Classification of lower limb rehabilitation exercises with multiple and individual inertial measurement units

Rashmin S. Tanna[1], Chandulal H. Vithalani[2]
[1]Electronics and Communication Department, AmrutlalVeerpal Parekh Technical Institute (AVPTI), Gujarat Technological University, Rajkot, Gujarat, India
[2]Electronics and Communication Department, Government Engineering College Rajkot, Gujarat Technological University, Rajkot, Gujarat, India

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ABSTRACT

Straight leg raise rehabilitation exercises (for both lying and seated position) for lower limb injuries play a critical role in terms of stress on joints after the injury. The primary objective of the paper is to find how accurately and efficiently a single and a two inertial measurement unit (IMU) sensor-based system could classify seated straight leg raise (SSLR) and lying straight leg raise (LSLR) exercises using machine learning. Inertial measurement units (IMUs) that include accelerometer and gyroscope were calibrated and tested, individual and combined, for classified seating as well as lying exercise and for different demanded personalities. Individual IMUs achieved about 96 % accuracy in binary classification. However, the combined (two) IMUs achieved about 96.8% accuracy. The merits of the proposed IMU based sensor system are that it is easy to install, cost effective and very useful for telemedical operations in pandemic situations like COVID-19. On the basis of these results, it could be concluded that the accuracy of a single IMU sensor system and a two IMU sensor-based system is approximately 96% and both were efficiently able to classify SSLR and LSLR exercises as well as identify the individual performing the exercise.

Corresponding Author:

Rashmin S. Tanna
Electronics and Communication Department, AmrutlalVeerpal Parekh Technical Institute (AVPTI)
Gujarat Technological University
Rajkot, Gujarat, India
Email: rashmintanna81@gmail.com

1. INTRODUCTION

Rehabilitation is one of the most requisite processes before and after the surgical reconstruction or replacement of a malformed or degenerated joint of living body. In addition to that, passive conditions also require the Rehabilitation in order to maintain or recover from the anguish, viz. orthopedic, neurological, pediatric, gynecological, diabetes, hypertension, weight loss or gain [1].

The presented work mainly centered towards the leg joint related rehabilitation. In that case straight leg arises activity is a very common, for quick recovery, in case of rehabilitation after total knee arthroplasty. In addition to that, such a rehab process does not require any high-end equipment and supervision of a trained exercise professional. It is very compatible with the homely environment [2]. Many reports are available about the incorrect alignment, poor quality of movement, and speed of movement, due to the lack of proper guidance [3]. In general, for lower limb exercise, there are three methods available for assessing movement such as depth-camera based systems, 3D motion capture systems and direct analysis carried out by a qualified physiotherapist. However, these methods do require a specialized person to handle the system and analyze the produced data [4]. For example, a time-consuming data processing with expertise to interpret the processed dataset and comment on the output is required for 3D motion capture systems. Although a fast and economical solution for motion capture device could be a single Microsoft Kinect v2 sensor, it has many limitations that made it unreliable to be used for wide variety of movements [5]. Visual assessment contains, generally, force plates, electromyography (EMG), footswitches, and motion capture systems. Pre-and post-processing of these usually requires assistance from a specialized assistant [6]. By looking at the current COVID-19 pandemic and lock down situation, it has not been encouraged, at least for senior citizens or single personals.

The possible solution for ease of operation and effective monitoring of the rehabilitation process is wearable sensor systems. The advantages of the wearable sensor systems are small in size, light weight, energy efficient, less maintenance, wireless connectivity, easy to set up single-handed, three-dimensional orientation of segments of individual limb along with inertial motion could be sensed, robust (could be used in unconstrained environment for real-world data acquisition), could track variety of body parts and postures and cost effective [7]. For fall detection based on wearable devices a combination of heart rate sensor and IMU suites better because multiple sensors can be incorporated in a wearable device without increasing its form factor [8]. In 2020, Gaetani *et al.* [9], a wireless myoelectric armband that controls the electronic system of a prosthetic limb was realized. Furthermore, Nie *et al.* [10] proposed a stair walking detection via long short-term memory (LSTM) network to prevent stair fall event by alerting caregiver for assistance as soon as possible. Inorder to reduce jitter issue while pose estimation due to illumination or orientation change in frame sequendce, an algorithm that incorporates sensor data with vision-based pose estimation was presented in [11].

Kianifar *et al.* [12] reported the analysis of three inertial measurement unit (IMU) sensors which shows that the classification done using support vector machine (SVM) classifier for 2-class problems could give 98% accuracy on a human motion dataset. Moreover, Giggins *et al.* proves that incorrect and correct movements during exercise could be differentiated while using one, two or three sensors with 83%, 82% and 81% average accuracy respectively. By increasing the sensors, the performance improves with good accuracy [13]. O'Reilly *et al.* [14] reports the single sensor utilization and its performance. In this study on 15 participants (injury free) for acceptable and unacceptable methods during exercises like single leg squats, simple lunges, squats and deadlifts accuracy of 89.5%, specificity of 89% and sensitivity of 90% were achieved.

If we consider straight leg raise rehabilitation exercises (for both lying and seated position), we could not find many reports regarding the ability and the use of the IMU system to accurately quantify the biomechanics [15]. The purpose of this study is to find out the (a) ability of IMUs, placed on shank and foot, used individually and in combination to differentiate between lying straight leg raise and seated straight leg raise exercise; (b) accuracy of identification of the individual performing the exercise using these IMU systems and (c) improvement in system efficiency while maintaining accuracy by optimizing the classification algorithm and by selecting the most significant features to train this algorithm [16]. Hence an IMU based solution could be proposed based on machine learning.

2. RESEARCH METHOD

Further approach is to utilize minimum numbers of the sensors. Each sensor's response was analyzed thoroughly for the twenty repetitions. Total Nine volunteers undergo the generation of Straight leg raise rehabilitation exercises (for both lying and seated position), with prior personal permission. In the nine volunteers there are four male and five female (four senior citizens, four Adult and one child) involved in the rehabilitation exercises. In anterior cruciate ligament (ACL) reconstruction rehabilitation protocol, "The quadriceps contraction prevents heavy stress on healing ACL graft by locking the knee. The leg is lifted to 45 to 60 degrees for about 6 to 8 seconds while keeping it straight. The leg is then slowly lowered back on the platform. Then, get into a better position for relaxing the muscles". In the present work IMU sensors are used to discriminate straight leg raise rehabilitation exercises using the data processing flow as shown in Figure 1.

After the proper relaxation, IMUs were introduced to the participant at two locations. One IMU sensor is kept 2 centimeters above the lateral malleolus on the shank and the second one is on the foot with IMUs facing upwards, similar arrangement was done by O'Reillyet *et al.* [17] and Seel *et al.* [18]. For all the study participants the location and the orientation of the IMUs were consistent. Initially, trials were made in order to determine the operating ranges for gyroscope and accelerometer and calibrate the sampling frequency in the IMU (wit motion BWT901CL and BMI160-inbuilt in mobile phone). Leg raise data was collected at 250 Hz frequency. Proper physical monitoring of physiotherapists helps the patients to get into the comfort position (both physically and psychologically) during the whole measurement cycles and trials [19]. For the detection of characteristic frequencies of the signal, a Fourier transform was used and it was found to be less than 50 Hertz. On the basis of shannon sampling theorem and nyquist criteria in

Jerri *et al.* [20], the sampling frequency must be kept twice of 50 Hz that is 100 Hz. From the pilot study of the data, the BWT901CL and BMI160 IMU were configured to stream with sensor ranges of magnetometer (+/-1 Ga), gyroscope (+/-500 º/s) and (+/-2 g) 3-axis accelerometer. The calibration of the IMUs was done based on these particular sensor ranges using the "Phyphox" android mobile application developed by RWTH Aachen University and Witmotion Calibration application [21].

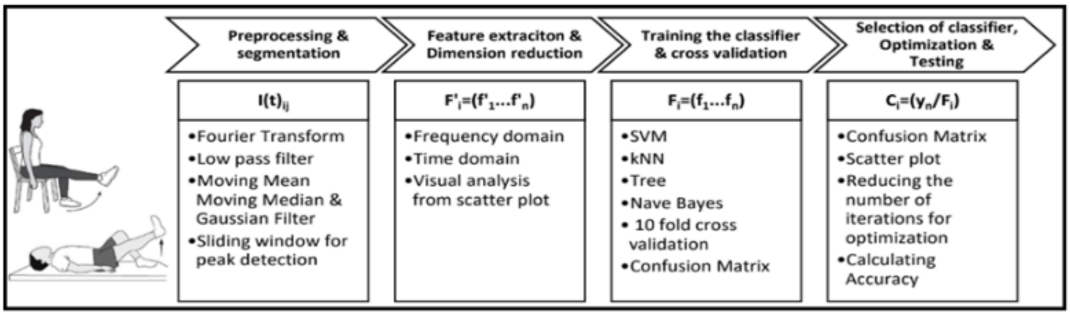


Figure 1. Flow of data processing in proposed method

MATLAB software was used for the analysis of data provided by the IMUs. Total twelve signals were obtained relative to each IMU; accelerometer (direction), gyroscope (position), angular velocity (position) and magnetometer (direction) in the x, *y*, *z axis*. Each of these signals were passed through a low pass filter at f_c=50 Hz, moving mean, moving median and Gaussian filter to get filtered $I(t)_{ij}$signals. In order to find where the participant has completed the given exercise at different speeds, extracted from IMU data, each repetition from each exercise was resampled with sample length 250 as suggested in [22]. From the above mentioned 12 signals, different features in time-domain as well as frequency-domain were computed to describe pattern of signal after exercise completion. Based on literature study and visual analysis these features were selected [23]. There is total twenty-nine features (details are tabulated in Table 1) per IMUs which were selected such as, Xavg, Yavg, Zavg, Xvar, Yvar, Zvar, Wxavg, Wyavg, Wzavg, Wxvar, Wyvar, Wzvar, Xstd, Ystd, Zstd, Xmax, Ymax, Zmax, Xmin, Ymin, Zmin, ACCmax, ACCmin, ACCavg, ACCstd, corrXY, corrYZ, corrZX, energy.$F = [f_1, f_2, \dots, f_{29}]$represents the extracted twenty-nine features from the real-time IMU data.$F_i = [f_{i1}, f_{i2}, \dots, f_{in}]$representsthe linear combinations of the original features, where 'n' is the dimension which are required to be reduced:

$$F_n = b_{1i}f_1 + b_{2i}f_2 + \cdots + b_{ni}f_n \tag{1}$$

where eigenvalues of the covariance matrix are represented by b_{ij}. Here only single node is used hence simplified (1) can be written as (2).

$$F_n = b_1f_1 + b_2f_2 + \cdots + b_nf_n \tag{2}$$

Further SVM (Support Vector Machine) method is mostly used to perform the classification of the data because of its unique properties such as effectiveness in high dimensional spaces, clear margin of separation between classes and number of dimensions is more than the number of samples as shown in Lai *et al.* [24]. We have two labels SSLR and LSLR in this research so a 1-vs-1 strategy was chosen in which using respective data from both the classes the SVMs are formed. SVM can solve this kind of binary classification problem:

$$D = \{(M, b_i | M \in R^m, b_i \in \{1, -1\})\}_{i=0}^{n} \tag{3}$$

where, '*n*' is the total sample count, $b_i$is a label belonging to 1 or -1, *'M'* is a matrix with m-dimension and *'i'* represents the serial number of the current sample. In order to map the training dataset into higher dimension of feature space SVM is used before classifying the training dataset with hyperplanes. Thus, an optimization equation described as below gets converted from the equation which is finding the maximum margin hyperplane (MMH) as follows:

$$\arg\min \omega, d\,\frac{1}{2}\|\omega\|^2$$
$$s.t.\, b_i(\omega.m_i - d) \geq 1, i = 1, .., n \tag{4}$$

where normal vector of a hyperplane is represented by $'\omega'$ and an offset from the origin along this normal vector is represented by *'d'*. Equation (3) can be expressed using the Karush-Kuhn-Tucker (KKT) conditions having Lagrangian multipliers, as (5):

$$L(\omega, d, a) = \frac{1}{2}||\omega||^2 - \sum_{i=1}^{n=270} a_i\{[b_i(\omega^D. m_i + d) - 1]\} \tag{5}$$

where, the Lagrangian multipliers vector is represented by *'a'*. With respect to $'\omega'$ the derivative of (4) gives

$$\omega = \sum_{i=1}^{n=270} a_i b_i m_i \tag{6}$$

and with respect to 'd' the derivative of (4) gives as (7).

$$\sum_{i=1}^{n=270} a_i b_i = 0 \tag{7}$$

A simplified Lagrangian dual problem after substituting (5) and (6) into (4) gives (8).

$$\begin{aligned} &\frac{argmax}{a} \sum_{i=1}^{n=270} a_i - \frac{1}{2} \sum_{i=1}^{n=270} a_i a_j b_i b_j m_i m_j \\ &s.t.\ a_i \geq 0, i = 1, \dots, n \\ &\sum_{i=1}^{n=270} a_i b_i = 0 \end{aligned} \tag{8}$$

In case of nonlinearly separable classes, constant C which is an error penalty and a slack variable are added to search a trade-off between an error penalty and a large margin. In case of non-linear separable problems, Lagrangian dual problem in its simple version is obtained as:

$$\begin{aligned} &\frac{argmax}{a} \sum_{i=1}^{n=270} a_i - \frac{1}{2} \sum_{i=1}^{n=270} a_i a_j b_i b_j \emptyset(m_i, m_j) \\ &s.t.\ C \geq a_i \geq 0, i = 1, \dots, n \\ &\sum_{i=1}^{n=270} a_i b_i = 0 \end{aligned} \tag{9}$$

'a_i'are the Lagrange multipliers that could be obtained by using SMO (Sequential Minimal Optimization algorithm). As per (4), an optimization hyperplane could be found and final ω could be calculated. For classification the decision function is:

$$f(M^D) = sgn\left[\sum_{i=1}^{n=90} a_i b_i \emptyset(m_i, m_j) - d\right] \tag{10}$$

where the two constants are$a_i$and *d*, the class label of SVM is $b_i$and the exercise testing set samples with labels b_i is represented as M.

2.1. Experimental setup

Initially the basic SVM was tested using wit Motion BWT901CL tied on the shank area. Figure 2 shows android app used and placement of sensors during the experiment. Total of 4 adults, 4 senior citizens and 1 child (9 volunteers) participated. First, they performed Seated straight leg raise exercise and then lying straight leg raise exercise with 20 repetitions each. This produced 1600 training observations and 1000 testing observations. We used 20 predictors and 18 response classes to train the SVM for binary classification to determine whether it can classify between SSLR and LSLR exercise or not. The 12 signals received from the IMU were passed through moving mean, moving median and Gaussian Filters to remove unwanted areas. Finally, classification was done with a full feature set [25]. Then only 29 important features were selected, and classification was done using them. Then after getting good accuracy in classification of type of exercise, we tried to identify the person doing the exercise and obtained good results [26].

Table 1. List of selected twenty-nine important features for the SVM classifier

Sr. No.	Feature	Variable name
1	mean acceleration along x axis	Xavg
2	mean acceleration along y axis	Yavg
3	mean acceleration along z axis	Zavg
4	variance of acceleration along x axis	Xvar
5	variance of acceleration along y axis	Yvar
6	variance of acceleration along z axis	Zvar
7	mean angular velocity along x axis	Wxavg
8	mean angular velocity along y axis	Wyavg
9	mean angular velocity along z axis	Wzavg
10	variance of angular velocity along x axis	Wxvar
11	variance of angular velocity along y axis	Wyvar
12	variance of angular velocity along z axis	Wzvar
13	standard deviation of acceleration along x axis	Xstd
14	standard deviation of acceleration along y axis	Ystd
15	standard deviation of acceleration along z axis	Zstd
16	maximum acceleration along x axis	Xmax
17	maximum acceleration along y axis	Ymax
18	maximum acceleration along z axis	Zmax
19	minimum acceleration along x axis	Xmin
20	minimum acceleration along y axis	Ymin
21	minimum acceleration along z axis	Zmin
22	maximum acceleration	ACCmax
23	minimum acceleration	ACCmin
24	average acceleration	ACCavg
25	standard deviation of acceleration	ACCstd
26	correlation of acceleration between x and y axis	corrXY
27	correlation of acceleration between y and z axis	corrYZ
28	correlation of acceleration between x and z axis	corrZX
29	acceleration energy	energy

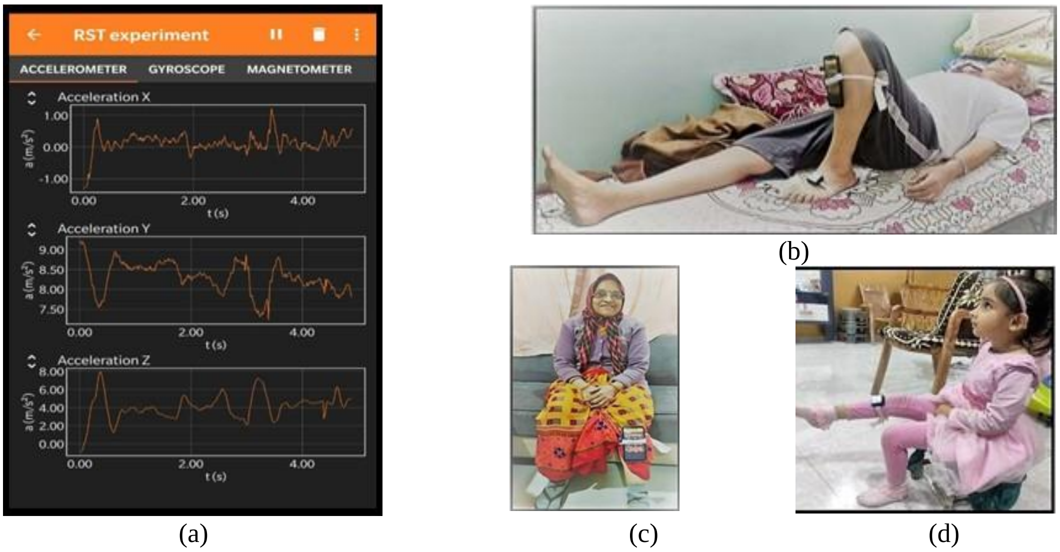


Figure 2. Android app and placement of sensors, (a) “Phyphox” android application and two senior citizens, (b) male LSLR & SSLR and (c) female performing LSLR & SSLR, and (d) child performing SSLR

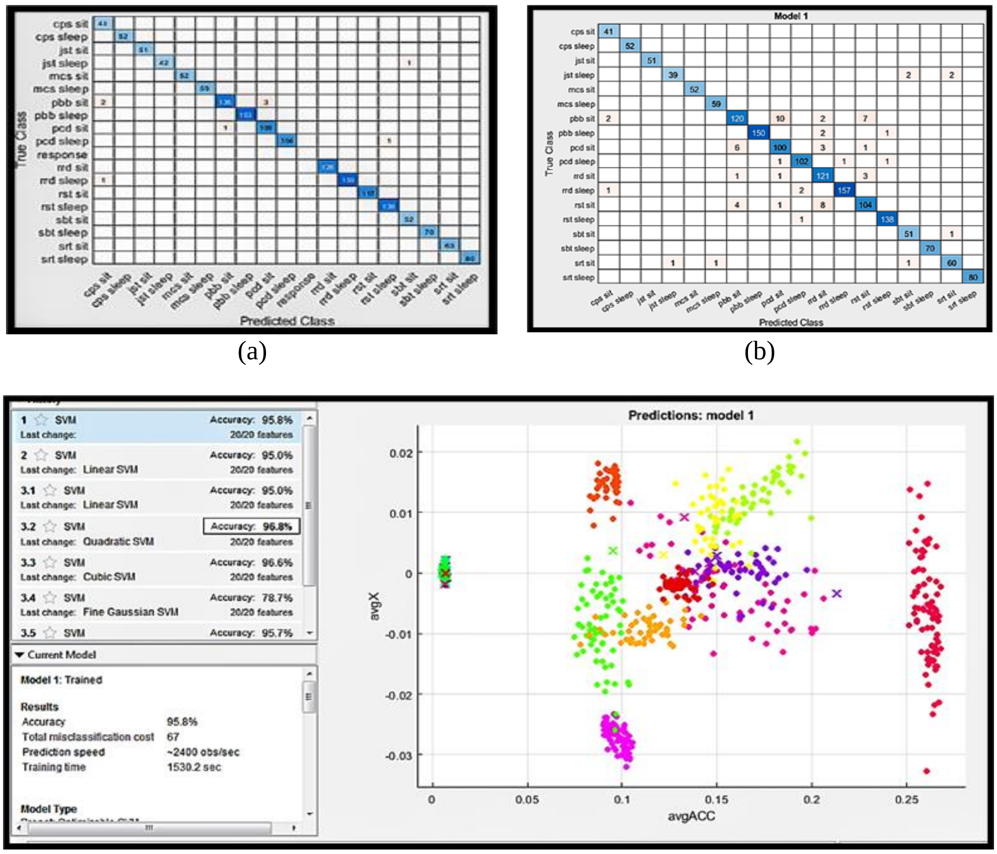
Then the same simple SVM was tested using the internal IMU sensor of the mobile phone Oneplus A5010 (snapdragon 835, 6GB RAM, 64GB ROM, Android OxygenOS ver. 10.0.1). The IMU was calibrated using the “phyphox” android app developed by RWTH Aachen University as shown in Figure 2(a). Total 7 (4 senior citizens, 2 adults and 1 child) participated in the experiment with placement of sensor as shown in Figure 2(b) and Figure 2(c). Both SSLR and LSLR exercises were performed with 20 repetitions per exercise. Total 9,250 observations for training and 5,000 test observations were produced. Finally, 20 predictors and 14 responses classes were used for the classification of exercises. The 12 signals received from IMU were filtered using moving mean, moving median and Gaussian filter. First classification was done using a full feature set from which most important 29 features were kept. Then after the experiment was conducted to identify the person comforters of the activity [27]. The third experiment was performed using both the IMU sensors. Figure 2(d) shows the WitMotion BWT901CL sensor was placed at the foot area and the IMU sensor in the mobile phone was placed at the shank area. Total 4 (2 senior citizens, 1 adult & 1 child) volunteers participated and performed both SSLR and LSLR exercises with 20 repetitions each. The optimized SVM with 470 training and 280 test observations gave good accuracy. Total 40 predictors and 8 response classes were used to classify the exercises. Finally, to identify the person performing the exercise the classification was done using only the top 29 important features. Table 1 shows the selected 29 features and the variable names assigned to them.

3. RESULTS AND DISCUSSION

All the results for each classifier were first discussed with individual IMUs and then both the IMUs combined. As discussed in the excremental section, after close examination only the top twenty-nine important features are selected for the SVM classifier. These features include mean, variance, standard deviation, max, min values and correlation of acceleration and angular velocity along x, y and z axis.

3.1. Classification with individual sensors

As single IMU (BWT901CL sensor on the shank area) isused for the observation of exercise data, Figure 3 shows the performance comparison of various SVM classifiers. The comparison is done in terms of Figure 3(a) confusion matrix which gives predicted class vs true class when the SVM classifier istrained, Figure 3(b) final confusion matrix when the classification is performed on test data and Figure 3(c) scatter plot as well as accuracy. From the available SVM, quadratic SVM shows the maximum accuracy for all kinds of the rehabilitation exercise parameters. Similarly, Figure 4 shows theperformancecomparison of various SVM classifiers while using single BMI160 inbuilt mobile sensor on the shank area. Comparison is shown in terms of confusion matrix of SVM classifiers after training in Figure 4(a) and after testing in Figure 4(b). Also, the scatter plot is shown in Figure 4(c) along with different SVM classifier's accuracy. The comparison shows that the cubic SVM has the highest accuracy, similar to the results shown in [28].



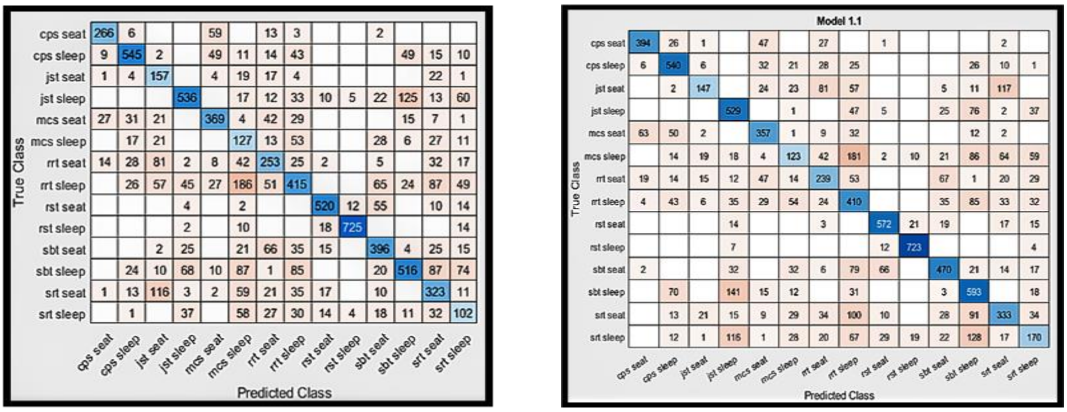
(a) (b)

(c)

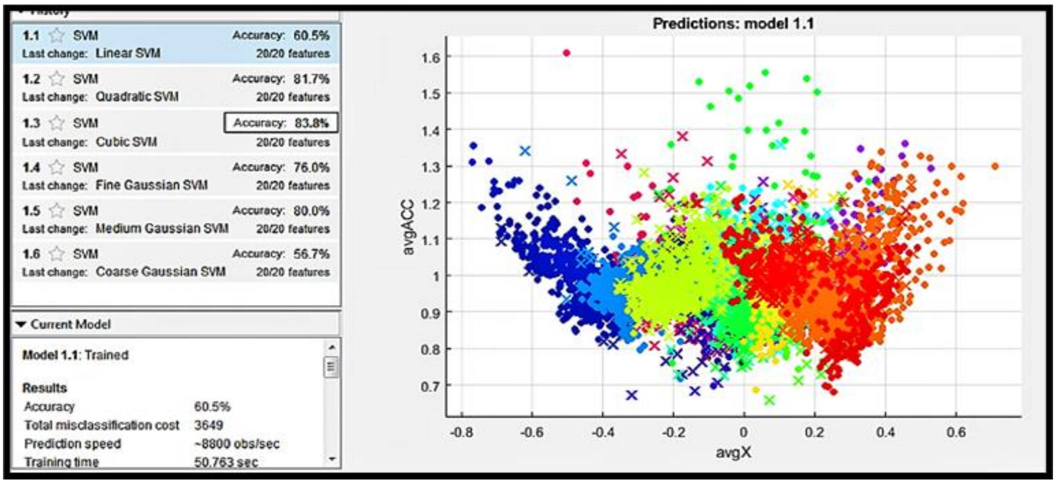
Figure 3. Performance comparison of various SVM classifiers while using single BWT901CL sensor, (a) after training confusion matrix, (b) after testing confusion matrix, and (c) scatter plot and accuracy

3.2. Classification with two sensor system

Following this protocol, exercises with all twenty-nine classifications were performed with two sensors; one is on the shank region and other is on foot. Figure 5 shows the performance comparison of various SVM classifiers while using combination of both the IMU sensors. Figure 5(a) showstheconfusion matrixafter training and Figure 5(b) shows after testing. The scatter plot and accuracy are shown in Figure 5(c).



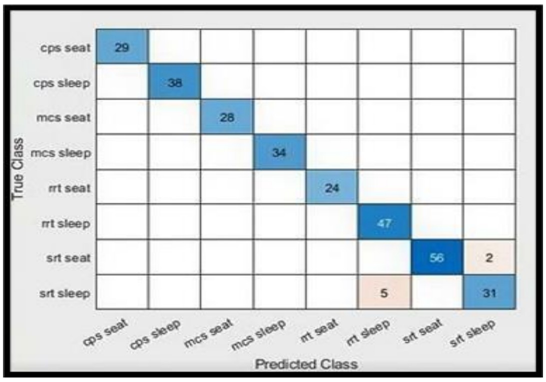
(a) (b)



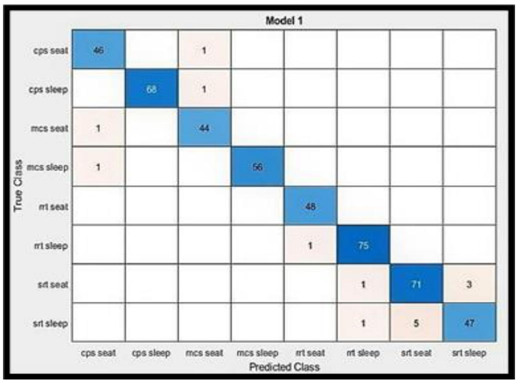
(c)

Figure 4. Performance comparison of various SVM classifiers while usingsingle BMI160 inbuilt mobile sensor, (a) After training confusion matrix, (b) After testing confusion matrix, and (c) scatter plot & accuracy

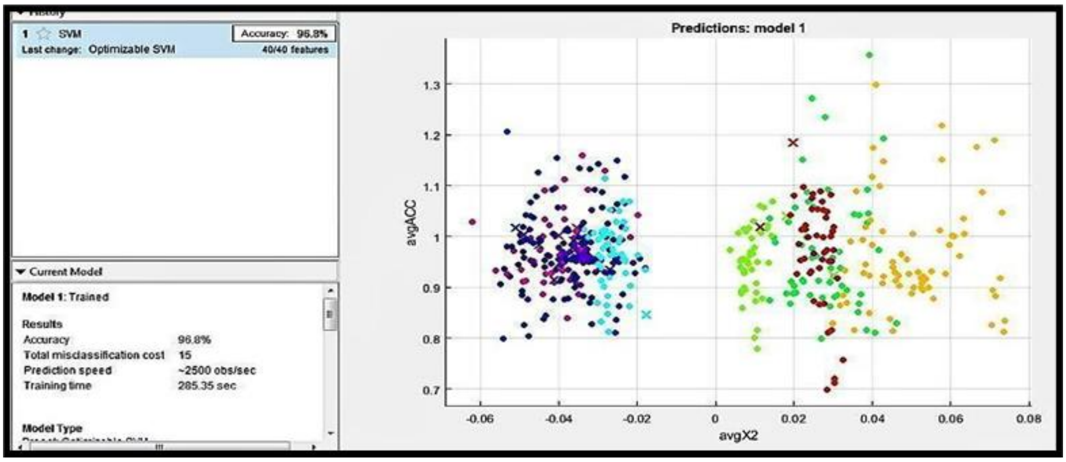
The overall result of both analyses is tabulated carefully in Table 2, in terms of accuracy of individual and both IMUs (sensors). The focus is only on the SVM method to study the observed data and its variation. In addition to that the k-Nearest Neighbor (kNN), Tree and Naïve Bayes method were ascertained with SVM, as suggested in [29]. In terms of Accuracy data (shown in Table 2), SSLR and LSLR exercise could be distinguished by a single IMU system with 96.8% and 83.8% accuracy. However, Two IMUs shows 96.8% accuracy. This reveals that the single IMU reaches very close to the two IMUs in terms of accuracy, on the shank region. Hence, it is prudent to use the single IMU, especially in the shank region, compared to two IMUs. It thence can reduce the complexity of the system and cuts the cost also. On examining the results, we observed that the classification of persons doing the exercise was done well by both individual sensor systems and two combined sensor systems. The single and both IMUs systems required perfect optimization of SVM before final implementation [30]. During optimization, a clear observation is that Quadratic SVM in a single sensor system gets optimized very quickly.



(a)



(b)



(c)

Figure 5. Performance comparison of various SVM classifiersusing combination of both the IMU sensors, (a) after training confusion matrix, (b) after testing confusion matrix, and (c) scatter plot and accuracy

Table 2. Accuracy of different types of classifiers when sensors are used individually as well as in combination

Classification Algorithm		Accuracy		
		Single Sensor System		Two sensor system
		WitMotion IMU (BWT901CL)	Mobile's Internal IMU (BMI160)	
	Linear SVM	95.0%	60.5%	96.8%
	Cubic SVM	95.8%	83.8%	95.2%
	Quadratic SVM	96.0%	81.7%	96.0%
Support	Fine Gaussian SVM	78.7%	76.0%	79.5%
Vector	Medium Gaussian SVM	81.6%	80.0%	80.8%
Machine (SVM)	Coarse Gaussian SVM	60.2%	56.7%	59.3%
	Fine kNN	94.1%	80.4%	88.6%
k-Nearest Neighbor	Weighted kNN	93.3%	79.8%	85.0%
(kNN)	Medium kNN	90.3%	77.6%	79.9%
Tree	Fine Tree	83.0%	70.7%	78.1%
Naïve Bayes	Gaussian Naive Bayes	79.9%	66.0%	72.4%

4. CONCLUSION

The Leg raise exercise is an essential part in strength and conditioning, rehabilitation and musculoskeletal injury risk screening. The low-cost wearable IMU technology with a cloud-based server could be used to store and transfer the exercise data from the IMUs. This means therapists without constant monitoring could assess patient compliance and technique during the prescribed exercise. This could be very helpful to senior citizens or single personals in a COVID-19 likepandemiclock down situation. The implemented IMU based system can classify SSLR and LSLR techniques very precisely. In addition to that a two or single IMU set-up could accurately identify the person doing the exercise. The accuracy of a single

IMU sensor on the shank region is similar to that of two sensors placed on the shank and foot region, i.e., around 96%. In future these data will be used to identify the pattern of the faulty joints or misalignment of the joints. Future work could also include other types of exercises for rehabilitation of different parts of the body and the proposed system could be used as a part of a bigger and more complex wearablesensor system for tracking multiple rehabilitation exercises. Future work could include three key areas: (a) developing and evaluating SSLR and LSLR classification systems in real world on naturally occurring deviations, (b) investigating additional analysis methodologies and collecting a large dataset for improving system accuracy and (c) inspecting the impact, usability and functionality of IMU based exercise inspection systems.

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BIOGRAPHIES OF AUTHORS

Rashmin S. Tanna is currently pursuing his Ph.D. in Electronics and communication Engineering from the Gujarat Technological University. He is M.E. in Communication Systems Engineering and is working as a Lecturer (EC) at A.V. Parekh Technical Institute, Rajkot, Gujarat, India. He has 10 yrs of teaching experience and his research interests include Machine Learning, artificial intelligence, IoT and Embedded Systems. He can be contacted at email: rashminstanna@gmail.com.

Dr. Chandulal H. Vithalani obtained his M.E. degree in Electronics and Communication Engineering from Gujarat University, India in 1998 and PhD degree in Electronics Engineering from Gujarat University in the year 2006. Currently, he is working as a Professor in the Department of Electronics Communication Engineering, L.D. College of Engineering, Ahmedabad (India). He has published 49 papers in National and International conferences and journals. His current research areas of interest are machine learning, embedded systems and image processing**.** He can be contacted at email: chvithalani@gecrajkot.ac.in.