Toward Emotion Aware Computing: An Integrated Approach Using Multichannel Neurophysiological Recordings and Affective Visual Stimuli

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Abstract—This paper proposes a methodology for the robust classification of neurophysiological data into four emotional states collected during passive viewing of emotional evocative pictures selected from the International Affective Picture System. The proposed classification model is formed according to the current neuroscience trends, since it adopts the independency of two emotional dimensions, namely arousal and valence, as dictated by the bidirectional emotion theory, whereas it is gender-specific. A two-step classification procedure is proposed for the discrimination of emotional states between EEG signals evoked by pleasant and unpleasant stimuli, which also vary in their arousal/intensity levels. The first classification level involves the arousal discrimination. The valence discrimination is then performed. The Mahalanobis (MD) distance-based classifier and support vector machines (SVMs) were used for the discrimination of emotions. The achieved overall classification rates were 79.5% and 81.3% for the MD and SVM, respectively, significantly higher than in previous studies. The robust classification of objective emotional measures is the first step toward numerous applications within the sphere of human–computer interaction.

Index Terms—Affective computing, EEG, emotion theory, human–computer interaction (HCI), Mahalanobis, neurophysiological recordings, support vector machines (SVMs).

I. INTRODUCTION

DURING the past few years, there has been a rapid development in the field of human–computer interaction (HCI). New methodologies in user interfaces were introduced aiming to improve the interaction between the human and the machine [1], [2]. Nowadays, computers are no longer viewed as merely computational tools, but as the enabling technology for new ways of cyber communication [3], cyber relationships [4], and cyber socialization [5], since they are equipped with all the necessary communication channels to interact with the users,

and the sensing abilities to infer user's attributes [1]. It is therefore imperative and unsurprising that computerized systems rapidly prevail in various socioemotional life aspects, such as e-health, education, telemonitoring of elderly people, and learning [3], [6], [7]. There are however many challenges that should be faced toward the achievement of successful HCI. Among them, the increasing heterogeneity of computer users, and the stricter demands for reduced user frustration while interacting with computers, which both are causing a shift of the adaptation requirements from the human user to the computer [8].

To be more realistic and robust, the HCI should follow the basic principles of communication among human beings [9]. Thus, machines should be equipped with socioemotional skills in order to naturally adapt to their users' emotional mood expressing feelings, such as frustration, confusion, disliking, or interest [10]. These arguments put recently, alongside the significance of embedding emotion recognition to HCI systems, gave birth to a newly introduced facet of human intelligence named as "emotional intelligence" within the more general field of ambient intelligence (AmI) [11]. The core element of emotional intelligence is one's ability to recognize the affective state of the person communicating with, so as to alter his/her own behavior according to this information. Embedding a subset of human emotional skills to machines will lead to the next generation of HCI technology, which will facilitate computers with the ability to adapt their function in a more human-like, effective, and efficient way [1].

But before dealing with emotion aware computing, a prerequisite of vital importance is to meet the theoretical assumptions associated with human emotion and emotional reactions. According to a currently widely accepted view, a simple but yet effective theory [12], [13], employed a bidirectional emotional model defined by two basic parameters/variables, namely, the affective degree of pleasantness and arousal. The model regards the various emotional states as being subordinate divisions placed in a 2-D emotional space formed by these two affective variables. Its divisions are correlated to the species survival, since emotions are based on either an appetitive or a defensive motivational system, according to the judged degree of pleasantness/unpleasantness it elicits (valence dimension). The activation level of the active motivational system defines the arousal dimension, whether the emotional state is regarded as calm or exciting [14]. To standardize an experimental framework for human emotions' research, the International Affective Picture System (IAPS) was developed by Lang [15]. The IAPS system

is based on the 2-D emotional theory, and provides normative ratings for pleasantness/valence and arousal. It is a collection of emotion evocative pictures, and has been widely used for assessing the human emotional processing in neurophysiological studies [16], [17], while providing normative ratings for pleasantness/valence and arousal.

In the field of HCI, there have been very few attempts applying cognitive models to experimental protocols used for eliciting emotional reactions [18], [19]. Previous research attempts that ignored these models have employed several human–computer communicative ways, such as facial expressions [20], face detection [21], vocal emotional cues [22], gesture recognition [23], [24], human motion analysis [25], and eye tracking [26]. These studies used techniques that were based on externally expressed emotions that do not necessarily capture innermost (actual) emotions difficult to be detected even during interaction between humans. Neurophysiological recordings seem to unveil this hidden information providing emotional patterns that characterize stimuli of different arousal or valence [27]. Emotional stimuli rated with different degrees of arousal or pleasantness evoke event-related potentials (ERPs) with different characteristics in terms of amplitude or latency [28], [29]. The neurophysiological methods seem to be also sensitive in differentiating how subjects perceive differently the same emotional stimuli. Recent studies reported differences between males and females in ERPs characteristics during the presentation of IAPS emotional stimuli [30]–[33].

Although neurophysiological recordings provide more objective measures for assessing the emotional state of the user, the problem of emotion classification is highly complex and has so far been faced only by using either simple classifiers or only statistical methods. Sophisticated classifiers and data mining techniques can help in this direction. The first research attempts using classifiers for emotions discrimination focused on the development of systems that were tested only on single persons [27], [34], or were based on features gathered from autonomic responses [27], [34], [35]. Although they classified the arousal emotional state quite successfully (with scores >80%), their classification scores for the valence dimension were relatively poor (50% for the unpleasant feelings) [27], [34].

The objective of this paper is to propose a novel methodological architecture that employs advanced classifiers with features linked to the bidirectional theory of emotion. We hypothesize that a careful combination of features extracted from neurophysiological signals recorded noninvasively from the human brain can provide much higher classification scores than previously proposed systems that were based on peripheral physiological measurements. To our best knowledge, this is the first attempt to classify the emotional state of a user by using advanced classifiers and data mining techniques applied to neurophysiological recordings. A likely success of this argument will open up new ways of approaching the introduction of a user-independent emotional classifier considering both the arousal and valence dimensions. Our approach employs (and compares) a distance-based classifier (Mahalanobis), and (with) three different support vector machine (SVM) kernels for the emotional classification, using a two-step discrimination procedure. The

classification rates obtained by the employed classifiers indicate the robustness of both the proposed framework and the classification procedure. In contrast to previous methodologies being tested on single persons, our approach was tested on a large group of subjects from both genders.

The remaining of this paper is structured as follows. Details about the experimental procedure and the methodology used for the feature extraction, selection, and classification are provided in Section II. The classification results acquired for each of the classifiers is given next in Section III and discussed in the Section IV of the paper.

II. MATERIALS AND METHODS

A. Experiment Overview

The work conducted was part of the AFFECTION collaborative project [36], between the Medical School of the Aristotle University of Thessaloniki, Greece, and the Brain Science Institute of RIKEN, Japan. Twenty-eight healthy, right-handed volunteers (equal number of male and female subjects) participated in the experiment with a mean age of 28.2 ± 7.5 for males and 27.1 ± 5.2 for females (mean $\pm$ SD). All subjects had normal or corrected to normal vision and no history of psychiatric or neurological illness. The study was approved by the local medical ethics committee.

The protocol employed emotion evocative visual stimuli selected from the IAPS collection in which the pictures (stimuli) can be depicted according to their valence and arousal ratings forming a 2-D Cartesian emotional space, as depicted in Fig. 1. The pictures were divided according to their distribution in four emotional categories: the upper right quadrant, denoted as HVHA, containing pleasant [high valence (HV)] and highly arousing stimuli [high arousal (HA)]; the upper left quadrant (LVHA) containing unpleasant [low valence (LV)] and highly arousing stimuli; the low right quadrant (HVLA) containing pleasant and low arousal stimuli (LA); and the low left one (LVLA) containing unpleasant and LA stimuli. One hundred and sixty pictures were totally presented to each subject, 40 from each emotional category.

Each single epoch consisted of a 500 ms prestimulus, and a 2 s poststimulus period. In the prestimulus period, a white fixation cross was presented on the screen in a black background. The stimulus appeared on the screen for 1 s after which the fixation cross came up again (see Fig. 2). The duration of the experiment was less than 5 min. During the experiment, the subjects were seated comfortably in an armchair. The pictures were presented to the subjects in a random order avoiding habituation effects [10], on a PC screen placed in front of their eyes at a distance of 80 cm. Stimulus delivery was controlled by the Presentation software (Neurobehavioral Systems, Albany, CA).

B. Neurophysiological Recordings

EEG was recorded with Ag/AgCl electrodes placed at 19 sites on the scalp according to the 10–20 International System. The sampling rate was set at 500 Hz. Reference electrodes were
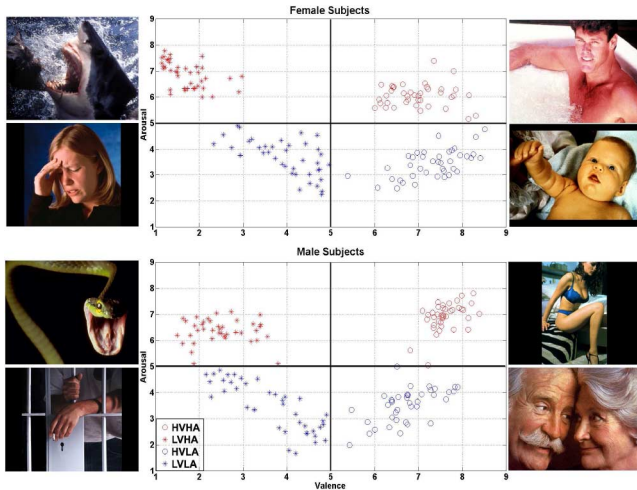
Fig. 1. Stimuli distribution in the 2-D emotional space formed by the arousal and valence dimensions for female (upper) and male (down) subjects.
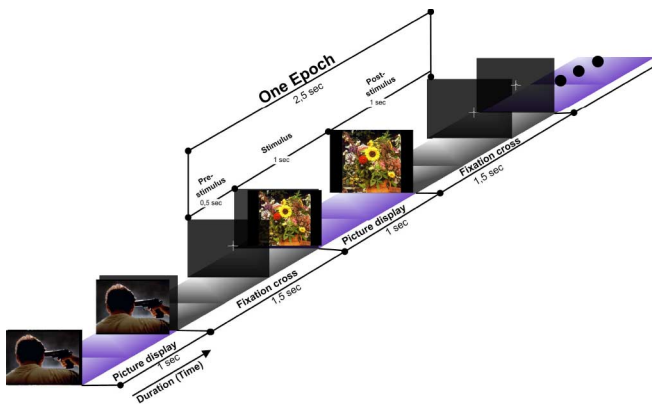

Fig. 2. Visualization of the experimental procedure adopted in this study. The visual stimuli are presented for 1 s in random order, while a fixation cross appears between successive stimuli for 1.5 s. A single epoch is also depicted in this figure as well as with its components (prestimulus period for 0.5 s, picture display for 1 s and poststimulus period for 1 s).

positioned at the mastoids. Electrode impedances were maintained during the recordings at less than 10 kΩ. Four additional electrodes were used for tracking vertical and horizontal eye movements.

C. Preprocessing

The signals were offline preprocessed by using the MATLAB-based EEGLAB tool [37]. The EEG signals were initially band-pass filtered using a low-pass IIR filter with cutoff frequency of 40 Hz, a high-pass IIR filter with cutoff frequency of 0.5 Hz, and a notch filter at 50 Hz. The ocular artifacts were then removed by using an adaptive filter based on the least mean squares (LMS) algorithm [38]. The LMS algorithm was selected, since it affects minimally the slow wave brain activity (delta and theta) that is under consideration in comparison with other artifact removal techniques [39]. Each trial's (ERP's) duration was 2.5 s. Each emotional state (HVHA, LVLA, HVLA, and LVHA) used 40 trials. The averaged trials (ERPs) were finally estimated for each subject and each emotional state.

D. Feature Extraction

1) EEG: The averaged ERPs extracted from three central electrodes (Fz, Cz, and Pz) located in the anterior–posterior midline were further analyzed. Recordings from only few electrodes were analyzed for simplicity. Our aim was to propose an effective, but also simple methodology suitable for real-life applications. Therefore, a compromise should have been made between the robust identification of emotional state, keeping the number of electrodes as minimal as possible. Five components were analyzed for each electrode. Each component is symbolized according to its polarity with a P for positive or N for negative deflection and with a number representing its latency considering the stimulus onset. Therefore, amplitude and latency features were extracted for the P100, N100, P200, N200, and P300 ERP components.

2) Event-Related Oscillations: The oscillatory activity for the delta, theta, and alpha frequency bands was obtained using the discrete wavelet transform (DWT) as described in [40]. DWT was used instead of traditional filtering techniques (e.g., digital filtering), since it employs varying time window analysis, offering thus high and accurate time resolution for each frequency band [40]. By using DWT, there is also no need for signal stationarity that is important when dealing with biosignals [41].

The initial step of the wavelet analysis is the choice of the wavelet function. Each function shares common properties. The family of biorthogonal wavelets of order three was used herein because it is the most suitable choice when dealing with the ERP wavelet analysis [40] as well as with their properties that constitute them as the most appropriate choice:

1) symmetry and smoothness in order to avoid phase distortion and discontinuity effects;
2) resemblance with the ERP waveforms;
3) maximum time-frequency resolution;
4) semiorthogonality.

The general type of the wavelet function is as follows:

$$\psi(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right) \tag{1}$$

where "*a*" is the "scaling parameter", since its variations are used to capture the signal's frequency content, and "*b*" is the translation parameter used for time localization. These parameters are taken at discrete values in DWT analysis in order to reject redundant information and to provide computational efficiency [42]. The multiresolution scheme [43] was used in this study.

The 500-Hz sampling frequency allowed six levels of decomposition (frequency bands). The EEG bands obtained were: 32–64 Hz (gamma), 16–32 Hz (beta), 8–16 Hz (alpha), 4–8 Hz (theta), and 0.5–4 Hz (delta), from which only three were analyzed (delta, theta, and alpha). Periodic data padding was set in order to limit boundary effects.

E. Feature Selection

Feature selection is one of the most important steps in pattern recognition or pattern classification and data mining, since

there is difficulty in measuring classification information in all features [44], [45]. It was thus employed here aiming to provide a subset of features better describing the problem under consideration. The features extracted from the EEG signal analysis that served as inputs to this selection phase were the amplitudes and latencies of ERP components [three channels × five components × two features (amplitude and latency)], and the EROs amplitudes [three channels × three frequency bands × one feature (amplitude)].

In this study, the classification of the biosignals was conducted by means of the SVM for which the SVMAttributeEval through the Waikato environment for knowledge analysis (WEKA) data mining environment was chosen for the SVM as an attribute evaluator and ranker as a search method [46]. The SVMAttributeEval evaluates the worth of each attribute by using an SVM classifier, while the ranker is used for ranking the selected attributes by using their individual evaluations. The ranker is commonly used in conjunction with attribute evaluators [46]. The LIBSVM Library was used for the SVM classifier. Taking the Mahalanobis distance (MD) function (see next) into account as the classifier, repeated measures of the analysis of variance (ANOVA) was performed by considering the valence and the arousal as within subjects' factor and gender as between subjects' factor. The ERPs' and EROs' features able to differentiate either arousal or valence better than a predefined threshold were selected. The threshold parameter was set at 0.025. [47].

F. Classification of Neurophysiological Data

1) Mahalanobis Distance: This minimum distance classifier was employed for the emotional classification of the biosignals. It is a simple yet robust technique, which is defined by the following (2)

$$dM = \sqrt{(x - \mu)\Sigma i^{-1}(x - \mu)^{\mathrm{T}}}, \qquad i = 1, \ldots, M. \quad (2)$$

Here, x is each instance for classification and μ is the vector containing the centroids for each feature in the form of a multivariate feature vector as defined by

$$x = (x_1, x_2, \ldots, xN)^T, \ \mu = (\mu_1, \mu_2, \ldots, \mu N)^T,$$

$$\text{where } N \text{ is the total number of features.} \quad (3)$$

Σ denotes the covariance matrix of the normally distributed training set for each class i that should be classified. The number of the different classes that should be classified is denoted as M.

Therefore, the proposed classification scheme regarding the MD classifier is the following two-step procedure:
1) During the first stage, use either the MD1.1 or the MD1.2 according to the gender information. Each one employs a different set of feature vectors in order to be gender specific. Classify each instance by labeling it as either high or low regarding the arousal dimension.
2) The valence discrimination is then performed given both the output of the first step and the gender information. Therefore, the MD2.1 is used for the stimuli labeled as highly arousing and derived from the male participants, while the MD2.2 is used for the low arousing stimuli from

the male subjects. Similarly, the MD2.3 and MD2.4 are used for the females, high and low, respectively.

2) Support Vector Machine: Given the training data x as well as with their labels y [47], the SVM classifier seeks the optimal solution of the problem described next

$$\min_{(w,b,\xi)} = \frac{1}{2}w^T w + C \sum_{i=1}^{l} \xi_\iota$$

$$\text{subject to } y_i(w^T \varphi(\chi_\iota) + b) \geq 1 - \xi_i$$

$$\xi_i \geq 0. \quad (4)$$

The function $\varphi(.)$ accepts as input argument the training vectors and maps them into a higher dimensional space, where the SVM seeks for a linear separating hyperplane with the maximal margin [48]. The ξ and b are parameters involved in the minimization function. The penalty parameter C is set to be nonnegative, whereas $K(x_i, x_j)$ is the kernel function. The kernel functions used in this study are the following:
1) linear: $K(x_i, x_j) = x_i T x_j$;
2) polynomial: $K(x_i, x_j) = (\gamma x_i T x_j + r)d, \gamma > 0$;
3) radial basis function (RBF): $K(x_i, x_j) = e^{-\gamma \|x_i - x_j\|^2}$, $\gamma > 0$

The next step utilized four distinct classifiers based on the MD function. For each instance, the classifier to be used was defined by the gender's subject and the valence information extracted from the decision tree. Different features originating from each one of the four types of analyses were used for each one of these classifiers in order to detect more accurately the arousal dimension. The emotion recognition architecture as well as the entire procedure is depicted in Fig. 3.

The C, γ, d, and r are kernel parameters. The choice of these parameters is a crucial step toward an accurate classification. As indicated in [49], the parameter definition was heuristically performed. After a series of experiments, the kernel parameters are illustrated in Fig. 3. In this figure, an overview of the proposed attribute selection and classification scheme is presented. More specifically, this figure visualizes the experimental model, which was formed according to the current trends in emotional theory and gender differences in affective picture processing [30], [50]. Therefore, the classification scheme is divided into two steps, since the two affective variables are orthogonal and are also regarded as independent ones in the emotional theory [51]. Moreover, the classifiers are gender specific, since sex differences occur during affective picture processing [50], [33]. The parameter values for the three SVM kernels are also reported. The number of selected attributes (NSA) used in each classifier is also presented.

The classification scheme and the values of the involved parameters are depicted analytically in the forthcoming section, whereas the best results achieved for each kernel function are also presented. Moreover, the results obtained by the MD metric are also depicted.
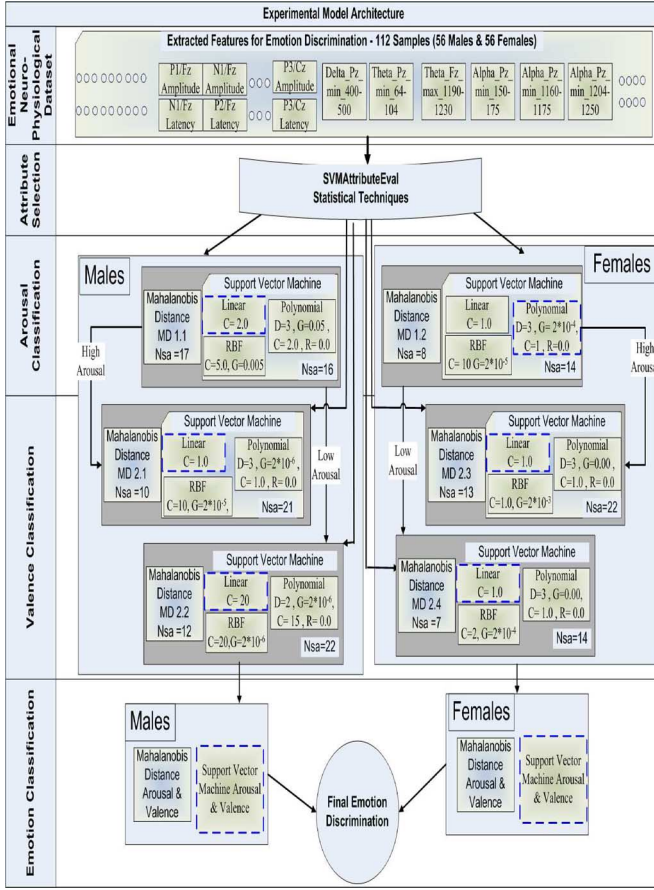
Fig. 3. Stimuli distribution in the 2-D emotional space formed by the arousal and valence dimensions for female (left) and male (right) subjects. The proposed feature selection and classification framework, which is derived from the bidirectional emotional model regarding the arousal and valence dimensions as independent emotional variables. Mahalanobis and the SVM (three kernels) classifiers are also presented. NSA index is also reported for each one discrimination scheme.

III. RESULTS

The classification rates are presented in Table I. The arousal classification for the whole (112) emotional set is initially performed in the first step employing two independent and gender-specific schemes. So, both the male and female classification blocks have as input an equal number (56) of data instances of neurophysiological importance, since there is an equal number of male and female participants in this study. After deriving the arousal dimension, the valence discrimination is performed by taking into consideration the obtained arousal and gender information.

Regarding the Mahalanobis classifiers, the classification steps involved the successive addition of a feature vector each time until the convergence of each classification scheme is reached. However, the number of features used in such a classifier is limited by the size of the covariance matrix. Excessive number of feature vectors may potentially cause scaling effects and serious accuracy problems. Therefore, the convergence criterion adopted for this distance-based classification assumes the addition of a new feature vector, in case it evokes a further improvement of the classification rate or strengthens its current

TABLE I
CLASSIFICATION RATES FOR EACH CLASSIFIER, STAGE, AND GENDER

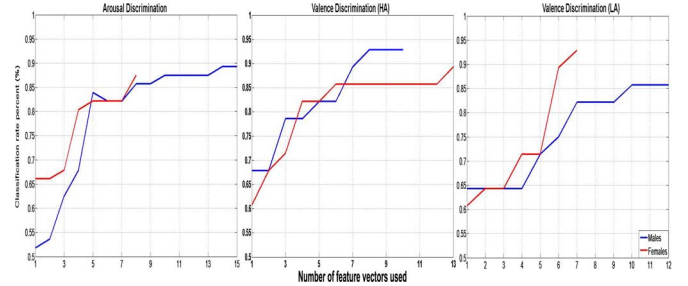| Classifier	Males			Females		
	Arousal (N=56)	Valence		Arousal (N=56)	Valence	
		Low Arousal (N=28)	High Arousal (N=28)		Low Arousal (N=28)	High Arousal (N=28)
Mahalanobis	89.29%	85.71%	92.86%	87.50%	92.86%	89.29%
Linear SVM	89.29%	82.14%	89.29%	83.93%	100%	92.86%
Polynomial SVM	82.14%	82.14%	89.29%	87.50%	85.71%	85.71%
RBF SVM	85.71%	64.29%	78.57%	85.71%	64.29%	85.71%

Fig. 4. Mahalanobis classifier's performance for both the male (blue) and the female (red) subjects during each attribute's addition for the arousal discrimination step (left) and for the valence discrimination step for high arousing stimuli (middle) and for the low arousing stimuli (right).

value only if the total number of the feature vectors used is smaller than the number of the columns of the covariance matrix. The application of this convergence criterion is visualized in Fig. 4, where the performance of each Mahalanobis classifier used in the proposed two-step architecture is reported.

Regarding the SVM classifiers, a ten-fold cross validation is used. A more detailed description of the classification schemes is given in Table II. The accuracy rates are reported in Table III, where the precision and recall features are presented as well as with the receiver operating characteristic (ROC) areas. The percentage of the true and false positive labeling is also described. The true positive percentage is the number of items, which are correctly classified to the positive class, whereas the false positive percentage is the number of items, which are incorrectly classified to the positive class.

Toward the evaluation of the system's accuracy, the overall classification rates are reported in Table IV, for each emotional category and for both classifiers (Mahalanobis and SVM) as derived by the proposed two-step classification framework. Regarding the SVM classifier, the kernel with the higher accuracy rate was selected for each one of the six discrimination schemes (see Fig. 3).

IV. DISCUSSION

In this piece of work, a classification (and a comparison) framework is proposed for the robust emotional discrimination of neurophysiological signals in line with the bidirectional theory of emotions. The adopted emotional theory suggests that an emotional state may be described by two distinct variables, which is the activation level it elicits and the degree of

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TABLE II
DETAILED DESCRIPTION OF THE CLASSIFICATION STATISTICS FOR THE SVM
CLASSIFIERS USED IN THE TWO-STEP CLASSIFICATION SCHEME

Classifier	Statistic	AM	AF	VM (HA)	VF (HA)	VM (LA)	VF (LA)
Linear SVM	NI	56	56	28	28	28	28
	CCI	50 89.3%	47 83.9%	25 89.3%	26 92.9%	23 82.1%	28 100%
	ICI	6 10.7%	9 16.1%	3 10.7%	2 7.1%	5 17.9%	0 0%
	KS	0.8	0.7	0.8	0.9	0.6	1.0
	MAE	0.1	0.2	0.1	0.1	0.2	0.0
	RMSE	0.3	0.4	0.3	0.3	0.4	0.0
Polynomial SVM	NI	56	56	28	28	28	28
	CCI	46 82.1%	49 87.5%	25 89.3%	24 85.7%	23 82.1%	24 85.7%
	ICI	10 17.9%	7 12.5%	3 10.7%	4 14.3%	5 17.9%	4 14.3%
	KS	0.6	0.8	0.8	0.7	0.6	0.7
	MAE	0.2	0.1	0.1	0.1	0.2	0.1
	RMSE	0.4	0.4	0.3	0.4	0.4	0.4
Radial Basis Function (RBF) SVM	NI	56	56	28	28	28	28
	CCI	48 85.7%	48 85.7%	22/28 78.6%	24 85.7%	18 64.3%	18 64.3%
	ICI	8 14.3%	8 14.3%	6/28 21.4%	4 14.3%	10 35.7%	10 35.7%
	KS	0.7	0.7	0.5	0.7	0.3	0.3
	MAE	0.1	0.1	0.2	0.1	0.4	0.4
	RMSE	0.4	0.4	0.5	0.4	0.6	0.6

AM: arousal males, AF: arousal females, VM: valence males, VF: valence females,
NI: number of instances, CCI: correctly classified instances, ICI: incorrectly classified
instances, KS: kappa statistic, MAE: mean absolute error, RMSE: root-mean-square error.

TABLE III
ACCURACY RATES FOR THE THREE SVM CLASSIFIERS DURING THE TWO-STEP
EMOTIONAL CLASSIFICATION FRAMEWORK

Classifier	Statistic	M-A		F-A		M-V (HA)		F-V (HA)		M-V (LA)		F-V (LA)	
		High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
Linear SVM	TP Rate												
	FP Rate												
	Precision												
	Recall												
	F-Measure												
	ROC Area												
Polynomial SVM	TP Rate												
	FP Rate												
	Precision												
	Recall												
	F-Measure												
	ROC Area												
Radial Basis Function SVM	TP Rate												
	FP Rate												
	Precision												
	Recall												
	F-Measure												
	ROC Area												

Scale: ■ 1 | 0.9 | 0.8 | 0.6 | ▨ 0.4 | 0.1-0.2 | □ 0

TABLE IV
SUMMARIZED DESCRIPTION OF THE CLASSIFICATION PERFORMANCE
OBTAINED BY EACH CLASSIFIER FOR THE FOUR EMOTIONAL CATEGORIES FOR
BOTH MALE AND FEMALE SUBJECTS

Classifier	HVHA	HVLA	LVHA	LVLA	Total
Mahalanobis	85.71% (24/28)	82.14% (23/28)	78.57% (22/28)	71.43% (20/28)	79.46% (89/112)
SVM	85.71% (24/28)	85.71% (24/28)	71.43% (20/28)	82.14% (23/28)	81.25% (91/112)

pleasantness/unpleasantness. Therefore, in close conjunction with this emotional model, the proposed framework introduces a two-step classification scheme. The first step is used to classify the elicited emotion as either high or low arousing, whereas the second step further categorizes the emotional data as pleasant or unpleasant. The gender information is also considered, since there are growing evidence of differences in the emotional processing between males and females [33], [50].

The novelty of this study lies on the use of EEG features in combination with a proposed two-step user-independent classification framework that integrates the basic notions of the bidirectional emotional model. The proposed system architecture is implemented by means of a distance-based (Mahalanobis) classifier as well as with three SVM kernels (linear, polynomial ad RBF). These classifiers were chosen instead of simpler ones [k-NN, Euclidean distance, discriminant function analysis (DFA)] due to their robustness, though their computational cost is quite high. Moreover, the Mahalanobis classifier eliminates the scaling of the coordinate axis as well as and correlation effects between the used features [52].

The SVM classifiers' training was performed using a ten-fold cross validation. Both the Mahalanobis classifier and the SVM kernels seem to have comparable performance. The reliable estimation of the emotional states by using the Mahalanobis classifier, requires an adequate number of feature vectors (in this study 112), since the classification is based on the estimated mean value of the feature vectors and the covariance matrix.

The idea of the neurophysiological measurements' contribution to the enhancement of the communication between users and machines is not an innovative one [3], [27], [34], [53]. Early attempts focused on the development of user-dependent classifiers by using multiple data segments from only a single subject [27], [34]. These studies employed "intentionally expressed emotions," such as those expressed by an actress [34]. The main goal of these studies was to highlight the advantages of the biosignal monitoring in the HCI field. Several limitations need to be confronted prior to their introduction in realistic systems. The development of an application should deal with stimuli presented in real life. It is necessary to simulate the likely variation of neurophysiological responses to the same emotional category or the overlapping responses occurred between different emotional states. There has been a recent shift in research work [18] toward the use of the IAPS collection, which provides a standardized database of photographic stimuli of realistic scenes as well as, their normative ratings for both the arousal and valence dimension. Due to the use of external stimuli, the simple classifiers [27], [34] adopted in the first works are

TABLE V
RECENT HCI STUDIES CONTAINING CLASSIFICATION FRAMEWORK FOR MULTIPLE SUBJECTS

Author	Classification	Emotional States	Bio-Signals	Classification Accuracy
Kim et al., 2004	Support Vector Machine (SVM)	Sadness, Anger, Stress, Surprise	Electro-cardiogram (ECG), Skin Conductance Temperature (SKT), Electro-Dermal Activity (EDA)	61.8o%
Nasoz et al., 03	k-Nearest Neighbors (kNN), Discriminant Function Analysis (DFA)	Sadness, Anger, Surprise, fear, Frustration, Amusement	EDA, Heart Rate, Body Temperature	69.28%
Katsis et al., 08	Adaptive Neuro-Fuzzy Inference System (ANFIS), SVM	High Stress, Low Stress, Disappointment, Euphoria	Facial Electro-Myo-Graph (EMG), Respiration, ECG, EDA	79.30%
Lisetti et al., 04	Marquardt Back-Propagation (MBP), k-NN, DFA	Sadness, Anger, Surprise, fear, Frustration, Amusement	EDA, Heart Rate, Body Temperature, Movement, heat Flow	84.10%

no longer robust. It has been shown that a neural net classifier [like the multilayer perceptron (MLP)] in combination with a large amount of data will provide high classification accuracy for both the arousal and valence dimension [18].

Despite the promising improvements of the previously developed classifiers when dealing with such types of stimuli, the need for long-time tuning and the user-dependency are still open issues. Several studies [35], [49], [54], [55], developed user-independent emotional classifiers with high classification rates (see Table V). Especially, two of them [49], [55] seem very promising, since they reported very high classification scores. They however required autonomic responses from long presented stimuli (45-min movie clips) in order to elicit emotions [55], or they focused on emotional states during specific tasks, such as driving [49]. All these studies used features derived from measurements of the autonomic nervous system. There is, however, strong evidence that features extracted from measurements of the central nervous system are more valuable indicators of the temporal brain activity [53], [11]. Despite the potential beneficiary role of adopting such EEG features toward the enhancement of the HCI quality, no systematic attempts have so far been made [47].

The proposed system may provide both a theoretical and a classification framework of key importance to applications in the field of the HCI. The neurophysiological patterning combined with the proposed classification procedure may be used in real-life architectures, which will be able to detect the emotional state of the users.

Then, anthropomorphic avatars may adapt its facial characteristics in order either to mirror the user's emotional mood in case of educational applications, such as virtual games, tutors, and specific web folkosonomies [7], [56], [57] or to take actions toward neutralizing their negative feeling in case of telemedicine (remote monitoring) applications [2]–[6].

Despite its novelty, the proposed methodology presents certain limitations. The selected electrode locations of the EEG signals used for further analysis were based on findings from previous works in the field [11], [28], [38], [47]. No effort was made to select the optimal electrode locations and the minimum number of electrodes that will optimize the classifying of the

four emotional states. There is definitely a need to further investigate this issue in an upcoming work. It is also important to note that the high classification rates of this study were derived from analyzing data recorded from many different subjects, but only on a single occasion and not repeatedly. It is however known that the neurophysiological responses to the same stimulus present day-to-day variations even when the participant exhibits the same emotion. Future studies should focus on the reduction of the intra-subject variability resulting in the formation of users' neurophysiological profiles, which will give rise to personalized emotion-aware applications. Future attempts may also focus on simultaneous recordings from both the central and autonomic nervous system, thereby enhancing the system reliability.

V. CONCLUSION

A novel methodology utilizing the bidirectional cognitive model in order to elicit neurophysiological emotional responses, which are then classified by means of data mining approaches was presented in this study. This integrative approach aimed to deal with a plethora of open issues in the field of emotion aware computing by enriching the multiphysiological affective arsenal with a robust classification framework in close connection to current trends of emotional theory and to recent findings dealing with the neuronal mechanisms involved in the affective picture processing by the central nervous system. It is imperative that formulating the scientific basis of emotion recognition may lead to an explosion of related applications. To this end, the importance of this work toward the robust discrimination of neurophysiological signals into emotional states/conditions evoked as responses to realistic stimuli cannot be overlooked.

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