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Neural Network-Based Improvement in Class Separation of Physiological Signals for Emotion Classification

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Abstract—**Computer scientists have been slow to become aware of the importance of emotion on human decisions and actions. Recently, however, a considerable amount of research has focused on the utilisation of affective information with the intention of improving both human-machine interaction and artificial human-like inference models. It has been argued that valuable information could be obtained by analysing the way affective states and environment interact and affect human behaviour. A method to improve pattern recognition among four bodily parameters employed for emotion recognition is presented. The utilisation of Autoassociative Neural Networks has proved to be a valuable mechanism to increase inter-cluster separation related to emotional polarity (positive or negative). It is suggested that the proposed methodology could improve performance in pattern recognition tasks involving physiological signals. Also, by way of grounding the immediate aims of our research, and providing an insight into the direction of our work, we provide a brief overview of an intelligent-dormitory test bed in which affective computing methods will be applied and compared to non-affective agents.**

Keywords— Neural Networks, Cluster Analysis, Emotion Detection, Pattern Recognition, Intelligent Environments

I. INTRODUCTION

Creating responsive living environments - intelligent-buildings - offers the potential for enhancing home based care service for people suffering from medical conditions. The operation of agents controlling such environments might be improved by including emotion sensing in their input space and utilising emotional information in decision making. Studies in neurology and psychology have shown in recent years that despite the popular belief that emotions interfere with logic and rational thinking, affective states play a role of paramount importance in the way humans make decisions [1, 2]. Moreover, the lack of emotional intelligence could impede the interaction between humans and their environments [3]. After an initial absence from the area, computer scientists have started to explore how emotional data could be employed to improve human-machine interactions and human-like inference capabilities. We are interested in how to obtain behavioural information from subjects inside inhabited environments. We believe that areas such as medicine and psychology could also benefit from models that describe the relationship between emotional states and behavioural and environmental conditions.

A. Emotion Detection

A unique definition of emotion is still difficult to agree upon. There is the evolutionary theory of Darwin, James' psychophysiological approach and Freud's psychodynamic model among others [4]. However, more agreement exists on the existence of common characteristics of emotional episodes such as subject alertness, overt expressions and behaviours, inclination to act in particular ways, and physiological changes combined with subjective feelings [4, 5]. The manner in which emotions are measured being related to the specific theory involved. Thus, subject's self-reports, behavioural rating techniques, projective approaches for evaluating behaviour products, physiological parameters, and analysis of facial and vocal expressions have been employed.

B. Physiological Emotion Detection

Two scientific areas have been traditionally associated with studies of bodily signals and emotions. Physiological psychology focuses on the analysis of behavioural response to physiological stimuli and psychophysiology evaluates the physiological responses produced by behavioural changes [6-8]. The physiological measures employed in emotional research 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 [6]. Facial and vocal expressions are also often used.

C. Computer-based Emotion Detection

The fact that human behaviour is affected by a variety of emotional conditions [2,9] has motivated computer scientists to investigate the idea that the modelling of rational decision making, human interaction and perception should, at least in part, be grounded in affective states. In computer science emotions have been mainly used in systems devoted to either mimicking emotional behaviour or detecting and utilising emotions. Three main methods have been suggested in emotion detection: facial recognition, speech recognition, and

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a combination of the two (bimodal). Recently, greater attention has been paid to internal bodily signs, especially those related to the autonomic nervous system and the brain. Hitherto, facial recognition has achieved the best results with 88-89% detection accuracy [10, 11] followed by physiological-based recognition with 81% [12], speech recognition (50-87.5%) [13, 14], and bimodal recognition (72%) [15]. It is worth noting that from a practical point of view physiological signals posses a crucial advantage over facial and vocal expressions in that they can be recorded, and then analysed based on algorithmic or auto-inference models that do not involve human intervention. Moreover, facial and vocal emotion recognition are often bound to specific gestures that make accurate real-world analysis difficult. Physiological signals are also easier to monitor although there still remain practical questions such as how physiological signals are affected by secondary causes such as physical exertion. However, the flexibility associated with the acquisition of physiological information is potentially more practical in terms of extracting agreed emotional states. Plus, issues such as physical exertion can always be taken into account within the context of future protocol designs. Robust pattern recognition can also be used for such situations. Although the work described in this paper allows us to benchmark our methods against existing work, the longer term objectives of the work, as introduced in the ‘Future Directions’ section below, are aimed at the deployment of non-laboratory based systems

II. METHODS

A. Data Set Description

Pattern recognition in emotion detection relies on acquiring detailed physiological data. Therefore the experiments presented in this paper were performed using the physiological data gathered in the hitherto most successful emotion recognition experiment, *i.e.* Picard *et al.* [12] [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: 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 involving eight emotional states (no emotion, anger, grief, hate, joy, platonic love, romantic love, and reverence).

B. Autoassociative Neural Networks (AANNs)

AANNs are a special type of Back-propagated Neural Networks (BPNNs) designed with a specific architecture and trained to learn the identity function, i.e., NN outputs equal NN inputs (see Fig. 1) [16]. The relationships acquired by the AANNs during training remain unaltered even when several input values are missing or corrupted. Two valuable outcomes derive from the utilisation and operation of an AANN. On the one hand, continuous analysis of the difference between actual and estimated input values (residual) could be employed to detect abnormalities in input signal patterns. For example when sensor readings are connected to the inputs of the AANN the outputs produce estimated sensor values for each

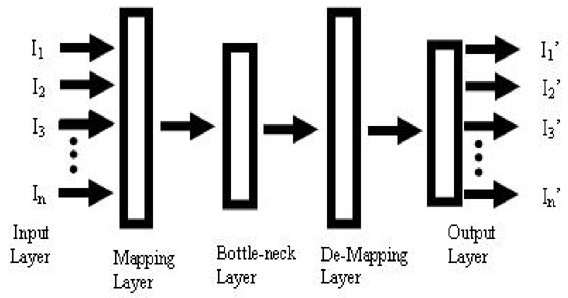

Figure 1. Construction of an Autoassociative Neural Network (after [16]).

of its inputs. Abnormalities are detected by continuously calculating the residual value and then utilising statistical measures such as the Sequential Probability Ratio Test (SPRT) to provide an indication of the moment when a sensor value deviates from its expected value. The same principle could be employed to detect changes in physiological signals when the emotional state of a subject changes from neutral to non-neutral. An SPRT-based decision module would be provided with the residual calculated between the actual physiological signals and their corresponding AANN estimated values. Since the AANN was trained to mimic the input behaviour associated with the neutral emotional state, the mean of the residual should be very close to zero under normal conditions and drift when the physiological status of the subject changes due to emotional episodes [17]. The combination of an AANN and the SPRT guarantees that a minimum number of data samples is required before an emotional change is detected thus allowing real-time analysis. The continuous evaluation of physiological signals could provide valuable information about how emotional episodes relate to various factors such as ambient conditions and behavior. Moreover, the identification of emotional states within an intelligent environment could increase the sophistication of the decision making from software agents.

On the other hand, the estimations provided by the AANN possess a higher degree of homogeneity than the one shown by the original data. If enough correlated information is provided to the AANN during training so that the relation of input parameters is accurately memorized; uncorrelated data such as noise is effectively eliminated at the output. The elimination of raw data outliers reduces overlapping and improves cohesion in output data.

It is important to mention that AANNs filtering properties are associated with the fact that outputs always map unknown input data to the closest point in the variable space of the training input data pattern [16]. As a consequence, mapping areas for similar data patterns would tend to be analogous and would differ from those of other input patterns.

C. Cluster Analysis

A cluster or class separation analysis provides an insight into the amount of redundancy and scatter within a given data set as well as the attribute(s) that contribute to an optimal separation of two or more classes. The Davies-Bouldin Index

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(DBI, [18]) was employed to evaluate the inter-cluster distance of various datasets encompassing information from two emotional classes, namely positive and negative. Thus, the DBI was estimated for various combinations of raw and calculated physiological attributes including output estimations from an AANN. It is worth mentioning that the DBI has been successfully utilised in studies that involve pattern recognition of physiological signals (e.g., [19]), where lower DBI indexes reflect a better class separation.

D. *Positive and Negative Emotional States*

As mentioned above, Healey's original data set comprised one state in which affective information was absent (no emotion) and seven actual emotional episodes, *i.e.*, anger, grief, hate, joy, platonic love, romantic love and reverence. Healey's experiments suggested that the polarity value of 3 of these 7 emotions was negative (anger, grief, and hate), 3 more were considered positive (joy, platonic love, and romantic love) and 1 remained neutral (see Table 1). Non-neutral emotional data (240120 samples) were labelled according to Healey's valence rating (positive or negative) and assembled into a single data set (Group A). The instantaneous DBI was then calculated for the two pattern classes contained in Group A. Instantaneous DBI indicates utilization of individual attribute values rather than statistical features obtained from a whole multi-frame data segment.

III. Results and Discussion

Two approaches were used in this study: 1) employing only instantaneous features, and 2) including segment based features as well. Results stemming from both approaches are summarized below.

A. *Instantaneous Features*

Initially the instantaneous DBI was calculated for the 15 combinations of the four original signals (MYOGRAM, BVP, SC, RESP) encompassed in Group A. Results demonstrated that the electromyogram possessed the best clustering separation with a DBI of 7.58 outperforming that from other attributes used either individually or in combination (see Fig. 2). The average DBI value was 102.35. Note that the number of attributes featured in a given calculation increases from left

TABLE I. Rated polarity for seven non-neutral emotions (as suggested by Picard et al. [12]).

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

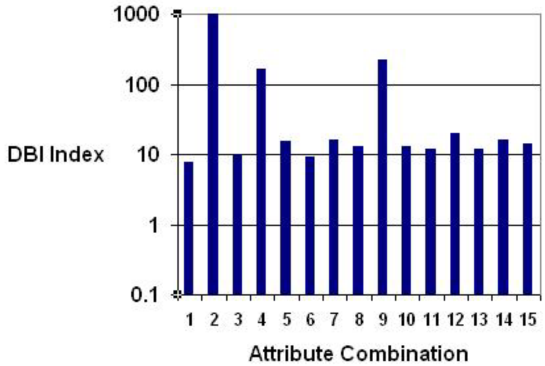

Figure 2. DBI values for combinations of 4 raw physiological attributes.

to right depending on the combinational factor (how many combinations could be obtained taking 1 parameter at a time, 2, 3, etc.). Thus, combination 1 to 4 included 1 attribute only whereas combination 15 encompassed 4 attributes.

B. *Instantaneous Plus Segment Based Features*

1) Eight Raw Attributes Selection: A second experiment was conducted with the data from Group A augmented to include 4 calculated parameters, namely the standard deviation of MYOGRAM, standard deviation of BVP, standard deviation of SC, and standard deviation of RESP. On this occasion the standard deviation of the electromyogram provided the lowest DBI index and thus the best theoretical classification capabilities (4.05) with an average DBI of 21.7 (see Fig 3).

2) Twelve Raw Attributes Selection: In order to increase differences in raw data, four additional calculated statistical features were then added to the 8 variables from Group A above, i.e. gradient of MYOGRAM, gradient of BVP, gradient of SC, and gradient of RESP. DBI calculations showed little improvement with respect to the results obtained with 8 attributes with a minimal DBI of 4.05 and an average value of 12.41.

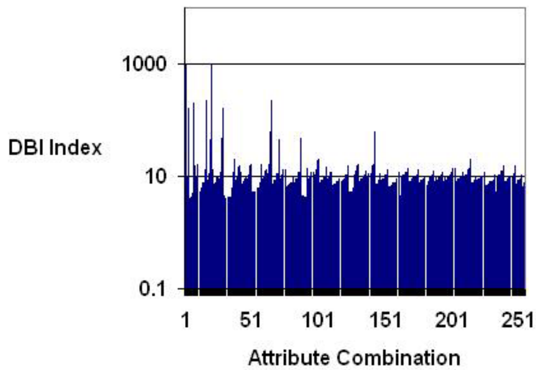

Figure 3. DBI values for combinations of 8 raw physiological attributes.

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3) AANN Estimations: Finally, an experiment was performed to investigate the effects AANNs filtering and mapping characteristics would have on the inter-cluster separation of non-neutral data. It was suggested that by training an AANN with data from the no-emotion state (thus creating a baseline), differences among the non-neutral emotional states would be increased and discrimination of positive and negative emotions would be consequently improved.

Healey's data relating to the no-emotion state (40001 samples) was employed to train an AANN (see Fig. 4) using the Neural Network Toolbox of MATLAB. The resulting trained AANN was then provided with the 4-variable non-neutral data from the original Group A.

Eight statistical features were calculated for the four AANN estimated values, i.e., 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 comprising 120060 samples for negative valence and 120060 for positive polarity were then employed to calculate the instantaneous DBI for each of the 12 attributes separately and for the combinations of them.

Results demonstrated that from the 4095 possible combinations of physiological attributes, the gradient of the SC' (combination 11) showed the lowest DBI value with 2.03, 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' (see Fig. 5). Not only did AANN estimations show the lowest DBI value, but also the lowest overall clustering index with an averaged value of 3.66 (see Table 2). These lower DBI values suggest that AANN estimations exhibited a better inter-cluster separation than that found in the original raw data.

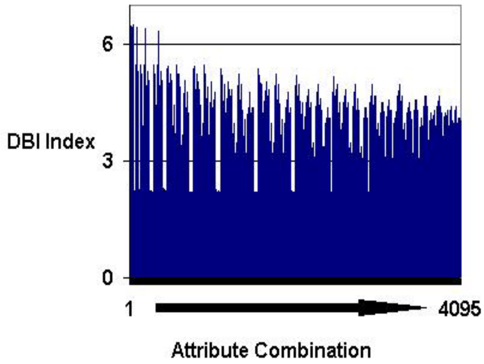

Figure 5. DBI values for combinations of AANN estimated physiological attributes.

IV. CONCLUSIONS

Emotional information represents a valuable source of information in many scientific areas such as medicine, psychology, and computing. However, accurate discrimination of emotional states is required if realistic results are expected. As a consequence, methods to improve the quality and performance of emotion recognition algorithms remain an area of great interest.

In this paper it was shown that the properties of AANNs could contribute to a greater inter-cluster separation of physiological data employed in emotion detection. Preliminary results, based on cluster analysis, demonstrated that the AANN estimated value of the gradient of skin conductance showed a better classification index than the one from raw data when distinguishing between negative and positive emotional episodes. The variation of DBI values among different sets of parameters also suggests that accurate detection results depend on a methodical selection of the attributes. Thus, it is suggested that clustering analysis is a valuable tool that should be utilised before indiscriminately using any signal features, to ensure that only the ones with the best potential class separation are used in actual classification tasks. The employment of cluster analysis also guarantees the elimination of data that could potentially diminish the performance of data mining algorithms.

It is worth noting that the generality of the methods proposed in the present study makes them suitable to be employed in any task of pattern recognition where physiological signals are employed.

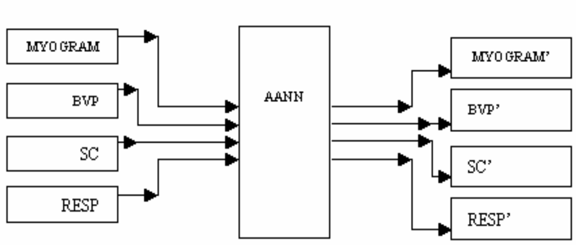

Figure 4. AANN trained to estimate 4 physiological signals.

V. FUTURE DIRECTIONS

The area of intelligent buildings has investigated the utilisation of behaviour and ambience information aiming at a closer interaction of a given subject with computer-based

TABLE II. DBI VALUES FOR DIFFERENT SETS OF PHYSIOLOGICAL ATTRIBUTES

Number of Attributes	Minimal DBI Value	Maximal DBI Value	Average
4 (raw data)	7.58	994.0	102.35
8 (raw data)	4.05	994.0	21.70
12 (raw data)	4.05	994.0	12.41
12 (AANN estimations)	2.03	6.54	3.66

systems and gadgets located inside occupied spaces. At the University of Essex the Intelligent Inhabited Environments Group (IIEG) will extend the study of habits and room conditions inside inhabited spaces to include physiological information. An intelligent agent that took account of bodily signals could be useful in discovering patterns of human behaviour based on the user's most probable emotional state. Moreover the suggested agent should be able to learn from user behaviour to correlate emotional states with his/her activities. Ultimately such agent would utilise emotion-behaviour relationships to assist the user in modifying the ambience according to known emotional states.

It is therefore important to be able to detect emotional variations in real time accurately and discriminate the affective states involved. The methods proposed in this paper are part of the continuous effort from the IIEG to investigate ways of making better embedded-agents; in this case detecting and utilising affective information. The intelligent Dormitory (iDorm) will play a major role in this research being a test-bed for intelligent inhabited environments. It has been designed to provide an environment in which various theories of adaptive intelligent agents can be analysed [20]. The iDorm, with emotion detection capabilities, could in the future represent a valuable tool not only for computer science research but also for various medical, psychological and social work.

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