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Real-time Physiological Emotion Detection Mechanisms: Effects of Exercise and Affect Intensity

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Abstract – **The development of systems capable of recognizing and categorising emotions is of interest to researchers in various scientific areas including artificial intelligence. The traditional notion that emotions and rationality are two separate realms has gradually been challenged. The work of neurologists has shown the strong relationship between emotional episodes and the way humans think and act. Furthermore, emotions not only regulate human decisions but could also contribute to a more satisfactory response to the environment, i.e., faster and more precise actions. In this paper an analysis of physiological signals employed in real-time emotion detection is presented in the context of Intelligent Inhabited Environments (IIE). Two studies were performed to investigate whether physical exertion has a significant effect on bodily signals stemming from emotional episodes with subjects having various degrees of affect intensity: 1) a statistical analysis using the Wilcoxon Test, and 2) a cluster analysis using the Davies-Bouldin Index. Preliminary results demonstrated that the heart rate and skin resistance consistently showed similar changes regardless of the physical stimuli while blood volume pressure did not show a significant change. It was also found that neither physical stress nor affect intensity played a role in the separation of neutral and non-neutral emotional states.**

Keywords – Emotions, Physiology, Intelligent Inhabited Environments, Exercise, Affect Intensity, Pattern Recognition

I. Introduction

Intelligence inside inhabited environments involves giving computers the ability to manage, analyse, and control the ambience in order to optimise user comfort, energy-consumption, safety, and work efficiency [1]. Actions taken by the agent should be comparable to those related to intelligent human activity.

Thanks to new advanced medical techniques and sophisticated scanning equipment, the study of the brain has gained momentum in recent years. Various neurological functions have been studied in an attempt to understand the myriad ways in which a human being acts, emotions being one of the most favoured by neurologists. Attempts to unravel the complex relationships between affective states and human behaviour have led to the idea that a lack of emotional expressiveness could impair the relationship of humans with their environment [2]. This is one of the reasons why computer scientists investigating interactive systems have turned to emotions in an effort to improve the adaptability of agents, increase the accuracy of decisions relating to human behaviour, and enhance machine interfaces. It is hoped that new more accurate applications with potential uses in medicine and psychology could be developed by including emotional information. Affective agents could for example, be used to monitor the physiological state of elderly or disabled people and adjust the ambience settings according to their stress levels. The relations between various environmental conditions and human behaviour could also be investigated using emotional information.

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A. Emotion Detection

Emotions are one of the most complex human attributes involving a wide variety of different aspects including physiological changes. Scientists have developed methods to analyse emotions ranging from self-reports to facial expressions. From these, computer scientists have preferred physical parameters that can be evaluated without the need of human intervention.

Facial, vocal, and polimodal emotion recognition have been used regularly in computer science to detect emotions. Recently more attention has been given to the analysis of bodily measures stemming from the autonomic nervous system and the brain. It is important to note that physiological signals remain the most objective manner for detecting emotions for computer science. Whilst facial expressions and vocal utterances can be more easily disguised, physiological measures are difficult to conceal or manipulate, thus becoming a more reliable representation of inner feelings.

B. Real-time Processing

The utilization of bodily signals to interactively recognize emotions relies on the detection of a physiological change caused by an affective stimulus and then the adequate classification of such change. Hitherto, the majority of methods employed to classify emotions using physiological signals have been based on off-line analysis of statistical features extracted from large quantities of data [3, 4]. Systems to dynamically detect, classify, and utilise emotions, based on instantaneous responses from the autonomic system are still lacking.

Using a combination of Autoassociative Neural Networks (AANNs) [5] and sequential analysis, a novel mechanism to detect changes in physiological signals associated with emotional states was developed [6]. By performing a continuous evaluation of the changes in one of several physiological parameters previously processed by an AANN, such a mechanism is able to detect changes in the autonomic response of a subject in real time. These changes are later categorized as belonging to either a neutral or a non-neutral emotional state.

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The main appeal of this methodology is that it does not require a great number of data samples to be gathered before a decision can be made. This is an important characteristic of interactive systems taking actions based on user's behaviour. It also represents a move closer to the implementation of a system that is capable of detecting emotions in everyday situations. Ordinary domestic environments could be equipped with recognition systems relating behaviour and affective states.

C. Robust Physiological Emotion Detection

In order to categorize a person's bodily signals with the emotional states they are associated with, the system will have to be able to operate in real time. This will facilitate the acquisition of information about the user and potentially improve the quality of the decisions made by agents in occupied spaces such as IIE. However, real-time processing also demands an improved level of robustness to ensure that factors such as the change in the physiological state of the user due to physical activities rather than emotional episodes, and the variation of affect intensity across individuals, do not affect the agent's performance.

This paper is aimed at analysing the extent to which physical exertion and affect intensity alter the physiological signals employed in emotion detection. Should the disturbances provoked by physical activities or affect intensity make the detection of emotional state unreliable, then appropriate compensation techniques would have to be developed for the detection system.

II. Methods

A. Experimental Set-up

1) Stimuli: Seven slide shows containing 21 photographs each (7 pleasant, 7 neutral, and 7 unpleasant) were assembled using a selection of images from the International Affective Picture System (IAPS) (Center for the Study of Emotion and Attention, 1999). The order of the stimuli was pseudo-randomised, i.e., manually done, with the restriction that no more than three pictures in the same affective category would be displayed consecutively. A detailed description of the pictures' contents can be found in [7].

2) Participants: Thirty-nine individuals responded to an advertisement and agreed to complete the Affect Intensity Measure (AIM) questionnaire [8]. The AIM scale has been widely employed in psychological studies and has been shown to possess sufficient reliability and validity [9] to evaluate affect intensity. From the initial 39 subjects, 6 women and 3 men aged 26 – 48 years took part in experimental sessions. Five were considered highly emotionally intense (scored more than 0.5 standard deviations above the mean AIM value [9]) and the remaining four (3 men and 1 female aged between 26 and 35) were in the medium- and low-emotional intensity scale (see Table 1).

TABLE 1. Summary of Results from the AIM Questionnaire.

Highest AIM Score	Lowest AIM Score	Standard Deviation	Mean	High-Intensity Threshold
5. 35	2. 375	0. 60	3. 77	4. 07

3) Determination of VO_2Max Values and Exercise Routine: In order to set up an exercise program that would produce comparable physical response from each individual it is necessary to evaluate his or her physical fitness and then use it as common parameter. Cardiorespiratory endurance is considered to be one of the most important components of physical fitness. The maximum oxygen uptake value (VO_2Max) or peak VO_2 is regarded as the most convincing measure of functional capacity of the cardiorespiratory system [10].

VO_2Max is usually calculated using maximal or submaximal graded exercise tests (GXTs). However, VO_2max can also be estimated without a GXT by using algorithmic formulations and data provided by subjects. The correlation value of the theoretical model with actual VO_2Max measurements is 0.78 with a standard error of 5.6 ml/kg-min [11].

A desired physical output can then be achieved by converting VO_2Max values into metabolic equivalents METs (1.0 MET = VO_2 / (3.5 ml/kg-min)) and then selecting an appropriate exercise routine (see Table 2). Since the purpose of this study was to analyse physical exertion under conditions that would resemble daily-life activities inside IIE, it was sufficient to use a low-to-moderate intensity exercise routine (up to 60% VO_2Max) rather than more demanding one. Thus, based on the mean VO_2Max score (see Table 3) and on previous studies involving the analysis of bodily measures after being stimulated by IAPS pictures and physical stress [7], participants were required to cycle for 25 minutes on a stationary "exercise bicycle" at no more than 10 M/hr equivalent to 27-57% of their theoretical VO_2Max value.

4) Sensoring Interface: The acquisition equipment included a finger clip with built-in sensors providing 3 physiological signals, i.e., heart rate (HR), skin resistance (SR), blood volume pressure (BVP), and 2 estimated parameters, namely the gradient of the skin resistance (GSR) and the speed of the changes in the data (CS - a measure of the signal's' entropy).

5) Experimental Procedure: Seven power-point (PP) slide shows (each one including a different IAPS picture set) were utilised to elicit emotions on participants while their physiological data was recorded. Before each slide show, subjects were instructed to stare at the centre of the screen and avoid explorative eye movements. Pictures were presented on a 17-in CRT monitor with a frame refresh rate of 75 Hz located at least 1.5 meters in front of the subject. With the exception of slide show 1, all the other presentations were designed to automatically display each picture for 6000 ms with blank intervals of 35000 ms.

TABLE 2. MET Values Associated with Various Physical Activities [11].

Activity, Description	METs
Bicycling, general, <10 mph, leisure	4. 0
Bicycling, 12-13. 9 mph, leisure, moderate effort	8. 0
Home Activities (Average)	3. 6

TABLE 3. VO_2MAX Values for Nine Subjects.

Highest VO_2Max Value (METs)	Lowest VO_2Max Value (METs)	Standard Deviation	Mean
14. 6	6. 97	2. 38	9. 47

Experiments were carried out over a four-day period. Upon arrival on day one subjects were asked to complete two questionnaires associated with their physical activities and one consent form and then shown slide show 1. This was a preliminary viewing session intended to give participants the opportunity to opt out from the experiment should they consider picture content unacceptable. In each of the subsequent days subjects viewed 2 slide shows separated by interval periods of 25 minutes in semi-recumbent position on day 2, 25 minutes cycling on the stationary bicycle followed by 25 minutes in semi-recumbent position on day 3, and finally 25 minutes of cycling on the stationary bicycle on day 4. Physiological data was recorded at 15-16 samples per second on a pc computer while the subject watched pictures on the screen.

B. Dataset Description

Data collection sessions produced 6 data sets per subject (one per slide show on days 2, 3, and 4). These files were named Pre25minRest (Slide show 2), Post25minRest (Slide show 3), PreExercise-1 (Slide show 4), Post25minExercise25minRest (Slide show 5), PreExercise-2 (Slide show 6), and Post25minExercise (Slide show 7). From the original 9 volunteers, only 5 completed the exercise routine on day 4. In addition, the information from one subject was lost due an error in the data storage procedure resulting in 42 usable files. The number of samples on each data set involved between 12123 and 18993 data samples which were later reduced to between 1871 and 2627 after the elimination of samples corresponding to the 35 sec. interslide periods. A further division on the data was made in accordance with the emotional content of the pictures they related to (neutral, positive, and negative). Additionally, emotional information was identified with a class number (1-neutral, 2-non-neutral) and assembled into 2 groups: BeforeExerciseOnly included neutral and non-neutral data collected throughout the viewing of slide show presentations 2, 3, and 4; and BeforeandAfterExercise involved neutral and non-neutral information from data colleted during the presentation of slideshows 2, 3, 4, and 5.

C. Wilcoxon Test

The Wilcoxon Two-sided Rank Sum Test provides a way to determine whether two independent data sets associated with a given parameter could actually be seen as two contributing parts of the same population instead of separate individual groups. Assuming that µ1 and µ2 are the mean values of the parameter contained in data set 1 and 2 respectively, the Wilcoxon test will estimate the probability P that the hypothesis H_0 that µ1 equals µ2 is true, i.e., the two data sets possess a high degree of similarity [12].

D. Clustering Analysis

A cluster or class separation analysis provides an insight into the amount of inter- and intra-cluster separation within a given data set and indicates the attribute(s) that contribute to an optimal separation of two or more classes. The DBI has been successfully utilised in studies that involve pattern recognition of physiological signals, where lower DBI indexes reflect a better class separation.

III. Results and Discussion

A. Similarity Test

A series of Wilcoxon tests were performed to evaluate the extent of physiological changes provoked by physical exertion and determine whether light exercise could disturb bodily signals beyond normal levels.

Results showed that the hypothesis that data obtained before (PreExercise-1 and PreExercise-2) and after exercise (Post25minExercise25minRest and Post25minExercise) possessed a high degree of similarity (H_0) was consistently false for HR and SC and true for BVP with a confidence factor of 0.05 (see Table 4 (a) and (b)). The changes in HR and SC associated with H_0=FALSE however were also present during trials in which no exercise was involved (Pre25minRest, Post25minRest, and PreExercise-1) (see Table 4 (c)).

TABLE 4. Results of the Wilcoxon Test Between a) PreExercise-2 and Post25minExercise; b) PreExercise-1 and Post25minExercise25minRest; c) Pre25minRest, Post25minRest, and PreExercise-1 (averaged value) (* denotes highly emotional subjects).

	Subject 2*	Subject 3*	Subject 5	Subject 6	Subject 8
	P/H_0	P/H_0	P/H_0	P/H_0	P/H_0
GSR	7.26E-01 TRUE	0.9058 TRUE	7.69E-04 FALSE	6.81E-09 FALSE	1.00E-08 FALSE
HR	0 FALSE	0 FALSE	1.12E-253 FALSE	0 FALSE	0 FALSE
BVP	0.842 TRUE	0.7552 TRUE	0.4856 TRUE	0.4776 TRUE	3.17E-01 TRUE
SR	0 FALSE	0 FALSE	0 FALSE	0 FALSE	0 FALSE
CS	6.15E-11 FALSE	6.21E-01 TRUE	1.71E-65 FALSE	0.0025 FALSE	2.60E-06 FALSE

a)

	Subject 2*	Subject 3*	Subject 5	Subject 6	Subject 8
	P/H_0	P/H_0	P/H_0	P/H_0	P/H_0
GSR	8.25E-06 FALSE	0.002 FALSE	0.19 TRUE	0.14 TRUE	4.50E-07 FALSE
HR	0 FALSE	0 FALSE	5.30E-176 FALSE	0 FALSE	0 FALSE
BVP	0.52 TRUE	0.54 TRUE	0.8 TRUE	0.1588 TRUE	8.20E-01 TRUE
SR	0 FALSE	0 FALSE	0 FALSE	0 FALSE	0 FALSE
CS	9.20E-19 FALSE	5.36E-08 FALSE	2.80E-13 FALSE	0.0122 FALSE	1.85E-01 FALSE

b)

	Subject 2*	Subject 3*	Subject 5	Subject 6	Subject 8
	P/H_0	P/H_0	P/H_0	P/H_0	P/H_0
GSR	0.06 -	0.01 -	0.28 FALSE	0.18 -	0.29 -
HR	3.00E-04 FALSE	0 FALSE	0 FALSE	6.00E-247 FALSE	5.89E-07 FALSE
BVP	0.34 TRUE	0.28 TRUE	0.54 TRUE	0.41 TRUE	0.70 TRUE
SR	2.86E-09 FALSE	0 FALSE	1.03E-19 FALSE	0 FALSE	6.33E-04 FALSE
CS	0.33 FALSE	0.10 -	0.01 -	0.02 -	1.53E-04 FALSE

c)

B. Class Separation Test

Preliminary results obtained from a clustering analysis and depicted in Table 5 showed that there was no significant difference in the lowest DBI values of physiological data before and after exercise in subjects with different degrees of affect intensity. Furthermore, bodily signals involving physical exertion demonstrated improved class separation on two occasions (See subjects 4 and 5 in Table 5).

TABLE 5. DBI VALUES FOR RAW DATA FROM 5 PHYSIOLOGICAL SIGNALS (* DENOTES HIGHLY EMOTIONAL INDIVIDUALS).

	BeforeExerciseOnly		BeforeandAfterExercise	
	Minimal Value	Mean	Minimal Value	Mean
Subject 1*	6. 96 (CS)	81. 37	7. 37 (CS)	111. 85
Subject 2*	9. 51(CS)	63. 41	14. 90(HR)	316. 92
Subject 3*	13. 02(GSR)	85. 07	16. 18(HR)	163. 56
Subject 4*	7. 21(CS)	71. 71	6. 18(CS)	82. 26
Subject 5	7. 30(HR)	85. 47	7. 08(HR)	125. 13
Subject 6	5. 32(HR)	97. 12	5. 92(HR)	153. 88
Subject 7	10. 83(HR)	157. 31	13. 24(CS)	387. 04
Subject 8	6. 15(HR)	172. 87	8. 50(HR)	294. 49

IV. CONCLUSIONS

This study supports the view that systems relying on physiological measures to recognize emotions in real-time and involving realistic situations should be able to operate reliably independent of the level of physical effort and different degrees of affect intensity of the person. In this paper two different experiments were undertaken to investigate the potential effects of low-to-moderate effort exercise and affect intensity on 5 physiological signals employed in real-time emotion detection. The results from the Wilcoxon test demonstrated that there was a change in HR and SC in all the trials whereas BVP remained very similar. This is true when comparing data before and after the exercise but was also true for data when no exercise was involved. It could be then inferred that any particular change caused by different levels of physical activity or the lack of it exists in resting conditions as well. Likewise, evidence from the DBI test supports the fact that affect intensity does not seem to play a crucial factor in the classification of the physiological response from individuals subjected to physical effort and emotional stress.

It is important to note that these experimental results indicate that no special adjustments are required to real-time data acquisition systems classifying emotions based on bodily data in order to take account of differences in levels of physical activity or affect intensity.

In terms of systems utilizing AANN, the findings presented above suggest that the use of data before exercise for the purpose of AANN training should not affect the detection of emotions after physical exertion.

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