JDCS 디지털콘텐츠학회논문지
Journal of Digital Contents Society
Vol. 19, No. 4, pp. 821-827 Apr. 2018

뇌파신호를 이용한 감정분류 연구

무하마드 주바이르[1] ·김 진 술[2]· 윤 장 우[3*]
[1]과학기술연합대학원대학교 정보통신네트워크과
[2]전남대학교 전자컴퓨터공학과
[3]한국전자통신연구원 초연결통신연구소

Research on Classification of Human Emotions Using EEG Signal

Muhammad Zubair[1] · Jinsul Kim[2] · Changwoo Yoon[3*]
[1]Information and communication networks Department, University of Science and Technology, Daejeon, Korea
[2]Department of Electronics and Computer Engineering, Chonnam National University, Gwangju, Korea
[3]Electronics and Telecommunication Research Institute, Daejeon, Korea

[요 약]

Affective Computing은 HCI (Human Computer Interaction) 및 건강 관리 분야에서 다양한 애플리케이션이 개발됨에 따라 최근 몇 년 동안 관심이 높아지고 있다. 이에 필수적으로 필요한 인간의 감정 인식에 대한 중요한 연구가 있었지만, 언어 및 표정과 비교하여 심전도 (ECG) 또는 뇌파계 (EEG) 신호와 같은 생리적 신호 분석에 따른 감정 분석에 대한 관심은 적었다. 본 논문에서는 이산 웨이블릿 변환을 이용한 EEG 기반 감정 인식 시스템을 제안하고 감정 관련 정보를 얻기 위해 다른 뇌파와 뇌 영역을 연구 하였으며, 웨이블릿 계수에 기초한 특징 세트가 웨이블릿 에너지 특징과 함께 추출되었다. 중복성을 최소화하고 피처 간의 관련성을 극대화하기 위해 mRMR 알고리즘이 피쳐 선택에 적용된다. 다중클래스 Support Vector Machine을 사용하여 4 가지 종류의 인간 감정을 크게 분류하였으며 공개적으로 이용 가능한 "DEAP" 데이터베이스의 뇌파 기록이 실험에서 사용되었다. 제안 된 접근법은 기존의 알고리즘에 비해 향상된 성능을 보여준다.

[Abstract]

Affective computing has gained increasing interest in the recent years with the development of potential applications in Human computer interaction (HCI) and healthcare. Although momentous research has been done on human emotion recognition, however, in comparison to speech and facial expression less attention has been paid to physiological signals. In this paper, Electroencephalogram (EEG) signals from different brain regions were investigated using modified wavelet energy features. For minimization of redundancy and maximization of relevancy among features, mRMR algorithm was deployed significantly. EEG recordings of a publically available “DEAP” database have been used to classify four classes of emotions with Multi class Support Vector Machine. The proposed approach shows significant performance compared to existing algorithms.

색인어 : 뇌파 신호, 감정 인식, 웨이블릿 변환, SVM

Key word : EEG signals, Emotion recognition, Wavelet transform, SVM

http://dx.doi.org/10.9728/dcs.2018.19.4.821

Received 18 April 2018; **Revised** 24 April 2018
Accepted 28 April 2018

***Corresponding Author; Changwoo Yoon**

Tel: +82-10-6888-1663
E-mail: cwyoon@etri.re.kr

Ⅰ. Introduction

Automatic detection and recognition of different emotional states is a leading topic in the fast growing research field of affective computing. Emotions are complex states of minds which influence all aspects of our daily life and significantly effects our health. By incorporating the knowledge of physiology, artificial intelligence, computer science, and biomedical engineering, various human emotion recognition algorithms and models have been proposed in the field of affective computing. Anxiety, depression and anger disturb human immune system and increase the risk of long-lasting diseases. Recent advancement in the field of IOT and sensor networks [1] have heightened the development of smart healthcare systems in order to improve the overall life quality. The development of an efficient human emotion recognition system could play a key role in regulating self-emotions and would introduce sophisticated applications in the field of education, entertainment and security.

Based on different theories of emotions, presented by psychologists and philosophers, several methods have been proposed for human emotion's identification using facial images [3], speech signals [4], gestures and physiological signals. In comparison to speech signals and facial images, physiological signals exhibit better representation of the true emotions experience during elicitation. Because, these involuntary signals are independent of people's will and could not be suppress and thus are capable to reflect the true emotions. On the other hand, in facial images true emotion can be hide and suppress and thus could lead us to false emotion prediction. Physiological signal such electrocardiogram, skin conductance or electromyogram etc. are triggered by Autonomous Nervous System activity, and thus cannot be controlled intentionally. Experimental evidence shows that activity of Autonomic Nervous System (ANS) effects physiological signals and such signals reflects the experienced emotional state efficiently [5], [6]. In this paper, an efficient and robust emotion recognition system is proposed. Using Discrete Wavelet Transform coefficients, improved wavelet energy feature were computed to enhance the classification performance of emotion recognitions systems.

This paper is organized as follows: In Section 2, we review different sequential steps involved in the development of emotions recognition system. In Section 3, along with the description of dataset, we illustrated the detailed methodology of feature extraction, feature selection and classification of different classes of emotions. Classification performance and concluding remarks are given in section 4 and 5 respectively.

Ⅱ. Literature Review

Emotion recognition from physiological signals has gain a lot of interest over the past few years. Several emotion identification systems and models have been proposed in the domain of affective computing yet a little attention has been paid to Electroencephalogram signals for emotion recognition. Literature reveals that performance of EEG based emotion recognition system highly correlated to data size, the type of stimulus used and the model of emotion adopted. The lack of standardization in different factors (data, stimulus, emotion model) of emotion recognition systems makes it hard to compare. However, the recent work done in this domain is reviewed briefly in this section.

2-1 Emotion modeling

Emotion is an involuntary mental and affective state of the mind and comprise of various components such as behavior, feelings and bodily changes. In order to classify and model emotion several approaches have been introduced. The two basic theoretical approaches for modeling emotions are discrete approach and dimensional approach. In discrete approach, emotions are classified into six basics discrete categories [2]. These emotion are happy, sad, anger, disgust, surprise and fear. All other emotions are either the combination of these basic emotion or special cases of basic emotions. On the other hand, dimensional approach characterize emotion by two dimensions which includes arousal (Intensity of emotion) and valence (pleasantness of emotion). Circumplex Model of Affects (CMA) [7] is one of the most widely used model of this approach in which emotions are distributed on a two dimensional space as given in figure 1.

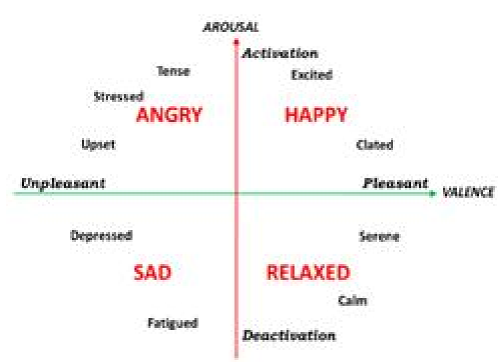

그림 1. 감정분석 원형 모델
Fig. 1. Circumplex model of emotions.

2-2 Emotion elicitation

Emotion elicitation is the most crucial step in the development of emotion recognition system. Numerous emotion evoking approaches have been proposed by researchers. During elicitation, the acquisition of specific physiological signals is performed in the presence of a given stimulus. These stimuli include audio clips, pictures and video clips and are capable of evoking different emotions. The most widely used databases for emotion elicitation are "International Affective Picture System" (IAPS) [8] and "International Affective Digitized Sound System" (IADS) [9], which provide a wide range of visual and auditory stimuli respectively.

2-3 Feature extraction and Classification

Emotion related information can be captured from EEG signals as features which can then be used in classification of different classes of emotions. These features can be computed in time and frequency domain either from raw EEG signals or its bands. Time domain features like mean, standard deviation and variance can be extracted from EEG signals in its raw form [11]. Similarly, frequency domain features can also be computed by decomposing EEG signal into different frequency bands (delta, theta, alpha, beta and gamma). Effectiveness of Fractal dimensions and High Order Crossings based feature vector extraction is presented in various articles [10, 11]. Beside this, Independent Component Analysis [12] and Discrete Wavelet Transformation [13] was also reported for higher classification performance. Furthermore, for classification of emotion using the extracted set of features various machine learning algorithms has been used in literature. Among these, the most frequently used classifiers are Support Vector machine [14], Neural Networks [15] and Quadratic Discriminant Analysis [16].

Ⅲ. Methodology

3-1 Dataset

Advancement in wearable sensors have boosted the interest of many researchers in the field of affective computing. Various databases of physiological signals (electrocardiogram, respiration, skin conductance, electromyogram and electroencephalogram etc.) are publically available. For instance MAHNOB-HCI [17] and ASCERTAIN [18] provides electrocardiogram, electroencephalogram and galvanic skin response signals for emotion recognition. A public available database "DEAP" is employed in this study. DEAP database was proposed by Koelstra et al. [19] which includes electrocardiogram, electromyogram (EMG), electrooculogram (EOG), respiration, galvanic skin response, skin temperature, blood volume recordings of sixteen male and sixteen female participants. For signals acquisition, Biosemi Active Two system was used. According to international 10-20 system EEG recording was conducted over the scalp with 32 electrodes as shown in figure 2. Forty different music videos, each of 60 seconds length, were used as stimulus. Heavily distorted signals from electrical noise, motion artifacts and EOG artifacts were filtered in the preprocessing stage. Down sampling from 512 Hz to 128 Hz was performed during preprocessing. In order to get the meaningful and information-rich bands of EEG signals, a bandpass frequency filter (4.0-45.0 Hz) was applied. For the elimination of eye blink artifacts blind source separation technique was adopted. In the last of experiment every subject performed self-assessment using Self-Assessment Manikins to evaluate and rate each music video in term of levels of arousal, valence, like/dislike, dominance and familiarity according to the level they experienced. The preprocessed EEG data released by Koelstra et al. [19] is used in this paper for the development of emotional recognition system.

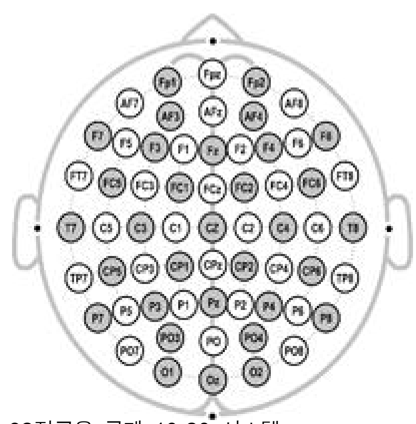

그림 **2.** 32전극용 국제 10-20 시스템
Fig. 2. International 10-20 system for 32 electrodes (Marked as gray)

3-2 Feature Extraction

1) Statistical-based features: Effective feature vector extraction techniques like fractal dimension and high order crossing are broadly used to deal with nonlinear and complex nature of EEG signals. However, statistical features such as mean of EEG signal, variance and standard deviation of EEG signals are also capable to discriminate different classes of emotions. For higher classification performance, we extracted statistical features from 32 channel EEG recordings of DEAP dataset which includes the following mentioned features.

- **Mean of the raw signal**

$$\mu_X = \frac{1}{N}\sum_{n=1}^{N} X(n) \tag{1}$$

- **The standard deviation of the raw signal**

$$\sigma_X = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(X(n)-\mu_X)^2} \tag{2}$$

- **The mean of the absolute values of the first difference of the raw signal**

$$\delta_X = \frac{1}{N-1}\sum_{n=1}^{N-1} |X(n+1) - X(n)| \tag{3}$$

- **The mean of the absolute values of the first signal of the standardized signal**

$$\overline{\delta_X} = \frac{1}{N-1}\sum_{n=1}^{N-1} |\bar{X}(n+1) - \bar{X}(n)| = \frac{\delta_X}{\sigma_X} \tag{4}$$

- **The mean of the absolute values of the second difference of the raw signal**

$$\gamma_X = \frac{1}{N-2}\sum_{n=1}^{N-2} |X(n+2) - X(n)| \tag{5}$$

- **The mean of the absolute values of the second difference of the standardized signal**

$$\overline{\gamma_X} = \frac{1}{N-1}\sum_{n=2}^{N-2} |\bar{X}(n+2) - \bar{X}(n)| = \frac{\gamma_X}{\sigma_X} \tag{6}$$

2) Wavelet-Based Features: Discrete Wavelet Transform" is an efficient analytical tool that is used widely for the analysis of non-stationary signals. Due to the non-stationary nature of EEG signals, we also employed DWT for time and frequency analysis. DWT, with successive high pass and low pass filters, can decomposed EEG signals into specific frequency bands. High pass and low pass filter of DWT produce detail and approximation coefficients respectively. "Daubechies Wavelet Transform" (db4) coefficients are considered best for its effectiveness in multi-resolution analysis of EEG signals. In this paper, we used a five levels "Daubechies" wavelet of order 4 in order to extract five different frequency bands (delta, theta, alpha, beta and gamma) from an EEG signal of 128 Hz.

After decomposing EEG signals into five different bands, wavelet energy and wavelet entropy was computed according to equation 7 and 8 respectively.

$$E_l = \sum_{2^{S-1}-1}^{2^{S-1}-1} |C_X(l,n)|^2 \quad , \; N = S^2, 1 < l < S \tag{7}$$

$$E_l = \sum_{n=1}^{2^{S-1}-1} |C_X(l,n)|^2 \log(|C_X(l,n)|^2) \tag{8}$$

표 1. 뇌파신호의 다중 주파수 대역 분리

Table 1. EEG signals decomposition into different frequency bands

Frequency	Decomposition Level	Frequency Band	Frequency Bandwidth (Hz)
0-4	A5	Delta	4
4-8	D5	Theta	4
8-16	D4	Alpha	8
16-32	D3	Beta	16
32-64	D2	Gamma	32

3-3 Feature Selection and Classification

Feature selection step helps to mitigate the issues related to dimensionality of feature space, over-fitting and model generalizability etc. Selecting a subset of most relevant and suitable features not only avoid the curse of dimensionality but also improves the classification performance of the model. Irrelevant and redundant feature increases the computational complexity and thus slows the training process and reduces the overall performance of the model. For this purpose, "maximum relevancy and minimum redundancy algorithm" (mRMR) was employed and implemented successfully for the selection of most relevant feature set. After feature selection, classification was performed using "Support Vector Machine" with radial basis function.

Ⅳ. Experimental Results

The set of selected features from EEG recording of 32 participants was used to classify four classes of emotions. The stimulus rating (valence and arousal score) gathered during self-assessment was divided into two categories of low and high. Thus four different classes of emotions were formed which can cover all the four quadrants of CAM. The classes includes, "high arousal/high valence (HAHV), high arousal/low valence

(HALV), low arousal/high valence (LAHV) and low arousal/low valence (LALV)". 70% of the total samples were used as training data for model training and the remaining 30% samples were used as test data for evaluation of the trained model. "Quadratic Discriminant Analysis" and "Support Vector Machine" was employed with Grid search technique for parameters optimization in order to classify emotion data. In this experiment, SVM performed better comparative to QDA with an overall classification accuracy of 49.7%.

The number of EEG channels were reduced in order to decrease the system complexity. In this regard, 15 EEG channels ("Fp1, Fp2, AF3, F3, F4, F7, F8, P7, O1, O2, P8, CP3, CP4, C4 and C3") from four major lobes of the brain were selected. Certain brain regions like left and right frontal lobes demonstrate specific activities in the presence of different types and levels of stimulus [11]. Similarly EEG bands are triggered in specific brain regions by different emotional states [20]. Figure 3 shows the event related potential (ERP) of a single channel frontal lobe EEG signal for 40 different events. Thus we can say that the classification of EEG based emotions highly depends on the channel and bands of EEG signals.

표 2. 분류정확도
Table 2. Classification accuracy

Method	HAHV	HALV	LAHV	LALV	Overall
QDA	44.4%	47.7%	45.1%	44.6%	45.4%
SVM	52.1%	49.1%	49.6%	48.3%	49.7%

The activity of all five bands in EEG recordings of selected channels were also investigated for four classes of emotions. For different sets of channels, model training was performed for each EEG band separately. Gamma band features extracted from Frontal lobe channels (FP1, FP2, F3 and F4) and temporal lobe channels (T7, T8) channels showed best classification performance (48.8%).

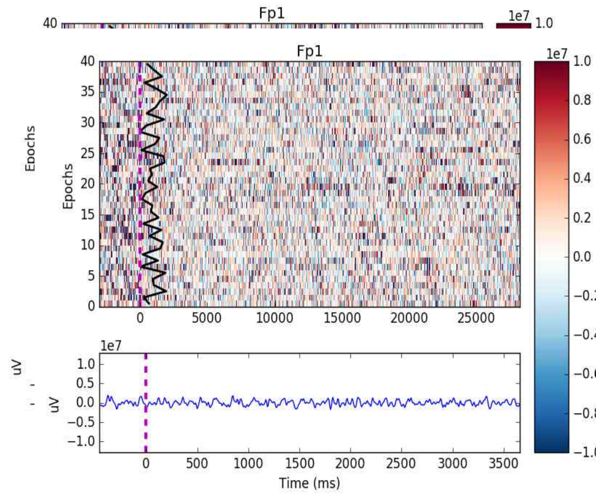

그림 3. 전두엽 채널 (Fp1)을 사용한 ERP 이미지
Fig. 3. ERP image using frontal lobe channel (Fp1)

Ⅴ. Conclusion

In this paper, we illustrated the development of an efficient emotions recognition system using electroencephalogram signals. DEAP database which includes 32 subjects' data, was employed. Decomposition of EEG signals into different frequency bands was performed using Discrete Wavelet Transformation. "Maximum relevancy and minimum redundancy" algorithm was used to select a suitable and significant feature set. The selected features were feed into "Support Vector Machine" for the classification of four levels of emotion.

The approach proposed in this paper can classify four classes of emotion efficiently using support vector machine. The following can be concluded from this work. Features, computed from DWT can effectively capture emotion related information. In terms of classification, Gamma band classified all classes of emotions efficiently compare to other bands. In this study, we also found a strong correlation between emotions and the gamma signals acquired from frontal lobe of the brain which validates the role of frontal lobe in emotion recognition system. Future work includes the fusion of EEG and ECG signals for higher classification performance.

Acknowledgement

This work was supported by Institute for Information & communications Technology Promotion (IITP) grant funded bythe Korea government (MSIP) (Development of SW fused Wearable Device Module and Flexible SW Application Platform for the integrated Management of Human Activity, R7118-16-1011).

참고문헌

[1] Bilal, Muhammad, and Shin-Gak Kang. "An Authentication Protocol for Future Sensor Networks." Sensors 17.5 (2017): 979.

[2] Paul Ekman, Emotions Revealed. TIMES BOOKS, 2003.

[3] L. Zhang, D. Tjondronegoro, "Facial expression recognition using facial movement features," IEEE Transactions on Affective Computing, vol. 2, pp. 219-229, 2011.

[4] K. Wang, A. Ning, B.N. Li and Y. Zhang, "Speech emotion recognition using Fourier parameters," IEEE Transactions on Affective Computing, vol. 6, pp. 69-75, 2015.

[5] J. Anttonen and V. Surakka, "Emotions and Heart Rate While Sitting on a Chair," Proc. SIGCHI Conf. Human Factors in Computing Systems, pp. 491-499. 2005.

[6] C.M. Jones and T. Troen, "Biometric Valence and Arousal Recognition," Proc. 19th Australasian Conf. Computer-Human Interaction, pp. 191-194, 2007.

[7] Posner et al. The circumplex model of affect: An integrative approach to affective neuroscience, cognitive development, and psychopathology.Dev. Psychopathol. 17, (2005).

[8] P. J. Lang, M. M. Bradley, and B. N. Cuthbert, "International affective picture system (IAPS): Affective ratings of pictures and instruction manual," Tech. Rep. A-8, 2008.

[9] M. M. Bradley and P. J. Lang, "The international affective digitized sounds (; iads-2): Affective ratings of sounds and instruction manual," Univ. of Florida, Gainesville, FL, USA, Tech. Rep. B-3, 2007.

[10] Sourina, Olga, and Yisi Liu. "A Fractal-based Algorithm of Emotion Recognition from EEG using Arousal-Valence Model." BIOSIGNALS. 2011.

[11] Petrantonakis et al. "Emotion recognition from EEG using higher order crossings." IEEE Transactions on Information Technology in Biomedicine 14.2 (2010): 186-197.

[12] Lan, Tian, et al. "Estimating cognitive state using EEG signals." Signal Processing Conference, 2005 13th European. IEEE, 2005.

[13] Murugappan et al."Classification of human emotion from EEG using discrete wavelet transform." Journal of Biomedical Science and Engineering 3.04 (2010): 390.

[14] S.Koelstraet al., "Single trial classificationof EEG and peripheral physiological signals for recognitionof emotions induced by music videos," in Proceeding of the International Conference on Brain Informatics (BI '10), pp. 89–100, Toronto, Canada, 2010.

[15] U. Wijeratneet al, "Intelligent emotion recognition system using electroencephalography and active shapemodels," in Proceedings of the IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES '12), pp. 636–641, 2012.

[16] Z. Khalili and M. H. Moradi, "Emotion recognition system using brain and peripheral signals: using correlation dimension to improve the results of EEG," in Proceedings of the International Joint Conference on Neural Networks (IJCNN '09), pp.1571–1575, Atlanta, Ga, USA, June 2009.

[17] M. Soleymani et al. A multimodal database for affect recognition and implicit tagging. IEEE Transactions on Affective Computing, 2012, 3. Jg., Nr. 1, S. 42-55.

[18] Subramanian R, Wache J, Abadi M, Vieriu R, Winkler S, Sebe N. ASCERTAIN: Emotion and personality recognition using commercial sensors. IEEE Transactions on Affective Computing. 2016 Nov 4.

[19] Koelstra, Sander, et al. "Deap: A database for emotion analysis; using physiological signals." IEEE Transactions on Affective Computing 3.1 (2012): 18-31.

[20] Daimi, Syed Naser, and GoutamSaha. "Classification of emotions induced by music videos and correlation with participants' rating." Expert Systems with Applications 41.13 (2014): 6057-6065.

무하마드 주바이르 (Muhammad Zubair)

2014: University of Science and Technology, Peshawar Pakistan
(Electrical Engineering, Bachelor of Science)

2015 ~ Present :Student (Integrative program)
Department of Information & Communication Networks
University of Science and Technology Korea
Area of Interest: Affective computing, Machine learning

김진술(Jinsul Kim)

2005년 : 한국과학기술원(KAIST) (공학석사)
2008년 : 한국과학기술원(KAIST) (공학박사)

2005년~2009년: 한국전자통신연구원(ETRI)
2009년~2012년: 한국나사렛대학교
2012년~현 재: 전남대학교 전자컴퓨터공학부 교수
※관심분야 : 미래 네트워크, SDN, NFV, MEC, QoS/QoE 품질 예측 및 측정, 모바일 미디어 처리, 멀티미디어 통신, etc.

윤장우(Changwoo Yoon)

1992년 : 포항공대(POSTECH) (공학석사)
2005년 : 플로리다대(U.Florida) (공학박사)

1992년~현재 한국전자통신연구원 책임연구원
2009년~현재 과학기술연합대학원대학교 교수
※ 관심분야: 뇌과학, 인지컴퓨팅, 인공지능, 웨어러블, IoT, 클라우드컴퓨팅, N-Screen, IPTV