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Paper:

Human-Wants Detection Based on Electroencephalogram Analysis During Exposure to Music

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We propose a method to detect human wants by using an electroencephalogram (EEG) test and specifying brain activity sensing positions. EEG signals can be analyzed by using various techniques. Recently, convolutional neural networks (CNNs) have been employed to analyze EEG signals, and these analyses have produced excellent results. Therefore, this paper employs CNN to extract EEG features. Also, support vector machines (SVMs) have shown good results for EEG pattern classification. This paper employs SVMs to classify the human cognition into "wants," "not wants," and "other feelings." In EEG measurements, the electrical activity of the brain is recorded using electrodes placed on the scalp. The sensing positions are related to the frontal cortex and/or temporal cortex activities although the mechanism to create wants is not clear. To specify the sensing positions and detect human wants, we conducted experiments using real EEG data. We confirmed that the mean and standard deviation values of the detection accuracy rate were 99.4% and 0.58%, respectively, when the target sensing positions were related to the frontal and temporal cortex activities. These results prove that both the frontal and temporal cortex activities are relevant for creating wants in the human brain, and that CNN and SVM are effective for the detection of human wants.

Keywords: wants detection, electroencephalogram, listening to music, convolutional neural networks, support vector machine

1. Introduction

Techniques for information and communication technology (ICT), Internet of Things, human computer interactions, human sensing, and human interface are being actively developed worldwide. One human interface in the ICT is the brain-computer interface (BCI). The BCI can connect the computer and human brain by analyzing brain activity, and the BCI often supports human life by controlling the environment around humans, for example, for an electric-wheelchair environment control system for patients. If a novel ICT system based on the BCI can measure the human mental and/or emotion conditions such as wants, decision-making, preference, relaxation, and excitement, the quality of life for humans can be improved. In particular, if human wants can be detected, the communication between a human and a computer becomes similar to the communication between two humans. In this paper, we focus on the wants present in the human mental condition, and we detect these wants by analyzing human brain activities.

The electroencephalogram (EEG) is often analyzed to create a BCI and for analyzing brain activities. EEG analysis methods [1] have been developed for various purposes, such as classifying emotions [2–9], detecting P300 waves, and classifying motor image EEG (hereinafter "MI-EEG") values [10]. EEG features are extracted using various methods such as the frequency analysis techniques [2, 11, 12], principal component analysis [13–16], independent component analysis [15, 17–19], deep neural networks [3], and convolutional neural networks (CNNs) [2, 6, 10, 11]. Other techniques include k-nearest neighbor classifier [20], linear discriminant analysis [21–23], artificial neural networks [15], multi-layer perceptron [6], support vector machines (SVMs) [5, 24], deep neural networks [3], and CNNs [2, 10, 11]. Chen et al. and Amin et al. were especially successful in classifying emotions and MI-EEG using CNN models. Also, Lotte et al. showed the effectiveness of CNN models by analyzing EEG signals [1].

In this paper, we propose a method to detect human wants. It is not clear how wants are created in the human brain. We assume that the frontal cortex and temporal cortex activities are related to the creation of wants because the frontal cortex activities are relevant to conscience and judgment. Also, the frontal cortex activities are related to creating human emotions. The temporal cortex activities are relevant to decision-making. The process of wants creation includes being conscious of the exogenous stimuli using the five human senses; therefore, wants creation involves the judgment of exogenous stimuli, creation of emotions, human thoughts, and decision-making ability. The frontal and temporal cortex activities may contain these factors. However, it is not clear whether or not decision-making is related to the creation of wants. In this paper, we confirm whether or not decision-making

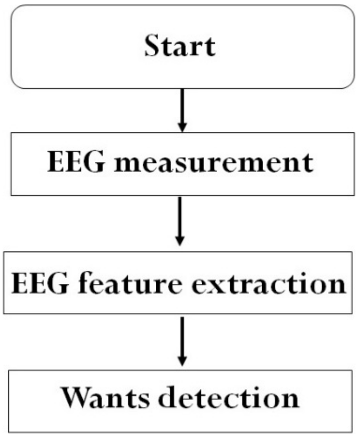

Fig. 1. The human-wants detection technique.

is related to the creation of wants. The sensing positions used to record the EEG signals are positions related to the frontal and temporal cortex activities. Then, the EEG features were extracted by using the CNN model because previous studies had great recognition accuracy for the CNN models. In general, EEG signals have intra- and inter-individual differences. To solve the problem of inter-individual differences, this paper creates a CNN model for each person. The problem of intra-individual differences in EEG signals can be resolved by using the CNN models developed in this paper. To show the effectiveness of the proposed method, we conducted experiments using real EEG data.

2. Methods

The proposed method consists of EEG measurements, EEG feature extraction, and human-wants detection. For the EEG signal measurements, we employed a simple electroencephalograph. For the EEG features extraction, we used a CNN to extract the EEG features required for detecting human wants. For the wants detection, we used an SVM. **Fig. 1** shows the procedure of the proposed method.

2.1. EEG Measurements

EEG signals were recorded using EPOC+ (Emotiv Inc.) [3, 4]. EPOC+ has a maximum of 14 channels and two reference channels; the 14 channels can record the neural activities of the brain from the scalp. For the two reference channels, the common mode sensing the active electrode and the driving right leg passive electrode were attached at the bone just behind the ear lobes, and the reference values were calculated. EPOC+ covers the positions AF3, AF4, F3, F4, F7, F8, T7, and T8 in the improved international 10-20 system. These sensing positions are positions related to the frontal and temporal cortex activities. **Fig. 2** shows the sensing positions in a part of the improved international 10-20 system. We recorded the EEG signals while the subject listened to music.

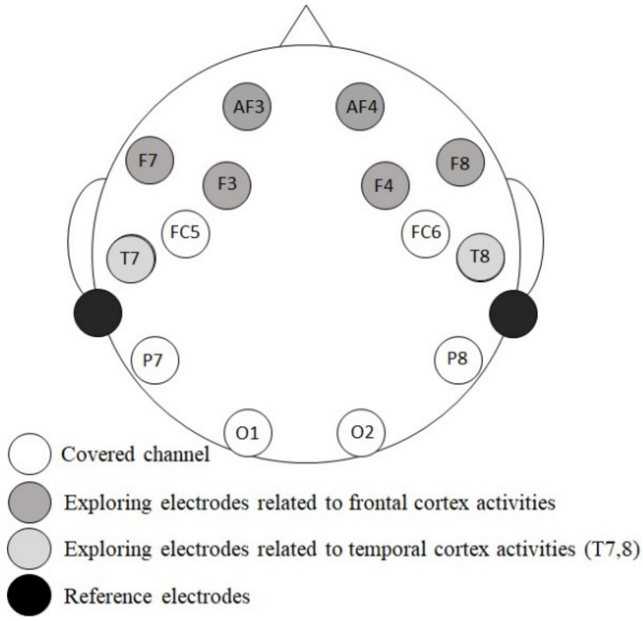

Fig. 2. Sensing positions for recording the EEG signals.

2.2. EEG Feature Extraction

The EEG feature extraction techniques include EEG signal normalization and feature extraction using a CNN. In the normalization step, the EEG signals are normalized based on the average, variance, and maximum and minimum values of all channels as follows:

$$\begin{cases} \mathrm{NormEEG(ch)} = \dfrac{\mathrm{EEG}'(\mathrm{ch}) - Mi}{Ma - Mi}, \\ \text{Subject to } \mathrm{EEG}'(\mathrm{ch}) = \dfrac{\mathrm{EEG(ch)} - Ave}{Var}, \end{cases} \quad . \quad . \quad (1)$$

where NormEEG is the normalized EEG signal that uses the maximum and minimum values. EEG$'$ is the normalized EEG signal that uses the average and variance values. EEG(ch) includes the recorded EEG signals and the channels. *Ave* and *Var* are the average and variance values, respectively, of the recorded EEG signals. *Mi* and *Ma* are the minimum and maximum values in the normalized EEG signals (EEG$'$) that use the average and variance values. CNNs are then used to extract the EEG features. A CNN consists of an input layer, two hidden layers, and a full-connection layer based on Chen's model [2]. We chose Chen's model because it exhibited very high accuracy in classifying human emotions. Convolutional and pooling layers are employed in the proposed method in the hidden layers. We used $N \times M$ filters for the convolutional layers, and the pooling layer employed the max pooling technique. The full-connection layer was used to extract features and reduce noise in the EEG signals. The full-connection layer connects the extracted features. Then, a dropout function (dropout ratio: p [%]) was implemented to avoid overtraining. **Fig. 3** shows the CNN structure for the proposed method. The output of the full-connection layer is the EEG features.

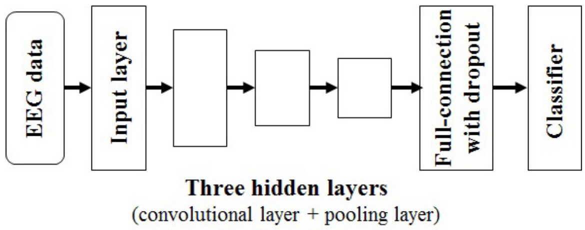

Fig. 3. Structure of the CNNs.

2.3. Wants Detection

In this paper, we selected the sensing positions to detect human wants. **Fig. 4** shows the kinds of sensing positions. Eight channels are in the frontal cortex and the temporal cortex, and six channels are in the frontal cortex. Four channels are in the prefrontal cortex. Also, the L3 channels and R3 channels are in the left frontal cortex and right frontal cortex, respectively. Then, we employed a linear SVM to detect the wants related to listening to music by classifying the signals as "wants," "not wants," and "other feelings." The selection of the sensing positions and the detection of wants were evaluated by calculating the recognition accuracy of wants detection as follows:

$$\mathrm{RecAcc} = \frac{\mathrm{Correct}}{\mathrm{Total}}, \quad \ldots \ldots \ldots \ldots \quad (2)$$

where RecAcc, Correct, and Total are the recognition accuracies for detecting the wants, the number of correctly classified data, and the total number of EEG signals, respectively.

3. Experiments

The subjects were volunteers from Tokushima University, Japan. The sample size included nine students (mean age = 22.7 years). After giving a detailed description of the experiment's purpose and procedures, we obtained written informed consent from the subjects based on the Declaration of Helsinki. The subjects wore EPOC+ devices to record the EEG signals while sitting on a chair; they kept their eyes closed in the laboratory and were exposed to some music. **Fig. 5** shows the timeline of the experiments. The EEG signals were recorded for 15 s while the subject was listening to music ("Listen to music" in **Fig. 5**). The subjects responded as to whether or not they wanted to listen to music ("Ans. Q." in **Fig. 5**). Ten sets of EEG measurements were carried out for each subject. In the CNN parameters, the sizes of the input layers were 8×128, 6×128, 4×128, and 3×128 for eight channels (frontal and temporal cortex), six channels (frontal cortex), four channels, and the L3- and R3-channels, respectively. The size of the two filters was 3×1 for eight and six channels and 2×1 for the four channels and the L3- and R3-channels. Then, the number of units of the hidden layers was 50. The number of units for the full-connection layer was 2,000. The p of the dropout rate in the full-connection layer was 50; 80% of the data sets were randomly selected as training data for the evaluation tests. Then, we assumed that the frontal and temporal cortex activities might become aware of the exogenous stimuli obtained through the five senses; the stimuli include the judgment of the exogenous stimuli, creation of emotions, human thoughts, and decision-making. However, it is not clear whether or not the decision-making process is related to the creation of human wants. In this experiment, we resolved this problem by comparing eight channels with six channels, four channels, and the L3- and R3-channels.

4. Results and Discussions

Table 1 shows the number of EEG signals as the subjects experienced "wants," "not wants," and "other feelings" while listening to music. The nine subjects were numbered from S1 to S9. The number of EEG signals for the wants, not wants, and other feelings was different for each subject. These results suggest that the subjects had different sensibilities and "kansei" (which means "feelings" in Japanese).

Table 2 shows the mean and standard deviation values of the recognition accuracy for classifying the wants, not wants, and other feelings by using data sets of all subjects. "Soft" is the softmax technique used to classify the wants. We confirmed that the mean of the recognition accuracy for eight channels was higher than that for six channels, four channels, and the L3- and R3-channels. Also, the mean and standard deviation of the recognition accuracy for eight channels by using SVM were 76.1% and 4.15%, respectively. These results suggest that it is possible to detect the wants regarding listening to music when the target sensing positions are selected related to the frontal and temporal cortex activities. Moreover, the recognition accuracy was not high probably because of the individual differences in the EEG signals and/or noise signals.

Table 3 shows the mean and standard deviation of the recognition accuracy for classifying the wants, not wants, and other feelings for every subject. S1 to S9 were the same as those shown in **Table 1**. A mean recognition accuracy of 90% or more was achieved for all the channels (eight, six, four, and the L3- and R3-channels) by using SVM. These results prove that it is possible to detect the wants regarding listening to music when the target sensing positions are selected related to the frontal and/or temporal cortex activities.

We compared the results obtained for the eight channels with the results obtained for the six channels, four channels, and the L3- and R3-channels. We found that the mean recognition accuracy of the eight channels was higher than those of the other channels (i.e., six channel, four channels, and the L3- and R3-channels). The eight channels were related to the frontal and temporal cortex activities, and other channels were related to the frontal cortex activities only. These results show that temporal cortex activities are related to the creation of wants. Also, decision-making can be included when creating a want.

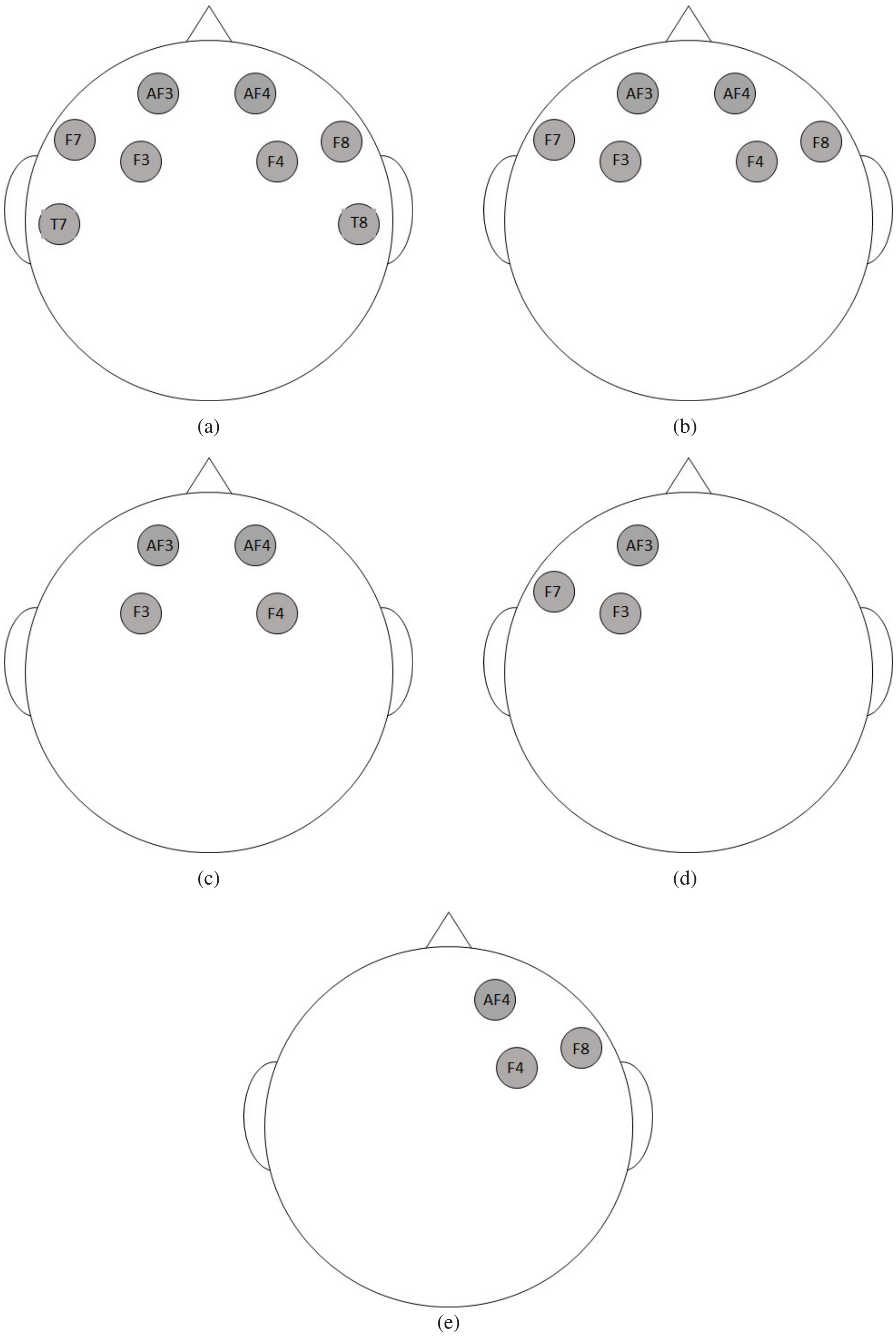

Fig. 4. Sensing positions for recording the EEG signals: (a), (b), and (c) have eight channels (frontal and temporal cortex), six channels (frontal cortex), and four channels (prefrontal cortex), respectively; (d) and (e) have L3-channels (left frontal cortex) and R3-channels (right frontal cortex), respectively.

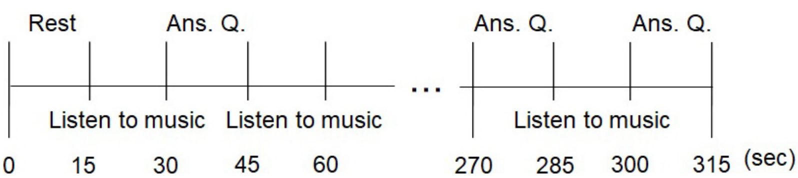

Fig. 5. Timeline of the experiments. "Ans. Q." indicates that the subject responded whether or not he/she wanted to listen to music continuously. "Rest" and "Listen to music" are the rest time and time for which they listened to the music, respectively. The subject answered a set of ten questions and listened to ten songs.

Table 1. Number of EEG signals for the wants, not wants, and other feelings of each subject.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	Total
Want	720	550	600	450	350	630	770	750	560	5,380
Not want	190	440	140	750	560	350	190	320	260	3,200
Other feeling	290	200	460	0	290	220	240	130	380	2,210

Table 2. Mean and S.D. of recognition accuracy to classify wants, not wants, and other feelings using data sets of all subjects [%].

		Eight-channels	Six-channels	Four-channels	L3-channels	R3-channels
Soft	Mean	67.2	53.6	50.2	51.1	51.0
	S.D.	5.13	3.76	0.54	0.68	1.21
SVM	Mean	76.1	58.7	52.3	53.3	53.6
	S.D.	4.15	4.16	1.38	1.46	1.43

Table 3. Mean and S.D. values of recognition accuracy to classify the wants, not wants, and other feelings for each subject [%].

			Mean	S1	S2	S3	S4	S5	S6	S7	S8	S9
8c	**Soft**	Mean	97.7	98.7	98.9	96.8	99.7	97.7	99.2	98.5	97.3	92.9
		S.D.	4.80	0.66	1.15	2.60	**0.17**	2.31	0.59	1.14	2.02	5.60
	SVM	Mean	**99.4**	**99.2**	**99.4**	**99.5**	**99.9**	**99.4**	**99.9**	**99.7**	**99.6**	**98.2**
		S.D.	**0.58**	**0.59**	0.98	**0.49**	**0.17**	**0.42**	**0.17**	**0.21**	**0.65**	**1.57**
6c	**Soft**	Mean	91.6	93.8	91.6	91.9	89.3	89.3	95.5	95.5	91.1	86.5
		S.D.	3.95	4.46	4.72	4.06	5.49	2.93	4.26	2.29	1.85	5.51
	SVM	Mean	98.0	98.1	98.9	98.0	98.6	95.3	99.3	99.3	98.8	95.8
		S.D.	1.25	2.00	**0.86**	1.33	0.88	1.80	0.57	0.55	0.59	2.69
4c	**Soft**	Mean	82.4	84.2	80.2	83.2	87.9	77.1	80.8	83.1	85.3	80.2
		S.D.	3.06	2.35	5.53	7.38	2.95	3.03	5.42	7.0	3.66	3.9
	SVM	Mean	91.8	93.2	90.2	92	94.8	86.5	93.8	92.3	95.9	87.7
		S.D.	2.98	1.73	3.1	4.5	1.59	2.89	2.82	3.03	1.19	3.39
L3c	**Soft**	Mean	83.1	86.8	84.1	85.8	87.1	83.3	84.0	79.8	82.7	74.2
		S.D.	3.79	4.07	3.67	4.90	2.97	3.78	7.51	7.57	9.47	9.11
	SVM	Mean	91.0	93.6	92.1	93.1	92.1	89.3	93.0	87.7	92.6	85.2
		S.D.	2.75	2.87	2.42	4.70	4.74	5.64	4.14	5.90	5.59	5.92
R3c	**Soft**	Mean	83.8	86.9	81.6	77.4	84.7	78.1	82.8	91.2	91.8	79.3
		S.D.	5.04	2.36	5.56	9.31	6.27	3.95	3.42	2.98	2.66	3.96
	SVM	Mean	90.9	94.0	90.1	87.0	88.4	85.6	93.6	97.4	97.3	85.1
		S.D.	4.51	1.45	3.54	5.87	4.47	4.10	1.99	0.96	1.26	5.55

We compared the results of each subject with those of all the subjects, and we found that the mean and standard deviation values of the recognition accuracy per subject were higher and lower, respectively, than the values of all the subjects. Also, the mean and standard deviation of the recognition accuracy were 76.1% and 4.15%, respectively. This was not an optimal result because it showed that there were individual differences in the EEG signals recorded when the subjects wanted to listen to music.

When the sensing positions were eight channels and the classifier was the SVM, the mean and standard deviations were 99.4% and 0.58%, respectively. These results prove that it is possible to detect wants and classify the wants, not wants, and other feelings by using the CNN model to extract the EEG features and the SVM implementation. Also, frontal and temporal cortex activities are related to wants and not wants.

5. Conclusions

This paper proposes a method for detecting human wants by using a CNN model and an SVM. The proposed method consisted of EEG measurements, EEG feature extractions, and wants detection. A wearable device (EPOC+) was employed for the EEG measurement, and the EEG signals were recorded while the subjects experienced wants, not wants, and other feelings as they listened to music. The sensing positions used to record the EEG signal were related to the frontal cortex (AF3, AF4, F3, F4, F7, and F8) and the temporal cortex (T7 and T8). In the EEG feature extraction, a CNN model was employed based on the algorithm model interfacing. For wants detection, we employed an SVM. To show the effectiveness of the proposed method, we conducted experiments using real EEG data. Based on the experimental results, we confirmed that the mean recognition accuracy of eight channels was higher than that of other channels (six channels, four channels, and the L3- and R3-channels). The eight channels were related to the frontal and temporal cortex activities, and six channels were related to the frontal cortex activities. These results suggest that the temporal cortex activities are related to wants creation, and it is possible to include decision-making in wants creation. The mean and standard deviation values for the detection accuracy were 99.4% and 0.58%, respectively. These results suggest that it is possible to detect the wants and classify the wants, not wants, and other feelings by using a CNN model to extract the EEG features and the SVM.

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References:

[1] F. Lotte, M. Congedo, F. Lecuyer, and B. Arnaldi, "A review of classification algorithms for EEG-based brain-computer interfaces: a 10 year update," J. Neural Eng., Vol.15, No.3, pp. R1-R28, 2018.

[2] J. X. Chen, P. W. Zhang, Z. J. Mao, Y. F. Huang, D. M. Jiang, and Y. N. Zhang, "Accurate EEG-based emotion recognition on combined features using deep convolutional neural networks," IEEE Access, Vol.7, pp. 44317-44328, 2019.

[3] R. M. Mehmood, R. Du, and H. J. Lee, "Optimal feature selection and deep learning ensembles method for emotion recognition from human brain EEG sensors," IEEE Access, Vol.5, pp. 14797-14806, 2017.

[4] H. Ullah, M. Uzair, A. Mahmood, M. Ullah, S. D. Khan, and F. A. Cheikh, "Internal emotion classification using EEG signal with sparse discriminative ensemble," IEEE Access, Vol.7, pp. 40144-40153, 2019.

[5] G. Zhao, Y. Ge, B. Shen, X. Ei, and H. Wang, "Emotion analysis for personality interface from EEG signal," IEEE Trans. Affect. Comput., Vol.9, No.3, pp. 362-371, 2018.

[6] B. Xing, H. Zhang, K. Zhang, L. Zhang, X. Wu, X. Shi, S. Yu, and S. Zhang, "Exploiting EEG signals and audiovisual feature fusion for video emotion recognition," IEEE Access, Vol.7, pp. 59844-59861, 2019.

[7] C. Qing, R. Qiao, X. Xu, and Y. Cheng, "Interpretable emotion recognition using EEG signals," IEEE Access, Vol.7, pp. 94160-94170, 2019.

[8] J. Chen, D. Jiang, and Y. Zhang, "A Common Spatial Pattern and Wavelet Packet Decomposition Combined Method for EEG-Based Emotion Recognition," J. Adv. Comput. Intell. Intell. Inform., Vol.23, No.2, pp. 274-281, 2019.

[9] R. Cabredo, R. Legaspi, P. Salvador Inventado, and M. Numao, "Discovering Emotion-Inducing Music Features Using EEG Signals," J. Adv. Comput. Intell. Intell. Inform., Vol.17, No.3, pp. 362-370, 2013.

[10] S. U. Amin, M. Alsulaiman, G. Muhammad, M. A. Bencherif, and M. S. Hossain, "Multilevel weighted feature fusion using convolutional neural networks for EEG motor imagery classification," IEEE Access, Vol.7, pp. 18940-18950, 2019.

[11] Q. Liu, J. Cai, S.-Z. Fan, M. F. Abbod, J.-S. Shieh, Y. Kung, and L. Lin, "Spectrum analysis of EEG signals using CNN to model patient's consciousness level based on anesthesiologists' experience," IEEE Access, Vol.7, pp. 53731-53742, 2019.

[12] N. M. Krishna, K. Sekaran, A. V. N. Vamsi, G. S. P. Ghantasala, P. Chandana, S. Kadry, T. Blazauskas, and R. Damasevicius, "An efficient mixture model approach in brain-machine interface systems for extracting the psychological status of mentally impaired person using EEG signals," IEEE Access, Vol.7, pp. 77905-77914, 2019.

[13] H. Lee and S. Choi, "PCA+HMM+SVM for EEG pattern classification," Proc. 7th Int. Symp. on Signal Processing and its Application, Vol.1, pp. 541-544, 2003.

[14] C. Wang, J. Zou, J. Zhang, M. Wang, and R. Wang, "Feature extraction and recognition of epileptiform activity in EEG by combining PCA with ApEn," Cogn. Neurodyn., Vol.4, No.3, pp. 233-240, 2010.

[15] T. Hoya, G. Hori, H. Bakardjian, S. Nishimura, T. Suzuki, Y. Miyawaki, A. Funase, and J. Cao, "Classification of single trial EEG signals by a combined principal + independent component analysis and probabilistic neural network approach," Proc. ICA2003, pp. 197-202, 2003.

[16] S. Jirayucharoensak, S. Pan-Ngum, and P. Israsena, "EEG-based emotion recognition using deep learning network with principal component based covariate shift adaptation," Sci. World J., Vol.2014, pp. 1-10, 2014.

[17] N. Mammone, F. L. Foresta, and F. C. Morabito, "Automatic artifact rejection from multichannel scalp EEG by wavelet ICA," IEEE Sens. J., Vol.12, No.3, pp. 533-542, 2011.

[18] A. Kachenoura, L. Albera, L. Senhadji, and P. Comon, "ICA: a potential tool for BCI systems," IEEE Signal Process. Mag., Vol.25, No.1, pp. 57-68, 2008.

[19] X. Bai, X. Wang, S. Zheng, and M. Yu, "The offline feature extraction of four-class motor imagery EEG based on ICA and wavelet-CSP," Proc. Chin. Control Conf., pp. 7189-7194, 2014.

[20] J. F. Borisoff, S. G. Mason, A. Bashashati, and G. E. Birch, "Brain-computer interface design for asynchronous control applications: improvements to the LF-ASD asynchronous brain switch," IEEE Trans. Biomed. Eng., Vol.51, No.6, pp. 985-992, 2004.

[21] B. Blankertz, G. Curio, and K. R. Muller, "Classifying single trial EEG: towards brain computer interfacing," Advances in Neural Information Processing Systems, NIPS 01, Vol.14, pp. 157-164, 2002.

[22] G. J. Mclachlan, "Discriminant analysis and statistical pattern recognition," J. Royal Stat. Soc., Vol.168, No.2, pp. 192-194, 2012.

[23] K. R. Muller, C. W. Anderson, and G. E. Birch, "Linear and nonlinear methods for brain-computer interfaces," IEEE Trans. Neur. Sys. Reh. Eng., Vol.11, No.2, pp. 165-169, 2003.

[24] T. Felzer and B. Freisieben, "Analyzing EEG signals using the probability estimating guarded neural classifier," Neural Systems and Rehabilitation Engineering, IEEE Trans., Vol.11, No.4, pp. 361-371, 2003.

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