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Incorporating verbal feedback into a robot-assisted rehabilitation system

Duygun Erol Barkana†,*, Jadav Das‡, Furui Wang‡, Thomas E. Groomes§ and Nilanjan Sarkar‡

†*Department of Electrical and Electronics Engineering, Yeditepe University, Istanbul 34755, TURKEY*
‡*Department of Mechanical Engineering, Vanderbilt University, Nashville, TN 37235, USA*
E-mail: {jadav.das, furui.wang, nilanjan.sarkar}@vanderbilt.edu
§*Department of Orthopaedics and Rehabilitation, Vanderbilt Stallworth Rehabilitation Hospital, Nashville, TN 37212, USA*
E-mail: tom.groomes@vanderbilt.edu

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SUMMARY
This paper presents a control architecture, which has the potential to monitor the task and safety issues, to provide assessment of the progress and alter the task parameters, and to incorporate patient's feedback in order to make the necessary modifications to impart effective therapy during the execution of the task in an automated manner. Experimental results are presented to demonstrate the efficacy of the proposed control architecture.

KEYWORDS: Rehabilitation system; Human intention recognition system; Hybrid systems.

1. Introduction

Stroke is a highly prevalent condition especially among the elderly that results in high costs to the individual and society.[1–3] In the last few years, robot-assisted rehabilitation for physical rehabilitation of the stroke patients has been an active research area to assist, monitor, and quantify rehabilitation therapies.[4–11] Robot-assisted rehabilitation has shown to provide repetitive movement exercise and standardized delivery of therapy with the potential of enhancing quantification of the therapeutic process for stroke patients.[4–11] Studies in this field suggest that robot-assisted rehabilitation results in improved performance of functional tasks.

There are two important issues that a robotic rehabilitation system needs to address. First, robotic rehabilitation systems need to monitor the task and safety issues comprehensively, to provide assessment of the progress, and to alter the task parameters to impart effective therapy. Generally, therapist administers the therapy where he/she monitors the progress of the tasks as well as patient's safety, and assesses whether the task needs to be updated based on the need of individual patient. As a result, a robotic system will likely to reduce the amount of time of the therapist as well as decrease his/her workload, and consequently, decrease the cost of treatment. MIT-MANUS,[4] MIME,[5] and GENTLE/s[6] are among the first rehabilitation robotic systems to implement safety. Second, robotic rehabilitation systems need to alter the presentation of the rehabilitation therapy task based on patients' feedback. Altering the presentation of the rehabilitation therapy is an important issue since patients or therapists should be able to express how they feel about the task, and necessary modifications need to be performed about the therapy. Recently developed rehabilitation devices like ARMin,[7] ADLER,[8] T-WREX,[9] HenRiE,[10] and HARMiS[11] provide assistance to the patients as needed based on the patients' position, velocity, and force feedback. However, these feedbacks only provide information about patient's motion capabilities, and it does not directly represent feelings of the patient or the therapist about the task execution. For example, if the patient does not feel comfortable to move his/her arm at a specified speed, then the therapist or the robot-assisted system may need to change the task execution to slow down. Note that, when a therapist manually administers rehabilitation therapy, he/she keeps the patient in the loop and adjusts the therapy which is time-consuming. Therefore, it is important for a robot-assisted rehabilitation system to alter the presentation of the rehabilitation therapy task automatically considering patients and therapists feedback. To our knowledge, none of the existing robot-assisted rehabilitation systems use feedback of both patient's and therapist's to modify the presentation of the task. Spoken words of stroke patients or therapists can be one of the available options to incorporate their verbal feedback into the robot-assisted rehabilitation system so that the necessary modifications on the robot-assisted rehabilitation can be made immediately.

In this work, we attempt to address how to augment the capabilities of a robotic rehabilitation system by enabling it to: (1) monitor the task and safety issues comprehensively, provide assessment of the progress, and alter the task parameters to impart effective therapy during the execution of the task in an automated manner; and (2) recognize patient's verbal feedback such that it can address his/her concern. This work is built upon our preliminary work on an intelligent control framework for robotic rehabilitation[12–16] to incorporate patient's feedback within the overall control

*Corresponding author. duygunerol@yeditepe.edu.tr, duygunerol@gmail.com

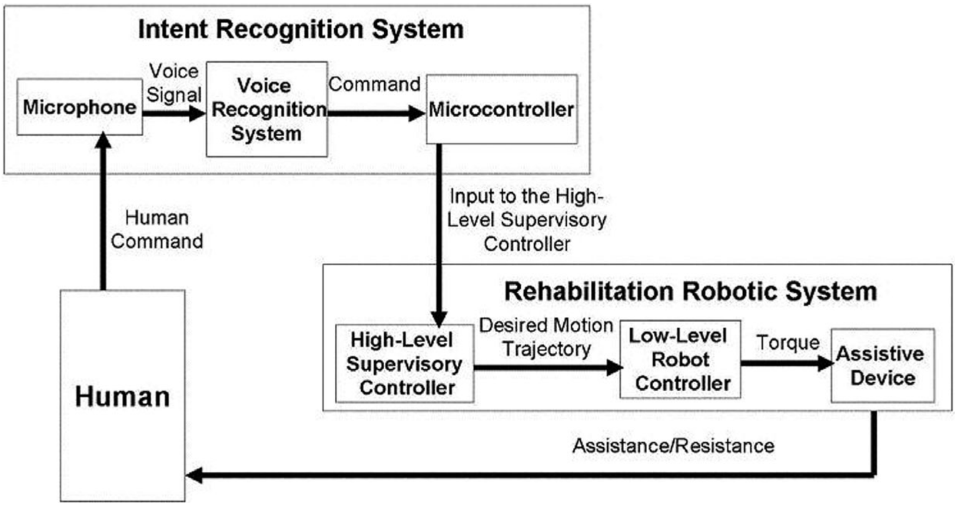

Fig. 1. Control architecture of a voice activated robotic rehabilitation system.

architecture. The paper is organized into the following sections. It first presents the intelligent control architecture in Section 2. A test-bed rehabilitation robotic system, a human intention recognition system, and one of the rehabilitation tasks that are used to demonstrate the versatility of the presented control architecture are presented in Section 3. Results of the experiments are presented in Section 4 to demonstrate the efficacy of the control architecture. Section 5 discusses potential contributions of this work and possible directions for future work.

2. Control Architecture

Let us first present the proposed framework in the context of one of the rehabilitation tasks, called the reaching task. The reaching task designed in this work requires a combination of shoulder and elbow movements, which could increase the active range of motion (AROM) in the shoulder and the elbow in preparation for later functional reaching activities in rehabilitation. In this task, the participants are asked to move their arms in the forward direction to reach a desired point in space and then bring it back to the starting position repeatedly within a specified time.

Stroke patients, in general, may not be able to track the desired motion trajectory in this reaching task because of their motor impairment. A low-level assistive controller will be used to provide robotic assistance to a patient's arm movement as and when needed to help him/her to complete the reaching task. In this architecture, an intention recognition system recognizes the patient's spoken words (e.g., fast, slow, continue, and stop) using a microphone and a voice-recognition technique and then converts the spoken words into control commands (Fig. 1). The control commands, which represent his/her intention during the task execution, are sent to the high-level supervisory controller. Once the high-level supervisory controller receives the commands, the decision-making module of the high-level supervisory controller generates sequences of control actions using its decision rules. Additionally, the high-level supervisory controller monitors the safety events during the execution of the reaching task to decide the necessary modifications of the task. The high-level supervisory controller presented in this work ideally plays the role of a human supervisor (therapist) who would otherwise monitor the patient's verbal feedback and safety and then assess whether the task needs to be updated. The high-level supervisory controller is designed considering the requirements of the therapy, and it can be easily modified and extended for new task requirements. The decision of the high-level supervisory controller is sent to the low-level assistive controller to update the task. The updated task is then executed by the low-level assistive controller. This cycle continues to complete the therapy.

3. Methodology

3.1. *Rehabilitation robotic system – a test-bed*

In order to present the efficacy of the proposed control architecture, we have used a PUMA 560 robotic manipulator as the robotic assistive device (Fig. 2). The manipulator is augmented with a hand attachment device (Fig. 2). The microcontroller board of the PUMA is replaced to develop an open architecture system to allow implementation of the advanced controllers (e.g., low-level assistive and high-level controllers). The technical specifications of the robotic manipulator can be found in ref. [17]. We interface the robot with MATLAB/Realtime Workshop to allow fast and easy system development. A computer monitor is placed in front of the subject to provide visual feedback about his/her motion trajectory during the execution of the task. The detailed discussion about the rehabilitation robotic system can be found in our previous work.[12–16,18]

Since in this work we are primarily interested in effecting assistance to the upper arm, we design a hand attachment device where the subject's arm is strapped into a splint. The PUMA 560 is attached to that splint to provide assistance to the upper arm movement using the assistive controller (Fig. 2). We further design a steel plate with proper grooves that hold two small flat-faced electromagnets (from Magnetool Inc.) that are screwed on it (Fig. 2). We attach a light-weight steel plate under the splint, which is then

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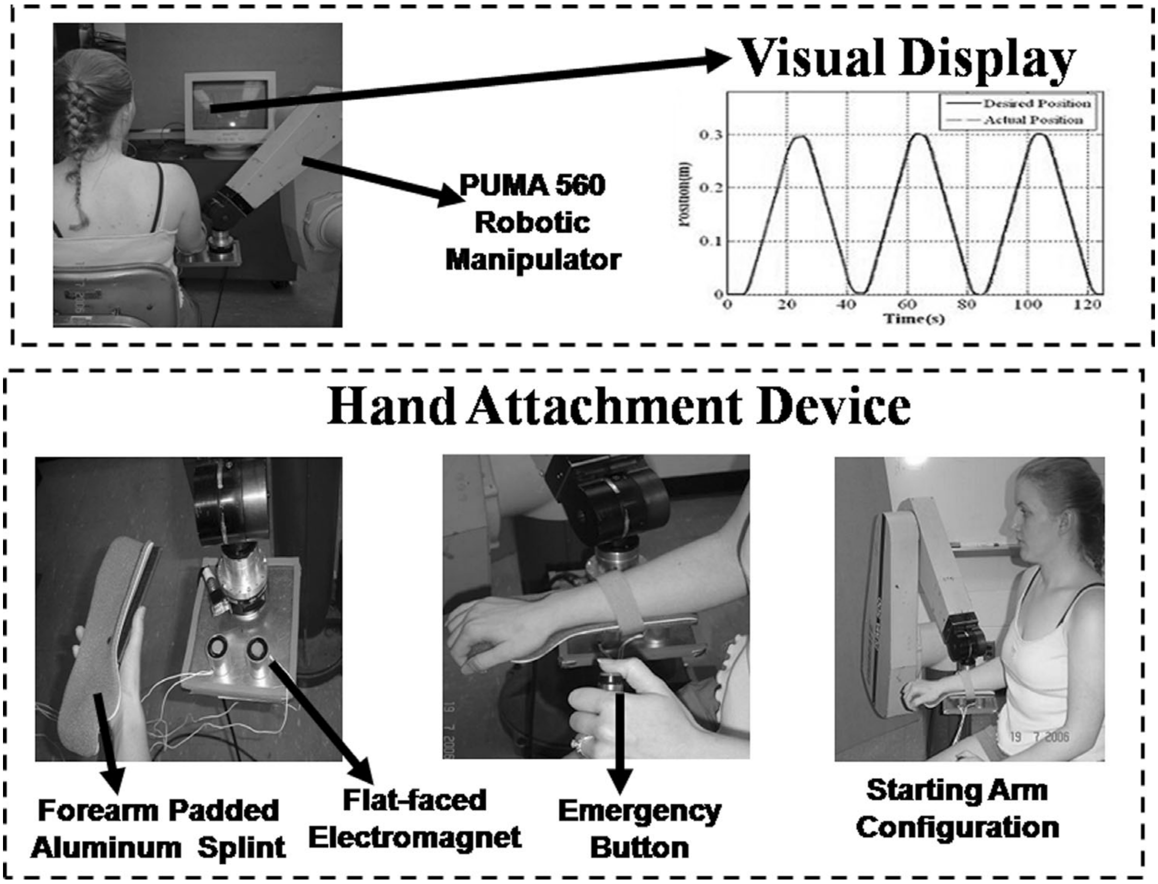

Fig. 2. Subject arm attached to robot.

attached to the electromagnets of the plate. An automatic release (AU) rectifier controller (Magnetool Inc.) is used to provide a quick release of these electromagnets. A push button, which is connected to the AU Rectifier Controller, is used to magnetize and demagnetize the electromagnets when the subject wants to remove the hand attachment device from the robotic manipulator in a safe and quick manner. Ensuring safety of the subject is a very important issue when designing a rehabilitation robotic system. Thus, in case of emergency situations, therapists can press an emergency button. The patient and/or the therapist can quickly release the subject's arm from the PUMA 560 by using the quick-release hand attachment device (as described above) to deal with any physical safety related events. This quick-release mechanism is identical to the mechanism used in GENTLE/s[6] and ADLER.[8] When the push button is pressed, electromagnets are demagnetized instantaneously and the subject is free to remove the splint from the robot. The safety mechanism in MIME is similar although the implementation is different in some cases (e.g., we introduce joint limits as a hypersurface in our high-level controller whereas in MIME it is implemented as a limit check since the control architecture is different from ours).

In this work, a proportional-integral-derivative (PID) position control is used as a low-level arm assistive controller for providing robotic assistance to a subject to complete the movement task. The subject receives visual feedback of both their actual position and the desired position trajectories on a computer screen, which is placed in front of them. Then the subject is asked to pay attention to tracking the desired position trajectory as accurately as possible, which keeps them focused on the task. If the subject deviates from the desired motion, then low-level assistive controller provides robotic assistance to complement the subject's effort to complete the task as required.

3.2. Human intention recognition system

Stroke patients may have difficulties to complete the rehabilitation tasks because of their limited upper extremity movements. It is important to include patient's feedback into the robot-assisted rehabilitation system so that it can immediately make the necessary modifications without therapist's intervention. Recognizing stroke patients' spoken words may be one of the available options to incorporate their feedback into the robot-assisted system.

Various speech recognition techniques have been developed over the years such as a grammar builder from the Microsoft Speech SDK 5.1,[19] fuzzy command interpreter,[20] Adaptive Input Neural Network (AINN).[21,22] MICROEAR (voice activated hardware) is developed in ref. [23] to recognize a word and then it returns a string which is then converted to a numerical code. Later, the code is compared with the listed words and sets the respective flags. Then the relevant functions form the character strings to be passed on to the robot controller to activate the robot motors using ASCII string. Hidden Markov Model (HMM) based automatic speech recognizers are developed to recognize the human voice in ref. [24]. The spoken word from the human is

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translated in the form of a quantified desired action for a robot system. New concepts of fuzzy coach-player system and subcoach to control robots with natural language commands are presented in ref. [25]. A probabilistic neural network based learning method is used to acquire the knowledge from such commands and then implemented in a Mitsubishi PA-10 redundant manipulator.

In our target application domain, we want to incorporate feedback from stroke patients. It is likely that many of the stroke patients may not have sufficient control over their articulatory muscles to communicate long and clear sentences. Moreover, the range of distortion of spoken words could be an issue in stroke patients. Considering these issues, we choose to develop a speech-recognition system that is capable of robustly identifying a few short phrases or words that have relevance with respect to the rehabilitation therapy. We use a well-known voice recognition method, called Mel-frequency cepstral coefficients (MFCCs) in this work.[26,27]

In this work, however, we have used a deterministic approach to speech recognition. Since in this application we have restricted the number of spoken words and since we have employed an individual-specific approach, such a deterministic approach is preferred to a more versatile learning approach. The subject informs his/her intention using simple words such as "fast," "slow," "stop," and "continue" during the rehabilitation task. However, these words can not be used directly as commands for the high-level controller in the control architecture. Initially, each subject is asked to speak each of the selected words three times. The signal is acquired using the data acquisition toolbox of MATLAB R2007a[28] with 8 kHz sampling frequency. An arithmetic average is computed from these three samples of the same word to account for within person variation of spoken words. The resultant sample normalized and is broken down in a series of frames each of which contains 256 data points. We compute 12 mel-frequency cepstral coefficients (MFCCs) for each frame. The frames and their MFCCs for each word for each person are stored in a set of two-dimensional arrays as reference. During the execution of the rehabilitation task, as the subject speaks any of the selected words, the start and end points of the sampled speech signal are detected and only the speech portion of the signal is sent to the feature extraction module. The end point determination concept used here is originally proposed in ref. [29] based on two features: short-term root-mean-square energy and zero-crossing-rate measures of the signal. The feature extraction module receives the speech portion of the signal and computes the same 12 MFCCs of the speech by splitting it into frames of 256 samples. The MFCCs are then sent to the pattern matching module to compare the MFCCs of the spoken word with those of the reference MFCCs of all the stored words and finds the best match using the least Euclidean distance measure among the MFCCs between the spoken word and the reference words. Then the pattern matching module generates a command signal for the high-level controller. In order for the high-level controller to receive the generated command, the command is initially sent to the microcontroller (Adapt9S12D -Technological Arts Company). The microcontroller transmits the command signal to the computer of the robotic rehabilitation system through a RS232 serial port. The command is used by the high-level controller to decide the next plan of action during the execution of the rehabilitation task.

3.3. Modeling of a rehabilitation task using hybrid System modeling technique

The proposed control architecture as described in Section 2 consists of a low-level arm assistive controller that is used to provide assistance to the subject's arm movement and a high-level supervisory controller to monitor the task and the patient's safety and to detect the patient's verbal feedback (intention) in order to make the necessary modifications on the task. In this work, we use hybrid system modeling technique to design the proposed control architecture. A hybrid system model has three parts, a "Plant," a "Controller" (supervisor), and an Interface[19,30,31] (Fig. 3). Similar hybrid system model has previously designed for same rehabilitation system and the details can be found in refs. [12–16]. First, we present the theory of the hybrid control systems. Then the design details of the hybrid control system used for one of the rehabilitation task, reaching task, is given.

The hybrid control systems consist of a plant which is generally a continuous system to be controlled by a discrete event controller (DES) connected to the plant via an interface in a feedback configuration.[30,31] If the plant is taken together with the interface, then it is called a DES plant model. The DES controller, which is called the high-level supervisory controller in this work, controls the DES plant. Let us first present the DES plant and then describe the DES controller (high-level supervisory controller).

3.3.1. DES plant model. The DES plant model is a nondeterministic finite automaton, which is represented mathematically by $G = (\tilde{P}, \tilde{X}, \tilde{R}, \psi, \lambda)$. Here, $\tilde{P}$ is the set of discrete states; $\tilde{X}$ is the set of plant symbols generated based on the events; and $\tilde{R}$ is the set of control symbols generated by the high-level supervisory controller. The function $\psi : \tilde{P} \times \tilde{R} \to 2^{\tilde{P}}$ is the state transition function. The output function, $\lambda : \tilde{P} \times \tilde{P} \to 2^{\tilde{X}}$, maps the previous and current plant states to a set of plant symbols. The set of DES plant model states $\tilde{P}$ is based upon the set of hypersurfaces that separates different discrete states.

The hypersurfaces defined in this work can be classified into two classes: (i) the hypersurfaces considering subject's capability to complete the task; (ii) the hypersurfaces considering the capability of the rehabilitation robotic system in order to ensure the execution of the rehabilitation task in a safe manner. The hypersurfaces are defined as follows: $h_1 = v - v_{high}$, $h_2 = v_{low} - v$, $h_3 = e$, $h_4 = \delta - \delta_{limit}$. Here, v is the actual speed of the robotic device; v_{low} and v_{high} are the lower and upper limits of the subject's desired speed range; e is binary variable representing the subject's intention to stop or continue the task; δ is the actual robotic device configuration vector; and δ_{limit} is the limit vector of the configurations. h_1 detects if the current task is too fast for the subject and he/she may want to decrease the speed; h_2 detects if the current task is too slow for the subject and he/she may want to increase the speed; h_3 detects whether the subject wants to continue or to stop the task; h_4 detects whether the

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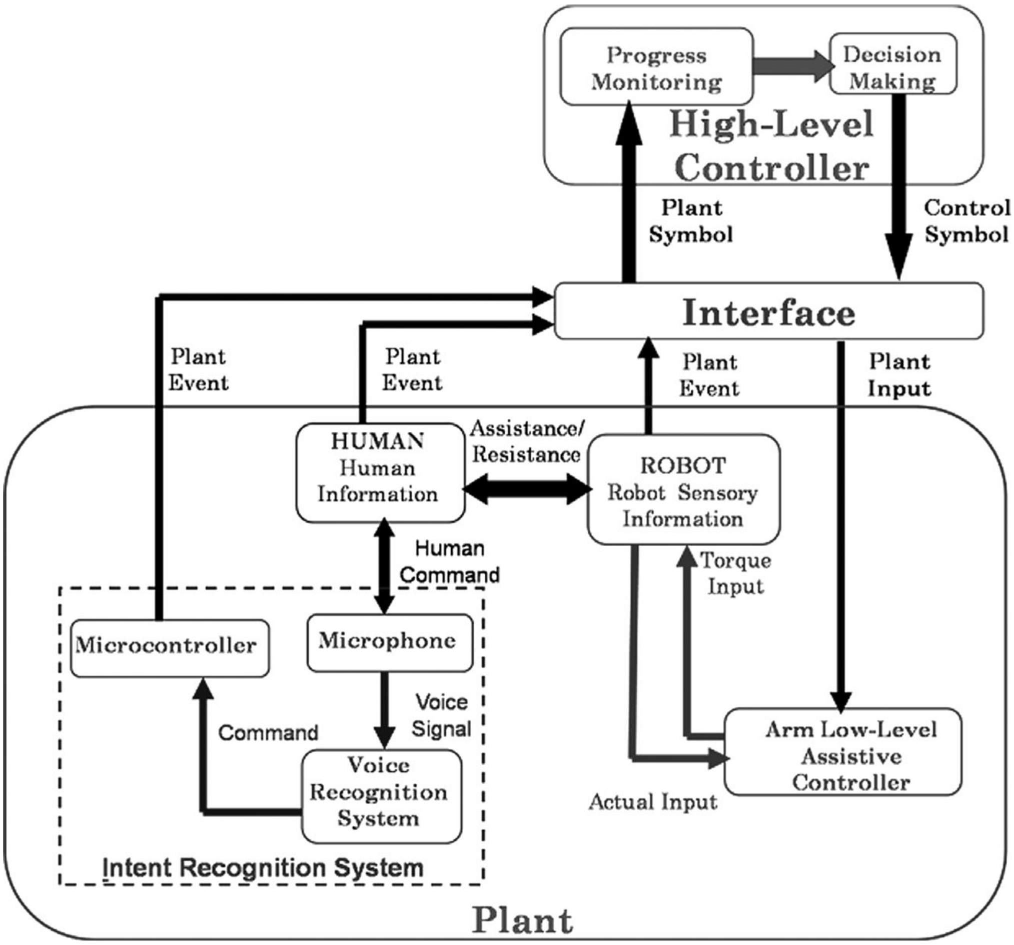

Fig. 3. Control architecture.

robotic system configurations, joint angles, torque, etc. are working in safe range.

The DES plant model is demonstrated in Fig. 4. Here, $\tilde{x}_i$ is the plant symbol, $\tilde{r}_i$ is the control symbol and $\tilde{P}_i$ is the plant state. Note that a temporary state P'_{0000} is introduced to distinguish the current state from the initial state. A plant event occurs when a hypersurface is crossed, which means the plant enters a new state. These plant events need not be distinct for each distinct hypersurface. A plant event generates a plant symbol to be used by the high-level supervisory controller. The plant symbol, $\tilde{x}$, is generated as an output function of the current and the previous plant state. We define the following plant symbols considering the hypersurfaces discussed before: (i) $\tilde{x}_1$, the subject wants to continue the task execution with the current speed; (ii) $\tilde{x}_2$, the subject wants to slow down and says the word "slow;" (iii) $\tilde{x}_3$, the subject wants to speed up and says the word "fast;" (iv) $\tilde{x}_4$, the subject wants to stop and says the word

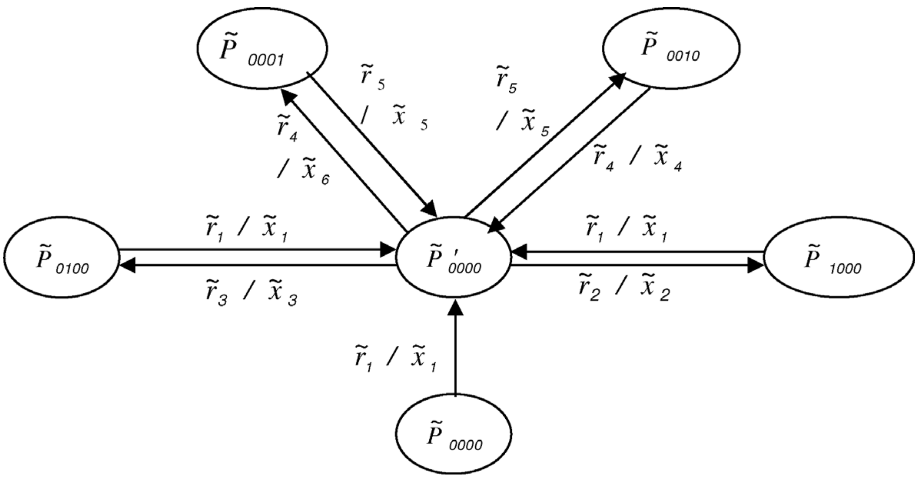

Fig. 4. DES plant for control architecture.

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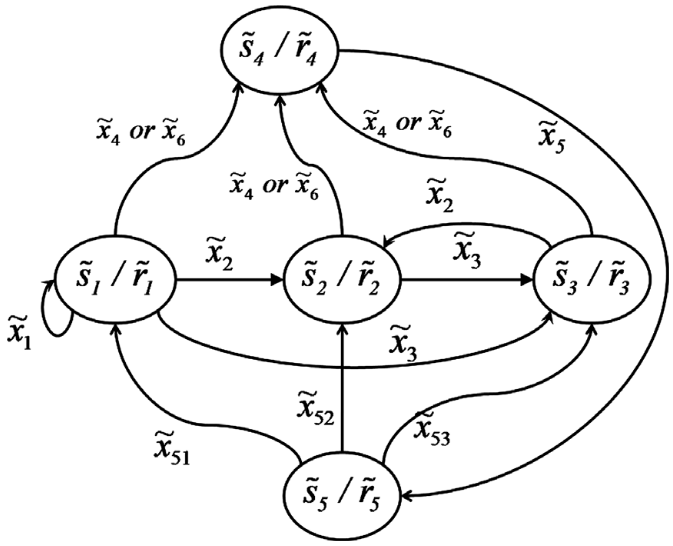

Fig. 5. High-level supervisory controller for reaching task.

"stop;" (v) $\tilde{x}_5$, the subject wants to continue the task and says the word "continue;" and (vi) $\tilde{x}_6$, safety-related issues happened such as the robot configurations are out of limits. Thus $\tilde{X} = \{\tilde{x}_1, \tilde{x}_2, \tilde{x}_3, \tilde{x}_4, \tilde{x}_5, \tilde{x}_6\}$ is the set of plant symbols. However, the plant symbol $\tilde{x}_5$ needs to be further subdivided to uniquely identify the exact plant state where the task execution is paused. If the subject says "continue" while performing the task with the initial conditions in the last state, then $\tilde{x}_{51}$ is generated. If the subject says "stop" while performing the task with slow speed, then $\tilde{x}_{52}$ is generated. Similarly, if the subject says "stop" while performing the task with fast speed, then the plant symbol $\tilde{x}_{53}$ is generated.

3.3.2. High-level supervisory control. The high-level supervisory controller is a discrete event system that is modeled as a deterministic finite automaton specified by $D = (\tilde{S}, \tilde{X}, \tilde{R}, \delta, \phi)$. Here, $\tilde{S}$ is the set of controller states, $\tilde{X}$ is the set of plant symbols generated by the event in plant, $\tilde{R}$ is the set of controller symbols generated by the high-level supervisory controller, $\delta : \tilde{S} \times \tilde{X} \to \tilde{S}$ is the state transition function, and $\phi : \tilde{S} \to \tilde{R}$ is the output function. The high-level supervisory controller for the reaching task is shown in Fig. 5.

In Fig. 5, the convention of labeling the arcs is to list the plant symbols, which enable the transition; the convention in the ellipse is to list the control states, followed by "/" and then the control symbols, which can be generated once the system enters the corresponding states. The control states and control symbols are defined in Table I.

Table I. Control states and control symbols.

i	$\tilde{s}_i$	$\tilde{r}_i$
1	Active with initial speed	Device on
2	Active with decreased speed	Device speed down
3	Active with increased speed	Device speed up
4	Idle	Device off
5	Active with previous speed	Device on

Table II. Human intention recognition system accuracy (%) for healthy subjects.

	Accuracy (%)			
Subject	Slow	Fast	Stop	Continue
1	90	100	100	100
2	80	100	100	100
3	100	100	90	100
4	90	100	80	100
5	90	100	90	100
6	90	100	100	100
7	100	100	100	100
8	100	90	100	100
9	100	100	100	100
10	90	100	100	100

Interface in this application is designed to recognize the above-mentioned plant symbols and control symbols. It is clear from the above discussion that the design of the various elements of the DES plant and the DES controller is not unique and is dependent on the task, the sensory information available from the robot-assisted rehabilitation system, and the subject's verbal feedback.

4. Results

The main focus of this paper is to present the control architecture which was shown in Fig. 5. However, the human intention recognition system is an important part of this new control framework that is responsible for generating the commands to the high-level controller based on patient's verbal feedback to modify the task requirements. Hence, we first summarize the validation of the evaluation of human intention recognition system.

4.1. Validation of human intention recognition system

Recognition accuracy of human intention recognition system has been checked with both healthy subjects and stroke patients. First, 10 healthy subjects were invited to our laboratory to record the voice signals of the four words which were "slow," "fast"' "stop," and "continue." Four females and six males, 20–32 years old, right-handed, unimpaired subjects participated in this study. Voice from each subject was captured by a microphone and then it was sampled by the data acquisition module in MATLAB R2007a at a sampling rate of 8 kHz using a sound card installed in the PC. Each single word was recorded three times and was then normalized every sample to an equivalent level to find the arithmetic average. Then the MFCCs of average signals of each word for each subject were computed to be used as the reference set for pattern matching.

Subsequently, each subject was asked to speak any of these four words 10 times in a random order and the output speech signal was recorded. We then analyzed how many times the voice recognition system correctly identified the spoken words for the healthy subjects (Table II). In general, it can be seen that the human intention recognition system successfully recognized the spoken words for all 10 subjects with high accuracies.

Table III. Human intention recognition system accuracy (%) for stroke subjects.

Subject	Accuracy (%) Slow	Fast	Stop	Continue
1	100	100	90	100
2	90	100	100	100
3	100	100	90	100
4	100	100	100	100

Additionally, we had evaluated the recognition accuracy of the proposed human intention recognition system with stroke patients. One female and three males subjects within the age range of 65–78 years took part in the study. Each patient was asked to speak any of these four words five times in a random order. The experiments were conducted at the Vanderbilt Stallworth Rehabilitation Hospital under the supervision of an occupational therapist. The stroke patients who participated in this study had no aphasia or language deficits interfering output of the speech. However, the quality and clarity of spoken words could be an issue. We then analyzed how many times the voice recognition system correctly identified the spoken words for the stroke patients (Table III). As can be seen from Table III, the proposed human intention recognition system successfully recognized the spoken words of stroke patients with recognition accuracy between 90% and 100%.

4.2. *Evaluation of the proposed control architecture*

4.2.1. Experiment procedure. Subject is seated in a height adjusted chair as shown in Fig. 2. The height of the PUMA 560 robotic manipulator has been adjusted for the subject to start the rehabilitation task in the same arm configuration. The starting arm configuration is selected as shoulder at neutral 0° position and elbow at 90° flexion position. The task requires moving the arm in forward flexion to approximately 60° in conjunction with elbow extension to approximately 0°. Subject is asked to place his/her forearm on the hand attachment device as shown in Fig. 2 when the starting arm configuration is fixed. The push button has been given to the subject that can be used during the task execution in case of emergency situations. The subject receives visual feedback of their position on a computer monitor on top of the desired position trajectory which is placed in front of him/her. Subject is asked to practice the tracking rehabilitation task (described in Section 2) 10 times to familiarize him/herself with the task.

4.2.2. Results. Since we experiment with unimpaired subjects who could ideally do the reaching task by themselves (unlike a real stroke patient), we instructed the subjects to be passive so that we can demonstrate that the proposed control architecture was solely responsible for the modification of the task based on subject's verbal feedback. Such an experimental condition is not only helpful to unambiguously demonstrate the efficacy of our proposed control architecture but also could occur when a low functioning stroke survivor participates in a rehabilitation therapy who will initially need continuous robotic assistance to perform the required rehabilitation task.

We had conducted two experiments to demonstrate the feasibility and usefulness of the proposed control architecture in enabling robotic assistance to a subject to complete the tracking task based on subject's verbal feedback (intention). The subjects were asked to express their intention using one of the following words: "fast," "slow," "stop," and "continue" during the execution of the task. We only presented one of the subjects' data to demonstrate the efficacy of the proposed control architecture. Initial desired velocity was selected as 0.02 m/s, which was chosen in consultation with an occupational therapist who works with stroke patients at the Vanderbilt Stallworth Rehabilitation Hospital.

In the first experiment (E1), the subject was instructed to modify the tracking task only once. When the tracking task started, $\tilde{s}_1$ became active and the initially defined task requirements were used to define the desired trajectory for the subject to be followed (Fig. 6I-middle). If the subject is comfortable with the initial task requirements then the task execution will be completed with the initially defined parameters (Fig. 6I-right). However if at point A, the subject said "slow" (he might feel the required motion is too fast for him) (Fig. 6II-left) and then the human intention recognition system compared the spoken word with the reference ones using the pattern matching module (as described in Section 3.2) and detected hypersurface h_2 was crossed then $\tilde{x}_2$ was generated. This event was recognized by the high-level controller through microcontroller. When $\tilde{x}_2$ was generated while $\tilde{s}_1$ was active, then $\tilde{s}_2$ state became active and $\tilde{r}_2$ was generated and sent to low-level controller to change the speed of the task (Fig. 6II-middle). Then the subject was required to continue the tracking task with a slower movement (Fig. 6II-right solid line). If the subject's intention to slow down the movement was not considered then the desired motion trajectory that the subject was required to follow would be the dashed line in Fig. 6II-right. This could create an unsafe operating condition because the subject could not continue the task execution with a high speed. Later, the subject said "fast" (he thinks the movement was too slow for him) (Fig. 6III-left) and then human intention recognition system detected h_3 was crossed then $\tilde{x}_3$ was generated. When $\tilde{x}_3$ was generated while $\tilde{s}_1$ was active, then $\tilde{s}_3$ state became active $\tilde{r}_3$ was sent to low-level controller (Fig. 6III-middle). Now the subject was required to move faster to complete the tracking task (Fig. 6III-right solid line). If the subject's intention to move faster was not considered then the desired motion trajectory that the subject was required to follow would be the dashed line in Fig. 6III-right. This could limit the subject's movement and affect the efficiency of the therapy because he/she was able to move faster than initial speed. The increment and decrement level of the desired motion trajectory was selected as 25% more and less, respectively. The range could be increased or decreased based on the subject's movement ability.

The corresponding actual motion trajectories of the subject were shown in Fig. 7. It could be seen from Fig. 7 that the subject was able to track the modified desired motion trajectories. Thus, the actual motion trajectory was same as the desired motion trajectory because the subject was passive and the arm low-level assistive controller provided necessary

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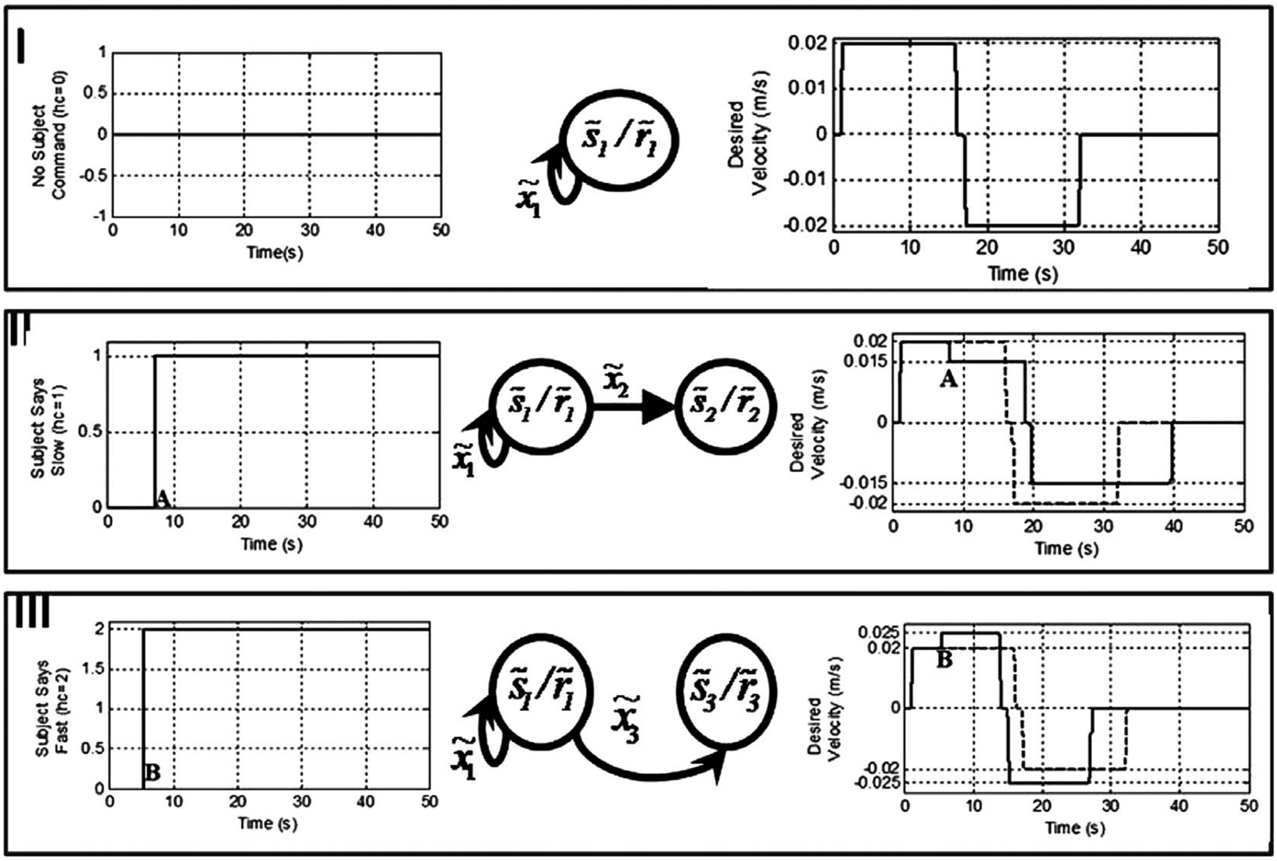

Fig. 6. Experiment 1 results.

robotic assistance to follow the desired motion trajectory to complete the task as required.

In the second experiment (E2), we asked the subjects to perform the same task as in the first experiment E1; however, in this case, the subjects were asked to modify the task more than once. This was done to simulate the movement of a stroke patient who may experience difficulty in performing the task with initially defined requirements. In this experiment, the subject started performing the execution of the task. Then at point A, the subject said "fast" (Fig. 8I)

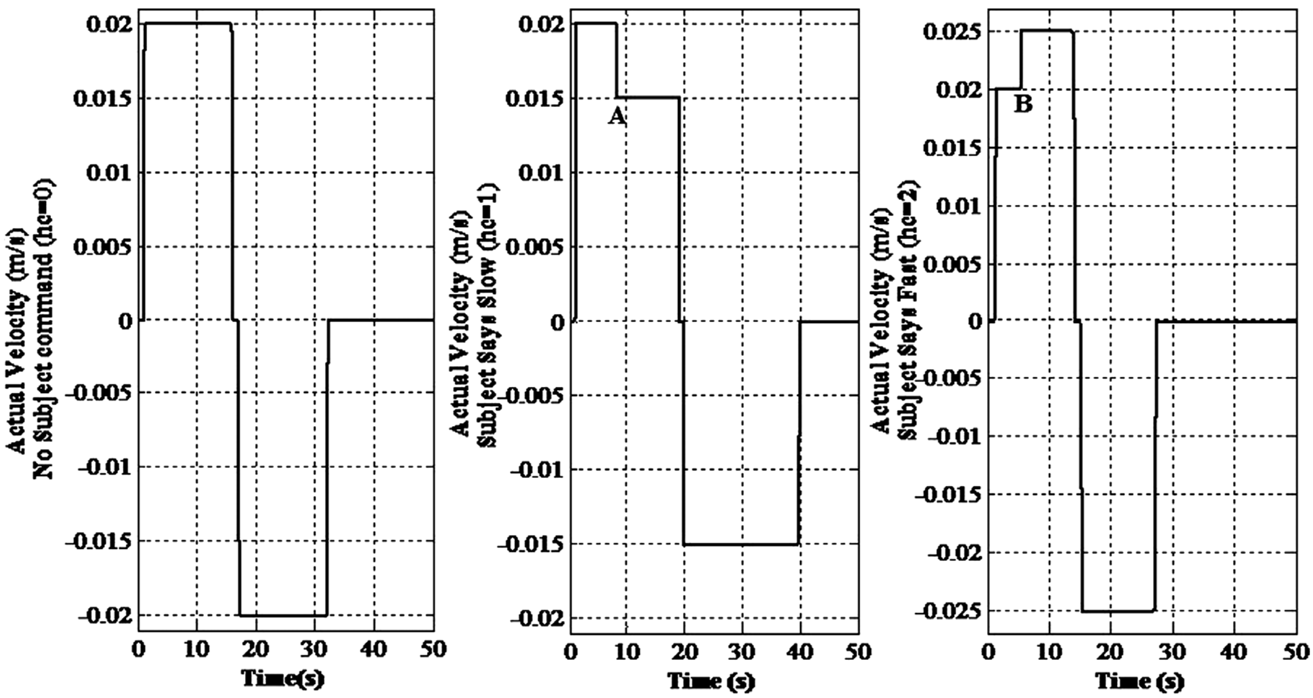

Fig. 7. Actual velocity trajectories for experiment 1.

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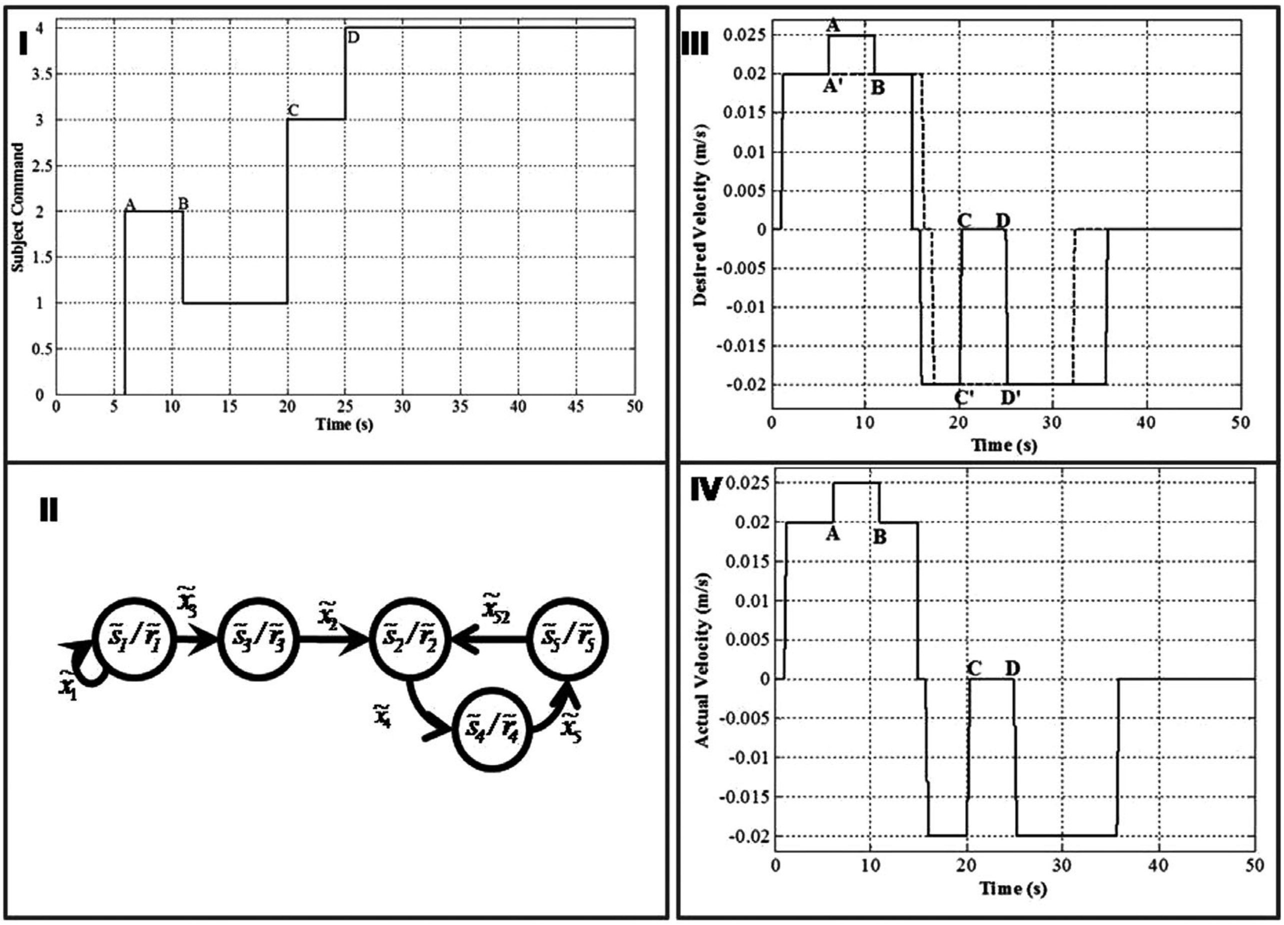

Fig. 8. Experiment 2 results.

then $\tilde{x}_3$ was generated, $\tilde{s}_3$ state became active, and $\tilde{r}_3$ was sent to low-level controller (Fig. 8II). Then the subject did not feel comfortable and he said "slow" at point B (Fig. 8I). When the subject said "slow" then $\tilde{x}_2$ was generated, $\tilde{s}_2$ state became active, and $\tilde{r}_2$ was sent to low-level controller (Fig. 8II). Additionally, we had assumed a safety event had occurred when the subject was performing the task. In this experiment, at some point of time during the task the subject wanted to pause for a while by saying "stop" word and then said "continue" word to restart the task execution where he resumed for completion of the rest of the task (Fig. 8I). When the subject said "stop" at point C, then $\tilde{x}_4$ was generated, $\tilde{s}_4$ state became active and $\tilde{r}_4$ was generated (Fig. 8II). Later when the subject said "continue" at point D, then $\tilde{x}_5$ was generated and $\tilde{s}_5$ state became active and instantaneously $\tilde{x}_{52}$ was generated to go back to state $\tilde{s}_2$ so that subject could continue the task execution where he resumed (Fig. 8II). This scenario might represent when a stroke patient wanted to pause for a while due to some discomfort. The corresponding desired motion trajectories had been generated dynamically as shown in Fig. 8III. On the other hand, if we did not use the proposed high-level controller, the desired motion trajectory would not have been automatically modified to register the intention of the subject to pause task execution, to move faster or slower. As a result, the motion trajectory would have followed the dashed line in Fig. 8III. In such a case, when subject wanted to move faster he would still move with initially defined speed at point A′ (Fig. 8III-dashed line). Furthermore, the desired motion trajectory would start at point C′ with non-zero velocity (Fig. 8III, dashed line), which could create an unsafe operating condition. In addition, since the desired motion trajectory computation would not have included the pause action, restarting the task at point C′ would not allow the completion of the task as desired.

High-level controller monitored the progress of the task and the subject's verbal feedback to make decisions on the modification of the task parameters. The corresponding actual motion trajectories of the subject were shown in Fig. 8IV. It could be seen from Fig. 8IV that the subject was able to track the modified desired motion trajectory to complete the task in a desired manner. The actual motion trajectory given was same as the desired motion trajectory because the subject was passive and the arm low-level assistive controller provided necessary robotic assistance to follow the desired motion trajectory to complete the task as required.

5. Discussion and Conclusion

In this paper, we have designed an intelligent control architecture: (1) to monitor the task and safety issues, to provide assessment of the progress, and to alter the task parameters, and (2) to incorporate patient's feedback in order to make the necessary modifications to impart effective therapy during the execution of the task in an automated manner. The control architecture is based on hybrid control that provides theoretical solidity to the existing rehabilitation approach. This architecture provides flexibility so that new safety features as well as new task requirements can be incrementally added to the system by designing new events either by adding new sensors or by further analyzing the current sensory information and by adding new decision rules in the high-level controller.

It is also important to include patient's feedback inside the control architecture because patients should be able to express how they feel about the task, which will then be used to make the necessary modifications about the presentation of the task to accommodate any problem patients perceive during the execution of the task. However, it is not possible to integrate spoken words into the system directly. Thus, we include patient's feedback as words in terms of events like other sensor events inside the control architecture.

As it could be seen from the above discussion hybrid system based control architecture could be useful in robot-assisted system in terms of monitoring safety, assisting patient, and incorporating patient's feelings, which are actually actions of the therapists during the therapy. Thus, the presented control architecture will be helpful to automate some of the actions of the therapists. During the therapy, if a task requirement changes or if the patient does not feel comfortable to move his/her arm at a specified speed, then he/she may speak out, and then a therapist/technician would need to adjust the computer code to reflect these changes. It is conceivable that one cannot anticipate all possible events that might occur during a rehabilitation task. The proposed hybrid system based control architecture provides a systematic procedure to effect changes such that the task execution could be automated. Instead of preprogramming numerous static trees based on if-then-else rules, it provides a dynamic mechanism of generating events that leads to necessary high-level decisions.

We have conducted experiments with unimpaired subjects to demonstrate the efficacy of the proposed control architecture. The results have shown that the task parameters can be determined dynamically based on subject's spoken words and safety-related events to generate the necessary motion trajectories at the required time using the proposed control architecture. The speed of motion is used as the task parameter in this paper. However, note that sometimes patients cannot move to the initially defined target positions because of their limited movement ability. Thus, in the case the proposed control architecture can be used to determine other task parameters such as a desired reaching position. Subjects can express their intention to move further away from the initially defined target position or closer to themselves using spoken words. In such a case, for example, the high-level controller in the control architecture can determine the target position based on the subject's verbal feedback while monitoring the safety-related events. Thus, new spoken words such as "further," "closer," etc. can be included inside the human intention recognition system and then related events and their decision rules can be defined inside the control architecture as new events.

The proposed control architecture, although implemented on a PUMA 560 robot, is independent of any particular robot and thus can be easily integrated into other existing robot-assisted rehabilitation systems.

As a future work, it is planned to investigate the efficacy of human intention recognition included methodology with severely impaired stroke patients and how it will influence patients' participation in the therapy regime.

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