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.

Keywords: fuzzy logic, physiological signal processing, wavelets, stress identification.

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 Healey et al. (2005), Vries et al. (2015), and Ren et al. (2014).

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 (2012). 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 Salazar-Ramirez et al. (2014), which proposed enhancements for the work of de Santos Sierra et al. (2011), 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. (2014), to quantitative analysis of measured physiological variations that emotions elicit in each person, e.g. in Sato et al. (2007). In particular, there are very specific physiological changes related to stress, as the phylogenetic substrates study made by Porges (2001), or the activity study of the autonomic nervous system shown in Kreibig (2010). As pointed in Cannon's researches, Cannon (1935), 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, Poon and Siniaia (2000). 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, Navarro (2002).

Some proposals measure physiological signals using intrusive devices, as the work of Coan and Allen (2004) 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, Subramanya et al. (2013). This work is based on using physiological signals that can be measured with 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 Martínez et al. (2012). 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. (2006), Wozniak et al. (2014), or Calvo-Rolle and Corchado (2014).

In the study of human emotional changes, and specifically in stress situation labeling, some Soft Computing approaches have a special applicability, as de Santos Sierra et al. (2011), and Sakr et al. (2010). 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, Nelson (2005), 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 Salazar-Ramirez et al. (2014) 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, Hong-tu and Jing (2010), for a more accurate R peak detection, recently appeared in works as Sasikala and Wahidabanu (2010), Talbi et al. (2011), de Lannoy et al. (2009), and Martis et al. (2014). 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 Gross and Levenson (1995) and CSEA-NIMH (1999). 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 figure 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 figure 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. Figure 2 shows examples of these two possible problems.

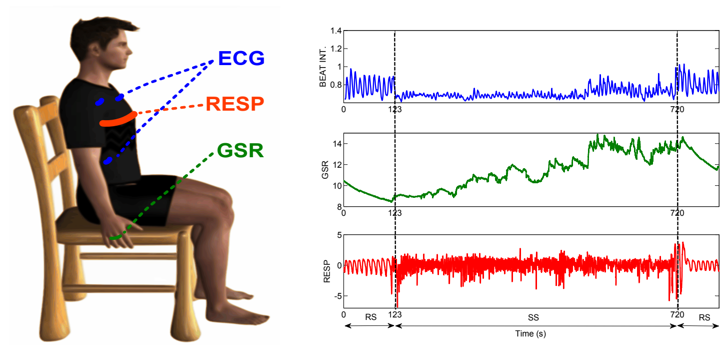

Figure 1: Electrode positioning scheme and collected data time series.

As in de Santos Sierra et al. (2011) 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 figure 2, which has been collected in the experiments for very significant as it has different artifacts and noises.

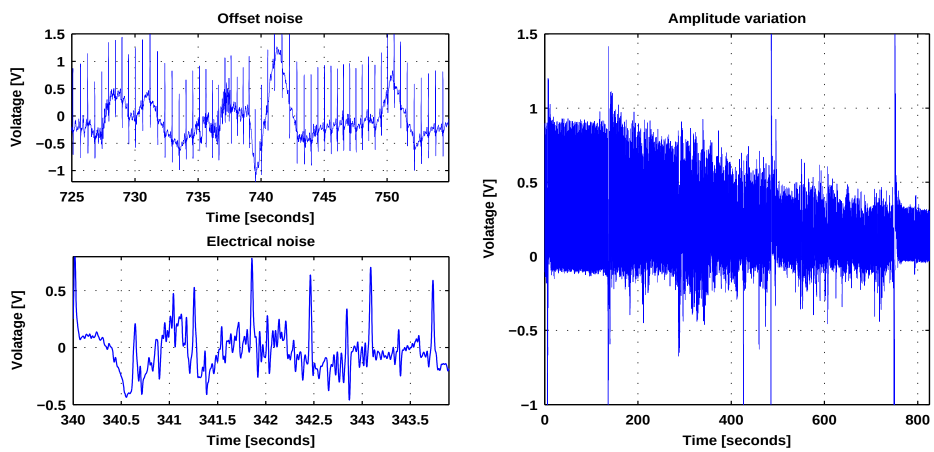

Figure 2: Different noises and artifacts produced in the ECG signal.

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 Sasikala and Wahidabanu (2010), one of the best methods to eliminate the offset produced by electrode movements is to apply a median filter to the ECG. 100ms is a suitable length for the filter as artifacts normally do not last for much longer. Figure 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.

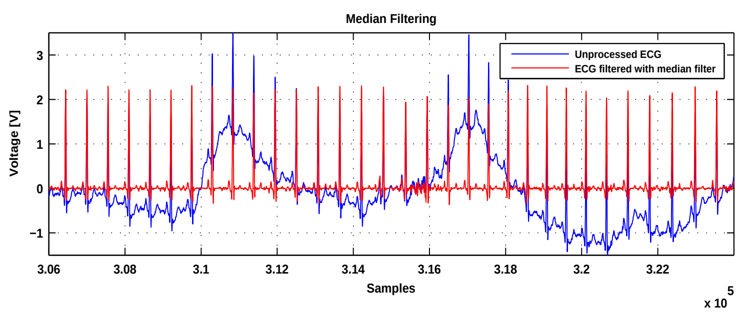

Figure 3: Offset artifacts removed from the original signal by applying the median filter.

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, Hong-tu and Jing (2010). Figure 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.

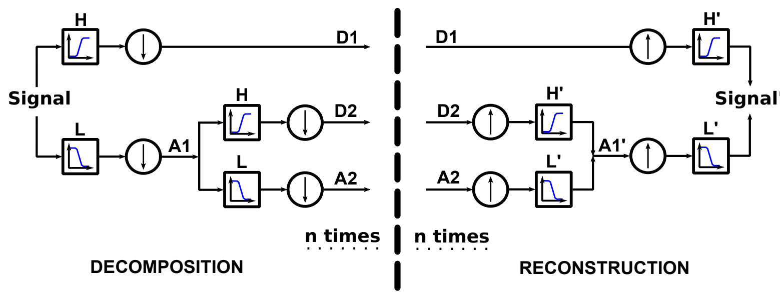

Figure 4: Wavelet decomposition and reconstruction scheme.

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.

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 figure 5. Although some information might be lost, the noise of the ECG is removed and its shape is still considerably well kept.

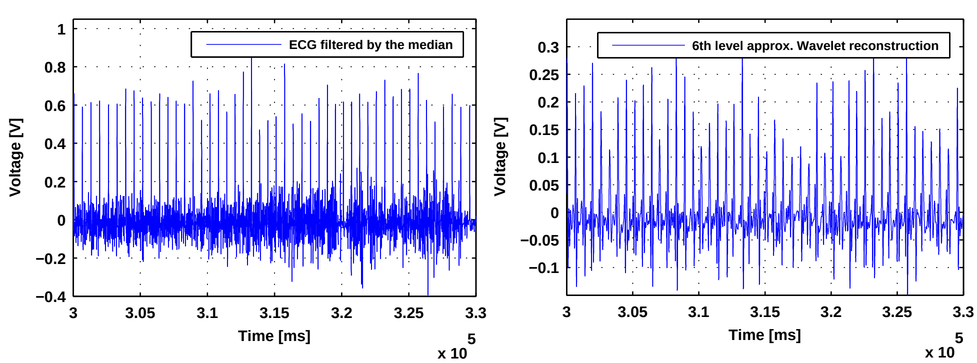

Figure 5: Noise filtering by the 6th wavelet approximation.

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 figure 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 figure 6):

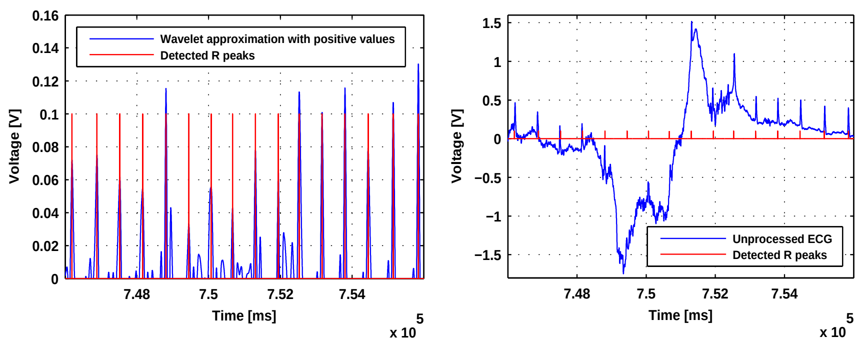

Figure 6: R peaks detected in the wavelet approximation and in the original ECG.

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):

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

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):

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

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. Figure 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:

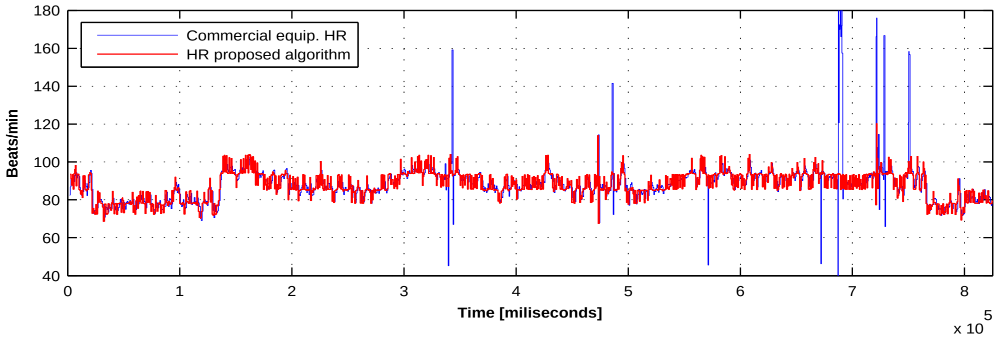

Figure 7: The calculated HR and the obtained from the commercial equipment.

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.

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.

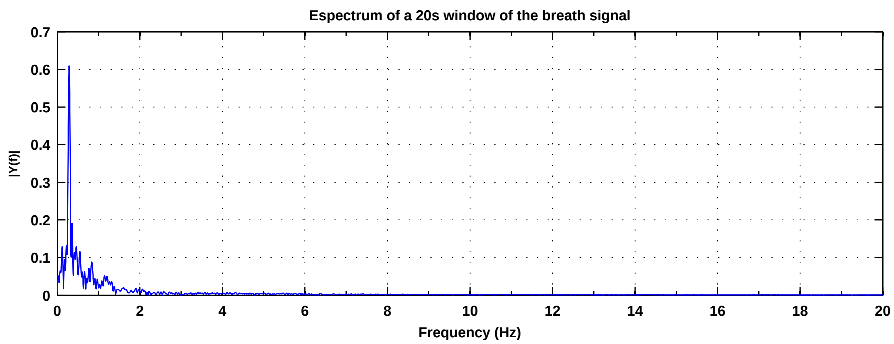

Figure 8: The frequency spectrum of a breath signal.

Knowing that most of the information is found in this range, pure sinusoidal waves from 0.01Hz to 0.5Hz 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. Figure 9 shows the results of the correlation calculus using different windows in the breath signal of a real subject. The selected window sizes are 20s, 40s and 60s with a moving step size of 10s.

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

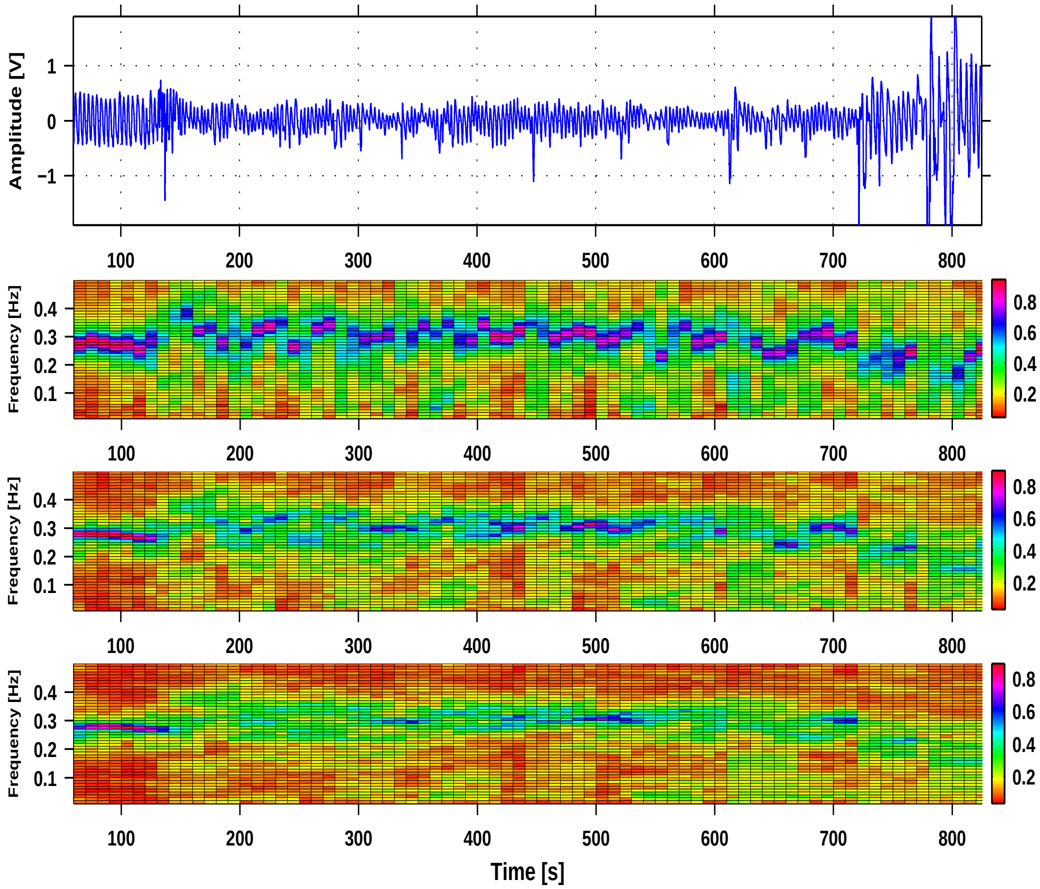

Figure 9: Correlation between pure sine waves and the RESP signal by different windows.

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 figure 10 (the graph on top depicts the breath signal and the bottom graph corresponds to the frequential standard deviation evolution).

Figure 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

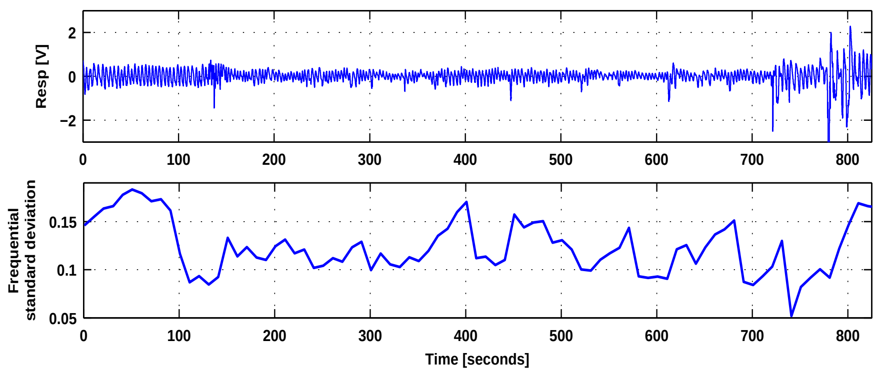

Figure 10: Standard deviation variation effect: Breath signal and frequential correlation.

standard deviation sometimes gets relatively high values which could lead the fuzzy system to a interpretation 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 figure 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.

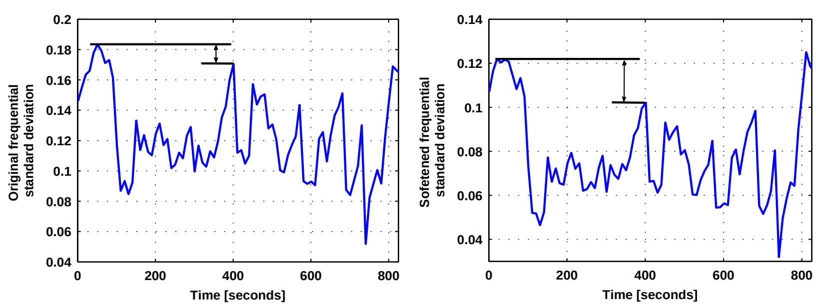

Figure 11: Peak differences increase after softening the standard deviation.

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 (2014). 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 de Santos Sierra et al. (2011), adding three enhancements: the R peak detection procedure presented in section 3, the use of the frequential 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 Salazar-Ramirez et al. (2014) the HR and average GSR membership functions had a Gaussian shape. This was based on the template method of de Santos Sierra et al. (2011), 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 figure 12.

As seen in figure 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

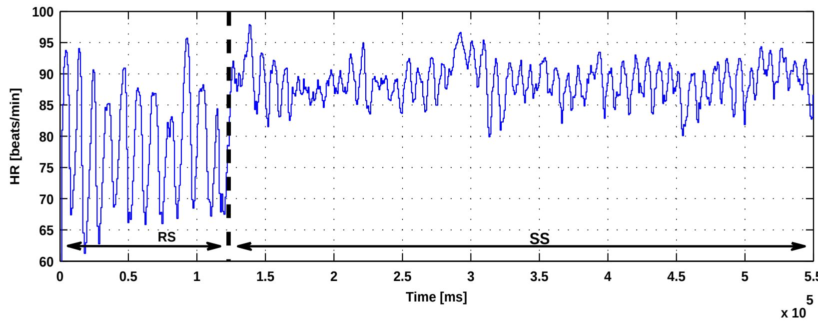

Figure 12: A HR signal with high pace variability.

stress as the HR membership functions would overlap producing false situations. Such problems are presented on the left side of figure 13, which shows the template method based membership functions for the subject of figure 12.

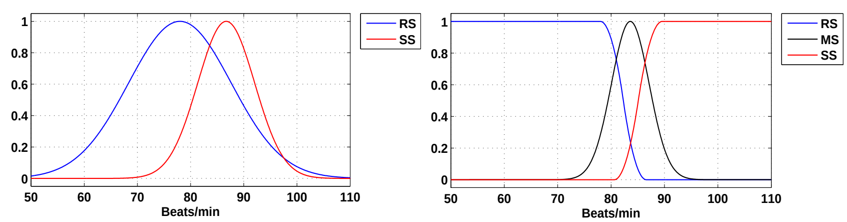

Figure 13: Overlapping of the HR membership functions.

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 figure 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 Salazar-Ramirez et al. (2014) and presents the same three function strategy. In de Santos Sierra et al. (2011) 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:

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]

5.2. The Inference Rule System

As done in Salazar-Ramirez et al. (2014), 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 Salazar-Ramirez et al. (2014).

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

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.

Table 3: Input variable relationships.

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

5.3. Comparative Results of Systems

The last step is to validate the system through simulation. All systems have been tested, the one from de Santos Sierra et al. (2011), 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 20s, 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 figure 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 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 (1980).

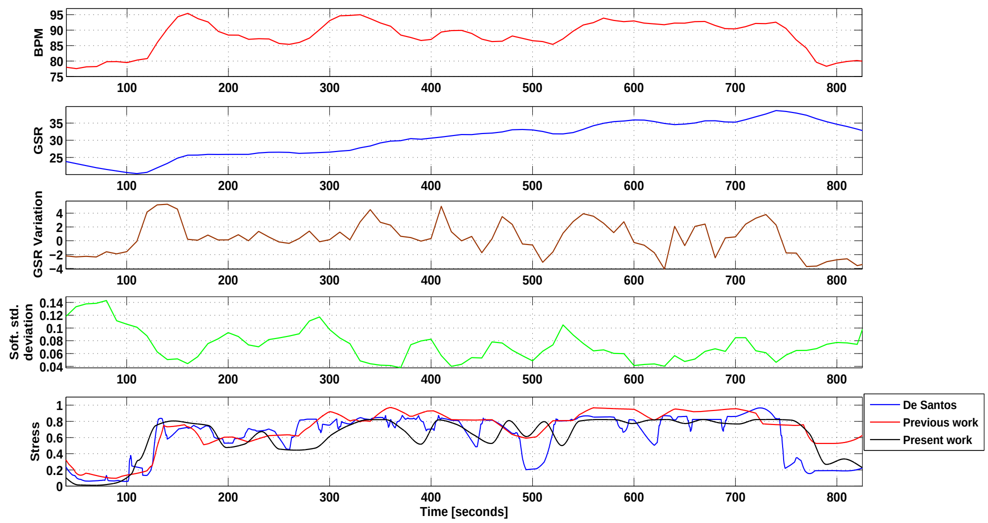

Figure 14: HR, GSR, GSR variation and RESP Standard Deviation inputs and estimated stress level outputs for the three methods.

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 Salazar-Ramirez et al. (2014) 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 de Santos Sierra et al. (2011) and the further work in Salazar-Ramirez et al. (2014).

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.

7. Acknowledgements

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8. References

Andujar, J. M., Barragan, A. J., 2014. Hybridization of fuzzy systems for modeling and control. RIAI 11 (2), 127–141.

Calvo-Rolle, J. L., Corchado, E., 2014. A bio-inspired knowledge system for improving combined cycle plant control tuning. Neurocomputing 126, 95–105.

Cannon, W. B., 1935. Stresses and strains of homeostasis. The American Journal of the Medical Sciences 189 (1), 13–14.

Coan, J. A., Allen, J. J., 2004. Frontal eeg asymmetry as a moderator and mediator of emotion. Biological psychology 67 (1), 7–50.

CSEA-NIMH, 1999. The international affective picture system: Digitalized photographs. Center of Research in Psychophysiology.

de Lannoy, G., De Decker, A., Verleysen, M., 2009. A supervised wavelet transform algorithm for r spike detection in noisy ecgs. In: Biomedical Engineering Systems and Technologies. Springer, pp. 256–264.

de Santos Sierra, A., vila, C. S., Casanova, J. G., Pozo, G. B. D., 2011. A stress-detection system based on physiological signals and fuzzy logic. Industrial Electronics, IEEE Transactions on 58 (10), 4857–4865.

Gross, J. J., Levenson, R. W., 1995. Emotion elicitation using films. Cognition & emotion 9 (1), 87–108.

Healey, J., Picard, R. W., et al., 2005. Detecting stress during real-world driving tasks using physiological sensors. Intelligent Transportation Systems, IEEE Transactions on 6 (2), 156–166.

Hong-tu, Z., Jing, Y., 2010. The wavelet decomposition and reconstruction based on the matlab. In: Proc. of the Third Int. Symposium on Electronic Commerce and Security Workshops (ISECS 2010), China.

Kreibig, S. D., 2010. Autonomic nervous system activity in emotion: A review. Biological psychology 84 (3), 394–421.

Lang, P. J., 1980. Behavioral treatment and bio-behavioral assessment: Computer applications. Technology in Mental Health and Delivery Systems, 119137.

Lee, C. K., Yoo, S., Park, Y. J., Kim, N. H., Jeong, K. S., Lee, B., 2006. Using neural network to recognize human emotions from heart rate variability and skin resistance. In: IEEE-EMBS 2005. IEEE, pp. 5523–5525.

López, D. R., Neto, A. F., Bastos, T. F., 2014. On line recognition of human actions based on patterns of rwe windows applied in dynamic moment invariants. RIAI 11 (2), 202–211.

Martínez, R., Irigoyen, E., Asla, N., Escobes, I., Arruti, A., 2012. First results in modelling stress situations by analysing physiological human signals. Proceedings of the IADIS International Conference e-Health, 171175.

Martis, R. J., Chakraborty, C., Ray, A. K., 2014. Wavelet-based machine learning techniques for ecg signal analysis. In: Machine Learning in Healthcare Informatics. Springer, pp. 25–45.

Navarro, X., 2002. Fisiologa del sistema nervioso autnomo. Revista Neurológica 35, 553–562.

Nelson, R. J., 2005. An introduction to behavioral endocrinology . Sinauer Associates.

Poon, C.-S., Siniaia, M. S., 2000. Plasticity of cardiorespiratory neural processing: classification and computational functions. Respiration physiology 122 (2), 83–109.

Porges, S. W., 2001. The polyvagal theory: phylogenetic substrates of a social nervous system. International Journal of Psychophysiology 42 (2), 123–146.

Ren, P., Barreto, A., Huang, J., Gao, Y., Ortega, F. R., Adjouadi, M., 2014. Off-line and on-line stress detection through processing of the pupil diameter signal. Annals of biomedical engineering 42 (1), 162–176.

Sakr, G. E., Elhajj, I. H., Huijer, H. A.-S., 2010. Support vector machines to define and detect agitation transition. Affective Computing, IEEE Transactions on 1 (2), 98–108.

Salazar-Ramirez, A., Irigoyen, E., Martinez, R., 2014. Enhancements for a robust fuzzy detection of stress. In: International Joint Conference SOCO14-CISIS14-ICEUTE14. Springer, pp. 229–238.

Sasikala, P., Wahidabanu, R., 2010. Robust r peak and qrs detection in electrocardiogram using wavelet transform. International Journal of Advanced Computer Science and Applications-IJACSA 1 (6), 48–53.

Sato, W., Noguchi, M., Yoshikawa, S., 2007. Emotion elicitation effect of films in a japanese sample. Social Behavior and Personality: an international journal 35 (7), 863–874.

Sharma, N., Gedeon, T., 2012. Artificial neural network classification models for stress in reading. In: Neural Information Processing. Springer, pp. 388–395.

Subramanya, K., Vishnuprasada, V. B., Kamath, S., 2013. A wearable device for monitoring galvanic skin response to accurately predict changes in blood pressure indexes and cardiovascular dynamics. In: INDICON 2013. IEEE, pp. 1–4.

Talbi, M., Aouinet, A., Salhi, L., Cherif, A., 2011. New method of r-wave detection by continuous wavelet transform. Signal Processing: An International Journal (SPIJ) 5 (4), 165.

Vries, J., Pauws, S., Biehl, M., 3 2015. Insightful stress detection from physiology modalities using learning vector quantization. Neurocomputing 151 (Part 2), 873–882.

Wozniak, M., Graa, M., Corchado, E., 2014. A survey of multiple classifier systems as hybrid systems. Information Fusion 16, 3–17.

An Enhanced Fuzzy Algorithm based on Advanced Signal Processing for Identification of Stress

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Abstract

Nowadays, it is crucial to promote, drive and develop the autonomy of everyone, and specifically in individuals with some disability, in order to improve their quality of life and achieve a best inclusion into the socio-cultural life.Therefore, the robust identification of stress situations can be a suitable and assistive tool for obtaining improvements in such 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.

Keywords: fuzzy logic, physiological signal processing, wavelets, stress identification.

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 peoples life quality. Several research tendencies try to improve the life quality of people with disabilities by focusing in the improvement the inclusion of people with disabilities in the socio-cultural life. Physiological signal measurements by non intrusive sensing systems, signal processing and analysis with soft computing techniques, identification and classification of human emotions and stressed situations, are some of the investigation approaches that are being performed in a high number of significant research groups (Healey et al. (2005); Vries et al. (2015); Ren et al. (2014)). Applying these studies to personal emotional blockage situations induced by a high stress levels is a field of huge interest (Sharma and Gedeon (2012)). The preliminary detection of blockage situation is a powerful assistive tool for elder people and persons with disabilities. This work presents an extended solution to the system presented in (Salazar-Ramirez et al. (2014)), which proposed enhancements for the work of De Santos in (de Santos Sierra et al. (2011)), where such situations are detected and identified.

There exist multiple studies that analyze the influence of human emotions in everyday life of people, from qualitative studies based on human behavior (López et al. (2014)), to quantitative analysis of measured physiological variations that emotions elicit in each person (Sato et al. (2007)). In particular, there are very specific physiological changes related to stress (Porges (2001); Kreibig (2010)). As pointed in Cannons researches (Cannon (1935)), when a person has to face a dangerous situation, the persons 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 (Poon and Siniaia (2000)). 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 (Navarro (2002)).

Some proposals measure physiological signals using intrusive devices, as cameras or electrode grids (Coan and Allen (2004)), 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 (Subramanya et al. (2013)). This work is based on using physiological signal that can be measured with 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 analysing 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 Martnez et al. discussed in (Martínez et al. (2012)). Such difficulty comes from the large amount of the data generated by analysing 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 (Lee et al. (2006); Wozniak et al. (2014); Calvo-Rolle and Corchado (2014)).

In the study of human emotional changes, and specifically in stress situation labelling, some Soft Computing approaches have a special applicability (de Santos Sierra et al. (2011); Sakr et al. (2010)). 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 (Nelson (2005)), 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 enhanced identification system of blockage situations in persons, based on the measurement of human physiological signals obtained by non-intrusive methods. This work proposes enhancing the system presented in (Salazar-Ramirez et al. (2014)) by improving the processing of the input signals and by using a new input variable, based on the RESP signal. Three main improvements are proposed. The first is to increase the robustness of the ECG processing using wavelets techniques for a more accurate R peak detection (Sasikala and Wahidabanu (2010); Hong-tu and Jing (2010); Talbi et al. (2011); de Lannoy et al. (2009); Martis et al. (2014)). The second is to apply more efficiently the GSR signal, decomposed in average and variations, into the Fuzzy strategy. The last improvement proposes to analyse the frequential composition of the RESP signal to use its standard deviation as an input of the detection system.

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 individuals 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 Gross (Gross and Levenson (1995)) and (CSEA-NIMH (1999)). These experiments consist on proposing to each individual 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 correspondent electrodes needed to collect the ECG and GSR as shown in figure 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 figure 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. During these periods, the hearts 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 interval between ECG beats is reduced and the RESP tends to be faster and more irregular. These changes proof that the subject is getting stressed.

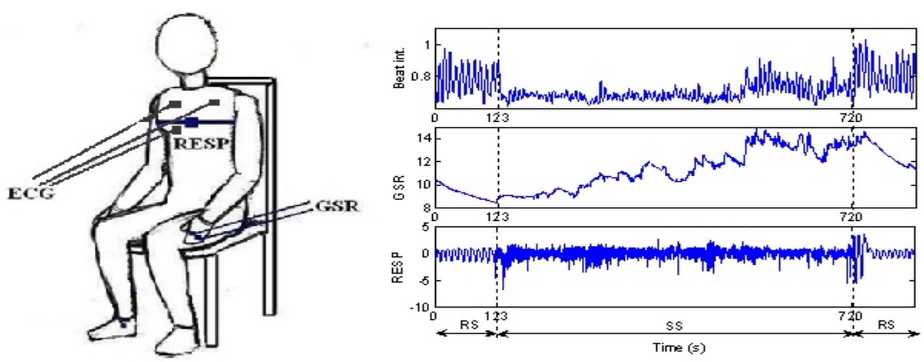

Figure 1: Electrode positioning scheme and collected data time series.

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. Figure 2 shows examples of these two possible problems.

As in (de Santos Sierra et al. (2011)) 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 the 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 figure 2, which has been collected in the experiments for very significant as it has different artifacts and noises.

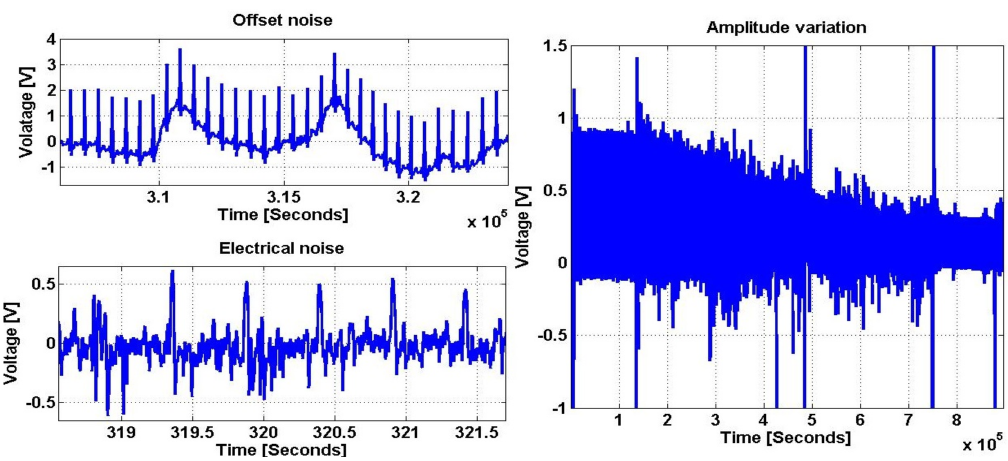

Figure 2: Different noises and artifacts produced in the ECG signal.

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 (Sasikala and Wahidabanu (2010)), one of the best methods to eliminate the offset produced by electrode movements is to apply a median filter to the ECG. 100ms is a suitable length for the filter as artifacts normally do not last for much longer. Figure 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.

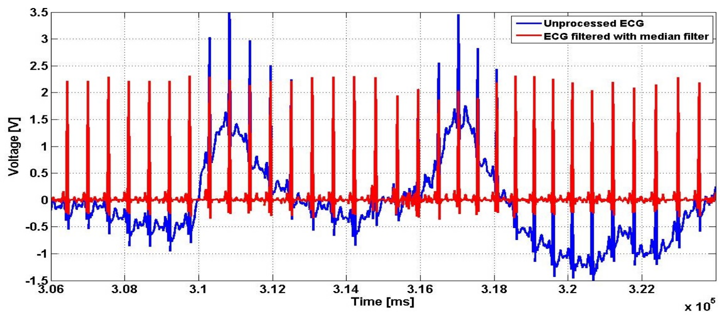

Figure 3: Offset artifacts removed from the original signal by applying the median filter.

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 the wavelet decomposition and reconstruction (Hong-tu and Jing (2010)). Figure 4 shows the diagram of how the wavelet processing is done (on the left and right sides of the diagram respectively).

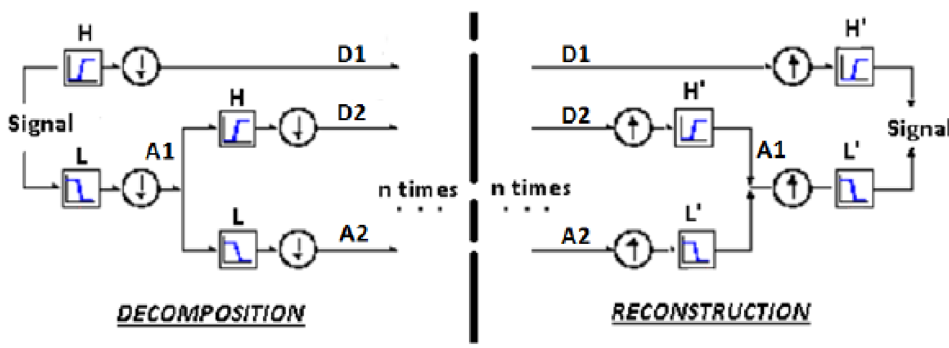

Figure 4: Wavelet decomposition and reconstruction scheme.

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. There are several wavelet families. Each one is composed by some different wavelets from whom one has to be chosen. Choosing the best is a tough task beyond this paper. Anyway, despite it might not be the best one, 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.

To remove the remaining noise on the ECG signal, this paper presents a signal decomposition developed in six iterations, using the third 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 figure 5. Although some information might be lost, the noise of the ECG is removed and its shape is still considerably well kept.

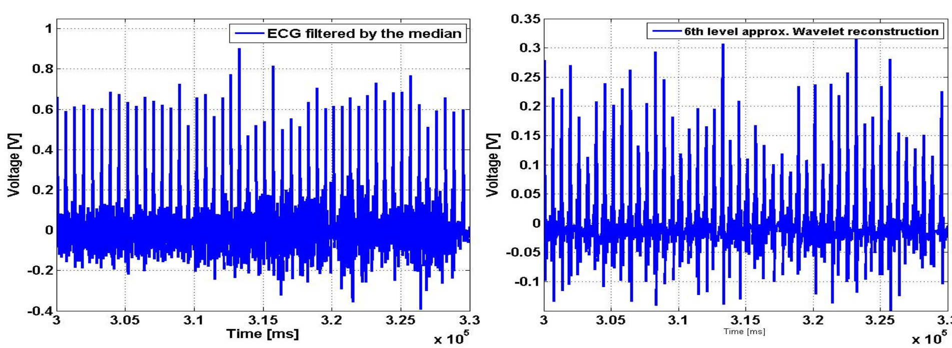

Figure 5: Noise filtering by the 6th wavelet approximation.

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 R peak 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 summing the average distance of the previous three peaks plus the position of the last peak. After the process of the estimation of the position and the sweeps the R peaks are correctly detected in the wavelet approximation, as it can be seen in figure 6.

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 figure 6):

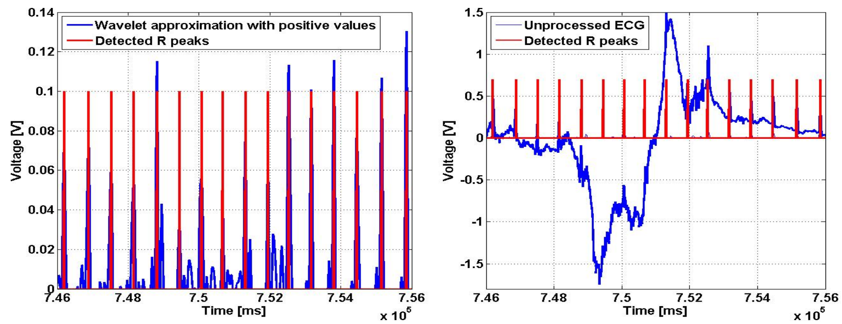

Figure 6: R peaks detected in the wavelet approximation and in the original ECG.

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):

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

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):

$$F_{beats} = 1/RR \rightarrow HR = F_{beats}/60$$

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. Figure 7 shows how the proposed method has a better performance than the one achieved by the commercial equipment from Biopac used during the experiments:

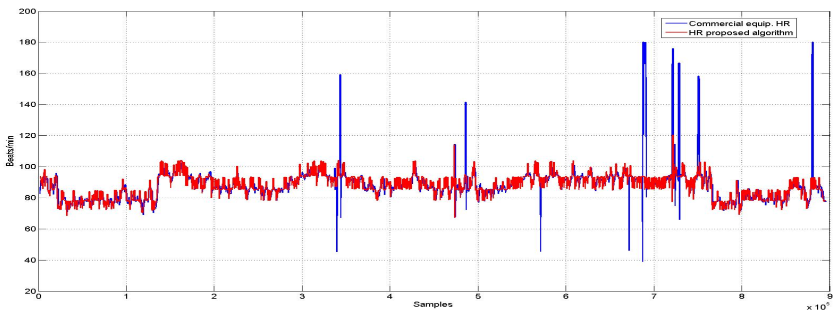

Figure 7: The calculated HR and the obtained from the commercial equipment.

4. Processing of the breath signal

Regarding the movements of the chest, it can be considered that, when relaxed, the human breathing tends to be relatively harmonic. When a subject takes air, the lungs inflate resulting in a movement similar to the ascending part of a sine. When exhaling that air, the lungs tend to do a movement similar to the descending part of a sine. On the other hand, when a person gets nervous or stressed, that persons 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 the blood. This phenomenon can provide valuable information when trying to detect a stressful situation.

4.1. Frequential analysis of the breath signal

When analysing 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. Before starting to calculate correlations, 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 having analysed different subjects breath signals it has been concluded that this range implies both stressed and relaxed situations.

Knowing the range where most of the frequential information is found, pure sinusoidal waves going from 0.01Hz to 0.5Hz have been chosen to cal-

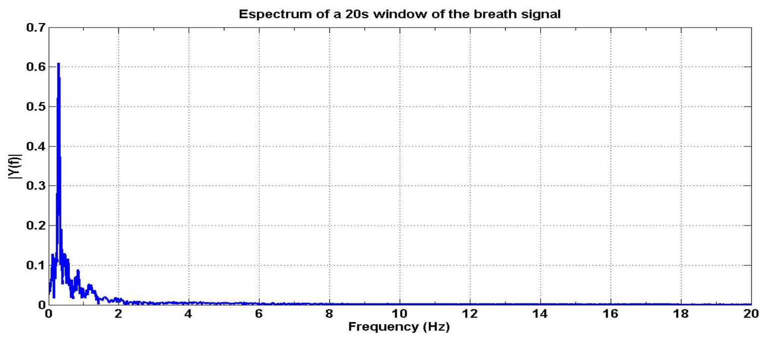

Figure 8: The frequency spectrum of a breath signal.

culate their correlation with the breath signal. Different window sizes have been used as it is also interesting to determine which length of the signal is the best to extract information related to stress. Figure 9 shows the results of the correlation calculus using different windows in the breath signal of a real subject. The selected window sizes are 20s, 40s and 60s with a moving step size of 10s.

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, peoples 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

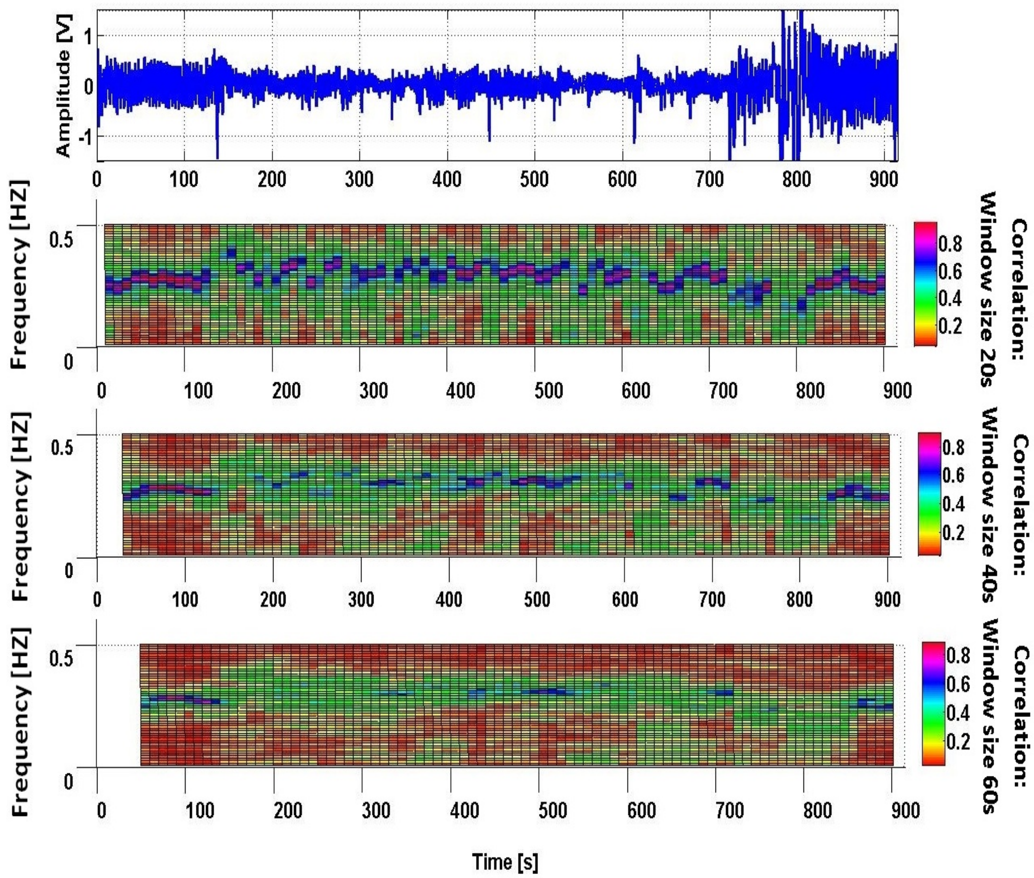

Figure 9: Correlation between pure sine waves and the RESP signal by different windows.

shown in figure 10 (the graph on top depicts the breath signal and the graph on the bottom corresponds to the frequential standard deviation evolution).

The standard deviation evolution of figure 10 depicts that at the beginning and ending of the text the standard deviation is bigger than in the middle part, the stressing part. Anyway, the standard deviation values get sometimes relatively high values which could lead the fuzzy system to a problem of interpretation. Because of that, it is interesting to increase the difference between the values of the relaxing and the stressing part. 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 the relaxing and stressful parts

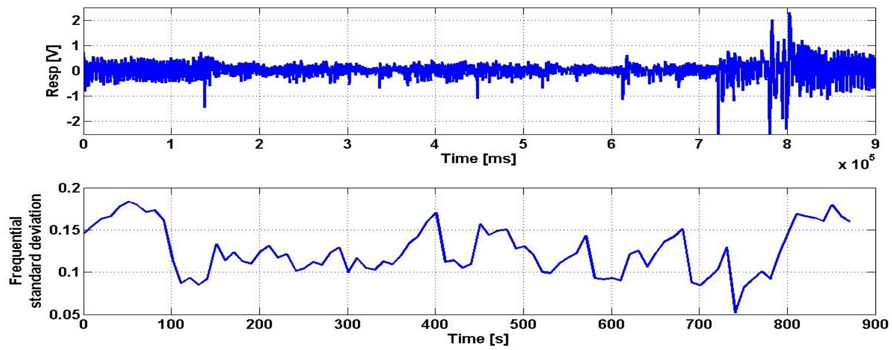

Figure 10: Standard deviation variation effect: Breath signal and frequential correlation.

have increased compared to what happened on the previous standard deviation signal (shown in figure 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.

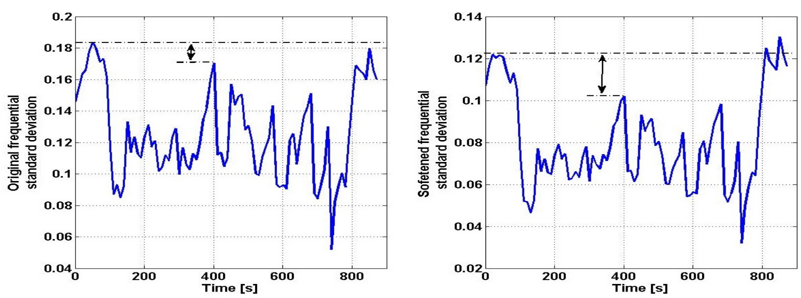

Figure 11: Peak differences increase after softening the standard deviation.

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 (2014). 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 de Santos Sierra et al. (2011), adding three enhancements: the R peak detection procedure presented in section 3, the use of the frequential 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 fuzzy logic system. First it will be explained how the membership functions are built and the reason to accomplish a decomposition of 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 about the stress level, 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 Salazar-Ramirez et al. (2014) the membership functions for the HR and the average GSR were designed to have a Gaussian shape. This was based on the templated method of de Santos Sierra et al. (2011), which proposed to design the membership functions using the average and standard deviation of those two variables during the two periods of the experiment, RS and SS.

Instead of this, the current work proposes to define a new intermediate medium stress (MS) membership function for both variables which will give flexibility to the system and permit to detect in a better way the transitions between a relaxed and a stressed state. More information about this point will be presented in the next section of this paper.

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 figure 12:

As seen in figure 12, the HR remains relatively concentrated around its average value during the SS part of the experiment. However, during the RS period, the HR rate 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

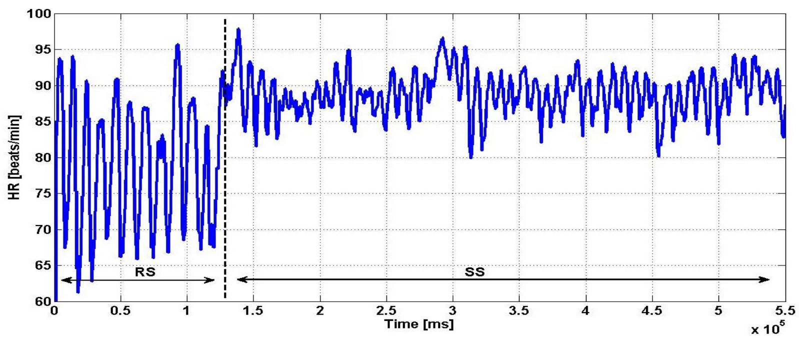

Figure 12: A HR signal with high pace variability.

false situations. Such problems are presented in figure 13, where the template method based membership functions of the subject of figure 12 are shown.

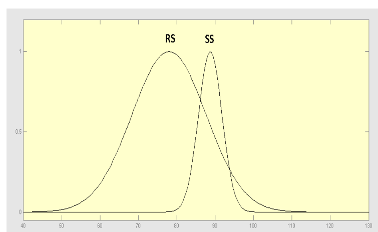

Figure 13: Overlapping of the HR membership functions.

Based on this criteria, for all the input variables three membership functions have been defined: RS, MS and SS. This approach proposes using trapezoidal functions for RS and SS and a MS triangular function filling the gap between RS and SS. Unfortunately, this work has not been able to design an automatic method to fine tune the membership functions and for the moment the tuning of the functions has to be done manually in order to adjust the system to the subject.

The last membership functions to be defined are the correspoding to the outputs. This paper continues with the approach of Salazar-Ramirez et al. (2014) and presents the same three function strategy followed with the inputs. In de Santos Sierra et al. (2011) it is only made the difference between non-stressed and stressed situations. To make the stress level detection more reliable, this system includes an intermediate stress level, the MS output function. The output has been normalized in an [0, 1] interval. Table 1 presents the details of the design of the membership functions:

Table 1: Definition of the membership functions.

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

5.2. The Inference Rule System

As done in Salazar-Ramirez et al. (2014), 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 Salazar-Ramirez et al. (2014).

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

An after analysis proved that the rule system was prone to have drastic changes easily. Subsequently, a 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.

Table 3: Input variable relationships.

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

5.3. Comparative Results of Systems

The last step is to validate the system through simulation. All systems have been tested, the one from de Santos Sierra et al. (2011), the one from then previous developments 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 20s, 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 it can be seen in figure 14, the proposed detection system is more accurate in identification of stress changes as the weight of the value of the GSR is not that important compared to its tendency respect to the 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 (1980).

6. Conclusions and Future Work

Several articles propose different methods to detect personal stress situations. This paper has presented a strategy based on a fuzzy logic to detect

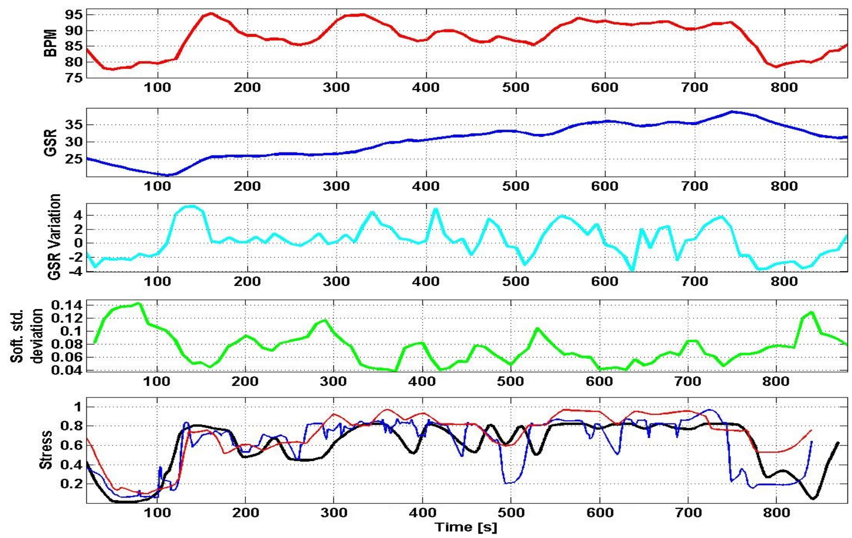

Figure 14: HR, GSR, GSR variation and RESP Standard Deviation inputs and estimated stress level outputs for the three methods.

those changes. This paper has proposed to continue with the line presented in Salazar-Ramirez et al. (2014) 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. This signal has not been commonly used and it has been found to be useful for detecting stress.

This work has also shown how it is possible to obtain successful results with a simple inference system. Anyway, this work still has the handicap that the tuning of the system has to be done with a prior knowledge about the physiology of the subject using it. This could be solved if other soft computing techniques were applied, as for example, if a neural network was used to create the input membership functions.

Finally, it is important to remark that physiological signal monitoring strategies can be very useful for other purposes, as e.g., detecting certain pathological symptoms in paraplegic people who lost the sensibility in the lower limbs, or detecting emotional blockage situations in persons with intellectual disability in order to get quick assistance from relatives or monitors.

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8. References

Andujar, J. M., Barragan, A. J., 2014. Hybridization of fuzzy systems for modeling and control. RIAI 11 (2), 127–141.

Calvo-Rolle, J. L., Corchado, E., 2014. A bio-inspired knowledge system for improving combined cycle plant control tuning. Neurocomputing 126, 95–105.

Cannon, W. B., 1935. Stresses and strains of homeostasis. The American Journal of the Medical Sciences 189 (1), 13–14.

Coan, J. A., Allen, J. J., 2004. Frontal eeg asymmetry as a moderator and mediator of emotion. Biological psychology 67 (1), 7–50.

CSEA-NIMH, 1999. The international affective picture system: Digitalized photographs. Center of Research in Psychophysiology.

de Lannoy, G., De Decker, A., Verleysen, M., 2009. A supervised wavelet transform algorithm for r spike detection in noisy ecgs. In: Biomedical Engineering Systems and Technologies. Springer, pp. 256–264.

de Santos Sierra, A., vila, C. S., Casanova, J. G., Pozo, G. B. D., 2011. A stress-detection system based on physiological signals and fuzzy logic. Industrial Electronics, IEEE Transactions on 58 (10), 4857–4865.

Gross, J. J., Levenson, R. W., 1995. Emotion elicitation using films. Cognition & emotion 9 (1), 87–108.

Healey, J., Picard, R. W., et al., 2005. Detecting stress during real-world driving tasks using physiological sensors. Intelligent Transportation Systems, IEEE Transactions on 6 (2), 156–166.

Hong-tu, Z., Jing, Y., 2010. The wavelet decomposition and reconstruction based on the matlab. In: Proc. of the Third Int. Symposium on Electronic Commerce and Security Workshops (ISECS 2010), China.

Kreibig, S. D., 2010. Autonomic nervous system activity in emotion: A review. Biological psychology 84 (3), 394–421.

Lang, P. J., 1980. Behavioral treatment and bio-behavioral assessment: Computer applications. Technology in Mental Health and Delivery Systems, 119137.

Lee, C. K., Yoo, S., Park, Y. J., Kim, N. H., Jeong, K. S., Lee, B., 2006. Using neural network to recognize human emotions from heart rate variability and skin resistance. In: IEEE-EMBS 2005. IEEE, pp. 5523–5525.

López, D. R., Neto, A. F., Bastos, T. F., 2014. On line recognition of human actions based on patterns of rwe windows applied in dynamic moment invariants. RIAI 11 (2), 202–211.

Martínez, R., Irigoyen, E., Asla, N., Escobes, I., Arruti, A., 2012. First results in modelling stress situations by analysing physiological human signals. Proceedings of the IADIS International Conference e-Health, 171175.

Martis, R. J., Chakraborty, C., Ray, A. K., 2014. Wavelet-based machine learning techniques for ecg signal analysis. In: Machine Learning in Healthcare Informatics. Springer, pp. 25–45.

Navarro, X., 2002. Fisiologa del sistema nervioso autnomo. Revista Neurológica 35, 553–562.

Nelson, R. J., 2005. An introduction to behavioral endocrinology . Sinauer Associates.

Poon, C.-S., Siniaia, M. S., 2000. Plasticity of cardiorespiratory neural processing: classification and computational functions. Respiration physiology 122 (2), 83–109.

Porges, S. W., 2001. The polyvagal theory: phylogenetic substrates of a social nervous system. International Journal of Psychophysiology 42 (2), 123–146.

Ren, P., Barreto, A., Huang, J., Gao, Y., Ortega, F. R., Adjouadi, M., 2014. Off-line and on-line stress detection through processing of the pupil diameter signal. Annals of biomedical engineering 42 (1), 162–176.

Sakr, G. E., Elhajj, I. H., Huijer, H. A.-S., 2010. Support vector machines to define and detect agitation transition. Affective Computing, IEEE Transactions on 1 (2), 98–108.

Salazar-Ramirez, A., Irigoyen, E., Martinez, R., 2014. Enhancements for a robust fuzzy detection of stress. In: International Joint Conference SOCO14-CISIS14-ICEUTE14. Springer, pp. 229–238.

Sasikala, P., Wahidabanu, R., 2010. Robust r peak and qrs detection in electrocardiogram using wavelet transform. International Journal of Advanced Computer Science and Applications-IJACSA 1 (6), 48–53.

Sato, W., Noguchi, M., Yoshikawa, S., 2007. Emotion elicitation effect of films in a japanese sample. Social Behavior and Personality: an international journal 35 (7), 863–874.

Sharma, N., Gedeon, T., 2012. Artificial neural network classification models for stress in reading. In: Neural Information Processing. Springer, pp. 388–395.

Subramanya, K., Vishnuprasada, V. B., Kamath, S., 2013. A wearable device for monitoring galvanic skin response to accurately predict changes in blood pressure indexes and cardiovascular dynamics. In: INDICON 2013. IEEE, pp. 1–4.

Talbi, M., Aouinet, A., Salhi, L., Cherif, A., 2011. New method of r-wave detection by continuous wavelet transform. Signal Processing: An International Journal (SPIJ) 5 (4), 165.

Vries, J., Pauws, S., Biehl, M., 3 2015. Insightful stress detection from physiology modalities using learning vector quantization. Neurocomputing 151 (Part 2), 873–882.

Wozniak, M., Graa, M., Corchado, E., 2014. A survey of multiple classifier systems as hybrid systems. Information Fusion 16, 3–17.