Dynamic Adaptive System for Robot-Assisted Motion Rehabilitation

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Abstract—**This paper presents a dynamic adaptive system for administration of robot-assisted therapy. The main novelty of the proposed approach is to close patient in the loop and use multisensory data (such as motion, forces, voice, muscle activity, heart rate, and skin conductance) to adaptively and dynamically change the complexity of the therapy and real-time displays of an immersive virtual reality system in accordance with specific patient requirements. The proposed rehabilitation system can be considered as a complex system that is composed of the following subsystems: data acquisition, multimodal human–machine interface, and adaptable control system. This paper shows the description of the developed fuzzy controller used as the core of the adaptable control subsystem. Finally, experimental results with ten subjects are reported to show the performance of the proposed solution.**

Index Terms—**Adaptable control systems, fuzzy, multimodal human–machine interface, rehabilitation robotics.**

I. Introduction

THE use of robotic devices, as a possible rehabilitation strategy to achieve motor recovery, can be justified because of its potential impact on better therapeutic treatment and motor learning [1]. In 2010, the American Heart Association (AHA) published a comprehensive scientific statement on nursing and interdisciplinary rehabilitation care of the stroke patient [2]. The statement provides an overview of the best available evidence for various screening tests and medical treatments, including traditional rehabilitation therapies and newer techniques, such as robot-assisted therapies. In short, upper-extremity robot-assisted therapy is already considered as Class I, Level of Evidence A, for stroke care in the outpatient and chronic care settings, and it is considered as Class IIa, Level of Evidence A, for stroke care in the inpatient. The meaning of classes and level of evidence is according to the AHA statement [2]: Class I is defined as "Procedure/Treatment should be performed/administered"; Class IIa is defined as "It is reasonable to perform procedure/administer treatment"; and Level of Evidence A is defined as "Multiple populations evaluated. Data derived from multiple randomized clinical trials or meta-analyse".

Despite the success of the upper-extremity robot-assisted rehabilitation procedure/treatment according to the AHA statement, researchers want to go beyond with the development of the new generation of robotic rehabilitation systems. The envisioned systems should be capable of deciding which interaction strategy to apply in different rehabilitative scenarios, taking into account the biomechanical, physiological, and emotional patient condition identified through unobtrusive sensors.

There are not so much examples of rehabilitation robotic systems considering patient physiological state and motor performance in the control loop. The first work using patient active power and motion accuracy measures to define the level of robot assistance at the beginning of a new block of exercises was published in 2003 by Krebs *et al.* [3]. The use of psychophysiological measurements to dynamically adapt the behavior of an automation system is not a new idea [4]. A most recent good review about methods for data fusion and system adaptation using autonomic nervous system responses in physiological computing was published last year by Novak *et al.* [5]. Other works by Novak *et al.* and Koenig *et al.* [6], [7] proposed to use psychophysiological measurements and task performance analysis to adjust the difficulty of a task performed with the assistance of the Haptic Master robot.

The two main goals of this paper are the following: 1) to present the proposed rehabilitation system to deliver sophisticated therapy for the patients and 2) to show the application of a fuzzy controller to adaptively and dynamically modify the therapy and real-time displays of a virtual reality system in accordance with the specific state of each patient using his/her physiological reactions. This paper reports experimental results with ten subjects to demonstrate that it is feasible to use a fuzzy controller to adaptively and dynamically modify the complexity of the therapy in real time.

II. Architecture of the Proposed Rehabilitation System

The two main goals of the proposed system for the administration of highly sophisticated therapy to stroke patients are: 1) to maximize patient motivation and involvement in the

Manuscript received October 31, 2013; revised January 31, 2014; accepted March 26, 2014. Date of publication May 14, 2014; date of current version August 23, 2016. This work was supported by the Spanish Government through the project "Interpretation of the human intention and performance through biomedical signals and analysis of kinematic and dynamic motion" (DPI2011-29660-C04-04).

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Digital Object Identifier 10.1109/JSYST.2014.2318594

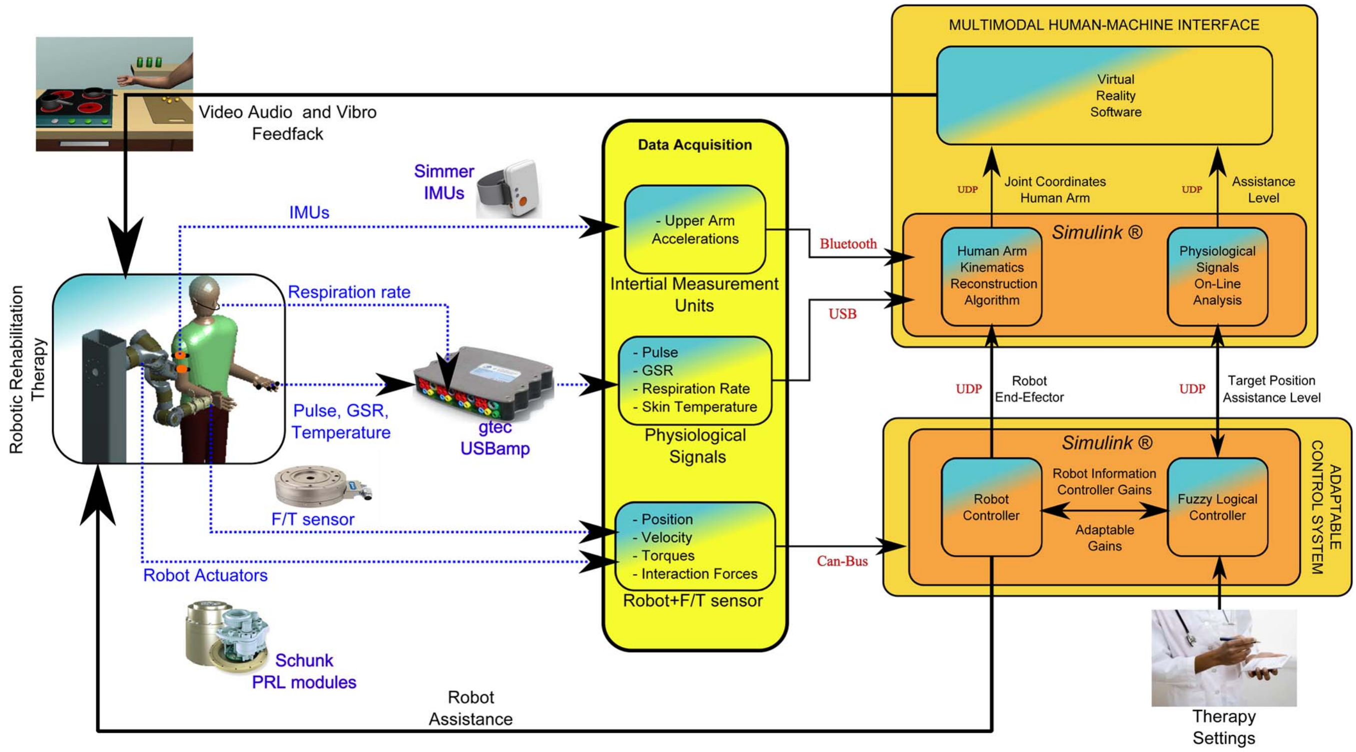

Fig. 1. Components of the proposed rehabilitation system.

therapy; and 2) to continuously assess the progress of the recovery from the functional and neurological viewpoint, with special attention to the issue of safety in human–robot interaction. The main novelty of the proposed approach is to close patient in the loop and use multisensory data (such as motion, forces, voice, muscle activity, heart rate, and skin conductance) to adaptively and dynamically change the complexity of the therapy and real-time displays of an immersive virtual reality system in accordance with specific patient requirements.

The proposed rehabilitation system can be considered as a complex system that can be divided into the following subsystems (see Fig. 1).

1) *Data acquisition*: The data acquisition system is composed of three main components as follows: 1) robot and force/torque sensors allow acquiring robot position, velocity, and torques and monitoring human–robot interaction forces; 2) two magneto-inertial sensors (from Shimmer) measure upper arm radial accelerations for the computation of the upper limb kinematics; 3) physiological sensors acquire heart rate, skin temperature, galvanic skin response (GSR), and respiration rate signals using a g.USBamp amplifier manufactured by g.tec.

2) *Multimodal human–machine interface (HMI)*: The multimodal HMI uses position, force, and physiological sensors to monitor user behavior and emotional state and to adaptively and dynamically adapt the system controller and auditory and visual feedback through the virtual reality software to maximize patient's motivation.

The HMI system can be divided into three main subsystems for the following: 1) analysis of patient physiological state through the physiological sensors [8], [9]; 2) analysis of patient motor behavior through position, force, and magneto-inertial sensors [10], [11]; 3) auditory and visual feedback provided through the virtual reality software for increasing patient motivation.

The system for monitoring patient physiological state carries out acquisition and processing of physiological signals to estimate the user's physiological state. After a revision of the scientific literature [6] and experiments with users [8], GSR, respiration rate, pulse, and skin temperature were used to estimate the user's physiological state.

The system for measuring patient biomechanical performance is composed of three subsystems: 1) the first one reconstructs the entire patient upper-limb kinematics; 2) the second part computes biomechanical indicators of patient performance; and 3) the last one fuses the computed indicators for the assessment of patient global biomechanical performance. Details on their implementation can be found in [10], [11].

The system for auditory and visual feedback provides two kinds of stimulus: 1) encouraging words and sounds, which contribute to motivate the user during the task execution, and congratulatory or consolatory words on task completion and 2) the user upper-extremity movement in a 3-D virtual environment using the information provided by the user upper-limb reconstruction.

3) *Adaptable control system*: The inputs of the adaptable control system are the information extracted from the patient biomechanical and physiological monitoring and analysis. The aim of this block is to update the robot interaction control and the immersive virtual reality

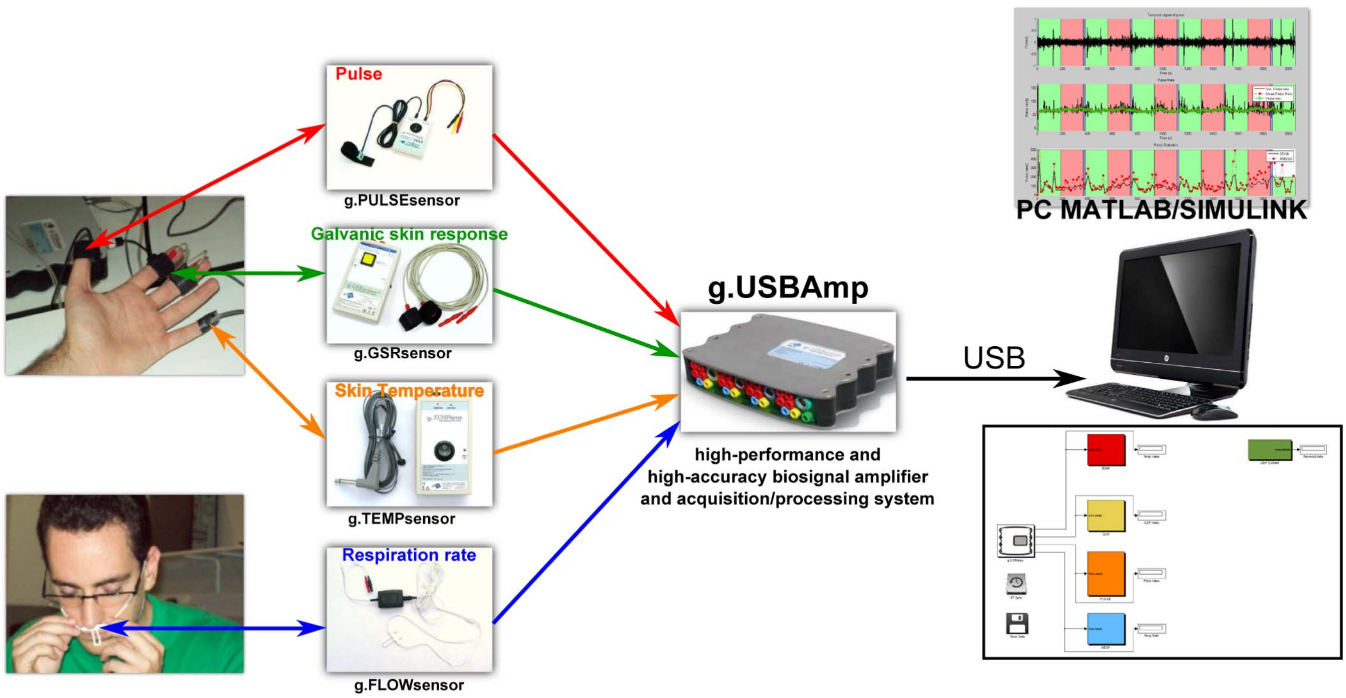

Fig. 2. Scheme of the equipment selected for monitoring user physiological state (Skin Temperature, Galvanic skin response, Pulse, and Respiration rate). All the sensors and the biosignal amplifier are manufactured by g.tec company.

system. Machine learning techniques [9], artificial neural networks, and fuzzy logic systems have been considered as candidate techniques for the development of the adaptable control system. The final solution implemented in this experiment is based on a fuzzy logic system in two hierarchical levels: first, the estimation of the subject's physiological state using the physiological signals, and, second, the estimation of level changes using the provided information about the estimation of physiological state.

III. Monitoring and Analysis of Patient Physiological Responses

A. Monitoring

It is well known that most physiological processes produce signals of several types: biochemical, in the form of hormones; electrical, in the form of current; and physical, in the form of pressure and temperature. These changes are controlled by the automatic nervous system, which manages heart muscles, smooth muscle, and various glands in our body. These bodily reactions can be measured, monitored, and classified corresponding to each emotion. These signals are called biosignals. This subsection presents the definition of the biosignals used in these experiments to estimate user physiological state. The hardware used for the signal acquisition is the g.USBAmp amplifier, which has 16 input channels. They are connected over software controllable switches to the internal amplifier stages and antialiasing filters before the signals are digitized with sixteen 24-bit analog-to-digital converters. The digitized signals are passed to a digital signal processor (DSP) for further processing. The DSP performs oversampling of the biosignal data, bandpass filtering, and notch filtering to suppress the power line interference and calculate bipolar derivations. These processing stages eliminate unwanted noise from the signal, which helps to ensure accurate and reliable classification [12]. The sampling frequency was adjusted to 256 Hz for pulse signal and 32 Hz for electrodermal activity (EDA), respiration rate, and skin temperature.

1) Pulse: Pulse is measured using a photoplethysmograph (PPG). PPG signal reflects changes in a blood flow, which goes from the center (heart) to the end (fingertips) in a wavelike motion, and it is affected by the heartbeat, the hemodynamics, and the physiological condition. The selected pulse sensor is the g.PULSEsensor, which is fixed on the user's finger (see Fig. 2).

2) Respiration Rate: Respiration rate measures how fast and deep a person is breathing, and it is affected by several conditions such as emotional state, mental stress, and physical load. The selected sensor for monitoring the respiration rate is the g.FLOWsensor (Fig. 2). It is fixed near the nose and mouth and is designed to measure the change in temperature during inspiration versus expiration using a thermocouple. The resulting respiration signal is very robust against movement artifacts.

3) EDA: EDA is a term used to describe changes in the skin's ability to conduct electricity. There are two main components of GSR signal.

1) Skin conductance level (SCL) measures the slow changes of GSR signal, and it can be computed as the mean value of skin conductance during a period of time.
2) Skin conductance response (SCR) measures the fast changes of GSR signal, and it is computed as the frequency of peaks of GSR signal [13]. The selected GSR sensor is the g.GSRsensor (see Fig. 2). This sensor

measures the conductance of the skin by fixing two sintered electrodes with Velcro straps on two fingers.

4) Skin Temperature: Skin temperature can be measured by determining the temperature on the surface of the skin. Similar to the electrodermal response, the skin temperature also depends on external factors. Furthermore, it is a relatively slow indicator of changes in emotional state. The selected skin temperature sensor is the g.TEMPsensor (Fig. 2).

B. Analysis of Physiological Signals

Here, the techniques used to extract relevant information from the user's physiological signals are described.

1) Pulse: Two approaches have been pursued for the analysis of signal: a temporal analysis and a frequency analysis. The frequency analysis is based on the signal fast Fourier transform (FFT) and is used to extract the maximum power component. Hence, mean heart rate is calculated. In the temporal analysis, the instantaneous heart rate has been computed through the reciprocal of the time between two consecutive peaks. To detect the peaks of the signal, two approaches have been implemented. The first approach uses a threshold identification and the signal derivative; the second one exploits a purposely developed peak detection algorithm.

   Other features relative to the pulse signal have been computed, in addition to heart rate; they are as follows: 1) mean heart rate: the average of the instantaneous heart rate in 15 s; 2) maximum heart rate every 15 s; 3) minimum heart rate every 15 s; 4) standard deviation of the NN intervals (NN is the interval between two heart periods); 5) square root of the mean squared differences of successive NN intervals; 6) PNN50: number of interval differences of successive NN intervals greater than 50 ms divided by the total number of NN intervals.
2) Respiration rate: In the same way as with the pulse signal analysis, two approaches have been pursued for the analysis of signal: a temporal analysis and a frequency analysis. The frequency analysis is based on the signal FFT and is used to extract the maximum power component. In the temporal analysis, the instantaneous respiration rate has been computed through the reciprocal of the time between two consecutive peaks. To detect the peaks of the signal, three different approaches have been implemented. The first approach uses a threshold identification and the signal derivative; the second approach uses an integrator block followed by a zero-crossing detector. The third approach uses the same peak detection algorithm as in the heart rate analysis implemented.
3) GSR: SCL and SCR are computed from GSR signal. SCL is computed as the mean of GSR signal during a period of time. To compute SCR, the signal is processed in three steps: 1) the signal is filtered using a low-pass filter, whose cutoff frequency was set at 5 Hz [14], to remove high-frequency noise from the signal; 2) a peak detection algorithm is applied to the filtered signal; and 3) the frequency of occurrence of events, taken as the number of events per minute, is the output parameter of the analysis of the SCR. A peak is defined as an event if the peak exceeds 0.05 μS and occurs within 5 s after the beginning of the increase in signal.
4) Skin temperature: For the online analysis of the temperature signal, the average over the last 5 s (to remove the effects of measurement noise) is used as the measured feature.

IV. Adaptable Control System

A machine learning system based on fuzzy logic has been developed to estimate the user physiological state [15]. To do this, a two-stage fuzzy logic system has been implemented that outputs both arousal–valence state and level of complexity of the rehabilitation therapy, as shown in Fig. 3. The first stage maps the user's physiological signals into a 2-D emotional space characterized by arousal–valence values [16], [17]. Then, the second stage maps the arousal–valence values into levels of difficulty of the robot-aided motor task, modifying robot behavior and virtual reality environment.

Each input variable of the fuzzy controller implemented in the proposed system is defined as a linguistic variable that can take "low," "medium," and "high" values. Then, the linguistic variables are modeled by fuzzy sets in the universe of discourse U, in which the variables are defined. A fuzzy set is characterized by a membership function $\mu_A(x)$. To determine the membership functions of the fuzzy controller of stage 1, the following procedure has been followed (it overcomes the limitations of the previous "trial and error" approach [8]).

1) Physiological data of subjects tested in the experiments in [8], and [9] have been gathered and preprocessed.
2) Physiological signals have been redefined considering the variation with respect to their value at rest (baseline).
3) The histogram of each physiological signal has been computed; then, the membership functions have been characterized taking into account the histogram distribution, mean value, and standard deviation of each signal. In Fig. 4, the histogram of the SCL signal and the characterization of the membership function based on the histogram profile are shown.

Once the membership functions are determined and the fuzzification module is completed, the fuzzy rule base module has been defined, selecting a set of 20 fuzzy IF-THEN rules, as follows.

1) Rule 1: If (SCL is high) then (Arousal is high).
2) Rule 2: If (SCL is med) then (Arousal is mid).
3) Rule 3: If (SCL is low) then (Arousal is low).
4) Rule 4: If (Pulse is high) then (Arousal is high).
5) Rule 5: If (Pulse is low) then (Arousal is low).
6) Rule 6: If (SCL is high) and (Pulse is low) then (Arousal is midHigh).
7) Rule 7: If (SCL is low) and (Pulse is high) then (Arousal is midLow).
8) Rule 8: If (SCL is med) and (Pulse is med) then (Arousal is mid).
9) Rule 9: If (Resp is high) then (Arousal is midHigh).
10) Rule 10: If (Resp is low) then (Arousal is midLow).

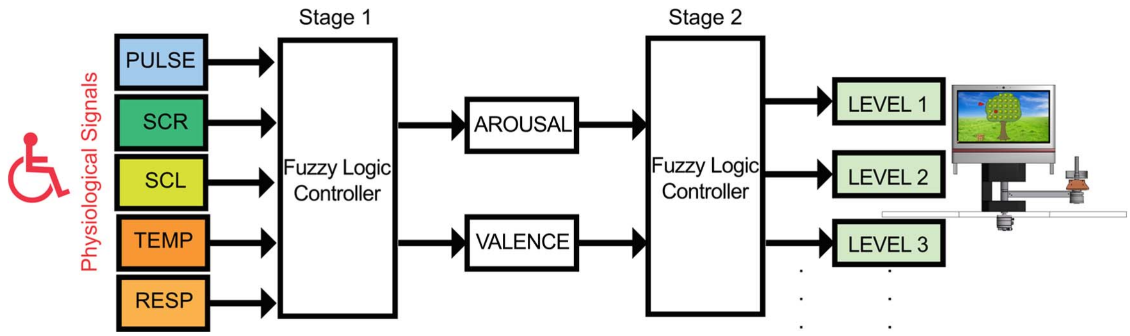

Fig. 3. Two-stage fuzzy logic system to 1) estimate the user physiological state and 2) modify the complexity of the therapy.

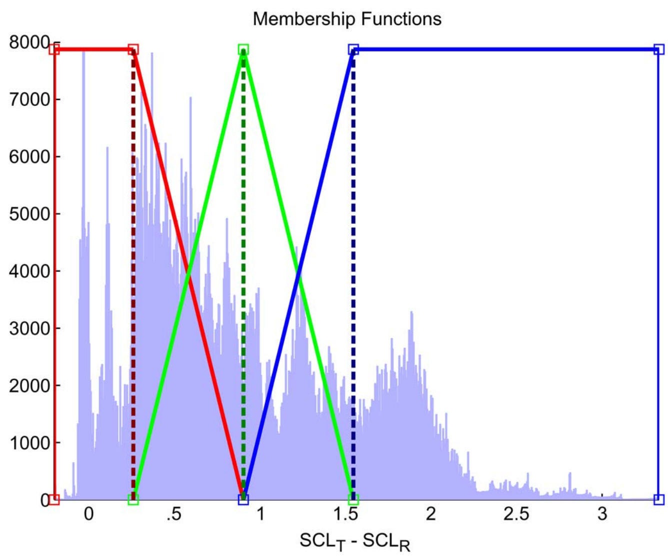

Fig. 4. Example of characterization of a membership function based on the statistical characteristics of the histogram of the SCL signal.

11) Rule 11: If (SCL is high) and (Resp is low) then (Arousal is midHigh).
12) Rule 12: If (SCL is low) and (Resp is high) then (Arousal is midLow).
13) Rule 13: If (SCL is high) and (Pulse is high) then (Valence is low).
14) Rule 14: If (SCL is low) and (Pulse is high) then (Valence is high).
15) Rule 15: If (SCL is med) and (Pulse is high) then (Valence is midHigh).
16) Rule 16: If (SCL is med) and (Pulse is low) then (Valence is midLow).
17) Rule 17: If (SCL is high) and (Pulse is low) then (Valence is low).
18) Rule 18: If (SCL is low) and (Pulse is low) then (Valence is low)(Arousal is low).
19) Rule 19: If (Temp is high) then (Valence is midLow).
20) Rule 20: If (Temp is low) then (Valence is midHigh).

The subsequent step has been the development of the fuzzy inference module. Fuzzy inference methods are classified in direct and indirect methods. Direct methods, such as Mamdani's and Sugeno's, are the most commonly used (these two methods only differ in how they obtain the outputs). In our case, the Mamdani method has been selected to implement the fuzzy inference module [18]. In the model of Mamdani, the fuzzy implication is modeled by Mamdani's minimum operator, the conjunction operator is min, the t-norm from compositional rule is min, and, for the aggregation of the rules, the max operator is used.

The last step in the development of the proposed fuzzy controller is the implementation of the defuzzyfication module. The defuzzification process implemented in the presented system is the well-known centroid of area or center of gravity. The Fuzzy Logic Toolbox of MATLAB software has been selected for the implementation of the fuzzy logic controller. Data used to implement the fuzzy logical controller have been taken from a previous work [9], where physiological signals of seven subjects were extracted in three different scenarios: relaxed, medium level of stress, and overstressed.

V. Experimental Validation

The final goal of our experiments is to show that the developed control system is able to adjust the complexity of the robotic therapy in accordance with the evaluation of patient global state and needs using the interpreted physiological measurements. The dynamical adaptation of the robotic assistance and the complexity of the therapy and real-time displays of a virtual reality system cause changes in physiological responses and, consequently, entails an update of the system.

A. *Experiment Description*

Accordingly to Novak *et al.* [5], system adaptation using physiological responses can be classified in three categories: adaptive automation, game difficulty adjustment, and adjustment of the audio or the visual properties of an application. Although this paper addresses all the three categories, the results presented here can be considered as a game difficulty adjustment.

The performed experimental trial consists of three main components: the area of activity (bounded by a black frame), the pointer (a green square representing user hand motion), and a series of blue rectangles of different sizes randomly moving across the screen. The task consists of freely moving in the gray area, by paying attention to avoid collisions with the blue rectangles. If a user touches a blue box or leaves the black

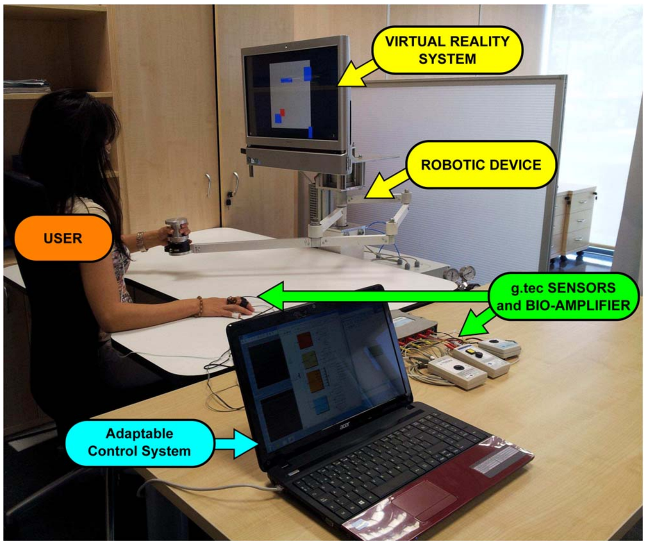

Fig. 5. Setup for the final experiment.

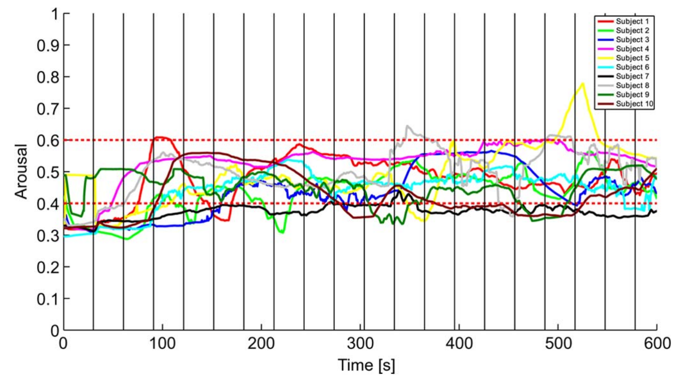

Fig. 6. Arousal estimation for all subjects.

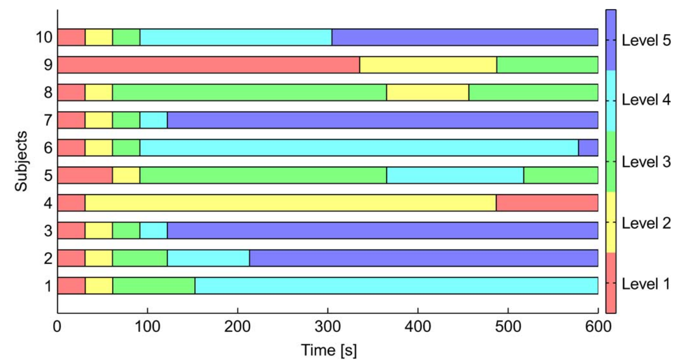

Fig. 7. Level changes during the experimentation for all subjects: 50% of the subjects finish the experiment in the highest level.

frame, the square representing his/her motion becomes red, and a shrill sound is heard (see Fig. 5). Five different levels of difficulty have been defined depending on the number of blue rectangles in the area of activity and their speed: one blue rectangle with low speed, three blue rectangles with low speed, three blue rectangles with medium speed, four blue rectangles with medium speed, and four blue rectangles with high speed.

The task was monitored by a pneumatic robotic device with two degrees of freedom designed by the Neuroengineering Biomedical Group at Miguel Hernández University. This device has been designed as a rehabilitation robot for patients who suffer from stroke or other neurological disorders. The system permits only horizontal motion involving flexion and extension of the shoulder and elbow and horizontal abduction and adduction.

The physiological signal processing and the fuzzy logical controller are implemented in a Simulink scheme. The communication between this Simulink scheme and the virtual reality system is carried out every 30 s by the User Datagram Protocol communication protocol. Three different actions are sent depending on the subject's physiological response: if the subject is relaxed, the action is to increase the current difficult level; if the user has a medium stress level, the action to send is to not modify the difficulty level; if the user is overstressed, the scheme sends an action to reduce the current difficulty level. The final setup for this experiment is shown in Fig. 5.

B. Collected Results

Ten students and staff members of the Bioengineering Institute of Miguel Hernandez University (nine males and one female) participated in the experiment. All were healthy, with no major cognitive or physical deficits. They were aged between 24 and 41; the mean age is 31 years, the median age is 29 years, and the standard deviation is 5.2 years.

The experimental protocol is explained below.

1) Subjects were informed of the purpose and procedure of the experiment.
2) An adaptation period of few minutes is given to the subjects.
3) The subjects remain in a relaxed state for 5 min to obtain baseline measurements.
4) The subjects perform the task for 10 min. The initial level is always the first one.

In Fig. 6, the estimation of arousal for all the tested subjects is shown. Horizontal dashed lines indicate the range of the medium stress level, whereas vertical lines indicate the 30-s intervals between fuzzy logical controller actions. In Fig. 7, the changes in task difficulty level for all the tested subjects are reported. Five subjects finish the experiment in the fifth level, one subject in the fourth level, three subjects in the third level, and one subject in the first level.

Finally, in Fig. 8, graphical results for two subjects (fifth and ninth) are shown in order to see the relation between arousal signal and level changes. As in Fig. 6, vertical lines indicate the 30-s intervals between fuzzy logical controller actions. As it is shown in the figure, if the arousal signal is under 0.4, the controller estimates that the subject is relaxed, and therefore, the output of the controller is to increase the level of complexity. If the arousal is between 0.4 and 0.6, the controller estimates that the subject has a medium stress level, and therefore, the output of the controller is not to modify the level of complexity. If the arousal is over 0.6, the controller estimates that the subject

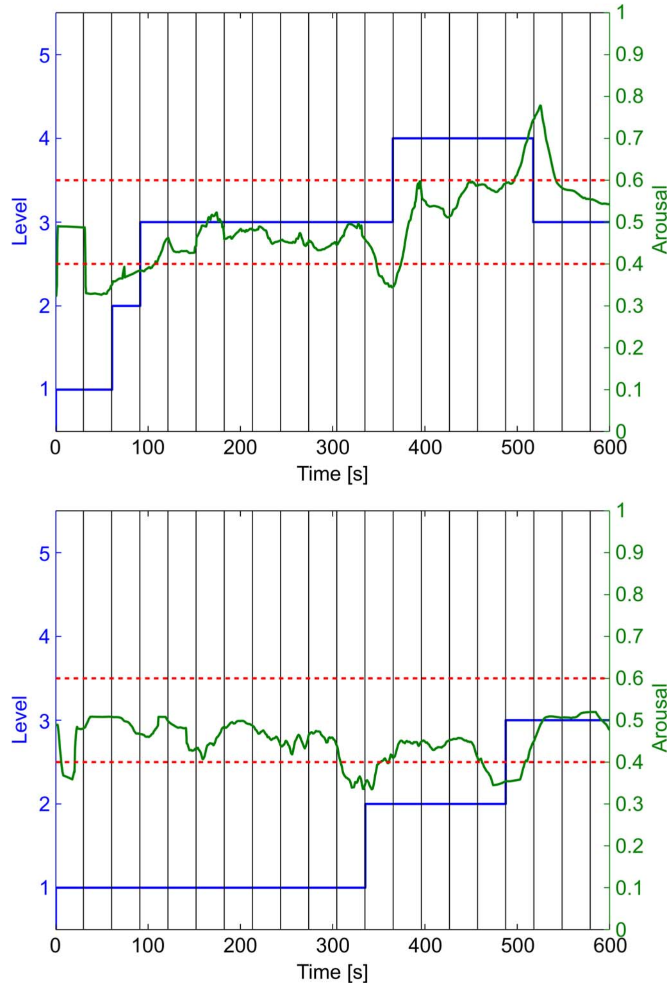

Fig. 8. Graphical representation of experimental results (arousal signal in green color and level change in blue color) for the fifth (top) and ninth (bottom) subjects.

is overstressed, and therefore, the output of the controller is to reduce the level of complexity.

The performance of the proposed control system can be compared using the leave-one-out cross-validation (LOOCV) with our previous work [9] for nine machine learning algorithms: perceptron learning algorithm, logistic regression, linear discriminant analysis, quadratic discriminant analysis, linear support vector machine, support vector machine [radial basis function (RBF) kernel], naïve Bayes, K-nearest neighbor, and K-center with RBFs. The data used as validation and training data for LOOCV are extracted from [9] with no principal components analysis computation. The proposed fuzzy logical controller has a performance result of 65.71% greater than the naïve Bayes (53.33%) and K-center with RBFs algorithms (61.60%) and nearly the same to those of the perceptron learning algorithm (69.73%) and the linear discriminant analysis (68%). The other five machine learning algorithms have better performance than the proposed fuzzy logic approach. However, the fuzzy logic approach has two interesting features to be a good candidate for implementing the core of the adaptive control system: the simplicity of its implementation; and it is not necessarily a training step with extensive data to compute the fuzzy controller.

VI. Conclusion

In this paper, the application of a fuzzy controller to automatically adapt the delivered therapy to the specific needs and demands of the patient has been presented, including experimental results, to corroborate the performance of the proposed approach. In general terms, our approach based on fuzzy logic systems works fine, but it still needs extensive evaluation. An interesting finding of our research is that the membership functions can be characterized with the statistical characteristics of the user's previous tests. In short, a histogram of the user's physiological reactions is used to define them accurately.

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