# A Preliminary Analysis of the Physiological Response Generated by Negative Thoughts

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***Abstract*—Positive and negative emotions have a great impact on the human organism. The main purpose of this work is to analyze the physiological effects of negative thoughts using affective computing techniques. With this aim, we carried out an experiment in which participants had to recall past negative experiences while their physiological signals were being collected. Then, using two algorithms based on biosignal analysis, we assessed their levels of stress and relaxation at each time. According to the results, 100% of the participants who had negative thoughts produced a physiological stress response. This is promising, since it could enable affective computing based systems to adapt to the emotional state of the users through the real-time monitoring of the physiological signals of the human body.**

***Keywords–Affective computing; Emotions; ECG; GSR; Negative thoughts.***

## I. INTRODUCTION

Feeling emotions, either positive or negative, is common in every human being. Nowadays, one of the most demanded skills in different social and/or labor environments [1] is knowing how to control emotions and thoughts generated as a reaction to particular situations. Affective computing provides useful tools for emotion recognition by developing algorithms and devices that can interpret human emotions [2].

We ourselves create our emotions, based on the interpretation we have of the information we receive [3] [4]. In our everyday life, we tend to generate thoughts, emotions and actions unconsciously [5]. Controlling and educating our thoughts is of paramount importance in order to have increasingly positive emotions and consequently, behaviors and actions that provide a greater well-being to our lives. In contrast, negative thoughts cause negative and frustrating emotions and actions. Because the physiological response of our organism is in sync with our thoughts, stressful thoughts or painful memories increase the cortisol, lower the defenses, deteriorate the physiology of the arteries, activate the nervous system, and accelerate the heart rate [6] [7].

To this regard, affective computing provides methods that recognize human emotions and help to identify what everyone is feeling and living [8]. This paper aims to analyze the effects of negative thoughts in the physiological response, more precisely, in those relating to the heart and sweat. To do so, Section II explains the experimental design used for collecting a physiological signal database related to stressful memories. Section II also presents the collected biosignals, as well as the studied population. Then, the analysis of the database is covered in Section III, providing explanations of the results obtained from the application of two affective computing algorithms. Finally, the conclusions and future lines of the work are presented in Section IV.

## II. METHODOLOGY

In this section, we describe the methodology of experimentation used to obtain the psychological database analyzed. This procedure has been certified by the corresponding ethical committee CEISH-UPV/EHU, BOPV 32 (M10_2016_189).

### A. *Experimental setup*

In order to analyze the physiological response to negative thoughts, we have designed an experiment where participants had to recall a problematic or stressful situation from the past using visualization techniques, while their electrodermal and heart activities were being captured. Several researches have shown that visualization techniques bring the imagination closer to the reality [9] [10].

The experiment had several stages and was conducted individually for each participant (see Fig. 1). In the first stage, we ensured the participants were comfortable in their position, described to them the experimental procedure and gave them a consent form to sign. Then, we connected the sensors to the participants and provided some time so that they could choose a stressful situation to use during the experiment.

In the second stage, at the start off of the experiment, the participants watched a relaxing video with the lights off. Thereon, we asked the users to close their eyes and let themselves be guided by the words of the experimenter while listening to quiet music in the background. In this first part of the visualization, the participants were induced into a deeper level of relaxation, and once they reached this state, they were asked to bring back the previously chosen stressful situation. Finally, using neurolinguistic programming techniques, the subjects were guided to solve that conflict [11]. Once the visualization was completed, a new relaxing

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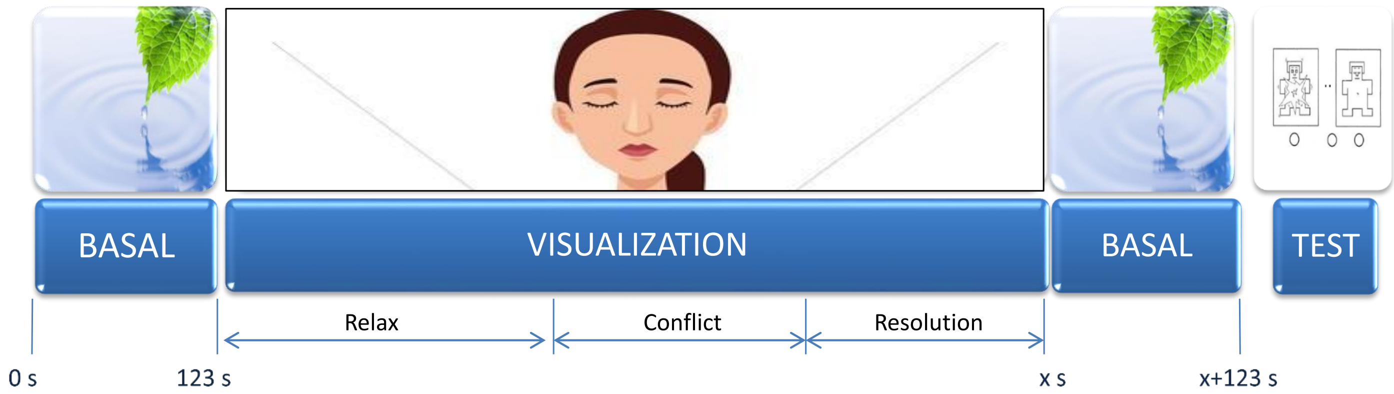


Figure 1. Stages of the experiment carried out.

video was projected to bring the participants back to a basal emotional situation.

The last stage of the experiment ended with the emotional evaluation using the Self-Assessment Manikin questionnaire [12] and a personal interview. Regarding the stages of the experiment represented in Fig. 1, it should be noted that although users had similar visualization duration records, these were not equal, since they were adapted to the participant's non-verbal communication at each moment.

Fourteen volunteer students from the Faculty of Engineering in Bilbao of the University of the Basque Country (UPV/EHU) were recruited for the experiment. However, due to technical problems, one of the participants was removed from the study. Thus, a total of 13 participants (9 males and 4 females), 19-22 years old (mean=20.30, standard deviation=0.94) were taken into account for the analysis.

### *B. Biosignals and data acquisition system*

This work is based on the study of two particular biosignals, the Heart Rate Variability (HRV) and the Galvanic Skin Response (GSR). The HRV is a signal derived from the electrocardiogram (ECG) and it is representative of the heart's activity. This signal provides information of the variation in time of the heartbeat, with high variability indicating a healthy heart. On the other hand, the GSR signal is representative of the conductive capacity of the skin's surface. This signal has been widely used in the area of electrophysiology, since besides providing information on the body's thermoregulatory activity, its variations are indicative of different psychological phenomena: nerves, surprise, anxiety, etc.

Regarding the regulation of the signals mentioned in the previous paragraph, this is managed by the autonomous nervous system and most of these regulatory functions take place in the hypothalamus. In turn, the hypothalamus is strongly connected with the amygdala, that is the part of the brain responsible for, among other functions, the emotional responses. Considering this connection, it is not surprising that emotional changes produce changes in the physiological balance of the organism, with the HRV and GSR signals being affected, among others, hence the reason we selected them for this study.

Concerning the materials used in the experiment, the capture of the aforementioned signals was done using the commercial hardware Biopac MP36 and its associated software Studentlab, which are considered a reference experimental equipment for gathering physiological signals. The acquisition was configured at a sampling frequency of 1000 Hz and was performed with the corresponding electrodes to collect the ECG and GSR signals. In addition, the room in which the experiment took place was equipped with a PC to store the signals and with the audiovisual material necessary to project the two relaxing videos (projector, screen and speakers).

## III. Results and Analysis

After collecting the aforementioned physiological signals, the next step of this study was to analyze the participants' physiological reactions to the experiment. Different algorithms can be used depending on what the study looks for. For instance, for continuous online analysis, some researchers have used algorithms such as fuzzy logic [13], support vector machines [14] or artificial neural networks [15] to compute physiological signals. However, in this case, the target of the experiment was to analyse whether the participants' negative memories had an impact on their physiology. Therefore, the results belong to the discrete domain, and thus, for the sake of continuity, we decided to use two algorithms previously developed by the research team, which assess both stress and relaxation in a discrete manner: algorithm 1 [16] and algorithm 2 [17], respectively, named ALG 1 and ALG 2 hereinafter.

ALG 1 was designed for detecting arousal of the Autonomic Nervous System (ANS) caused by a stressful experience. The output of ALG 1 varies discretely from 0 to 6 according to the intensity and duration of the arousal, output 0 meaning that there is no stressful arousal. Then, output levels 1, 3 and 5, respectively, correspond to the detection of a short-duration arousing alert of low, medium and high-intensity. Finally, output levels with even numbers (2, 4 and 6) correspond to the detection of ANS activations that last for longer than 30s. For instance, ALG 1 will trigger output level 1 if it detects an ANS activation of low intensity. If the activation lasts over 30s, then ALG 1 will trigger output level 2. Accordingly, output levels 4 and 6 would be triggered when 3 and 5 activation levels lasted for longer than 30s. Therefore, even-number outputs stand for sustained stressful activations.

On the other hand, ALG 2 is used for detecting the opposite type of reaction: the inhibition of the ANS or a relaxing response. In the case of ALG 2, its output is bounded to the [-3, 0] range and, as it happened with ALG 1, level 0 is related to the absence of any relaxing response. Then, similarly to ALG 1, output levels -1, -2 and -3 correspond to low, medium and high-intensity relaxation responses, respectively. However, unlike ALG 1, the outputs of ALG 2 do not take into account the time-length inhibition of the ANS.

After applying both algorithms to the physiological signals of the participants, we obtained similar results to the ones shown in Fig. 2. The three a) graphs of the figure show the data of the subject 12 of the experiment, whereas the three b) graphs correspond to the subject 5. The first two graphs of each participant correspond to the HRV and GSR signals respectively, plotting green the raw signal and black the low-pass filtered signal. Then, the third graph shows the outputs of both ALG 1 (in red) and ALG 2 (in blue). Although only data from two participants is depicted in Fig. 2, these physiological patterns are also representative physiological reaction patterns of the other volunteers. The first main pattern, shown in charts a) of Fig 2., represents those subjects that could recall a negative memory which had a physiological impact on the organism (subject 12, for instance). On the other hand, the patterns shown in charts b) of Fig. 2, correspond to subject 5 and are representative of the cases in which the participant did not get involved or that could not recall a negative memory.

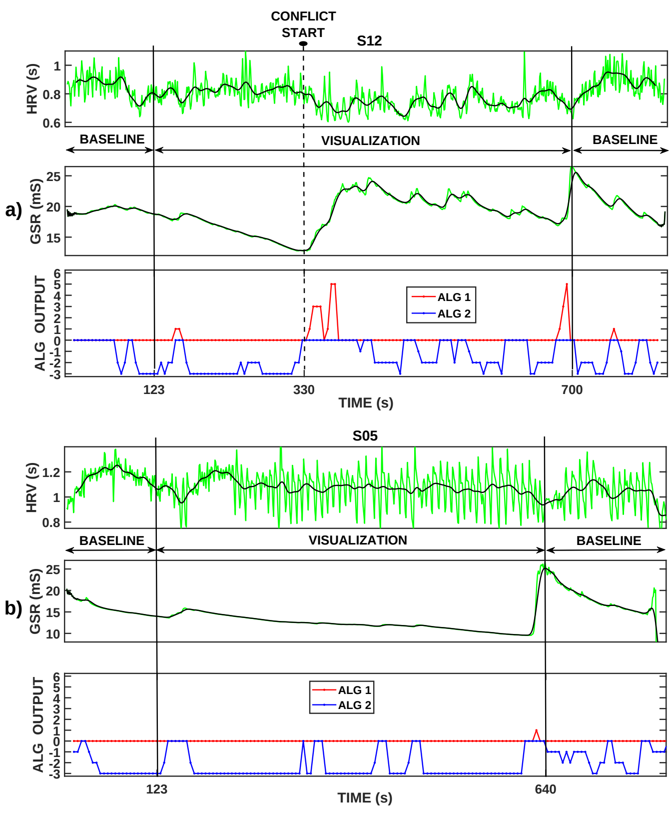


Figure 2. Physiological signals (HRV and GSR) and algorithm outputs. The charts of a) corresponds to subject 12 and the charts of b) to subject 5.

According to Fig. 2 a), subject 12 was able to relax during the beginning of the visualization stage. However, his ANS activated when he started remembering his conflict and bad memories came to his mind. This activation produced an acceleration of the cardiac rhythm, along with the subsequent decrease of the HRV and an increase in the sweating. Looking at the third graph, it is possible to see how the two types of physiological patterns were correctly detected by both ALG 1 and ALG 2.

On the contrary, Fig. 2 b) presents another type of situation in which subject 5 did not feel stressed at all during the experiment. According to the personal interview, subject 5 could not manage to remember any personal conflict and so, no negative memories were recalled. This absence of negative memories were clearly reflected in the outputs of the algorithms, which indicated high levels of relaxation during the conflict evoking stage.

As seen in Fig. 2, there are significant differences in how participants reacted during the experiment. Most of them mentally recalled a personal conflict, but three of them did not do so, either because they could not manage to do it, they did not want to face again such a delicate experience, or because they did not want be involved in the experiment. This information is summarized in Table I, where the first row gives the identification code of the subjects and the second (S.E.) gives the information on whether they recalled the personal conflict (Y) or not (N). Finally, the last row ($S_{max}$) presents the maximum ANS activation level detected by ALG 1.

TABLE I. SUMMARY OF THE EXPERIMENTAL DATA AND ALGORITHM OUTPUTS.

| | *Subjects* | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *1* | *2* | *3* | *4* | *5* | *6* | *7* | *8* | *9* | *10* | *11* | *12* | *13* |
| S.E. | N | Y | Y | Y | N | Y | Y | Y | Y | N | Y | Y | Y |
| $S_{max}$ | 0 | 3 | 3 | 3 | 0 | 3 | 5 | 5 | 1 | 0 | 3 | 5 | 5 |

The content of Table I shows how ALG 1 gives an output value that is coherent with the information provided by the participants in their respective interviews. For all the subjects who stated that they had felt stressed, the algorithm detected all those ANS activations with different intensity levels (see Fig. 2 and Table I). Besides, ALG 1 gave a 0 stress level output for the three participants that were unable to either evoke the conflict or get stressed, whereas ALG 2 detected high relaxation levels for those subjects (output level -3).

Hence, this preliminary study corroborates the hypothesis that negative thoughts generate similar physiological variations to the ones that stress produces on the organism: all the subjects that thought about and recalled a conflictive situation suffered from ANS activations (getting a 100% accuracy for the used detection algorithms).

## IV. CONCLUSIONS

The study presented in this work shows the steps of an analysis relating physiological changes to negative thoughts. For this initial analysis stage, we designed an experimental setup in which 13 participants had to recall a personal conflict using guided visualization techniques. As mentioned in Section III, it has been possible to confirm that not all the participants could recall a negative situation of such characteristics. This work also corroborates Schachter's and Singer's cognitive theory [18] that stated that it is not the stimulus the one which produces the emotional reaction on the organism, but the person's cognitive perception of the stimulus. Besides, in the case of all the participants that could evoke a past conflict, their

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organism reacted in the same manner as if they were going through a stressful situation. These results help to provide adaptations according to the emotional state of the users based on the physiological information of the human body.

As future lines, we would like to widen the study by adding new biomarkers related to stress, such as cortisol or electroencephalographic signals. By doing this, we aim to clarify to what extent the negative thoughts can affect the organism. Besides, this initial study is limited to a very reduced population. Therefore, we plan to expand the cases of study to a larger population. Finally, we are designing a new set of experiments in which bad thoughts and feelings are elicited with other types of techniques from the field of psychology and also using audio-visual stimulation.

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