# Activity Recognition of Local Muscular Endurance (LME) Exercises using an Inertial Sensor

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**Abstract.** In this paper, we propose an algorithmic approach for a motion analysis framework to automatically recognize local muscular endurance (LME) exercises and to count their repetitions using a wrist-worn inertial sensor. LME exercises are prescribed for cardiovascular disease rehabilitation. As a technical solution, we propose activity recognition based on machine learning. We developed an algorithm to automatically segment the captured data from all participants. Relevant time and frequency domain features were extracted using a sliding window technique. Principal component analysis (PCA) was applied for dimensionality reduction of the extracted features. We trained 15 binary classifiers using support vector machine (SVM) to recognize individual LME exercises, achieving overall accuracy of more than 98%. We applied grid search technique to obtain the optimal SVM hyperplane parameters. The learning curves (mean $\pm$ stdev) for each model is investigated to verify that the models were not over-fitted and performed well on any new test data. Also, we devised a method to count the repetitions of the upper body exercises.

**Keywords:** Local Muscular Endurance, Human Activity Recognition, Cardiovascular Disease, Principle Component Analysis, Support Vector Machine.

## 1 Introduction

Regular and appropriate exercise facilitates rehabilitation from chronic diseases such as cardiovascular disease (CVD). However, adherence to community based exercise and rehabilitation programmes is extremely low. Uptake and adherence to such programmes are very less [1]. Delivering a home-based programme via a mobile-phone can address some of these adherence issues (e.g., access to a targeted programme, travel time). However, the motivation to complete the exercise may be reduced because it is not being measured or seen by others (instructor or fellow exercisers). One solution is to use a wearable sensor to recognize when a person is exercising and to record specifically how many repetitions they are performing. As a scientific solution, activity recognition and repetition counting during exercises can be studied under the broader category of human activity recognition (HAR) with the help of miniaturized and accurate wearable multi-modal wireless sensors [2, 5, 6, 8]. The specific exercises associated with cardiac rehabilitation are LME exercises (Table 1).

The use of wearable 3D accelerometer and gyroscope can provide accurate translational and rotational data [3, 5, 6, 8]. Use of variable sensors for ambulatory motions and HAR is discussed in [6] and specific to the detection of asymmetric running using time and frequency features is discussed in [3]. The scope of this paper is to design and implement a novel automated system for the recognition of specific LME exercises and counting the number of repetitions using a wearable inertial sensor.

In this paper, a Shimmer3 sensor unit (Shimmer, Ireland) is utilized to capture fifteen different LME exercises from six different participants. Segmentation is performed and statistical time-frequency domain features [4, 9] are extracted from the segmented data. PCA is then used to reduce the dimensionality of the feature vectors [10]. Activity recognition is studied using SVM. We applied a grid search algorithm [14] to obtain optimized hyperplane parameters and kernel options to overcome the overfitting of the trained classifier. A suitable counting mechanism, using peak-to-peak detection or threshold crossing, is examined to determine the number of repetitions for the upper body exercises only (future work will apply these to the lower limb exercises). The final results, including the training and validation accuracy, f-score, precision, recall for all 15 exercises, are presented and discussed. For illustration purposes, we chose one LME exercise (i.e. Bicep Curl) to demonstrate all the intermediate results and fully describe the entire proposed framework.

## 2 Proposed Framework

The major components of our framework are illustrated in Fig. 1. This end-to-end pipeline structure consists of five steps to recognize and count the repetitions of each exercise. Each component is discussed in detail in section 3.

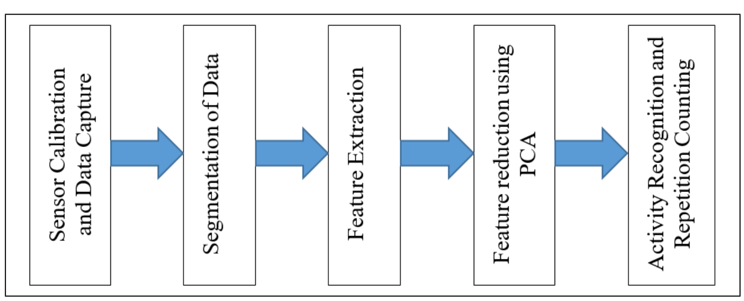


**Fig. 1.** End-to-end pipeline of the proposed framework

# 3 Methodology

## 3.1 Sensor Calibration and Data Capture

Data collection is carried out using Shimmer3, a lightweight and miniaturized wearable sensor encompassing a 3D accelerometer, 3D gyroscope, a 3 MHz MSP430 CPU with Bluetooth connectivity for remote access and a microSD card for local storage. The Shimmer unit is calibrated to obtain consistent and accurate data. The 3D accelerometer ($\pm$2g) data is used to recognize the activities and data from the accelerometer or gyroscope are used for determining the repetition count. Data is collected from six healthy participants performing the exercises at a sampling rate of 512 Hz. The Shimmer sensor is securely placed on the right wrist of the participant using an elastic wrist strap. The sensor placement and orientation are shown in Fig. 2.

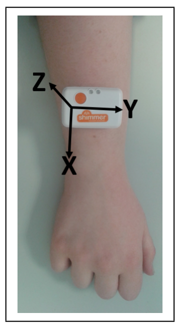


**Fig. 2.** Illustration of sensor placement and sensor orientation on right wrist

An experimental protocol is followed during data capture. Once the sensor is turned on, each participant claps three times which indicates the beginning of each recording. Subsequently, participants remain stationary for 5 seconds to ensure no random noise is introduced to the main signal before performing the exercise. Each participant then has to perform the exercise for 40 seconds. The trial is concluded with a further 5 seconds pause followed by three claps indicating the conclusion of the trial. Data collected with this approach for the Bicep curl is shown in Fig. 3. An identical protocol is used for all 15 exercises listed in Table 1. In addition the activity classification model needs to learn/identify when the person is not performing an exercise. Data capture is carried out for quasi static arbitrary (random) movements, such as participants standing still or actions which can be referred as non-performing an exercise.

## 3.2 Segmentation of Data

A segmentation algorithm is designed and implemented to automatically annotate the entire dataset (i.e. for each of 15 LME exercises and random movements

**Table 1.** List of LME exercises

| Upper Body LME Exercises | | | |
|---|---|---|---|
| Ex 1 | Bicep Curls | Ex 6 | Pec Dec |
| Ex 2 | Triceps extension (right arm) | Ex 7 | Trunk twist |
| Ex 3 | Upright row | Ex 8 | Side Bends - alternating sides |
| Ex 4 | Lateral raise (arms up) | Ex 9 | Bent Over Row (right arm) |
| Ex 5 | Frontal raise (arms up) | Ex 10 | Press up against wall |
| Lower Body LME Exercises | | | |
| Ex 11 | Squats | Ex 14 | Standing bicycle |
| Ex 12 | Lunges - alternating sides | Ex 15 | Leg lateral raise (right) |
| Ex 13 | Calf raises | | |

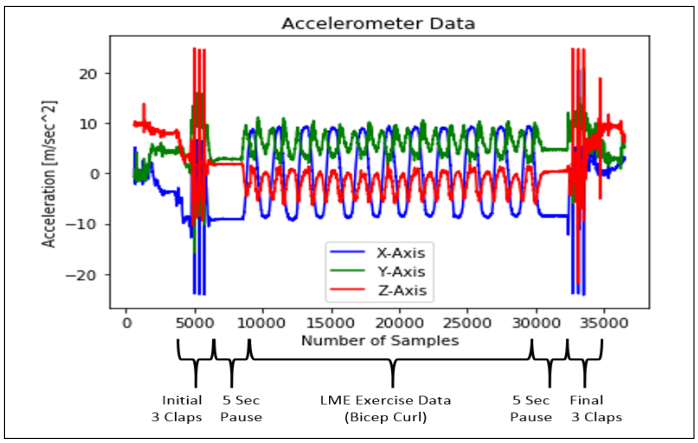


**Fig. 3.** Illustration of data capture protocol with accelerometer data for the Bicep Curls

from all 6 participants) for further analysis. The algorithm automatically detects the initial three claps from the accelerometer data and captures the activity signal for a period of 30 seconds in between the initial and final pause periods. The 30 seconds of segmented data is annotated as (**Class1**). Similarly, segmentation is carried out on the random movement accelerometer data and labeled as (**Class0**). The annotated signals are then passed on to the next part of the pipeline to extract more meaningful features from the accelerometer data. The segmented activity signal of the Bicep Curls with a period of 30 seconds is shown in Fig. 4.

Segmented data from four participants are used for training the model and for cross validation using SVM (discussed in classification section). Data from two participants are used for testing the model. For each exercise, segmented data (**Class1**) are concatenated with random movement data (**Class0**) from four participants. The concatenated data set is then subjected to feature extraction.

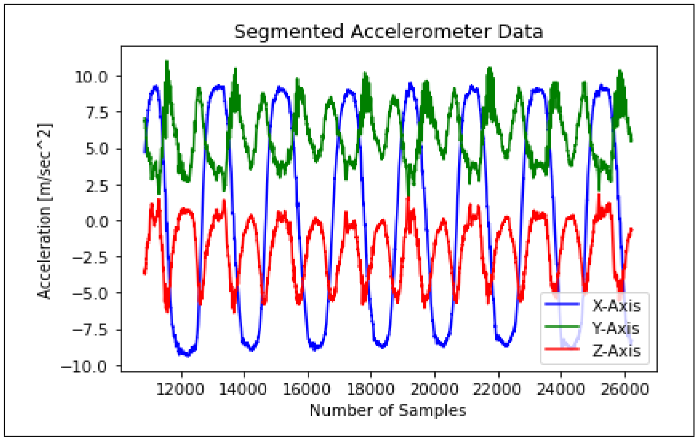


**Fig. 4.** Segmented Bicep Curls data for 30 seconds

### 3.3 Feature Extraction

As each repetition lasts approximately for 4 seconds, a sliding window of 4 seconds with 50% (2 seconds) overlap is used for feature extraction from segmented 3D accelerometer data. Statistical features, which are widely used in the field of HAR (i.e., mean, standard deviation, min and max values, RMS values, Pearson correlation coefficients, FFT coefficients and entropy values), were computed from each window [4, 7, 9–11]. A feature vector comprising of n=24 features, is computed and extracted from each 4 second window. Extracted time and frequency domain features are listed in Table 2. These feature vectors are input to the next phase of the pipeline for dimensionality reduction.

**Table 2.** List of time and frequency domain features

| Number of features | Feature description |
|---|---|
| 6 | Mean and Std Deviation from accelerometer, gyroscope |
| 6 | Minium and Maximum on each axis |
| 3 | RMS values on accelerometer on each axis |
| 3 | Pearson correlation coefficients between the axis |
| 3 | Energy from FFT coefficient on each axis of accelerometer |
| 3 | Entropy value computed from each axis of accelerometer |

### 3.4 Feature reduction using PCA

The total **n** extracted features give an **n**-dimensional perception classification problem. The basic understanding is to have the minimum **k** correlated features that can completely define the characteristics of the underlying classification problem [4, 10]. PCA is a linear transformation of a number of correlated features into a smaller set of uncorrelated features. The significance of PCA is to obtain the reduced dimensionality from the feature set and to have fewer significant, meaningful relationships among the features. Normalizing and computing the correlation matrix among the extracted time-frequency features to obtain the Eigenvectors and associated values is the primary stage of PCA. Eigenvectors are sorted in descending order based on their corresponding Eigenvalues. The first principle component corresponds to the maximum variability of the original data and succeeding components add up to the remaining variability. In our analysis, we performed PCA on the data set and retained Eigenvectors that explain the variance of 98%, as shown in Fig. 5, which is discussed in section 4. The computed PCA components are used as input to the activity recognition model.

### 3.5 Activity Recognition and Repetition Counting

SVM classifiers (one SVM model for each exercise) with optimum hyperplane parameters are used to recognize each LME exercise from the random movement [5, 12]. SVM is a supervised learning method that tries to minimize the cost function while enabling the identification of different classes (**Class1**) and (**Class0**), while maximizing the margin between margin vectors. In developing our approach for exercise classification, the model needs to learn from the input feature set $\mathbf{X}$ and the output target set $\mathbf{Y}$. Learning occurs with the mapping $\mathbf{X} \longmapsto \mathbf{Y}$ with some object, $\mathbf{x} \in \mathbf{X}$ and with class label $\mathbf{y} \in \mathbf{Y}$. To recognize whether a specific exercise is being performed or not can be thought of as a binary classification problem with model input values $\mathbf{x} \in \mathbb{R}^n$ and the output target value $\mathbf{y} \in \{\pm 1\}$. The SVM model is then trained with the training set $(x_1,y_1)$, $(x_2,y_2)$ $\cdots$ $(x_m,y_m)$. The basic linear SVM classifier $\mathbf{y} = f(\mathbf{x},\alpha)$ with $\alpha$ the hyperplane parameters, weight $(w)$ and y-interceptor $(b)$, of the function is shown in equation ( 1) [12].

$$f(x,(w,b)) = w \cdot x + b \tag{1}$$

The objective of the developed model is to minimize the cost function $I[f_m]$ or the associated empirical error with the linear fit over $m$ training set (see( 2)).

$$I[f_m] = \frac{1}{m} \sum_{i=1}^{m} l(f(x_i,\alpha), y_i) \tag{2}$$

where $l$ is the zero-one loss function. Optimized fit can be obtained by minimizing the error through minimizing $\parallel w \parallel^2$ subject to the satisfaction of relations( 3).

$$\begin{aligned} (w \cdot x_i + b) &\geq +1, \quad if \;\; y_i = +1 \\ (w \cdot x_i + b) &\leq -1, \quad if \;\; y_i = -1 \end{aligned} \tag{3}$$

A statistical model is considered best fit if it approximates the target function with a smaller error. When the model learns from the underlying data set and the effect is negative on the new data set, then the model is termed over-fitted or overlearned. If the relationship between the target function and training sets provided are more nonlinear, the model fails to learn the relationship. Typically, when the new data is added to the model, the model fails to learn from the data and it yields an output with the memorized behaviour from the training data. This results in a poor predictive performance of the model and even small noises or fluctuations can be classified as an activity and therefore efficiency of the classification model reduces on unseen data.

Regularization and cross validations are used to overcome the overfitting problem. An additional parameter $\lambda R(f)$ can be added (see( 4)) to smooth the cost function to minimize the overall error and the term $\lambda R(f)$ is the regularization parameter [12]. The value of regularization parameter $\lambda$ emphasizes the significance of misclassification. In kernelized SVM higher the value of regularization may lead to overfitting and lower the value leading to under-fitting.

$$I[f_m] = \frac{1}{m}\sum_{i=1}^{m} l(f(x_i, \alpha), y_i) + \lambda R(f) \tag{4}$$

We also used 10-fold cross validation where we randomly split the training dataset into 10 folds without replacement; with 9 folds used for the model training and one fold used for testing. This procedure is repeated 10 times so that we obtain 10 models and performance estimates. The described technique is applied to all developed models (one for each exercise) and the precision, recall and F-Score parameters are computed to validate the performance of each model.

SVMs can be easily kernelized to solve nonlinear classification problems as well. The basic idea behind the kernel methods to deal with such linearly inseparable data is to create nonlinear combinations of the original features to project them onto a higher dimensional space via a mapping function where it becomes linearly separable. We implemented a grid search hyperplane parameter optimization technique to improve the performance of the designed models by finding the optimal combination of hyperplane parameter values, including the regularization parameters and kernel options. [4, 12]

Reporting repetition count after each exercise is an important feedback for the patient. A best suitable axis from the accelerometer or gyroscope sensor is selected for this purpose and a Savitzky - Golay filter [15] of order 4 with a 2 second window is used for smoothing the data. Two algorithms are tested: one using peak-to-peak (**PP**) detection and another using threshold crossing (**ThC**). A threshold value of 75% of the difference between max and min peaks is used. Results obtained for Bicep Curl is shown in Fig. 8. The algorithms are studied on all upper body LME exercises. A similar approach will be used subsequently for lower body LME exercises.

## 4 Results

The study involves fifteen LME exercises (Table 1), with six participants and 30 seconds of segmented and annotated data. We developed a python script to

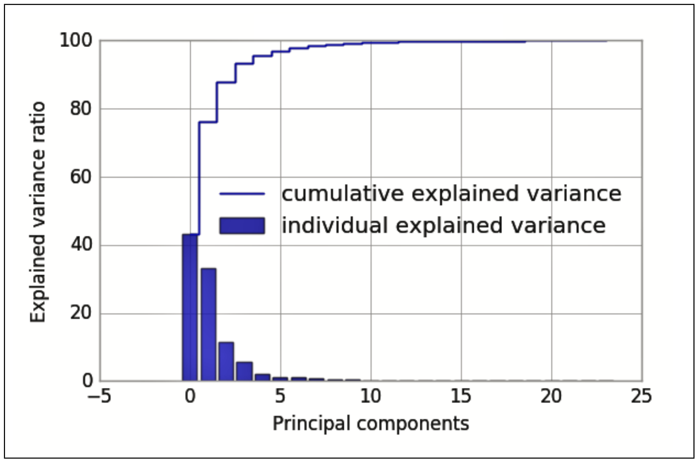


**Fig. 5.** Plot of principle components vs explained variance ratio and plot of cumulative explained variance for Bicep Curls.

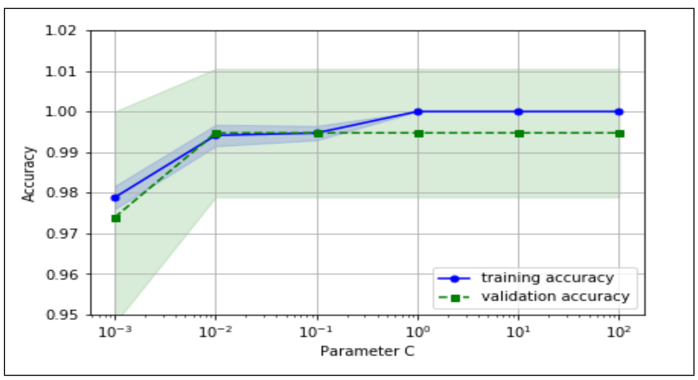


**Fig. 6.** Plot of calculation of C value required to attain desired Accuracy for Bicep Curls.

extract 24 time-frequency features per a single window of 4 seconds duration for each exercise from each participant. PCA is performed on the training data set and 10 principle components which explain the variance of more than 98% are retained from the 24 features. A plot of principle components with descending significance and cumulative variance ratio is shown in Fig. 5. A grid search algorithm is used to find the optimum hyperplane parameters such as gamma, C and the kernel to be used with SVM for each exercise. The low C parameter value indicates the smooth decision surface. Both gamma and C parameters are usually well within the range of $10^{-3}$ to $10^{3}$. The cross-validation curve is shown in Fig. 6. The gamma parameter in SVM represents the influence of a single training example with values varying from low, indicating far reach, to high, indicating close reach. The number of training samples required to attain

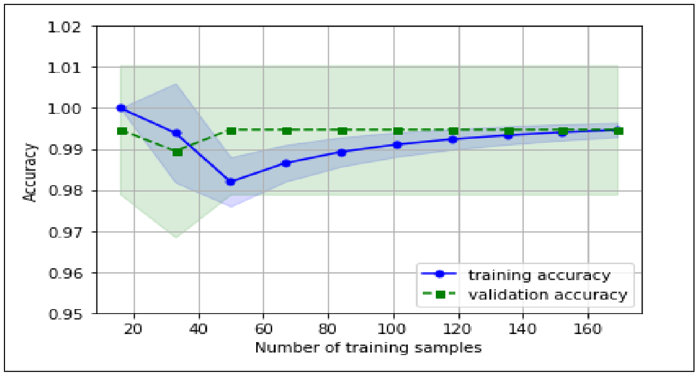


**Fig. 7.** Plot of number of training samples vs Accuracy for the Bicep Curls exercise.

accuracy of $\geq 98\%$ is shown in Fig. 7 for the Bicep Curls. From Fig. 7, it can be seen that with a total number of approximate 100 samples, validation accuracy is close to the training accuracy.

The gray shade surrounding the learning curves indicate the tolerance level (mean  stdev) in Fig. 6 and Fig. 7. From these plots, it is evident that validation accuracy almost matches the training accuracy, indicating our model is not suffering from overfitting. It also illustrates that the number of subjects used in this study is sufficient. The optimum hyperplane parameters and the type of kernel are selected using a grid search algorithm for the SVM model of each exercise (see Table 3). Statistical performance measures of the SVM for recognizing each exercise are listed in Table 4. The proposed framework recognizes LME exercises ( 1) with an overall accuracy $\geq 98\%$.

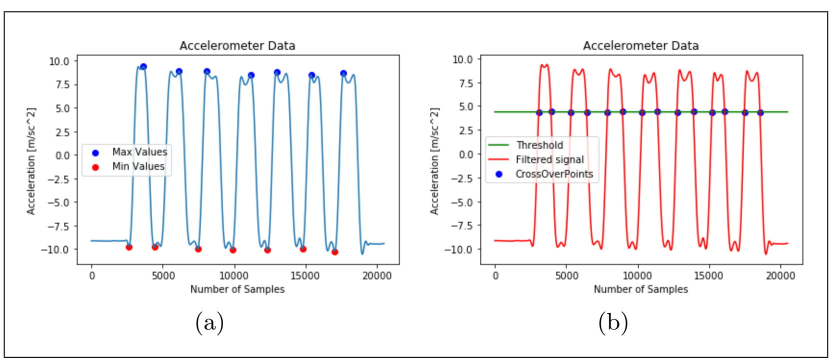


**Fig. 8.** Demonstration of repetition counting for the Bicep Curls: (a) Peak-to-peak method. (b) Threshold Cross method.

**Table 3.** Optimum hyperplane parameter and kernel selection for each LME exercise

| Exercise | Best Score | Gamma Value | C Value | Preferred kernel |
|---|---|---|---|---|
| Ex 1 | 0.9935 | 0.1 | 0.1 | linear |
| Ex 2 | 1.0000 | 0.1 | 1.0 | rbf |
| Ex 3 | 0.9869 | 0.1 | 0.1 | linear |
| Ex 4 | 1.0000 | 0.1 | 1.0 | rbf |
| Ex 5 | 0.9864 | 0.01 | 10.0 | rbf |
| Ex 6 | 0.9935 | 0.01 | 100.0 | rbf |
| Ex 7 | 1.0000 | 0.01 | 100.0 | rbf |
| Ex 8 | 1.0000 | 0.1 | 0.1 | rbf |
| Ex 9 | 1.0000 | 0.1 | 0.01 | linear |
| Ex 10 | 1.0000 | 0.1 | 0.001 | linear |
| Ex 11 | 0.9804 | 0.1 | 10.0 | linear |
| Ex 12 | 1.0000 | 0.1 | 0.001 | linear |
| Ex 13 | 1.0000 | 0.1 | 1.0 | rbf |
| Ex 14 | 0.9935 | 0.1 | 0.01 | linear |
| Ex 15 | 1.0000 | 0.1 | 0.1 | rbf |

**Table 4.** Performance measures for each LME exercise

| Exercise | Precision | Recall | F1 score |
|---|---|---|---|
| Ex 1 | 1.000 | 1.000 | 1.000 |
| Ex 2 | 1.000 | 1.000 | 1.000 |
| Ex 3 | 1.000 | 1.000 | 1.000 |
| Ex 4 | 1.000 | 1.000 | 1.000 |
| Ex 5 | 1.000 | 1.000 | 1.000 |
| Ex 6 | 1.000 | 1.000 | 1.000 |
| Ex 7 | 1.000 | 1.000 | 1.000 |
| Ex 8 | 1.000 | 0.963 | 0.981 |
| Ex 9 | 1.000 | 1.000 | 1.000 |
| Ex 10 | 1.000 | 1.000 | 1.000 |
| Ex 11 | 1.000 | 1.000 | 1.000 |
| Ex 12 | 0.963 | 0.963 | 0.963 |
| Ex 13 | 1.000 | 0.963 | 0.981 |
| Ex 14 | 1.000 | 1.000 | 1.000 |
| Ex 15 | 1.000 | 0.963 | 0.981 |

Fig. 8(a) represents the peak-to-peak method used to count the repetition for bicep curls where the user has performed seven repetitions and the algorithmic count are marked on the graph. A count for repetition is considered when a pair of max and min is calculated. A threshold value of 75% of the max to min difference is computed. A repetition is counted when the threshold value is crossed twice. Fig. 8(b) represents the threshold-cross method used to count the repetitions for the Bicep Curls where the user has performed seven repetitions with a computed threshold of 4.3766 m/sec$^2$. The sensor and axis, and associated method that determines the number of repetition for each upper body LME exercise is listed in Table 5.

**Table 5.** Sensor and Axis, and associated method for correctly determining the number of repetitions

| Exercise | Sensor & Axis that Correctly Identified the Repetition Count | Accurate Method |
|---|---|---|
| Ex 1 | Accelerometer: X - axis<br>Gyroscope: Z - axis | Accelerometer: PP, ThC<br>Gyroscope: ThC |
| Ex 2 | Accelerometer: X - axis | Accelerometer: PP, ThC |
| Ex 3 | Accelerometer: X - axis | Accelerometer: PP, ThC |
| Ex 4 | Accelerometer: X - axis | Accelerometer: PP, ThC |
| Ex 5 | Accelerometer: X - axis<br>Gyroscope: Y - axis | Accelerometer: PP, ThC<br>Gyroscope: PP, ThC |
| Ex 6 | Gyroscope: X - axis | Gyroscope: PP, ThC |
| Ex 7 | Gyroscope: Y - axis | Gyroscope: PP |
| Ex 8 | Accelerometer: Z - axis | Accelerometer: PP |
| Ex 9 | Accelerometer: X - axis | Accelerometer: PP |
| Ex 10 | Accelerometer: X - axis | Accelerometer: PP, ThC |

## 5 Conclusions

In this paper, we described a novel framework, with a wrist worn inertial sensor, capable of automatically segmenting and recognizing whether individual LME exercise that were prescribed for cardiovascular rehabilitation were performed or not. The proposed framework employs optimized SVM training algorithm in conjunction with the selected time-frequency feature extraction technique to effectively recognize the LME exercises with more than 98% accuracy. Using the PCA technique, the dimensionality of the computed feature vectors are reduced while more than 98% of the variance is retained. All hyperplane parameters are tuned and different kernels are investigated to optimize the performance of the training models. The learning curves are also plotted to ensure that the model is not over-fitted. Finally, the number of times each exercise is performed was calculated by detecting the peaks of the signals along with utilizing the pre-defined threshold values.

## 6 Acknowledgement

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## References


1. Davies, Philippa, Fiona Taylor, Andrew Beswick, Frances Wise, Tiffany Moxham, Karen Rees, and Shah Ebrahim. "Promoting patient uptake and adherence in cardiac rehabilitation." Cochrane Database Syst Rev 7, no. 7 (2010).
2. Mitchell, Edmond, Amin Ahmadi, Noel E. O'Connor, Chris Richter, Evan Farrell, Jennifer Kavanagh, and Kieran Moran. "Automatically detecting asymmetric running using time and frequency domain features." In Wearable and Implantable Body Sensor Networks (BSN), 2015 IEEE 12th International Conference on, pp. 1-6. IEEE, 2015.
3. Ahmadi, Amin, Franois Destelle, Luis Unzueta, David S. Monaghan, Maria Teresa Linaza, Kieran Moran, and Noel E. O'Connor. "3D human gait reconstruction and monitoring using body-worn inertial sensors and kinematic modeling." IEEE Sensors Journal 16, no. 24 (2016): 8823-8831.
4. Ahmadi, Amin, Edmond Mitchell, Chris Richter, Francois Destelle, Marc Gowing, Noel E. O'Connor, and Kieran Moran. "Toward automatic activity classification and movement assessment during a sports training session." IEEE Internet of Things Journal 2, no. 1 (2015): 23-32.
5. Bulling, Andreas, Ulf Blanke, and Bernt Schiele. "A tutorial on human activity recognition using body-worn inertial sensors." ACM Computing Surveys (CSUR) 46, no. 3 (2014): 33.
6. Bao, Ling, and Stephen Intille. "Activity recognition from user-annotated acceleration data." Pervasive computing (2004): 1-17.
7. Mortazavi, Bobak Jack, Mohammad Pourhomayoun, Gabriel Alsheikh, Nabil Alshurafa, Sunghoon Ivan Lee, and Majid Sarrafzadeh. "Determining the single best axis for exercise repetition recognition and counting on smartwatches." In Wearable and Implantable Body Sensor Networks (BSN), 2014 11th International Conference on, pp. 33-38. IEEE, 2014.
8. Attal, Ferhat, Samer Mohammed, Mariam Dedabrishvili, Faicel Chamroukhi, Latifa Oukhellou, and Yacine Amirat. "Physical human activity recognition using wearable sensors." Sensors 15, no. 12 (2015): 31314-31338.
9. Zhang, Mi, and Alexander A. Sawchuk. "A feature selection-based framework for human activity recognition using wearable multimodal sensors." In Proceedings of the 6th International Conference on Body Area Networks, pp. 92-98. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), 2011.
10. Smith, Lindsay I. "A tutorial on principal components analysis." Cornell University, USA 51, no. 52 (2002): 65.
11. Preece, Stephen J., John Yannis Goulermas, Laurence PJ Kenney, and David Howard. "A comparison of feature extraction methods for the classification of dynamic activities from accelerometer data." IEEE Transactions on Biomedical Engineering 56, no. 3 (2009): 871-879.
12. Scholkopf, Bernhard, and Alexander J. Smola. Learning with kernels: support vector machines, regularization, optimization, and beyond. MIT press, 2001.
13. Breiman, Leo, Jerome Friedman, Charles J. Stone, and Richard A. Olshen. Classification and regression trees. CRC press, 1984.
14. Bergstra, James, and Yoshua Bengio. "Random search for hyper-parameter optimization." Journal of Machine Learning Research 13, no. Feb (2012): 281-305.
15. Savitzky, Abraham, and Marcel JE Golay. "Smoothing and differentiation of data by simplified least squares procedures." Analytical chemistry 36, no. 8 (1964): 1627-1639.