A Wearable Monitoring System for At-Home Stroke Rehabilitation Exercises: A Preliminary Study

Hee-Tae Jung¹, Joonwoo Park², Jugyeong Jeong³, Taekyeong Ryu³, Yangsoo Kim³, and Sunghoon I. Lee¹

Abstract—When stroke survivors perform rehabilitation exercises in clinical settings, experienced therapists can evaluate the associated quality of movements by observing only the initial part of the movement execution so that they can discourage therapeutically undesirable movements effectively and reinforce desirable ones as much as possible in the limited therapy time. This paper introduces a novel monitoring platform based on wearable technologies that can replicate the capability of skilled therapists. Specifically, we propose to deploy five wearable sensors on the trunk, and upper and forearm of the two upper limbs, analyze partial to complete observation data of reaching exercise movements, and employ supervised machine learning to estimate therapists’ evaluation of movement quality. Estimation performance was evaluated using F-Measure, Receiver Operating Characteristic Area, and Root Mean Square Error, showing that the proposed system can be trained to evaluate the movement quality of the entire exercise movement using as little as the initial 5s of the exercise performance. The proposed platform may help ensure high quality exercise performance and provide virtual feedback of experienced therapists during at-home rehabilitation.

I. INTRODUCTION

Stroke is a leading cause of death and disabilities in adults, and the majority of its survivors suffer from upper extremity paresis [1]. There is scientific evidence that repetitive rehabilitation exercises and training could improve motor abilities as a result of motor learning processes [2]. Among many, a reaching movement is a fundamental component of daily movement that requires the coordination of multiple upper extremity segments [3]. It is shown that repetitive reaching exercises improve the smoothness, precision, and speed of arm movements [4]. To continue to improve and to sustain motor function, it is clinically important that patients continue to engage in rehabilitation exercises even outside the clinical settings [5], which emphasizes the importance of the home-based therapy.

While conducting such exercise, it is important to execute movements in an appropriate and quality manner as it helps the brain reorganize the damaged synaptic connections to perform appropriate movements [6]. Patients need to suppress compensatory behavior (e.g. swinging the torso to move the limbs) and coordinate joint movements, which affect the quality of the overall reaching performance [7]. Providing customized coaching has been shown to maximize the long-term adherence to the recommended exercise regimen and ultimately optimize clinical outcomes [8]. However, patients often show poor adherence to the prescribed home-based exercises mainly due to a lack of appropriate coaching [9], which heavily relies on the qualitative evaluation of movement performance.

A number of studies attempted to build monitoring systems using data collected from a set of wearable inertial sensors to estimate quality of rehabilitation exercise movements [10]–[12]. These studies envisioned wearable technologies that could be deployed in patients’ home and community settings to monitor the quality and appropriateness of the performed exercise movements. However, they required patients to complete the entirety of the given motor task before receiving feedback. It can be disturbing for patients to find out that their exercise movement was inappropriately performed after completing its execution, each of which require significant efforts from them for a relatively long period of time. This may negatively impact their adherence to at-home rehabilitation programs as well as their therapeutic outcomes. In practical clinical settings, on the other hand, therapists would evaluate the quality of exercise movements within a couple of seconds since movement initiation so that they discourage therapeutically undesirable movements as early as possible and induce coordinated joint movements of the affected extremity with minimum compensation.

This paper aims to overcome the limitation of the conventional approach and introduces a novel monitoring platform based on wearable technologies, which can be used to promote therapeutically meaningful and realistic practice of at-home rehabilitation exercises in stroke survivors. Our
primary research goal is to analyze movement data obtained from five wearable sensors placed on the trunk and upper limbs during the execution of task-oriented exercise movements to evaluate their quality regarding compensation and inter-joint coordination. Especially, to replicate the timely evaluation capability of therapists, we employ a supervised machine learning approach using partial to complete observation of patients’ movement data. Our secondary objective is to analytically validate our observation and hypothesis that therapists’ decisions regarding patients’ inappropriate performance of exercise movements can be effectively made using only the initial portion of movement data.

II. DATA COLLECTION

A total of five stroke survivors (66.6 ± 15.9 years old) were recruited from Heeyeon Rehabilitation Hospital, South Korea. Inclusion criteria entailed to recruit cognitively competent mild-to-moderately affected post-stroke patients who scored P or higher on their affected arm joints at the muscle manual test (MMT). Also, patients needed to have had no visual neglect and scored 24 or higher at the Mini-Mental State Examination (MMSE) to ensure that patients could visually identify reaching targets and understand the instructions of the therapist. 40.00% of the patients were right-hemiparesis, and the rest were left-hemiparesis. Table I summarizes the demographics of the recruited subjects.

A total of five nine-axis inertial sensors (MTw Awinda, Xsens, Netherlands) were placed on the upper body using Velcro straps: one on the torso, and upper and forearms bilaterally. Patients were asked to place the paretic hand at the origin of the grid while placing the unaffected hand on a designated location on the table to avoid interrupting the movement of the paretic limb. Then, the therapist instructed patients to reach for a series of predefined targets. The grid was marked on the table so that both the therapist and patients could identify the target positions in terms of the orientation and distance with respect to the origin, i.e., a point on the table that aligns with the median plane. The granularity of the orientation was 10° and that of the distance was 0.1m. Figure 1 illustrates the actual experimental setting. During the data collection, the therapist was not allowed to provide any assistance to the patient during the execution of the reaching movement.

Such criteria is intended to indicate that a patient has some movement in each joint through its limited or full ROM against gravity.

Synchronized inertial sensor data was streamed to a laptop and recorded at 100Hz during the data collection sessions. The orientation of the corresponding body segments in the form of quaternions was extracted offline from the stored data after the data collection was complete. The experiments were video-recorded, which the therapist used to identify the start and the end of each reaching movement and to evaluate its quality in terms of compensation and inter-joint coordination.

III. DATA ANALYSIS

A. Overview

In this work, \( p \) denoted a set of targets for reaching exercise movements. For each \( p_n \) sensory data \( \Xi \) was recorded and processed to compute movement quality features \( X(\Xi) \). The therapist’s evaluations \( Y \) of movement quality (TABLE II) were correlated to the computed features using supervised machine learning \( f: X \rightarrow Y \). The following subsections describe the analytic pipeline employed in this study.

B. Establishment of Movement Quality Evaluation Criteria

To the best of our knowledge, there exists no established evaluation criteria that regards compensation and inter-joint coordination for the reaching exercise. Hence, we had to devise our own. See Table II for the observed movement quality of the patients for the corresponding labels. Although we devised a 3-scale monitoring system, it is important to note that one may employ a larger data set and expand categories further to consider additional and more refined movement quality, such as precision and different types of compensation strategies, using our approach.

C. Movement Performance Features

The sensor readings and anatomical geometry of the human body were used to approximate relative joint angles between two consecutive body segments. They, in turn, were used to compute intermediate features \( X \) that describe the qualitative traits of exercise movements. The features used in this study were largely motivated from the kinematic parameters surveyed in the literature [13], which were devised to complement the conventional assessment tools and to quantify the qualitative motor performance when patients engage in the task-oriented exercise. Empirical studies provide evidence that, given the same task and targets, difference in the motor performance of stroke patients

<table>
<thead>
<tr>
<th>Patient</th>
<th>Age</th>
<th>Sex</th>
<th>Side</th>
<th>MMT (affected side)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>72</td>
<td>F</td>
<td>right</td>
<td>shoulder F, elbow F</td>
</tr>
<tr>
<td>B</td>
<td>72</td>
<td>F</td>
<td>right</td>
<td>shoulder P+, elbow P+</td>
</tr>
<tr>
<td>C</td>
<td>80</td>
<td>F</td>
<td>left</td>
<td>shoulder P+, elbow F+</td>
</tr>
<tr>
<td>D</td>
<td>70</td>
<td>F</td>
<td>left</td>
<td>shoulder P, elbow F</td>
</tr>
<tr>
<td>E</td>
<td>39</td>
<td>F</td>
<td>left</td>
<td>shoulder F, elbow F-</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Label</th>
<th>Observation</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>No or minimum movement at the affected hand; compensatory joint angle movements using the trunk and the affected shoulder</td>
</tr>
<tr>
<td>1</td>
<td>Isolated joint angle movements; minimum or no compensatory joint angle movements using the trunk and the shoulder</td>
</tr>
<tr>
<td>2</td>
<td>Close to normal or normal joint coordination</td>
</tr>
</tbody>
</table>

TABLE I

DEMOGRAPHIC AND CLINICAL INFORMATION ABOUT THE PARTICIPATING STROKE SURVIVORS

TABLE II

EVALUATION CRITERIA FOR THE OBSERVED MOVEMENT QUALITY IN COMPENSATION AND INTER-JOINT COORDINATION
and normally functioning people can be observed in these parameters [14]. It is also suggested that these parameters can capture how stroke patients recruit different degrees of freedom to compensate for motor deficits that is not observed in neurologically intact individuals [15]. Typically, most kinematic parameters are computed using the Cartesian position of the end effector in practice. However, in this study, to better represent the joint-specific compensation and movement coordination, our features were extracted from individual joint movement angles.

1) Peak velocity (PV) - Peak velocity of each joint is associated with the amount of muscular activation during upper extremity movement. In this work, PV for both shoulders, elbows, and trunk angles ($x_{1:5}$) was used.

2) Percentage of movement time at peak velocity (PPV) - PPV is related to the sensory feedback a patient requires to correct target-directed movements, which is affected by performance in inter-joint coordination. In this work, PPV of the corresponding PV ($x_{6:10}$) was used.

3) Movement time (MT) - Movement time is related to movement efficiency, which partially reflects movement quality in inter-joint coordination. In this work, MT ($x_{11}$) was computed by the difference between the deactivation time and the activation time of the affected shoulder and elbow joints combined ($v_{\text{shoulder}} + v_{\text{elbow}}$). Activation time was defined as the time that the velocity in the combined joint angle movement first exceeded $k \times PV$ whereas deactivation time was defined in a similar way where $k = 0.05$.

4) Angle Amplitude (AA) - The amplitude of joint movements can represent the amount of contribution the joint made during the execution of the exercise movement, which reflects the amount of compensation. In this work, AA for each joint was computed by the difference between the maximum and the minimum joint angles of both shoulders, elbows, and trunk respectively ($x_{12:16}$).

5) Angle Amplitude Percentage (AAP) - Depending on the location of the given target, the scale of induced joint movements may naturally be different. Hence, to reflect the amount of contribution in the joints for the reaching movement, the AA of each joint over the sum of all the AAs was computed ($x_{17:21}$).

6) Activation Time Percentage (ATP) - To reflect the quality of joint coordination when initiating the reaching movement, the percentage at activation time of each joint within the MT for both shoulders, elbows, and trunk was computed ($x_{22:26}$).

7) Activation Time Percentage Difference (ATPD) - To further focus on the coordination between the shoulder and the elbow of the affected upper extremity, the difference between ATPs of the shoulder and the elbow was computed ($x_{27}$).

8) Movement units (MU) - A number of movement units is related to the smoothness of the upper extremity during the execution of exercise movement. One movement unit is defined as a pair of one acceleration and one deceleration. Their counts for the affected shoulder, the elbow and the trunk ($x_{28:30}$) within the MT were used.

To see if we can evaluate the quality of reaching movements early in the beginning of movement execution, aforementioned features were computed for the movement data that was observed during the entire duration and also during the initial $t = 1s, 3s, 5s$ of the exercise. In our dataset, the shortest duration observed for a single reaching movement was 0.98s, the longest was 16.34s, and the mean duration was $4.58(\pm 3.13)s$.

D. Classification and Evaluation

In this study, we employed model trees that is known to outperform competing decision tree approaches [16]. The performance of the trained classifier was subsequently evaluated using ten-fold cross validation in F-Measure, area

### Table III

Analytic Results on the Initial Length of the Data Required to Make Accurate Estimation of Movement Quality, Using the Paired T-Test (T Statistics, P-Value).

<table>
<thead>
<tr>
<th>Measurement</th>
<th>vs 5 sec</th>
<th>vs 3 sec</th>
<th>vs 1 sec</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-Measure</td>
<td>1.46, .18</td>
<td>4.43, .0016</td>
<td>9.71, .0001</td>
</tr>
<tr>
<td>ROC Area</td>
<td>2.13, .06</td>
<td>3.29, .0094</td>
<td>13.05, .0001</td>
</tr>
<tr>
<td>RMSE</td>
<td>-2.30, .05</td>
<td>-7.19, .0001</td>
<td>-14.70, .0001</td>
</tr>
</tbody>
</table>
under the Receiver Operating Characteristic curve (ROC Area), and root mean square error (RMSE), and compared to the labels that the therapist provided regarding the quality of movement as the ground truth. This analytic pipeline to estimate the quality of movements was repeated using the dataset of the entire and the initial 1s, 3s, and 5s of the exercise duration. The impact of the length of the motion data on the estimation accuracy was analyzed using the paired $t$-test. We used MATLAB for data processing and employed the ClassificationViaRegression class in Weka 3.8.1 for the implementation of the model trees to train classifiers.

IV. RESULTS

Figure 2 illustrates the estimation accuracy for the quality of movement in terms of F-Measure, ROC Area, and RMSE. The average performances measured from ten-fold cross validation were 79.29% in F-Measure, 0.91 in ROC Area, and 0.32 in RMSE when the complete movement data was used. Such performance decreased gradually as shorter observation of the movement data was used. Specifically, F-Measure dropped to 77.61%, 75.78% and to 69.61% when the observation duration was 5s, 3s, and 1s, respectively. ROC Area dropped to 0.89, 0.88, and to 0.84. RMSE increased to 0.32, 0.34, and to 0.37. The difference in measurements achieved using the full data and the data of the initial 5s were not statistically significant while the rest differences were statistically significant (see Table III).

V. DISCUSSIONS AND CONCLUSION

With the goal of maximizing the functional recovery of the stroke patients in at-home therapy sessions, we proposed to take a supervised learning approach to build a monitoring system that can evaluate qualitative performance in the target-specific exercise movement.

Considering the fact that 30.77% of the collected movement data was executed longer than 5s, the performance of the proposed system is promising since the performance difference is statistically insignificant even when the classifier used the partial movement observation of initial 5s. However, the performance of all the measurements dropped significantly when the partial data of 3s or less was used. This may be due to the fact that the kinematic parameters that motivated the design of our features were mainly to analyze the complete movement execution. Hence, informative qualitative traits might not be properly captured by the features used in this study when observation on the movement execution was too short.

The current work is limited by the small data size with a few post-stroke subjects as well as the female dominancy in the dataset. With a larger dataset with more gender-balanced human subjects, we expect to achieve greater performance and generality. In addition, we may expand the number of evaluation categories to provide the appropriate verbal or physical intervention to stroke patients, allowing the execution of their exercise movements to be more therapeutically meaningful even when the access to therapists is limited.

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REFERENCES


