A Preliminary System for the Automatic Detection of Emotions based on the Autonomic Nervous System Response

Asier Salazar-Ramirez[1], Raquel Martinez[1], Andoni Arruti[1], Eloy Irigoyen[2], J. Ignacio Martin[1] and Javier Muguerza[1]

[1]*Dept. of Computer Architecture and Technology, University of the Basque Country (UPV/EHU), Donostia-San Sebastián, Spain*

[2]*Dept. of Automatic Control and Systems Engineering, University of the Basque Country (UPV/EHU), Bilbao, Spain*

Keywords: Emotion, Film Clip, ECG, GSR, Finite State Machine.

Abstract: People's life quality is being improved thanks to the advances in medicine and to the promotion of health. One of the pillars for having a healthy life is to know and to take care of the emotions of oneself. Due to the close relationship between the emotions and the responses of the autonomic nervous system, the aim of this work is to study and detect the physiological patterns produced by two of the basic human emotions: surprise and contentment. The work presents a preliminary system that processes and analyzes two non-invasive physiological signals (the galvanic skin response and the heart rate variability) and that uses a finite state machine for the detection of the activation of the sympathetic nervous system. The work also presents the experimental procedure that was designed in order to elicit different emotions in laboratory conditions. The F-score results obtained for the correlation of the analyzed emotions and the physiological patterns were F_1=1.00 and for surprise and F_1=0.94 for contentment.

1 INTRODUCTION

Nowadays, there is an increasing concern among informatics engineering research groups about applying technical knowledge to systems that allow the improvement of people's life quality. Besides, there are medical groups that look for technological solutions in order to improve the diagnostical processes through the automatic detection of certain pathologies that currently are only detected empirically. In addition, entities from the social spheres request the development of tools that help people with autonomy problems recover their independence, as due to any kind of disability they might be in danger of social exclusion. Therefore, the ensemble of these three disciplines converges in a common objective that is to help people that suffer from any kind of disease or disability.

Being able to detect automatically certain psycho-physiological patterns permits to improve human-computer interaction (Soegaard and Dam, 2013). Moreover, detecting these patterns can also be useful for helping understand how people suffering from autism or brain paralysis feel, if something pleases them or if they are suffering any kind of pain, among other things ((Rice et al., 2015),(Johnson and Picard, 2017),(Giusiano et al., 1995),(Carcreff et al., 2018)).

The affective computing is the discipline that studies and develops systems and devices in order to recognize, interpret, process and stimulate human emotions (Picard, 2010). Within its fields of study, a relevant subject consists on identifying how people react emotionally when facing certain specific events. The intention of identifying these reactions is to help the previously mentioned collectives to improve their communication with the environment, their personal autonomy and their life quality. When an individual lives any positive or negative situation his organism produces a psycho-physiological response that produces subsequently an emotion ((Cannon, 1935),(Schachter and Singer, 1962),(Kreibig, 2010)). Due to this reaction, monitoring the physiological variables of the body is one of the methods that enable the detection of these emotional changes.

When facing any stimuli, the physiological response of the body is controlled by the Central Nervous System and the coordination that this system applies between the Autonomic Nervous System (ANS), the Endocrine System, the Immunologic System... The ANS, through its two components,

Salazar-Ramirez, A., Martinez, R., Arruti, A., Irigoyen, E., Martin, J. and Muguerza, J.
A Preliminary System for the Automatic Detection of Emotions based on the Autonomic Nervous System Response.
DOI: 10.5220/0006900600460052
In *Proceedings of the 6th International Congress on Neurotechnology, Electronics and Informatics (NEUROTECHNIX 2018)*, pages 46-52
ISBN: 978-989-758-326-1

which are the Sympathetic Nervous System (SNS) and the Parasympathetic Nervous System (PNS), is the system responsible of balancing the organism. The "fight or flight" theory ((Cannon, 1935), (Porges, 2001)) poses that the peripheral physiological signals that are regulated by the SNS are the ones that provide information on the arousal or activation of the brain. On the other hand, the PNS is related to the relaxation of the body as mention (Cacioppo et al., 2007), (Pérez-Lloret et al., 2014) and (Benedek and Kaernbach, 2010). The peripheral physiological signals that are regulated by the ANS are various: the cardiac rhythm, the respiration, the sweating, the corporal temperature, the diameter of the eye pupils, the brain activation, etc.

In order to further study the relationship between emotions and the physiological signals, the research team designed an experiment where, in laboratory conditions, seven of the basic emotions were induced in the participants while their physiological signals were being collected. The chosen eliciting stimulus was the visualization of video clips. The physiological signals that were acquired were the cardiac activity and the sweating as they can be registered by non-invasive means. Nevertheless, despite seven emotions were induced during the experiment, only two of them were taken to the study presented in this article as they are the ones that have the clearest relationship with the SNS: surprise and contentment.

Finally, after the experimental part was finished and the physiological signal database had been registered, the research group used the finite state machine (FSM) developed in (Martinez et al., 2017) to detect, classify and rate the activation of the SNS.

This work presents the study of the physiological patterns of the SNS that are related to the emotions of surprise and contentment. In order to do so, an experiment was done where some of the biosignals of the participants were collected while emotions were being induced on them by means of projecting video clips. Later, those biosignals would be analyzed by the FSM in order to detect the reactions on the SNS of the two mentioned emotions.

2 MATERIALS AND METHOD

In order to study the relationship between emotions and the physiological changes, the research team designed an experiment for inducing certain emotional states in the participants sitting it. During the experiment the electrocardiogram (ECG) and the sweating of the participants, also called galvanic skin response (GSR), were collected. The stimulus chosen to elicit those emotions was the visualization of video clips, which is a method validated in several research works ((Gross and Levenson, 1995),(Martinez et al., 2009),(Gilman et al., 2017)).

2.1 Participants

A total of 32 subjects, aged between 21 and 35 (mean=26 y SD =3.1), participated voluntarily in the experiment (7 male and 25 female). All the participants were students or workers of the university.

2.2 Materials

The set of video clips that were used to elicit the emotions in the laboratory was an adaptation to the Spanish population (Martinez et al., 2009) of the audiovisual database published by (Gross and Levenson, 1995). The adaptation consists on using the database of (Gross and Levenson, 1995) updating it with more recent video clips and adding clips showing real life stories and situations, being all of them adapted to the Spanish culture. The new audiovisual database, validated in different Spanish cities, proposes the use of 20 films that can be used to induce the following seven basic emotions: contentment, amusement, disgust, fear, surprise, sadness and anger.

Specifically, the database contained three clips for each emotion but for contentment, that had only two: for amusement, "When Sally met Harry", "Bote" and "Concejal"; for anger, "Cry Freedom", "El bola" and "Te doy mis ojos"; for fear, "Shining", "The Ring" and "The Ring 2"; for sadness, "Champ", "Omayra" and "Nasija"; for surprise, "Capricorn one", "La monja" and "El orfanato"; for disgust, "Autopsy", "Pink Flamingos", "Hostel"; and finally, for contentment, "Dolphin", and "BBC". The films have last between 32 and 214 seconds (M=256, SD=71).

2.3 Assessment Instruments

The assessment of the emotional responses of the participants was done by collecting their impressions through two questionnaires already validated by the psychological community in the existing literature. The first questionnaire, designed by (Gross and Levenson, 1995), is the Post film Questionnaire (PFQ). This survey is used to assess the capacity of each clip for eliciting each of the emotions. In addition, the PFQ also collects information on whether the subjects had previously seen the clip or not. The second questionnaire is the Self-Assessment Manikin and it is used to assess the emotions from a dimensional point of view or paradigm (Lang, 1980).

2.4 Procedure

All the sessions of the experiment took place in the audiovisual projection room of the university, assessing the emotional responses and collecting the physiological signals to be studied from two participants per sessions. Prior to starting the test the participants received an explanation on the objective and the procedure of the experiment, the documentation they had to fulfill, the questionnaires and the physiological signals that were going to be collected. In addition, the participants were explained that the experiment had passed all the requirements of the ethical committee of the university and that all their privacy rights were preserved and that all the laws related to these experimental procedures were being respected.

Despite being 20 clips, not all of them were used in every experiment; the clips were divided in 6 different projection sets, using 5 of clips in each of those sets. At the beginning of all the projections a welcome message was displayed on the screen (15 seconds). After the welcome video the same sequence was repeated five times, being this sequence composed of a neutral video (60 seconds), the emotion eliciting clip and a message asking the participants to fulfill the corresponding questionnaires in paper format (80 seconds). The sequence followed in the experiment is shown graphically in Figure 1.

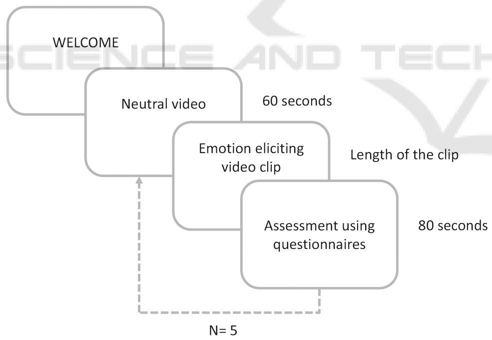

Figure 1: Temporal sequence of the projections of the clips during the experiment.

The data acquisition system used to collect the physiological signal was the BIOPAC MP150. The sweating was measured through the galvanic skin response (GSR) and SS3LA gel electrodes were used on the participants non-dominant hand to collect the signal. In addition, the cardiac activity was studied by analyzing the electrocardiogram (ECG) and to collect it the three terminals of the SS2LB electrodes were placed on the chest of the participants.

2.5 Psycho-physiological Analysis

The design of the experiment was to aiming to elicit anger, sadness, contentment, fear, surprise, amusement and disgust. Due to the complexity of identifying certain emotions from the physiological signals, this work has only studied those emotions that present a clear and specific physiological pattern, which are: contentment, related to the sympathetic inhibition states, and surprise, related to activation states.

The physiological patterns associated to the activation of the SNS correspond to the acceleration of the cardiac rhythm and to an increase of the sweating. On the other hand, those changes related to its inhibition are the relaxation of the cardiac rhythm and the decrease if the sweating.

As previously mentioned, the signals collected during the experimentation were the ECG and GSR. Anyway, as the only indicator of heart activity to be used was the cardiac rhythm, during the phase of analysis the researchers decided to use the Heart Rate Variability (HRV) instead of using the ECG itself. The HRV is the signal that provides information of the time changes between each heartbeat of the ECG (Thayer et al., 2010). Thus, when the cardiac activity accelerates the time between heartbeats decreases and so does the HRV. On the contrary, if the heart beats relaxed then the time intervals between heartbeats get greater and it produces bigger HRV values.

On the one hand, Figure 2 depicts the evolution of the physiological variables when, during the projection of one of the clips, a participant in the experiment gets eventually shocked (marked with SS). On the other hand, Figure 3 shows how the physiological variables tend to relax during the projection of a clip corresponding to contentment.

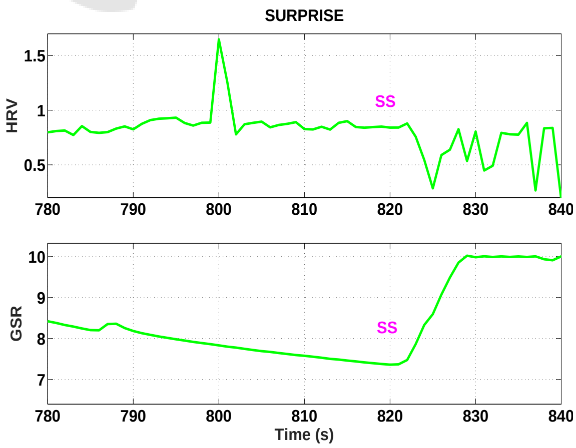

Figure 2: Physiological signals for surprise.

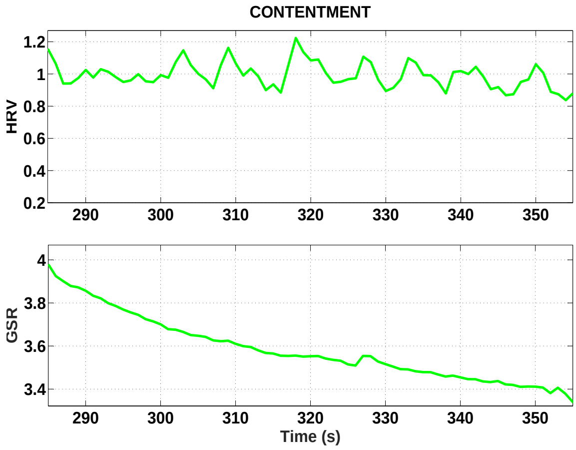

Figure 3: Physiological signals for contentment.

Analyzing Figure 2 it can be seen that there is an increase in the GSR and a big decrease in HRV in the moment of the shock happens. Looking at Figure 3 it can be seen that the reaction to the contentment clips is opposite to what happened in Figure 2, there is a clear decrease of the GSR and the cardiac rhythm remains stable.

2.6 Automatic Detection of the Emotional States

The identification of emotions by the automatic detection of physiological change patterns was done using the system designed by (Martinez et al., 2017). The detection system is a finite state machine (FSM) that detects, rates and classifies the arousal of the SNS. When the FSM detects a SNS arousal it rates it depending on its intensity: Low Alert, Medium Alert, High Alert. In addition, if the activation lasts for longer than 3 iterations, then the system changes its classification from alert to stress: Low Stress, Medium Stress or High Stress. Therefore, the output of the FSM can vary within seven states, one for the absence of arousal and six for activation states. The numerical outputs of the FSM for the classified states labels are the following: 0= No Arousal, 1=Low Alert, 2=Low Stress, 3=Medium Alert, 4=Medium Stress, 5=High Alert and 6=High Stress.

In order to analyze the signal throughout the whole experiment the researchers chose a sliding window approach where the window had a width of 20 seconds and slided using 5 second steps. The characteristics of the physiological signals that were used as inputs for the FSM were the slopes of both GSR and HRV signals, the multiplication of the two slopes between them and the amount of consecutive windows computed by the machine for the detected state.

Despite the FSM is further explained by (Martinez et al., 2017), Figure 4 provides a graphic explanation on how it works. Each of the circles of Figure 4 stand for one of the seven classified levels of stress, being 0 the default state. If the subject eventually suffers a SNS arousal, then a transition condition is triggered and it makes the FSM change its state. For instance, if the activation was not very intense, Activation Response 1 (AR1) would trigger taking the FSM from state 0 to state 1 (Low Alert). In the same way, if the activations were medium or high then AR2 and AR3 would trigger and the states would change to state 3 and 5 respectively.

Once one of the alarm states has been reached, the FSM starts checking whether the values of physiological signals are maintained for the following iterations: (S_AR condition). On the one hand, if S_AR is not fulfilled then the machine goes back to its default 0 state. On the other hand, if after three window sliding iterations (n=3, i.e., 15 seconds) S_AR is still true, then n=3 condition is triggered and the FSM changes its output from alarm state 1, 3 or 5 to the corresponding stress state 2, 4 or 6 respectively. After that happened, in the next iteration the machine would go back to the default 0 state and would wait there until a new activation happened. Anyway, if the machine was in an alarm or stress state and an activation of greater intensity took place, then the machine would move from the current state to a higher intensity alarm state. For example, if the current state was 1 or 2 and AR2 happened, then the FSM would change to state 3.

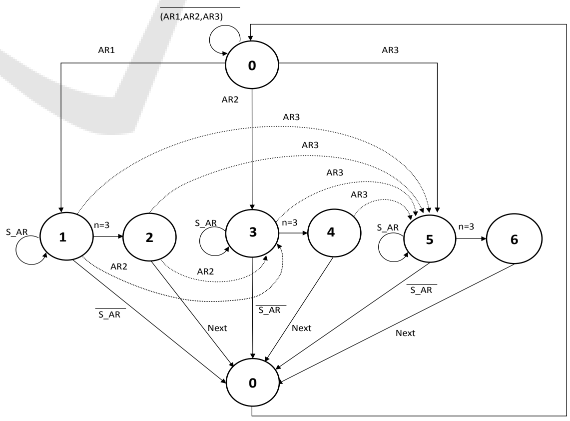

Figure 4: State transition diagram of the FSM.

3 RESULTS

This section presents the results obtained from the use of the FSM on the physiological signals collected in the experiments as inputs. As previously mentioned, the emotions that were studied were surprise and contentment. For the clips targeting surprise, in the instant of the shock, the physiological signals should experiment an increase of the sweating and a decrease of the HRV, being them correlated to a medium-high level of arousal. The adaptive function of the surprise is to warn the body that something not expected is taking place. Because of that, it is the shortest of all the emotions and it is immediately followed by the emotion produced after the assimilation of what is happening in the new event (Verduyn and Lavrijsen, 2015) . As it is a short emotion that does not necessarily remain during the time, the output of the FSM for this emotion can be either alert or stress depending on its duration. On the other hand, when the subject visualizes the clip for contentment tends to relax and there is no SNS activation. Thus, looking to the physiological signals, the GSR decreases and the HRV remains at the same values or increases. This reaction gives evidence that there is no sympathetic activation, hence the output of the FSM is equal 0.

Figure 5 and Figure 6 illustrate both the physiological signals of a participant of the experiment and the output of the FSM for the signals collected in the projections. In the case of Figure 5 the signals depicted correspond to surprise. On the other hand, Figure 6 depicts those signals collected during the clip for contentment.

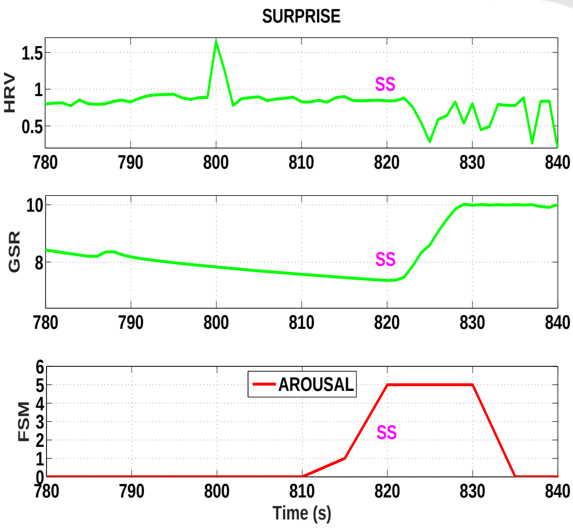

Figure 5: The physiological signals and the output of the FSM during the clip of surprise.

In order to determine the degree of success of the detection system, the researchers have analyzed the outputs of the detection system during the projections of the clips targeting surprise and contentment. For surprise, it is considered as a positive result if in the moment of the shocking images the system's output was 3, 4, 5 or 6 corresponding to Medium Alert, Medium Stress, High Alert or High Stress respectively. Consequently, a positive result for contentment would be when the system gives an output of no activation, i.e., the output equals 0.

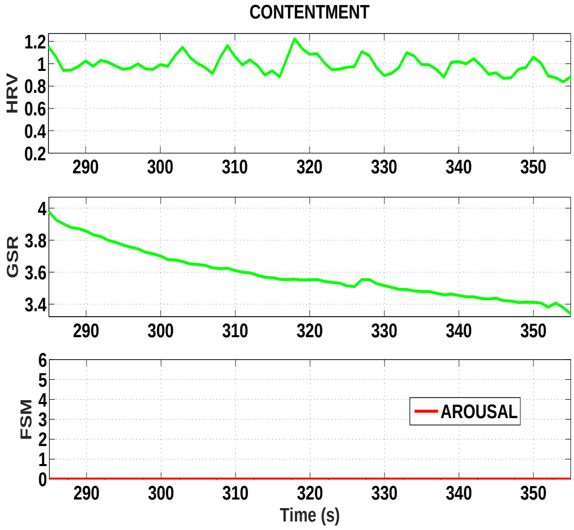

Figure 6: The physiological signals and the output of the FSM during the clip of contentment.

Table 1 shows the results that have been obtained in the research. The columns reflect the results obtained in the following way: Manual Label stands for the amount of clips labeled by the researchers for each emotion; True Positive (TP) stands for the states correctly detected by the FSM; False Negative (FN) stands for the cases in which the algorithm should have detected a state but did not do it; False Positive (FP) represents the cases where the algorithm has detected certain states without them being previously labeled for that state. The performance of the system has been estimated using Precision (P), Recall (R) and the F-Score (F_1), whose calculation formulas are presented in equations (1), (2) and (3) respectively. The best possible score for these indicators is 1 and the worst is 0.

$$P = \frac{TP}{TP+FP} \tag{1}$$

$$R = \frac{TP}{TP+FN} \tag{2}$$

$$F_1 = \frac{2 \cdot P \cdot R}{P+R} \tag{3}$$

Table 1: Statistical results of the automatic detection.

Emotion	Manual Label	FSM					
		TP	FN	FP	Precision	Recall	F_1
Contentment	19	17	2	0	1.00	0.89	0.94
Surprise	9	9	0	0	1.00	1.00	1.00

As shown in Table 1, the results for surprise achieved a Precision of 1.00, a Recall of 1.00 and a F_1 score of 1.00. For contentment the results obtained were 1.00 for Precision, 0.89 for the Recall value and 0.94 for the F_1. Therefore, considering the performance rates obtained by the algorithm, it can be said that the combination of the chosen signal characteristics and the FSM results in a valid system for detecting the emotional states of surprise and contentment.

Anyway, it is not a trivial issue to recognize and to classify an specific emotion. Due to this reason several authors prefer to classify grouped by clusters. For example, (Canento et al., 2011) achieved 80%, 70% and 70% success rates using the leave one out cross validation methodology with a k-NN classifier in order to distinguish between positive and negative, positive and neutral and neutral and negative emotions respectively. Other authors prefer to classify emotions in a dimensional manner paying attention to valence and arousal. This is the case of (Kim and Andr, 2008) who presented a novel scheme of emotion specific multilevel dichotomous classification that achieved success rates of 95% and 70% for subject-dependent and subject-independent emotion classification respectively. Finally, (Soleymani et al., 2015) presented an specific emotion classification distinguishing between fear, sadness, frustration, happiness, please and satisfaction. The classification was done using an artificial neural network and due to the complexity of the classification the network achieved an accuracy of 55.8%.

Thus, it seems clear that the success rates decrease quickly as the classification gets more emotion-specific. The FSM presented in this work has only been used to classify between two specific emotions and so, despite it has been proved to be effective for this certain problem, it would be recommendable to expand the study to other emotions and see how it performs as the classification gets more complex.

4 CONCLUSIONS

The aim of this work was to study the response of the SNS during the elicitation of emotions through the interpretation of physiological signals. Specifically, two of the seven basic emotions have been taken to analysis, surprise and contentment for being directly related to ANS activation and inhibition respectively. The research team developed an experiment to induce the studied emotions in laboratory conditions while, at the same time, the sweating and the cardiac activity of the subjects was collected. The stimulus chosen to elicit the emotions was the visualization of audiovisual clips. The chosen clips elicited both contentment and surprise to the participants. Anyway, the clips only elicited surprise as long as the subjects had not previously seen the clip, as pointed by (Martinez et al., 2009).

The physiological signals collected during the experiment were used as inputs of an algorithm that detects and classifies the activation of the SNS. The signals confirmed that the SNS got active when the participants were surprised by the clip and as a consequence the output of the FSM gave values of medium or high alert or stress. When the subjects felt that the abnormal or hazardous sensation was over the activation of the SNS stopped, giving confirmation to what posed by (Schachter and Singer, 1962) . On the contrary, during the visualization of the clips of contentment the physiological signals responded according to the pattern of inhibition of the ANS (Cacioppo et al., 2007) and, because of it, the output of the FSM was 0 which corresponds to the ANS not being active.

The results obtained from the performance analysis (F-score) of the FSM were F_1=1.00 and F_1=0.94 for surprise and contentment respectively, and so the algorithm gets validated as a useful tool for the study of the activation of the SNS.

As a future approach the researchers propose the study of other emotions in order to see their relationship with the ANS. To do so, it would be necessary to expand the amount of used physiological signals, including to the study signals as the respiration, the photoplethysmography or the encephalography.

ACKNOWLEDGEMENTS

This work was partially supported by the Department of Education, Universities and Research of the Basque Government under Grant IT980-16 and by the Ministry of Economy and Competitiveness of the Spanish Government and the European Regional Development fund- ERFD (PhysComp project, TIN2017-85409-P).

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