On the Classification of Emotional Biosignals Evoked While Viewing Affective Pictures: An Integrated Data-Mining-Based Approach for Healthcare Applications

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***Abstract*—Recent neuroscience findings demonstrate the fundamental role of emotion in the maintenance of physical and mental health. In the present study, a novel architecture is proposed for the robust discrimination of emotional physiological signals evoked upon viewing pictures selected from the International Affective Picture System (IAPS). Biosignals are multichannel recordings from both the central and the autonomic nervous systems. Following the bidirectional emotion theory model, IAPS pictures are rated along two dimensions, namely, their valence and arousal. Following this model, biosignals in this paper are initially differentiated according to their valence dimension by means of a data mining approach, which is the C4.5 decision tree algorithm. Then, the valence and the gender information serve as an input to a Mahalanobis distance classifier, which dissects the data into high and low arousing. Results are described in Extensible Markup Language (XML) format, thereby accounting for platform independency, easy interconnectivity, and information exchange. The average recognition (success) rate was 77.68% for the discrimination of four emotional states, differing both in their arousal and valence dimension. It is, therefore, envisaged that the proposed approach holds promise for the efficient discrimination of negative and positive emotions, and it is hereby discussed how future developments may be steered to serve for affective healthcare applications, such as the monitoring of the elderly or chronically ill people.**

***Index Terms*—Affective computing, data mining, decision tree, EEG, emotion theory, evoked potential response, healthcare remote monitoring, International Affective Picture System (IAPS), Mahalanobis distance.**

Manuscript received November 24, 2008; revised August 11, 2009. First published January 8, 2010; current version published March 17, 2010. This work was supported in part by a grant from the Greek General Secretariat for Research and Technology and in part by the Postgraduate Medical Informatics Programme, Aristotle University of Thessaloniki, Greece.

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Digital Object Identifier 10.1109/TITB.2009.2038481

I. Introduction

RECENT developments have witnessed numerous advances of telemedicine that enable the remote monitoring of elderly or chronically ill people. An emerging research issue concerning such applications is their enrichment with machine emotional intelligence through the robust emotion recognition in order to mimic what is required for human–human communication and the support of decisions about daily tasks [1]. This view is further supported by recent evidence of the direct linking of emotional ability impairments with decision making, according to studies on patients with frontal-lobe damages [2], [3]. Frequent mood changes may be indicators of early psychological disorders, since affective states of depression, anxiety, and chronic anger negatively influence the human immune system [4]. Thus, the efficient monitoring of human emotional states may provide important and useful medical information with diagnostic value, especially for the elderly or the chronically ill people. Such monitoring may take the form of either a "subjective route" (psychology-oriented approach—by means of monitoring/observing questionnaire responses of subjects/patients) or a more "objective route" (neurophysiology-oriented approach—by means of monitoring the subject's biosignals). To follow the latter approach, distinct signatures of either positive or negative emotions can be derived by recording neurophysiological signals, such as electrodermal activity (EDA), ECG, or EEG [5], [6]. Moreover, recent advances in neuroscience research practice and theory development facilitate both the methodological as well as the theoretical investigation of the neuronal mechanisms involved in emotional processing. More specifically, the bidimensionality theory of emotions proposes that the nature of emotional experience is primarily determined by two main dimensions, namely, valence (pleasure) and arousal [7]–[10]. Valence spans from attraction and pleasure to aversion and displeasure, whereas arousal is a more general property of the stimulus and refers to the level of activation, regardless of the direction (whether pleasant or unpleasant) [11]. This is consistent with an underlying bimotivational system: the appetitive (approach) and the aversive (avoidance) motivational system that vary along the arousal dimension [12], with evolutionary roots that serve to the species survival [13].

In accordance with the model of the aforementioned cognitive theory, a standardized photograph collection, named as International Affective Picture System (IAPS) [14], has been developed to provide a set of normative emotional visual stimuli used for experimental paradigms. In this system, emotions are regarded as points on the 2-D affective space, which is formed by the affective dimensions of valence and arousal. The combination of these two dimensions forms four emotional categories, which incorporate several discrete human emotions, such as joy, pleasure, excitement, melancholy, anger, fear, and disgust. Moreover, it derives from theory that valence and arousal are two orthogonal, independent dimensions of the emotional stimulus. This leads to an assumption that any emotion-related biosignals (especially, those evoked upon viewing of IAPS pictures), may initially get differentiated according to one of the aforementioned dimensions (e.g., their valence dimension), and then, the other (e.g., their arousal dimension), leading to clear and theory-supported pathway for subsequent signal discrimination/classification.

Current ongoing research on emotion discrimination is focused on the investigation of specific neurophysiological signatures for each emotion [15]. Electrophysiological measurements that assess the human brain activity, such as EEG seem to be sensitive to emotional states, since they capture alterations of the brain activity derived from specific neural networks that play a crucial role in the occurrence of emotional states such as fear. For example, autonomic measurements such as EDA are also sensitive to emotional stimuli and can serve as indexes of responses to emotional alterations [16].

To extract robust features leading to emotional discrimination, there is a need for multiphysiological recordings from both the central and the autonomic nervous systems. Recently, this has been further empowered by technological advances, thus rendering physiological sensing less invasive and gradually helping toward increasing the user's comfort (e.g., reduced size sensors [17] or wearable computers [18], [19]). Sensors can nowadays, even be placed in shoes, hats, gloves, etc. assuring the long-term physical contact with the subject [20], [21].

Thus, provided that multiphysiological signals contain enough signatures, true representative of an emotion, a decision-support system could be coupled to them, but also engaged to classify the derived features/patterns recognition techniques providing information about the subject's emotional state to the required healthcare thread (e.g., the nearest hospital or the family doctor or the health centre/elderly care centre). In this way, computers are envisaged as having affective capabilities, since they may detect a wide variety of negative feelings, such as melancholy, stress, frustration, anxiety, anger, and fear and facilitate a suitable healthcare service with emotional state alerts.

However, one of the key factors influencing recent advances in healthcare information systems deals with the use of robust data mining techniques used to extract knowledge from medical databases, which can be semantically represented via domain ontologies [22], [23]. Machine learning techniques, such as decision trees (like the so-called C4.5 algorithm [24]) and distance-based functions (like the Mahalanobis distance [25]), can then be used to differentiate cognitive procedures in a simple and robust way [26]. The derived results can then be described in a structured way by using ontologies to provide platform independency, easier intercommunication, and to facilitate the interchange of information for research purposes.

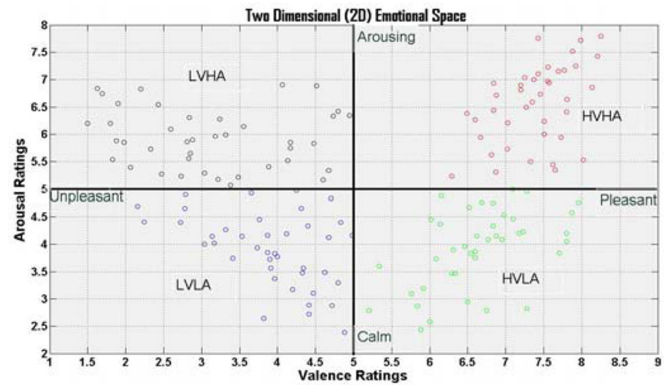

Fig. 1. Visualization of the emotional ratings for the pictures used as the evoking stimuli. Pictures in the 2-D emotional space are defined by the valence (degree of pleasantness) and the arousal (activation level) dimension (stemming from the hypothesized bidirectional emotional model).

Therefore, this study aims to contribute to the ongoing research of affective computing used for healthcare applications by providing a novel technique for emotion recognition. It makes use of classification rules derived from the C4.5 algorithm and pattern classifier based on the Mahalanobis distance. It further favors the role of multiphysiological recordings for the enhancement of emotion discrimination and the use of metadata structure designs via the Extensible Markup Language (XML) for linking the various system components [27]. Finally, it envisages to provide examples of good practice for integrative approaches in the field of affective computing applications.

Therefore, in the remaining part of the paper, the experimental procedure and the preprocessing steps are described in the Section II. Theoretical and analytical steps regarding the feature extraction procedure are reported in Section III, followed by the detailed presentation of the data mining and pattern recognition techniques, as well as with the derived result/output. Finally, the last section is dedicated to the discussion of the results in the light of the envisaged future applications.

II. Materials and Methods

A. Experiment Overview

This part of paper employed emotion-evoking pictures from the IAPS collection. The aforementioned bidirectional emotional model was employed so that each picture to be defined as either pleasant or unpleasant and high or low arousing. Therefore, a 2-D Cartesian emotional space, as depicted in Fig. 1, is defined by regarding the orthogonal axes of valence and arousal. In this view, the vertical axis represents the degree of arousal varying from calm to high arousing, whereas the horizontal axis depicts the degree of pleasantness ranging from unpleasant to pleasant. Each axis is scaled from 1 to 9. So, the upper right quadrant contains pleasant and highly arousing stimuli (e.g., erotic scenes, human couples), while the upper left part of the emotional space contains calm and pleasant scenes, like nice landscapes. On the other hand, the third quadrant contains melancholic scenes, and finally, the fourth one is regarded to contain fearful scenes.

The passive colored viewing methodology was employed in order to examine the affective reactions of healthy persons by studying the modulation of both the autonomic and the central nervous systems. The photographs depicted natural scenes, objects, wild animals, human bodies, and social reactions varying in terms of the two main emotional variables and were chosen regarding the Western cultural origin. Forty pictures were selected from each one of the previously reported quadrants. Each picture had a specific (L for Low, H for High) valence–arousal dimension belonging to one out of the four affective conditions [high-valence high-arousal (HVHA), low-valence low-arousal (LVLA), low-valence high-arousal (LVHA), and high-valence low-arousal (HVLA)]. Repetitive stimuli were presented from each one of the four (emotion conditions). Each picture was presented for 1 s. A central fixation cross was presented for 1500 ms between two successive visual stimuli. The sequence of the four conditions (or else blocks) was randomly selected for each subject. Twenty-eight healthy, right-handed volunteers (14 females and 14 males) participated in the study with a mean age of 28.2 ± 7.5 for males and 27.1 ± 5.2 for females (mean $\pm$ SD). The volunteers were undergraduate or postgraduate students of the Aristotle University of Thessaloniki or members of the Medical Informatics Laboratory of the same University. Pictures were presented to the subjects using a PC monitor. The experiment was part of the AFFECTION collaborative project [28] between the Laboratory of Medical Informatics at the Medical School of the Aristotle University of Thessaloniki, Greece, and the Brain Science Institute, RIKEN, Japan.

The stepwise sequence adopted toward the robust identification of discrete human emotions is visualized in Fig. 2. The methodological procedure shown in Fig. 2 is divided into distinct layers, describing the recording conditions, the preprocessing, the feature extraction steps, and the feature selection. Each one of the aforementioned layers is presented in the forthcoming sections. The classification of the emotional instances as well as the overall accuracy rates are presented in the last two layers of Fig. 2 and described thoroughly in the Section III.

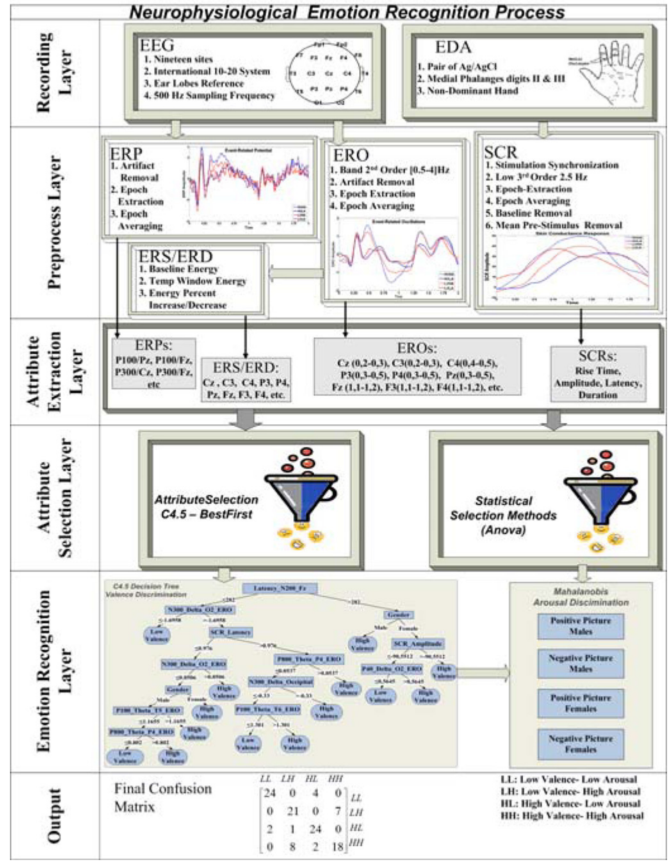

Fig. 2. Overall stepwise description of the proposed methodology/architecture for emotion classification based on emotion evocative stimuli selected from the IAPS collection. For presentation convenience, different layers are depicted, namely, the recording and preprocessing layers, the attribute extraction and selection layers, the emotion recognition layer, and the output. For each layer, details of features or algorithms used are provided (see, individual cross-reference points in the text of appropriate sections).

B. Neurophysiological Recording

The neurophysiological recordings contained simultaneous measurements of both EEG and EDA, as presented in the first layer of Fig. 2. The central nervous activity was recorded from 19 active sites distributed across the scalp, according to the International system 10–20 [29] and with reference electrodes positioned at the mastoids. The Nihon Kohden 911 (Nihon Kohden, Japan) device was used. All electrode impedances were maintained at less than 10 kΩ during the experimental session. Electrooculographic (EOG) activity was also recorded via four Ag-AgCl electrodes. The EDA was recorded using a pair of Ag/AgCl placed on the medial phalanges digits II and III of the nondominant hand. The current supply was kept constant and the voltage change, representing the inverse conductance value, was recorded using a dc amplifier. The sampling rate for all the recordings was set at 500 Hz.

C. Preprocessing

1) Central Nervous System Data: An off-line preprocessing procedure, as described in the left part of the preprocessing layer of Fig. 2, took place in the MATLAB environment by means of the EEGLAB software, which is as follows.

1) Digital filtering:
   a) A high-pass IIR filter with cutoff frequency at 0.5 Hz was first applied in order to remove linear trends in the recording signals.
   b) Then, a notch filter with center frequency at 50 Hz was applied in order to remove any interference from the mains and industrial noises.
   c) Finally, a low-pass IIR filter with cutoff frequency at 40 Hz was employed for high-frequency noise removal.

The aforementioned filters were elliptic, short IIR, and support multichannel recordings. Phase distortions are avoided by employing forward and reverse filtering. The width of transition interval between the stop and passbands was set at 1 Hz. Finally, the ripple amplitude in the passband was set at 0.0025 dB and at 40 dB in the stopband.

2) Artifact removal:
The removal of ocular artifacts was performed by means of an adaptive filter based on the LMSs algorithm. Due to the fact that several features regarding slow wave (delta and theta) activity are taken into consideration (see, the next section), this step was of primary importance. The specific algorithm was selected because of its simplicity and its usability in nonstationary signals like the biological ones as well as its performance when compared to other traditional artifact rejection techniques [30]. A more detailed application of the specific algorithm in the estimation of delta wave activity can be found in [31].

3) Epoch formation—average signal computation:
The procedures involved in this preprocessing step were the following:
   a) data synchronization with the picture onsets;
   b) formation of data segments (epochs), time-locked to the stimulus onsets and consisting of a 500-ms prestimulus period, followed by the picture-viewing period (1 s) followed by one more second corresponding to the fixation cross display. Total epoch duration was 2.5 s;
   c) the same procedure was repeated for all 40 pictures contained in each one of the four emotional categories.
   d) Mean epoch (average signal) was computed for each emotional category.

2) Autonomic Nervous System Data: As presented in the right part of the second layer of Fig. 2, the preprocessing steps used for the skin conductance were:

1) digital filtering of the EDA by means of a fourth-order Butterworth low-pass filter;
2) then, the average signal for each block category and for each subject is performed similarly with the EEG case.

D. Feature Extraction

1) Event-Related Potential (ERP) Features: As described in the feature extraction layer of Fig. 2, the ERP components from the average signals of the three central electrodes located in the anterior–posterior midline were analyzed by computing their amplitude and latency. Therefore, 15 amplitude and 15 latency features were computed, which are as follows:

1) an early positive deflection, 100 ms after the stimulus onset, named as P100;
2) an early negative peak (N100) occurring 150–175 ms after the stimulus onset;
3) a more delayed positive peak (P200), with an approximate latency of 200 ms;
4) a negative deflection (N200) observed around 250 ms;
5) a late positive potential occurring 300–400 ms.

2) Event-Related Oscillatory Activity Extracted by Digital Filtering: The EEG channels were further filtered in order to obtain the wave activity of the delta and theta frequency bands. Similarly with [32], the bandpass digital-filtering approach was used. The filters used were the Butterworth passbands due to their maximally flat and with no ripples frequency response. However, in comparison with the aforementioned elliptic filters, the Butterworth have slower roll-off. Therefore, a requirement for a higher order is posed for the achievement of the particular stopband specifications.

TABLE I
DESCRIPTION OF EROs FEATURES DERIVED FROM THE DELTA (0.5–4 HZ) AND THETA (4–8 HZ)

	Delta Wave Activity Features		Theta Wave Activity Features	
	Name	Description	Name	Description
1	P200	Max (200:300 ms)	P40	Max(60:90 ms)
2	N300	Min (300:400 ms)	P100	Max(90:125 ms)
3	P400	Max (400:500 ms)	P200	Max(175:225 ms)
4	P600	Max (600:800 ms)	N200	Max(225:275 ms)
5	N1100	Min (1100:1200 ms)	P300	Max(300:350 ms)
6	P1200	Max (1200:1500 ms)	N300	Max(350:400 ms)
7	-		P450	Max(425:475 ms)
8			P800	Max(775:825 ms)

The filtering was applied in the raw EEG data, and then, the synchronization and averaging processes took place, as described in the previous section. The average across epochs event-related oscillations (EROs) served to provide localized features for the delta and theta frequency bands. Due to their different frequency content, the number of extracted features was significantly larger for the theta band. The analysis was conducted for every one of the 19 electrodes. Six features were computed for the delta frequency band and eight for the theta frequency band. Their polarities and latencies are described in Table I.

3) Event-Related Synchronization (ERS)/Desynchronization (ERD) Computation: According to [33], the ERS/ERD method may track more precisely than ERPs the changes in the local neuronal activity. Therefore, this technique was applied on the average signal, following the procedure presented next:

1) set the frequency band of interest (in our case the delta band ranging from 0.5–4 Hz);
2) set as reference period (RP), the prestimulus interval lasting for 500 ms, prior to the stimulus onset;
3) set the period of interest (IP) to be the stimulus display period lasting for 1 s;
4) compute the expression: (IP − RP)/RP × 100;
5) positive values of the expression indicate ERS, whereas negative values indicate ERD;
6) compute the aforementioned percentage value for each one of the nineteen electrodes.

4) Autonomic Features Based on Skin Conductance: Finally, the averaged EDA for each emotional state served for the extraction of the amplitude of the autonomic response due to the stimulus display. Temporal features of the skin conductance response (SCR) were also computed. More specifically, a semi-automated algorithm was employed in order to detect SCRs. For each potential response, three points were detected based on changes of the signal's derivative, which are as follows.

1) The initiation of the response was regarded the point of a deflection larger than a predefined threshold.
2) The peak value is defined as the point where the derivative turns to negative sign.
3) The end of the response is regarded as the point where the signal's decrease is diminished.

Then, the derived features were the following.

1) The SCR amplitude, regarded as the conductivity difference among the peak point and the initiation point.
2) The latency of the peak point with regards to the stimulus onset.
3) The rise time corresponding to the temporal interval between the peak and the start point.
4) The overall duration of the autonomic response, i.e., the interval between the end and the start point.

E. Feature Selection

The task of feature selection is an important one involved in pattern recognition or data mining problems, since it is employed in datasets with high dimensionality or with features that may not provide valuable information [34]. Therefore, it is initially employed as a preprocessing technique in order to define a subset of attributes that describe, in an efficient way, the data and may lead to knowledge extraction. During this phase, the feature space is investigated and the attribute subsets are evaluated by means of a subset evaluator used to assign a worth to each feature subset combined with a search method for the determination of the search style, which is going to be adopted [35].

The feature selection is performed either by employing the entire training set or by cross validation, Considering the task of emotional valence discrimination used in this study, as described in the attribute selection layer in Fig. 2, the classifier subset evaluator was chosen to be combined with the BestFirst search method. This particular evaluator evaluates the attribute subsets formed by 11 cross validation, while the J48 classifier estimates their contribution. Finally, the BestFirst employees a greedy hill-climbing technique augmented with a backtracking facility. Considering the Mahalanobis classifier, statistical analysis of the derived features was performed by means of repeated measures of analysis of variance (ANOVA) with arousal and valence as within subjects' factor and gender as between subjects' factor [15]. The threshold of feature selection rule was intentionally set as "p value lower than 0.001," in order to facilitate robust classification.

F. Classification

After the feature extraction process, the algorithm C4.5 [24] was used in order to create a decision tree for the accurate valence discrimination. The selection of the specific algorithm was adopted, since it is an efficient learning technique for the representation of rule classification. The algorithm finds the most robust feature for the initial splitting of the datasets. Upon dealing with real data like in this case, the presence of noise may cause unnecessary splits. Thus, the C4.5 algorithm, after an initial tree creation, selects suspect subtrees and prunes them. Therefore, a new tree is created that is tested on a separate dataset in comparison with the initial training dataset. The pruning continues as long as there is improvement on the classification results [24]. The classification was performed using the J48 classifier (a Java implementation of C4.5 Classifier) in the Waikato Environment for Knowledge Analysis (WEKA).

The confidence factor used for pruning was set at $C = 0.25$, whereas the minimum number of instances per leaf was set at $M = 2$. The accuracy of the decision tree was measured by means of an 11-fold cross validation. This implies that the training data were divided into 11 subsets. One of these was regarded as the test set and the remaining served for the training procedure. After the tree creation, the method's accuracy was defined by the test set classification and by computing the percentage of the correct classifications. The result obtained by subtracting the accuracy from the absolute 100% was regarded as the error rate. The described procedure was repeated 11 times in order to compensate for the sampling bias. Each time, a new test set was withheld and the overall accuracy was determined by averaging the accuracies found.

The next step utilized four distinct classifiers based on the Mahalanobis distance 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. 2.

The feature extraction procedure for each subject resulted in a multivariate vector of the form: $x = (x_1, x_2, \ldots, x_N)T$. Then, the mean value for all the instances was computed and stored in the vector $\mu = (\mu_1, \mu_2, \ldots, \mu_N)T$. The covariance matrix Σ was then computed. Finally, the Mahalanobis distance was computed by

$$D_M = \sqrt{(x-\mu)^T \Sigma^{-1} (x-\mu)}. \tag{1}$$

Regarding our application, for each one instance, the Mahalanobis distance was computed using the mean value for the high- and the low-arousal condition. Then, the instance was classified as high arousing if the distance between the instance and the centre of the high-arousing group was smaller compared with the distance between the same instance and the low-arousing group. The classification procedure is depicted in the emotion recognition layer of Fig. 2.

III. Results

The classification rates for both the valence discrimination using the C4.5 algorithm as well as for the arousal stage using the Mahalanobis distance-based metric are presented in Table II.

The decision tree formed to perform valence discrimination is presented in Fig. 2. As depicted in the derived rule-based algorithm, the tree root that is the latency of the N200 Fz ERP component (recorded at the frontal site of the anterior–posterior midline) is the feature, which is able to perform the most efficient discrimination. Then, the features selected from the attribute selection layer are used. As presented in Fig. 3, the algorithm consists of both ERP and oscillatory components (EROs) derived from the theta and delta bands. Moreover, skin

TABLE II
CLASSIFICATION (SUCCESS) RATES FOR THE TWO-STEP EMOTION DISCRIMINATION TASK

Step #	Total # of Instances	Genders taken into account	Dimension to be classified	Remarks/ Limitations	Dimension specific Classification success rates	
					Low	High
1	112	Both	Valence	all stimuli	75.00%	80.36%
2a	28	Males	Arousal	pleasant stimuli	78.57%	64.29%
2b	28	Males	Arousal	unpleasant stimuli	85.71%	92.86%
2c	28	Females	Arousal	pleasant stimuli	92.86%	64.29%
2d	28	Females	Arousal	unpleasant stimuli	85.71%	57.14%

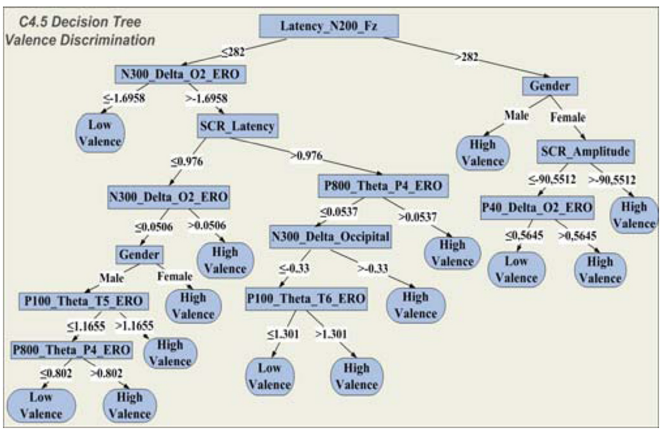

Fig. 3. Visualization of the decision tree as it is generated by the C4.5 algorithm using an 11-fold cross validation for performing valence discrimination.

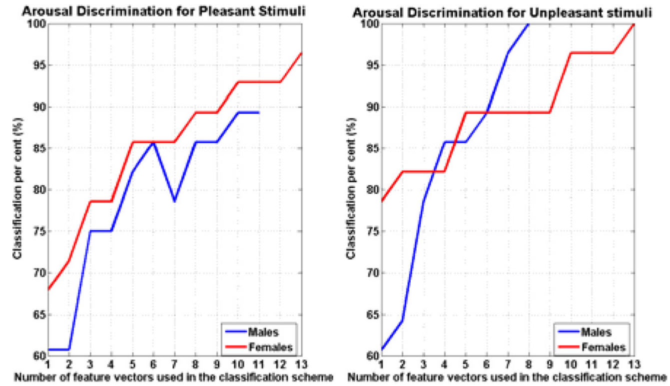

Fig. 4. Mahalanobis classifier performance during arousal discrimination for both the (blue) male and (red) female subjects after attribute addition for the (left) pleasant and (right) unpleasant stimuli.

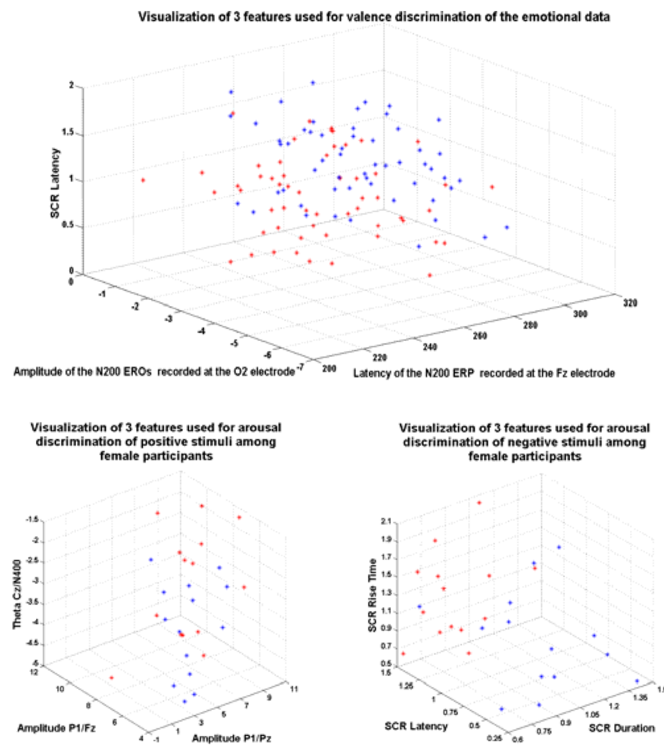

Fig. 5. Examples of complexity visualizations for the classification problem. Distribution of three features used for (top; a) valence discrimination and (bottom; b) arousal discrimination during the first and second step of the classification process, respectively. Since, the second step is gender specific, two examples are shown for female data: complexity distributions for (bottom-left) pleasant and (bottom-right) unpleasant stimuli. Blue and red denote the low and high conditions in each case (valence for the top one and arousal for the two bottom ones).

conductance features like SRC amplitude and latency, as well as, the gender information are also taken into consideration.

The classification output derived from the decision tree is used as an input to the second layer (arousal discrimination). Therefore, in case that a misclassification occurs in the first step, this results in the wrong classification of the instance, irrespective of the Mahalanobis classifier output. The performance of the Mahalanobis classifiers is depicted in Fig. 4. The addition of features gradually enhances the performance of these classifiers. Apart from classification labeling, uncorrelated distances of each emotional instance are also calculated, thereby providing a more qualitative and descriptive measurement of the activation level.

The problem complexity is presented in Fig. 5 by visualizing the feature distribution of the three most robust features for both the valence [see Fig. 5(a), top] and the arousal discrimination stages [see Fig. 5(b), bottom; left and right]. As depicted in this figure, there is great overlap among the instances, especially regarding their valence dimension. On the other hand, as shown in Fig. 5(b) (bottom), the variability is significantly reduced in case of emotional features derived from participants of the same gender differing along their arousal dimension only. Tables III and IV report examples of summary statistics of the features used during the valence discrimination task and for the arousal discrimination of pleasant stimuli viewed by female participants.

The classification using the C4.5 algorithm was performed by means of an 11-fold cross validation. The accuracy rates as well as other statistical measurements regarding the algorithm performance are reported in Table V. More specifically, the first and the second lines show the number and the percentage of the cases that were correctly and incorrectly predicted, respectively. The third line illustrates the kappa statistic that measures the agreement of predictions with the pleasant and unpleasant emotional instances. Finally, the last two lines demonstrate the

TABLE III
SUMMARY STATISTICS FOR THE FEATURES USED DURING THE VALENCE DISCRIMINATION STAGE

No.	Feature Name	Mean HV	Mean LV	Standard Deviation HV	Standard Deviation LV	Min HV	Min LV	Max HV	Max LV
1	Latency_N200 Fz	279.75	263.43	19.66	22.64	242	208	302	302
2	N300_Delta_O2 ERO	-0.78	-1.08	0.65	0.79	-2.30	-2.99	0.46	0.15
3	SCR Latency	1.03	0.79	0.39	0.37	0.27	0.13	2.00	1.55
4	P100_Theta_T6 ERO	0.70	0.74	0.42	0.44	0.10	0.12	1.64	2.29
5	P800_Theta_P4 ERO	0.65	0.57	0.37	0.26	0.16	0.14	1.94	1.28
6	N300_Delta_Occipital	0.68	0.66	0.29	0.26	0.17	0.24	1.44	1.60
7	P100_Theta_T5 ERO	0.76	0.79	0.48	0.45	0.06	0.18	2.35	2.36
8	SCR Amplitude	78.72	50.99	70.62	48.62	7.61	1.36	425.17	257.85
9	P40_Delta_O2 ERO	0.45	0.53	0.29	0.34	0.00	-0.04	1.18	1.53

TABLE IV
SUMMARY STATISTICS FOR THE FEATURES USED DURING THE AROUSAL DISCRIMINATION OF PLEASANT STIMULI VIEWED BY FEMALE PARTICIPANTS

No.	Feature Name	Mean HV	Mean LV	Standard Deviation HV	Standard Deviation LV	Min HV	Min LV	Max HV	Max LV
1	Amplitude P1/Pz	0.74	2.57	1.83	3.22	-2.08	-5.35	4.15	6.75
2	Amplitude P1/Fz	2.49	4.11	1.92	2.25	-0.39	1.19	6.81	10.07
3	Theta Cz N400	-2.33	-1.82	1.06	1.05	-4.61	-3.68	-0.91	-0.30
4	Theta Pz N400	-2.11	-1.54	0.88	0.66	-4.12	-2.94	-0.84	-0.55
5	Delta P3 P1500	1.67	1.12	1.11	1.09	-0.63	-0.51	3.32	3.11
6	Delta P3 N1000	-1.64	-0.74	0.66	0.71	-2.77	-1.92	-0.59	0.48
7	Delta P4 N1000	-1.92	-0.75	0.76	0.86	-3.40	-2.29	-0.68	1.13
8	Delta Fz Feat3	3.44	4.11	1.27	1.83	2.00	1.53	5.51	7.64
9	Delta Pz Feat4	-2.60	-1.31	1.12	1.38	-5.12	-5.55	-1.12	0.23
10	Amplitude P3/Pz	3.97	2.13	3.83	4.21	-2.92	-7.70	13.09	9.24
11	Delta P3 P1200	1.21	0.71	1.22	0.72	-0.31	-0.56	3.66	1.69
12	Delta P4 P1500	1.85	1.00	0.99	1.46	-0.09	-2.55	3.49	2.78
13	Amplitude P3/Cz	0.97	-0.80	3.27	2.36	-3.71	-5.52	6.75	4.09

TABLE V
SUMMARY STATISTICS OF THE C4.5 CLASSIFICATION PERFORMANCE USED FOR VALENCE DISCRIMINATION

Emotional Valence Identification Task Stratified cross-validation Summary	
Total Number of Instances	112
Correctly Classified Instances	89 / 112 79.46%
Incorrectly Classified Instances	23 / 112 20.54%
Kappa Statistic	0.5893
Mean Absolute Error	0.2239
Root Mean Squared Error	0.4362

mean absolute error and the root mean squared error that provide measurements of the difference between the predicted values and the real ones.

The detailed accuracy for each valence condition is presented in Table VI. In specific, Table VI illustrates the percentage of correctly classified items [true positive (TP) rate] as well as the percentage of the emotional instances that were wrongly classified as items of the class under consideration [false positive (FP) rate]. Moreover, the precision feature is derived by dividing the number of elements that were correctly classified with the total amount of instances that were classified in the class under consideration, whereas recall is the number of the correctly classified elements divided by the total number of the real elements of the class under consideration. Moreover, the precision

TABLE VI
DETAILED ACCURACY FOR EACH VALENCE CONDITION

Valence Condition	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area
High	.804	.214	.789	.804	.796	.822
Low	.786	.196	.8	.786	.793	.822

TABLE VII
SUMMARY OF THE CLASSIFICATION RESULTS OBTAINED BY THE TWO-STEP EMOTION RECOGNITION ARCHITECTURE BY MEANS OF THE DECISION TREE LEARNING ALGORITHM AND THE MAHALANOBIS DISTANCE FUNCTION

	HVHA	HVLA	LVHA	LVLA	Total
Correctly Classified Instances	18 / 28	24 / 28	21 / 28	24 / 28	87 / 128
Classification Accuracy	64.29%	85.71%	75.00%	85.71%	77.68%

feature is derived by dividing the number of elements that were correctly classified with the total amount of instances that were classified in the class under consideration, whereas recall is the number of the correctly classified elements divided by the total number of the real elements of the class under consideration environment.

The last layer of Fig. 2 visualizes the final confusion matrix in which the diagonal elements represent the number of correctly classified instances for each emotional category, while the remaining matrix elements report the incorrect classification result. The system classification accuracy for each one of the four emotional categories [HVHA, HVLA:, LVHA, and low-valence low-arousal (LVLH)] as well as the overall emotion recognition rate are described in Table VII.

IV. DISCUSSION

In this part of paper, multichannel and type physiological recordings from both the central and the autonomic nervous systems were used in order to identify a person's emotional state. Taken into account the bidirectional emotion theory model that accounts emotions as mixtures of two (orthogonal and independent) dimensions, namely, valence and arousal, a stepwise identification methodology was followed herein, whereby emotions are discriminated first with respect to their first dimension (valence in this case) and the second one (arousal). Specific biosignal features were initially (during the first step/stage; valence dimension discrimination) fed into a data mining approach, which is the C4.5 decision tree algorithm and were later (during the second step/stage; arousal dimension discrimination) combined with classifier based on the Mahalanobis distance metric. The average recognition (success) rate was 77.68% for the discrimination of four emotional states differing both in their arousal and valence dimensions. The extracted features were easy to compute and could be derived relatively fast even though not in real time. However, their relatively fast computation can reliably provide the result of the user's emotional state during a short temporal window.

The identification of unpleasant emotions and especially their arousal classification to either threaten-related or melancholic events is of key interest to the system. Even though information of a pleasant mood is important for the specific target groups like the elderly or the chronically ill, the negative emotions are those that require much attention and demand actions to be taken by healthcare systems. Consequently, special effort was given during the architecture design of the current analysis framework in order to be able to recognize the activation level elicited by the various stimuli. This fact is indicated by the choice of the Mahalanobis classifier that is able to perform robust classification (see Fig. 4), while it also calculates the distance of an emotional instance from the mean values obtained for the four emotional categories. Therefore, apart from the classification labeling, a further quantitative description is also obtained, unlike the case of a rule-based algorithm. Furthermore, classification is not focused on a specific subject like previous efforts [36], but it is user-independent in order to be used reliably for remote monitoring and other healthcare applications, where there is a need to deal with greatly varying individual differences.

The proposed classification schema is characterized by its novelty since it combines data mining and pattern recognition techniques. The two-step architecture design dissects the problem to exploit recent neuroscience findings dealing with gender differences during emotional processing as well as with arousal discrimination and selection of either the appetitive or the aversive motivation system. Adopting this way, the decision tree algorithm is used with the appropriate features of differentiating the datasets according to their valence dimension and gender information. Then, in the next step, the tree output as well as the gender data are combined with appropriate features for the task of arousal discrimination.

An XML metadata schema was applied for linking the various subsystems and for describing the overall system output, thereby providing platform independency [27] and a possibility for future connection with other systems like advanced human–computer interaction environments with avatars [20] or with a healthcare/hospital computerized system. It can also provide consistent feedback to the healthcare practitioners about the person's health and mood and to holds the capability of easily extending it to inform them in case of emergencies. Moreover, the choice of XML facilitates the easier interconnectivity between the various subsystems, thereby offering an integrated approach. More specifically, if any changes are conducted on a specific system component/part, these will not influence the design of the remaining system components. For example, the decision tree could be changed or another pattern recognition technique may be added without affecting anything else, apart from the emotion recognition subsystem. In a similar way, the emotion specification or the signal description may be altered without dealing with changes of the other components of the application. In short, this architecture serves well the connection of the proposed recognition system with the aforementioned avatar environment which could be provided with information of the subject's current emotional state in order to adjust its behavior according to the subject's feelings [20], [28], [36]–[39]. In addition ontologies may also be used for the establishment of a semantic framework for the standardization of the emotion description, which is expected to enhance the knowledge exchange between researchers from different groups [23], [40].

Future work will focus on the incorporation of features from other (mainly autonomic nervous system) physiological signals. The combination and fusion of these additional data will allow for a more detailed emotion recognition through each one of the four categories used here. For example, let us consider the case of fear and anger—they are both negative feelings belonging to the high-arousal condition. However, a different approach should be adopted in order to process successfully these discrete human emotions. The integration of these approaches involves a combination of data mining techniques, neuroinformatics, and ontology engineering. More subjects could also be included in order to provide faster reactions to negative emotions by means of real-time detection of such situations. Consequently, real-time noise rejection techniques and single trial feature extraction should be adopted to enhance the accuracy and detection speed of the proposed application.

V. Conclusion

To summarize, in this paper, a novel stepwise emotion recognition approach was presented based on neurophysiological affective data of both the central and the autonomic nervous systems by combining a data mining approach with the more classic distance-based classification algorithms, like the Mahalanobis metric. The concept behind the stepwise approach stemmed from recent neuroscience evidence that supports the bidirectional emotion theory model, whereby valence and arousal can account as two distinct dimensions of any emotion. The overall success rates achieved were quite satisfactory when compared to those achieved in literature. Therefore, the proposed approach holds promise for efficient discrimination of negative and positive emotions, and it is envisaged that future developments of the infrastructure presented here are steered to serve for affective healthcare applications, such as the monitoring of the elderly or the chronically ill.

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