Daily Activity Recognition Using Wearable Sensors Via Machine Learning and Feature Selection

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***Abstract*—Human activity recognition has been the focus of significant research due to its various applications. Bio-signals acquired by wearable inertial sensors is one type of data that can be used to accomplish that task. Also, machine learning techniques have become a standard pattern discovery tool in such a problem. This has stimulated the construction of many publicly available datasets to learn from, with variations in the number of sensors and activities, among others. The Human Gait Database (HuGaDB) is a state- of-the-art (SOTA) example of such datasets, and is considered the most comprehensive to date.**

In this paper, we incorporate four feature selection techniques along with four different classifiers to attain the highest recognition accuracy. Extensive analysis is first applied to determine the optimal number of features, which is then fed to four different techniques of sequential feature selection. We demonstrate that higher recognition accuracies are achievable with significant reduction in the number of features. We also show that sequential forward floating feature selection with the random forest classifier yields the highest recognition accuracies.

***Index Terms*—Activity recognition, feature selection, machine learning, wearable sensors**

I. Introduction

Recognizing human activities using inertial sensors located on the body has been extensively studied in the literature [1]. This is due to the diverse applications and technologies that can benefit from such information, such as remote healthcare monitoring, tele-medicine, and tracker devices for sportive motion [2]. Throughout the past few decades, machine learning techniques have been at the heart of bio-signal recognition and analysis, thanks to their ability to discover patterns and learn mappings effectively. Along the same lines, there has been significant research work that aims at constructing and labeling datasets that are sufficient to learn from. Numerous datasets are publicly available. The main aspects of variation among those datasets are: 1) the number of activities considered during the acquisition process of the bio-signals, 2) the characteristics of the sensors that are used to acquire the bio-signals, e.g., their type, position, number, and the sensor placement (x, y, and z) [3].

The Human Gait Database (HuGaDB) [4] is one of the most recent datasets in the literature, features the following advantages with regards to the problem of action recognition from inertial wearable sensors:

1) The dataset has covered the largest number of actions in the literature–twelve actions. These actions are diverse in the sense that they include both static and dynamic activities.
2) In HuGaDB, the signals from an accelerometer, a gyroscope, and an Electromyography (EMG) sensors are acquired from the thigh, shin, and foot of the right and left legs. Given that three placements are used for each type of sensor, this results in the acquisition of a total of fifty-four signals (eighteen signals from each of the three types of sensors).
3) Compared to previous datasets, HuGaDB features an unprecedented amount of details in the human gait including segmented annotations which help study the transition between different activities. The data was gathered from 18 healthy, young, adult participants.

The aforementioned characteristics–of the dataset–provide a rich source of information to learn mathematical models, which consequently benefits the accuracy of recognition.

In this paper, we employ four feature selection techniques along with four different classifiers on the HuGaDB. Fusion of differnt information aquired from different sensor types and locations, and its impact on the level of accuracy is investigated via applying classification and feature selection techniques. Using feature selection leads to fewer model parameters. It also enhances the action detection capability and reduces the computational complexity and time. We further show that, using optimal feature selection, higher recognition accuracies can be attained with an average of half the number of features that were originally acquired. We adopt several Sequential Feature Selection techniques, namely, Sequential Forward Selection (SFS), Sequential Backward Selection (SBS), Sequential Forward Floating Selection (SFFS), and Sequential Backward Floating Selection (SBFS). We also determine the optimal number of features, and then apply machine learning algorithms to the best sensor position and placement. In particular, we apply four classification techniques, namely, random forest (RF), k-nearest neighbors (k-NN), support vector machines (SVM), and decision trees (DT), and we present a comparison of their performance. It is worth mentioning that there are alternatives for the adopted methods in the literature of feature selection, such as ensemble feature selection. Meanwhile, our focus was not on finding the best feature selection method, but to investigate the impact of using feature selection compared to the results in [5].

The main goal of the proposed method is to reduce the number of sensors, axes, and features without compromising accuracy. Hence, the system speed and the classification performance increase while the training and inference time decrease. Figure 1 depicts the pipeline of the proposed method. Data collected from different positions, sensors, and activities passes through a pre-processing step where normalization and feature extraction take place. Afterwards, the best sensor position and placement are determined. Finally, the optimal number of features is computed and the same steps–of the previous stage-are repeated after incorporating sequential feature selection.

The rest of the paper is organized as follows. Section II presents the related work in the literature. Section III describes the dataset used in this research and explains the proposed method. Results and discussion are given in Section IV. We conclude the work in Section V.

II. Related Work

The literature of activity recognition from wearable sensors is enormous. Proposed methods in this field have focused on quantifying the impact of a variety of aspects on the detection and classification accuracies of actions. These aspects include the types of wearable sensors, the number of sensors and their placement, the features extracted from the signal, the number of subjects, and the number of studied activities. Accelerometers, gyroscopes, and magnetometers are among the commonly used wearable sensors for activity recognition. Accelerometers measure linear acceleration, while gyroscopes have been proposed in the literature to be used in combination with the accelerometer to overcome the angular velocity rotations problem. The accelerometer-gyroscope combination has proved effectiveness in identifying activities that involve joint rotation. This work studies different placements/positions of accelerometer and gyroscope on both legs. In the following lines, we highlight some of the most recent techniques in the literature, that are the most relevant to the scope of the proposed research.

In [6], the data was collected from a gyroscope and an accelerometer located on the waist amid performing six different activities. K-Nearest Neighbors (kNN), Artificial Neural Network Multi-layer Perceptron (MLP), Support Vector Machines (SVM), Bayes classifier, Minimal Learning Machine (MLM), and Minimal Learning Machine with Nearest Neighbors (MLM-NN) were used for action classification. The dimension of the signals applied on the aforementioned classifiers was first reduced using Principal Component Analysis (PCA) as one possible and a classical technique for feature selection. In [7], six body movements were collected using an accelerometer from a smartphone. Decision Tree (DT), Random Forest (RF), Bagging, and Adaboost classifiers were used. The Fast Correlation-based Filter and the Relief-F feature selection methods were applied to the signal.

In [8], a three-axis accelerometer and a two-axis gyroscope were adopted for data gathering, and placed on seven different body positions. Ten activities were performed and Baeysian classification was used for action classification. Important features were selected by solving a sparse representation $L1$ minimization problem. The authors of [9] incorporated a RF classifier on five different activities. A wearable accelerometer was placed on the chest, and the selected features were the root mean squared value and the mean value of max and min sums. Finally, in [10], eleven features were extracted from an accelerometer on the waist, and the signals were collected for six activities. K-NN and Naive Bayes were used to classify the activities. For feature selection, the Relief-F and the sequential forward floating selection methods were used.

III. Dataset and Feature Construction

A. Dataset Description and Preprocessing

This research adopts the HuGaDB (Human Gait Database) [4] as the dataset for learning and inference. It involves twelve different action classes. The data was collected from four females and fourteen males using three different wearable sensors (accelerometer, gyroscope, and EMG) placed on three different positions on each leg (shin, thigh, and foot). As a preprocessing step, the mean of the data is shifted to zero and the variance is normalized, i.e., the data has unit variance.

B. Feature Extraction

In our work, we extract fourteen different features, namely, mean, variance, standard deviation, minimum, maximum, standard deviation auto-correlation, mean auto-covariance, skewness, mean crossing rate, standard deviation auto-covariance, mean auto-correlation, standard deviation auto-covariance, kurtosis, and jitter. Table Ishows the definitions of some of the adopted features. We adopt a fixed-width sliding window technique with 100 samples and 50% overlap [11]. The fourteen features are computed for the signals acquired from the x, y and z axes. The magnitude of the readings of each accelerometer and gyroscope is also considered in our experiments as will be discussed in Section IV.

C. Feature Selection

Feature selection in general is used for dimensionality reduction. We used four variants of the Sequential feature algorithms (SFAs), namely, Sequential Forward Selection (SFS), Sequential Backward Selection (SBS), Sequential Forward Floating Selection (SFFS), and Sequential Backward Floating Selection (SBFS). The first one (SFS) is a simple greedy algorithm in which we start from an empty set. Iteratively, we select the next best feature that maximizes a particular cost function–the recognition accuracy in our case–when combined with the set of already selected features. In SBS, we start from the set containing all features and eliminate features sequentially in order to maximize the cost function.

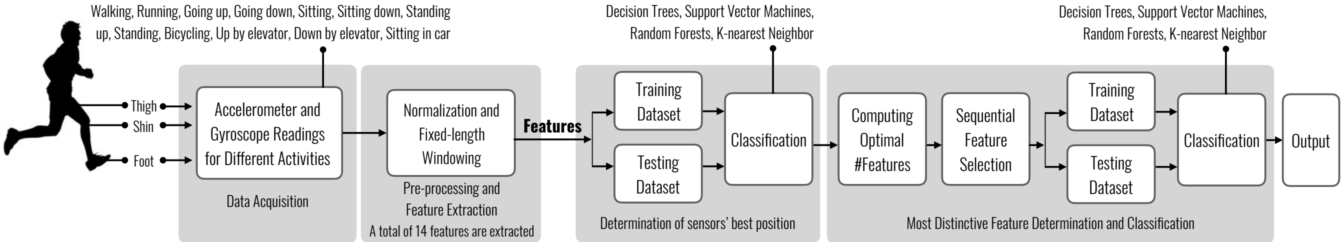

Fig. 1: The architecture of the system adopted in the proposed research.

TABLE I: Definition of some of the statistical features adopted in the proposed research

Feature	Description	Feature	Description
Standard Deviation Auto-correlation	Deviation of the resemblance between a given time series and its lagged version	Standard Deviation Auto-covariance	Deviation of a measure of how much two random variables vary from each other
Mean Auto-covariance	Mean value of how two random variables vary from each other	Mean Auto-correlation	The mean value of the resemblance between a given time series and its lagged version
Skewness	Degree of asymmetry of each signal	Kurtosis	degree of spikiness of each signal
Mean Crossing Rate	The sum of signal changes from the above average to the below average and vice versa	Jitter	Different between previous and next reading

The floating variants, SBFS and SFFS, are extensions to the simple forms SFS and SBS algorithms. The only addition is that the floating algorithm has an added exclusion or inclusion step to extract features once they have been included (or excluded), so that a wider number of features subset combinations can be tested. This research explores the potential of feature selection algorithms in improving the recognition performance. This is done by selecting the group of most-indicative features that reflect and relate the most to the problem. SFS-based algorithms are used in many applications for their simplicity and accuracy [12].

D. *Machine learning methods*

We adopt the follwing set of machine learning techniques to recognize the patterns from the extracted data [13]:

1) Random Forest (RF): works by creating multitudes and outputting classes from decision trees at training time with reference to mode of each class.
2) K-Nearest Neighbors (k-NN): is a non-parametric algorithm used for regression and classification.
3) Support Vector Machine (SVM): undergoes identification by locating the hyper-plane that maximizes the margins between different data classes.
4) Decision tree (DT): has the ability to predict target values by applying simple decision borderlines from the data features.

IV. Results and Discussion

A. *Optimal sensor placement*

For determining the best sensor placement for the gyroscope and the accelerometer, six-different algorithms were applied on the data corresponding to each of the three sensor placements in addition to the data corresponding to their magnitude. We refer to the latter as '*mag*' in the rest of this document. Two sensors are placed in three different places on each leg; hence, we end up with 24 attributes per leg, which yields a total of 48 attributes. The abbreviations lf, ls, lt and mag refer to the three different locations of the sensors and their magnitude [lf-left foot, ls-left shin, lt-left thigh, mag-magnitude]. The results demonstrated that the attributes with the higher accuracy were the x-axis of the left thigh in the accelerometer sensor and the y-axis of the left thigh of the gyroscope sensor with accuracy of 90.7% and 86.80%, respectively. Hence, the following discussion focuses on these particular attributes. A comparison of the results obtained by the various adopted machine learning algorithms is shown in the first two rows of Table II.

B. *Optimal Number of Features*

We determine the optimal number of features by using cross-validation with SFS to score different feature subsets and select the highest scoring group of features. The curve in Fig. 2 shows an example of that on the y-axis of the gyroscope sensor. It is shown that the curve reaches the optimum accuracy (performance) when the optimal number of features are captured. This takes place when $N = 8$, where the variability in the performance is minimum, followed by a gradual decline in the accuracy. We argue that this decline is due to adding the non-informative features to the model learning process. The sky-blue shaded area (surrounding the blue curve) shows the variability of cross-validation, one standard-deviation above and below the accuracy score shown in the curve.

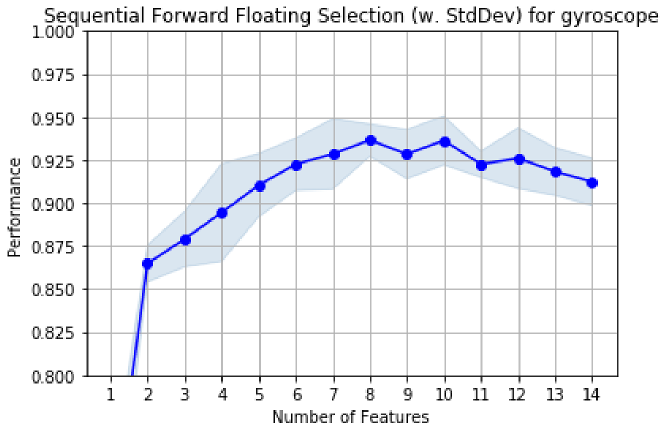

Fig. 2: The relation between performance and number of features for the gyroscope y-axis .

TABLE II: Action recognition accuracies using all features

Sensor Type/Position	*DT*	*SVM*	*RF*	*KNN*	*Features*
Acc_lt_x	*88.1%*	*89.4%*	*90.7%*	*79.1%*	*14*
Gyro_lt_y	*85.8%*	*83.9%*	*86.8%*	*66.9%*	*14*
Acc_lt_x,Gyro_lt_y	*90%*	*89.4%*	*94.7%*	*71.5%*	*28*
Acc_lt_x,y,z,mag	*92.03%*	*93.6%*	*95%*	*83.9%*	*56*
Gyro_lt_x,y,z,mag	*87.9%*	*88.6%*	*92.5%*	*81.2%*	*56*
Acc,Gyro_lt_x,y,z,mag	*95.1%*	*95.4%*	*96.8%*	*84.8%*	*112*

C. Comparison Between All and Selected Features

After selecting the optimal N features for each best position, a comparison is made between all features and 4 types of feature selection (SFS, SBS, SFFS, and SBFS), using four machine learning algorithms (SVM, RF, K-NN, and DT). This comparison is applied on each best axis individually, namely, x-axis of the accelerometer on the left thigh and y-axis of the gyroscope on the left thigh. Afterwards, this comparison is made with the signals of these best single axes combined/concatenated together. The same simulation will be repeated on the concatenation of all parameters (x-, y-, z-axes and magnitude) once for accelerometer sensor on the left thigh, then for gyroscope also on the left thigh. Finally we added the combination of both parameters to our comparison.

D. Discussion

Table II shows the classification accuracies achieved by different classifiers on the following sensor placements: x-axis of accelerometer(Acc-lt-x) on the left thigh and y-axis of gyroscope(Gyro-lt-y) on the left thigh, and their combination that is denoted by (Acc-lt-x, Gyro-lt-y). It also shows the classification accuracies that corresponds to signals acquired from the x, y, z axes and their magnitude. The number of features used in each try is shown in the last column. In our experiments, the best accuracy was achieved with Random Forest classifier, the combination of best single axes achieved 94.7% with 28 features, and 96.8% for all parameters combination with 112 features. In Table III, sequential forward floating feature selection has been shown to outperform other

TABLE III: Action recognition accuracies using Sequential forward floating feature selection

Sensor Type/Position	*DT*	*SVM*	*RF*	*KNN*	*Features*
Acc_lt_x	*89.8%*	*91.5%*	*91.67%*	*82%*	*7*
Gyro_lt_y	*88.1%*	*85.2%*	*88.7%*	*87.8%*	*8*
Acc_lt_x,Gyro_lt_y	*91.6%*	*91.2%*	*96.9%*	*75%*	*15*
Acc_lt_x,y,z,mag	*94.2%*	*95.1%*	*96.2%*	*85.1%*	*23*
Gyro_lt_x,y,z,mag	*89%*	*90.1%*	*94.4%*	*82.9%*	*26*
Acc,Gyro_lt_x,y,z,mag	*96.4%*	*97%*	*98.4%*	*86.3%*	*37*

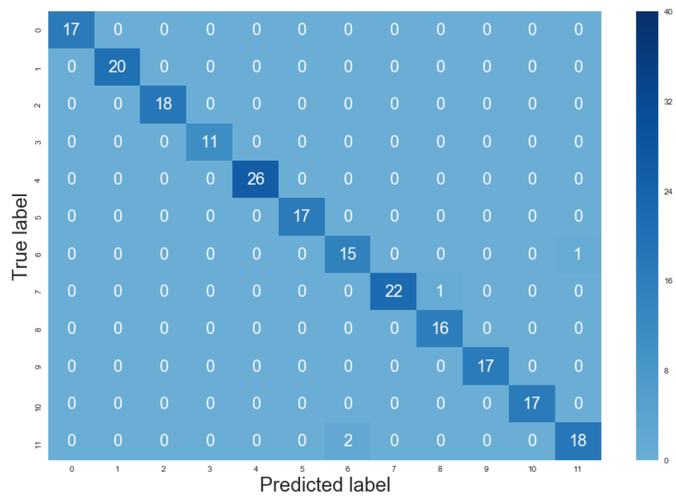

Fig. 3: The confusion matrix corresponding to the RF classifier, after feature selection, applied on the left thigh after merging the data of the accelerometer and the gyroscope.

feature selection types. It is clear from the table that the classification accuracy achieved with feature selection is better than that with all features by 96.9% and only 15 features for single axis, and 98.4% with only 37 features for all parameters selected. Fig. 3 shows the confusion matrix corresponding to the RF classifier, after feature selection, applied on the left thigh after merging the data of the accelerometer and the gyroscope.

V. CONCLUSION

This research is concerned with the activity recognition problem through a triaxial accelerometer and triaxial gyroscope worn on the thigh, shin, and foot on both legs. Our main goal is to build a system that is able to achieve high recognition accuracies with minimum input parameters. Towards that goal, we considered a comprehensive dataset, and were able to determine the best combination of sensor placement-classifier, in terms of recognition accuracy, that is the x-axis of accelerometer on the left thigh, and the y-axis of gyroscope on the left thigh, using RF classifier. We further improved the aforementioned results by adopting feature selection techniques. We carried out extensive analysis to determine the optimal number of N features. Afterwards, we evaluated four different techniques of sequential feature selection. The results obtained from the proposed pipeline showed that sequential forward floating feature selection with the random forest classifier yields the highest recognition accuracies. We also showed that we could achieve higher recognition accuracies, with 100% reduction (two times) on average in the number of features.

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