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# Real-time detection of emotional changes for inhabited environments

Mr. Enrique Leon
E-mail: eeleon@essex.ac.uk
Dr. Graham Clarke
E-mail: graham@essex.ac.uk
Dr. Victor Callaghan
E-mail: vic@essex.ac.uk
Dr. Francisco Sepulveda
E-mail: fsepulv@essex.ac.uk

Department of Computer Science,
University of Essex
Wivenhoe Park, Colchester CO4 3SQ,
United Kingdom.
Telephone: +44 1206 872790, Facsimile: +44 1206 872788

Abstract
The utilisation of emotional information in computer systems that interact with humans has become more prevalent during the last few years. The various channels through which emotions are expressed provide valuable information about the way humans think and behave and have been successfully employed to assist the inference mechanism of interactive computer applications. In this paper a novel approach to detect changes in the emotional status of a subject is presented. It is argued that the proposed methodology will be able to detect emotional changes in real time utilising physiological measures and a combination of Artificial Neural Networks (ANNs) and statistical mechanisms. Clustering analysis is used to show that the myogram signal was the most suitable attribute to distinguish between two emotional states. Results show that the suggested mechanism is able to accurately distinguish changes from neutral to non-neutral emotional states. Emotional information could be employed to improve user interaction in inhabited environments.

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# Real-time detection of emotional changes for inhabited environments

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Department of Computer Science, University of Essex, Wivenhoe Park, Colchester CO4 3SQ, United Kingdom.

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The utilisation of emotional information in computer systems that interact with humans has become more prevalent during the last few years. The various channels through which emotions are expressed provide valuable information about the way humans think and behave and have been successfully employed to assist the inference mechanism of interactive computer applications. In this paper a novel approach to detect changes in the emotional status of a subject is presented. It is argued that the proposed methodology will be able to detect emotional changes in real time utilising physiological measures and a combination of Artificial Neural Networks (ANNs) and statistical mechanisms. Clustering analysis is used to show that the myogram signal was the most suitable attribute to distinguish between two emotional states. Results show that the suggested mechanism is able to accurately distinguish changes from neutral to non-neutral emotional states. Emotional information could be employed to improve user interaction in inhabited environments.

Keywords: emotion detection, inhabited intelligent environments

## 1. Introduction

Emotions have shaped a great part of the world we know. History is full of examples in which affections have stirred up the fortitude needed to determine the fate of civilizations, the survival of entire nations and the success of scientific endeavours. And yet emotions have been regarded as something that science should view as harmful to reasoning. This manner of thinking permeated the ideas of computer scientists and efforts made to mimic the operation of the human mind have largely ignored emotions. The ultimate aspiration of Artificial Intelligence, i.e. to produce human-scale performance inference capacity, has for a long time ignored emotional states.

Thanks to recent findings in the area of neuroscience, computer scientists have gradually accepted the fact that emotions are as important as reason in modelling our decisions and actions [1, 2]. Investigators such as Damasio [3], De Souza [4], and Ledoux [5] have demonstrated that emotions affect our actions and thoughts and, moreover, that the lack of emotional aptitude could greatly impair our relation with the environment [3]. As a consequence, applications in which humans and computers interact have revealed an increased interest in emotions as a valuable source of information and computer scientists have increasingly been interested in the idea of providing machines with the ability to interpret and 'experience' emotions in what has been called emotional or affective computing [6].

In emotional computing, Picard [6] has recognised two types of emotional systems: those in charge of emotion recognition or analysis and those devoted to predict and generate emotions (emotion synthesis). Accordingly, some scientists have implemented computing systems whose behaviour resembles emotional episodes while some others have focused on machines that detect and utilise emotional states. Our work is along the latter line of research.

## 2. Emotion Recognition

Little agreement exists among the various theories concerned with the different aspects surrounding emotional states. The word “emotion” possesses several connotations that make a unique, exact definition unfeasible. However, more consensus has been achieved on what emotional states involve within science. It has been agreed that emotions are characterised by the awareness of a given situation, overt expressions and behaviours, readiness to act, and physiological changes supplemented with subjective feelings [7, 8].

The acceptance that explicit physical manifestations of many types accompany emotional states has encouraged researchers to propose methods for recognizing and measuring emotions, as they are experienced. Self-reporting, techniques of behavioural rating, projective techniques for evaluating behaviour products, physiological parameters, and analysis of facial and vocal expressions have been employed to determine emotional states [7-9]. From these, Computer Science has primarily employed cognitive methods for emotion synthesis while physical mechanisms have been more widely used in emotion detection. The advantage of physical manifestations over other emotional expressions is that they can be analysed in real time without human intervention using fixed-algorithmic or auto-inference models.

Hitherto the majority of computer-based proposals for detecting emotions have directed efforts to the utilization of facial and vocal expressions and just a few have undertaken physiological analysis. A reason for this might relate to the fact that the meaning of some physiological signs of emotions still continues to be debated whereas face recognition, for example, has achieved more extensive agreement among scientists. However, it is worth mentioning that physiological emotion recognition involves two main advantages over its facial and vocal counterparts. Facial and speech recognition are usually based on fixed models that require well-defined gestures or utterances that make real-time emotion detection difficult whereas physiological signals can be obtained during normal activity without the need for cumbersome equipment thus making data acquisition less intrusive.

## 3. Physiological Emotion Detection

In 1884 William James suggested that emotional states are experienced as a result of physiological changes [8]. Thus, a human being first realises bodily reactions and then perceives emotions as a consequence of the activity response from muscles and internal organs. Carl Lange drew the same conclusions three years later and researchers started referring to James' proposal as the James-Lange Theory [8]. A major point in James' argument was that emotions with strong physiological activation can be identified by specific patterns of bodily changes.

It is worth mentioning that, until the early 1980's, efforts to determine the specific physiological attributes of emotions achieved only modest success. However, in 1983 Ekman et al. were able to distinguish between anger, fear and sadness (using skin temperature) and between happiness, disgust, and surprise and anger, fear, and sadness (using heart rate). More recently, Levenson[10], Prkachin et al.[11], and Keil et al.[12] have made attempts to verify the somatovisceral manifestations associated with emotions aiming at detecting various affective states.

There has been a modest amount of computer science research into affective computing and the estimation of emotional episodes based on physiological signals. Picard et al.'s approach [13] to detect anger, hate, grief, platonic love, romantic love, joy, reverence and the neutral state was based on the utilization of statistical methods, namely Sequential Floating Forward Search (SFFS) and Fisher Projection (FP). Picard et al. employed various statistical features calculated from the respiration, skin conductance, blood volume pressure (BVP) and electromyogram measured from the masseter (a muscle in the jaw involved with chewing) of a single individual collected over a period of 20 days. Each day's acquisition session resulted in 2001 samples per emotion per signal. The total number of samples collected by Picard was 40020 for each of the eight targeted emotions. The statistical features with the closest characteristics were selected by means of SFFS and then presented to the FP for classification. Despite its high level of correct classification (83%), Picard et al.'s method was limited in the sense that statistical features were calculated over one-day periods and local temporal variations (minutes, hours) were not taken into account, making real-time detection difficult. Kim et al. [14] suggested the utilization of a support vector machine (SVM) classifier using a shorter signal monitoring time than the one utilised by Picard et al. Using three physiological signals to classify four emotions, Kim's method achieved 61.2% correct classification.

Nevertheless, the generalization of these results is questionable since the physiological data were collected from subjects whose ages ranged between five and eight years only. Nasoz et al. [15] conducted a study to detect various emotional states using three physiological measurements (skin galvanic response (GSR), skin temperature, and heart rate). Instead of using statistical features, Nasoz et al. employed normalised signals and provided them to two separate classification methods: k-nearest neighbour (KNN) and Discriminant Function Analysis (DFA). The best results were achieved with the DFA method: 90% correct classification for fear, 87.5% for sadness, 78.58% for anger, 56.25% for surprise and 50% for frustration. Nasoz et al.'s approach is suitable for real-time detection since it does not require the collection of entire data sets before providing a hypothesis of the emotion experienced by the user. However, this method lacks the adaptability found in pattern detection mechanisms such as Artificial Neural Networks ANNs. For example ANNs can be retrained on-line if necessary, they are less prone to be affected by noisy or corrupted inputs, and have been designed to be multivariable, thus making them more suitable to be employed in highly interactive real-world applications that involve sensors.

Other researchers have focused on detection of very specific emotions for practical purposes. For example, Healey et al. [16] detected user's mood using physiological and behavioural changes and then related those mood states to musical preferences. In another study, Healey [17] developed a model for detecting stress (while a subject drove an automobile) based on physiological signals and statistical methods. Ark et al. [18] implemented an adaptable computer environment based on physiological signals acquired though a computer mouse which include somatic activity (mouse movement), skin resistance, skin temperature, and heart rate. Fernandez [19] utilised somatovisceral arousal to detect frustration in computer users based on galvanic skin response (GSR) and blood volume pressure (BVP). Fernandez's approach employed statistical features in conjunction with Hidden Markov Models to identify the "frustration" that arises when humans interact with poorly interactive computer programs.

A novel mechanism for the real-time detection of emotional changes is proposed below based on the utilisation of Artificial Neural Networks (ANNs). The suggested mechanism is suitable to detect the bodily variations attributed to emotional episodes when a subject's neutral affective status is altered. Furthermore, it is argued that the characteristics of the methodology presented in this paper make it appropriate for implementation inside inhabited environments where real-time behaviour-based controls are employed.

## 3. Methods

### *3.1 Autoassociative Neural Networks*

Autoassociative Neural Networks (AANNs) are a special type of back-propagation neural network (BPNN) designed with a specific architecture; they are trained to learn the identity function, i.e., outputs should equal inputs [20]. A most important characteristic of AANNs is that even in the presence of several abnormal or corrupted inputs they are still able to provide estimations for both faulty and healthy inputs. As a consequence, AANNs have been successfully utilised to perform Sensor Failure Detection, Identification and Accommodation (SFDIA) [21].

In SFDIA, sensor readings are connected to the inputs of the AANN, and the output of the AANN produces estimated sensor values for each of its inputs. Failures are detected by calculating the error (residual henceforth) between each sensor value and its corresponding estimation [22]. Figure 1 illustrates the design of an AANN.

[Figure 1 goes here]

Another important attribute of AANNs is that they can be employed to perform noise filtering. Because input variations (due to sensor calibration, distortion, noise, etc.) are not correlated, AANN outputs, which are based on correlated data used for training, remain unchanged.

### *3.2 Sequential Probability Ratio Test (SPRT)*

AANNs are often utilised in conjunction with the Sequential Probability Ratio Test (SPRT) to establish the fault hypothesis in a SFDIA process. The SPRT has been shown to be an optimal classification method to determine whether a pattern class belongs to either of two categories, e.g., faulty or healthy. The SPRT's main advantage is that it requires a minimal number of measurements in order to draw its conclusion [23].

Based on the continuous evaluation of the targeted parameter, the SPRT calculation stops whenever the likelihood ratio increases beyond an upper limit or decreases beyond a lower threshold. Such boundaries are established based on the solution spaces related to two desired hypothesis. Considering that the measured parameter is a continuous function

*A(t)* that should be categorized according to two stochastic processes $A_1(t)$ and $A_2(t)$, both possessing a normal distribution with means $\mu_1$, $\mu_2$ and standard deviation $\sigma^2$, the calculation of the SPRT at stage *x* is:

$$LOG(SPRT)_x = \frac{(\mu_1 - \mu_2)}{\sigma^2} \sum_{x=1} \left[ A(t)_x - \frac{1}{2}(\mu_1 + \mu_2) \right]$$

and the decision boundaries are given by

If

$$LOG(SPRT) > LOG(e^{A_1}) \quad \text{then} \quad A(t) = A_1(t)$$

If

$$LOG(SPRT) < LOG(e^{A_2}) \quad \text{then} \quad A(t) = A_2(t)$$

Where $e^{A_1}$ and $e^{A_2}$ are the probability error of misclassifying *A(t)* into process $A_1$ and $A_2$ respectively.

**4. Detection of emotional changes**

*4.1 Data set description*

The task of pattern recognition in emotion detection requires physiological data that possess adequate characteristics if successful results are expected. Thus, instead of collecting new data, physiological information from the hitherto most successful emotion recognition experiment, i.e. Picard et al. [13], was employed [Jennifer Healey, Rosalind W. Picard (2002), Eight-emotion Sentics Data, MIT Affective Computing Group, http://affect.media.mit.edu]. Healey's data set comprised four physiological signals, namely, electromyogram (MYOGRAM) obtained from the masseter, blood volume pressure (BVP), skin conductance (SC) and respiration rate (RESP) collected from a single individual over a period of 20 days, resulting in 2001 samples per day per emotion.

*4.2 AANN architecture and training*

An AANN was trained to memorize the input mapping of the four physiological signals provided in Healey's data. Emotional changes would be detected by continuously analysing the residual between the actual input values and the estimations provided by an AANN trained to memorize *neutral* emotion data.

Training of the AANN was performed utilising the MATLAB implementation of the Levenberg-Marquardt algorithm in combination with Bayesian regularization [24] for enhanced generalization. Training data comprised 2001 samples obtained from a 20-point moving average of the total 40020 neutral-emotion samples originally provided by Healey et al. The purpose of using averaged data is to 1) smooth sensor signals, and 2) enhance MATLAB's performance while not compromising overall performance

In order to increase convergence speed, data provided to the AANN was scaled to fall in the range between 0 and 1. This is useful to reduce weight values and increase algorithm performance. The structure and architecture of the AANN employed for training is depicted in Figure 2 and Table 1.

[Figure 2 goes here]

[Table 1 goes here]

*4.3 Statistical Feature Selection*

Accurate detection of emotional status depends greatly on the appropriate evaluation of the input parameters and the calculated residual. Thus, a clustering index evaluation was performed to detect the signal attribute or attributes that would most contribute to the optimal separation of the neutral and non-neutral emotional states. This needs to be done a priori to ensure that only the features with the best potential class separation are used.

The instantaneous Davies-Bouldin cluster separation Index (DBI) was calculated for the 15 combinations of data involving the four AANN inputs. Instantaneous estimation of DBI implies the utilization of individual attribute values instead of statistical features obtained from the whole data set or a multi-frame data segment. The entirety of the physiological data, 320160 samples, (2001 per day per emotion) was split into two groups. Group 1 contained data related to a neutral emotional state whereas group 2 included the information concerning the remaining emotions (i.e., anger, grief, hate, joy, platonic love, romantic love and reverence).

It is worth mentioning that the DBI has been successfully utilised in studies that involve pattern recognition of physiological signals (e.g., [25]). Lower DBI indexes reflect a better class separation.

Results from our a priori analysis showed that the attribute with the lowest DBI was that of the electromyogram, with a value of 7.57. This value was better than for other attributes used either individually or in combination. Thus, the electromyogram parameters were used as main features subsequently.

*4.4 Decision Module*

With the intention of determining whether a given set of physiological measurements belongs to a neutral or a non-neutral emotional estate, we provided a SPRT-based decision module with the residual between the actual electromyogram value and the value estimated by AANN for each of the data samples (see Figure 3). Since the AANN was trained to mimic the input behaviour, the mean of the residual should be very close to zero with a standard deviation similar to that of the noise introduced by the sensing device. When the electromyogram value drifts because of a change in the physiological status of the subject, the mean value of the residual deviates from zero. The SPRT value is then altered and the likelihood ratio is displaced to either of the two solution spaces. It is worth mentioning that even though MYOGRAM is the only measurement employed by the decision module, the relationship with the other three parameters is needed for projecting the targeted variable into the AANN estimation model.

[Figure 3 goes here]

**5. Results and Discussion**

The experimental embodiment of the proposed method was tested using Healey's data for the seven non-neutral emotional states. The neutral data was scaled to fall between a range from 0 to 1 using the minimal and maximal values of the whole set of neutral information. Data was provided to the AANN in a manner that resembled real-time data acquisition, i.e., data from the neutral states was not subjected to any previous filtering nor statistical pre-processing and was sampled at the original rate utilised during data acquisition (20hz). It is worth noting that the utilization of averaged neutral data during AANN training is just a manner of improving learning convergence speed by removing data outliers and does not affect the estimation properties of the AANN. In fact the operation of the AANN inherently involves a filtering process which does not have any adverse effect on the overall input mapping and actually improves the separation of the memorized and un-memorized data.

There are two major outcomes from the above experiments. On the one hand, it was found that, based on the available information, the electromyogram (EMG) was the physiological measure with the most significant properties to participate in emotional pattern recognition when two emotional states are involved. The EMG gave better class separation on its own than the other attributes alone or in combinations (which included EMG as well) (see Table 2 for a summary of the results). However, it has to be said that Healey's experimental data was obtained from a longitudinal (single subject) study and generalization of these results should thus be avoided.

[Table 2 goes here]

On the other hand, it was concluded that the likelihood ratio provided by the SPRT module was sufficient to detect variations in physiological signals provoked by emotional episodes. Table 3 shows the accuracy provided by the SPRT module when detecting variations in physiological signals provoked by emotional episodes. Non-neutral emotional states were accurately detected in the entirety of cases using just a few data samples. Table 3 also depicts the number of data samples involved in the SPRT calculations in order for the decision module to establish a solution hypothesis. For example, in the case of the anger state days 1 and 5, the SPRT value moved beyond the non-emotional threshold once 6 and 8 data samples were provided. In the same manner the likelihood ratio had to be estimated using 575 data samples before the decision module had enough information to establish a verdict for the reverence state in day 7.

[Table 3 goes here]

The discrepancy in the number of samples employed by the SPRT to detect emotional changes could be attributed to the fact that Healey's data lacked markers indicating when emotional episodes actually start or finish during data acquisition. As a consequence, the number of data samples required before a noticeable physiological change was identified was variable. However the AANN memorized the information of the neutral state accurately and responded to data from the non-neutral states immediately.

## 6. Conclusions

It was demonstrated that the utilization of clustering analysis (in particular the calculation of the Davies-Bouldin Index) is a valuable mechanism to provide a better insight into the intrinsic characteristics of data employed in pattern detection. Using combinations of four physiological signals, it was found that the electromyogram contributed to the best cluster separation when neutral and non-neutral states are involved.

It has also been shown that the SPRT provides an optimal mechanism to distinguish between two possible pattern classes when it is employed in combination with an Autoassociative Neural Network (AANN). Due to its memorizing properties, input variations attributed to emotional changes were accurately detected by an AANN trained with data from a neutral emotional state. It is suggested that because of the properties of Artificial Neural Networks (ANNs) to resist input perturbations caused by sensor malfunctioning or distortion, and because similar approaches have been employed in on-line validation mechanisms, the proposed methodology could be employed in real-time decision making systems.

**7. Future Work**

Although the detection of changes in the emotional status of a given subject provides valuable information per se, it is desirable to fully exploit the intrinsic value of bodily signals and obtain detailed information about the emotional episodes experienced by a given subject. In that respect, estimations from an AANN similar to the one presented in this paper could be employed to classify emotional states based on their dimensional characteristics, i.e., intensity (high or low arousal), similarity (similar or dissimilar), and polarity (positive or negative) employing SPRT-based decision modules.

As a part of ongoing research from the Intelligent Inhabited Environment Group at the University of Essex, investigating the hypothesis that the detection and classification of emotions will provide valuable information about the behaviour of a subject in a domestic environment. It is hoped that by combining emotional information with ambient conditions and existing habits, a computer agent would be able to establish affective-behaviour relationships and be able to utilise such information to appropriately customise the ambience inside an inhabited environment. However, the operation of a real-time system inside inhabited environments demands high reliability, ubiquity and adaptability. Therefore the implementation of the emotion detection method described above entails an analysis of the degree to which neutral emotional information is shared among potential users and whether a user-dependant approach would be the most appropriate agent mechanism.

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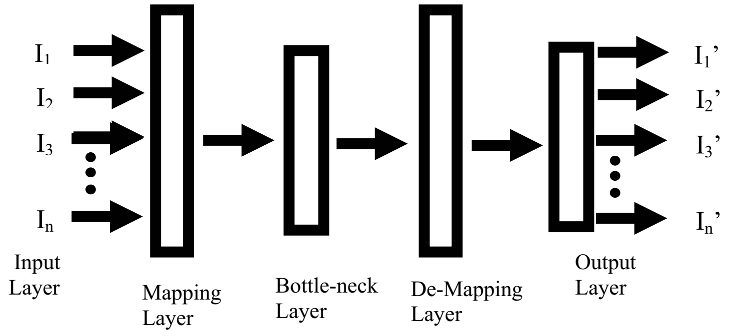


*Figure 1. Architecture of an autoassociative neural network (After [22]).*

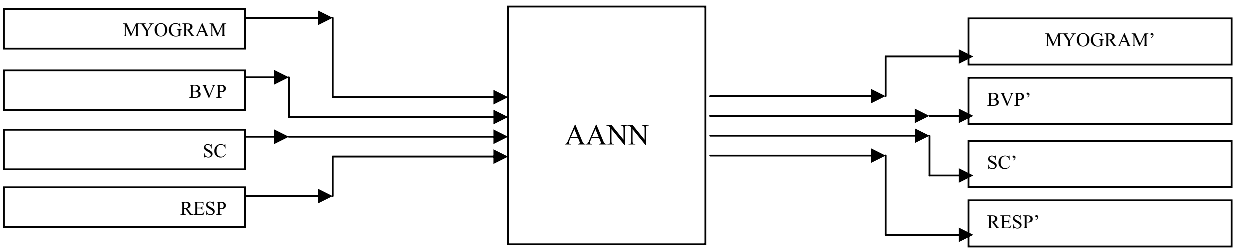


*Figure 2. Training of the AANN employed to detect emotional changes.*

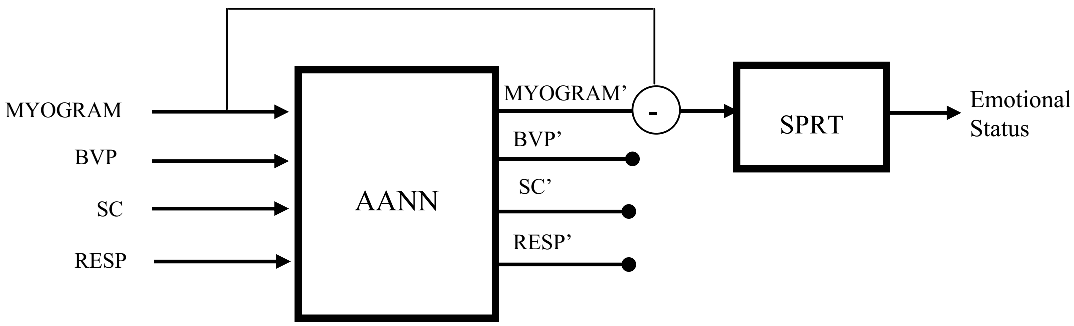


*Figure 3. AANN estimations are compared to actual electromyogram values and the difference between the two (i.e., the residual) was utilised to detect emotional changes.*

| **Layer** | **Number of Neurons** | **Transfer functions** |
|---|---|---|
| Input | 12 | Linear |
| Mapping | 18 | Logarithmic sigmoidal |
| Bottle-neck | 4 | Logarithmic sigmoidal |
| De-mapping | 18 | Logarithmic sigmoidal |
| Output | 12 | Linear |

*Table 1. Characteristics of the AANN for emotion detection.*

| Attribute combination | DBI 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 2. DBI Indexes for the total number of attribute combinations.*

| | Number of samples before detection | | | | | | |
|---|---|---|---|---|---|---|---|
| | Anger | Grief | Hate | Joy | Love | Platonic | Reverence |
| Day | | | | | | | |
| 1 | **6** | **2** | **1** | **4** | **12** | **3** | **1** |
| 2 | **1** | **2** | **12** | **1** | **1** | **2** | **10** |
| 3 | **1** | **1** | **3** | **1** | **6** | **11** | **9** |
| 4 | **3** | **2** | **2** | **5** | **3** | **5** | **5** |
| 5 | **8** | **2** | **2** | **2** | **7** | **3** | **6** |
| 6 | **3** | **8** | **2** | **4** | **1** | **3** | **81** |
| 7 | **3** | **2** | **2** | **29** | **6** | **18** | **575** |
| 8 | **1** | **4** | **1** | **1** | **5** | **7** | **10** |
| 9 | **5** | **2** | **5** | **9** | **1** | **1** | **1** |
| 10 | **1** | **1** | **1** | **2** | **2** | **1** | **1** |
| 11 | **2** | **1** | **3** | **11** | **8** | **6** | **1** |
| 12 | **1** | **1** | **1** | **1** | **1** | **1** | **1** |
| 13 | **1** | **1** | **1** | **5** | **1** | **14** | **1** |
| 14 | **12** | **2** | **14** | **1** | **1** | **3** | **1** |
| 15 | **1** | **5** | **2** | **8** | **13** | **8** | **5** |
| 16 | **1** | **4** | **9** | **1** | **4** | **2** | **1** |
| 17 | **2** | **1** | **1** | **14** | **3** | **1** | **1** |
| 18 | **3** | **2** | **10** | **11** | **10** | **1** | **1** |
| 19 | **9** | **1** | **1** | **1** | **5** | **1** | **4** |
| 20 | **1** | **3** | **10** | **3** | **1** | **5** | **1** |
| Detection rate | **100%** | **100%** | **100%** | **100%** | **100%** | **100%** | **100%** |

*Table 3 . Number of data samples analysed by the decision module before detecting changes in emotional status.*