed acyclic graph which captures the qualitative dependence structure of the distribution, and a numerical component which specifies a conditional probability distribution and facilitates the computing of any probability of interest over various variables. Also, a Bayesian network is a graphical model that denotes a joint probabilistic distribution among variables of interest based on their probabilistic relationships. We constructed a network and used it for computer-based diagnosis and prediction. For example, consider a case in a database consisting of a set of faulty behaviors, as well as the fault determined to have caused those behaviors. Assume that the database contains many such cases from previous episodes of faulty behavior. The Bayesian method can be used to construct from the database a probabilistic network that captures the probabilistic dependencies between findings and faults. Such a network can then be applied to diagnose future cases of faulty behavior by deriving an *a posteriori* probability distribution over the possible faults [9]. In a Bayesian network, an arc from node A to node B can be informally interpreted as indicating that A "causes" B. The simplest statement of conditional independence relationships encoded in a Bayesian network can be stated as follows: a node is independent of its ancestors given its parents, where the ancestor/parent relationship is with respect to some fixed topological ordering of the nodes. Therefore, for a Bayesian network consisting of n nodes that show random variables $(x_1, x_2, ..., x_n)$, we have the following representation for the joint probability distribution:

$$p(x_1, x_2, ..., x_n) = \prod_{i=1}^{n} p(x_i \mid x_{p_i}), \tag{2}$$

where $p(x_i \mid x_{p_i})$ is the local conditional probability distribution associated with node i and p_i is the set of indices labeling the parents of node i (p_i can be empty if node i has no parents) [8]. The conditional independence relationship allows us to represent the joint probability distribution more compactly and conveniently; this is useful for parameter estimation in emotion recognition. Fig. 2 shows an example of a simple Bayesian network.

In order to use the Bayesian network correctly, we need to structure learning and parameter learning on

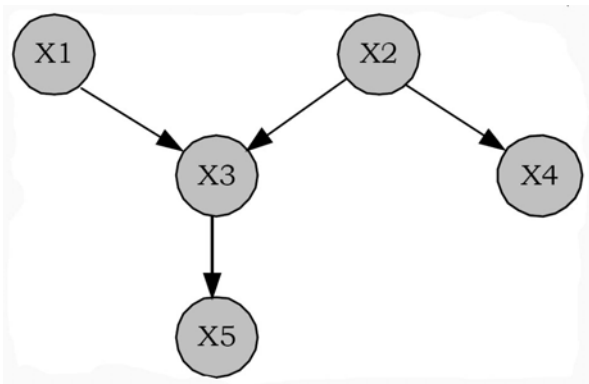


Fig. 2. Example of a simple Bayesian network.

Bayesian network. This subject is described in more detail in [19]. From the database face image, we acquired the mean feature vectors of each emotion. Then, the input facial image feature was compared with the mean feature vector of each emotion in the database. The differences between the input and database feature vectors are important indicators for the recognition of emotion.

3. EXPERIMENTAL DATA ACQUISITION

3.1. Psychological emotion experiment

To assess the mental condition of a human, researchers often use a dimension model and a foundation emotion model. Wundt classified three dimensions: pleasant/ unpleasant feeling, excitement/calmness, and tension/ relaxation. Russell combined existing research and considered two dimensions: pleasant/unpleasant feeling and awakening/sleeping. Fig. 3 is an adaptation of Russell's figure showing how several different emotions can be described using valence and arousal dimensions [12].

In contrast, Ekman, a leader in foundation emotion theory, asserted that there are six foundation emotions: happy, surprise, fear, anger, disgust, and sadness [13]. We selected six foundation emotions for our study. Along this line, Mark D. Korhonen proposed a new method to develop a methodology to create valid models of time-varying continuous emotional content for a genre of music [14].

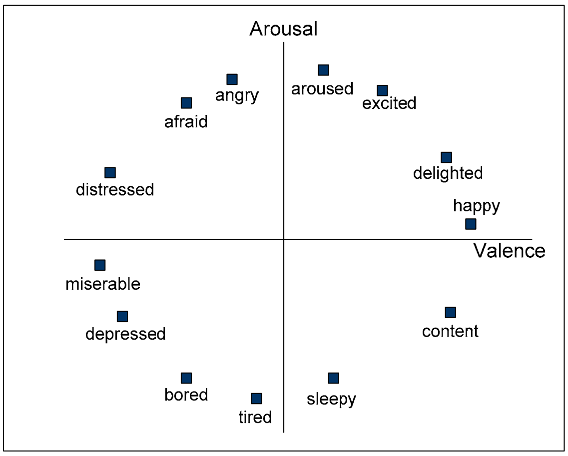


Fig. 3. Example of an emotion plot in two-dimensional emotion space [12].

Fig. 4. Pictures of EEG experiment.

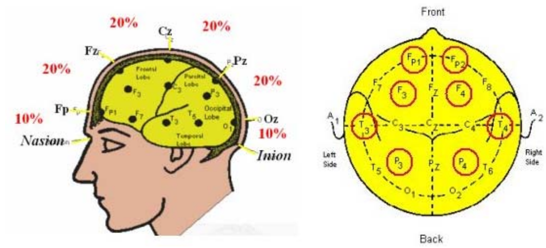


Fig. 5. Coordinates of EEG electrodes.

In our study, human emotions were induced by audio-visual pictures broadcast on TV instead of static pictures. The experiments were carried out in a private room where noise and room temperature were controlled to maintain uniformity. We altered light levels in the room to control the amount of stimulus. Fig. 4 shows pictures from the experiment.

3.2. Experimental measurement method

We measured the EEG signals that represent electrical activity in the human brain. We used eight measurement points in the international 10-20 system. Fig. 5 shows the measurement points used in this study.

In this study, we used a QEEG-8 with eight channels (LAXTHA, Inc.) to measure the EEG. Eight electrode sensors were fixed to each human's scalp, and we measured the resultant brain activity. The measured data were transmitted to a PC by some device such as RS-232.

3.3. EEG signal analysis method

The EEG signals display complex brainwave patterns. It is not useful to visually observe original brainwave patterns. Tarun Mandan proposed using features based on power spectral density as a descriptor of the compression of a long-term EEG in an intensive care setting to obtain the temporal evolution of recurrent patterns [15]. We used power spectrum analysis which classified the signals according to frequency, and shows the magnitude or power of the decomposed frequency.

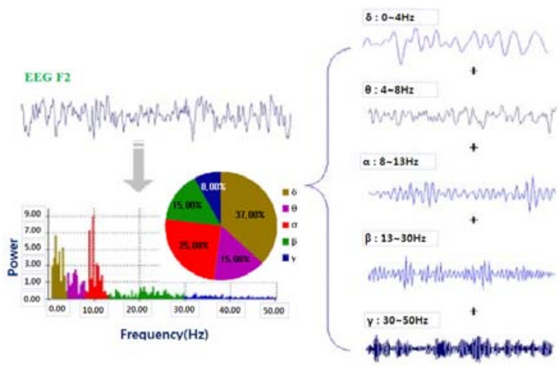


Fig. 6. Power spectrum transformation.

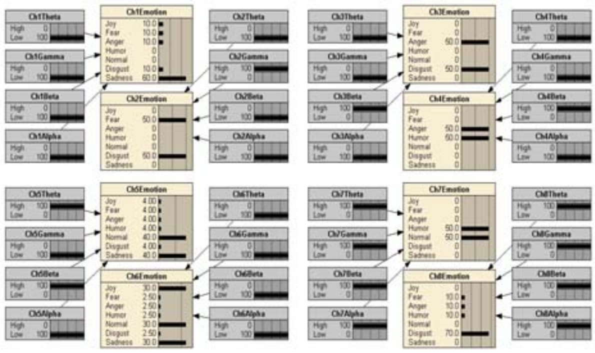


Fig. 7. Bayesian network structure for emotion recognition.

As a different way of approach about EEG signal analysis method, Arnaud Delorme attempted to regulate power at 12 Hz over the left- and right-central scalp area to control the altitude of a cursor moving toward target boxes placed at the top-, middle-, or bottom-right of a computer screen [16]. We measured EEG signals from 0 Hz to 50 Hz; these were transformed into power spectra using FFTs. We measured delta (0~4 Hz), theta (4~8 Hz), alpha (8~13 Hz), beta (13~30 Hz), and gamma (30~50 Hz). Fig. 6 shows the power spectrum transformation of one brainwave point divided into five parts. Fig. 7 shows the results of relative power values as specific emotions.

3.4. Comparative analysis method of EEG signals

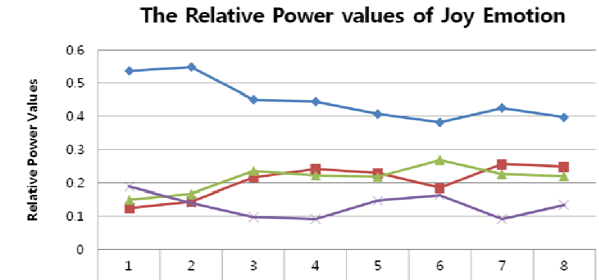
The calculated relative power values were compared with the database for emotion recognition. The resulting values clearly differed by individual. We estimated emotions using probability inference in order to account for the differences. When we compared the results with the database, the mean values of the database were the standards of the value judgements. If a measured value was higher than the mean, the value was allocated a positive binary number. The binary values were used to calculate probability inference using a Bayesian network. Fig. 7 shows the Bayesian network structure. Fig. 7 was produced by Netica software (Norsys Software Corp., Vancouver, B.C., Canada).

4. EXPERIMENTAL RESULTS

4.1. EEG experimental result

We use audiovisual pictures to induce six emotions. The resulting waves were analyzed using the power spectrum analysis method. From the results, we determined that there are small differences between emotions, and we calculated the relative power values of the emotions. The calculated values show a percentage of total ranges. Fig. 8 shows one of the emotions calculated using (1).

Because the experimental results for each emotion were different, we used a Bayesian network to compare the results. We then defined the subject's emotion with the highest value of probability. This emotion is expressed both by text and the avatar. Fig. 9 shows the emotion recognition simulator.



	1	2	3	4	5	6	7	8
4~8Hz	0.5375	0.5495	0.451	0.4454	0.4071	0.3817	0.4261	0.397
8~13Hz	0.1244	0.1444	0.2159	0.242	0.2292	0.1846	0.2567	0.2485
13~30Hz	0.1495	0.1666	0.2362	0.2222	0.2175	0.2697	0.2263	0.2202
30~50Hz	0.1893	0.1405	0.0981	0.0915	0.1473	0.1647	0.0918	0.135

Fig. 8. Relative power values of joy.

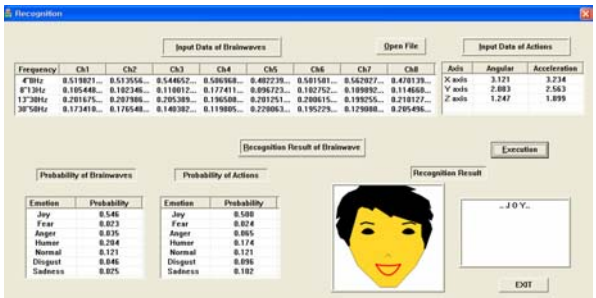


Fig. 9. Emotion recognition simulation program.

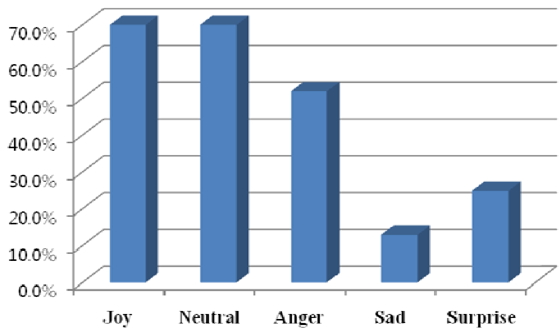


Fig. 10. Emotion recognition performance.

The simulator was an inputted brainwave data file, and it showed calculated probability values using a Bayesian network, the avatar, and the text of various emotions. Fig. 10 provides a "joy" example. From the simulator, we obtained a recognition performance for "joy."

This expression system is preliminary research for a brain-computer interface (BCI).

5. CONCLUSION AND FUTURE WORK

In this study, we classified human brainwaves according to emotions and compared the results. We used audio and visual pictures to induce emotions, and the brainwaves were transformed into power spectrum values using a FFT. We removed signals in the low frequency range to eliminate artifacts of brainwaves and the remaining signals which are selected frequency ranges were calculated with relative power values. Because human emotions cannot be measured accurately, we used probability inference and a Bayesian network. In comparing results, many emotions showed different probability values, but "anger" and "sadness" show similar probability values.

Future research should consider human knowledge as well as human emotions. We will research BCI in relation to real-time sensing, which should be particularly useful in the care of the physically handicapped and the elderly.

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