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# An enhanced fuzzy algorithm based on advanced signal processing for identification of stress

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ABSTRACT

Nowadays, it is crucial to promote and develop the autonomy of people, and specifically of individuals with some disability, in order to improve their life quality and achieve a better inclusion into socio-cultural life. Therefore, the identification of stress situations can be a suitable assistive tool for improving their socio-cultural inclusion. This work presents important enhancements and variations for an existing fuzzy logic stress detection system based on monitoring and processing different physiological signals (heart rate, galvanic skin response and breath). First, it proposes a method based on wavelet processing to improve the detection of R peaks of electrocardiograms. Afterwards, it proposes to decompose the galvanic response signal into two components: the average value and the variations. In addition, it proposes to extract information out the breath signal by analyzing its frequential composition. Finally, an improved response in detecting stress changes is shown in comparison with other previous works.



## 1. Introduction

Emotional Intelligence is an alive field of research, where some studies deal with human emotion measuring. These tendencies are within the approach of the assistive technologies, which have the target of improving people's life quality. Several research tendencies try to improve the autonomy of people with disabilities by focusing on improving their inclusion in socio-cultural life. Physiological signal measurements by non intrusive sensing systems, signal processing and analysis with Soft Computing techniques, identification and classification of emotions and stress situations, are some of the approaches that are being studied in a high number of significant research groups as [9,21,29].

Applying these studies to emotional blockage situations induced by a high stress levels is a field of huge interest as presented by Sharma and Gedeon [26]. A prompt detection of blockage situations is a powerful assistive tool for elder people and persons with disabilities. It is normal for people with special needs to have a caregiving person to help them when needed. For instance, a device capable of detecting blockage situations could be useful to inform the caregiver about a blockage taking place, helping them to give a quick assistance so the care-dependant person can overcome that difficult situation as fast as possible. This work presents an extended solution to the system presented in [23], which proposed enhancements for the work of [7], where such situations are detected and identified with the intention to be used in cases as the presented above.

Multiple studies analyze the influence of human emotions in people's everyday life, from qualitative studies based on human behavior as developed by López et al. [14], to quantitative analysis of measured physiological variations that emotions elicit in each person, e.g. in [25]. In particular, there are very specific physiological changes related to stress, as the phylogenetic substrates study made by Porges [20], or the activity study of the autonomic nervous system shown in [11]. As pointed in Cannon's research works, [3], when a person has to face a dangerous situation, the person's body prepares to confront that situation and generates a physiological response known as "fight-fly". This response increases the activity of the sympathetic nervous system producing changes as the increase of the heart rate frequency in order to provide more blood to the body. This change also produces the respiratory system to activate as a bigger blood flow requires more oxygen, [19]. Moreover, some other changes take place in the body such as the dilation of eye pupils to improve the vision or the increase of sweat secretion, [17].

Some proposals measure physiological signals using intrusive devices, as the work of [4] using cameras or electrode grids, to analyze and classify human emotions. Other lines are based on working with non-intrusive devices, as those having electrodes integrated in wearable devices or clothing accessories, [27]. This work is based on using physiological signals that can be measured with

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hidden devices, as the electrocardiogram (ECG), the galvanic response of the skin (GSR) and the movement produced by the subjects breathing (RESP).

Currently, processing and analyzing real physiological signals is a very interesting challenge in Biomedical Engineering. The complexity of such variables is remarkable, being higher than it seems a priori, as discussed in [15]. Such difficulty comes from the large amount of the data generated by analyzing the captured time series and from the countless noises and artifacts that appear in data entries. To solve these kinds of problems Soft Computing techniques have been highlighted considerably, as developments presented by Lee et al., Wozniak et al., Calvo-Rolle and Corchado [2,13,30].

In the study of human emotional changes, and specifically in stress situation labeling, some Soft Computing approaches have a special applicability, as [7], and [22]. These allow researchers to add undefined indexes that can be detected looking at physiological data time series during blockage situations. Due to the complex equilibrium between parasympathetic and sympathetic nervous systems, [18], at the present time it has not been possible to define the exact link between blockage situations and their associated physiological changes. But, as presented below, the measured ECG, GSR and RESP signals allow to see such changes in data time series.

The objective of this work is to continue developing an enhanced identification system for blockage situations based on the measurement of non-intrusively obtained human physiological signals. The work proposes to enhance the Matlab® based system presented in [23] by improving the processing of the input signals and adding a new input variable, based on the RESP signal. Three main improvements are proposed. First it proposes to increase the robustness of ECG processing using wavelet techniques, [10], for a more accurate R peak detection, recently appeared in works as [6,16,24,28]. The second is to decompose the GSR signal into its average and variation components to improve the efficacy of the Fuzzy strategy. The last improvement proposes process the RESP signal in order to get the frequential composition of the breath and to use its standard deviation as an input of the detection system. This combination of advanced signal processing and the addition of a third signal gives the system a higher immunity to false detections and implies an innovative approach to the strategy followed by the previous works where only two input signals were used.

## 2. Experimental stage

When humans are involved, the design of an experimental stage has to be performed with special care, considering and respecting all laws and each individual's rights. Eliciting of emotional blockage situations is a very specific work line considered within the human emotions study. In the present work, a particular experimental stage was designed based on the previously established by authors as [5,8]. These experiments consist on proposing a challenge of dexterity for solving a 3D puzzle in a limited period of time, in order to elicit a stress situation which will lead to an induced emotional blockage. In each experiment, each subject was previously informed about the elicitation process, and all the legal rules for testing on human beings were fulfilled. At the end of the experiment they were asked to fill a questionnaire where they explained how they had felt during the experiment.

During the experiment, volunteers were connected to the electrodes needed to collect the ECG and GSR as shown in Fig. 1. In addition, a chest band was used to measure the movements produced by the breathing, the RESP signal. Regarding to these signals two main states can be distinguished in Fig. 1: Relax State (RS) and Stressed State (SS). These states are directly linked with the three main parts of the experiment. During the relaxing phases (RS) of the beginning and ending of the experiment the three variables acquire values and tendencies that show that the subject is relaxing. In these two phases, the heart beats at a normal pace, the sweating is low and the breathing is harmonic. On the other hand, while solving the puzzle (SS), the GSR increases (the subject sweats more), the ECG beat period is reduced and the RESP tends to be faster and more irregular. These changes prove that the subject is getting stressed.

Unfortunately, using electrodes has disadvantages that difficult the extraction of information. The movements of the person can produce different artifacts in the ECG that make it difficult to extract the information. Moreover, as the gel of the electrodes gets drier the conductivity between the skin and the electrode reduces, and so, signal amplitude decreases and noises appear easily. Fig. 2 shows examples of these two possible problems.

As in [7] it is proposed to use the heart rate (HR) signal as an input to measure the stress level, this paper proposes to make the HR calculation more robust in order to strengthen a subsequent fuzzy stress detection. To accomplish the task this paper proposes to use median filtering and wavelet analysis for detecting ECG peaks. The signal that has been used to prove the effectiveness of the method is the shown in Fig. 2, which has been collected in the experiments for very significant as it has different artifacts and noises.

## 3. Enhancement of the R peak detection

### 3.1. Median filtering

When using electrodes, offset is one of the most common artifacts that appear in collected ECG signals. As stated in [24], one of the best methods to eliminate the offset produced by electrode movements is to apply a median filter to the ECG. 100 ms is a suitable length for the filter as artifacts normally do not last for much longer. Fig. 3 shows how the offset is successfully removed from the original ECG by applying this filter. Anyway, the median filter maintains the shape of the signal, enabling the identification of R peaks.

### 3.2. Wavelet analysis

Once the offset is removed from the signal, the next step is to remove the noise which will be done using a wavelet decomposition and reconstruction, [10]. Fig. 4 shows the diagram of how the wavelet processing is done (on the left and right sides of the diagram respectively).

In the left side of the diagram, decomposition is shown. In each stage, the signal is divided into two parts: A and D coefficients. The A coefficients have low frequency information and the D coefficients the high frequency information. These two parts are obtained by filtering and applying a dyadic downsample to the original signal. Depending on the desired coefficients a different decomposition filter has to be applied: the H high pass filter for D coefficients and the L low pass filter for A coefficients. On the right side of the diagram the reconstruction process is depicted, which is the opposite to what is done in the decomposition. Note that the reconstruction filters H' and L' are not the same as the H and L filters used during the decomposition.

The last decision is to choose the specific wavelet to be used in the analysis. Choosing the best is a tough task beyond this paper. Anyway, the use of a wavelet is considered to be correct if it enables the perfect reconstruction of the original signal. Thus, this paper proposes to use the third wavelet of the Coiflet family (with its correspondent filters), which allows the reconstruction of the ECG.

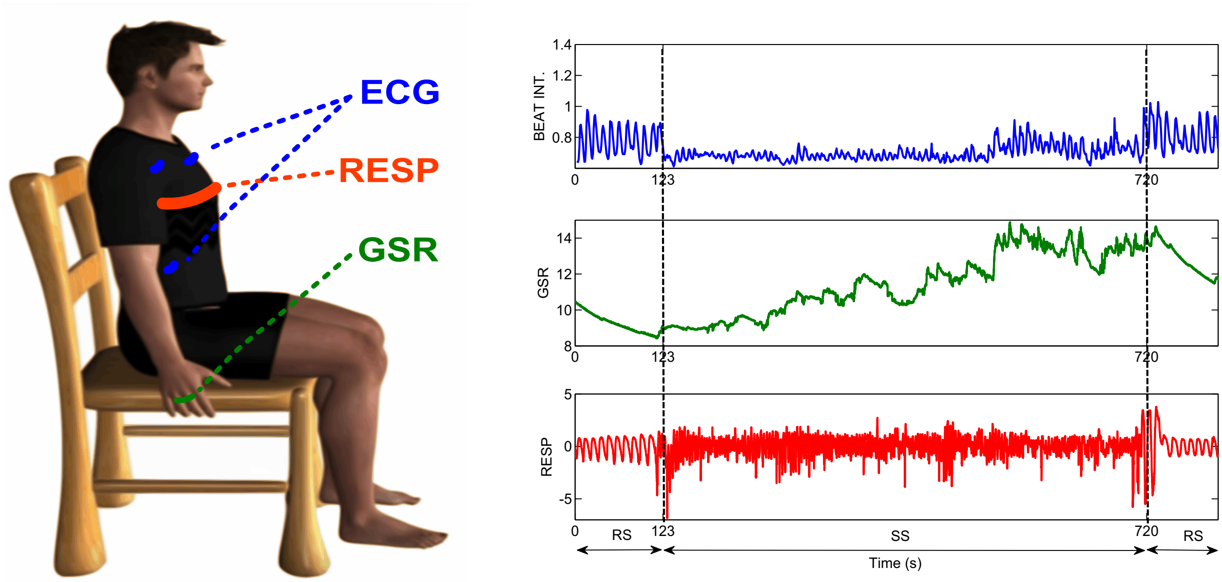


**Fig. 1.** Electrode positioning scheme and collected data time series.

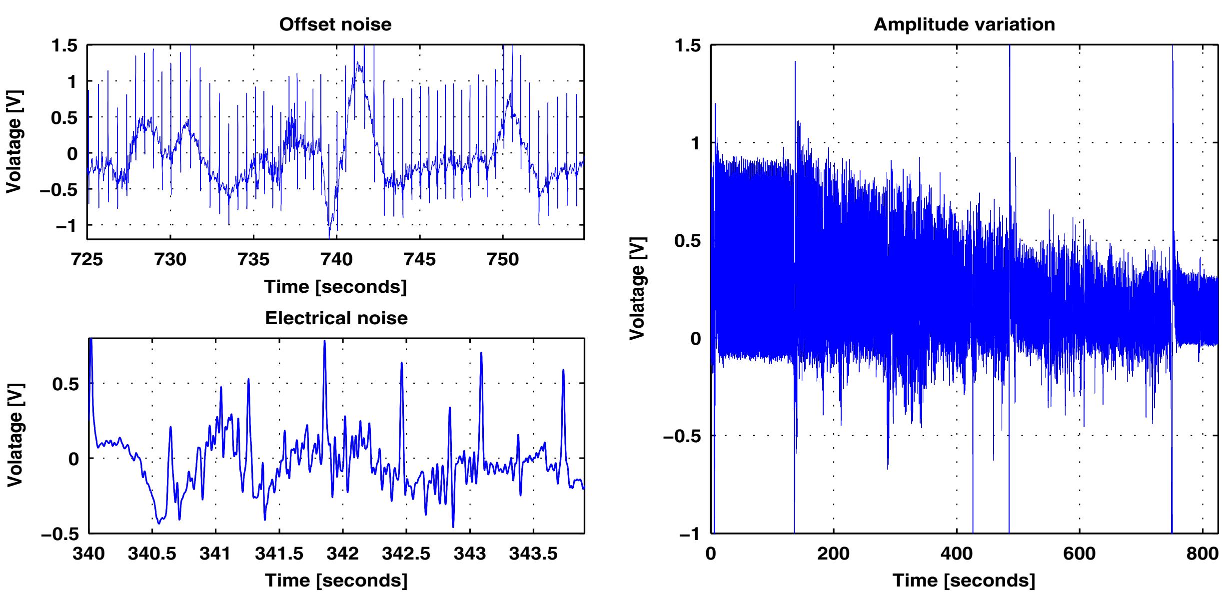


**Fig. 2.** Different noises and artifacts produced in the ECG signal.

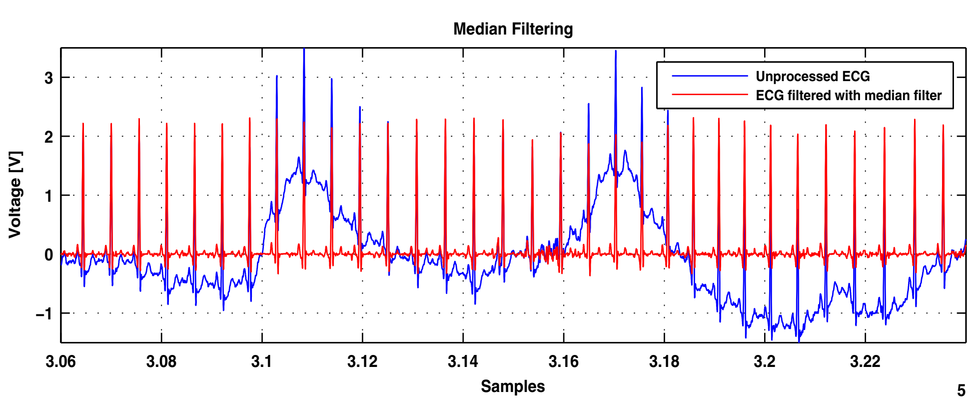


**Fig. 3.** Offset artifacts removed from the original signal by applying the median filter.

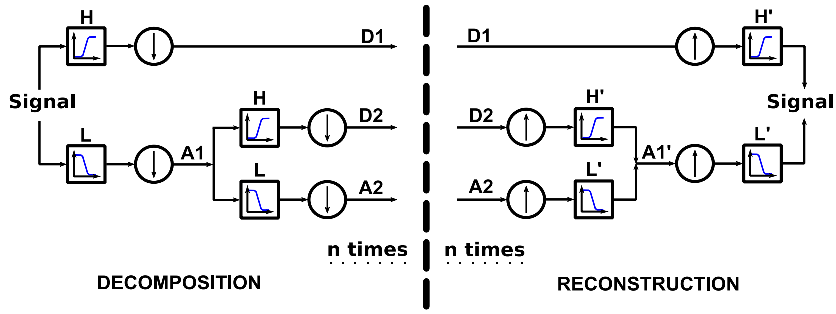


**Fig. 4.** Wavelet decomposition and reconstruction scheme.

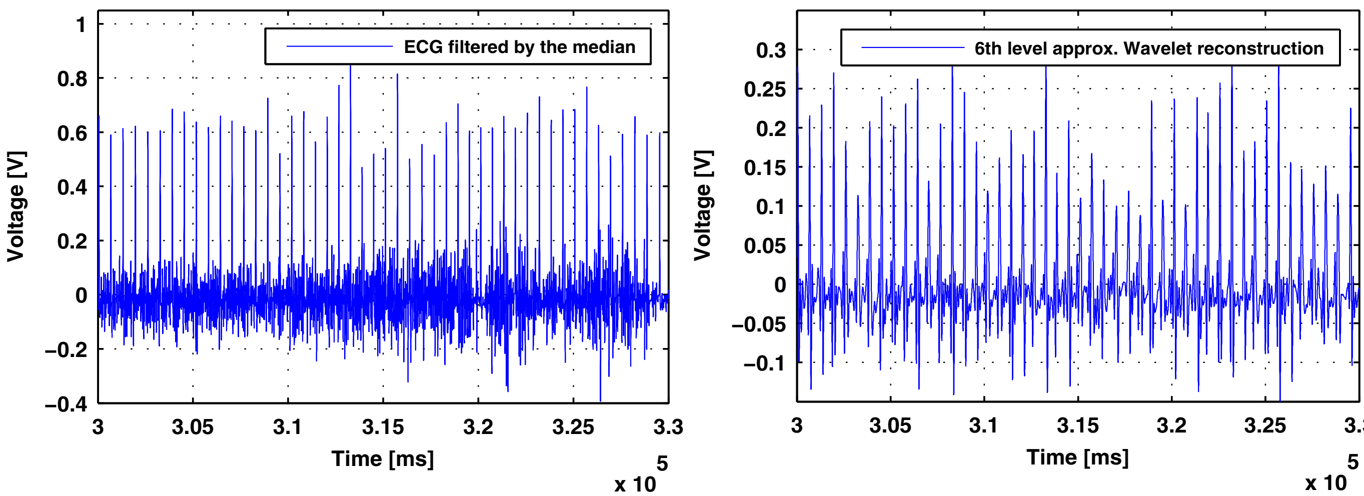


**Fig. 5.** Noise filtering by the 6th wavelet approximation.

To remove the remaining noise on the ECG signal, this paper presents a signal decomposition developed in six iterations, using the above mentioned Coiflet wavelet. Afterwards, the reconstruction is made using the approximation form by using the A coefficients. If that process is applied to the ECG filtered by the median, the sixth level wavelet approximation is obtained, shown in Fig. 5. Although some information might be lost, the noise of the ECG is removed and its shape is still considerably well kept.

As the R peaks are placed in the positive part of the graphic, the used wavelet approximation has been limited to its positive values. The next step to detect the R peaks is to calculate an estimation of the position where the next peak is likely to be located and to sweep the signal around that point to find where exactly the maximum of the signal is. The estimated position is calculated by summing the average distance of the previous three peaks plus the position of the last peak. After this estimation and sweeping process, the R peaks are correctly detected in the wavelet approximation, as shown in Fig. 6. So far, no initialization process has been designed for this algorithm, so the position of the first three peaks has been selected manually.

The final step is to verify whether the detected R peaks match the real R peaks of the original unprocessed ECG signal and that they have been detected despite the presence of artifacts or noises (see Fig. 6):

### 3.3. Heart rate calculation

For detecting stress, one of the proposed inputs for the detection fuzzy system is the HR signal. Once all the R peaks have been detected, it is easy to calculate the time difference between consecutive peaks. The signal that shows the time intervals between peaks is RR signal and it is needed to calculate the HR. It is obtained by (1):

$$RR_i = (Peak\_position_i - Peak\_position_{i-1})/F_{sample} \quad (1)$$

As the RR stands for the varying period of the R peaks, the frequency of the heart beats is obtained by inverting the RR signal. Continuing with the calculus, the HR value will be obtained if the frequency of the heart beats is multiplied by 60, as the heart rate stands for the number of beats per minute, shown in (2):

$$F_{beats} = 1/RR \rightarrow HR = 60 * F_{beats} \quad (2)$$

To use the fuzzy stress detection system it is necessary to have a good HR signal clean from noises or artifacts. The HR calculated using the proposed method analysis fits perfectly those characteristics. Fig. 7 shows how the proposed method has a better performance than the achieved by the commercial equipment from Biopac® used to collect the signals of the experiments:

## 4. Processing of the breath signal

It can be considered that, when relaxed, the human breathing tends to be relatively harmonic. When air is taken, the lungs inflate resulting in a movement similar to the ascending part of a sine. When exhaling that air, the lungs do a movement similar to the descending part of a sine.

On the other hand, when a person gets nervous or stressed, that person's breathing becomes less harmonic. This variation of the breathing pace is due to the acceleration of the heart movements which force the lungs to move faster in order to maintain the oxygen transfer to blood. This phenomenon can provide valuable information when trying to detect a stressful situation.

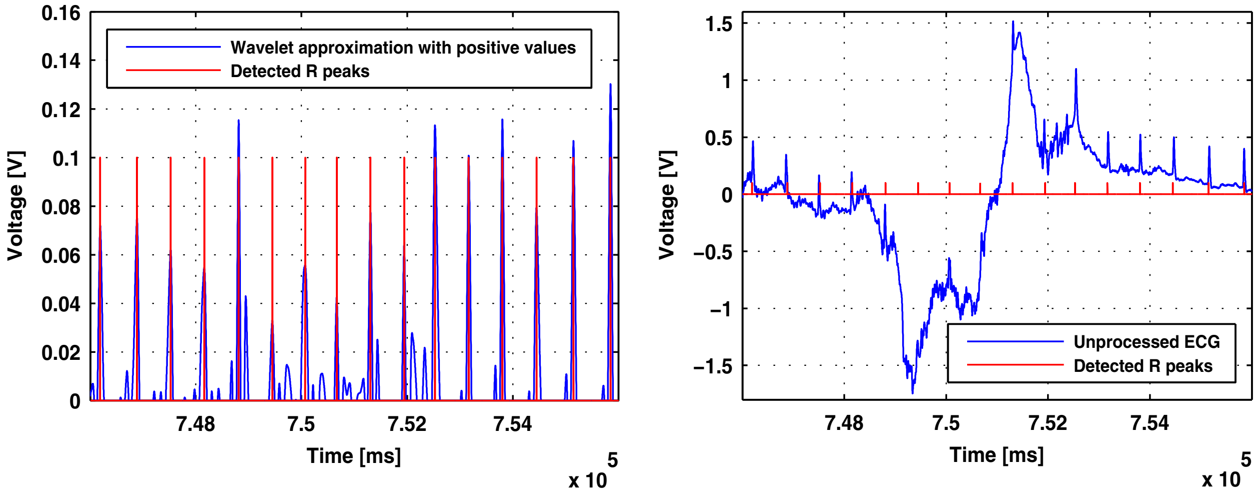


**Fig. 6.** R peaks detected in the wavelet approximation and in the original ECG.

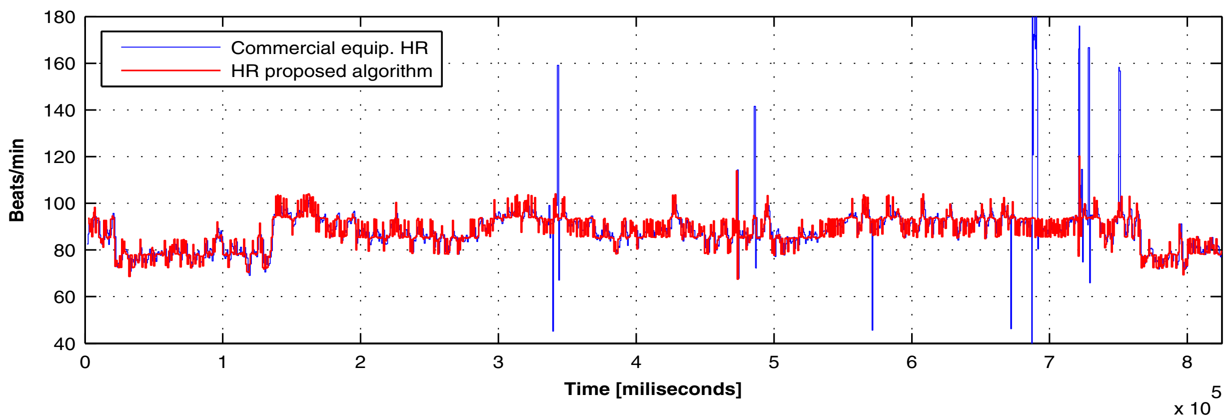


**Fig. 7.** The calculated HR and the obtained from the commercial equipment.

### 4.1. Frequential analysis of the breath signal

When analyzing how harmonic a signal is, the first step is to do a frequential analysis of that signal. This paper proposes to calculate the correlation between the breath signal and different frequency pure sine waveforms. This method has been chosen because it permits to focus in certain frequency components without having to pay attention to unnecessary intermediate or out of range frequencies.

In order to know where frequential information is concentrated, a wider spectral analysis has been done. From this spectral analysis it can be inferred that most of the information concentrates in lower frequencies, in the [0,0.5] Hz range (Fig. 8). After analyzing different subjects' breath signals it has been concluded that this range implies both stressed and relaxed situations.

Knowing that most of the information is found in this range, pure sinusoidal waves from 0.01 Hz to 0.5 Hz have been chosen to calculate their correlation with the breath signal. Different window sizes have been used as it is also interesting to determine which signal length is the best to extract information related to stress. Fig. 9 shows the results of the correlation calculus using different windows in the breath signal of a real subject. The selected window sizes are 20 s, 40 s and 60 s with a moving step size of 10 s.

The results of the correlation analysis show that during the beginning and the end of the experiment the highest levels of frequential correlation are mainly concentrated around a certain frequency. In addition, as several green spots appear (when the correlation value looks low), it is possible to deduce that during the stressful part the correlation values get bigger in a wider range of frequencies.

### 4.2. Statistical analysis and softening process

As mentioned before, the frequency correlation calculus shows that the frequential distributions are different during the relaxed and the stressful parts of the experiment. Therefore, this work proposes to use the standard deviation of the correlation values as an input of the Fuzzy system. The standard deviation seems to be a useful parameter when trying to detect stress. On the one hand, while stressing, the breath loses frequential concentration and most of the values obtained from the correlation tend to be closer from the average value. On the other hand, when relaxed, people's breath becomes more harmonic producing a frequential correlation increase around a point and a decrease in the other frequential areas. It also alters the value of the standard deviation of the correlations that gets bigger as all the values get further from the average value. This standard deviation variation effect is shown in Fig. 10 (the graph on top depicts the breath signal and the bottom graph corresponds to the frequential standard deviation evolution).

Fig. 10 depicts that at the beginning and ending of the test the standard deviation is bigger than in the middle part, the stressing part. Anyway, the standard deviation sometimes gets relatively high values which could lead the fuzzy system to a interpretation

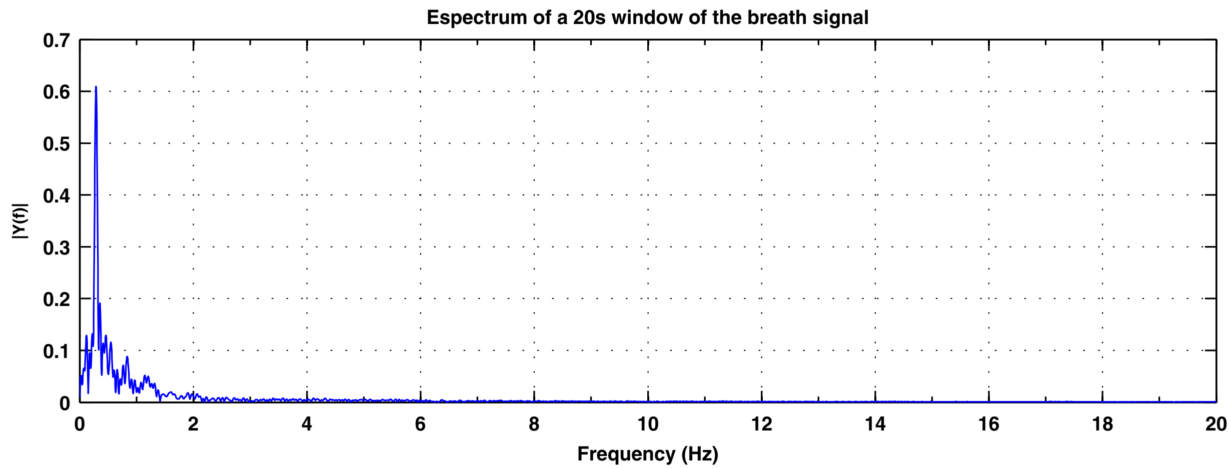


**Fig. 8.** The frequency spectrum of a breath signal.

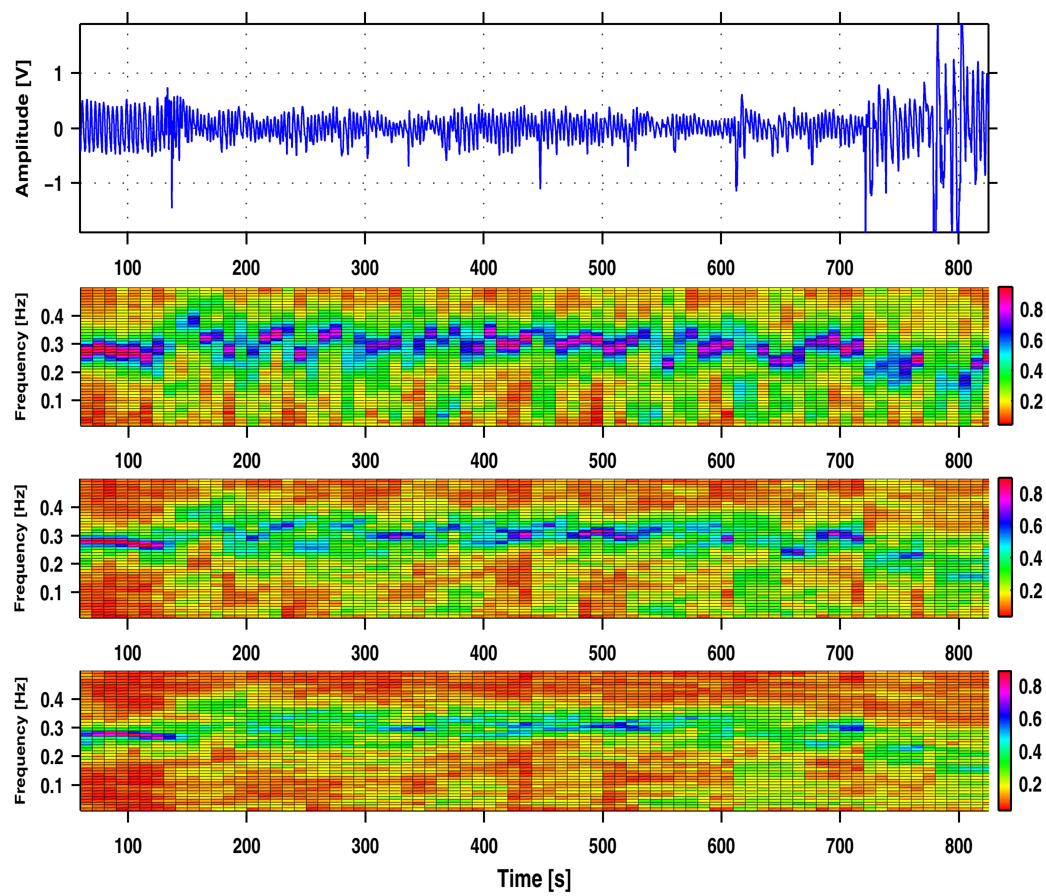


**Fig. 9.** Correlation between pure sine waves and the RESP signal by different windows.

problem. Because of that, it is interesting to increase the difference between the values of the relaxing and the stressing parts. A good method to do it is to multiply the standard deviation by the RMS value of the RR signal mentioned in Section 3.3. By combining them a new signal is obtained, where the level differences between relaxing and stressful parts have increased compared to what happened on the previous standard deviation signal (shown in Fig. 11). This last signal enables to distinguish easily between stressed and relaxed states and so, it has been used as an input for the fuzzy detection system.

## 5. Proposed stress detection fuzzy system

The fuzzy logic systems are a paradigm of Computational Intelligence area widely used in identification problems, as introduced by Andujar and Barragan [1]. The fuzzy system proposed in this paper has the aim to detect continued stress situations in order to improve the social inclusion of people with disabilities and, subsequently, their life quality. The fuzzy system is based on the one posed in [7], adding three enhancements: the R peak detection procedure presented in Section 3, the use of the frequential

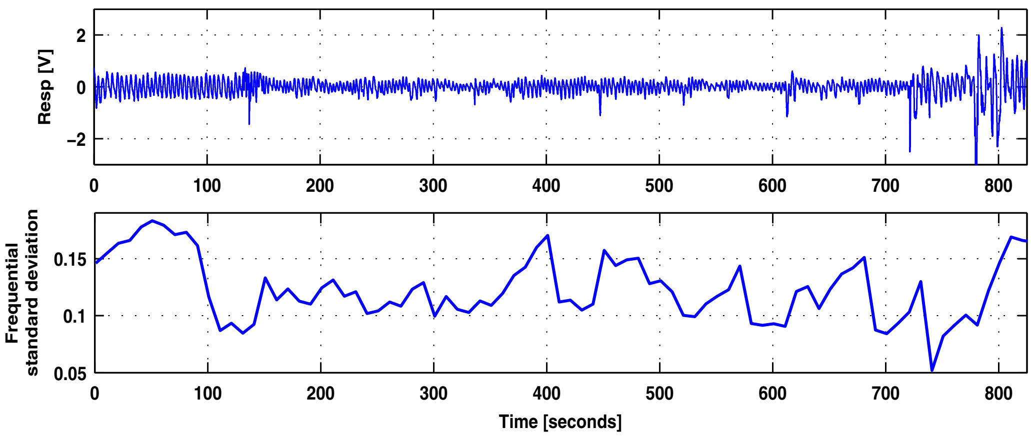


**Fig. 10.** Standard deviation variation effect: Breath signal and frequential correlation.

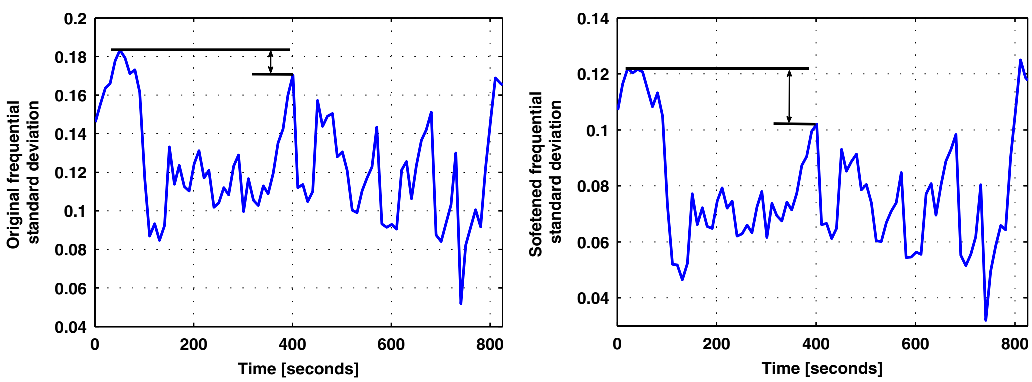


**Fig. 11.** Peak differences increase after softening the standard deviation.

component standard deviation of the RESP as an input, and the GSR signal decomposition shown later in the current section.

This section will present the Matlab® based fuzzy logic system. First it will be explained how to build the membership functions and the reason to do decompose the GSR signal. Second, the output membership functions will be explained. Then, the rules that relate the inputs to the outputs will be presented. Finally, results of the stress detection will be shown.

### *5.1. Input membership functions and GSR decomposition*

As the GSR represents the level of conductance of the skin, and hence its moisture, it can be considered to have an accumulative nature. Thus, despite the amplitude gives some information, the variations of the signal respect to its previous values provide much better indicators of changes in stress. In order to improve the detection, this paper proposes to decompose the GSR signal into two components: the average value and the variations.

In the work presented in [23] the HR and average GSR membership functions had a Gaussian shape. This was based on the template method of [7], which proposed to design the membership functions using the average and standard deviation of the variables during the two periods of the experiment, RS and SS.

Instead, the current work proposes to define a new intermediate medium stress (MS) membership function which will give flexibility to the system allowing to detect better transitions between relaxed and stressed states.

Moreover, this strategy avoids the overlapping of the HR membership functions. Sometimes people have high HR pace variations which are perfectly normal and do not necessarily mean a transition to stress, as it happens in the RS part of Fig. 12.

As seen in Fig. 12, the HR remains relatively concentrated around its average value during the SS part of the experiment. However, during the RS period, the HR varies highly and in certain points it even reaches the same values as in the SS part. Despite that having such HR variations is perfectly normal, using the template method would lead to difficulties when detecting stress as the HR membership functions would overlap producing false situations. Such problems are presented on the left side of Fig. 13, which shows the template method based membership functions for the subject of Fig. 12.

Based on this criteria, three membership functions have been defined for all input variables: RS, MS and SS. This approach proposes to use trapezoidal functions for RS and SS and a different MS function filling the gap between RS and SS, as shown on the right of Fig. 13. This paper proposes to use a triangular shape for GSR variations and Gaussian shapes for HR and average GSR MS functions. Unfortunately, it does not present an automatic method to fine tune the membership functions, and for the moment, the function tuning has to be done manually in order to adjust the system to each subject.

The last membership functions to be defined are the corresponding to the output. This paper follows the approach of [23] and presents the same three function strategy. In [7] it is only made the difference between non-stressed and stressed situations. To make the stress level detection more reliable, this system includes the intermediate stress level MS triangular output function. The output has been normalized in an [0, 1] interval. Table 1 presents the details of the design of the membership functions:

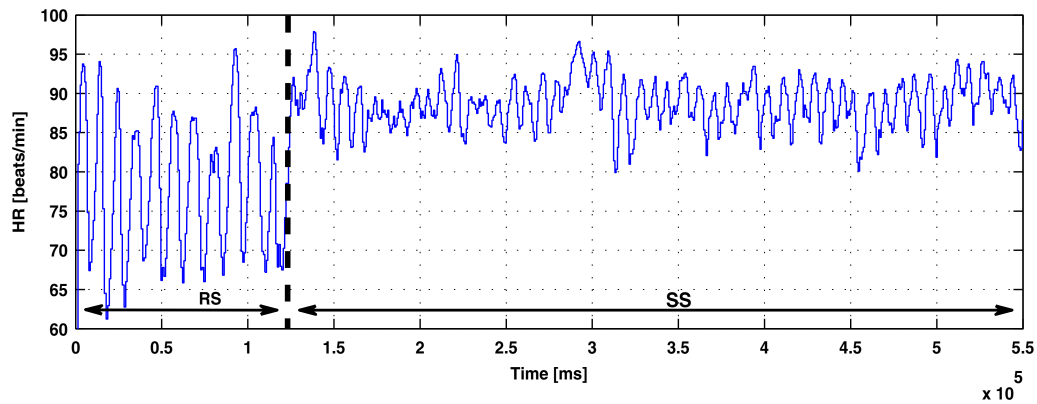


**Fig. 12.** A HR signal with high pace variability.

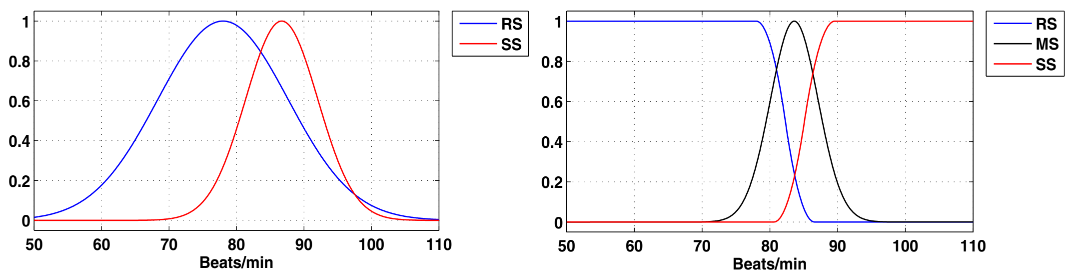


**Fig. 13.** Overlapping of the HR membership functions.

**Table 1**
Definition of the membership functions.

| Variable | Definition | States | Shape | Shape edges |
|---|---|---|---|---|
| Input: | | RS | Trapezoidal | Variable |
| Hear | Variable | MS | Gaussian | Variable |
| Rate | | SS | Trapezoidal | Variable |
| Input: | | RS | Trapezoidal | Variable |
| Average | Variable | MS | Gaussian | Variable |
| GSR | | SS | Trapezoidal | Variable |
| Input: | | RS | Trapezoidal | [−2, −2, −0.75,0] |
| GSR | [−2.2] | MS | Triangular | [−0.5,0,0.5] |
| variation | | SS | Trapezoidal | [0,0.75,2,2] |
| Output: | | RS | Trapezoidal | [0,0,0.275,0.475] |
| Stress | [0,1] | MS | Triangular | [0.25,0.5,0.75] |
| level | | SS | Trapezoidal | [0.525,0.725,1,1] |

**Table 2**
Previous variable relationships.

| State of variable 1 | State of variable 2 | Conclusion |
|---|---|---|
| SS | SS | SS |
| SS | RS | MS |
| RS | SS | MS |
| RS | RS | RS |

*5.2. The inference rule system*

As done in [23], the inference system variable linkage has been done matching the inputs in pairs. Again, the variables have been connected with IF AND IF THEN rules. Anyway, the main difference proposed in this paper comes from the criteria of using three membership functions for the inputs. In that previous phase, most of the input variables had only two membership functions and so, it was difficult to define when to activate the MS output function. In that phase, the MS output would be activated when the states of the inputs were opposite to each other. Table 2 summarizes it what was done in [23].

**Table 3**
Input variable relationships.

| State of variable 1 | State of variable 2 | Conclusion |
|---|---|---|
| SS | SS | SS |
| MS | MS | MS |
| RS | RS | RS |

An after analysis proved that the rule system was prone to have drastic changes easily. Subsequently, the MS function was added to the input variables in order to give plasticity to the system. With it, establishing the relationships between variables has become much simpler: the RS output activates when both variables are RS, the MS output activates when both variables are MS and the same the SS output. Lastly, it is important to note that all the relationships do not weight the same when determining the detected stress level. This input variable linkage approach can be seen in Table 3.

*5.3. Comparative results of systems*

The last step is to validate the system through simulation. All systems have been tested, the one from [7], the one from the previous work and the proposed in this paper. To compare results, these systems have used the same variables, with the difference that the proposed in this paper has a fourth input as it needs to consider the softened RESP Standard Deviation. As stress does not have strong dynamics, the simulations have used inputs that refreshed every 20 s, time fast enough to represent the stress variations correctly. The used HR signal has been taken from the HR calculated in Section 3 using the robust R peak detection method proposed in this paper. Additionally, the GSR signal has been preprocessed as mentioned ahead.

As shown in Fig. 14, the proposed system is more accurate identificating stress changes as the weight of the instant GSR value is not that important compared to its tendency respect to the

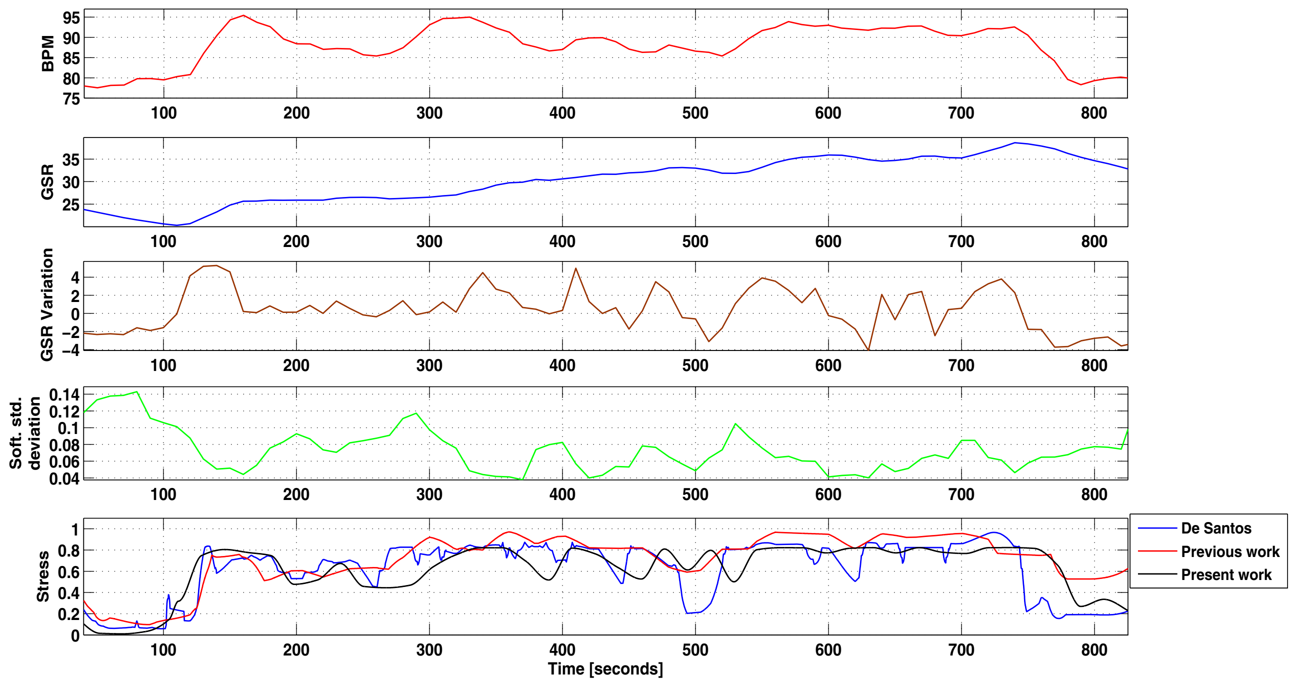


**Fig. 14.** HR, GSR, GSR variation and RESP Standard Deviation inputs and estimated stress level outputs for the three methods.

previous points, and the softened value of the RESP Standard Deviation becomes more important in order to decrease sharp transitions. Anyway, it is difficult to assure which one represents better the reality as stress is an abstract and subjective matter and the only way to quantify it is to ask the volunteers to complete the normalized survey known as the Self-Assessment Manikin presented by Lang [12].

## 6. Conclusions and future work

This paper has presented an enhanced and renewed strategy based on a fuzzy logic and the simultaneous use of three physiological signals (ECG, GSR and RESP) to detect personal stress situations. This line has continued the work presented in [23] and has remarked the importance of the input signal processing. It has shown that important information can be extracted from physiological signals by applying certain mathematical strategies, as happened when detecting R peaks or when decomposing the GSR signal. In addition, it has proposed to use the RESP signal as it contains information about the stress level of people. All these improvements have been showed in comparison with the results of [7] and the further work in [23].

This work has also shown how it is possible to obtain successful results with a simple inference system. For further developments, outside the scope of this work, the prior tuning of the system will be solved applying other soft computing techniques, as for example, a neural network to create the input membership functions.

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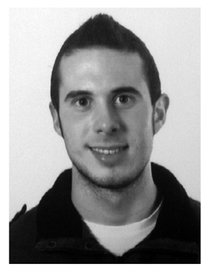

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