Emotional state recognition using advanced machine learning techniques on EEG data

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***Abstract*—This study investigates the discrimination between calm, exciting positive and exciting negative emotional states using EEG signals. Towards this direction, a publicly available dataset from eNTERFACE Workshop 2006 was used having as stimuli emotionally evocative images. At first, EEG features were extracted based on literature review. Then, a computational framework is proposed using machine learning techniques, performing feature selection and classification into two at a time emotional states. The procedure described in this paper investigates and assess the effectiveness of selection and classification techniques providing improved classification accuracy. The proposed methodology is able to obtain accuracy of 75.12% in classifying the two emotional states comparing with similar studies using the same dataset.**

Keywords-emotion recognition; EEG; feature selection; classification; machine learning

I. INTRODUCTION

Human emotional states detection and their appropriate representation are of great interest lately, leading to the development of many applications towards this. There are various methods that can be employed for emotion recognition such as imaging techniques (fMRI, PET, etc.) [1, 2], biosignals (EEG, ECG, GSR, EMG, etc.) [3, 4], videos (facial expressions, body postures, gestures, etc.) [5-7]. Among them Electroencephalogram (EEG) is considered a reliable tool that it is used widely in clinical practice mainly for neurological dysfunctions [8, 9] but also for the examination of upper cognitive functions [10] and the recognition of affective states [4]. It provides high temporal resolution and in combination with its low cost and the fact that it is semi invasive, portable and not harmful for human health makes it appropriate for extensive use for emotion analysis.

Lately, methods based on machine learning receive great attention as the recent advances lead to promising results for a wide range of applications in medicine including computer-aided diagnosis. Regarding psychophysiology, machine learning techniques have been employed to disease detection [11] as well as emotion state discrimination.

Many studies of affect adopt the circumplex model [12] for the representation of emotions, where emotional states can be mapped using arousal and valence axes. Valence, which extends from sadness to joy, constitutes an index of perceiving an emotion as positive or negative while arousal, which extends from calm to excitement, reflects how strongly each feeling is perceived.

The purpose of this paper is the investigation, evaluation and comparison of advanced feature selection and classification methods providing the most appropriate of them to address effectively the problem of discrimination between calm, exciting positive and exciting negative emotional states.

II. DATA AND EXPERIMENTAL PROCCESS

In this section, the experimental procedure, the protocol followed and the public available dataset used in this study is described.

A. Dataset description

The data that were analyzed in this study come from the public available eNTERFACE Workshop 2006 database (Project #7: "Emotion Detection in the Loop from Brain Signals and Facial Images") [13]. The dataset consists of EEG, functional Near-Infrared Spectroscopy (fNIRS), along with some peripheral biosignals (respiration, Galvanic Skin Response, blood volume pressure) and video recordings. The devices were synchronized using a trigger mechanism and the recordings were stored in Biosemi Data Format (BDF) files. Although the combination of signals from different modalities has been reported to be efficient in emotion recognition, the acquisition of many signals may interfere with user and would make a real life application unpractical. As the research interest focuses on EEG processing, only the EEG signals were used in this analysis.

B. Experimental procedure and protocol

During the experiment, participants were asked to watch, on a screen in front of them, emotionally evocative images and try to be aware of their emotional state. The images used in this experiment are part of the International Affective Picture System (IAPS) standardized database [14], which contains 900 images able to evoke various emotions. Each image has been assessed in two 9-scale ratings regarding the arousal and valence intensity. Based on these empirical valence and arousal scores, Savran et al. [13] determined 3 images subsets corresponding to the emotional states of calm (C), exciting positive (EP) and exciting negative (EN) with 106, 71 and 150 images respectively.

The experimental procedure included 3 phases, each of them having 30 trials. Each trial started with a 3-second appearance of a dark screen with a cross in the center, followed by 5 images (block), each lasting 2.5 seconds, that all belonged to the same emotional class and then again a black screen was presented for 10 seconds. The session ended with participants assessing the images they had previously seen with a rating for each of the arousal-valence axes. The order of the blocks was random, but all three emotional classes were represented by the same number of trials in each session, namely 10 trials for each class. This procedure is graphically represented in Figure 1.

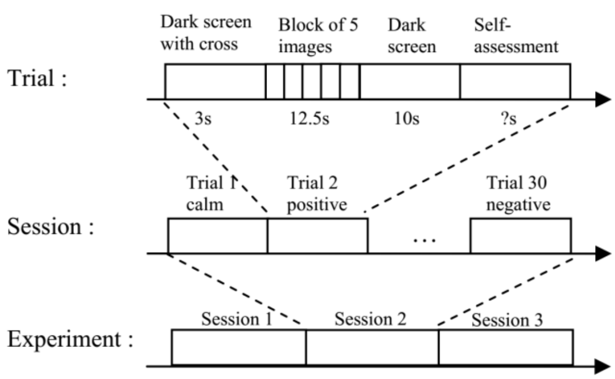

Figure 1. Schematic description of the experimental protocol (figure taken from [13])

The population of the study was five right-handed males of age 22-38 years old. The Biosemi Active 2 acquisition system was used, and the signals were acquired from the channels AF3, AF4, F3, F1, Fz, F2, F4, FT7, FC5, FC3, FC1, FCz, FC2, FC4, FC6, FT8, T7, C5, C3, C1, Cz, C2, C4, C6, T8, TP7, CP5, CP3, CP1, CPz, CP2, CP4, CP6, TP8, P9, P7, P5, P3, P1, Pz, P2, P4, P6, P8, P10. PO7, PO3, POz, PO4, PO8, O1, Oz, O2, Iz. The sampling rate was 1024 Hz (except for one session's sampling rate that was 256 Hz).

III. METHODS

In this section, the proposed methodology of this study is described. The workflow of the proposed system is described in Figure 2.

The last two submodules contain machine learning techniques that were evaluated and compared, in order to determine the best combination of methods and tuning parameters that could more accurately discriminate among the emotional states.

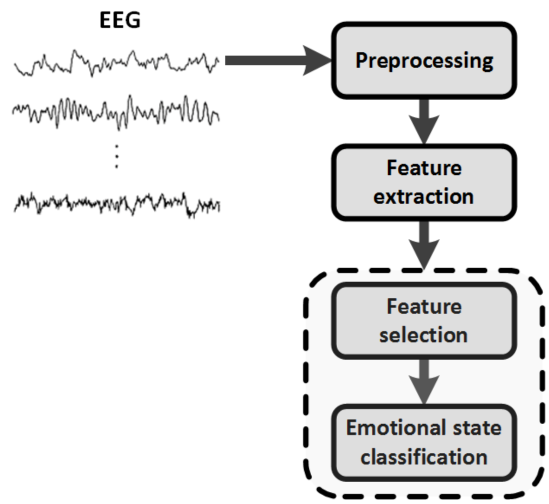

Figure 2. System's submodules workflow

A. Preprocessing

The preprocessing step included flawed trials exclusion, 50Hz noise and muscle activity artifacts removal by applying a bandpass filter 4-45 Hz. Given that spatially adjacent channels exhibit strong correlation [15], in order to reduce computational complexity, the channels F3, Fz, F4, T7, C3, Cz, C4, T8, P7, P3, Pz, P4, P8, O1, O2 (that correspond to the 10/20 system), and not all the channels (that correspond to the 10/10 system), were finally used in the analysis.

B. Feature extraction

In this study, the following features were extracted from EEG signals:

- **Signal power** in bands
  - theta (4-8Hz)
  - alpha (8-13Hz)
  - beta (13-30Hz)
  - sub-gamma (30-45Hz)
  - alpha1 (8-10Hz)
  - alpha2 (10-13Hz)
  - beta1 (13-15Hz)
  - beta2 (15-18Hz)
  - beta3 (18-22Hz)
  - high beta (25-30Hz)
  - gamma1 (30-35Hz)
  - gamma2 (35-40Hz)
  - gamma3 (40-45Hz)
- **Frontal alpha asymmetry.** Valence is considered to be related to the difference in alpha band power between symmetric areas of specific frontal areas [16, 17].
- **Peak frequency in alpha band** is considered to differentiate between emotions [18].

- **Hjorth parameters** activity, mobility and complexity can successfully discriminate between different mental states [19].
- **Cross-correlation of frequency band powers**
  - theta-alpha
  - theta-beta
  - theta-gamma
  - theta-gamma3
  - alpha-beta
  - alpha-gamma
  - alpha-gamma3
  - beta-gamma
  - beta-gamma3
  - gamma-gamma3

This procedure led to a total of 28 features for each channel that feed the features selection and classification submodules.

C. *Feature selection*

Along with feature extraction, feature selection is a crucial part of the classification process. It does not only facilitate dimensionality reduction but it also feeds the classification module with the most relevant and significant features for the discrimination.

In this study five feature selection methods were evaluated:

- the ReliefF algorithm [20]
- a Sequential Forward Selection greedy algorithm using a Gaussian Support Vector Machine (SVM) classifier's accuracy as evaluation criterion,
- MID scheme of min-Redundancy- Max-Relevance (mRMR) algorithm [20, 21]
- MIQ scheme of min-Redundancy- Max-Relevance algorithm [18, 20, 21]
- linear Recursive Feature Elimination algorithm using a SVM classifier's accuracy as evaluation criterion (linear SVM-RFE).

D. *Classification*

The discrimination between the emotional states was performed evaluating and comparing the classifier schemes that are presented in TABLE I.

The feature selection and classification processes were performed in pairs of emotional states, thus leading to three independent conditions: discrimination between (i) calm (C) and exciting positive (EP), (ii) calm and exciting negative (EN) and (iii) exciting positive and exciting negative emotional states.

In order to assess the performance of each classification scheme two different performance measures were used, the Accuracy and the Area Under the ROC Curve (AUC).

The Accuracy is given by the equation

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN},$$

where TP is the true positive, TN the true negative, FP is the false positive and FN the false negative cases.

TABLE I: METHODS AND PARAMETERS USED IN THE ANALYSIS

Extracted Features	EEG frequency band power Asymmetry Peak frequency in alpha band Hjorth parameters Cross-correlation between EEG band powers
Feature selection methods	select all variables ReliefF Greedy Sequential Forward Selection (criterion: Gaussian SVM) mRMR, MID-scheme mRMR, MIQ-scheme linear SVM-RFE
Classification schemes	Trivial classifier Naïve Bayes (NB) classifier Artificial Neural Networks (ANN) with 3 hidden layers Artificial Neural Networks with 5 hidden layers Artificial Neural Networks with 10 hidden layers Decision Trees (DT) Random Forest (RF) with 50 Trees and node size: 1 Random Forest with 50 Trees and node size: 5 Random Forest with 50 Trees and node size: 9 Random Forest with 100 Trees and node size: 1 Random Forest with 100 Trees and node size: 5 Random Forest with 100 Trees and node size: 9 K-Nearest Neighbors (KNN), K=1 K-Nearest Neighbors, K=5 K-Nearest Neighbors, K=10 Support Vector Machines (SVM) with Gaussian Kernel
Nested CV parameters	$k_{out} = 3$, $k_{in} = 5$

Accordingly, the second performance measure used is the area under the Receiver Operating Characteristic (ROC) curve [22] which is a visualization performance method widely used in different research fields, with machine learning, psychology and social sciences being among them [23]. It is considered to be a better performance measure than accuracy because it is independent of class distribution [24]. Nevertheless, accuracy is also used in this study because it enables the comparison with other studies' performance. Trivial classifier only classifies in the most frequent class, and is used as a reference point, since it is considered to represent random classification.

E. *Cross Validation*

In this study, all feature selection methods and classification schemes (combinations of classifier and parameters) are cross-validated in order to evaluate their performance and select the best combination. Since the typical k-fold Cross Validation method has been indicated to overestimate performance when used for hyper-parameter optimization [24] we used k_{out}-k_{in}-fold Nested Cross Validation [24] instead. Five iterations of Nested Cross Validation were performed for each condition and each channel. In each iteration, both feature selection methods and classifiers training were implemented after splitting the dataset in training and testing sets. The mean value of both accuracy and AUC was calculated over all iterations.

IV. RESULTS

This section describes the results of the discrimination process among calm (C), exciting positive (EP) and exciting negative (EN) emotional states. The highest mean AUC that was achieved by the feature selection/classification procedures was 0.7581, corresponding to 75.12% classification accuracy. This value results from the condition EP-EN and the channel O1 and it is illustrated in Figure 3.

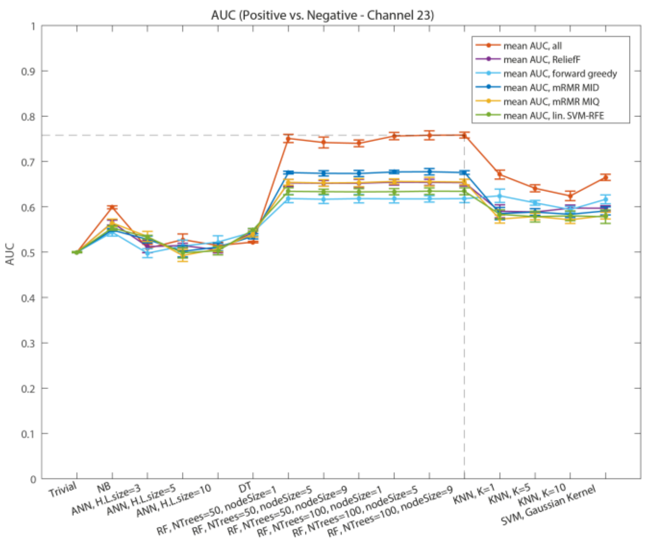

Figure 3. A typical AUC variation (mean ± s.d.) according to feature selection and classification scheme used, in condition's EP/EN best channel (O1).

It can be observed that the best classification scheme is the Random Forest classifier with 100 trees and node size 9 and the involvement of all features (no features removed). This variation is typical for most channels examined. Hence, Random Forest performs best in terms of classification accuracy for the problem under investigation.

Even if the best AUC is achieved when discriminating the EP-EN emotional states, the pairs C-EP and C-EN performs similarly well reaching an AUC of 0.7572 and 0.7561, respectively. The best performing classifier is again the Random Forest. The 10 best performances in terms of their AUC and accuracy are summarized in TABLE II.

It can be observed that the channels that are most implicated in the best discrimination ability are in occipital (O1, O2), parietal locations (P7, Pz) of head.

An investigation of other studies using this dataset was performed in order to compare with them the results of this study. The accuracies achieved in these studies as well as the accuracy of the current study are presented in TABLE III.

According to TABLE III, this study yields good accuracies as compared with other studies that used the same dataset.

In addition, there were also studies dealing with the same problem but using different own datasets (and not the one described in [13]) which are presented in TABLE IV.

TABLE II. BEST PERFORMANCES OF THE SYSTEM ACHIEVED FOR ALL CONDITIONS AND FOR SPECIFIC CHANNELS AND CLASSIFICATION SCHEMAS (NOTE: EP: EXCITING POSITIVE, EN: EXCITING NEGATIVE, C: CALM)

Condition	Channel	Classification system	AUC (mean)	Accuracy (mean)
EP-EN	O1	RF, #Trees=100, nodeSize=9	0.7581	0.7512
C-EP	O1	RF, #Trees=100, nodeSize=5	0.7572	0.7506
C-EN	O1	RF, #Trees=100, nodeSize=9	0.7561	0.7559
C-EP	P7	RF, #Trees=100, nodeSize=9	0.7338	0.7277
C-EN	P7	RF, #Trees=100, nodeSize=9	0.729	0.7229
EP-EN	P7	RF, #Trees=100, nodeSize=1	0.7288	0.7238
C-EN	F3	KNN, K=1	0.7171	0.7191
C-EP	O2	RF, #Trees=100, nodeSize=5	0.7149	0.7088
C-EN	Pz	KNN, K=1	0.7125	0.7144
EP-EN	Pz	KNN, K=1	0.7092	0.7112

TABLE III. OTHER STUDIES METHODOLOGIES AND ACCURACIES ACHIEVED USING THE DATASET THAT WAS ALSO USED IN THIS STUDY

Study	Dataset used	Methods	Best Accuracy received
Horlings et al. (2008) [18]	Dataset described in [13]	mRMR, SVM, ANN	40%
Khalili et al. (2008) [25]	Dataset described in [13]	GA, KNN	65%
Khalili et al. (2009) [26]	Dataset described in [13]	Quadratic classifier, GA, Correlation Dimension	76.66%
Singh et al. (2013) [27]	Dataset described in [13]	Naïve Bayes	64%
This study	Dataset described in [13]	Random Forest, Nested CV	75.12%

These studies provide diverse accuracy levels but their direct performance comparison is not possible due to the different datasets used.

V. DISCUSSION

This paper investigated various selection and classification schemes for the discrimination among emotional states. The analysis presented, showed that the best classification scheme achieved accuracies of 75.59%, 75.06% and 75.12% for the three pairs of classes clam/exciting negative (C-EN), calm/exciting positive (C-EP), exciting positive/exciting negative (EP-EN) respectively. These results are improved as compared to other studies using the same dataset and objective. Kumar et

TABLE IV. OTHER STUDIES METHODOLOGIES AND ACCURACIES ACHIEVED USING OWN DATASETS

Study	Dataset used	Methods	Best Accuracy received
Hoseini et al. (2010a) [28]	IAPS images	GA, Elman NN	79%
Hoseini et al. (2010b) [29]	IAPS images	T-Test. LDA, SVM	80.1, 84.9%
Chanel et al. (2006) [30]	IAPS images	Naïve Bayes, FDA	54, 55%
Kumar et al. (2016) [31]	DEAP Dataset	backward SFS, LS-SVM, ANN	64.84%

al. [31] used data from the "Database for Emotion Analysis using Physiological Signals" (DEAP) [32] to classify in low/high valence and low/high arousal, with accuracy 61.17% and 64.84% respectively. In [30], where data were acquired in a way much similar to the data of this study, discrimination between calm emotions and exciting emotions was achieved with accuracy 54-55%. Various studies such as [18, 25, 27] have used the same database as did this study and achieved accuracies of 40%, 65% and 64% respectively. Khalili et al. (2009) [26], that also used the same dataset, attained a slightly better performance. This can be attributed to the fact that Leave-One-Out method was used in this paper and not 3-5-fold Nested Cross Validation, as used in our approach, which is more conservative in the classification accuracy estimation.

The emotional label each block of images is given, was defined by the standardized IAPS ratings. However, there are cases that the emotions an image evokes to a participant can differ enough from its IAPS score [30]. Therefore, the classification accuracy could have been even better if the participants' own assessments have been taken into consideration.

The classification scheme that seems to be the most efficient in addressing the problem under investigation is the Random Forest with node size 9. Besides, the analysis showed that the better discrimination is apparent in occipital (O1, O2) and parietal (P3, P7) channels. This can be partially attributed to the fact that this experiment involved the use of visual stimuli.

The whole procedure of the analysis, which included the comparison of all possible combinations of feature selection methods and classifiers with different parameters (in total 96 combinations), was time-consuming. The search of the outperformed classification scheme was part of the research questions set in this study. Once a classification scheme was selected, it needed a runtime of about 12 seconds.

A future work could include different options about some of the analysis parts. The use of sliding time windows could reveal how much time after stimulus appearance is necessary before the classification could be done successfully. Moreover, more efficient feature selection methods could be applied, as proposed in [33]. Besides, multiclass classification, usage of all 64 channels' data and additional classifiers, like non-linear SVM-RFE, could be examined. At a later stage, more and specific emotions could be recognized, making the implementation of this study more efficient and closer to real life.

The potential applications of an EEG-based emotion recognition method are numerous. To name a few, music therapy dealing with pain management or depression [34], supporting facially paralyzed patients on expressing their emotions [35], facilitating the health care of persons with communicative disorders [36], monitoring surgeons' stress levels during an operation [37], or as an extension to self-monitoring systems [38].

REFERENCES

[1] K. L. Phan, T. Wager, S. F. Taylor, and I. Liberzon, "Functional neuroanatomy of emotion: a meta-analysis of emotion activation studies in PET and fMRI," Neuroimage, vol. 16, pp. 331-348, 2002.

[2] C. J. Hattingh, J. Ipser, S. Tromp, S. Syal, C. Lochner, S. J. B. Brooks, and D. J. Stein, "Functional magnetic resonance imaging during emotion recognition in social anxiety disorder: an activation likelihood meta-analysis," Front Hum Neurosci, vol. 6, p. 347, 2013.

[3] N. Sharma and T. Gedeon, "Objective measures, sensors and computational techniques for stress recognition and classification: A survey," Computer Methods and Programs in Biomedicine, vol. 108, pp. 1287-1301, 2012.

[4] M. Soleymani, S. Asghari-Esfeden, Y. Fu, and M. Pantic, "Analysis of EEG signals and facial expressions for continuous emotion detection," IEEE Transactions on Affective Computing, vol. 7, pp. 17-28, 2016.

[5] H. Gunes and M. Piccardi, "Bi-modal emotion recognition from expressive face and body gestures," Journal of Network and Computer Applications, vol. 30, pp. 1334-1345, 2007.

[6] I. Kotsia, S. Zafeiriou, and I. Pitas, "Texture and shape information fusion for facial expression and facial action unit recognition," Pattern Recognition, vol. 41, pp. 833-851, 2008.

[7] G. Giannakakis, M. Pediaditis, D. Manousos, E. Kazantzaki, F. Chiarugi, P. Simos, K. Marias, and M. Tsiknakis, "Stress and anxiety detection using facial cues from videos," Biomedical Signal Processing and Control, vol. 31, pp. 89-101, 2017.

[8] U. R. Acharya, S. V. Sree, P. C. A. Ang, R. Yanti, and J. S. Suri, "Application of non-linear and wavelet based features for the automated identification of epileptic EEG signals," Int J Neural Syst, vol. 22, p. 1250002, 2012.

[9] V. Sakkalis, "Applied strategies towards EEG/MEG biomarker identification in clinical and cognitive research," Biomarkers, vol. 5, pp. 93-105, 2011.

[10] V. Sakkalis, M. Zervakis, and S. Micheloyannis, "Significant EEG features involved in mathematical reasoning: evidence from wavelet analysis," Brain Topography, vol. 19, pp. 53-60, 2006.

[11] W. Mumtaz, A. S. Malik, M. A. M. Yasin, and L. Xia, "Review on EEG and ERP predictive biomarkers for major depressive disorder," Biomedical Signal Processing and Control, vol. 22, pp. 85-98, 2015.

[12] J. Russell, "A circumplex model of affect," J. Personality and Social Psychology, vol. 39, pp. 1161-78, 1980.

[13] A. Savran, K. Ciftci, G. Chanel, J. Mota, L. Hong Viet, B. Sankur, L. Akarun, A. Caplier, and M. Rombaut, "Emotion detection in the loop from brain signals and facial images," 2006.

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

[15] K. Srinivasan, J. Dauwels, and M. R. Reddy, "Multichannel EEG compression: Wavelet-based image and volumetric coding approach," IEEE journal of biomedical and health informatics, vol. 17, pp. 113-120, 2013.

[16] A. Albajes-Eizagirre, L. Dubreuil-Vall, D. Ibáñez, A. Riera, A. Soria-Frisch, S. Dunne, and G. Ruffini, "Quantitative EEG for Brain–Computer Interfaces," EEG/ERP Analysis: Methods and Applications, p. 157, 2014.

[17] G. Giannakakis, D. Grigoriadis, and M. Tsiknakis, "Detection of stress/anxiety state from EEG features during video watching," in 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2015, pp. 6034-6037.

[18] R. Horlings, D. Datcu, and L. J. Rothkrantz, "Emotion recognition using brain activity," in Proceedings of the 9th international conference on computer systems and technologies and workshop for PhD students in computing, 2008, p. 6.

[19] M. Vourkas, S. Micheloyannis, and G. Papadourakis, "Use of ann and hjorth parameters in mental-task discrimination," in Advances in medical signal and information processing, 2000. First international conference on (IEE conf. publ. no. 476), 2000, pp. 327-332.

[20] R. Jenke, A. Peer, and M. Buss, "Feature extraction and selection for emotion recognition from EEG," IEEE Transactions on Affective Computing, vol. 5, pp. 327-339, 2014.

[21] H. Peng, F. Long, and C. Ding, "Feature selection based on mutual information criteria of max-dependency, max-relevance, and min-redundancy," IEEE Trans Pattern Anal Mach Intell, vol. 27, pp. 1226-1238, 2005.

[22] T. Fawcett, "An introduction to ROC analysis," Pattern Recognition Letters, vol. 27, pp. 861-874, 2006.

[23] J. A. Swets, Signal detection theory and ROC analysis in psychology and diagnostics: Collected papers: Psychology Press, 2014.

[24] I. Tsamardinos, A. Rakhshani, and V. Lagani, "Performance-Estimation Properties of Cross-Validation-Based Protocols with Simultaneous Hyper-Parameter Optimization," International Journal on Artificial Intelligence Tools, vol. 24, p. 1540023, 2015.

[25] Z. Khalili and M. Moradi, "Emotion detection using brain and peripheral signals," in 2008 Cairo International Biomedical Engineering Conference, 2008, pp. 1-4.

[26] Z. Khalili and M. H. Moradi, "Emotion recognition system using brain and peripheral signals: using correlation dimension to improve the results of EEG," in Neural Networks, 2009. IJCNN 2009. International Joint Conference on, 2009, pp. 1571-1575.

[27] M. Singh, M. M. Singh, and N. Singhal, "Emotion Recognition along Valence Axis Using Naïve Bayes Classifier," International Journal of Information Technology & Knowledge Management, vol. 7, pp. 51-55, 2013.

[28] S. A. Hosseini and M. A. Khalilzadeh, "Emotional stress recognition system using EEG and psychophysiological signals: Using new labelling process of EEG signals in emotional stress state," in Biomedical Engineering and Computer Science (ICBECS), 2010 International Conference on, 2010, pp. 1-6.

[29] S. A. Hosseini, M. A. Khalilzadeh, and S. Changiz, "Emotional stress recognition system for affective computing based on bio-signals," Journal of Biological Systems, vol. 18, pp. 101-114, 2010.

[30] G. Chanel, J. Kronegg, D. Grandjean, and T. Pun, "Emotion assessment: Arousal evaluation using EEG's and peripheral physiological signals," in International Workshop on Multimedia Content Representation, Classification and Security, 2006, pp. 530-537.

[31] N. Kumar, K. Khaund, and S. M. Hazarika, "Bispectral Analysis of EEG for Emotion Recognition," Procedia Computer Science, vol. 84, pp. 31-35, 2016.

[32] S. Koelstra, C. Muhl, M. Soleymani, J.-S. Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, and I. Patras, "Deap: A database for emotion analysis; using physiological signals," IEEE Transactions on Affective Computing, vol. 3, pp. 18-31, 2012.

[33] T. Alotaiby, F. E. A. El-Samie, S. A. Alshebeili, and I. Ahmad, "A review of channel selection algorithms for EEG signal processing," Eurasip Journal on Advances in Signal Processing, vol. 2015, p. 1, 2015.

[34] Y. Liu, O. Sourina, and M. K. Nguyen, "Real-time EEG-based emotion recognition and its applications," in Transactions on computational science XII, ed: Springer, 2011, pp. 256-277.

[35] D. O. Bos, "EEG-based emotion recognition," The Influence of Visual and Auditory Stimuli, pp. 1-17, 2006.

[36] K. Osaka, S.-i. Chiba, T. Tanioka, C. Kawanishi, I. Nagamine, F. Ren, S. Kuroiwa, T. Tada, R. Yamashita, and M. Kishimoto, "Estimating emotion changes using electroencephalographic activities and its clinical application," in Natural Language Processing and Knowledge Engineering, 2005. IEEE NLP-KE'05. Proceedings of 2005 IEEE International Conference on, 2005, pp. 830-834.

[37] D. G. Duru, A. D. Duru, D. E. Barkana, O. Sanli, and M. Ozkan, "Assessment of surgeon's stress level and alertness using EEG during laparoscopic simple nephrectomy," in Neural Engineering (NER), 2013 6th International IEEE/EMBS Conference on, 2013, pp. 452-455.

[38] Y. Andreu, F. Chiarugi, S. Colantonio, G. Giannakakis, D. Giorgi, P. Henriquez, E. Kazantzaki, D. Manousos, K. Marias, and B. J. Matuszewski, "Wize Mirror-a smart, multisensory cardio-metabolic risk monitoring system," Computer Vision and Image Understanding, vol. 148, pp. 3-22, 2016.