Emotional Valence Detection based on a Novel Wavelet Feature Extraction Strategy using EEG Signals

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Abstract: This paper presents a novel feature extraction strategy in the time-frequency domain using discrete wavelet transform (DWT) for valence level detection using electroencephalography (EEG) signals. Signals from different EEG electrodes are considered independently for the first time in order to find an optimum combination through different levels of wavelet coefficients based on the genetic algorithm (GA). Thus, we take into consideration useful information obtained from different frequency bands of brain activity along the scalp in valence level detection, and we introduce a new set of features named the cross-level wavelet feature group (CLWF). The effectiveness of this approach is strongly supported by the analytical results of experiments in which EEG signals with valence level labels were collected from 50 healthy subjects. High accuracy was achieved for both 2-level (98%) and 3-level valence detection (90%) by applying leave-one-out cross validation using a probabilistic neural network (PNN). In addition, light-weighted sets with less than half EEG recording electrodes are proposed, which can achieve a high accuracy (86% for 3-level valence detection) with offering convenience of users and reducing computational complexity.

1 INTRODUCTION

Emotion assessment is essential for gaining a deeper understanding of human beings and preventing lifestyle diseases. A large body of literature indicates that negative emotions have harmful effects on people's health (Sirois, 2003), whereas positive emotions foster good physical health (Salovey and Rothman, 2000).

Several emotion modeling approaches have been proposed in the existing literature, including discrete models (Darwin, 1872), appraisal models (Arnold, 1950), and dimensional models (Wundt, 1905). We adopt a category of dimensional models that consider multidimensional space, where each dimension represents a fundamental property shared among all emotions in this study. Many researchers (Constantinou et al., 2013) agree that emotions have at least two indexes, including valence and arousal, and emotion can therefore be represented through complex interactions related to valence and arousal. In the emotion model proposed by Russell (Russell, 1980), arousal represents a quantity that varies from calm to excitement, whereas valence represents a quantity that varies from positive to negative.

In previous studies, the voice signal has been considered to be an effective signal for emotion related analysis. An emotional valence detection system was designed by using speech features with about 50% accuracy (Tahon et al., 2012). A large number of researchers have adopted physiological signals for evaluating different levels of valence. Picard et al. proposed a method for positive and negative classification with 87% accuracy using electromyography (EMG), galvanic skin response (GSR), respiration, blood volume pulse (BVP), and electrocardiogram (ECG) signals (Picard et al., 2001). In this research, we study the valence dimension of the emotion model proposed by Russell, which is related to positive versus negative affect.

The interest in using electroencephalography (EEG) for valence detection has increased recently because of the latest significant developments in brain-computer-interface (BCI) research. The fact is that ignoring a user's emotional state with any interface dramatically impedes the performance and leads to a bad user experience. BCI systems are now being developed for a wide range of applications in areas such as healthcare, gaming, security, and marketing. These applications can benefit largely from knowing and adapting their operations according to users' emotional states. This emotion information can then be utilized to provide a better user experience by controlling the BCI through affect. It has been shown that a correlation exists between emotions and brain activity (Nardi, 2011), especially in the prefrontal cortex and the amygdala (Adolphs et al., 2003). A small amount of research on emotion related classification is based on EEG, and most of this research has not been able to obtain good results compared with the performance using other physiological signals. Based on the asymmetry represented by EEG signals, the mean accuracy for three valence classes (negative, neutral, and positive) of picture stimulations was reported to be 44% based on frequency domain features and 49% based on combining time and frequency domain EEG features(Schaaff and Schultz, 2009). By combining EEG and some physiological signals (heart rate and pulse), Takahashi and Tsukaguchi achieved a recognition rate of 62.3% with a neural network (NN) classifier and 59.7% with a support vector machine (SVM) for classifying pleasure and displeasure (Takahashi and Tsukaguchi, 2003). Hosseini adopted entropy analysis of EEG signals and achieved pleasure and displeasure classification with an accuracy of 72.35% using SVM (Hosseini, 2011).

The objective of this study was to find effective features and to formulate a robust method that can distinguish between different valence levels with high accuracy from EEG signals. Affective pictures were adopted in this research to elicit different valence levels. In section II, the experimental design and recording protocol are introduced. In section III and IV, the analytical model including feature extraction and optimization is described. The results are discussed in section V, and finally, in section VI, conclusions that have been drawn based on the proposed research and perspectives are discussed.

2 EXPERIMENTAL DESIGN

2.1 Valence Elicitation

Three levels of valence have been defined based on arousal-valence space based on the emotion model proposed by Russell (Russell, 1980). The most widely adopted emotion elicitation technique is to use pictures to evoke various emotion states based on valence-arousal space (Katsis et al., 2011). We adopted a very popular picture-based, emotion-evoking database called the International Affective Picture System (IAPS) (Lang et al., 2008), which contains pictures labeled with values of valence and arousal. We chose pictures with a small range of valence values but a large variance of arousal values in order to collect data that would ensure a robust model of valence detection. The IAPS labels respective pictures for males and females, so we selected different pictures for male and female subjects in order to achieve the same valence level elicitation. The positioning in terms of valence and arousal of the pictures selected for the three levels of valence is illustrated in Fig. 1 against all pictures for males and females, respectively.

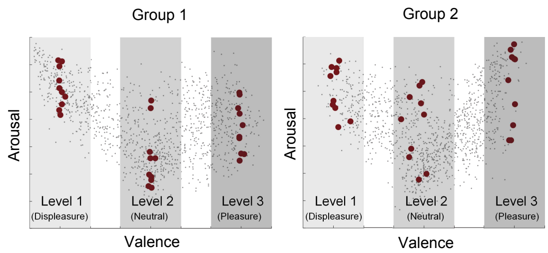

Figure 1: Two groups of pictures selected from IAPS for valence stimulation for Females (Group 1) and Males (Group 2). The red dots represent the pictures selected from IAPS among all pictures, shown as gray dots.

2.2 Experimental Protocols

The experiments were designed to stimulate a certain level of valence from viewing multiple pictures from the IAPS database. The subjects were required to sit in a dark room and look at the pictures that appeared on a screen. The protocol of the stimulation procedure used with each subject is illustrated in Fig. 2. We collected EEG signals from 50 healthy Japanese subjects (35 males and 15 females). The ages of the subjects ranged from the 20s to the 70s. The EEG signals were recorded by a *Nihon kohden EEG-1200* using electrodes placed according to the international 10-20 system; the sampling rate of EEG signal acquisition was 1000 Hz. This experiment was conducted with the permission from Research Ethics and Safety committee of The University of Tokyo.

2.3 EEG Dataset

EEG signals are affected by noise such as pulses, line noise, and artifacts. The noise generated from eye blinks is the most difficult type to deal with by using signal processing techniques such as wavelet analysis. For this reason, the subjects were asked to refrain from blinking their eyes during the experiments. A filter was applied to delete the line noise at 50 Hz. Previous research (Murugappan et al., 2010) shows that the

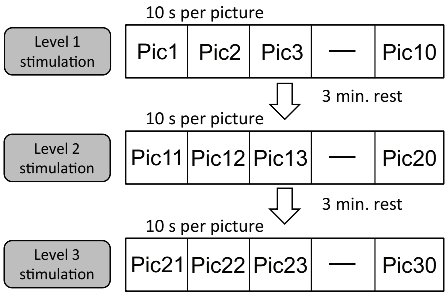

Figure 2: Valence stimulation procedure.

emotions are not only correlated to the brain activity recorded in the frontal area but also to that recorded in other areas, and therefore, higher accuracy was obtained by using EEG electrodes along all the scalp. We used 16 channels (Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6) for analysis based on the International 10-20 system. On the basis of the correlation theory of brain activity asymmetry and emotions (Alves et al., 2008), our approach is to compare the frontal area, the posterior area, and the entire area of brain activity with electrodes on both left and right brain hemispheres, and this approach gains a better understanding of how emotion states can be interpreted using EEG signals in different areas. The test cases using different combinations of EEG electrodes are illustrated in Fig. 3.

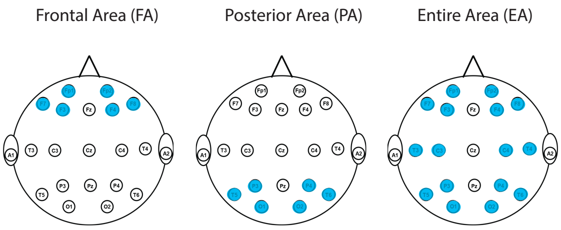

Figure 3: Test cases of brain activity in different areas.

3 METHODS

3.1 Wavelet Analysis

We adopted discrete wavelet decomposition (Morlet, 1984) to better understand the frequency and location information of the EEG signals. The discrete wavelet decomposition definition is expressed as

$$T_{m,n} = \int_{-\infty}^{\infty} f(t)\psi_{m,n}(t)dt, \tag{1}$$

$$\psi_{m,n}(t) = a_0^{-m/2}\psi(a_0^{-m}t - nb_0), \tag{2}$$

where $\psi_{m,n}(t)$ is a wavelet mother function, the integer m controls wavelet dilation, and n controls translation. Here, a_0 is a specified fixed dilation setup parameter set at a value greater than 1, and b_0 is the location parameter, which must be greater than 0. Also, $T_{m,n}$ are the discrete wavelet values given on a scale-location grid of index m,n, which are known as wavelet coefficients or detail coefficients.

Wavelet analysis has been successfully used for feature extraction and for many classification tasks based on EEG (Sherwood, 2009). No objective method for mother wavelet selection has been developed so far for classification, and the methods are mostly empirical. We selected Daubechies 5 wavelet (Db5) since it has been adopted successfully for modeling complex signals such as EEG signals (Liu and Xu, 2010), and we applied seven levels of wavelet decomposition, which is determined by taking the EEG frequency bands into consideration.

3.2 Statistical Parameters

Statistical parameters shows effectiveness on demonstrating affective states from physiological signals (Van den Broek and Westerink, 2009). Several statistical parameters including mean, standard deviation (*std*), skewness, and kurtosis are used in this study to demonstrate the characteristics of transformed EEG signals using discrete wavelet decomposition.

3.3 Genetic Algorithm (GA)

We adopted a genetic algorithm (Holland, 1975) for feature selection. The GA mimics the process of natural evolution to find beneficial adaptations to a complex environment. A *chromosome* in GA is an encoding that represents the decision variable of an optimization problem. A finite set of chromosomes in GA is called a *population*. Each chromosome is rated by the fitness function on its ‘fitness’, which determines how good it is in solving the optimization problem. *Crossover* refers to the generation of two new offspring by mating two parental chromosomes. A *mutation* simply flips randomly the binary value of one or more bits. Crossover and mutation provide opportunities for chromosomes that have higher fitness values to evolve.

The reasons why we adopt GA are shown in the following. According to previous studies, the correlation theory of brain activities asymmetry and emotions were proved by researchers (Alves et al., 2008). GA allows us to realize our proposal to select appropriate information from each EEG electrode and eventually obtain the overall pattern of brain activities monitored by multiple EEG electrodes. Other data-driven feature selection approaches cannot give attention to the overall pattern of brain activities. The selected features can be only extracted from one or several EEG electrodes so that it fails to demonstrate the whole brain activities asymmetry since there is no priori biological knowledge applied on those algorithms. These considerations are supported by a recent paper proposed in a similar application concerning neuroimaging (Chu et al., 2012), as they have two findings related to feature selection including data-driven feature selection was no better than adopting whole data and a priori biological knowledge was effective to guide feature selection. As for the implementation of GA with proposed features, we generalized our problem of wavelet level selection according to different EEG positions to an optimization issue of minimizing the *fitness function*.

3.4 Principal Component Analysis (PCA)

PCA (Jolliffe, 2002) is a common visualization method that is applied through dimensionality reduction by performing a covariance analysis between factors. Technically, a principal component can be defined as a linear combination of optimally weighted observed variables, the first k principal components capture the greatest variance in the data among all k-dimensional orthonormal linear combinations of the original variables. In our case, PCA was used for feature space visualization to observe the separability of different valence levels by specific features.

3.5 Probabilistic Neural Network (PNN)

Artificial neural networks are effective when used with such signals as EEG since they are very robust in dealing with non-linear and complex signals. Moreover, the fault tolerance of artificial neural networks is necessary in order to reduce the influence of noise. PNN (Specht, 1990) is one kind of artificial neural network that has been proven to be suitable for classification tasks by many researchers (Sivakumar and .Kannan, 2009). The operations are designed into a multi-layered feed-forward network with four layers. In this work, PNN is adopted considering its characteristics of fast training process and additional training samples can be added without extensive retraining, which make it practical for model improvement when we have large training database. The inputs of PNN were the optimized features, and the output was the predicted valence level.

4 IMPLEMENTATION

4.1 Cross-level Wavelet Feature Extraction

The statistical parameters have been shown to be useful for extracting features from raw or processed EEG signals. Although time or frequency domain features from EEG signals failed to provide good accuracy for valence detection (Schaaff and Schultz, 2009), (Takahashi and Tsukaguchi, 2003), (Hosseini, 2011), we explore new possibilities in time-frequency domain features. Murugappan et al. conducted a study on clustering different emotions by wavelet features from EEG signals using 24 and 63 channels (Murugappan et al., 2007) and represented the potential of time-frequency features for identifying emotions. The theory of wavelet decomposition can roughly takes into consideration EEG frequency bands. The frequency information of each decomposition level is listed in Table 1.

Table 1: Frequency range of different wavelet decomposition levels with EEG frequency band information.

Decomposition level	Frequency range (Hz)	EEG frequency band
A7	0-4	Delta
D7	4-8	Theta
D6	8-16	Alpha
D5	16-32	Beta
D4	32-63	Low gamma
D3	63-125	High gamma
D2	125-250	—
D1	250-500	—

Our strategy is to formulate a novel cross-level wavelet feature group (CLWF) for valence detection based on GA, as opposed to the strategy of extracting a mono-level wavelet feature group (MLWF). EEG consists of a multi-channel system that can record a great deal of information with a lot of noise. Much research has focused on how to omit a number of electrodes and select the most useful ones in order to achieve a moderate level of performance (Arvaneh et al., 2011). The studies that have adopted wavelet features have only considered a single decomposition level or have combined levels from all EEG electrodes (Sherwood, 2009). However, those studies ignore the fact that useful information for classification may be represented in different frequency ranges among different EEG electrodes. If we implement this idea

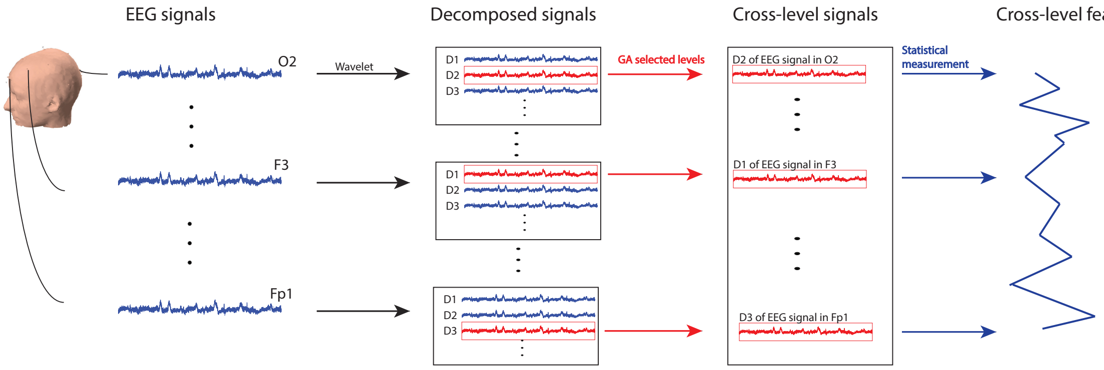

Figure 4: Schematic of cross-level wavelet feature estimation from EEG signals.

by a brute-force search, the order of magnitude for the searching cases will be n^m, where m is the number of EEG electrodes, and n represents the levels of wavelet decomposition. For instance, there will be 152,587,890,625 cases with 16 EEG electrodes and 5 levels of wavelet decomposition, which makes it extremely difficult to find the optimized feature combinations. Thus, GA is introduced in this step to solve this optimization issue. The fitness function is designed as Eq. 3.

$$Fitness = 1 - Accuracy \tag{3}$$

Accuracy is calculated using the leave-one-out cross validation (LOOCV) method based on PNN. The input feature for GA is a matrix with n levels of wavelet decomposition for all EEG electrodes. A chromosome is an array of numbers that represent levels of wavelet coefficients related to EEG electrodes; the GA will select one level from each electrode to formulate the optimized CLWF. GA parameters are given in Table 2.

Table 2: GA parameters.

Population size	10 chromosomes
Elite count	2
Mutation rate	0.01
Crossover rate	0.8

A relatively limited population size and high mutation rate as well as the LOOCV design in the fitness function are for preventing overfitting in GA. A schematic of the entire process of feature estimation is illustrated in Fig. 4. In this figure, EEG signals from positions *O2*, *F3*, and *Fp1* are used as examples to illustrate the feature extraction process. The best combination of wavelet coefficients (those indicated in red in Fig. 4) are selected based on GA from a huge number of combinations, and the statistical parameters are calculated for a later classification process.

4.2 Reduced Set of EEG Electrodes

We explore different sets of EEG electrodes to further understand the functional area for emotional activities, and reduce the number of EEG electrodes for the convenience of users and computational simplicity. Besides two comparison sets of frontal and posterior areas, the same GA approach is performed to find another optimized set of EEG electrodes placement for each subject. The input for GA is a matrix with n levels of wavelet decomposition for all EEG electrodes; the GA will select less than a certain number of electrodes for the reduced set. Multiple electrodes are needed to understand the difference of brain activities in different brain areas, we consider 6 electrodes are appropriate based on preliminary attempts and for comparisons with the other two sets using 6 electrodes mentioned in Fig. 3.

4.3 Classification

Since each EEG record corresponds to a picture stimulation from IAPS, it is easy to give labels to the classification tasks. The approach is to consider two testing scenarios for each individual including two valence levels (level 1: displeasure, level 3: pleasure) and three valence levels (level 1: displeasure, level 2: neutral, level 3: pleasure) for model validation by calculating the accuracy based on LOOCV using PNN.

5 RESULTS AND DISCUSSION

Our goal was to formulate robust features for valence detection using EEG signals, so the discernibility of different valence levels achieved by the proposed features was visualized using PCA. From the PCA results shown in Fig. 5, we cannot observe any distinct structures in feature space by using statistical

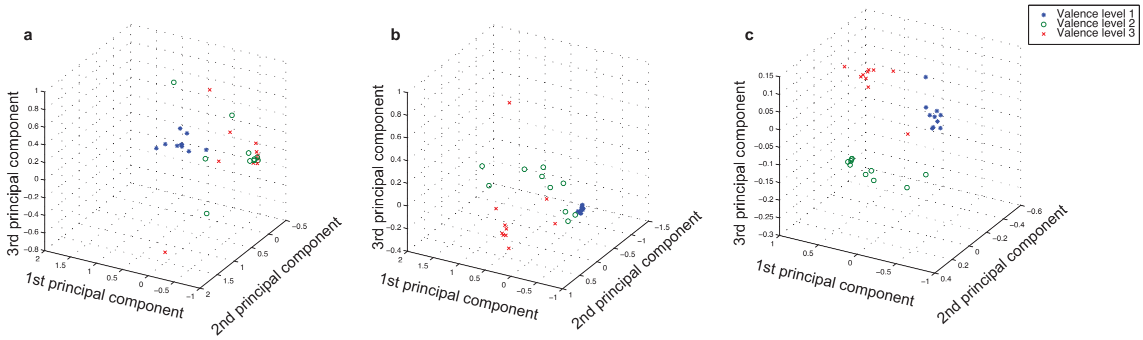

Figure 5: Visualization of feature space using PCA. a, First 3 principal components of features (*std*) calculated from raw EEG signals. b, First 3 principal components of MLWF, which were the *std* calculated using the best performance level after wavelet decomposition. c, First 3 principal components of CLWF, which were the *std* calculated using the cross-level decomposed signals from discrete wavelet decomposition selected using GA.

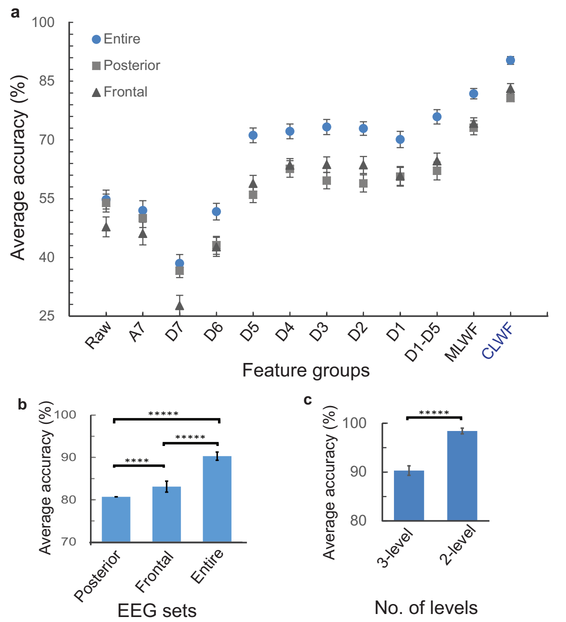

Figure 6: Average results for valence detection on 50 participants using different feature groups and EEG sets. a, Average accuracy for 3-level valence detection using 12 different feature groups (mean ± s.e.m). b, Comparisons of effectiveness for 3-level valence detection using EEG signals in different brain areas by proposed features (CLWF); ****p<0.00001, *****p<0.000001 by anaysis of variance (ANOVA) plus Tukey's Honestly Significant Difference (HSD) test. c, Comparison of 2-level (L1: 98.4% and L3: 97.8% respectively) and 3-level (L1: 94.0%, L2: 86.6%, and L3: 90.2% respectively) overall valence classification accuracy using proposed features (CLWF); *****p<0.000001 by paired t-test.

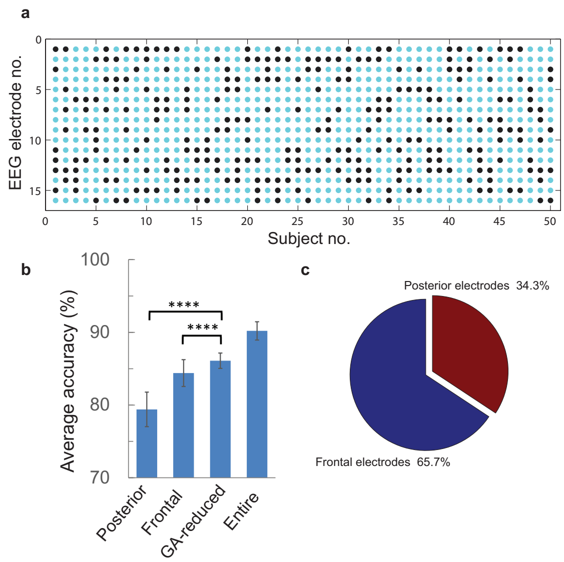

Figure 7: GA based EEG electrodes reduction. a, GA-reduced EEG electrodes distribution; no. 1-16: Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6. b, Comparison results of GA-reduced EEG sets; ****p<0.00001 by ANOVA plus Tukey's HSD throughout the figure. c, Selected electrodes' brain area summary.

measurements such as mean, kurtosis, and skewness based on raw EEG signals, but a clearer structure can be observed using statistical measurement *std*, although there are also overlaps between different valence levels (Fig. 5a). We confirmed from the test results on the simplest two-level valence detection, 80% accuracy was obtained by using *std*, while near or slightly better than chance accuracy (ranging from 50% to 60%) was obtained by using the other three statistical measurements.

Based on these facts, *std* was selected for further analysis in order to develop our new strategy for feature extraction. After applying wavelet decomposition, we tested the performance using PNN by LOOCV and selected the optimum performance wavelet decomposed level. Then the features were visualized using PCA (Fig. 5b), which indicates that the discernibility was further improved compared to the original features extracted based on raw EEG signals.

Fig. 5c illustrates the proposed cross-level wavelet features in this work. We obtained clearer clusters by plotting them using the first three principal components, which proves the robustness of the proposed strategy to extract features. Fig. 6a shows the average accuracy by adopting different groups of features for three valence levels classification. To study the results illustrated by Fig. 6a, we firstly apply analysis of variance (ANOVA) to check if the means representing average accuracy are unequal. It turns out that at lease one mean is different by $p<0.000001$, and then we apply Tukey's Honestly Significant Difference (HSD) test to find which means are unequal. We found that every pair of means including proposed feature group are significantly different by $p<0.000001$. Some pairs of means are not significantly different by the condition of $p>0.05$, they are A7 and D6, Raw and D6, Raw and A7, pairs between D1, D2, D3, D4, and D5.

Generally, the EEG signals from the frontal area are more effective for valence detection than the ones from the posterior area. However, just as in the research results demonstrated by Murugappan et al. (Murugappan et al., 2007), (Murugappan et al., 2010), our classification results also indicate that the accuracy can be improved by covering the entire area with more EEG electrodes. Fig. 6b shows comparisons using data from frontal area, posterior area, and entire area of EEG signals with $p<0.00001$ for all pairwise comparisons by ANOVA plus Tukey's HSD. Our findings are also consistent with the emotion theory proposed by Heller, which argues that the frontal and parieto-temporal regions are involved in emotion (Heller, 1993).

Our proposed cross-level wavelet feature group (CLWF) that is searched from $D1-D5$ (higher EEG frequency bands that can produce much better average accuracy from different EEG electrodes based on GA can largely improve the classification performance to an accuracy of 98% with two-level and 90% with three-level valence detection. Fig. 6c illustrates the comparison of 2-level and 3-level valence detection using proposed features with $p<0.000001$ by paired t-test. In contrast, the accuracy can be improved very much comparing to simply combining all the levels from $D1-D5$ shown in Fig. 6a. The results demonstrate the importance and practicability of the cross-level strategy for extracting features in the time-frequency domain for valence level detection using EEG signals. Our analytical results that provide higher accuracy by using EEG signals collected from the entire area are consistent with an important statement in Borod's emotion model (Borod, 1992), in which emotions are represented in cortico-limbic networks rather than in particular areas of the brain.

Electrodes selected by GA for each subject are illustrated in Fig. 7a in which a blue dot indicates "a selected electrode" and the results using the reduced set of EEG electrodes for 3-level emotional valence detection are illustrated in Fig. 7b for comparisons with other set of electrodes. As we can see, a better accuracy (86.1%) can be achieved using the reduced set of EEG electrodes compared with frontal and posterior area EEG electrodes. Another finding shown in Fig. 7c from statistical summarization of the electrodes selected from 50 subjects shows that more frontal area electrodes (65.7%) are selected compared with posterior area electrodes (34.3%), which is also consistent with the viewpoint that frontal area brain activities can better demonstrate emotion (Heller, 1993).

6 CONCLUSIONS AND FUTURE WORK

We proposed a new strategy to extract time-frequency domain features from EEG signals in cross levels of wavelet decomposition coefficients with different EEG electrodes for valence level detection. The proposed features (CLWF) substantially increase the accuracy compared to conventional features extracted directly from EEG signals or from transformed signals in the time-frequency domain. We achieved 83% accuracy using 6 EEG electrodes and 90% accuracy using 16 EEG electrodes for three-level valence detection, and 97% accuracy using 6 electrodes and 98% accuracy using 16 electrodes for two-level valence detection by using the proposed features.

The results show the importance of taking into consideration information in different frequency bands with different EEG electrodes, as it results in higher accuracy than that achieved when only considering a single level or combined levels of wavelet decomposed signals from different EEG electrodes. A GA-reduced light-weight set of EEG electrodes is also proposed with competitive accuracy (86%) for 3-level valence detection for increasing usability and further reducing computational complexity. Future work on interpreting the physiological meanings will be necessary and a user-independent model will be proposed based on EEG for valence detection.

The results achieved in this research would be interests of practitioners in a number of related field such as health informatics and BCI. This work gives hints of many paths for future model development. We emphasize a work with more comprehensive study of applying different machine learning technologies on our new proposed features.

REFERENCES

Adolphs, R., Tranel, D., and Damasio, A. R. (2003). Dissociable neural systems for recognizing emotions. *Brain and Cognition*, 52(1):61–69.

Alves, N. T., Fukusima, S. S., and Aznar-Casanova, J. A. (2008). Models of brain asymmetry in emotional processing. *Psychology & Neuroscience*, 1(1):63–66.

Arnold, M. (1950). *An Excitatory Theory of Emotion*. McGraw-Hill, New York, xxiii edition.

Arvaneh, M., Guan, C., Ang, K. K., and Quek, C. (2011). Optimizing the channel selection and classification accuracy in eeg-based bci. *IEEE Transactions on Biomedical Engineering*, 58(6):1865–1873.

Borod, J. C. (1992). Interhemispheric and intrahemispheric control of emotion: a focus on unilateral brain damage. *J Consult Clin Psychol*, 60(3):339–348.

Chu, C., Hsu, A.-l., Chou, K.-h., Bandettini, P., and Lin, C. (2012). NeuroImage Does feature selection improve classification accuracy? Impact of sample size and feature selection on classification using anatomical magnetic resonance images. *NeuroImage*, 60(1):59–70.

Constantinou, E., Bogaerts, K., Diest, L. V., and den Bergh, O. V. (2013). Inducing symptoms in high symptom reporters via emotional pictures: The interactive effects of valence and arousal. *Journal of Psychosomatic Research*, 74(3):191–196.

Darwin, C. (1872). *The Expression of the Emotions in Man and Animals, with an Introduction, Afterword, and Commentaries by Paul Ekman*. Oxford Univ Press, Oxford, 3rd edition.

Heller, W. (1993). Neuropsychological mechanisms of individual differences in emotion, personality, and arousal. *Neuropsychology*, 7,:476–489.

Holland, J. H. (1975). *Adaptation in Neural and Artificial Systems*. University of Michigan Press, Ann Arbor, Michigan, 1st edition.

Hosseini, S. A. (2011). Emotion recognition method using entropy analysis of eeg signals. *International Journal of Images, Graphics, and Signal Processing*, 3(5):30–36.

Jolliffe, I. T. (2002). *Principal Component Analysis*. Springer,, 2nd edition.

Katsis, C., Katertsidis, N., and Fotiadis, D. (2011). An integrated system based on physiological signals for the assessment of affective states in patients with anxiety disorders. *Biomedical Signal Processing and Control*, 6:261–268.

Lang, P. J., Bradley, M. M., and Cuthbert, B. N. (2008). International affective picture system (iaps): Technical manual and affective ratings. *Technical Report A-8*.

Liu, J. and Xu, J. (2010). Compared study of the analyzing methods for eeg data. In *Proc. of 3rd IEEE International Conference on Computer Science and Information Technology*, volume 9, pages 445–448.

Morlet, J. (1984). Decomposition of hardy functions into square integrable wavelets of constant shape. *SIAM. Math. Anal*, 15(4):723–736.

Murugappan, M., Ramachandran, N., and Sazali, Y. (2010). Classification of human emotion from eeg using discrete wavelet transform. *Journal of Biomedical Science and Engineering*, 3:390–396.

Murugappan, M., Rizon, M., Nagarajan, R., Yaacob, S., Zunaidi, I., and Hazry, D. (2007). Eeg feature extraction for classifying emotions using fcm and fkm. *International Journal of Computers and Communications*, 1(2):299–304.

Nardi, D. (2011). *Neuroscience of Personality: Brain Savvy Insights for All Types of People*. Radiance House, 1.0 edition.

Picard, R. W., Vyzas, E., and Healey, J. (2001). Toward machine emotional intelligence: analysis of affective physiological state. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 23(1):1175–1191.

Russell, J. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, 39(6):1161–1178.

Salovey, P. and Rothman, A. J. (2000). Emotional states and physical health. *The American psychologist*, 55(1):110–121.

Schaaff, K. and Schultz, T. (2009). Towards emotion recognition from electroencephalography signals. In *3rd International Conference on Affective Computing and Intelligent Interaction*. Institute of Electrical and Electronics Engineers.

Sherwood, J. (2009). On classifiability of wavelet features for eeg-based brain-computer interfaces. In *Proceedings of International Joint Conference on Neural Networks*. Institute of Electrical and Electronics Engineers.

Sirois, B. C. (2003.). Negative emotion and coronary heart disease. *Behavior Modification*, 27(1):83–102.

Sivakumar, A. and .Kannan, K. (2009). A novel feature selection technique for number classification problem using pnn - a plausible scheme for boiler flue gas analysis. *Sensors and Actuators B: Chemical*, 139:280–286.

Specht, D. F. (1990). Probabilistic neural networks. *Neural Networks*, 3:110–118.

Tahon, M., Degottex, G., and Devillers, L. (2012). Usual voice quality features and glottal features for emotional valence detection. In *the 6th International Conference of Speech Prosody*. Tongji University Press.

Takahashi, K. and Tsukaguchi, A. (2003). Remarks on emotion recognition from multi-modal bio-potential signals. In *Proc. of IEEE International Conference on Systems, Man, and Cybernetics*. Institute of Electrical and Electronics Engineers.

Van den Broek, E. L. and Westerink, J. H. D. M. (2009). Considerations for emotion-aware consumer products. *Applied ergonomics*, 40(6):1055–64.

Wundt, W. (1905). *Grundriss der Psychologie [Fundamentals of Psychology]*. Engelman, Leipzig, 7th edition.