Towards a robust real-time emotion detection system for intelligent buildings.

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Abstract

The last few years have witnessed an increasing interest from computer scientists in the role emotions could play in the adaptability of artificially intelligent mechanisms. Evidence from neurologists suggests that affective states are crucial in the interaction between an individual and the environment. Furthermore, emotions often dominate our actions and some times override reasoning in the process of making decisions. In this paper an analysis of the use of Autoassociative Neural Networks (AANN) in the context of real-time physiological emotion detection for intelligent inhabited environments (IIE) is presented. Two main studies were undertaken: On one hand the effects of altered physiological responses stemmed from various degrees of emotive intensity and on the other hand the possible consequences of physical arousal not related to emotional expressiveness It is argued that the use of AANN contributes to an improved separation of emotional classes and a more accurate recognition of affective states in individuals with a varying degree of emotional responsiveness. It is also postulated that AANNs robustness is not affected by physiological disturbances associated with physical activities thus setting the basis for emotion recognition in real-life scenarios.

Introduction

The fact that human behaviour is significantly affected by a variety of emotional conditions [1, 2] has contributed to a renewed interest from computer scientists in the investigation of affective states as a mechanism to achieve a more realistic modelling of rational decision making and human interaction and perception. The area of affective computing encompasses the different approaches related to the synthesis (simulation) and analysis (detection) of emotional states. Emotion synthesis has been often utilised to provide artificial agents with increased adaptability. For example, 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 [3]. The PETTEI project at Texas A&M University focused on the implementation of an agent with evolving emotional capabilities [4]. Generally however, the detection of changes in emotional states has been employed to improve the relationships and interaction between humans and machines. An example of the latter is the “affective wearable” proposed by Healey et al. which is capable of detecting musical preferences based on emotional information contained in physiological measures [5].

Emotion Detection

For decades, emotions have been the centre of numerous scientific studies trying to describe, analyse, and evaluate various aspects of affective states. The main outcome of these endeavours is a wide agreement among different theorists that emotions include awareness of a given situation, overt expressions and behaviours, readiness to act, and physiological changes supplemented with subjective feelings [6, 7]. Instruments used to measure emotions depend on the emotional theory involved and include self-reports of feelings, projective techniques to evaluate behaviour products, methods of behavioural rating, physiological parameters, and examination of facial and vocal expressions.

Computer scientists evaluating emotional states have preferred physical rather than psychological expressions because they can be investigated interactively without the need of human intervention.

Computer-based emotion detection

Three methods have been traditionally employed in computer science to detect emotional states: facial recognition, speech recognition, and a combination of the two called bimodal. In recent times, however, methods relying in the utilisation of physiological signals stemming from changes in the autonomic nervous system and the brain have been extensively investigated. It is worth noting, that the best results have been obtained by facial recognition (88-89% detection accuracy) [8, 9] followed by physiological (81%) [10], speech (50-87.5%) [11, 12], and bimodal detection (72%) [13]. Nonetheless, physiological signals remain the most promising and objective manner for detecting emotions in computer science. While facial expressions and vocal utterances can be more easily disguised, physiological measures are difficult to manipulate and therefore a more reliable representation of inner feelings.

Physiological Emotion Detection

The use of bodily signals to detect emotions in interactive applications relies on the detection of an affective change and the adequate classification of such change. Physiological measures usually employed in the analysis of emotional changes 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.

Hitherto, however, computing methods used to classify emotions using physiological signals have been only based on the off-line analysis of statistical features extracted from great amounts of data. Systems to dynamically detect, classify, and utilise emotional dimensions based on instantaneous responses from the autonomic system have not been developed.

Real-time detection of emotional changes

Using a combination of Autoassociative Neural Networks (AANNs) and sequential analysis, a novel mechanism to detect changes in physiological signals associated with emotional states was developed [14]. This approach to detecting changes in emotion is based on a real-time continuous evaluation of changes in one of several physiological parameters (this bodily measure being previously processed by an AANN using the remaining signals). The main appeal of the suggested methodology is that it does not need to amass a great number of data samples before a decision can be made. This is an important characteristic required by interactive systems that depend on user's behaviour to take action, and it represents the key to the implementation of emotion recognition inside intelligent inhabited environments (IIE).

Autoassociative Neural Networks (AANNs)

AANNs have been widely used in Sensor Failure Detection, Isolation, and Accommodation (SFDIA) to evaluate the moment in which sensor readings deviate from their expected value. AANN estimated values are often used to replace the faulty sensor in the control unit software while measures to prevent failure dissemination are taken. SFDIA is achieved by the continuously examination of the difference between the actual sensor value and the estimation of that sensor provided by the AANN. This difference, often referred to as residual, is subjected to a classification mechanism usually the Statistical Probability Ration Test (SPRT).

The same principle can be utilised to detect changes in physiological signals when the emotional status of a subject changes from one affective state to another. If an AANN was trained to mimic the input behaviour of a given emotional state, e.g. neutral, the mean of the residual between a given physiological signal and its AANN estimated value would remain very close to zero for the data associated with such emotional state and will diverge when the subject's physiological status changes due to a different emotional state arising [14, 15]. The combination of an AANN and the SPRT guarantees that only the minimum number of data samples is required before an emotional change is detected.

AANNs possess not only exceptional associative properties but also improved filtering capabilities [16]. If enough correlated information is provided to the AANN during training, permitting an accurate characterisation of the relation between input parameters, uncorrelated data such as noise is effectively eliminated from the networks outputs. The elimination of raw data outliers reduces overlapping and increase data homogeneity. As a consequence physiological signals processed by an AANN have been shown to deliver a better separation of emotional classes than that found in the raw data [15]. When an AANN is trained to memorize a given data pattern, e. g., the neutral emotional state, the estimations associated with previously unknown inputs presented to the AANN are projected into a wider variable space. Hence AANNs producing an increment in the inter-cluster separation of physiological data related to various emotional states.

Selection of classification attributes

A central issue in the design of an effective AANN real-time detection mechanism is the selection of the physiological attribute that will subsequently be employed by the decision module (SPRT) to recognise emotional categories. This is done a priori to ensure that only the feature with the optimal class separation is used thus avoiding the utilisation of information that could actually render the recognition process less effective.

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 that contributes to an optimal separation of two or more classes. Previous studies involving cluster analysis demonstrated that a AANN-based electromyogram signal contributes to the best cluster separation of neutral and non-neutral states [1]. Regardless of the generalisation of this result (it was based on the use of emotional data collected from a single subject over a 20-day period), it does demonstrate the validity of the methods employed.

Universality of a real-time emotion detection system: Effects of emotional intensity and physical exertion on AANN estimations

Being real-time is an important attribute for systems that interact with the user hoping to use current emotional information. Real-time processing facilitates the acquisition of information and improves the quality of decisions made by agents in IIE. Nonetheless, immediate response is not the only challenge faced by IIE agents detecting emotions. Factors such as the change in the physiological state of the user due to physical activities rather than emotional episodes and the variation of emotive response across individuals could affect agent performance. An accurate assessment of the current affective state of the user should be possible under any circumstances if a realistic implementation of a real-time emotion detection mechanism is expected.

The purpose of the present study is to investigate the associative and filtering properties of AANNs in the presence of data from various individuals whose emotional intensity ranges from low to very high. Experiments were also carried out to see if physical exertion has any effect on the class separation of the AANN estimations. The experiments and results presented in this paper will establish the basis for translating real-time emotion detection from highly controlled lab conditions into real-life experimentation inside IIE.

Methods

Experimental Set-up

Stimuli

Five 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 with the restriction that no more than three pictures in the same affective category would occur consecutively. A detailed description of the pictures' contents can be found in [17].

Participants

Previous studies involving the characterization of emotions using physiological responses have repeatedly failed to demonstrate whether subjects taking part in experiments actually experienced emotions during the data acquisition phase [18]. One way to guarantee a desired physical response to a given emotional stimuli is to select participants based on a priori examination of their affective intensity. In the present study, however, emotional intensity is employed as an illustrative rather than a discriminatory parameter. The desirable generalization of the methods presented here might be better evaluated by including individuals in the entire emotional spectrum instead of only highly responsive subjects.

The Affect Intensity Measure (AIM) [19] has been widely used in psychological studies to evaluate the degree to which an individual reacts to emotional episodes. The AIM has been demonstrated to possess sufficient reliability and validity to evaluate emotional responsiveness [18]. Subjects with high AIM scores are expected to respond in a stronger mental and physiological way to emotional stimuli than people with low AIM levels.

In response to an open invitation, thirty-nine individuals (21 females and 18 males) voluntarily agreed to complete the AIM questionnaire. From these, 6 women and 3 men in the age range 26 – 48 years, took part in the emotion detection experiments; five were found to be highly emotionally intense (scored more than 0.5 standard deviations above the mean AIM value [18]) 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).

Highest AIM Score	Lowest AIM Score	Standard deviation	Mean	Intensity threshold (Mean + 0.5 Std. Dev.)
5.35	**2.37**	**0.58**	**3.77**	**4.07**

Table 1. Summary of results from the AIM questionnaire.

Procedure

Experiments were carried out over a three-day period. 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 (a measure of the signals entropy) (CS).

On day one, subjects completed two questionnaires relating to their physical activity and one consent form before being shown a preliminary picture show (slide show 1). The information contained in the two questionnaires was used for estimating the subjects' cardiovascular endurance (VO_2max values) and subsequently employed to calculate the physical output needed in the exercise routine. The purpose of the preliminary slide show (which did not involve the recording of data and was manually controlled) is to give participants the opportunity to opt out from the experiment should they consider picture content unacceptable. Subsequent slide shows were designed to automatically display each picture for 6000 ms with blank intervals of 35000 ms.

Day two comprised the presentation of two more picture shows (slide shows 2 and 3). This time, however, subjects wore the sensing device while they watched the pictures on the screen and their physiological information was stored on a PC computer. A 25-minute rest period was given between the two viewing sessions.

Similar to day 2, subjects viewed two slide shows on the third day of the experiments (slide shows 4 and 5) and wore the finger-clip while their bodily response was recorded on the computer. In this occasion instead of resting immediately after the first presentation of the day, they exercised for 25 minutes on a stationary bicycle and rest for another 25 five minutes before watching the second slide show. This approach is based on previous studies involving the analysis of bodily measures after being stimulated by IAPS pictures and physical stress [17].

Dataset Description

Data collection sessions produced 4 data sets per subject (one per slide show on days 2 and 3). The information from one subject was lost due an error in the data storage procedure resulting in 32 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. inter-slide 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) producing 12 files per subject.

Emotional information was identified with a class number (1-neutral, 2-non-neutral) and assembled into 4 groups: Dataset 1 comprised neutral information collected during photo presentations 2, 3, and 4; Dataset 2 encompassed neutral and non-neutral data from presentations 2, 3, and 4; Dataset 3 contained neutral information collected throughout the viewing of slide shows 2, 3, 4, and 5, and finally, Dataset 4 contained both neutral and non-neutral information acquired during the presentation of slideshows 2, 3, 4, and 5.

AANN training

Eight AANNs (one per subject) were trained to memorise pre-exercise neutral information using Dataset 1 and then validated using Dataset 2. Similarly, eight additional AANNs (again one per participant) were trained with Dataset 3 and tested using Dataset 4.

The estimations for Dataset 2 and Dataset 4 provided by the AANNs were then subjected to a Davies-Bouldin cluster analysis to identify the attribute that provided the best separation of neutral and non-neutral emotional states. The calculation of the Davies-Bouldin Index (DBI) [20] has been demonstrated to be a good indicator of the inter-cluster separation in experiments involving pattern recognition in physiological measures [21]. The lower the DBI value the better the class separation. It is worth mentioning that in this study, an instantaneous DBI value was employed indicating utilisation of individual attribute values rather than statistical features obtained from a whole multi-frame data segment.

A class analysis was then performed to evaluate the performance of an AANN trained with Dataset 1 (neutral data prior exercise) when presented with never-seen data that had been potentially disturbed by physical exertion (Dataset 4). Finally, the separation of positive and negative emotional classes found in AANN estimated values was investigated. For this purpose, Dataset 2 was divided into Dataset 2a (class number=2) involving information about the positive dimension and Dataset 2b (class number=3) encompassing samples collected during negative elicitation (neutral data was eliminated). An AANN was then trained using Dataset 2a and then examined with Dataset 2a+2b.

It is expected that, because of the capacity to memorize input patterns and the associated noise filtering mentioned before, AANN estimations will project emotional classes in a wider variable space thus increasing class separation.

Results

Preliminary results showed that in the totality of the cases, AANN estimations exhibited lower DBI values for neutral and non-neutral emotional classes than the one obtained in raw data (see Table 2). Table 2 also shows that DBI values for data sets not involving post-exercise information were smaller than their post-exercise counterparts (compare the results for Dataset 1 vs Dataset 3 and Dataset 2 vs. Dataset 4).

It is also evident that the attribute that provided the best separation between neutral and non-neutral emotional states varied from subject to subject in all the different trials. In the case of highly emotional intense subjects these attributes remained the same before exercise (Dataset1) and after the exercise when AANN are involved (Dataset 4).

	Including information before exercise only				Including information before and after exercise			
	Raw Data (Dataset2)		AANN Estimations for Dataset 2 when trained with Dataset 1		Raw Data (Dataset 4)		AANN Estimations for Dataset 4 when trained with Dataset 3	
	Minimal Value	Mean	Minimal Value	Mean	Minimal Value	Mean	Minimal Value	Mean
Subject 1*	6.96 (CS)	81.37	5.79(CS)	14.70	7.37 (CS)	111.85	7.23(CS)	18.07
Subject 2*	9.51(CS)	63.41	6.78 (BVP)	17.92	14.90(HR)	316.92	10.79(CS)	27.84
Subject 3*	13.02(GSR)	85.07	5.71(BVP)	34.87	16.18(HR)	163.56	9.39(GSR)	24.14
Subject 4*	7.21(CS)	71.71	6.09(CS)	23.33	6.18(CS)	82.26	5.83 (CS)	73.94
Subject 5	7.30(HR)	85.47	3.59(HR)	11.73	7.08(HR)	125.13	5.48(HR)	38.87
Subject 6	5.32(HR)	97.12	4.39(GSR)	42.24	5.92(HR)	153.88	5.71(CS)	95.73
Subject 7	10.83(HR)	157.31	5.59(CS)	93.42	13.24(CS)	387.04	9.32(CS)	95.09
Subject 8	6.15(HR)	172.87	5.66(HR)	32.89	8.50(HR)	294.49	7.04(HR)	97.57

Table 2. DBI values for raw and AANN data for 5 physiological signals (denotes highly emotional individuals).*

Table 3 shows the class separation of estimations provided by an AANN trained with pre-exercise data in the presence of unknown post-exercise data. The AANN was able to appropriately estimate physiological values never presented before and still provide a better class separation with respect to the one found in raw data. It can also be said that in the majority of the cases, the class separation obtained from the AANN generalisation abilities are even a better than that of AANN estimations derived from memorising training (Compare the last columns of Table 2 and table 3).

	Raw Data (Dataset 4)		AANN Estimations for Dataset 4 when trained with Dataset 1	
	Minimal Value	Mean	Minimal Value	Mean
Subject 1*	7.37 (CS)	111.85	6.45(CS)	18.36
Subject 2*	14.90(HR)	316.92	6.47(BVP)	194.21
Subject 3*	16.18(HR)	163.56	9.61(BVP)	27.45
Subject 4*	6.18(CS)	82.26	5.90(CS)	22.29
Subject 5	7.08(HR)	125.13	4.81(HR)	57.72
Subject 6	5.92(HR)	153.88	5.68(GSR)	18.69
Subject 7	13.24(CS)	387.04	6.57(CS)	102.73
Subject 8	8.50(HR)	294.49	7.80(HR)	44.06

Table3. DBI values for raw data and AANN estimations for unknown physiological information (denotes highly emotional individuals).*

Finally, the analysis on positive and negative emotional data drew the results shown in Table 4. It was found that when an AANN was trained to memorise the positive emotional state and then provided with both positive and negative information, AANN estimations exhibited lower DB indices than the ones obtained from raw data. These results are consistent with the reduced DBI values previously shown in the analysis of neutral and non-neutral emotions.

	Raw Data (Dataset 2a+2b)		AANN estimations for Datset 2a+2b when trained with Dataset 2a	
	Minimal Value	Mean	Minimal Value	Mean
Subject 1*	8.20(CS)	169.41	5.57(HR)	10.17
Subject 2*	10.88(SR)	192.04	9.59(BVP)	16.71
Subject 3*	3.50(CS)	79.59	2.85(CS)	15.21
Subject 4*	4.63(CS)	135.59	4.54(GSR)	68.77
Subject 5	6.36(HR)	147.07	4.09(BVP)	5.36
Subject 6	5.31(CS)	42.32	5.22(GSR)	33.89
Subject 7	10.78(GSR)	56.86	7.18(GSR)	55.08
Subject 8	7.36(HR)	363.95	3.80(HR)	20.47

Table4. DBI values for raw data and AANN estimations of positive and negative emotions (denotes highly emotional individuals).*

Discussion

The results shown in Table 2 clearly demonstrate that AANN estimations exhibit an improved separation of neutral and non-neutral emotional classes for all subjects than the one based upon raw data. It was evidenced that when an AANN is trained using data from one emotional state (neutral in this case), the distance between the estimations for that emotional state and for data from other affective states increases. It is worth noting that these associative properties displayed by AANN were not affected by the difference in the emotional responsiveness of the various participants. In fact, the lowest DBI values and thus the best class separation of neutral and non-neutral states were obtained from data belonging to individuals not considered to be emotionally intense (see results for subject 5 and 6 in Table 2).

Another important outcome derived from the above experiments is that the performance of the AANN was not affected by physiological changes associated with physical exertion. It is clear that there is a minor deterioration in the class separation of the raw data before and after exercise (see DBI calculations for Datasets 1 and 3) but this did not affect the associative or filtering attributes of the AANNs.

The fact that physical activities do not affect the class separation of AANN estimations is even more dramatically confirmed in Table 3. Trained with neutral pre-exercise data, an AANN produced estimated values for physiological data obtained after the exercise routine when bodily signals were still being potentially affected or disguised by the arousal from the earlier physical exertion. AANN estimations not only showed an improved class separation in comparison with raw post-exercise data but also with respect to estimations from an AANN trained with post-exercise data.

It is also important to mention that AANNs were capable not only to improve the class separation between neutral and non-neutral emotional states but also between positive and negative emotional states as depicted in Table 4.

Conclusion

Real-time emotion detection is a promising source of information for highly-interactive user-oriented applications. The use of emotional information in intelligent agents could potentially develop into symbiosis between humans and their (computing) environment. It is of particular importance to analyse the benefits emotion detection could bring to agents inside IIE.

Agents fitted in inhabited spaces interact with a variety of users in several ways in order to learn from them and take actions. This type of agents responds or adapts to the immediate preferences of the user, and to his/her unpredictable behaviour and possibly eclectic life style. This ability to respond to a range of different users and situations becomes an even greater challenge for affective agents relying on physiological signals often disturbed by numerous factors.

In this paper an analysis was presented to demonstrate that the real-time detection of emotional changes in inhabitable spaces is possible under a number of circumstances including physical activity and for a variety of people. By analysing the effects of emotional intensity and physical exertion on the performance of the core component of a real-time emotion detection mechanism, i.e., the AANNs, the crucial issue of the universality of such detection methodology was addressed.

The encouraging results discussed above suggest that physical activities do not completely disguise the physiological characteristics used to classify emotional dimensions and therefore will not reduce the performance of the AANNs once a detection systems faces real-life situations inside IIE. Likewise, it was established that emotional responsiveness is not a factor influencing the real-time classification of affective states using these methods.

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