Recovery Prediction in the Framework of Cloud-Based Rehabilitation Exergame

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Abstract. In this paper, we propose a framework of a cost-effective, entertaining, and motivating home-based upper limb rehabilitation system which consists of a cloud system and a client interface. The framework provides real-time feedback to the patient subject, summarizes the feedback after each session, and predicts the rehabilitation performance. As an implementation of the framework, a Kinect sensor is used to collect real-time data for upper limb joints of the subjects while they are participating in rehabilitation exergames. The Dynamic Time Warping (DTW) algorithm is then applied to compare the movement pattern of a patient subject with the movement pattern of a healthy subject. Next, the Auto-Regressive Integrated Moving Average (ARIMA) is utilized to forecast the rehabilitation progress of the patients based on their performance history. The prototype of this system is tested on six healthy individuals and one patient. The results show that the patients' movement patterns have a similar curve shape to the healthy individuals' movement patterns and, hence, the DTW algorithm can be used as an effective index to describe the rehabilitation statuses of the subjects. The forecasting method is briefly tested by feeding the rehabilitation status history.

Keywords: Home-based Rehabilitation Framework, Model Matching, ARIMA Prediction, Virtual Reality.

1 Introduction

According to the World Health Organization (WHO), there are about ten million people who are injured in traffic accidents and fifteen million people who suffer from strokes every year. Of those, six million of those suffering from traffic-related injuries and five million of the stroke patients are permanently disabled [1,2]. These people need a special rehabilitation program that starts when the patient is admitted to the hospital and does not end, even after the patient has been discharged from the hospital. Also, in many cases, stroke patients suffer from depression, which leaves family members and caregivers to wonder how

C. Stephanidis and M. Antona (Eds.): UAHCI/HCII 2014, Part III, LNCS 8515, pp. 256–265, 2014.

they can motivate the patients and better engage them in the rehabilitation program.

Arm rehabilitation is a restorative process that aims to hasten and maximize the recovery of the patients in order to get them as close as possible to pre- injury levels. Researchers have revealed that duration, capacity, and intensity of the training session have a huge impact on the rate of rehabilitation improvement [3]. However, adhering to the strict guidelines of a long-term rehabilitation process might be cumbersome for many patients who do not have access to rehabilitation es in their communities. Consequently, those people are required to travel a long distance to get treatment. In addition, a long-term rehabilitation process can be expensive and unaffordable for patients who do not have adequate public or private health insurance.

Many therapists recommend that patients perform a daily life activity, such as making coffee, in order to improve their upper limb movements. Since such tasks may be dangerous for a patient with an arm injury, researchers have developed virtual and augmented reality systems where tangible objects are associated with a virtual object that simulates the real object [4,5]. The current technological advancements have brought new perspectives to the rehabilitation process. Researchers have designed computerized rehabilitation robotic tools associated with virtual environments and games which are meant to be used at home. Therapists use these tools to track the progress of patients. However, two of the common inconveniences for many of these rehabilitation devices are related to their bulky shape and the complexity of their deployment. Consequently, these shortcomings make them impractical for home training because they require the presence of an expert. Cost is also an important factor for many patients when acquiring such devices. For these reasons, most of the robotic-assisted therapy devices are commonly used in clinic centers or hospitals.

Besides informing family and close friends, showing the real progress to the patients is another significant motivating factor. This can increase the self-satisfaction, engagement, and enjoyment levels of patients [6]. Many time-series matching algorithms have been used to compare kinematics data obtained from patients with the data from healthy people [7,8]. However, those algorithms are used in systems where the user is required to wear a garment (which is a difficult task for many stroke patients.)

In this paper, we propose the framework of a cost-effective, entertaining, and motivating home-based upper limb rehabilitation system which consists of a cloud system and client interface. The framework provides real-time feedback to the patient subject, summarizes the feedback after each session, and predicts the rehabilitation performance. In addition, this framework shows a new style of home-based rehabilitation system that motivates the patients by engaging family and friends in the rehabilitation process, and allowing therapists to remotely assess the progress of the patients and adjust the training strategy accordingly. As an implementation of the framework, a Kinect sensor is used to collect real-time data from the upper limb joints of the subjects while they are participating in rehabilitation exergames [9,10]. The Dynamic Time Warping (DTW) algorithm is then applied to compare the movement pattern of a patient subject with the movement pattern of a healthy subject. Next, the Auto-Regressive Integrated Moving Average (ARIMA) is utilized to forecast the rehabilitation progress of the patients based on their performance history. The prototype of this system is tested on six healthy individuals and one patient. Results show that the patients' movements have a similar curve shape to that of the healthy individuals and hence the DTW algorithm can be used as an effective index to describe the rehabilitation status. The forecasting method is briefly tested by feeding the rehabilitation status history.

2 Framework Architecture

The high level architecture of the proposed cloud-based rehabilitation exergame is shown in Figure 1. The aim of this framework is to motivate patients through social engagement and provide doctors with a tool for continuous observation and rehabilitation strategy predictions. The major components of the proposed framework are briefly explained as follows:

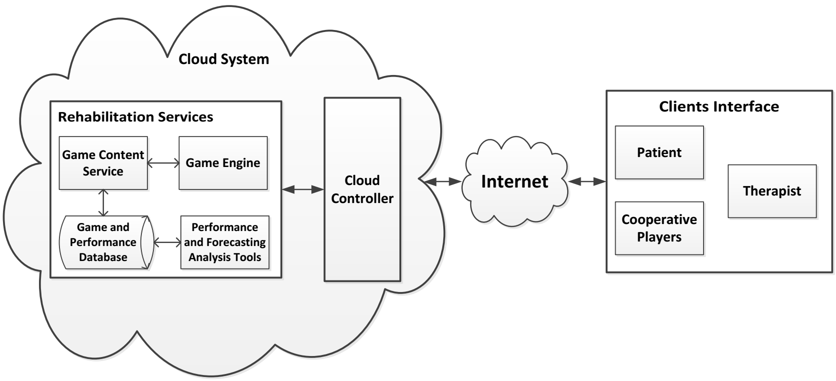

Fig. 1. The cloud-based rehabilitation exergame framework

Client Interface: Stroke patients and therapists are the users of the rehabilitation game system. The cooperative gamers (e.g., family members of the patient) are engaged in the rehabilitation exergames in order to motivate the patient subject in their rehabilitation process. A Kinect sensor is used to connect the system's users with each other through a cloud environment. Therapists guide the patients and monitor their progress through the rehabilitation course. Additionally, therapists can change the difficulty level of the rehabilitation exercises for both the patients and the cooperative players whenever it is needed.

Rehabilitation Services: Services needed by the users are provided through this module. It consists of game content services, game engine services, and performance assessment and rehabilitation forecasting services. The game content service is responsible for monitoring all the game-related logic by the help of the game and performance database. Moreover, it manages the connection between different system users and provides them with the necessary data. It should be noted that the game engine also performs logical operations and is responsible for synchronization. The difficulty level of the game is automatically adjusted at real-time to adapt to the patient's performance. As an implementation, a cloud-based rehabilitation exergame that has been developed for stroke rehabilitation is the Basketball game, which can be played by single or multiple users. The physical setup of the game is shown in Figure 2. The Basketball game is designed to measure the kinematics of the upper limb of the patient in the vertical direction. The performance evaluation module provides the clients with real-time feedback about the performance of the patients. The rehabilitation prediction module gives the doctors a prediction about the prospective recovery of the patients, depending on their rehabilitation history.

Cloud Controller: This component is responsible for instantiating a game session. Like a facilitator, this enables the communication between the gamers and the exergame servers. The cloud controller provides several services (including authentication, profile and activity management, game statistics, and notification management) to manage the whole exergame framework.

(a) (b)

Fig. 2. Physical Environment of the Basketball game. (a) Experiment view. (b) Avatar view.

3 Forecasting of Rehabilitation Performance

We consider the movement pattern of a healthy subject (replacement, velocity, and acceleration) as a template, and the differences between the patient's movement pattern. This template indicates the recovery status of the patient. Specifically, a healthy subject's movement pattern is given as:

$$Healthy\,Subject's\,Pattern: \begin{cases} R_{healthy} = \left[R_{healthy,1}\ R_{healthy,2} \cdots R_{healthy,m} \right]^T \\ V_{healthy} = \left[V_{healthy,1}\ V_{healthy,2} \cdots V_{healthy,m} \right]^T \\ A_{healthy} = \left[A_{healthy,1}\ A_{healthy,2} \cdots A_{healthy,m} \right]^T \end{cases} \tag{1}$$

and a patient's movement pattern as:

$$Patient's\,Pattern: \begin{cases} R_{patient} = \left[R_{patient,1}\ R_{patient,2} \cdots R_{patient,n} \right]^T \\ V_{patient} = \left[V_{patient,1}\ V_{patient,2} \cdots V_{patient,n} \right]^T \\ A_{patient} = \left[A_{patient,1}\ A_{patient,2} \cdots A_{patient,n} \right]^T \end{cases} \tag{2}$$

To quantify the movement pattern between a healthy subject and a patient subject, we find a correspondence matching between these two patterns

$$\begin{aligned} &\Theta\left(Healthy\,Subject's\,Pattern,\ Patient's\,Pattern\right) = \\ &\left[\Theta\left(R_{healthy}, R_{patient}\right)\ \Theta\left(V_{healthy}, V_{patient}\right)\ \Theta\left(A_{healthy}, A_{patient}\right) \right]^T \end{aligned} \tag{3}$$

where $R_{healthy}$, $V_{healthy}$, $A_{healthy}$ are the replacement, velocity, acceleration of the healthy subject. $R_{patient}$, $V_{patient}$, $A_{patient}$ are the replacement, velocity, acceleration of the patient subject. The optimized correspondence relation satisfies [7]

$$\hat{\Theta} = arg\,min \begin{bmatrix} \sum_{i=1,j=1}^{i=m,j=n} \frac{d(R_{healthy,i}, R_{patient,j}) p_{i,j}}{\sum_{i=1,j=1}^{i=m,j=n} p_{i,j}} \\ \sum_{i=1,j=1}^{i=m,j=n} \frac{d(V_{healthy,i}, V_{patient,j}) q_{i,j}}{\sum_{i=1,j=1}^{i=m,j=n} q_{i,j}} \\ \sum_{i=1,j=1}^{i=m,j=n} \frac{d(A_{healthy,i}, A_{patient,j}) r_{i,j}}{\sum_{i=1,j=1}^{i=m,j=n} r_{i,j}} \end{bmatrix} \tag{4}$$

By using the above optimization criteria, the cumulative distance representing the unmatching part can be calculated as

$$D_{unmatching} = \begin{bmatrix} \sum_{i=1,j=1}^{i=m,j=n} \frac{d(R_{healthy,i}, R_{patient,j}) p_{i,j}}{\sum_{i=1,j=1}^{i=m,j=n} p_{i,j}} \\ \sum_{i=1,j=1}^{i=m,j=n} \frac{d(V_{healthy,i}, V_{patient,j}) q_{i,j}}{\sum_{i=1,j=1}^{i=m,j=n} q_{i,j}} \\ \sum_{i=1,j=1}^{i=m,j=n} \frac{d(A_{healthy,i}, A_{patient,j}) r_{i,j}}{\sum_{i=1,j=1}^{i=m,j=n} r_{i,j}} \end{bmatrix} \tag{5}$$

Then the patient's rehabilitation status is modeled as a combination of the elements of $D_{unmatching}$, i.e.,

$$\begin{cases} S_{rehabilitation} = w_1 \cdot D_{unmatching}[1] + w_2 \cdot D_{unmatching}[2] + w_3 \cdot D_{unmatching}[3] \\ w_1 + w_2 + w_3 = 1 \end{cases} \tag{6}$$

Although the patient's rehabilitation status ($S_{rehabilitation}$) at a given time gives the doctors an indication about the current situation of the patient, it does not help them to answer a simple, yet important question that patients and family members usually ask: what is the timetable for the recovery process? To answer this question, researchers have proposed statistical theories that are based on specific achievements by the patients [11,12]. However, these achievements may differ from one patient to another, and hence the prediction results have individual differences. In this paper, we forecast the recovery of the patients depending on their initial conditions and their progress rate. We use the Auto-Regressive Integrated Moving Average (ARIMA) model to forecast the future progress of the patients depending on their rehabilitation status $S_{rehabilitation}$ [13].

4 Results and Discussion

4.1 Model Matching

The reference dataset samples are obtained from six healthy people. The sets consist of ninety time series of kinematics values, i.e., the replacement, the velocity, and the acceleration (thirty series for each value). Two types of model matching approaches are applied: (1) real-time model matching that is used when the patient competes against a healthy subject, and (2) off-line model matching that is used when the patient competes with another patient, or he/she is performing the rehabilitation exergame alone. In the first approach, we compare the time series of the patient and the healthy subject in real-time and adjust the difficulty level of the game for both according to the patient's performance. In some cases, when the patient subject has difficulty completing the exergame task, a message is sent to the healthy subject asking them to slow down. In the second approach, the performance of the patient is compared to the reference movement pattern of a healthy subject that has already been stored in the system. The rehabilitation status ($S_{rehabilitation}$) is calculated and the difficulty level of the game changes accordingly.

The model matching result (between the healthy subjects and a patient subject) is shown in Figure 3 where (a), (b) and (c) correspond to the model matching results of replacement, velocity, and acceleration, respectively. The unit we use is: time in s, replacement in cm, velocity in cm/s, and acceleration in cm/s^2. We conclude that while the patient's movement pattern has a similar curve shape to the healthy subject's movement pattern, there are more isolations. The model matching differences (i.e., dynamic time warping distance) are 0.17, 0.11, and 0.13 respectively, corresponding with the replacement, velocity, and acceleration's case. In this paper, for simplicity, we choose $w_1 = w_2 = w_3 = \frac{1}{3}$ in the calculation of rehabilitation status (Equation 6) and thus $S_{rehabiltation} = 0.41$.

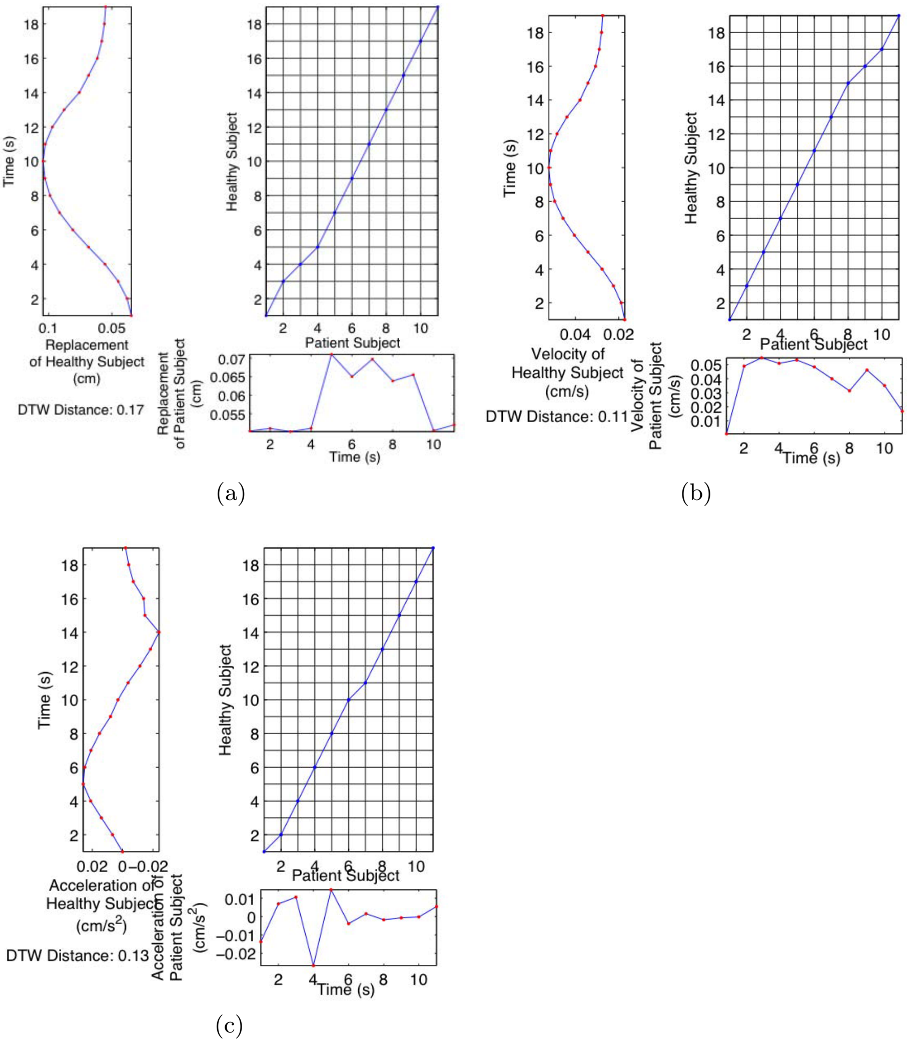

Fig. 3. Model matching between patient and healthy subject. (a) Replacement. (b) Velocity. (c) Acceleration.

4.2 Rehabilitation Prediction

The values of the rehabilitation status $S_{rehabilitation}$ are applied in the ARIMA predication model. Four rehabilitation sessions are conducted on one patient each week for seven weeks. The data obtained from the first six weeks is used for the model training, while the rest of the data is used for prediction. In this paper, we provide a simulation for short-term rehabilitation status prediction. To test the method used in creating rehabilitation prediction models, we suppose the measured rehabilitation status obtained in a continuous seven weeks as 0.41,

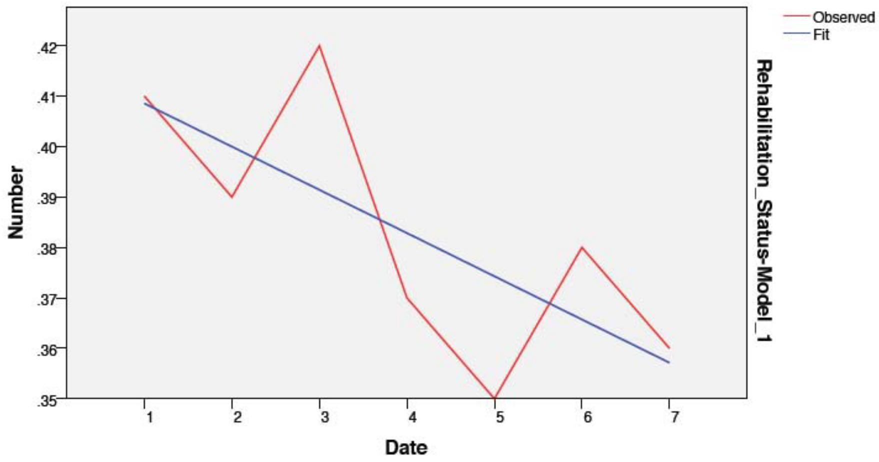

Fig. 4. Rehabilitation status prediction

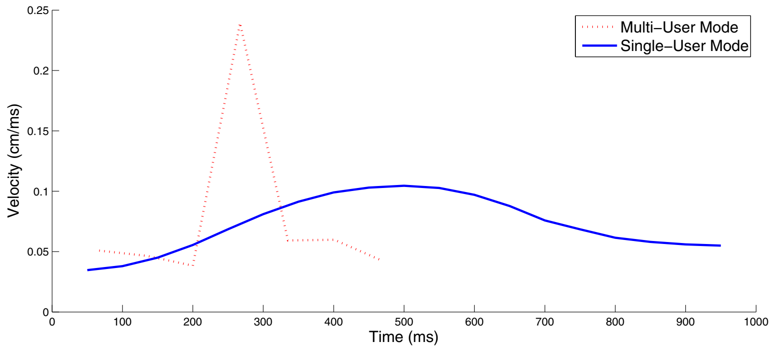

Fig. 5. The velocity comparison of the arm in reaching the final target under single-player mode and multi-player mode

0.39, 0.42, 0.37, 0.35, 0.38, 0.36, and we give the prediction model by our method in Figure 4. Here, the model type we used is ARIMA (0,0,0). The number of predictors is 1 and stationary R^2 is 0.522.

4.3 Multi-player's Benefit

The measurement of the hand velocities under single-user mode and multi-user mode are compared in Figure 5. As many previous studies have shown [14], the trajectory of the hand velocity is a bell-shaped curve. In addition, the results are consistent with what we expected: in the multi-user environment the players were competing with each other and thus, the time needed to complete the exercise decreased about 50% as shown in Figure 5.

5 Conclusion and Future Work

A new framework of a cloud-based upper limb rehabilitation system and its implementation is presented in this paper. The system allows the therapists and the caregivers to engage and interact with the treatment sessions remotely. A model matching algorithm is used to compare the performance of the patient with the performance of healthy subjects and give real-time feedback. The most innovative component, in addition to the rehabilitation status assessment method, is the forecasting method that provides patients, therapists, and family members a prospective idea about the progress of the patients. The comparison of the rehabilitation performance in single-user mode and multi-user mode shows that the multi-player exergames can increase the motivation of the patient to engage more in the training sessions. Our future work will be including a long-term study with ten patients to determine the accuracy of the system in predicting the progress of the patients. Moreover, we are planning to involve other kinematics parameters in the rehabilitation evaluation and test whether these parameters increase the accuracy of rehabilitation assessment.

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