Smartphone-based Tele-Rehabilitation System for Frozen Shoulder Using a Machine Learning Approach

Kanmanus Ongvisatepaiboon and Jonathan H. Chan*
Data and Knowledge Engineering Laboratory,
School of Information Technology,
King Mongkut's University of Technology Thonburi,
kanmanus.ong@mail.kmutt.ac.th;
jonathan@sit.kmutt.ac.th (*Corresponding author)

Vajirasak Vanijja
IP Communication Laboratory,
School of Information Technology,
King Mongkut's University of Technology Thonburi,
vachee@sit.kmutt.ac.th;

Abstract— Frozen shoulder is a very painful condition that affects patients' daily life. Patients with frozen shoulder have to go to a hospital or medical center to get appropriate rehabilitation. Transportation to the hospital raises healthcare costs and the process can be time-consuming. We have developed a telerehabilitation system which allows patients to perform an at-home exercise. According to our existing system, it is only available for high-end smartphones with multiple sensors that include accelerometer, gyroscope, and magnetic field sensors. In this work, we propose a novel approach using machine learning to estimate the arm angle of rotation using only the accelerometer sensor. Results show that reasonable accuracy can be obtained so that it may be used with lower-end Android smartphone devices that only have an accelerometer available. A web-based interface enables the medical practitioner such as a physiotherapist to monitor and administer an appropriate rehabilitation program for more effective recovery.

I. INTRODUCTION

Due to stressful daily routines, many people have some form of shoulder problem, especially frozen shoulder. This is a condition that affects a patient's lifestyle on a daily basis. Patients with frozen shoulder would not be able to move their arm as usual. They normally have to travel to a hospital or medical center to get proper rehabilitation. Transportation raises healthcare costs and time, which may reduce their motivation and determination to seek proper treatment. Tele-rehabilitation is a useful technique that can assist in this problem by allowing patients to do regular exercise at their home and communicate with physiotherapist through today's modern communications (e.g. Internet). This technique is not much different than the traditional face-to-face rehabilitation methods. Frequent and regular exercise can effectively improve the condition. Patients are assigned to do a simple at-home exercise by raising their affected shoulder to the limit of the patient's tolerance, in order to break up adhesions at the joint capsule. A universal goniometer is a tool to measure the shoulder joint range of motion (ROM) when monitoring progress [1].

Our prior work [2] proposed a framework of this telerehabilitation system, which allows patients to perform the correct exercise, while physiotherapists monitor and analyze the progress. This system can eliminate some useless processes and tends to improve conditions of shoulder problems. Physiotherapists can also customize three parameters, i.e. number of rounds, target angle, and a reminder date and time, to be appropriate for each patient. ROM measurements are the most important data to be collected, since they will have an effect on the condition level.

In recent years, many researchers in the neuro-engineering and rehabilitation field have tried to adapt technologies with physical therapy to improve rehabilitation methods. Since technologies are rapidly evolving, many tools and techniques have been proposed to improve both technical and operational methods.

Kim et al. [3] used the accelerometer and gyroscope sensors in a smartphone to measure the rotation displacement and therefore measure the shoulder joint range of motion. The accuracy of the sensors are adequate to use in rehabilitation exercises. However, the scope of their work is limited to local data collection and analysis.

Pan et al. [4] proposed to use two accelerometer sensors and a built-in smartphone sensor, which is also an accelerometer sensor, to increase the accuracy of the shoulder joint range of motion. However, this method requires additional devices and multi-stage preparation.

Ferriera [5] implemented rehabilitation games using a single smartphone to measure the shoulder joint ROM and showing a feedback on the computer screen. This work used an orientation sensor, which is software-generated data available in the Android platform, to find the shoulder joint ROM. In particular, individual games were used to calibrate each of the three software components of the smartphone for ROM measurement.



Other work uses image processing and Microsoft Kinect device for the ROM measurement, which can enhance the therapy process [6] [7].

According to the previous works, most of them focused on the accuracy and reliability of the measurement, thus requiring additional devices and complex preparation. In our prior work, we proposed to use a single smartphone which contains accelerometer, gyroscope, and magnetic field sensors to provide the necessary monitoring measurement to enable effective telerehabilitation. However, there are only selected smartphone models that have all these three built-in sensors. Therefore, in this work, we propose to create a model for estimating the shoulder joint ROM by using only data from one accelerometer sensor, which is contained in vast majority of devices. Then, people with cheaper smartphones will be able to use this application. We believe this is the first published attempt to use a machine learning approach to estimate the angle of rotation using only the accelerometer sensor in a smartphone.

II. METHODOLOGY

A. Overall System Architecture

We have developed a tele-rehabilitation system for patients with frozen shoulder (Fig. 1). There are two main parts in this system: client side (a smartphone) and server side.

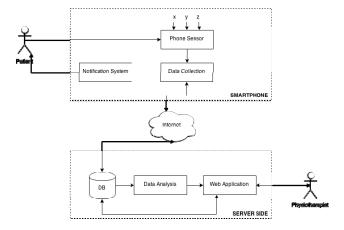


Fig. 1. Smartphone-based Tele-Rehabilitation System for Patient with Frozen Shoulder

The smartphone application was implemented on the Android platform, since it is one of the most popular platforms with the largest number of devices in the world [8]. The hardware performance could not be summarized since there are various manufacturers making devices on the Android platform. Some of them are using a low quality hardware to reduce the cost, thus smartphone models would be a performance variable.

A reminder notification will be sent to remind patients to perform an exercise task at the assigned date and time, which is the same concept as a pill reminder application. With this feature, patients would not forget to do an exercise task at the proper time

The first time, physiotherapists have to create an account for each patient on the web application. Then, patients will be able to login to their account through the application on their smartphone device (Fig. 2). After logging in, all assignments and results will be synchronized between the smartphone and server. An uncompleted task will be shown as 'Ready' with yellow background. After finishing the task, the word will be changed to 'Complete' with blue background and will be changed to 'Synced' with green background after finishing synchronization (Fig. 3).



Fig. 2. A screenshot of the Login page



Fig. 3. A screenshot of the List Item page

A smartphone device must be placed on the elbow by using an armband as shown in Fig. 4. After choosing an exercise task, patients will be asked to do a simple calibration process by just standing straight for five seconds, then the program will use the average of this data to subtract from the real angle when performing an exercise. Sensor data will be saved into the database of the device, SQLite database, in 100 milliseconds intervals.

At the end of the exercise, sensor data stored in the device's database will be sent to the cloud via the Internet. However, if there is no network connection, data will be synchronized again the next time the application is opened.

Regarding the web application, physiotherapists can manage and customize patients and exercise tasks. They can also see the results, graphs, and summary, which can be used to analyze the condition level. Physiotherapists can customize three parameters, which are number of rounds, target angle, and a reminder date and time, to be matched with each patient. Sample screenshots of the task list and results visualization are shown in Fig. 5 and 6, respectively. The medical practitioner is able to adjust the rehabilitation routine accordingly for each patient.



Fig. 4. A sample armband used for placing a smartphone on the elbow



Fig. 5. A screenshot of the task list in the web application



Fig. 6. A screenshot of the Results page in the web application

B. Experiment

In this experiment, two high-end smartphone models (i.e. Samsung Galaxy S5 and Oppo Find 7A) were used to gather the sensor data. The smartphone devices were placed on the elbow using an armband. Three physical built-in sensors (i.e. accelerometer, gyroscope, and magnetic field) and one software-generated sensor, rotation vector sensor, were stored in the device's database every 100 milliseconds.

The main researcher was assigned to raise his left arm from the initial position, stand straight with arms parallel at side, to the target angle at 120 degrees for ten times. The results from two smartphone models were analyzed and discussed in the next section.

We used a machine learning approach based on multiple linear regression (MLR) to build a model of the *roll* angle value obtained from the Android software-derived rotation sensor. Raw data from the accelerometer, gyroscope, and magnetic field sensors were collected in a controlled manner to build a MLR model, as shown below:

$$\mu_{v} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \tag{1}$$

where μ_y is the roll angle, x_1 , x_2 , and x_3 are the x, y, z components of the raw/normalized accelerometer data, and β_0 , β_1 , β_2 , and β_3 are the corresponding coefficient parameters of the model.

Data analysis and modeling were performed mostly using R [9]. In particular, the linear model function *lm* was used to build the multi-linear model. Weka [10] was also used to validate and reinforce the results.

III. RESULTS AND DISCUSSION

Since the common smartphone only has the accelerometer sensor, we built a correlation model between the roll angle value and the accelerometer sensor data. The training model was developed using the Samsung S5. The multiple R-square value is 0.9929 and the model coefficients are presented in Table I.

For comparison purposes, the models for using gyroscope and magnetic sensors alone are shown in Tables II and III respectively. These results show that using simple multiple linear regression to build a model of rotation angle based on raw accelerometers is quite acceptable. However, the other two mobile sensors are not suitable as standalone sensors.

TABLE I. THE COEFFICIENTS OF ACCELEROMETER SENSOR DATA

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-62.05380	0.60552	-102.480	<2e-16
left_accX	3.14794	0.09919	31.737	< 2e-16
left_accY	5.75333	0.04141	138.952	< 2e-16
left_accZ	1.04332	0.24070	4.335	1.71e-05

TABLE II. THE COEFFICIENTS OF GYROSCOPE SENSOR DATA

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-62.846	1.720	-36.544	<2e-16
left_gyroX	1.930	18.735	0.103	0.918
left_gyroY	11.950	9.886	1.209	0.227
left_gyroZ	1.562	5.376	0.290	0.772

TABLE III. THE COEFFICIENTS OF MAGNETIC FIELD SENSOR DATA

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-126.8540	49.4854	-2.563	0.0106
left_magX	-0.1415	0.4260	-0.332	0.7398
left_magY	-3.5824	0.7675	-4.668	3.76e-06
left_magZ	0.9680	1.4693	0.659	0.5103

TABLE IV. THE COEFFICIENTS OF NORMALIZED ACCELEROMETER SENSOR DATA

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-59.8800	0.5492	-109.030	<2e-16
left_accX	31.7669	0.8596	36.956	< 2e-16
left_accY	55.5208	0.3815	145.540	< 2e-16
left_accZ	10.5863	1.9846	5.334	1.36e-07

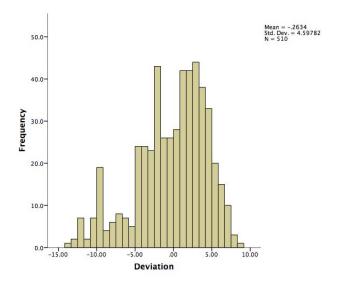


Fig. 7. Histogram of deviation in the normalized model on the test phone

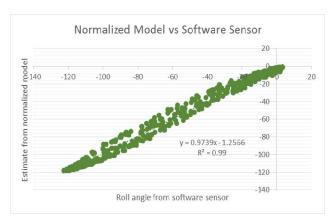


Fig. 8. Goodness of normalized model on the test phone

The Android rotation sensor is based on a software compilation with all three sensors. Further improvement, as indicated by the t-values, was obtained by normalizing the raw accelerometer data first, as shown in Table IV. The corresponding R-square value is 0.995, which may be taken to mean the accuracy of the regression analysis is 99.5%.

Next, to test the developed model, the Oppo phone was used to perform the same exercise. The results show that the normalized model provides a reasonable estimation on the test phone when comparing to the actual angle of rotation (see Fig. 7 and Fig. 8). The histogram of the deviation between the normalized raw accelerometer data and the rotation angle from the rotation vector sensor is presented in Fig. 7. The results indicate a pseudo-normal distribution with the majority of the measurements within five degrees of the actual values (for a target angle of 120 degrees). The goodness of fit shows an R-

square value of 0.99 but there is an offset for both the slope and the intercept in Fig. 8. Nonetheless, these results are promising and future work will be undertaken to further improve upon this model. In addition, field tests will be undertaken with lower-end phones as well as with actual user usability testing.

The same MLR models were obtained using Weka with the Linear Regression module as a classifier. A summary of raw and normalized data model building based on 10-fold cross validation is shown in Table V. Note that the correlation coefficient R is shown in Weka rather than the R-square value reported earlier. These results also show that normalization helped to improve model performance as expected.

Perhaps a more significant outcome is shown in Table VI for model testing with the test phone. It is clear from the comparison results on the errors that normalization is needed to obtain more robust performance.

TABLE V. TEN-FOLD CROSS VALIDATION MODEL TRAINING RESULTS FROM ACCELEROMETER SENSOR DATA

	Raw data	Normalized data
Correlation coefficient	0.9964	0.9975
Mean absolute error	2.8189	2.3046
Root mean squared error	3.5569	2.9820
Relative absolute error	7.3833%	6.0360%
Root relative squared error	8.4579%	7.0909%

TABLE VI. TEN-FOLD CROSS VALIDATION MODEL TESTING RESULTS FROM ACCELEROMETER SENSOR DATA

	Raw data	Normalized data
Correlation coefficient	0.9923	0.9950
Mean absolute error	5.1837	3.6958
Root mean squared error	6.1154	4.6009
Relative absolute error	12.4654%	8.8875%
Root relative squared error	13.4391%	10.1108%

IV. CONCLUSIONS

This work presents a smartphone-based tele-rehabilitation system for patients with shoulder problems. In particular, we proposed the use of machine learning in the form of multiple linear regression to estimate the rotation angle of an Android smartphone using only raw readings from the accelerometer sensor. Further improvement was obtained by normalizing the raw accelerometer data first. The results show that the accuracy is acceptable and this approach should be able to use in lower-end Android smartphones for patients with frozen shoulder problems to perform tele-rehabilitation from home. Thus, a medical practitioner is able to monitor the patient's progress and adjust

the rehab program as necessary for an effective treatment using the provided web interface.

For future work, we will consult and work with a medical practitioner more closely to implement the developed system and perform usability studies. Moreover, lower end smartphones will be used to validate our hypothesis and we are planning to extend to other platforms such as iOS and Windows.

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