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Optimised Attribute Selection for Emotion Classification Using Physiological Signals

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Abstract - **Researchers in medicine and psychology have studied emotions and the way they influence human thinking and behaviour for decades. Recently computer scientists have realised the importance of emotions in human interactions with the environment and a considerable amount of research has been directed towards the identification and utilisation of affective information. Particular interest exists in the detection of emotional states with the intention of improving both human-machine interaction and artificial human-like inference models. Emotion detection has also been employed to explore applications that relate emotional states, habits and ambient conditions inside inhabited environments. Valuable information can be obtained by analysing the way affective states that influence behaviour are altered by environmental changes. In this paper an analysis of the properties of four physiological signals employed in emotion recognition is presented. Class separation analysis was used for determining the best physiological parameters (among those from a list chosen a priori) to use for recognizing emotional states. Results showed that the masseter electromyogram was the best attribute when distinguishing between neutral and non-neutral emotional states. Using Autoassociative Neural Networks for improving cluster separation the gradient of the skin conductance provided the best results when discriminating between positive and negative emotions.**

Keywords – **Cluster Analysis, Emotions, Pattern Recognition, Physiology**

I. Introduction

Scientists often think of emotions as being something completely unrelated and even harmful to rationality. When developing human-machine interaction models, computer scientists have repeatedly overlooked the fact that emotions are frequently more important than reason in modelling our decisions and actions [1,2]. In fact, the lack of emotional expressiveness could impair the relation of humans with their environment [3]. Therefore, research into mechanisms to obtain behavioural information from subjects inside inhabited environments has increasingly placed attention on human emotional states and their relevance to intelligent interactive agents [4]. Areas such as medicine and psychology could benefit from models that describe the relationship between emotional states and behavioural and environmental conditions.

A. Emotions and Artificial Intelligence (AI)

Since human behaviour is affected by a variety of emotional conditions [2,5] the modelling of rational decision making, human interaction and perception should, at least in part, be founded on a user's affective state. Hitherto emotion detection has been utilized to provide artificial agents with a more realistic human-like behaviour or to operate computerized devices. For example, the "affective wearable" device proposed by Healey et al. is capable of detecting musical preferences based on emotional information embedded in physiological measures [6]. Cañamero has analysed the effect emotions have on the survival capacities of agents when contending for resources in an artificial world where it was demonstrated that agents with emotions outperformed their emotionless counterparts [7]. The PETTEI project at Texas A&M University focused on the implementation of an agent with evolving emotional capabilities [8].

B. Emotion Detection

Although there is a considerable amount of controversy among different theories with regard to the exact definition of emotion, more agreement exists on what it involves. Emotions include awareness of a given situation, overt expressions and behaviours, readiness to act, and physiological changes supplemented with subjective feelings [9, 10]. In order to measure emotions, scientists have developed a variety of methods such as self-reports of feelings, techniques of behavioural rating, projective techniques for evaluating behaviour products, physiological parameters, and analysis of facial and vocal expressions.

C. Physiological Emotion Detection

The specific role physiological signals play in emotional expression has been investigated mainly within two scientific areas. Physiological psychologists focus on the analysis of behavioural response to physiological stimuli. Psychophysiologists are more interested in the physiological responses produced by behavioural changes [10-13]. The physiological measures usually employed include one or more of the following: Heart rate, blood volume, blood pressure, skin resistance or conductance level (Galvanic Skin Response, GSR), electroencephalogram, papillary response, electrooculogram (eye movement), gastrointestinal motility, electromyogram (muscle activity), skin temperature, brain potentials, and respiration rate [11]. Other measures include facial and vocal expressions.

D. Computer-based Emotion Detection

Efforts conducted by computational scientists have been mainly focused on three ways of detecting emotions: facial recognition, speech recognition, and a combination of the two (bimodal). Recently, greater attention has been paid to internal bodily manifestations, especially those related to the autonomic nervous system and the brain. Hitherto, the best results have been obtained by facial recognition (88-89% detection accuracy) [14, 15] followed by physiological-based recognition (81%) [16], speech recognition (50-87.5%) [17, 18], and bimodal recognition (72%) [19]. It is worth noting that because they do not require specific gestures or utterances, physiological signals represent the most promising and objective manner for detecting emotions in computer science. Furthermore, bodily signals can be recorded and analysed based on algorithmic or auto-inference models that do not require human intervention.

II. Methods

A. Statistical Selection Of Attributes

Data Set Description

Pattern recognition in emotion detection relies on physiological data acquired meticulously. Thus, physiological information previously shown to possess desired homogeneity characteristics and employed in the hitherto most successful emotion recognition experiment, i.e. Picard et al. [16], was utilized [Jennifer Healey, Rosalind W. Picard (2002), Eight-emotion Sentics Data, MIT Affective Computing Group, http://affect.media.mit.edu]. Healey's data set involves four physiological signals, i.e., electromyogram (MYOGRAM) obtained from the masseter muscle, blood volume pressure (BVP), skin conductance (SC) and respiration rate (RESP) collected from a single individual over a period of 20 days and comprising eight emotional states (no emotion, anger, grief, hate, joy, platonic love, romantic love, and reverence).

Statistical Feature Selection

In order to detect the signal attribute or attributes that contribute to an optimal separation of emotional sates, a class separation evaluation was performed based on the Davies-Bouldin Index (DBI, [20]). This needs to be done prior to any emotion detection process to ensure that only those features with the best potential class separation are used.

III. Results and Discussion

A. Neutral and Non-Neutral Emotional States

The instantaneous DBI was calculated for the 15 combinations of the four available signals (MYOGRAM, BVP, SC, RESP). Instantaneous DBI indicates that individual attribute values are chosen instead of statistical features obtained from the whole data set or multi-frame data segments. Healey's original data set (320160 samples, 2001 per day per emotion) was split into two groups. Group 1 contained data related to the no-emotion state (*neutral*) whereas Group 2 included the information concerning the remaining emotions (i.e., anger, grief, hate, joy, platonic love, romantic love and reverence). The DBI has been successfully utilised in studies that involve pattern recognition of physiological signals (e.g., [21]), lower DBI indexes reflecting a better class separation. Results showed that the clustering separation provided by the electromyogram outperformed that from other attributes used either individually or in combination (see Table I).

B. Positive and Negative Emotional States

A second study was conducted to classify non-neutral emotions according to their polarity dimensional value (positive or negative). Only those with positive or negative valence were considered (see Table II). The original set of 4 signals (MYOGRAM, BVP, SC, RESP), was expanded to include 8 calculated statistical features: standard deviation and gradient of MYOGRAM, standard deviation and gradient of BVP, standard deviation and gradient of SC, and standard deviation and gradient of RESP.

The Instantaneous DB Index was calculated for the 240120 samples involving anger, grief, hate, joy, platonic love, and romantic love states. Data were divided into group one encompassing data from positive emotions (120060 samples) and group 2 containing information from negative emotions (120060 samples). Results are shown in Fig. 1.

TABLE I
DBI Indexes for 15 Attribute Combinations

Attribute combination	DB Index
MYOGRAM	7.59
BVP	451.73
SC	17.67
RESP	59.88
MYOGRAM ,BVP	13.47
MYOGRAM ,SC	13.88
MYOGRAM, RESP	20.28
BVP,SC	21.37
BVP, RESP	71.18
SC, RESP	24.94
MYOGRAM, BVP, SC	16.21
MYOGRAM, BVP, RESP	23.40
MYOGRAM, SC, RESP	19.08
BVP, SC, RESP	27.60
MYOGRAM, BVP, SC, RESP	20.87

TABLE II.
Polarity Values for Seven Non-neutral Emotions as Suggested by Picard et al. [16]

Emotional State	Polarity
Anger	Negative
Grief	Negative
Hate	Negative
Joy	Positive
Platonic Love	Positive
Romantic Love	Positive
Reverence	Neutral

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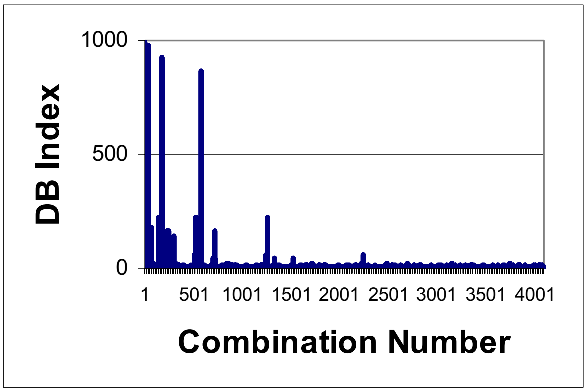
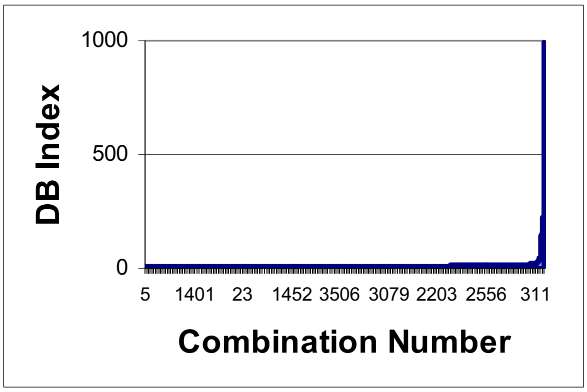


a)



b)

Fig. 1. DB indices for combinations of 12 raw physiological attributes. a) Number of attributes per combination and b) maximum DBI values.

Note that the number of attributes featured in a given calculation increases from left to right depending on the combinational factor (how many combinations could be obtained taking 1 parameter at a time, 2, 3, etc.). Thus, combination 4095 included 12 attributes whereas combination 1 to 12 encompassed 1 attribute only. The lowest DBI value was that of combination 5 (the standard deviation of the MYOGRAM) with 4.05.

Original data comprising group 1 and 2 were then provided to an Autoassociative Neural Network (AANN) previously trained with neutral emotional data (see Fig. 2). AANNs are a special type of back-propagated neural networks trained to learn the identity function, i.e., inputs equal outputs [22]. It is argued that because of the memorizing properties of AANN, estimations for data not provided during training (i.e. non-neutral emotions) tend to show an increased inter-cluster spread and thus a lower DBI value.

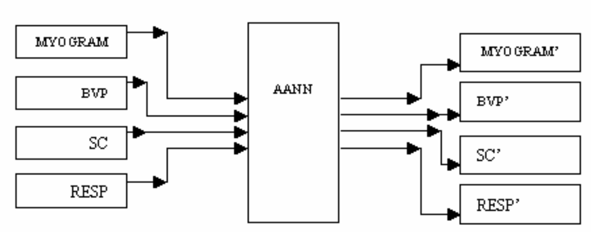


Fig. 2. Training of the AANN employed to detect emotional changes.

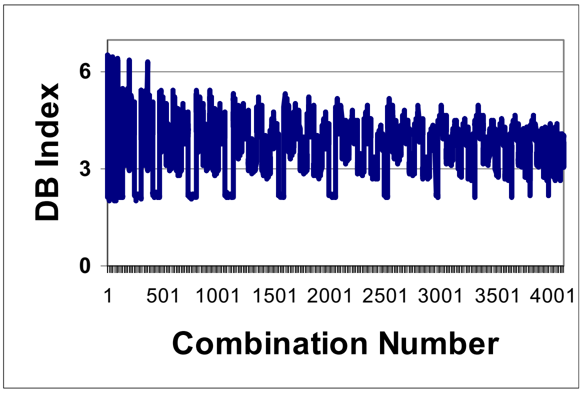
The same eight statistical features employed before were calculated from the four estimated signals provided by the AANN: standard deviation and gradient of MYOGRAM', standard deviation and gradient of BVP', standard deviation and gradient of SC' and standard deviation and gradient of RESP'. The resulting data were divided according to their polarity value resulting in 120060 samples for negative valence and 120060 for positive polarity. The two data sets were then utilized to calculate the instantaneous DBI for each of the 12 attributes separately and for the combinations of them.

Fig. 3 shows the results obtained for the 4095 combinations of physiological attributes. The attribute combination with the lowest DB Index was that of the gradient of the SC' with 2.034, followed by combination 74, the gradient of SC' and the MYOGRAM', and combination 56, the gradient of the SC' and the standard deviation of MYOGRAM'. These DBI values suggest that AANN estimations exhibited a better cluster separation than the one found in the original raw data. When provided with non-neutral information the AANN model trained with neutral data projected estimations into a wider variable space increasing the inter-cluster separation.

IV. Conclusions

By employing the attributes that provided the best clustering separation, more accurate results and shorter processing times in pattern recognition should be expected. Moreover, attribute selection contributes to the elimination of data that could have undesirable effects on clustering algorithms.

Experimental results showed that the masseter electromyogram was the best attribute when distinguishing between neutral and non-neutral emotional states. The gradient of the skin conductance provides the best results when discriminating between positive and negative emotions. It was also shown that AANN could be employed to enhance the inter-clustering spread of data in emotional pattern recognition.



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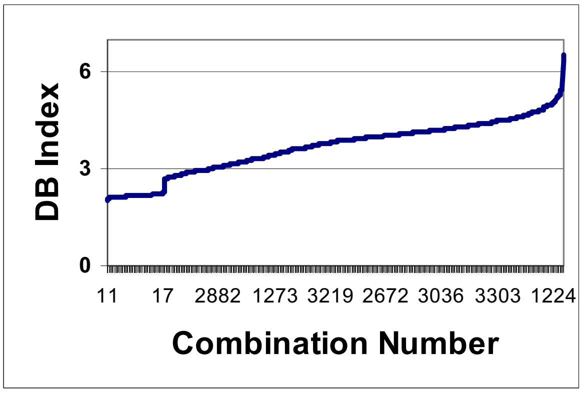

b)

Fig. 3. DB indices for combinations of 4 estimated physiological attributes and calculated statistical features. a) Number of attributes per combination and b) maximum DBI values.

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