A Fuzzy-Based Adaptive Rehabilitation Framework for Home-Based Wrist Training

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***Abstract*— Computer-based rehabilitation systems have emerged as promising assistive tools for effective training and diagnosis and gained popularity in clinical settings. For many patients, home-based rehabilitation can be really beneficial in their therapy journeys since it can eliminate the obstacles encountered by many of them in clinics, such as travel distance and cost. However, an effective home-training system requires a good adaptation mechanism that conforms to both the patient's abilities and the therapist's performance requirements. This paper introduces a Web-enabled wrist rehabilitation framework that adopts the fuzzy logic approach to provide adaptive tasks for the patient while considering the therapist training guidance. We also assess the effectiveness of the framework while coping with different training parameters by simulating a number of performance scenarios and experimenting with normal subjects. Simulation results, as well as experimental analysis, demonstrated the ability of the proposed framework to adapt to patient's performance and therapist's feedback.**

***Index Terms*— Fuzzy logic, medical measurement, stress ball, tangible user interface, wrist rehabilitation.**

I. Introduction

ARM injuries occur frequently in society, especially among poststroke patients, athletes, and workers of physically demanding professions. Statistics revealed that 85% of poststroke survivals are left with various contractures and deficiencies in their upper extremity movements, especially in the hand and wrist areas [1]. Meanwhile, almost 4.7% of male textile workers and 16.7% of female metal manufacturing workers suffer from chronic pain in their upper limb at one point in their lives [2]. Chronic wrist pain is also largely reported among athletes [3]. As researchers have pointed out in [4] and [5], such injuries result quite often in deficiencies in some or all of the following muscle strengths: 1) pronation: turning the forearm with the palm facing down; 2) supination: turning the forearm with the palm facing up; 3) wrist extension: bending the wrist to move the back of the hand toward the forearm; 4) wrist flexion: bending the wrist to move the palm of the hand toward the forearm; 5) radial deviation: side bending the wrist toward the thumb; and 6) ulnar deviation: side bending the wrist toward the little finger.

To regain some or all of their preinjury capabilities, patients normally undertake a rehabilitation course which duration depends on the severity of the injury. Most of traditional physical therapy is carried out in specially equipped rehabilitation centers located in hospitals or physiotherapy clinics that are often located in major cities. Consequently, patients living in rural areas and villages might have limited access to such facilities in their regions and might have to make frequent long trips to seek therapy. This can be really problematic on the long term for many who might be forced to skip some of the sessions, and therefore have their treatment negatively affected and delayed. Another important problem for many patients is related to the high cost of each session, especially for those without a proper insurance coverage.

To minimize the inconvenience of distance and cost for many patients, training from home can be an ideal solution. Home-based rehabilitation has evolved in recent years as a cost-effective and convenient alternative to traditional clinical rehabilitation [6]. Potential benefits associated with home rehabilitation include improved empowerment (earlier return to home and family), reduced cost (in some studies, home rehabilitation costs have been shown to be lower than hospital-based in-patient rehabilitation [7]), and minimized therapist to patient ratio (since the patient requires minimum supervision). Home-based hand training normally includes using primitive passive devices such as wrist weights, tubing and dumbbells. However, patients tend to lose interest in using these devices because of their repetitive nature which can cause boredom. Furthermore, the patient's performance progress is unknown to the therapist because of the inability of those devices to capture and store/transmit performance information.

Fortunately, the tremendous development in the field of sensory technologies has created the opportunity of tracking human's motion in a precise and robust manner. 3-D tracking cameras and accelerometers are widely used in rehabilitation applications [11]–[14]. This has drawn new horizons for medical applications, particularly for remote health monitoring and assessment. In the meantime, studies have shown that multimedia, including Virtual Reality (VR) and haptics, has some potential benefits when it comes to therapy and is an

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effective and entertaining way for aiding in the rehabilitation of patients [8]. For this reason, many researchers, such as [9] and [10] have introduced a variety of computerized training tools associated with multimedia games targeted for home usage; such tools can store the patient's performance in databases that can be accessed by the therapist to monitor the patient's progress.

In this paper, we introduce and assess an adaptive home-based rehabilitation framework. In a previous work [15], we conducted a series of tests with a number of healthy users to examine the effect of tilting the wrist in various angular positions on a number of performance parameters. We found out that there exists a correlation between the task angles (the different tilting positions of the wrist), the velocity and the jerkiness of the wrist. In other words, the velocity and the jerkiness increase exponentially with higher task angles. These findings were used here to implement a fuzzy-logic-based adaptation (FLA) engine that is aimed to lead to a potentially shortened therapeutic procedure. The behavior of the framework is evaluated by assessing the effectiveness of the proposed adaptation module while coping with different levels of exercise performance parameters, namely the velocity and the jerkiness.

The rest of the paper is organized as follows. In Section II, we review some of the related work accomplished in the field of computerized hand rehabilitation. In Section III, we present the proposed home-based rehabilitation framework and elaborate its merits. In Section IV, we simulate and experimentally verify the behavior of the adaptation engine. Finally, we conclude our findings in Section V and provide perspectives for future work.

II. Related Work

Computer-based rehabilitation has gained recently significant attention, especially after the revolutionary advancements in motion sensors technology. Herein, we highlight some of the works achieved in upper limb rehabilitation, notably the computer vision, inertial motions techniques, and Web application frameworks.

A. Computer Vision-Based Rehabilitation

Alamri *et al.* [16] used an iWear CamAR tracking camera clipped on an iWear VR920 Head mounted display [17] to build an augmented-reality (AR) upper limb rehabilitation framework. The framework comprises two exercises that require the patient to achieve a task that is based on the activity of daily life concept [23] through manipulating a tangible object in an AR superimposed over a real environment set up. Key training metrics are computed in real-time from the captured data to provide an easy assessment to the therapist. Evett *et al.* [21] tracked the hand movements and gestures via two types of cameras, optical and thermal. Using a markerless approach, the system is able to detect the hand's position by tracking the center of moments of the hand contour. Gesture recognition is accomplished by Hu's moments matching [22] with the K-nearest neighbor algorithm. No information was given on how the performance of the patient could be measured or assessed. In another work, Duff *et al.* [20] presented an adaptive mixed reality (physical and virtual) training system that uses visual and musical cues (auditory) as a form of feedback. Multiple 3-D infrared-based motion capture cameras that were used to derive the kinematic features recorded the upper extremity movements of the patient. The kinematics were used to drive the media feedback and to adapt the system's parameters based on a number of developed computational algorithms and tools. The author conducted a pilot study with three stroke survivors based on the wolf motor function test (WMFT). The patients showed significant improvements in their movements as mentioned by the authors.

The Kinect motion sensing device [18] from Microsoft has recently emerged as a useful and low-cost tracking device for rehabilitation [24]–[25]. For instance, in [19], it was deployed to track the therapist hand movements that define a trajectory for the patient that his/she has to imitate. We suggested a means to measure the patient performance based on the error between trajectories; however, the effectiveness of such assessment was not explored at that stage. Chang *et al.* [26] evaluated the Kinect-based rehabilitation with two students suffering from motor impairments. We reported that Kinect can be a viable tool for therapy but more tests have to be performed to assess its benefits.

B. Intertial-Based Rehabilitation

Inertial measurement units (IMUs) have been widely used to collect mobility and motion data among patients [27]–[30]. In [31], an accelerometer-based wearable arm rehabilitation monitoring device was developed to provide poststroke patients with quantified data pertained to their training. The system was equipped with real-time monitoring and data logging mechanisms that can store the training information of the patients. In [32], an accelerometer was mounted on a glove to capture the kinematics of the wrist when playing a software game. Vibro-tactile feedback was generated upon successful completion of a game set to add fun to the exercise. The same concept was applied in [34] where an accelerometer was attached to a passive dumbbell that was used to play a car racing game.

Inertial sensors embedded in smart phones started playing recently an important role in physical therapy. For instance, Deponti *et al.* [33] proposed the use of an android-based mobile phone as a ubiquitous game therapy. Using the smart phone, a doctor can define a rehabilitation exercise where motion sequence is computed using the position and motion sensors already integrated inside the phone. Patients should repeat the exercise at home and the performance logs are checked by the physician on the next appointment. Caulfield *et al.* [35] presented an overview of a mobile-based exercising platform. Here, the acceleration detected by the smart phone is sent over Bluetooth to an android tablet that evaluates the performance of the user by comparing it with a predefined motion template set by a physical therapist. A number of visual feedbacks are displayed on the tablet's screen to guide the patient through the exercise.

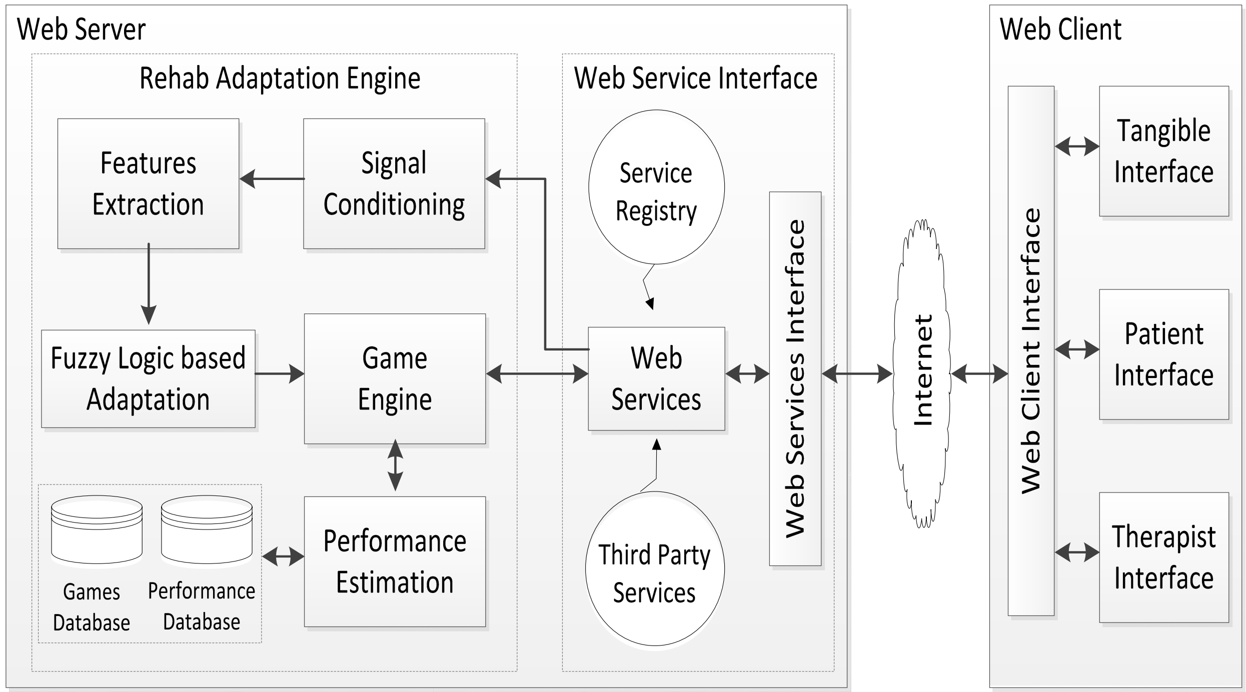

Fig. 1. Web-enabled home-based rehabilitation software architecture.

C. Web Application Frameworks

The availability of massive communication, computation, and storage resources over the Internet led to an unprecedented possibility of creating, publishing, and dissemination of vast amount of data for diverse applications; medical and in particular rehabilitation applications are no exception. For instance, Service-Oriented Architecture (SOA) [36] has been extensively used to provide tele-medicine and tele-health care applications and services [37]–[40], and in particular tele-rehabilitation frameworks [41]–[43].

An AR serious game framework for home-based rehabilitation that is capable of executing rehabilitation exercises, without geographic or time limitations, is proposed in [41]. The system utilizes social media infrastructure to enable ubiquitous access to rehabilitation exercises. In a similar work [44], we proposed a Web-based home-based rehabilitation system that provides both therapeutic instruction and support information. The system supports rehabilitation interventions, provides a 3-D visual display, and measures the quality of patient's performance. However, the system does not provide any adaptation as per the patient's specific needs and therapist feedback.

III. Proposed Framework

The goal of this paper is to develop a wrist rehabilitation framework that could be deployed in any computerized therapy system that is based on tracking the wrist motion of the patient (Fig. 1). The architecture is composed of a Web client subsystem and a Web server subsystem. The Web server subsystem is composed of the Client Interface and the Rehabilitation Engine.

A. Web Client

The Web Client is a software component that provides various stakeholders (such as the patient, therapist, or a third party) access to the home-based rehabilitation system over the Web. The Web Client is composed of the elements described below.

1) Kinematics Acquisition Interfaces: These interfaces are used by the patient to interact with the rehabilitation games, and embed various sensors to measure the performance of the patient during a rehabilitation session. Examples of such sensors include accelerometers, gyroscopes, tracking cameras, etc., to measure body movements and interaction forces.

2) Patient Interface: The Patient Interface provides the patient with the means to interact with the system (to facilitate personalization of home-based rehabilitation) or to communicate with the therapist. Patient Interfaces are classified as conventional input/output interfaces such as keyboard, mouse, or monitor (in case the patient can use them) and nonconventional interfaces such as intelligent tangible devices and haptic interfaces.

3) Therapist Interface: The Therapist Interface enables the clinician/therapist to monitor the patient's performance by retrieving information extracted during the game sessions. In addition, it allows the therapist to set the following two performance thresholds:

a) Normality threshold (N_{Th}): This index represents the minimum "rate of goodness" that a therapist might require his/her patient to achieve in order to be considered within the normal range. The maximum value of this index could be 1; however, such value would mean that the patient should perform like a healthy person to be considered progressing.

b) Task progress step size (S): This is the maximum number of degrees that can increase/decrease from one task iteration to the next. For instance, supposing S is set to 5° and a patient is performing a reaching task that requires him or her to supinate the wrist to 45°. Consequently, the angle of the next task would be incremented by a maximum of 5° (in case the patient had a normal performance).

c) Web client proxy: The Web Client Proxy is a software application that provides services for retrieving, presenting, and traversing Web contents on the World Wide Web (HTML interpreter and Simple Object Access Protocol for exchanging structured information via the Web). It also facilitates the communication between the Web interfaces and the Web server.

B. Client Interface

The Client Interface is located at the server side and provides abstract interfacing to individual clients. The client is typically located in a physically remote place.

1) Web Services: This component hosts a pool of Web services that provide various functionalities for both the patient and the therapist (such as a Web service to retrieve patient's performance information and provide a proper display, a Web service to facilitate real-time interaction between the game engine and the patient, a Web service to perform signal conditioning, etc.).

2) Service Registry: The Service Registry enables clients to discover and access Web services by storing information about the services functionalities as well as their interfaces (how to access the Web services).

3) Third-Party Services: These are services that are hosted by third-party service providers to provide assistive functionalities (such as certain type of signal processing or graphics display Web services).

4) Web Services Interface: This interface has a similar functionality as the Web Client Proxy. It is a software application that implements HTML interpreter and SOAP messenger for exchanging structured information with the client.

C. Rehabilitation Engine

The rehabilitation engine is the unit where all the training data is analyzed and the game state decisions are made.

1) Signal Conditioning: Signal conditioning is the process of digitizing and calibrating the motion devices associated with the rehabilitation system. For example, in the case of a tracking camera device(s), the fudicial markers should be properly calibrated with the lens(es) of the camera(s). For inertial devices, analog signals are converted into digital values and the direct current offsets are removed.

2) Features Extraction: Feature Extraction is the process of extracting or computing the metrics of interest throughout the rehabilitation exercise. Particularly, the proposed framework incorporates three types of parameters that feed the adaptation engine.

a) Task angle: The task angle (θ) is the angle associated with the current task within a game session. In other words, θ is the patient's wrist tilt in degrees while performing a particular task or exercise (i.e., Supination, Pronation, etc.). Regardless of the type of tracking device used, the possible movements of the wrist can be detected by finding the accelerations on the x, y, and z coordinates. These accelerations are then used to determine the pitch (α), roll (β), and yaw (δ) using (1), (2), and (3), respectively

$$\text{Pitch} : \alpha = \tan^{-1}\left(\frac{A_x}{\sqrt{A_y^2 + A_z^2}}\right) \tag{1}$$

$$\text{Roll} : \beta = \tan^{-1}\left(\frac{A_y}{\sqrt{A_x^2 + A_z^2}}\right) \tag{2}$$

$$\text{Yaw} : \delta = \tan^{-1}\left(\frac{\sqrt{A_x^2 + A_y^2}}{A_z}\right) \tag{3}$$

where A_x, A_y, and A_z are the accelerations on the three axes.

b) Average angular velocity: The angular velocity ($v(t)$) of the wrist provides a good indication on the ability of a patient to perform his or her daily-life tasks in a timely manner. Achieving a speed close to a healthy person can avoid any clumsiness in the patient's hand movements. Since the velocity while performing a task is not constant and varies in time, we compute instead the average angular velocity ($\dot{\theta}$) for a particular task using (4)

$$\dot{\theta} = \frac{1}{t_2 - t_1}\int_{t_1}^{t_2} v(t)dt \tag{4}$$

where t_1 is the starting time of the task and t_2 is the time when the reaching of an object is achieved.

c) Jerkiness: By definition, jerkiness (J) is the rate of change of acceleration and is used to indicate how smooth the velocity of the wrist is for a specific exercise. It is defined by (5). Please note that Jerkiness is measured in gravity per milliseconds throughout this paper

$$J = \int_{t_1}^{t_2} \sqrt{\left(\frac{d^3x}{dt^3}\right)^2 + \left(\frac{d^3y}{dt^3}\right)^2 + \left(\frac{d^3z}{dt^3}\right)^2}\, dt \tag{5}$$

where x, y, and z are the 3-D coordinates of the wrist. Jerkiness is a very well-known metric in biomedical engineering. The smaller it is, the smoother is the wrist velocity.

3) Fuzzy Logic-Based Adaptation: The FLA unit constitutes the core of the rehabilitation system since it makes decisions on producing the appropriate intensity level of a task within a session based on the performance of the patient in the previous task of the same session. Therefore, the changes are done per-task rather than per-session. Normally, a patient's progress is evaluated by a therapist who scrutinizes different performance factors and chooses an appropriate exercise accordingly. Therefore, it is very sensible to have an intelligent decision maker that can mimic the human reasoning. Fuzzy set theory has been developed to offer that capability and to fulfill that ambiguous goal.

A patient suffering deficiencies in the wrist might not be able to achieve the full range of motions (ROMs). In addition, his or her wrist speed and steadiness might be below normal

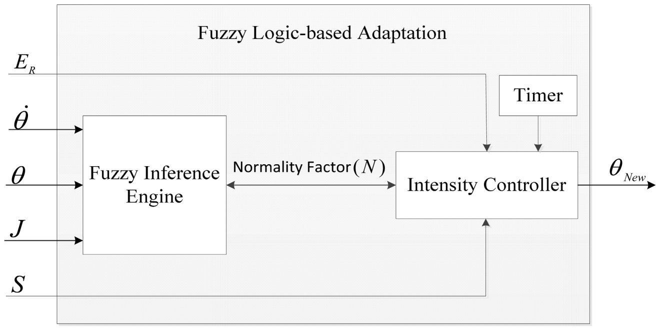

Fig. 2. FLA model deployed into the rehabilitation system.

and may require proper training for recovery. We take all these factors into account to design an FLA engine that monitors five inputs to make decisions that are represented in one output. As shown by the model in Fig. 2, the FLA is composed of a fuzzy inference engine (FIS), an intensity controller (IC) and a timer.

a) Fuzzy inference engine: The aim of the FIS is to decide on the normality factor (N_{FIS}) of the exercise based on three inputs: task angle (θ), average angular velocity ($\dot{\theta}$), and jerkiness (J). In other words, the FIS gives a quantified value that describes how well a patient performed after accomplishing a certain task by producing a crisp value N on a scale between 0 and 1.

The fuzzification and defuzzification membership functions (Fig. 3) are chosen as linear triangular membership functions for their higher computational efficiency. The fuzzy labels small (SM), average (AV), high (HI), and very high (VH) are the linguistic terms of the membership functions. The universe of discourse of each membership function was standardized based on the previous benchmarks determined in [15]. Then, an empirical analysis was performed to optimize these function parameters to improve the FLA performance.

The fuzzy rules associated within the FLA were defined to convey the logic that the normality factor is considered HI or close to HI when both the average angular velocity and jerkiness are "normal" or close to "normal" within a particular task angle. Here, the state "normal" would depend on the size of the task angle in effect (please refer to the "Evaluation" section in [15] for more clarification). We have defined 41 rules of the form

If (θ is θ_i and $\dot{\theta}$ is $\dot{\theta}_j$ and J is J_k) **Then** N_{FIS} is N_{FISijk}

where $i = 1$ to 4, $j = 1$ to 3, $k = 1$ to 4, and θ_i, $\dot{\theta}_j$, J_k and N_{FISijk} can be any of the fuzzy labels defined on each variable's membership function.

We have adopted the "min" and "max" operators as the t-norm and s-norm operators while the defuzzification method was chosen to be the center of area.

b) Intensity controller: The IC updates the intensity of the next task (exercise) within a session based on three inputs: the normality factor (N_{FIS}), the task progress step size (S), and the task reach error (E_R). E_R (6) is the error between the task angle to reach and the maximum reach achieved by the patient (θ_P). A positive value of E_R means that the patient was not able to accomplish the goal of the exercise, and therefore

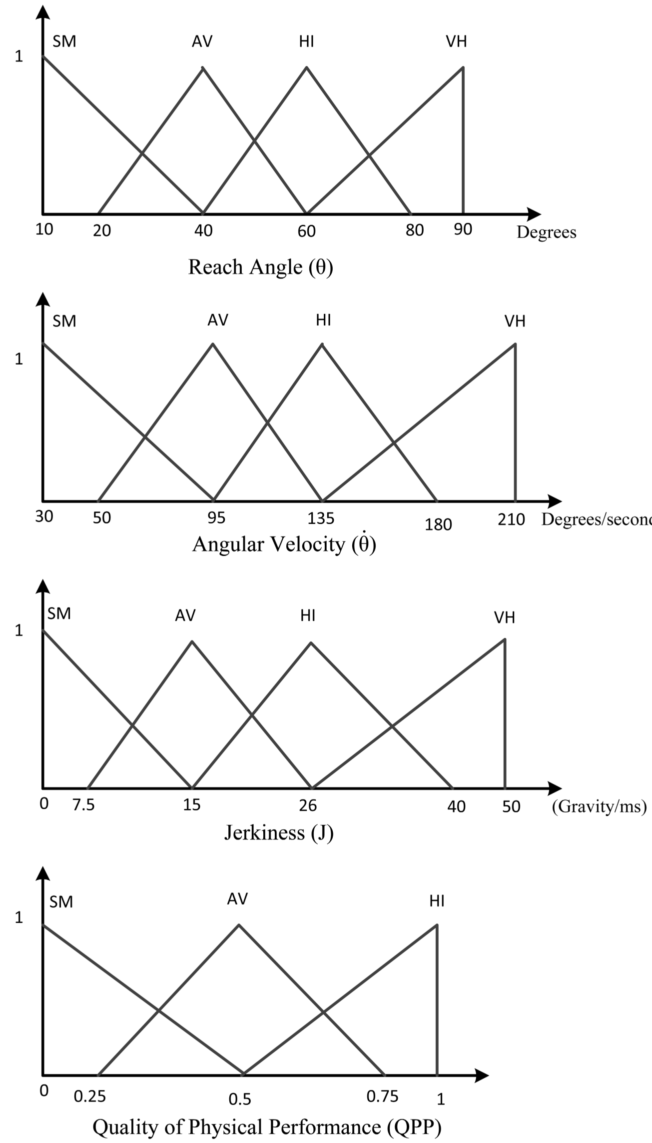

Fig. 3. FLAs membership functions.

could not reach the required task angle. It is worth noting that a negative value of E_R is simply ignored here because that would mean that the patient has exceeded the intended task angle

$$E_R = \theta - \theta_P. \tag{6}$$

Fig. 4 shows a flowchart of the functions accomplished by the IC. The following is a detailed description of the algorithm.

Step 1: The process begins by listening to a timer that expires at a custom time interval (T_{task}) defined as

$$T_{\text{task}} = T_{\text{Th}} - T_{\text{current}} \tag{7}$$

where T_{current} is the current time within the task and T_{Th} is the therapist's task-expiry-time of choice. Note that T_{task} is higher than 0 as long as the patient's task play time does not exceed the therapist's predefined time interval.

Steps 2 and 3: The intensity controller continuously checks whether or not the current task is finished within the

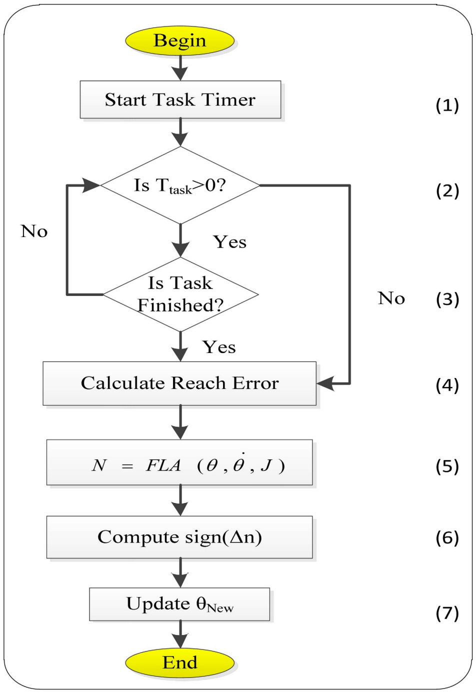

Fig. 4. FLAs work flowchart.

allocated T_{Task}. If the task in effect is not finished and the timer is not expired, the IC keeps monitoring the status until one of the two conditions changes. If the timer expires or the task is finished, the process jumps to Step (4).

Step 4: At this stage, the reach error can be either 0 or a positive value. Obviously, if a patient successfully finishes a task the reach error is always 0 since he/she is able to achieve the goal (i.e., move the cup onto the plate). On the contrary, the reach error is a positive value if the timer expires while the patient is still attempting to finish the task. In this case, we assume that the wrist ROM capabilities is less than that required by the task (i.e., patient is not able to rotate his or her wrist to a particular degree).

Step 5: Once the reach error is determined, the FIS evaluates the quality of performance (QoP) by producing a task-specific normality factor (N_{FIS}). It is worth noting that even if the patient was not able to finish a certain task, the FIS evaluates the QoP of the task based on the maximum ROM achieved.

Step 6: Once N_{FIS} is assessed, it is compared with the therapist's predefined normality threshold (N_{Th}) using

$$\Delta n = N_{\text{FIS}} - N_{\text{Th}} \tag{8}$$

where Δn is the deficiency distance. A nil or positive value of Δn would mean that a patient has achieved a reasonable performance; otherwise, the patient's performance needs to be improved. Δn is then plugged into the following sign function:

$$\text{sign}(\Delta n) = \begin{cases} +1, & \text{if } \Delta n \geq 0 \\ -1, & \text{if } \Delta n < 0. \end{cases} \tag{9}$$

Here, $\text{sign}(\Delta n)$ is a function that returns either $+1$ or -1 depending on the patient's deficiency distance.

Step 7: The ICs last function consists of generating the value of the reach angle for the next iteration for the rehabilitation task using

$$\theta_{\text{New}} = \theta_{\text{Old}} + \text{sign}(\Delta n) \cdot (N_{\text{FIS}} \cdot S) - E_R \tag{10}$$

where θ_{New} is the reach angle of the next task within the game and θ_{Old} is the reach angle of the previous task.

4) Game Engine: The Game Engine receives the task performance evaluation from the FLA component and reconfigures the game setup to match the patient's abilities and the therapist expectations. For instance, the Game Engine might increase or decrease the difficulty of the game, change the game graphics and/or sounds, or the temporal features of the game (such as required task completion time), etc.

5) Performance Estimation: This component receives the features derived by the features extraction component, and computes a quality of performance index that represents the overall quality of patient's performance. Other parameters can be included in the performance estimation component such as patient's physiological and/or psychological measures.

6) Rehabilitation Datastore: The Rehabilitation Datastore is composed of two databases, namely the Game Database and the Performance Database. The Game Database stores information regarding the rendering and the configuration of various rehabilitation games (such as the games graphics and default settings). The Performance Database stores information computed by the Performance Estimation component. This includes the raw data captured using the utilized interface, performance parameters (such as task angle/velocity, jerkiness, tremor, among others).

IV. System Performance Analysis

The goal of the performance analysis is to demonstrate the abilities of the proposed solution to adapt the rehabilitation task (game difficulty) in accordance with the patient's performance. The performance analysis includes a simulation study that investigates various patient behaviors (namely normal, decreasing, and increasing performances) and an experimental study where the simulation results are compared to experimental data captured with normal subjects.

A. Simulation Analysis

To verify the performance of the proposed framework, we simulate one motion only (rather than the six wrist motions), namely the supination. The two performance parameters considered for adaptation are the average velocity ($\dot{\theta}$) and the movement jerkiness (J). In our previous work [15], we derived (11) and (12), which define an approximation of the normal wrist movement kinematics on the supination motion, where the coefficients were derived and found as shown in Table I

$$\dot{\theta} = \varphi \cdot e^{\tau_M \theta} \tag{11}$$

$$J = \mu \cdot e^{\alpha_M \theta}. \tag{12}$$

The fuzzy system accepts the reach angle (θ), the average velocity ($\dot{\theta}$), and the movement jerkiness (J), and returns the normality factor (N_{FIS}) which is used to compute the new

TABLE I
COEFFICIENTS FOR THE AVERAGE VELOCITY AND JERKINESS INTERPOLATION

Type of Motion (M)	ϕ	τ	μ	α	Reach Angle Constrains
Supination	41.07	0.019	3.82	0.024	$10 \leq \theta \leq 90$

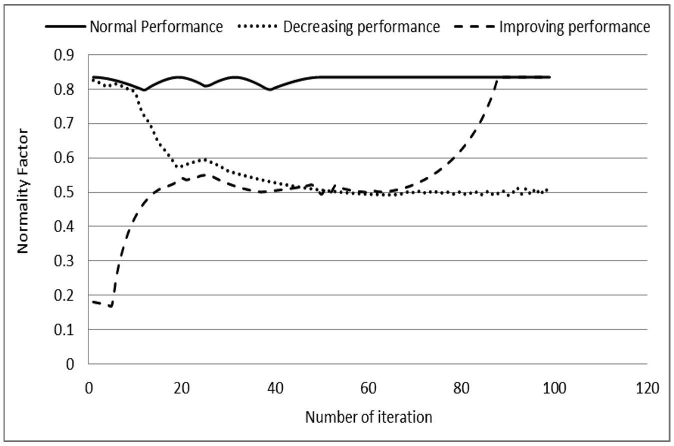

Fig. 5. Adaptation under various conditions (improving, deteriorating, and normal performances).

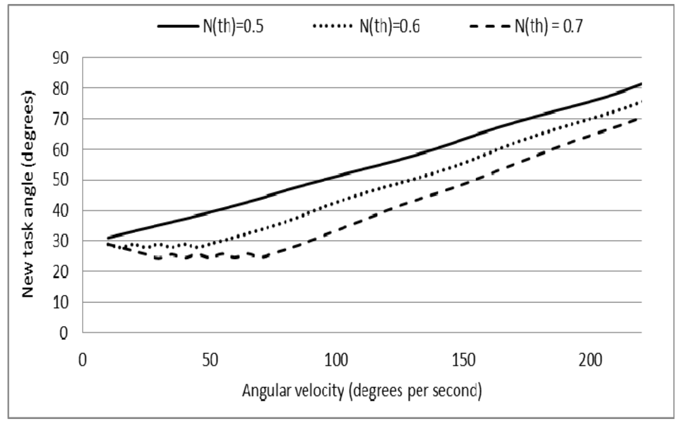

Fig. 6. New task angle versus average velocity.

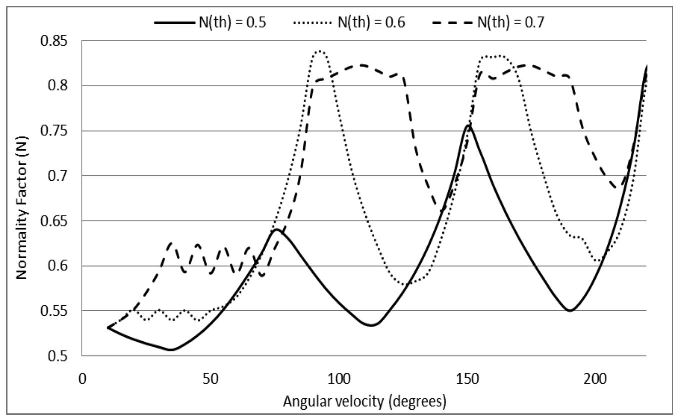

Fig. 7. Normality factor (N) versus average velocity.

task angle for the next iteration of the rehabilitation task. The simulation was implemented in Java using Eclipse IDE and performed on an Intel i7-2640M, 8 GB RAM PC.

1) Adaptation Scheme Simulation Analysis: In this simulation, various patients' performance scenarios are evaluated: normal performance, deteriorating performance, and improving performance (Fig. 5). For a normal condition, values for the average velocity and the jerkiness were computed using (11) and (12), respectively. As shown in Fig. 5, the normality factor (N_{FIS}) has maintained almost a constant maximum value since the patient's performance is optimal. However, when deterioration in the average velocity and jerkiness was introduced, the patient's performance is decreased and thus the normality factor (N_{FIS}) has decreased over the iterations. Finally, when an improvement is simulated (starting with low performance values for the average velocity and jerkiness and change them toward normal conditions) the normality factor has increased steadily. This behavior demonstrates the ability of the proposed system to adapt to various performance patterns.

2) Average Velocity Simulation Analysis: The average velocity analysis examines the variations of the normality threshold (N_{Th}), that is assigned by the therapist, as function of the average velocity. Fig. 6 shows the new task angle versus the average velocity for various values of N_{Th} where $\theta = 30°$ and $J = 0$ (N.B a jerkiness equals to 0 means that the patient is performing with excellent jerkiness). An increase in N_{Th} implies that the patient has to perform well before the system increases the difficulty of the rehabilitation task; otherwise the rehabilitation task is made easier to cope with the limited abilities of the patient.

Therefore, a small value of N_{Th} is usually set at the beginning of the rehabilitation process, and as the patient's performance improves, the therapist increases N_{Th} until the patient reaches the target normal performance. Therefore, the therapist can define how challenging the rehabilitation task is for the patient in order to optimize recovery. Fig. 7 shows the normality factor (N_{FIS}) variations as function of the average velocity for various values of N_{Th}. Again, an increase in N_{Th} implies a smaller variations in the normality factor and eventually a finer adaptation.

3) Jerkiness Simulation Analysis: The jerkiness analysis investigates the impact of the jerkiness (J) onto the normality factor (N_{FIS}) and thus the adaptation. As shown in Fig. 8, the new task angle (θ_{new}) increases as the jerkiness (J) increases until J becomes too high to be normal and thus θ_{New} starts decreasing in order to reduce the difficulty of the rehabilitation task.

On the other hand, as N_{Th} increases, the jerkiness at which the new task angle (θ_{New}) starts decreasing, decreases. For example, for $N_{\mathrm{Th}} = 0.5$ the jerkiness at which θ_{New} starts decreasing is $J = 28$ (see Fig. 8) and it increases to about 40 for $N_{\mathrm{Th}} = 0.7$. This is due to the fact that a small value of N_{Th} means a decreased tolerance with jerkiness (the adaptation continues to increase the new task angle even with increased jerkiness) whereas a higher N_{Th} implies that the adaptation is more sensitive to jerkiness; an excessive

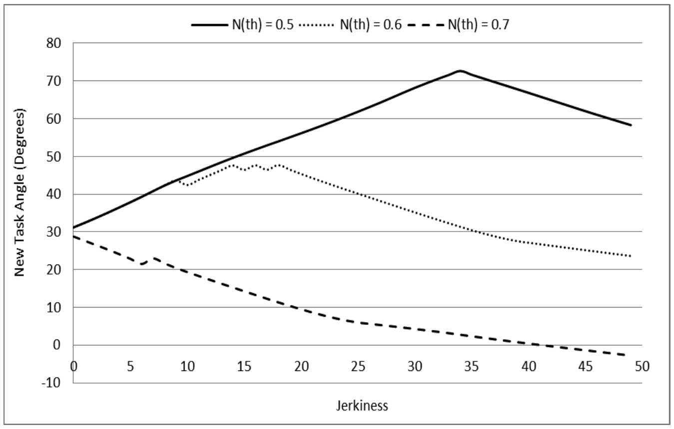

Fig. 8. New task angle (θ) versus jerkiness.

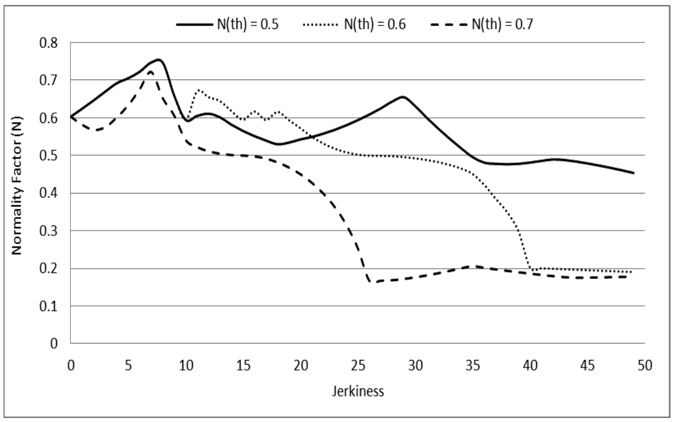

Fig. 9. Normality factor (N) as function of increased jerkiness.

increase in jerkiness results in a decreased (θ_{new}). Therefore, the therapist can set N_{Th} in accordance with the patient's abilities and needs. Similarly, Fig. 9 shows various patterns of decreasing normality factor (N_{FIS}) as function of an increasing jerkiness (J).

B. Experimental Analysis

Twelve (12) subjects took part in the experimental study (six male and six female subjects) with five trials each. The task assigned to the subjects was to play the cup and plate game where the player should grasp a cup and place it on a plate (shown in Fig. 10) using a tangible stress ball interface [15] (Fig. 11). The stress ball interface embeds 6 degrees of freedom inertial measurement unit (IMU) to capture human hand kinematics (including pitch, roll, and yaw motions), force sensors to capture the interaction forces, and a vibro-tactile motor to provide haptic feedback to the user. The captured data is processed using the FLA engine and the game difficulty (in the case the reach angle) is related to the patient's performance.

The normality factor (N) is computed for a total of 100 iterations per rehabilitation task, and then averaged over 60 trials (12 subjects multiplied by three trials each) so the results are statistically significant. Fig. 12 shows a comparison between the experimental results and the simulated results

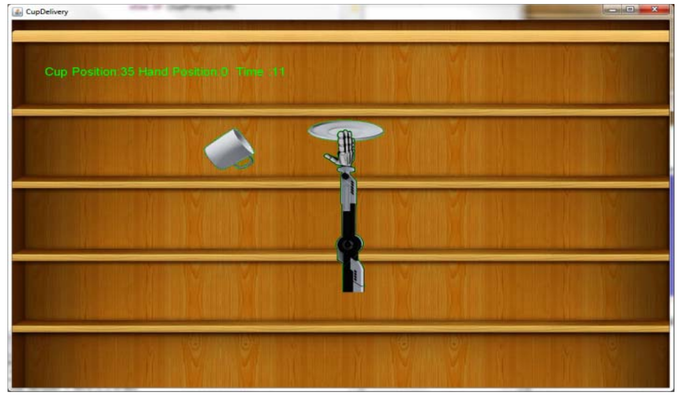

Fig. 10. Cup and plate game [15].

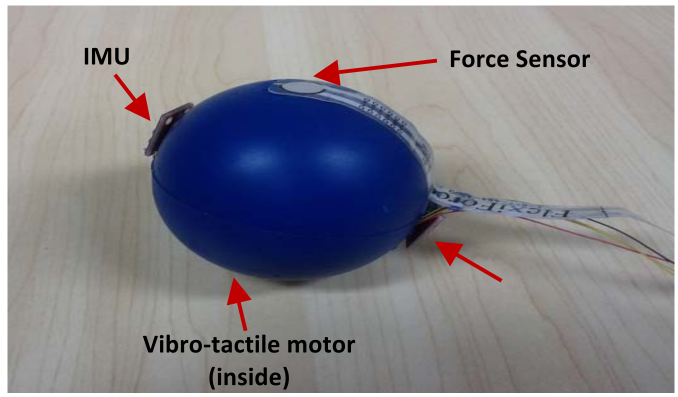

Fig. 11. Tangible stress ball interface [15].

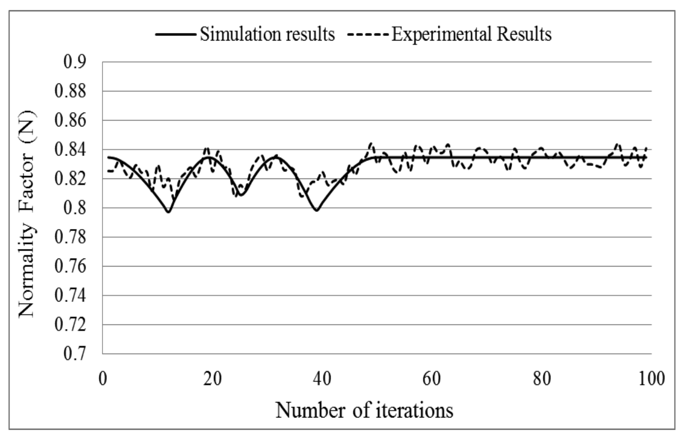

Fig. 12. Experimental results as compared with simulation results.

for N. Overall, the experimentally computed N has matched the simulated one and thus the performance of the proposed adaptation scheme is verified with normal subjects. In our immediate future work, we plan to perform a thorough experimental analysis with patients to confirm the effectiveness of the adaptation scheme for home-based rehabilitation.

V. Conclusion

In this paper, we proposed an adaptive home-based wrist rehabilitation framework by utilizing a fuzzy inference system that can evaluate the patient's performance and provide adaptation for the rehabilitation task. Simulation results are presented to demonstrate the ability of the proposed approach to adapt to various performance behaviors as well as to analyze the impact of varying properties such as the therapist threshold for normality estimation. Our immediate future work is to experiment the system with patients and confirm with the simulation results. Further analysis of various variables and their effectiveness on the overall behavior of the system will also be elaborated.

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