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A Self-Paced Relaxation Response Detection System Based on Galvanic Skin Response Analysis

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ABSTRACT Relaxation helps to reduce physical, mental, and emotional pressure. Relaxation techniques generally enable a person to obtain calmness and well-being by reducing stress, anxiety, or anger. When a person becomes calm the body reacts physiologically, producing the so-called Relaxation Response (RResp) which affects the organism in a positive manner, no matter if it is during a state of relaxation or in the middle of a stressful period. The goal of this paper is to design a system capable of identifying automatically the RResps of a subject by analyzing a single physiological signal, the galvanic skin response (GSR). To do so, a team composed of psychologists, neurologists, and engineers designed two experiments for inducing RResps in the participants while their GSR signals were being collected. The team analyzed the data and identified three different levels of RResp that can be quantified using only two easily calculated GSR features. Moreover, the use of the surface produced by GSR and its linear approximation is totally novel. Finally, the data were classified using decision tree strategies for each of the experiments and, after seeing that the obtained trees were similar, the team synthesized them in a single classification system. The F1 values obtained by the generalized classifier scored between 0.966 and 1.000 for the data collected in both experiments.

INDEX TERMS Affective computing, decision trees, electrodermal activity (EDA), galvanic skin response (GSR), machine learning, relaxation response.

I. INTRODUCTION

According to the World Health Organization definition of the term [1] "health is a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity". In recent years there has been a shift in the paradigm with regard to psychology and medicine focusing health towards that state of well-being. This new perspective is evidenced by the current tendency of tackling positive variables and preventive attitudes instead of the negative and pathological aspects that have been traditionally addressed in the literature [2]–[5].

Backed by psychology, the new tendencies propose the understanding and the strengthening of positive factors as a method to enable individuals and communities to improve their life quality, and, subsequently, as a tool to avoid the pathologies that derive from adverse life conditions [6]. Relaxation techniques, among others, are one of the most commonly used methods to achieve welfare [7]–[9]. In fact, if mental or physical relaxation is achieved, particularly effective results can be obtained when seeking to improve some of the most common problems of clinical psychology, such as stress, anxiety disorders or depression [10]–[12]. Moreover, it is thought that relaxation techniques present no undesired side effects and that they produce a positive physiological response in the human organism [13], [14]. Moreover, they can be used just for the sake of improving life quality or for self-knowledge without necessarily aiming to treat any specific health problem [7].

The possibility to detect whether an individual is becoming relaxed is evidently of interest when considering the approach of using relaxation techniques as a tool to improve personal welfare. Currently there exist biofeedback techniques that allow experts to assess if a subject is becoming

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relaxed or not. Furthermore, if relaxation takes place, then these techniques enable the experts to rate how strong that relaxation is [15]–[17]. These techniques are based on collecting, monitoring and interpreting the physiological signals of the subject, a far from simple matter. Thus, they must be used by an expert in this field.

When a person relaxes there are certain physiological changes that take place in the organism producing what Benson [18] called a Relaxation Response (RResp). RResps are produced by an activation of the Autonomic Nervous System (ANS). The ANS is composed of two main branches: the Sympathetic Nervous System (SNS) and the Parasympathetic Nervous System (PNS). As posed by Canon [19] the SNS becomes active when the subject perceives a stimulus representative of danger or alarm (known as the fight or flight response). Therefore, the SNS becomes active during stressful events and is inhibited either when these finish or during relaxation. On the other hand, the PNS acts complementarily to the SNS: it is activated during relaxation and inhibited during stress [20]–[24]. Thus, RResps not only take place during relaxation but also when a stressful event ends. Finally, it is important to remark that people can react differently to the same stimulus. This phenomenon may occur because people have different perceptions of the environment which can highly influence the cognitive perception produced by a certain stimulus [25].

There exist several physiological signals that can be useful to evaluate the state of the ANS and human emotions: respiration, cardiac activity, sweating, eye pupil dilation, among others [26]–[33]. At the same time, the organs that regulate these signals can be innervated by different nervous branches; for instance, the heart and the lungs are innervated by both the SNS and the PNS. However, the sweat glands are exclusively innervated by the cholinergic branch of the SNS and, because of this, sweating is only affected by the activation of the SNS. This particularity makes sweating a good signal to show whether relaxation is taking place by detecting the absence of SNS activations. The study presented in this work was carried out using only the signal of the sweating. This signal called Galvanic Skin Response (GSR) is also known as Electrodermal Activity (EDA) or Skin Conductance (SC). In addition to its capability to show relaxation, this signal has the advantage that it can be collected noninvasively using skin contact electrodes [34], [35]. Therefore, it is easy to collect which is a great advantage both for the implementation of a technological solution and towards the ease of use of that solution from the point of view of the final users.

Different evidence indicates that it is possible to detect different emotional states from the psycho-physiological perspective using biosignals. There are articles in the current literature that study states of relaxation using biosignals [36], [37]. Other research papers focus on the study of stress and use relaxation in order to compare its parameters against those of stress [38]–[43]. Nevertheless, this research team has been unable to find any work that develops an automatic method for detecting RResps.

For this reason, this work proposes a supervised learning algorithm based on Decision Trees (DT) that allows physiological changes towards relaxation to be automatically detected by analyzing the GSR in 20s time windows. In addition, the algorithm not only detects these changes but also classifies them depending on their intensity. This strategy has already been used for studying medical and emotional patterns due to the ease of interpretation of their rules [44]–[47]. Therefore, besides making the use of biofeedback techniques easier for non-experts, it also helps to detect which relaxation techniques work best for each individual and enables the results obtained from relaxation techniques to be optimized.

In order to create the algorithm, this work proposes that two features of the GSR signal are extracted in 20s windows: the slope of the GSR and the surface area comprising the difference between the GSR signal itself and its linear regression. This second feature is one of the main contributions of this research as its use is completely new and, apart from having great physiological significance, it has also a low computational load.

As the problem analyzed in this work covers different areas of engineering, medicine and psychology, it was necessary to build a multidisciplinary team that encompassed all these areas. Thus, all the experiments, analysis and developments carried out during this research have benefited from the collaboration and supervision of the Department of Neurology of the Cruces University Hospital, where a relevant research line is focused on Parkinson diseases [48] and of the Instituto Burmuin [49], a center of psychology of the Basque Country.

II. MATERIALS AND METHODS

This section presents the different stages of the study: the experimental process, the analysis of the data and the construction of the detection and classification algorithm itself. The sequence of these stages is depicted in Fig. 1.

First, the methodology followed in the experiments will be detailed and the required materials will be listed. After that, the population that took part in the experiments and the various databases collected will be presented.

After collecting the data there will be a data analysis phase in which two types of analysis will be done. First the data will go through a qualitative analysis looking to find relationships between the changes and the trends of the GSR signal and the emotional changes of the subject. Later, the collected data will be quantitatively analyzed and the main features of GSR will be parametrized in order to detect and quantify the intensity of the RResps that took place during the experiments.

Finally, the section will end with the presentation of the classifiers based on DT algorithms that enable the automatic detection and classification of the RResps that took place in the data collected from the experimental stage.

A. EXPERIMENTAL SETUP

When facing any data analysis problem, the first objective is to build a database which is wide and varied enough so that the study is generalized and significant. Thus, in order

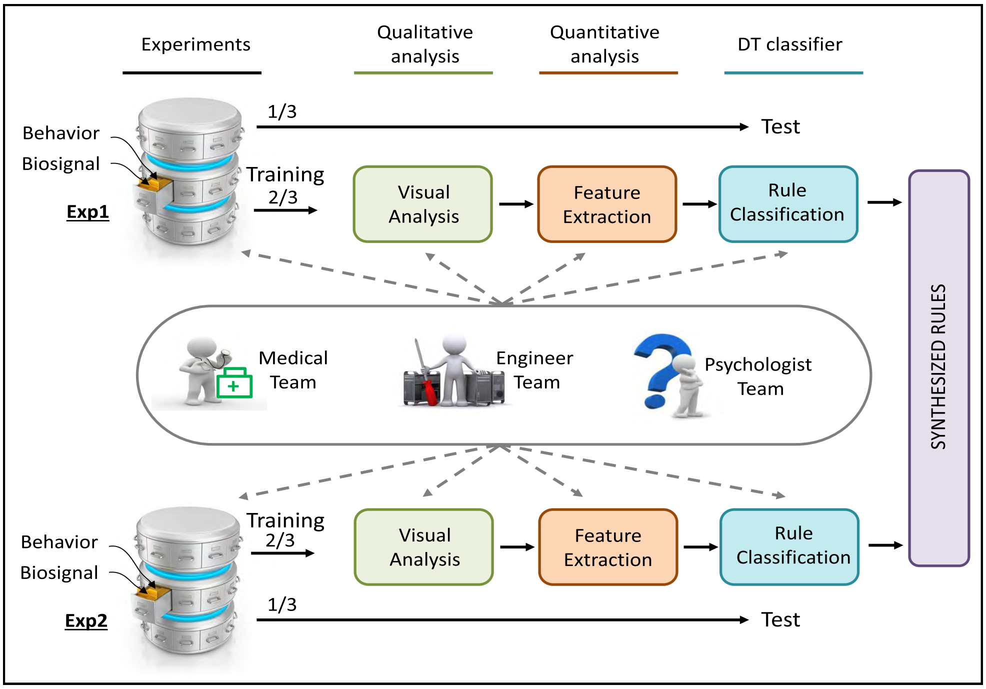

FIGURE 1. Sequence of the stages until the development of the algorithm.

to create such a database, the research team had to design an experimental stage in which RResps could be induced in the volunteers participating in the experiment while, at the same time, the physiological signals of those participants were being collected.

The current literature collects several relaxation techniques that are able to produce an activation of the PNS and subsequently produce an RResp: meditation [13], [16], [17], controlled breathing [50], listening to relaxing music [27], [28], visualizing images [51] and videos [52]...Once again, it is important to bear in mind that these responses also take place when a stressful event finishes.

Hence, this research presents two different experiments having both the intention of eliciting parasympathetic activation in the participants, and, at the same time, taking records of their emotional states and of their physiological variables. Aiming to tackle the problem from two perspectives, each of the experiments will involve different relaxation techniques and situations. Following this approach, two different databases have been collected for each of the experiments that will be later taken to analysis: a physiological database and a behavioral database.

1) EXPERIMENT 1

In a previous study this research group built an algorithm for detecting situations of human stress by means of physiological signal processing. To do so, the team designed an experiment (Exp1 from now on) whose goal was to induce stress on the participants who had previously been taken to a state of relaxation. It is considered that the databases collected in that experiment are not only useful for the study of stress but also to study and to search for the RResp dealt in this work. After all, in this experiment, in addition to the SNS activations of stress, RResp also take place in two kinds of scenarios: there is RResp produced by relaxation techniques and RResp produced by the ending of a stressful event.

This experiment is composed of three phases in which the GSR and the heart rate variability (HRV) of the participants would be constantly collected. Although only GSR will be used for RResp detection, the team also considered to collect the HRV as it would be useful as an extra support in the labeling stage. The first phase consists in taking the subject to a basal state of relaxation by watching a relaxing video (2 minutes) that displays natural landscapes while relaxing music is played. The second phase starts once the video has ended. In this second phase the participants have to complete a wooden 3D puzzle within 10 minutes. Finally, after those 10 minutes, the subjects watch again the relaxing video in order to finish the experiment in a relaxed manner.

As said previously, in these experiments both physiological and behavioral databases were collected. Hence, in order to build the second, the researchers assessed the behavior and emotions of the participants in different ways [30]. On the one hand, based on direct observation, the registers were marked with labels (M) at those moments at which a significant event was detected (beginning of the puzzle solving phase, a puzzle piece falling down, the subject finishing the puzzle, taking a deep breath trying to relax...). On the other hand, once the participants had finished the experiment they were asked to fulfil the SAM questionnaire [53]. Finally, in order to confirm that the information collected by the other two methods, the participants went through personal interviews where they were asked about how they had felt during the three phases of the experiment. In those interviews they were also asked about how they had felt in the moments where the researchers had marked the registers. The aim of these last questions was to confirm that the marks had not been taken due to a misinterpretation of the researchers and that the notes related to those marks were consistent with the feelings of the participants. If there was a mismatch between what noted and what the participants had felt, then the mismatching mark would be removed from the register to prevent false information from corrupting the behavioral database.

The experiments were carried out in a laboratory equipped so that four participants could take part at the same time. In their seating place each participant found the consent survey they had to sign, a dismantled 3D puzzle, the instructions of the puzzle and the data acquisition system. The signals were collected using BIOPAC MP36 hardware (Biopac Systems Inc., USA) working at a 1000Hz sampling rate. The data registers were created using Biopac's Acqknowledge 3.7.1 software. Gel electrodes were used to collect the signal and they were placed in the ring and little finger of the non-dominant hand so that the electrodes caused as little disturbance as possible when solving the puzzle.

The population undertaking the experiment consisted of 166 participants (125 male and 41 female) aged 19-45 years old (mean = 22.8, SD = 3.1). All subjects were engineering students at the University of the Basque Country (UPV/EHU). Before doing the experiments the whole process had been approved by the corresponding ethical committee CEISH-UPV/EHU, BOPV 32 (M10_2016_189). Lastly, prior to beginning the experiment, the researchers provided the participants with an explanation on the experiment. The participants were also told that all their privacy rights would be preserved and that all laws related to these experimental procedures were being respected [54].

2) EXPERIMENT 2

Aiming to do a more thorough analysis of all possible RResp, the team designed a second experiment (Exp2) with the help of the Instituto Burmuin. Instituto Burmuin is a psychological medical center that works with most modern neurophysiology and biofeedback techniques in order to provide customized assistance for different types of health problems.

In this second experiment the psychologists induced the participants into relaxation using different techniques in four stages giving an experimental time per participant of 12 minutes. First, subjects were taken to a basal state. Then they were asked to breathe deeply at a certain pace displayed on a computer screen. After that, they carried out attentional breathing and lastly, with their eyes closed, they did guided muscular relaxation. As in Exp1, both GSR and HRV signals were collected throughout the whole experiment. In addition, before and after the experiment the psychologist carried out an emotional tracking of the participants in order to build the behavioral database.

This second experiment took place in a room within the installations of Instituto Burmuin. The room was equipped with a single acquisition system, a computer and the consent sheet for the sole participant of each experimental session. The acquisition system used for this experiment was ProComp Infiniti System w/ BioGraph Software - T7500M set up at a 256Hz sampling rate. As the participants did not need to use their hands, this time the electrodes were placed in the ring and middle fingers.

A total of 18 volunteers aged between 32 and 56 (mean = 40.22, SD = 9.14) participated in the second experiment: 4 male and 14 female. As with the first experiment, this second experiment had already been approved by the corresponding ethical committee and met all the criteria required by the current regulations (CEISH-UPV/EHU, BOPV 32 (M10_2016_189)).

3) DATA PREPARATION

The last step of the experimental setup is to prepare the data for the analysis, a particularly important stage if a machine learning classifier is to be used. Preparing the data correctly and dividing it into different subsets plays an important role as there has to be total independence between the training and test datasets: the decisions of the classifier could be biased if this condition is not preserved.

First of all, the researchers took into account the nature and structure of the experiment so that both the training and test datasets contained instances from all the phases of the two experiments. In addition, as the physiological signals were going to be analyzed with a sliding window methodology (explained in subsection II.C), the team took care of window overlaps and divided each participant's data into smaller partial data segments. Each segment was disjointed from the others by discarding the time windows that overlapped with the contiguous segments.

Finally, having the smaller disjointed segments 2/3 of them were randomly selected for building the training database. The remaining 1/3 of the segments were used for testing the classifier. As the registers of Exp 1 and Exp 2 have different duration, the segment length in each experiment was chosen to be also different: Exp 1 segments had a duration of 115s and the ones of Exp 2 lasted for 95s.

B. QUALITATIVE ANALYSIS

Once all the data had been collected the next step of the research was to analyze the databases in a qualitative manner in order to identify RResps in the GSR and associate them to the different emotional states.

The sweating signal is composed of two main components: the Skin Conductance Level (SCL) and the Skin Conductance Response (SCR) [55]. The SCL corresponds to the slow variations of the level of the signal and it is representative of the cumulative humidity of the skin. On the contrary, the SCR corresponds to the fast variations and it is the phasic component which is representative of the SNS activations. These activations of the SNS stimulate the sudomotor nerves

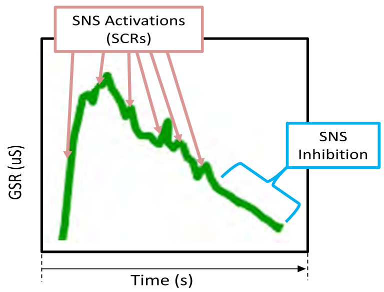

FIGURE 2. SNS activations and inhibitions are reflected in the GSR evolution.

that produce sudden bursts of the GSR signals. According Benedek and Kaernbach [56] and Sugenoya, Iwase, Mano and Ogawa [57], the amplitude of the SCR increases when the SNS activations are greater. Therefore, as shown in Fig. 2, it can be considered that SCRs are good indicators of the presence and the intensity of SNS activations.

For this analysis it is also important to consider, as was pointed out by Benson *et al.* [18], that when an RResp takes place it is not the sympathetic part that becomes active, but the parasympathetic. This makes the glands stop ejecting sweat and the GSR decrease. A deeper physiological analysis of the GSR signal reveals that an RResp will take place if the GSR level is not increasing and depending on the dynamic of the signal two conclusions can be reached. First, if the decrease is maintained and linear it stands for a very relaxed RResp: a clear SCL decrease can be observed in GSR signals. On the other hand, the situations in which SCRs appear but the SCL presents slight decreases stand for RResps that take place in response to the ending of an stressful event.

Furthermore, it is important to bear in mind that, unlike other physiological signals such as the heart rate, the baseline value of the GSR it is not significant on its own. The baseline value of the GSR depends on several factors such as the ambient temperature, the gain of the acquisition system, the device used to collect the signal, etc. With this in mind, attention must be focused on the trends of the signal within specific time windows: if there is sympathetic activation GSR will increase and, if not, decrease.

Having laid out the premises for the physiological analysis, the researchers studied the registers establishing relationships between what happened in the physiological and in the behavioral databases. To do so, Fig. 3 depicts the evolution of the GSR of four different subjects, two of them belonging to Exp1 (A and B) and the other two to two of the four stages of Exp2 (C and D). In order to have unified visualization criteria, all the signals have been resampled at a sample rate of 1Hz and have been processed and plotted using Matlab® software. On the one hand, the signals of Exp1 clearly show the different stages of the experiment: a first stage where the relaxation video is shown, a second puzzle solving phase and the final stage where the video is shown again. On the other hand, it can be seen that the signals of Exp2 are shorter as the experiment only consisted of a single relaxation stage.

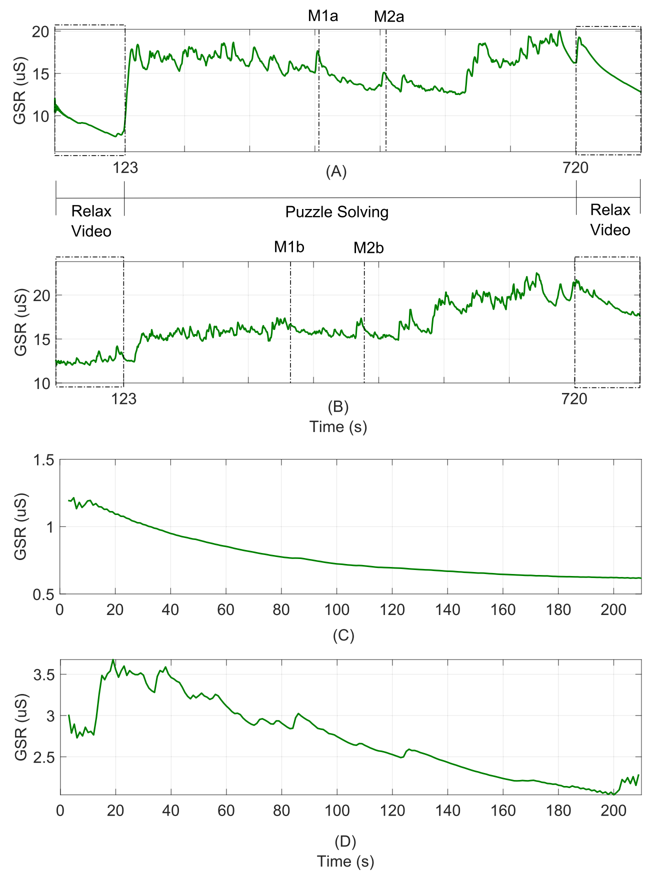

FIGURE 3. Collected GSR signal registers. Subjects A and B belong to Exp1 and subjects C and D to two of the four stages of Exp2.

A first analysis of the signals of Exp1 shows that the responses of the 166 participants were different despite them all having done the same test. This is due to the fact that it is the perception of the subject (and not the stimulus itself) that produces the emotional and the subsequent physiological responses. For example, in Fig. 3, Subject A stated that he was able to relax during both relaxation videos (intervals marked with the dash-dotted line). This can be clearly seen in the GSR as it decreases regularly without SCR reactions. However, Subject B said that he had not been able to relax during the first video because he was nervous and that he had only been able to relax a bit during the second video but not as much as he would have liked.

As well as collecting the impressions of the participants, the researchers marked the registers with labels related to RResp during the puzzle-solving phase. After checking that what marked by observation was coincident to what the participants expressed in the personal interviews it was time to analyze the physiological signals in relation to the collected label marks. These labels indicate that an RResp is taking place due to the ending of a stressful event. For example, at the time corresponding to label M1b the subject stopped trying to solve the puzzle and took a break to breathe deeply and in M1a the researchers could see that the subject felt like giving up the puzzle-solving. M2a and M2b show other examples of this type of situation. Therefore, it seems obvious that a great part of the information collected from the experiments is related to psychological aspects and hence the importance of collecting the behavioral databases is confirmed.

Regarding Exp2, the records of the experiment also show interpersonal differences. A clear and constant relaxation can be observed by looking at the signal of subject C. However, the signal of subject D shows eventual sympathetic activations that produce SCR which proves the RResp is not maintained despite the subject experiencing a general a trend towards relaxation.

After the analysis of both databases (which took into account the physiological signal dynamics, the linguistic expressions used by the participants in the reviews, etc.) the researchers and the experts agreed to catalogue three labels for relaxation states: ''Low Relaxation Response'' (LRResp), ''Medium Relaxation Response'' (MRResp) and ''High Relaxation Response'' (HRResp). In addition, they also decided to include a label representing the states in which no relaxation is happening: ''No Relaxation Response'' (NRResp).

C. QUANTITATIVE ANALYSIS

This section will present the different approaches used for the analysis of GSR and that have enabled the extraction of the features that characterize GSR in relation to the RResps.

When analyzing a signal it is crucial to bear in mind its nature. Like most physiological signals, GSR is a non-stationary signal and its characteristics vary over time. Hence, the analysis of the signal has to be independent from the specific time interval in which the signal is going to be analyzed.

A common approach when analyzing these types of biosignals is an analysis based on sliding time windows [29], [37] The windowing of a signal consists in segmenting it in fixed time intervals and to extract the features of the signal for each of those fixed intervals. Thus, choosing the proper window length plays a key role when interpreting the meaning of the obtained results. Depending on the nature of the signal, the required window length may differ: it is crucial to find a suitable compromise so that the window is long enough to give the sufficient amount of information. But, at the same time, the window has to be short enough so that the signal processing does not have a substantial computational cost and so that the desired statistical results do not get distorted. In previous researches of the literature the size of the windows used to analyze GSR varies between 10s and 300s [29], [37], [58], [59]. In order to give continuity research line stated in [30], in this study the researchers have decided to use a 20s window sliding every 5s as it provides a sufficiently large setting to obtain information about the nervous system activation while not being very temporal and computationally costly. In addition, as mentioned in a review of the state of the art of GSR processing in [60], choosing such a window size has its own physiological reason: ''features extracted from the tonic component express the sympathetic tone and are often computed within time windows of 20s, since the upper cut-off frequency of the tonic component is about 0.05 Hz''. Therefore, the chosen window size permits to study not only the phasic component (SCR) of the GSR but also the tonic component (SCL) and even to combine both to create more powerful features as the new one presented in this work.

The qualitative analysis carried out with the help of the experts on neurology and psychology was crucial for defining the features that represent the RResp as simply and clearly as possible. The selected features are, on one side, the slope of the GSR (sGSR) within the window and, on the other side, the surface area (aGSR) produced by the linear regression of the GSR and the GSR itself (being both signals normalized within the analyzed window). The graphical representation of the two features (sGSR and aGSR) is depicted in Fig. 4.

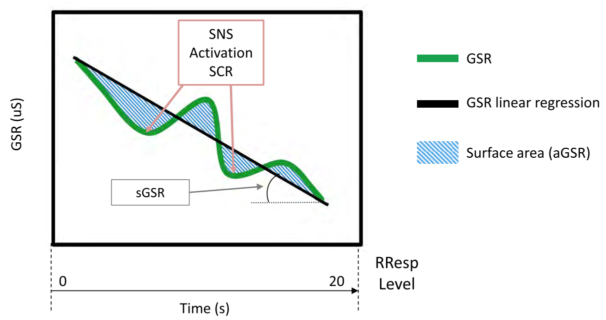

FIGURE 4. The features extracted in each time window: GSR slope and surface area.

Although several research have already used the sGSR [61] and other GSR features related to emotions and stress ([60], [62], [63]) the design of the second feature (aGSR) is one of the main contributions of this research as it is innovative, has a low computational cost and because it is independent from the subject, the acquisition system and the environmental conditions. Other researchers have worked with different features such as statistical parameters, increments, nonnegative convolution, frequential features, areas under the curve, etc. ([37]–[40], [56]). Most of the studies that imply the use of areas in GSR decompose the signal to obtain the phasic and tonic components. After the decomposition they analyze the areas of those components separately [64], [65]. Some others analyze the area under the raising half part of SCRs [66], [67]. Nevertheless, to the extent of the authors' knowledge, what done for proposed aGSR feature has not been previously used in the literature as it takes the signal as a whole for calculating the linear regression and does not need any component decoupling.

RResps correspond to parasympathetic activations and to sympathetic inhibitions, and, as previously explained, there can be relaxation responses even if SCRs take place. Taking this into account, it is possible to conclude that the GSR will oscillate vigorously around its linear regression if several SCRs take place. On the contrary, the shape of the GSR will be very close to its linear regression if no SCRs take place (glands will not eject any sweat). Therefore, it is possible to conclude that the closest to a straight line the GSR is, the deeper the RResp. This statement justifies the use of the proposed feature (aGSR) as a good indicator of the proximity of the GSR signal to its linear regression and, subsequently, as an indicator of the intensity of RResps: the aGSR value will be smaller if fewer SCRs take place.

III. RESULTS

First, this section presents the comparison between different classifying algorithms by means of which the authors decided to use Decision Trees (DT) for the detection system presented in this work. The authors used 2/3 of the data from Exp1 and Exp2 to train the algorithms and saved the remaining 1/3 for testing them and to calculate their performance indicators.

In addition, after justifying the use of DTs for being the best option for this case, this section presents the synthesized classification rule system that was built as a consequence of the rules and performances of the DT classifiers built for Exp1 and Exp2 being similar.

A. CLASSIFIER ALGORITHM SELECTION

Before building the automatic RResp detection system it was necessary to label the signals to indicate the different relaxation states that appear. Thus, the experts analyzed in a random order the physiological (includes both GSR and HRV signals) and behavioral databases and labeled the GSR signal with the aforementioned four labels: LRResp, MRResp, HRResp and NRResp. This way, every analyzed window of the signals was related to a relaxation state label and to certain physiological feature levels, all of which were used as inputs to the classification system.

First of all, the main labeling process was done by a research team member with knowledge on both human psychology and physiology. After that, experts (psychologists from Instituto Burmuin and neurophysiologists from Cruces University Hospital) did a thorough analysis labeling the data and marked the points where they disagreed to what labeled by the previous expert. The expert team had already worked with the research team in previous work [30] and has wide experience dealing with this kind of signals. Finally, all the experts gathered together to discuss about the database and to reach general consensus on the labeling.

Having labeled the data, the team used the data from Exp1 and Exp2 to train and test different types of classifiers with the intention of choosing the best for detecting RResps. Using Weka platform [68], the team compared the performance indicators of the following 12 classification algorithms: 1R rule, Decision Tree (DT), k-NN (1-NN and 5-NN), Naive Bayes (NB), Radial-Basis Network (RBF), Support Vector Machine (SVM), Logistic Regression (LR), Ada Boost (AdaB, combining 10 decision trees), Bagging (Bag, combining 10 decision trees), Random Forest (RF) and Multi-Layer Perceptron (MLP). The authors chose these algorithms for being the state of the art in machine learning and because they belong to different paradigms: rule based, tree based, distance based, probabilistic, function based and ensemble of classifiers. All these algorithms were tested using Weka's default parameters and settings.

The performance of a classification system can be given by three statistical indicators: the Precision (P), the Recall (R) and the F1 score [69]. These indicators are defined by (1), (2) and (3), which are calculated using the values of: True Positives (TP), False Positives (FP) and False Negatives (FN). All the three performance indicators are bounded in the [0, 1] domain, being 0 the worst result possible and 1 the best.

$$R = TP/(TP + FN) \tag{1}$$

$$P = TP/(TP + FP) \tag{2}$$

$$F_1 = 2 \cdot P \cdot R/(P + R) \tag{3}$$

The statistical results of the 12 algorithms for both Exp1 and Exp2 can be seen in Table 1. Looking at the results, it can be seen that the algorithms based on trees are the ones that perform the best with very similar results. Therefore, the authors chose to use DTs [70] for their simplicity and because they have explanatory properties (unlike the other tree based algorithms). This is a big advantage as it makes it possible for clinicians who are not experts in classifying algorithms to understand the boundaries of the selected features and their meaning related to relaxation responses. Moreover, using DTs also permitted the authors to merge the rules obtained from the two experiments and create the new synthesized set of rules that will be presented in the next subsection. The DTs used in this work, which were obtained using Weka's default setting, correspond to the C4.5 (J48 pruned tree) algorithm.

TABLE 1. Comparison between different classifiers.

Classifier	Exp 1			Exp 2		
	P	R	F1	P	R	F1
1R	0.649	0.682	0.665	0.773	0.797	0.785
DT	0.990	0.990	0.990	0.992	0.992	0.992
1-NN	0.978	0.978	0.978	0.969	0.969	0.969
5-NN	0.978	0.977	0.978	0.966	0.965	0.965
NB	0.822	0.797	0.809	0.859	0.823	0.840
RBF	0.955	0.955	0.955	0.953	0.953	0.953
SVM	0.913	0.912	0.913	0.814	0.739	0.740
LR	0.888	0.888	0.888	0.952	0.951	0.951
AdaB	0.989	0.989	0.989	0.992	0.992	0.922
Bag	0.990	0.989	0.989	0.992	0.992	0.992
RF	0.991	0.992	0.991	0.992	0.992	0.992
MLP	0.952	0.951	0.952	0.892	0.864	0.878

B. SYNTHESIZED RULE SYSTEM

First, as DTs had been chosen as the best option for classifying the different states related to RResps, the authors considered interesting to make a deeper analysis of the trees obtained for each experiment. The rules that were obtained from the training phase are those presented in Fig. 5, where aGSR and sGSR respectively stand for the area and the slope within the analyzed windows of the GSR signal.

```
J48 pruned tree Experiment 1
----------------------------------------------------
aGSR <= 0.069998
|   sGSR <= 0.000021
|   |   sGSR <= -0.04861: -3 (1494.0)
|   |   sGSR > -0.04861
|   |   |   aGSR <= 0.039991: -3 (361.0/45.0)
|   |   |   aGSR > 0.039991: 0 (92.0)
|   sGSR > 0.000021: 0 (295.0)
aGSR > 0.069998
|   sGSR <= -0.050193
|   |   aGSR <= 0.199712: -2 (1846.0/16.0)
|   |   aGSR > 0.199712
|   |   |   sGSR <= -0.300083: -1 (689.0/13.0)
|   |   |   sGSR > -0.300083
|   |   |   |   sGSR <= -0.289222
|   |   |   |   |   sGSR <= -0.294407: 0 (11.0/2.0)
|   |   |   |   |   sGSR > -0.294407
|   |   |   |   |   |   sGSR <= -0.292119: -1 (4.0)
|   |   |   |   |   |   sGSR > -0.292119
|   |   |   |   |   |   |   sGSR <= -0.291568: 0 (2.0)
|   |   |   |   |   |   |   sGSR > -0.291568: -1 (3.0/1.0)
|   |   |   |   sGSR > -0.289222: 0 (539.0/6.0)
|   sGSR > -0.050193: 0 (3374.0)

J48 pruned tree Experiment 2
--------------------------------------
aGSR <= 0.069816
|   sGSR <= -0.071428: -3 (247.0)
|   sGSR > -0.071428
|   |   sGSR <= -0.017014: -3 (4.0)
|   |   sGSR > -0.017014: 0 (3.0)
aGSR > 0.069816
|   sGSR <= -0.2889
|   |   aGSR <= 0.203202: -2 (128.0/3.0)
|   |   aGSR > 0.203202
|   |   |   sGSR <= -0.3014: -1 (84.0)
|   |   |   sGSR > -0.3014
|   |   |   |   sGSR <= -0.2939: 0 (2.0)
|   |   |   |   sGSR > -0.2939: -1 (3.0)
|   sGSR > -0.2889
|   |   aGSR <= 0.196464
|   |   |   sGSR <= -0.049283: -2 (49.0)
|   |   |   sGSR > -0.049283: 0 (50.0)
|   |   aGSR > 0.196464: 0 (457.0)
```

FIGURE 5. The sets of rules extracted from the decision trees for each experiment.

As shown in Fig. 5, certain decision rules have been marked within differently shaped color boxes. The reason for these distinctions is that these rules are the ones considered to be the most important when classifying and choosing the label best suited for the input features. Given their importance, these rules have been chosen to build the synthesized classification system that will be useful for detecting and classifying the RResps of both Exp1 and Exp2.

Then, the authors decided to check how the DT classifiers performed for each RResp level. The class dependent performances of the classifiers can be seen in Table 2. The first two columns of Table 2 present the labels for the different states and the number of times the experts have labeled them in each of the experiments. The second block, composed of six columns, shows the values obtained after using a DT specifically built for each of the experiments. In addition, in order to measure the stability and sensibility of the algorithms, the third block (also consisting of six columns) gives the results obtained after crossing the DT classifiers. This means that the DT built for Exp1 was used with the data of Exp2 and vice versa. Finally, the rows named as Exp1 and Exp2 provide the averaged results obtained by the two classifiers. These averaged values have been calculated by weighting the results according to the number of cases of each label.

After observing that the results obtained by crossing the classifiers were very good and that the decision rules of both DTs were similar, the researchers decided to group and unify them in a single synthesized system. To do so, the team studied both sets of rules with the help of the experts and decided that the rules that had greater importance were those highlighted in Fig. 5. Then the team studied the intersections of the rules belonging to the same labels and finally built the unified rule system presented in Table 3.

The values that define the rules of Table 3 have been obtained by calculating the average feature values of the highlighted rules that are similar in both experiments and that lead the classification to a same label. Then, for the sake of simplicity, those averages have been rounded to get a number with two decimal digits. For example, in the case of LRResp, taking the feature values highlighted in red in Figure 5, the rounded average values of aGSR and sGSR are calculated as shown in (4) and (5) respectively.

$$\begin{aligned} aGSR &= (aGSR_{Exp1} + aGSR_{Exp2})/2 \\ &= (0.1997 + 0.2032)/2 = 0.2014 \approx 0.2 \end{aligned} \tag{4}$$

$$\begin{aligned} sGSR &= (sGSR_{Exp1} + sGSR_{Exp2})/2 \\ &= -(0.3000 + 0.3014)/2 = -0.3007 \approx -0.3 \end{aligned} \tag{5}$$

In addition, it is important to note that regarding HRResp, there are situations that are only considered by the tree

TABLE 2. Statistical indicators of the results of the DTs for each experiment and crossing the classifiers.

State	Manual label	DT						Crossed DT					
		TP	FN	FP	P	R	F1	TP	FN	FP	P	R	F1
Exp1	4354				0.990	0.990	0.990				0.965	0.965	0.965
NRResp	2177	2153	24	6	0.997	0.989	0.993	2140	36	95	0.957	0.983	0.970
LRResp	349	342	7	15	0.958	0.980	0.969	335	14	11	0.968	0.960	0.964
MRResp	923	909	14	4	0.996	0.985	0.990	901	22	14	0.985	0.976	0.980
HRResp	905	905	0	20	0.978	1.000	0.989	824	81	34	0.960	0.910	0.935
Exp2	513				0.992	0.992	0.992				0.992	0.992	0.992
NRResp	257	256	1	1	0.996	0.996	0.996	256	1	1	0.996	0.996	0.996
LRResp	44	43	1	1	0.977	0.977	0.977	43	1	2	0.956	0.977	0.966
MRResp	87	85	2	1	0.988	0.977	0.983	85	2	1	0.988	0.977	0.983
HRResp	125	125	0	1	0.992	1.000	0.996	125	0	0	1.000	1.000	1.000

TABLE 3. The set of decision rules of the unified classification system.

State	Synthesized/unified rules
LRResp	(sGSR<-0.3) AND (aGSR>0.2)
MRResp	(sGSR<-0.05) AND (0.07<aGSR<0.2)
HRResp	((-0.05<sGSR<0) AND (aGSR<0.04)) OR ((sGSR<-0.06) AND (aGSR<0.07))
NRResp	Any other situation

TABLE 4. Performance indicators of the unified classification system.

State	Manual label	Unified rules					
		TP	FN	FP	P	R	F1
Exp1	4354				0.994	0.994	0.994
NRResp	2177	2176	1	9	0.996	1.000	0.998
LRResp	349	339	10	12	0.969	0.969	0.969
MRResp	923	909	14	4	0.996	0.985	0.990
HRResp	905	905	0	0	1.000	1.000	1.000
Exp2	513				0.992	0.992	0.992
NRResp	257	257	0	2	0.992	1.000	0.996
LRResp	44	42	2	1	0.977	0.955	0.966
MRResp	87	85	2	1	0.988	0.977	0.983
HRResp	125	125	0	0	1.000	1.000	1.000

designed for Exp1: when sGSR$> -0.04861 \approx -0.05$ and aGSR$\leq 0.03999 \approx 0.04$. In order not to leave these situations out of the consideration of the new system they have been added to the other rules by means of a logic OR (see Table 3). The results of the new unified system, shown in Table 4, were better than the ones obtained by the experiment specific DTs of Table 2.

After checking the performance measures of the unified system, the researchers decided to evaluate the system's behavior over time. This performance can be seen in Fig. 6, where the signals of subjects A and B correspond to two participants of Exp1, and C and D to Exp2. For each subject two signals are being shown. The first signal, in green, is the GSR of the subject and the second, in blue, corresponds to the output of the unified classification system. This output of the system is updated every 5s (the sliding window step size) and it gives a discrete output that goes from 0 to -3 in unitary steps. Each of the four output levels corresponds to one of the RResp labels that were presented in Subsection 2.2: NRResp $= 0$; LRResp $= -1$, MRResp $= -2$ y HRResp $= -3$.

The graphs of Fig. 6 show that during relaxation events the output of the classifier corresponded to medium (-2) or high relaxation (-3) RResp values. The classifier gave -2 and -3 outputs for participant A during the relaxation videos and during the relaxation events marked by the researchers. In the case of subject B the classifier gave the same outputs during the second relaxation video and in the marked relaxation event labels. Regarding Exp2, subject C relaxed throughout the whole experiment. Nevertheless, subject D found it hard to relax at the beginning of the experiment (as he pointed in his personal interview) and he was not able to achieve a state of relaxation until approximately 60s had passed.

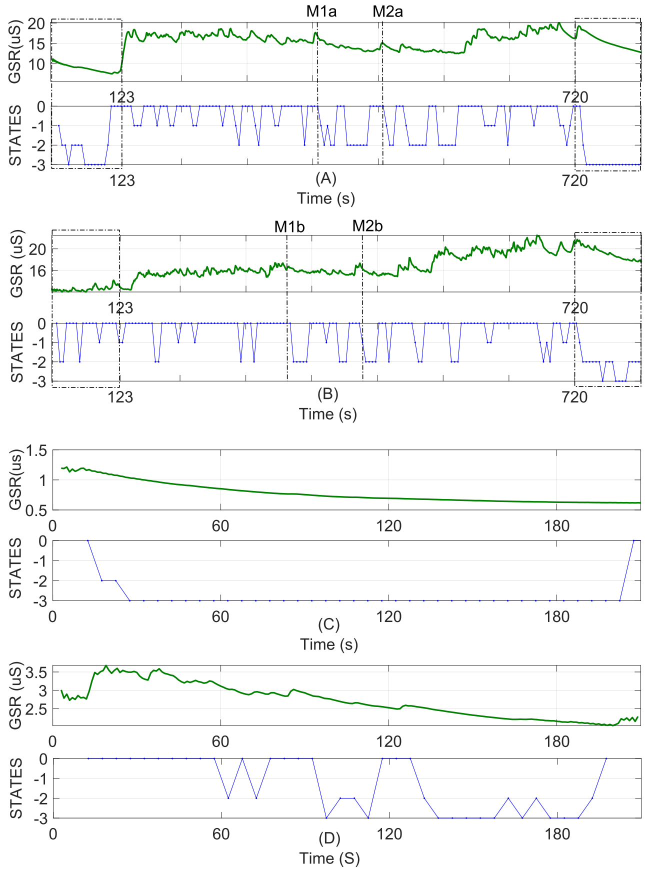

FIGURE 6. GSR biosignals (top) and outputs of the unified classification system (bottom). Subjects A and B correspond to Exp1 and subjects C and D to two of the four stages of Exp2.

IV. DISCUSSION

Relaxation is a state of the body that produces both physical and psychological benefits. Historically, relaxation has been mainly studied from the perspective of psychology. To date, a few studies have worked on the automatic detection of emotions and have also studied relaxation. Nevertheless, most of these have focused on comparing relaxation against stress and then statistically comparing them. Thus, the studies specifically focused on automatically detecting when a subjects starts to relax are practically non-existent.

However, the benefits of positive psychology and relaxation are well known among professionals of medicine and psychology. Therefore, the number of researches and publications on this subject has vastly increased in recent years. Following this trend and offering a solution to a problem which, to the extent of the authors' knowledge, has not yet been dealt with by the literature, this work proposes an innovative method for automatically detecting RResps and for technologically supporting the new types of preventive measures of medicine and psychology that also have therapeutic properties.

This work has followed a methodology in which GSR signals have been collected during two types of experiments specifically designed to elicit RResp in the participants, not only in deep relaxation situations but also as a response to the ending of a stressful event. The methodology has been supported by professionals from the fields of medicine, psychology and engineering throughout the experimental, data analysis and algorithm building processes.

The study of the nature of the GSR signal and the psycho-physiological responses of the participants taking part in the experiments resulted in the classification of relaxation with four different labels: NRResp, LRResp, MRResp and HRResp. The detection of these four different relaxation states has been achieved by analyzing exclusively the GSR of the hand using 20s windows with 5s sliding steps. The approach of using the surface produced by the GSR and its linear regression is one of the main contributions of this research. The benefits of using this feature are that it is not computationally costly and that it has high physiological significance. In addition, its robustness has been proven by the strong results obtained in two experiments whose goals were completely different: the first was aiming to produce stress while the second targeted relaxation.

Finally, DT techniques have been used to classify the relaxation patterns that take place in the human organism. Initially the researchers built a DT specifically for each of the experiments but after analyzing the results decided to unify them in a single synthesized system. The comparison between the results of Table 2 and Table 4 shows that the new unified classifier obtained better results than the specific DT algorithm for Exp1 (F1_GENERALISED = 0.994 vs F1_DT = 0.990) and the same results for Exp2. This improvement is due to a modification in the rule that stated that any GSR slope beneath 0.000021 corresponded to the HRResp state. The rule was modified by adjusting this value to 0 and this enabled the number of false positives to be reduced from 20 to 0 in Exp1 and from 1 to 0 Exp2. In addition, the new unified system also improved the classification of LRResp states in Exp1 reducing false positives from 15 to 12 cases.

V. CONCLUSION

This study presents a Decision Tree (DT) technique based classification method for detecting the entrance in personal relaxation states, also called Relaxation Responses (RResp). This classifier uses only two inputs to the system being both features extracted from 20s windows of the Galvanic Skin Response (GSR) signal: the slope of the GSR and the surface area produced by the GSR itself and its first order regression. The study presents the experimental methodology followed and the data analysis stages so it is possible to reproduce the same scenario faced by the researchers. The proposed set of features and classification algorithm has the following properties:

- The features have low computational cost and have great significance from a physiological perspective. Therefore, they are suitable for different types of situations as were the two experiments presented in this work.
- The proposed system is robust to changes in the acquisition system, such as the signal collection sensors or signal conditioning gain.
- The algorithm is capable of classifying three different levels for the detected RResps depending on their intensity and a null level for the absence of RResps.
- As it is based on DT techniques, it is easy to interpret how the classifier takes decisions regarding classification. In addition, it is also easy to modify the decision rules in order to fine-tune the algorithm or to adapt it for other situations.

A future approach for this work would be to modify the classification algorithm to differentiate between different types of RResps, i.e., if the detected RResp corresponds to the ending of a stressful event or if it is produced by the application of relaxation techniques. In addition, the authors see expanding the study to populations of different ages as an interesting future approach. Most of the registers of this work corresponded to young people. Therefore, it would be interesting to test the performance of the proposed features and classifiers with data collected from people of other ages as their physiological reactions could be different. Another future line is to implement the proposed algorithm in a portable hardware solution so that it could be easily used by a hypothetical final user.

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