SmartWatch as a Kinaesthetic System for Shoulder Function Assessment

Srinivasan Jayaraman
Sr.Scientist
Medical Device Development
TATA Consultancy Services
Portland, OR, USA
srinivasa.j@tcs.com

Joseph Joshy
Medical Device Development
TATA Consultancy Services
Bangalore, India
joshy.joseph2@tcs.com

Ponnuraj Kirthi Priya
Scientist
Medical Device Development
TATA Consultancy Services
Bangalore, India
p.kirthipriya@tcs.com

Murali Poduval
Orthopedic Surgeon & Domain Consultant
Engineering & Industrial Services
TATA Consultancy Services
Mumbai, India
murali.poduval@tcs.com

Ajay Balakumaran Thangavel
Medical Device Development
TATA Consultancy Services
Bangalore, India
p.ajay@tcs.com

***Abstract*—Management of shoulder pathologies involves measurement of range of motion (ROM) as well as assessing the quality and efficiency of that motion using different clinical tests. This work describes the preliminary results of using a smart watch to capture the direction of movement, velocity and ROM of the shoulder joint. ROM is the available amount of movement of a joint in different directions which can be either passive, active or active assisted. With the collected dataset and the proposed method, ROM could be estimated with a 9° error. Shoulder function or motion identification was validated by two different methods: i) rule engine and ii) machine learning approach. Rule base engine method was able to successfully identify the motions with accuracy of 91.94% and ML method with 10-Fold Validation reported a best performance of 94.17%. Proposed method, currently tested for some active motions of the shoulder, has the potential to be a very useful assist in quantifying and monitoring rehabilitation of the shoulder joint in multiple clinical situations.**

***Index Terms*—Pervasive Healthcare, Shoulder Joints, Range of Motion, motion, Remote monitoring, gradient boost classification, Rehabilitation.**

I. Introduction

The shoulder is a ball and socket type of joint connecting the upper limb to the thorax. The upper limb is suspended from the thorax allowing it free mobility in all directions. This is made possible by a complex interaction of muscles and ligaments in the region. The shoulder itself is described as a shoulder girdle which consists of the glenohumeral joint, the acromioclavicular joint, the scapulothoracic joint and the sternoclavicular joint. When one describes shoulder motions it is usually a combination of movements at these joints. Predominantly, movements occur at the glenohumeral and scapulothoracic joints and clinically are distinguished by stabilizing the scapula during the process of clinical examination of the shoulder. The movements of the shoulder are classified as Flexion (forward movement), Extension (backward), Abduction (elevation) and rotations. Combined movements include movements like circumduction (ball throwing action) and actions like combing the hair and reaching into a rear pocket. Hand function is enabled and made more efficient by not only shoulder mobility but also by elbow positioning, forearm rotation and wrist positioning, this can be easily understood if we picture the act of writing, how the entire limb needs to be in the correct position for the hand to execute writing. It has been reported that shoulder pain is a very common symptom and is in fact present in 18-26% of adults [1]. Shoulder pain/injury can be persistent and disabling in terms of an individual's ability to carry out daily activities both at home and in the workplace. There are also substantial economic costs involved, with increased demands on health care, impaired work performance, substantial sickness absence, and early retirement or job loss.

Measuring and characterizing shoulder motion is outwardly simple but incredibly complex in reality. Due to the complex anatomy and physiology of shoulder joints, it is difficult to achieve a definite diagnosis using the patient's history alone. The recovery of shoulder function from various afflictions and from surgical interventions by staged rehabilitation has a long and often tedious course requiring commitment from the treating physiotherapist, the patient and the care providers. Clinically relevant outcomes in joint surgery and rehabilitation are determined by the increase in range and efficiency of motion in human joints as well as by the function achieved and patient satisfaction indices. Currently, in-clinic, this is attempted by a qualitative approach supported by quantitative measurement of joint motion using aids like goniometry and visual estimation of range. Outcome scoring systems [2] like the DASH, the Oxford score and the Constant score have ROM as an important component. The character of motion is determined by clinical examination only. Some other systems have been exploited for the observational analysis of shoulder motion. This includes

- Marker based system. i.e., Vicon™
- Markerless system. i.e., Microsoft Kinect™
- Robot-assisted system
- Wearable system (Apple Watch, Fitbit, Samsung gear, Shimmer and so on)

With the advent of precision surgical technology, the number of interventions performed for the shoulder has exponentially increased and so have the needs for quantifying, characterizing and analysing ROM as a surrogate marker for the improvement or deterioration of the shoulder. Further, continuous measurement would provide objective clinical insights into the recovery process , add more value in assessing outcomes and in the longer term, an accumulation of this data is likely to help in designing a dynamic biomechanical model of the shoulder more closely representative of the joint than currently available.

The trend in wearable has enabled countless application such as human activity recognition, gait analysis and exercise recognition, heart rate monitoring and treatment [3-8]. For instance, smartwatches have the capability to detect and distinguish gross motor movements such as walking, jogging, cycling, swimming and sleeping. Some applications extend to track activity levels and basic exercise as part of patient progress, but range of motion in larger ball and socket joints like the hip and shoulder using unobtrusive sensing is still a challenge. Kumar *et al.,* 2015 [9] developed an automated portable wireless sensor system to measure ROM in all planes of the major joints of the upper extremities (UE) (shoulder, elbow, radio-ulnar and wrist) and lower extremities (LE) (hip, knee and ankle). Their measurements highly correlated with those of goniometer with 95 percent of the cases had errors less than 10° and 20° in the major joints of UE and LE respectively. Authors [12-15] have also mentioned that studies focusing on shoulder ROM, type of movement and speed of motion are relatively less compared to the knee. Hence we hypothesize that estimation of ROM in terms of objective values, direction and speed would be a valuable tool for the clinician. In addendum, the ability to use a wearable to estimate ROM data not only quantitatively but also in the type and speed of movement and to understand the insight is a valuable tool.

In this study, we aim to monitor the shoulder joint motion by quantitative measure of ROM, and kinaesthesia of shoulder using a smartwatch; thereby assessing the limit of active motion and the ability to passively reposition the arm in space. Kinaesthesia [16] is defined as the sensation of the motion to locate the different parts of the body and to evaluate their movement (velocity and direction). This solution will aid clinicians in providing objective values to the range of motion and it also has the potential to empower, enable and motivate the patient in the course of their treatment by providing curated insights into the progress of treatment.

II. Methodology

A. Study Population

Data was collected in two-phases for validation: 1) controlled or stepwise motion for ROM and 2) natural motion for shoulder motion identification. Phase I, 25 healthy volunteers with a mean age of 28±4 years, height of 161.1±1.96 cm and body mass of 60.1±7.13 Kg and for phase II, 50 healthy volunteers with age of 30±3 years with a 25% overlap of volunteers in these two phases without impacting the conduct or outcome of the study.

III. Experimental Protocol

The inclusion criteria was healthy adult from 20- 50 years of age, who had no history of upper limb injury or disease, no history of movement disorders, no history of shoulder disease or treatment for shoulder pain and no known neurological disorders, either central or peripheral that had the potential to impair their participation in the study. Gen-3 apple watch was adapted for this study. To maintain the watch orientation across subjects, it was planned to keep the watch aligned perfectly and facing outside. We planned to test the three principal movements abduction, flexion and extension. Participants were instructed to repeat each upper limb motion thrice.

1. *Phase I data collection Protocol*: Participant stands in a neutral position. This position of rest/neutral means, subject adapts a posture holding their upper limb by the side of the body with palm touching the thigh. Data recording would be started by the investigator with an initial 10 sec of waiting time in the neutral position. Instruction was provided to participant to start the upper limb motion, for example Flexion as follows

- *Acceleration Phase*
  - Lift the right hand in forward direction, to an angle of 45° (Palm facing the ground) and wait for manual measurement using goniometer
  - Move forward toward an approximate angle of 90° and wait for manual measurement
  - Move the right hand to an angle of 135° and wait for manual measurement
  - Move the right hand to an angle of 180° or max degrees (Thumb pointing to the left) wait for manual measurement
- *Deceleration Phase* is the reverse of accleration phase, the participant would perform 180°, -135°, -90°, -45° wherein the subject would bring the arm stepwise from an elevated position back to neutral position with manual measurement; after this investigator shall stop the recording.
- Similarly, data collection process would be adapted for Abduction activities as well
- In case of extension, participants were instructed to move their hand backward direction to a maximum distance without changing the posture. During the wait time at max angle this angle is noted manually and then hand would be moved to neutral position followed by a resting phase of 5 sec. Finally, investigator would stop the recording.

2. *Phase II data collection Protocol*: In phase-II participants were instructed to perform flexion, extension, and abduction without any resting or waiting period for continuous data collection.

A. Data Establishment

Sensor position is characterized by its location (left or right hand), placement (apple watch crown directed toward the palm or elbow) and orientation. To maintain homogeneity in the study, we restricted ourselves to the right upper limb, with apple watch's crown facing towards the elbow as shown in Fig. 1(i), which is similar to R2 position of Straczkiewicz *et al.,* 2019 [12]. Raw dataset is composed of time series

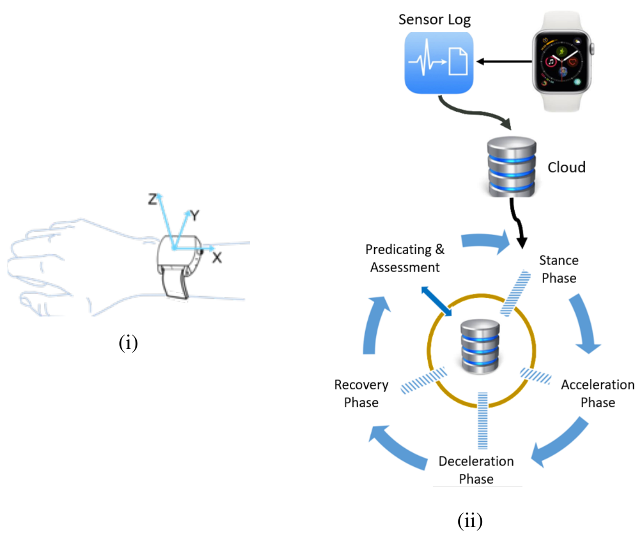


Fig. 1: (i) Apple Watch Coordination Representation and (ii) System Functional Block Diagram and Analytical Engine Architecture

accelerometer, gyroscope and magnetometer values gathered with Apple watch. While the user wears the watch and performs the designated actions, data is logged using a 3rd party logging app at a sampling rate of 30 Hz. In this study, three different movements were considered: flexion, extension, and abduction in static and standing phase. Each sample in the dataset is composed of apple watch's in-built sensor for one complete action: stance phase (no action), acceleration phase of the hand, deceleration phase and recovery phase or neutral position as shown in Fig. 1(ii). Once the data is recorded by the logging app, it was pushed to iCloud and retrieved for offline analysis and interpretation.

B. Analysis

First Watch was attached to the goniometer's movable arm, keeping the other arm fixed, enabling collection of data at every 45 $^{\circ}$ angle; called as "Gonio-data". Subsequently, data was collected with the assistance of volunteers as has been described earlier in this paper, for the 3 specific hand movements. To assess the accuracy of the developed algorithm between the goniometer-data and watch in a subject, only ROM was tested. ROM was measured using goniometer

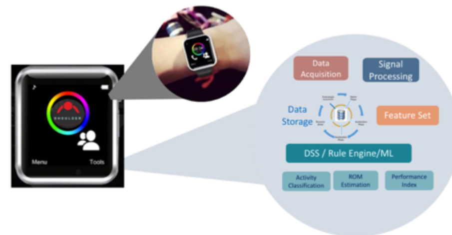


Fig. 2: System Overview

manually with an approximation or maximal angles during flexion and abduction, and extension correspondingly. Further, to detect the 3 different shoulder motions, a rule engine based (REb) algorithm and ML approach was adapted and their performance was compared.

C. Rule Engine Approach

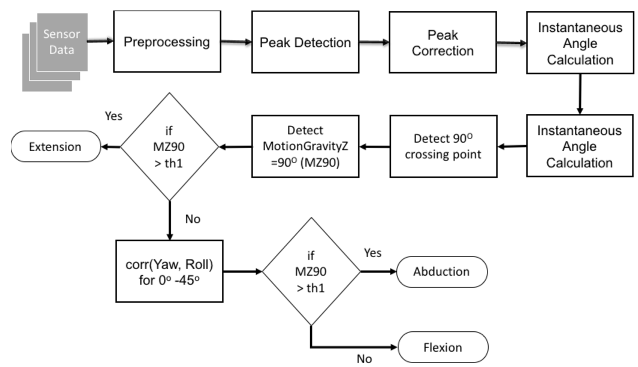


Fig. 3: Rule Engine based Algorithm Flow Chart for Motion Classification

Raw signal was normalized, and threshold-based noise removal was performed. Step by step process of motion classification is shown in Fig 3.

D. Machine Learning Approach

Raw accelerometer data was filtered using 3rd order LP Butterworth filter with a cutoff frequency of 20 Hz. Feature parameters such as root mean square; square root of amplitude; kurtosis; skewness; peak to peak value; crest factor; impulse factor; margin factor; shape factor; kurtosis factor; frequency factor; RMS frequency; Root variance frequency; R1xy-correlation between Motion gravity X,Y; R1yz-correlation between Motion_gravity Y,Z; R1xz-correlation between Motion_gravity XZ; R2xy-correlation between Acclerometer_acc X,Y; R2yz-correlation between Acclerometer_acc Y,Z; R2xz-correlation between Acclerometer_acc X,Z; R3xy-correlation between Motion_rotation X,Y; R3yz-correlation between Motion_rotation Y,Z; R3xz-correlation between Motion_rotation X,Z; R4ry-correlation between roll & Yaw; R4yp-correlation between pitch & Yaw; R4rp-correlation between roll & pitch, tilt angle, and signal magnitude area were extracted as shown in Equations (1-15)

$$X_{rms} = (\frac{1}{N}\sum_{i=1}^{N}(x_i^2))^{\frac{1}{2}} \quad (1)$$

$$X_{sra} = (\frac{1}{N}\sum_{i=1}^{N}\sqrt{(x_i)})^{\frac{1}{2}} \quad (2)$$

$$X_{kv} = \frac{1}{N}\sum_{i=1}^{N}(\frac{x_i - x^2}{\sigma})^4 \quad (3)$$

$$X_{sv} = \frac{1}{N}\sum_{i=1}^{N}(\frac{x_i - x^2}{\sigma})^3 \quad (4)$$

$$X_{ppv} = max(x_i) - min(x_i) \quad (5)$$

$$X_{cf} = max(|x_i|)/(\frac{1}{N}\sum_{i=1}^{N}(x_i^2)^{\frac{1}{2}} \quad (6)$$

$$X_{if} = max(|x_i|)/(\frac{1}{N}\sum_{i=1}^{N}(|x_i|) \quad (7)$$

$$X_{mf} = max(|x_i|)/(\frac{1}{N}\sum_{i=1}^{N}\sqrt{(x_i)})^2 \quad (8)$$

$$X_{sf} = X_{rms}/(\frac{1}{N}\sum_{i=1}^{N}(|x_i|) \quad (9)$$

$$X_{kf} = X_{kv}/X_{rms} \quad (10)$$

$$X_{fc} = \int_0^{+\infty} f \cdot s(f)df / \int_0^{+\infty} s(f)df \quad (11)$$

$$X_{rmsf} = (\int_0^{+\infty} f^2 \cdot s(f)df / \int_0^{+\infty} s(f)df)^{\frac{1}{2}} \quad (12)$$

$$X_{rvf} = (\int_0^{+\infty} (f - X_{fc})^2 \cdot s(f)df / \int_0^{+\infty} s(f)df)^{\frac{1}{2}} \quad (13)$$

$$X_{sma} = \sum_{i=1}^{N}(|acc_x| + |acc_y| + |acc_z|) \quad (14)$$

$$Tilt_{Angle} = \cos^{-1}(\sum_{i=1}^{N} Acc_x) \quad (15)$$

from accelerometer, roll, yaw, pitch, motion gravity and motion rotation data corresponding to each shoulder motion activity.

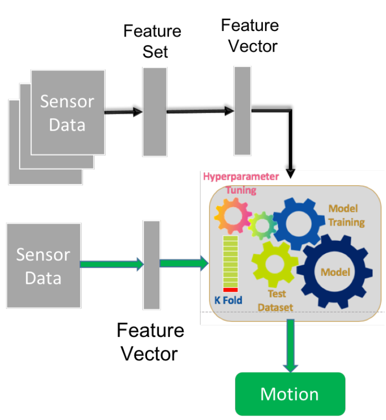


Fig. 4: Functional Flow Chart of ML Approach.

E. Statistical Analysis

Each trial was processed, and shoulder angle was estimated form the watch sensor and were compared with goniometer reading using root mean square error (RMS_{error}) technique.

$$RMS_{error} = \sqrt{\sum_{i=0}^{n}\frac{(x_{o_k} - x_{e_k})^2}{N}} \quad (16)$$

Where (x_{o_k}) represent the ground truth or goniometer data, estimated data from Apple watch (x_{e_k}), and N represents the total number of iterations for each step say 45°. In addition, Bland-Altman plots were performed for various ROM such as 45°, 90°, 135°, and 180°; to understand the difference between the measurements of the estimated ROM (x_{e_k}) from watch and goniometer (x_{o_k}).

IV. Numerical Results

This work has been divided into two-parts: i) ROM estimation and ii) motion classification. Here, we considered 3 shoulder motion such as flexion, extension, abduction that are commonly used in day to day activity. These activities were identified using two approaches: a) Rule engine-based approach, and b) ML based approach.

A. Shoulder Range of Motion (ROM) Estimation

In ROM estimation, 25 health subjects participated, and each performed 3 tasks (flexion, extension, abduction) with a repetition of 3 times for each position (45°, 90°, 135°, 180°) of motion. Table I shows the RMS_{error} between the estimated ROM (x_{e_k}) and goniometer data. Result infers an error of 9°, which is less than the current state of art system [9]. In agreement with the RMS_{error} result, the Bland-Altman plots (Fig 5), shows discrepancies between the estimated ROM (x_{e_k}) and goniometer measures. A mean difference of 2.07 ±1.96 between the true goniometer and ROM_{est} for extension shoulder function is reported. Thus, Bland-Altman plots Fig. 5 shows that < 2% of the estimated angle measured was out of the boundary of goniometry measurement for extension. Fig. 7 shows the results for flexion to 90° and 180 ° and the discrepancies between the x_{e_k} and goniometer measures. A mean difference of 8.41±1.96 and 12.58 ±1.96 was found here respectively compared to 7.3±1.96 and 8.51±1.96 for

TABLE I: Estimated Range of Motion Accuracy

Movements	**No of Trail**	**Degrees**	**Error in Degree**	**RMS_{error}**
Flexion	70	45°	6.8°	9.3
		90°	8.5°	11
		132°	9.9°	13.55
		180°	9.9°	12.51
Abduction	65	45°	5.8°	9.55
		90°	8.85°	12.51
		135°	12.2°	14.19
		180°	10.1°	14.33
Extension	64	˜Max	10°	12.01
Average			9.1	12.05

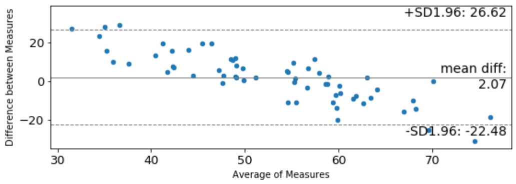


Fig. 5: Bland – Altman plot for Extension Motions average angle measured between goniometer Vs smartwatch

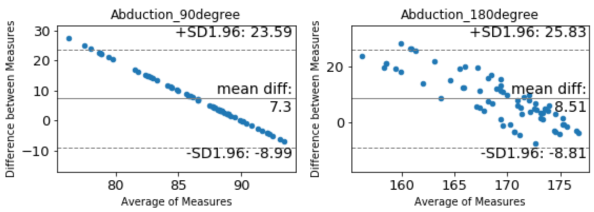


Fig. 6: Bland – Altman plot for Abduction Motions Average Angle Measured between Goniometer Vs Smartwatch

shoulder abduction in Fig. 6. Results infer that the proposed method achieved smaller deviations around the bias, no outliers for the achieved smaller deviations around the bias, and no outliers for all the indices over the 95% confidence interval. Thus, the suggested estimated ROM (x_{e_k}) metric could be

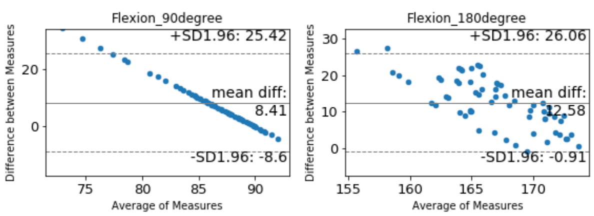


Fig. 7: Bland – Altman plots for the average angles measured using goniometer against smartwatch for Flexion

a surrogate of traditional ROM metrics. However, a large error has been observed at certain ROM degrees specifically at flexion (>135°), and abduction (>90°). To improve the accuracy and for causal analysis of ROM_{est} algorithm, we tested the algorithm with "gonio-data"; the result showed an error rate of <8°. This error could be due to two reasons: i) during extension most of the subjects were not able to maintain the max degree for manual measurement, ii) at maximum or targeted angle, more noise was observed than at other stages of measurement, possibly due to the effect of the tremble of the hand and limb in extreme positions. However, this needs further investigation of either filtering technique or ground truth techniques like electronic goniometer or video approach.

B. Shoulder Motion Performance Validation

1) (REb) Motion Identification: Raw data collected for ROM estimation was used for shoulder motion identification. Even though ROM validation was performed for the targeted degrees, for motion identification full cycle of data was considered i.e. starting to end of one motion, say flexion. It has been observed that clear distinguishable pattern pertains between flexion and extension as shown in Table II. This leads

TABLE II: Performance Comparison Matrix for Various Shoulder Motion using REb

	Flex	**Abd**	**Ext**	**Class Overview**	**Precision**
Flex	90	0	0	90	100%
Abd	19	72	0	91	79.12%
Ext	3	0	89	92	96.74%
Truth Overall	112	72	89	273	
Recall	80.35%	100%	100%		

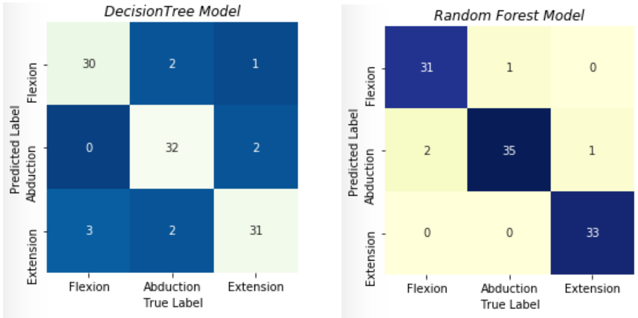
to 100% accuracy of Extension classification or identification. However, the result shows 3 misclasses because one subject accidentally made a swing movement of their arm, leading to a mix of flexion and extension. Even though the dominant action was extension, the flexion action was identified during the starting and the ending stage of the protocol that resulted as a flexion motion. Distinguishing the flexion and abduction motion of shoulder was more complex, as they followed the same pattern of movement i.e. Z axis moving again the gravity. Also, the X and Y-axis movement of hand was also very similar. In general, during day to day activities, flexion-based action is pre-dominant comparing to abduction, so, we adapted a weighted decision fusion approach. The cost function of flexion was given more weight leading to 100% accuracy than abduction, so abduction accuracy is low as shown in Fig. 4. REb approach was implemented and tested using Python.

2) ML Approach: Data was evaluated on 5 different ML models with the training dataset of 409×170 and testing dataset of 103×170. Feature reduction technique has been applied and the 170 features has been reduced to top 50 features. Validation has been done using two methods: a) 80-20% dataset performance and b) 10 fold cross-validation as shown in Table III. The best performance was 94.17% using

TABLE III: Performance Comparison Matrix using Fusion Techniques for various Motion Classification

Method	**Validation**	**Motion**	**Precision**	**recall**	**F-Score**
Decision Tree Model	Data Split 80%-20%	Flex	0.91	0.91	0.91
		Abd	0.94	0.89	0.91
		Ext	0.86	0.91	0.89
		Accuracy=90%			
Random forest		Flex	0.91	0.91	0.91
		Abd	0.94	0.89	0.91
		Ext	0.86	0.91	0.89
		Accuracy=96%			
Gradient Boosting	10-Fold Validation	Accuracy=94.17%			
Ada Boost		Accuracy=87.55%			
Extra Tree		Accuracy=87.99%			
Random Forest		Accuracy=93.38%			

gradient boosting classification techniques for feature fusion dataset and its confusion matrix is shown in Fig. 8(i). Further, these results infer that the ML based approach performed better for flexion and abduction although with a cost of high computation. However, rule base engine would be a promising result for flexion and extension identification with lightweight algorithm that could be used as lightweight processor (e.g. non-DSP processor).



(i) (ii)

Fig. 8: Confusion Matrix of Best Performed System for Motion Classification

V. Conclusion

We have demonstrated the ability of using a smartwatch for continuous and quantitative shoulder function assessment by estimating the ROM and its corresponding motion classification, in conjunction with rule engine for lightweight microcontroller and complex ML approach. This solution will add to the armamentarium of the physician, surgeon and rehabilitation specialist by providing objective values to the range of motion in the clinic, therapy and the home environment to speed up and enhance management protocols in both surgical, non-surgical and sports medicine. As a future scope, a) we are extending this approach for other motion identification such as internal and external rotation, and specific activities of daily living b) we intend towards real-time shoulder function assessment and integrate to gamification platform, thereby it could be a rehabilitation tool.

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