Physiology-based Recognition of Facial Micro-expressions using EEG and Identification of the Relevant Sensors by Emotion

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Keywords: Emotions Recognition, Physiological Signal EEG, Facial Expressions, Models Construction.

Abstract: In this paper, we present a novel work about predicting the facial expressions from physiological signals of the brain. The main contributions of this paper are twofold. a) Investigation of the predictability of facial micro-expressions from EEG. b) Identification of the relevant features to the prediction. To reach our objectives, an experiment was conducted and we have proceeded in three steps: i) We recorded facial expressions and the corresponding EEG signals of participant while he/she is looking at pictures stimuli from the IAPS (International Affective Picture System). ii) We fed machine learning algorithms with time-domain and frequency-domain features of one second EEG signals with also the corresponding facial expression data as ground truth in the training phase. iii) Using the trained classifiers, we predict facial emotional reactions without the need to a camera. Our method leads us to very promising results since we have reached high accuracy. It also provides an additional important result by locating which electrodes can be used to characterize specific emotion. This system will be particularly useful to evaluate emotional reactions in virtual reality environments where the user is wearing VR headset that hides the face and makes the traditional webcam facial expression detectors obsolete.

1 INTRODUCTION

1.1 Context and Motivation

Affective Computing (Picard, 1997) is the general frame-work that considers emotions in human computer interaction. In particular, the overall objective is to make computers able to perceive, feel and express emotions. However an important goal remains to detect human emotions. Several studies have been successfully conducted to detect emotions using models that track facial expressions with camera or webcam with, for instance, CERT (Littlewort et al., 2011), or FaceReader (Lewinski, den Uyl and Butler, 2014)…etc. The obtained results in these studies showed a high accuracy that has never been reached with other approaches using physiological data.

The joint efforts of researchers in machine learning, affective computing, physiological computing (Fairclough, 2010) and neuroscience are producing innovative methods for emotional and affective states recognition by analysing data collected with subjective methods (self-report, expert annotation) or objective methods (log files, Kinect, camera, eye-tracking and electrophysiology-cal sensors: EDA, HR, EMG, EEG, Respiration rate,…) .

Thanks also to breakthrough advancements in computer vision, facial expressions detection technology has reached commercial-level maturity and has become more common, e.g. with Kinect 2 in Xbox, software like Facereader, iMotions FACET, and NVISO. However, so far, all the focus has been on external assessment methods and to the best of our knowledge, no attempt has ever been made at detecting facial micro-expressions from EEG signal. A micro-expression (Ekman, 2007) is a brief spontaneous facial expression, unconscious (involuntary) and hard to hide as it lasts between 1/24 and 1/15 of a second. Because of their short duration, micro-expressions are identifiable only by trained peoples or in videos where the person's face is recorded. Software like FACET and FaceReader analyses videos frame by frame to extract the micro-expressions.

Micro-expressions are important because they give the spontaneous emotions of the users, which can be detected using facial expression software. However, it is not always possible to record the person’s face; for example with low luminosity or

Benlamine, M., Chaouachi, M., Frasson, C. and Dufresne, A.
Physiology-based Recognition of Facial Micro-expressions using EEG and Identification of the Relevant Sensors by Emotion.
DOI: 10.5220/0006002701300137
In *Proceedings of the 3rd International Conference on Physiological Computing Systems (PhyCS 2016)*, pages 130-137
ISBN: 978-989-758-197-7

when the person is moving his face or when he is using VR headset to interact with an immersive virtual reality environment. In such situations, physiological measures like EEG represent a promising alternative that could potentially solve these problems. Moreover EEG devices are being increasingly used as they present a practical low cost solution and help building interesting accurate models to track and assess users' states. EEG features can improve recognition of affect and facial expressions.

Recent studies in the field of neuroscience have found a relation between neural activations and emotions using the technique of Functional Magnetic Resonance Imaging, or fMRI. For example, (Kassam, Markey, Cherkassky, Loewenstein and Just, 2013) show, through an experiment with 10 participants using fMRI, that there are consistent patterns of neural activation for all emotion categories within and between participants. In the meanwhile, several works has shown that emotional states can be recognized from EEG signal with reasonable accuracy (AlZoubi, Calvo and Stevens, 2009; Chaouachi, Chalfoun, Jraidi and Frasson, 2010; Chaouachi and Frasson, 2012; Chaouachi, Jraidi, and Frasson, 2015; Heraz and Frasson, 2007; Jraidi, Chaouachi and Frasson, 2013; Liu, Sourina and Nguyen, 2011; Lu, Zheng, Li and Lu, 2015). So, it seems sensible then to consider cerebral activity as input for detecting facial expressions rather than user's face images or videos. All this leads us to believe that a correlation between EEG features and facial micro-expressions should be investigated.

1.2 Objectives

Knowing now the importance of micro-expressions for emotion detection, we aim to build a predictive model of these emotional micro-expressions from EEG signals. With such a model, it will be possible to predict spontaneous facial expressions having as input cerebral activity signal using Emotiv Headset. More precisely, we aim to answer two questions: (1) How well can we predict facial expressions from the brain signals of participants? (2) Which EEG features are important for the prediction?

To reach these objectives, we will proceed according to the following steps: 1) measuring emotional reactions of a user confronted to specific emotional pictures using FACET system, 2) measuring the corresponding EEG signals and train machine learning models that correlates the micro-expressions with the EEG signals, and 3) predict the emotion only from the model and check the accuracy of the model.

The organization of this paper is as follows: section 2 presents the design of our experimental approach and methodology for the EEG-based facial expressions recognition. We show how we can evaluate emotions using a well-known set of emotional pictures. We detail the material used for the experimentation and the different measures obtained. Results and discussions are presented in section 3. We finally show how our model can predict the micro-expressions from EEG signals. We conclude this study with a presentation of the scope of use of this model as well as our future work.

2 METHODS

2.1 Participants

Twenty participants (7 women, 13 men) were recruited for our study. Their ages ranged from 21 to 35 years and all of them came from a North American University. All participants were right handed and comparable in age, sex and education.

2.2 IAPS Pictures Selection

We selected 30 pictures from IAPS (International Affective Picture System) (Lang, Bradley and Cuthbert, 2008) with regard to their affective ratings (valence, arousal) after consulting the IAPS documentation. The selected pictures are well distributed throughout the space (Figure 1). We grouped those pictures in 8 emotion categories: Joy, Calm, Excitement, Engagement, Frustration, Anger, Sadness, and Surprise.

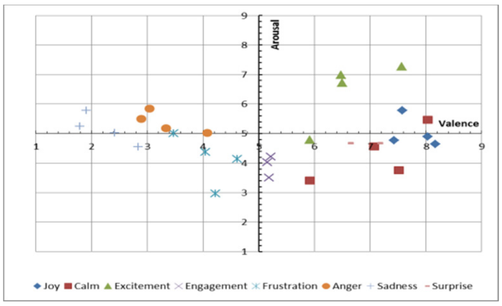

Figure 1: IAPS pictures' affective ratings distribution and their categories of emotion.

2.3 Experimental Procedure

The participants were received and introduced to our laboratory. A consent form was given to the participant to read and sign it in order to register his agreement about doing the experiment. They were seated in front of a computer and a webcam. The participant's chair was adjusted to maintain good view of their faces to the webcam.

The experiment design was synchronized by iMotions Attention Tool which is a software plat-form that permit multi-sensors study (eye tracking, facial expressions detection, EEG, GSR …) with automatic synchronization. We have recorded data of facial expressions using FACET module and EEG using Emotiv Epoch headset. IAPS Pictures with the same emotion category were displayed 6 seconds one by one, separated by a noise screen of 5 seconds to accomplish a relaxation phase before the projection of the next picture. After that, a form appears asking the user to choose one from the eight emotion categories that best represent his global feeling about the previewed pictures. The same procedure was repeated for each of the eight emotion categories. The goal of this form is to have the user's subjective confirmation of the emotion he/she supposed to feel seeing the pictures. The chart below (Figure 2) shows the percent of the self-reported emotion categories by the IAPS pictures groups. We configured FACET to analyse frame by frame the videos of the user's face to extract his/her micro-expressions.

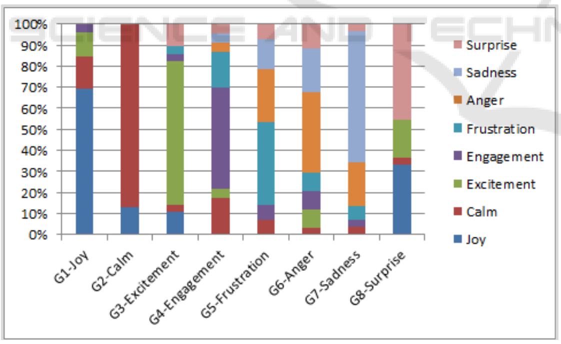

Figure 2: Self-reported emotions by pictures groups.

2.4 Measures and Materials

In this study, we have used the following tools.

2.4.1 iMotions FACET Module

The FACET module detects and tracks facial expressions of primary emotions using real-time frame-by-frame analysis of the emotional responses of users via a webcam. A commercial webcam is used for the user face recording (Webcam Logitech Pro C920). The captured image is 1920 x 1080 pixels with 24-bit RGB colours, acquired at 6 frames/sec. The FACET module is the commercial version of CERT (Computer Expression Recognition Toolbox) (Littlewort et al., 2011) which is a robust facial micro-expressions recognition software with an accuracy that reaches 94% (Emotient, 2015). The resulted data file contains two columns (Evidence and Intensity) for-each of the following categories: Joy, Anger, Surprise, Fear, Contempt, Disgust, Sadness, Neutral, Positive Valence, and Negative Valence.

2.4.2 Emotiv EPOCH EEG

Physiological data were recorded during the session using the Emotiv EEG headset. The headset contains 14 electrodes that must be moist with a saline solution (Contact lens cleaning solution). The electrodes are spatially organized with respect to the International 10–20 system. They are located at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4 (see Figure 3) with two other reference nodes (that would be placed behind the ears). The generated data are in µVolt with a sampling rate of 128 Samples/sec. The signal's frequencies are between 0.2 and 60Hz.

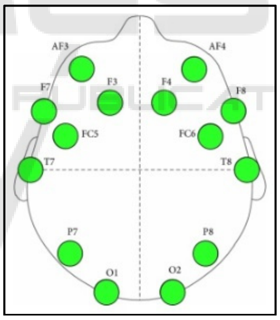

Figure 3: Data channels placement of the Emotiv Headset.

3 DATA ANALYSIS

3.1 Facial Expressions Data

Taking the webcam stream as input, the FACET system classifies each frame and provides two values for each emotion category, namely: Evidence and Intensity. The Intensity number is a value between 0 and 1, which denotes the estimation by expert human coders of the intensity of an expression. While the Evidence number is a value between -3 and 3 that represents the presence of an expression. For an easier interpretation, the

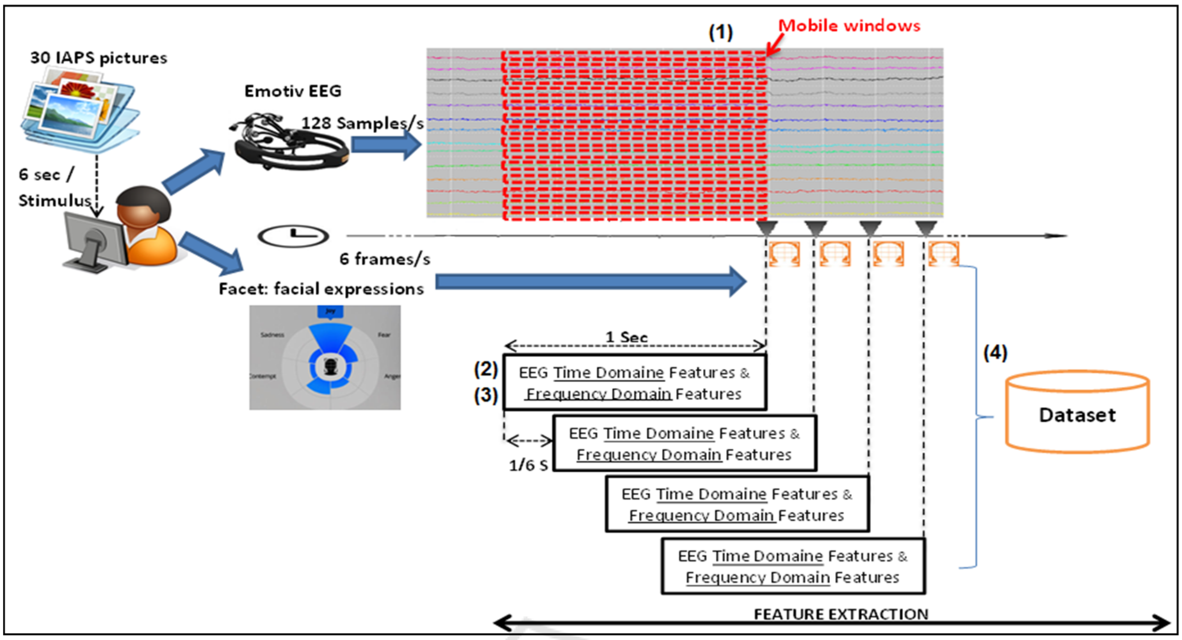

Figure 4: Pipeline of dataset construction for EEG-based Facial Expressions recognition.

Evidence number has been transformed into emotion probability between 0 and 1, using this formula (as in FACET guide) (Facet, 2013):

$$P_{Emotion} = \frac{1}{1+10^{-Evidence}} \quad (1)$$

We computed the probability of each emotion in our dataset. These probabilities will be considered as ground truth in the models training phase.

3.2 Dataset Creation

Building the dataset is an important process that has a big impact in the robustness and the accuracy of the resulting machine learning models.

The figure above (Figure 4) illustrates the entire pipeline that we have designed for the construction of our dataset for EEG-based Facial Expressions recognition. We developed a java program that uses 14 first-in first-out queues of size 128 of reals as mobile windows of 1 second EEG data from each electrode (each window contains 128 samples). (1) For each FACET frame time (every 1/6 sec) the program reads the content of each window and (2) performs statistical analysis to extract time-domain features and (3) spectral analysis to extract frequency-domain features. (4) The program records in a separate CSV file the FACET frame Time, the computed Time-domain and Frequency-domain features of each electrode (Table 1) and the probability value of each emotion category.

The frequency-domain features are computed by applying FFT on the 128 samples contained in each window for each FACET Frame Time. By using the Fast Fourier transform (FFT), we calculated the magnitudes (in μV^2) in frequency domain for the corresponding frequency bands (delta [1–4 Hz[, theta [4–8 Hz[, alpha [8–12 Hz[, beta [12–25 Hz[, and gamma [25–40 Hz[ ) with the application of hamming window to smooth the signal. The FACET frame rate is 6 frames per second, so each window receives, every 1/6 sec, 22 new EEG values (128/6=21.33 ~ 22).

Table 1: Computed features from EEG Signals.

Frequency-domain EEG Features (5 Features)	delta [1–4 Hz[, theta [4–8 Hz[, alpha [8–12 Hz[, beta [12–25 Hz[, and gamma [25–40 Hz[
Time-domain EEG Features (12 Features)	Mean, Standard Error, Median, Mode, Standard Deviation, Sample Variance, Kurtosis, Skewness, Range, Minimum, Maximum and Sum

The time-domain features (Table 1) are also computed based on each window that contains 128 samples for each FACET Frame time. Therefore, the used epoch length in this study is 128 samples. The twelve features of the EEG signal indicated above are extracted in the time domain. For each FACET Frame time, we computed from each window: Minimum, Maximum, Mean and Sum values. The Range represents the difference between the

Minimum and Maximum. The Mode is the most commonly occurring value. The Variance measures the spread between the values in the window and the Mean. A variance of zero indicates that all the values are identical. The standard deviation is the square root of the variance. The standard Error is the standard deviation divided by the square root of the window size.

Kurtosis is a descriptor of the shape of a distribution which represents the distribution's width of peak. A Gaussian distribution has a kurtosis of zero; a flatter distribution has a negative kurtosis, and a more peaked distribution has a positive kurtosis. Skewness is a measure of the asymmetry of a distribution relative to its mean; a distribution can be negatively skewed when the left tail is longer or positively skewed when the right tail is longer, and a symmetrical distribution has a skewness of zero.

We have not used a window containing average values from all electrodes because we assumed that each emotion has its own activated area in the brain (Kassam et al., 2013). The Machine learning algorithms will select features from the suitable electrodes for the prediction of specific emotion category values.

The total number of computed features from all the electrodes is 238 (17 features per electrode: 5 frequency-domain features + 12 time-domain features). The collected dataset contains 21553 data points (1078 data point per participant; 36 data point per stimulus). We have created 10 CSV files where we put together all the extracted EEG Features and one emotion category extracted from FACET data. Each file was entered as an input to the WEKA machine learning toolkit (Hall et al., 2009) for generating EEG-based regression model to predict the values of one emotion category.

4 RESULTS AND DISCUSSIONS

For every one of the 10 emotion categories, a regression model was generated. Three machine learning algorithms were used to predict the numeric values of each emotion category; namely IBk (K-nearest neighbours classifier), Random Forest (classifier constructing a forest of random trees) and RepTree (Fast decision tree learner).We used 10 fold validation in our test phase. For the prediction of the emotion classes' values, we have chosen dependent criteria: Correlation Coefficient (CC), Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) to evaluate the goodness of different machine learning algorithms.

Table 2: Comparison between machine learning methods.

Emotion	IBk			Random Forest			RepTree		
	CC	MAE	RMSE	CC	MAE	RMSE	CC	MAE	RMSE
Joy	0.85	0.02	0.05	0.91	0.02	0.05	0.72	0.03	0.07
Anger	0.88	0.05	0.09	**0.92**	0.05	0.08	0.83	0.07	0.10
Surprise	0.85	0.02	0.04	0.90	0.02	0.03	0.76	0.02	0.05
Fear	0.89	0.04	0.08	**0.92**	0.05	0.07	0.78	0.07	0.10
Neutral	0.87	0.05	0.10	0.91	0.06	0.09	0.74	0.08	0.14
Contempt	0.79	0.03	0.07	0.85	0.04	0.06	0.63	0.05	0.08
Disgust	0.88	0.03	0.06	**0.92**	0.03	0.05	0.63	0.05	0.08
Sadness	0.89	0.03	0.06	**0.92**	0.03	0.06	0.83	0.04	0.08
Positive	0.85	0.05	0.11	0.91	0.06	0.09	0.76	0.08	0.13
Negative	0.86	0.10	0.16	0.90	0.11	0.14	0.80	0.13	0.18

Compared to IBk (k=1 neighbour) and RepTree methods, Random Forest obtains higher correlation coefficient and lower error rates such as MAE and RMSE for all emotion categories, as illustrated in Table 2.

In order to find the optimal EEG features for each emotion category, we used a feature selection method called ReliefF over Random forest algorithm to choose an optimal feature set of size 24 (10% of the initial features set). The experimental results performed on the different emotion categories are presented in Table 3.

Table 3: Random forest models results with reliefF feature selection method.

Emotions	R.F. (selection of 24 Attributes)		
	CC	MAE	RMSE
Joy	0.8336	0.0266	0.0585
Anger	0.8888	0.0612	0.0872
Surprise	0.8272	0.0219	0.0428
Fear	0.8949	0.0516	0.0744
Neutral	0.8854	0.0648	0.0971
Contempt	0.8266	0.0374	0.0607
Disgust	0.9196	0.0307	0.0483
Sadness	0.8854	0.0401	0.0640
Positive	0.8647	0.0655	0.1012
Negative	0.8878	0.1093	0.1439

In the experiments, a 10-fold cross validation method was used for evaluation. It is notable that Random Forest method performs well even with 24 features. The 24 selected EEG features by emotion category are presented in Table 4.

Table 4: The selected 24 attributes by ReliefF over Random Forest for each emotion category.

Emotion	The selected 24 attributes (10% of features set)
Joy	P8_Mode, T8_Mode, P8_Range, T8_Minimum, T8_Range, P8_Maximum, T8_Maximum, T8_Standard_Deviation, T8_Standard_Error, P8_Minimum, T8_Median, P8_Median, T8_Sum, T8_Mean, FC6_Standard_Error, FC6_Standard_Deviation, FC6_Minimum, P8_Standard_Error, P8_Standard_Deviation, T8_Delta, P8_Mean, P8_Sum, T8_Beta, P7_Range
Anger	P7_Range, P8_Range, P8_Maximum, P7_Standard_Deviation, P7_Standard_Error, P8_Mode, P8_Minimum, P7_Maximum, AF4_Range, P8_Median, AF3_Mode, F3_Range, T7_Skewness, P7_Gamma, P8_Standard_Error, P8_Standard_Deviation, P7_Median, P7_Beta, P7_Alpha, P8_Sum, P8_Mean, AF3_Maximum, P7_Mode, P7_Delta
Surprise	P7_Mode, P7_Range, P7_Maximum, P8_Skewness, P7_Minimum, P7_Standard_Error, P7_Standard_Deviation, P7_Kurtosis, P7_Median, P7_Sum, P7_Mean, P8_Kurtosis, P7_Skewness, T7_Sample_Variance, T7_Mode, P8_Minimum, T7_Standard_Deviation, T7_Standard_Error, T7_Kurtosis, P7_Sample_Variance, O1_Skewness, O2_Kurtosis, F8_Kurtosis, O1_Kurtosis
Fear	FC6_Standard_Error, FC6_Standard_Deviation, FC6_Minimum, P8_Range, P8_Minimum, FC5_Minimum, FC6_Range, P8_Maximum, P7_Range, T8_Minimum, P8_Median, FC5_Standard_Error, FC5_Standard_Deviation, P8_Mean, P8_Sum, P8_Standard_Deviation, P8_Standard_Error, FC6_Delta, T7_Delta, FC6_Sample_Variance, FC6_Mode, P8_Mode, T7_Skewness, P7_Skewness
Neutral	P8_Mode, P8_Range, P8_Maximum, T8_Mode, P8_Minimum, T8_Minimum, T8_Range, T8_Maximum, P8_Median, P8_Mean, P8_Sum, P8_Standard_Error, P8_Standard_Deviation, P7_Range, FC5_Minimum, T8_Standard_Deviation, T8_Standard_Error, FC6_Mode, FC6_Standard_Deviation, FC6_Standard_Error, FC6_Range, FC6_Minimum, P8_Theta, FC5_Standard_Error
Contempt	T8_Mode, P8_Mode, T8_Minimum, FC6_Mode, F7_Minimum, FC6_Standard_Error, FC6_Standard_Deviation, FC6_Minimum, FC6_Range, FC5_Minimum, T7_Delta, FC5_Mode, T8_Maximum, F8_Mode, T8_Range, F7_Range, F7_Mode, FC6_Delta, F8_Range, FC5_Standard_Error, FC5_Standard_Deviation, F7_Maximum, T7_Beta, F8_Minimum
Disgust	P8_Maximum, P8_Mode, P8_Range, P7_Range, P8_Minimum, P8_Median, P8_Mean, P8_Sum, P8_Standard_Deviation, P8_Standard_Error, O1_Minimum, AF4_Range, FC5_Minimum, AF4_Minimum, F7_Minimum, P7_Standard_Deviation, P7_Standard_Error, P7_Maximum, F8_Maximum, FC5_Standard_Error, FC5_Standard_Deviation, T7_Skewness, AF4_Standard_Deviation, AF4_Standard_Error
Sadness	P8_Range, P8_Maximum, P8_Mode, P8_Minimum, P7_Range, P8_Standard_Deviation, P8_Standard_Error, P8_Median, P8_Beta, P8_Theta, P8_Sum, P8_Mean, P8_Alpha, P7_Kurtosis, P8_Gamma, P7_Maximum, AF3_Range, P7_Standard_Deviation, P7_Standard_Error, P8_Delta, AF3_Minimum, AF3_Maximum, P8_Sample_Variance, P8_Skewness
Positive	P8_Mode, T8_Mode, T8_Minimum, T8_Range, P8_Range, P8_Maximum, T8_Maximum, P8_Minimum, T8_Standard_Deviation, T8_Standard_Error, FC6_Standard_Deviation, FC6_Standard_Error, P7_Range, T8_Median, FC6_Range, T8_Sum, T8_Mean, FC6_Minimum, T8_Beta, FC6_Mode, P8_Median, P8_Standard_Error, P8_Standard_Deviation, T8_Delta
Negative	P8_Range, P8_Maximum, P8_Minimum, P7_Range, F7_Minimum, P8_Median, P8_Sum, P8_Mean, P8_Standard_Error, P8_Standard_Deviation, F3_Range, T8_Minimum, T8_Range, F7_Standard_Error, F7_Standard_Deviation, F7_Range, P7_Gamma, AF4_Range, FC5_Mode, P7_Standard_Error, P7_Standard_Deviation, FC5_Minimum, P7_Maximum, FC6_Standard_Deviation

From the results in Table 4, we have identified the most suitable EEG electrodes by emotion category as illustrated in Table 5.

Table 5: Random Forest selected EEG electrodes by emotion category.

Emotion	Selected Electrodes
Joy	P8, T8, FC6
Anger	P7, P8, AF4, AF3, F3, T7
Surprise	P7, P8, T7, O1, O2, F8
Fear	FC6, P8, FC5, FC6, P7, T8, T7
Neutral	P8, T8, P7, FC5, FC6
Contempt	T8, P8, FC6, FC5, T7, F8, F7
Disgust	P8, P7, O1, AF4, FC5, F7, F8, T7
Sadness	P8, P7, AF3
Positive	P8, T8, FC6, P7
Negative	P8, P7, F7, F3, T8, AF4, FC5, FC6

These results are very important, since this is the first time we identify the most reliable sensors for each emotion category. In previous study, Liu and colleagues (Liu et al., 2011) implemented a real-time EEG-based emotion recognition algorithm based on fractal dimension calculation of six different emotions using only AF3, F4 and FC6 electrodes. Our proposed model has better accuracy, more adaptability to all users and several advantages besides. In fact, the identification of the most active electrodes detected by our model gives us a deep understanding of how the brain reacted with regard to emotional elicitation. Furthermore, we note that the P8 is a common electrode for all emotion categories. The P8 sensor position is localized on the parietal lobe of the right cerebral hemisphere of the brain. This result is consistent with the study of Sarkheil and his colleagues (Sarkheil, Goebel, Schneider and Mathiak, 2013), and confirms the role of the right IPL (Inferior Parietal Lobule) in decoding dynamic facial expressions. So, the right IPL is not only involved in decoding the others' facial expressions but also in generating our own facial expressions. The same consistency holds for the F4 sensor that was completely excluded by our model and F3 sensor that was only used to detect Anger and Negative emotions. In fact, the two sensors are located in the frontal lobe which is, according to the study of Lough et al. (Lough et al., 2006), related to the modification of emotions to generally fit socially acceptable norms.

With these results, our EEG-based facial expressions prediction approach provides a simple and reliable way to capture the emotional reactions of the user that can be used in learning, games, neurofeedback, and VR environments.

5 CONCLUSION

This work shows that user's facial expressions are predictable from EEG physiological signals. The emotion recognition problem is considered from regression perspective taking as ground truth the detected facial expressions' data from webcam-based facial expressions recognition software (FACET). The experiment results revealed that facial expressions can be recognizable from specific EEG sensors by the mean of specific time-domain and frequency-domain features. Our experimental design and features construction method has enhanced the physiological emotions recognition accuracy reaching performances similar to computer vision technics. This finding suggests that the used EEG features were sufficiently implemented for the prediction of facial expressions from EEG with high accuracy. This accuracy is compared with FACET output and not against the self-reported emotional state of the user which is out of the scope of this current study and would be an interesting direction for further work with larger sample size. With the advances in the technology of EEG and appearance of new EEG headsets with dry sensors and wireless transmission of physiological data to mobile applications (Chi et al., 2012; Samsung, 2015), emotions assessment with EEG equipment will be more common in our daily life. Therefore, we are considering the integration of our models in a virtual reality environment to test their performances in real-time conditions and detect the user's facial reactions even with VR headset that hides his face.

ACKNOWLEDGEMENTS

The research presented in this paper has been supported by funding awarded by the Natural Sciences and Engineering Research Council of Canada (NSERC) and Beam Me Up Games.

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