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Physical Human Activity Recognition Using Wearable Sensors

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Abstract: The present paper deals with the classification of physical daily living human activities using wearable inertial sensors. The whole process of activity recognition is described starting from sensors' placement, followed by data pre-processing and ending with data classification. Human activity recognition is done using three inertial sensor units worn by healthy subjects at key points of upper/lower body limbs (chest, right thigh and left ankle). To recognize twelve human activities, four supervised machine learning techniques namely: k-Nearest Neighbors (k-NN), Support Vector Machines (SVM), Supervised Learning Gaussian Mixture Models (SLGMM) and Random Forest (RF) as well as three unsupervised machine learning techniques namely: K-means, Gaussian Mixture Models (GMM) and Hidden Markov Model (HMM), are used and compared in terms of correct classification rate, F-measure, recall and precision. Both raw data and extracted/selected features are considered as classifier inputs. The feature selection is performed using wrapper approach based on random forest algorithm. The results show that the k-NN presents the best performances compared to other algorithms. In the case of unsupervised machine learning techniques, HMM gives the best results.

Keywords: activity recognition; wearable sensors; smart spaces; data classifiers; accelerometers; physical activities.

1. Introduction

In recent years, the percentage of elderly with respect to younger population has shown a considerable increasing. The involvement of this aged population into the active society has gained essential importance in the last decade. The facilitation of elderly people's daily activity lives, improvements of their safety and increased autonomy have become recently a source of interest to the scientific committee. One of the research areas undertaken by researchers regards the human activities recognition using new technologies such as wearable devices that represents sensors that can be worn by human and accessories integrating computer and advanced electronic devices. Understanding and identifying human activities, may help improving healthcare systems by assisting elderly and dependent people. Human activity monitoring and identification have variety of applications. One of the significant application areas is the remote monitoring of elderly people living alone, physical or mentally disabled people and children. Those populations need continuous support to prevent unpredictable accidents such as fall, etc. Wearable health monitoring devices may cover different types of miniature wearable, implantable or in vivo sensors. Biosensors can measure body and skin temperature, heart rate, electrocardiography (ECG), electroencephalography (EEG), electromyogram (EMG). Sensors measuring the heart rate, blood pressure, and temperature are also considered as wearable sensors. Inclinometers and goniometers are other types of wearable sensors that are used to measure upper/lower limbs kinematics [1]**.** Through real-time processing and data transmission, healthcare suppliers will be able to monitor and control unpredictable events that may happen in elderly or handicapped people during everyday living activities [2]. Taking a broad view from above mentioned applications, wearable sensors can be used in various areas where a typical human motion is involved. Remote monitoring system is represented in Figure 1. In this example, elderly individuals in home-based rehabilitation interventions are equipped by mobility assistive devices; motions can be monitored through sensory captured data. Subject's records are transmitted using wireless communication. Emergency service centers are reported about detected falls by alarm messages in order to give non-delay assistance to patients. Wearable sensors cover the physiological and biochemical sensing, as well as motion sensing [3]. Illnesses such as seizures, hypertension, dysthymias, and asthma can be diagnosed and treated by physiological monitoring. Even though there are potentially worthy gains of a remote monitoring system using wearable sensors, still there are big challenges in terms of limitations in technological (for instance batteries) advancements [4]. To make wearable sensors ease of use and comfortable for wearer, continuous reduction in size of these sensors is another challenge to address.

Among wearable sensors, inertial ones have been mainly used for navigation aircraft, ships, land vehicles and robots. Also they are valuable for shock and vibration analysis in the motorized industry. Rapid development of micro electromechanical systems (MEMS) had a great influence on the development of inertial sensors in terms of size, weight and cost reduction [5]. This development worked in favor of the development of inertial body-worn sensors system and their use for studying, understanding and recognizing daily living activities. These sensors are able to collect data of daily living activities under free-living conditions over extended periods of time. Inertial sensor placements on the human body play also an important role in the recognition of daily living activities.

Vision-based system with single or multiple video cameras is another major technique used to recognize home daily living activities. These visual motion-capture systems are suitable when activities are mainly performed in small areas, such as office or house environment. Currently, Microsoft has released the Kinect sensor that contains both RGB and Infra-Red (IR) cameras. Although, this sensor has several advantages such as low cost, depth information and ability to operate anytime, even at night, it has however some disadvantages [6]. Indeed, the Kinect sensor has low performance in natural lighting, which causes shadowing of the points of interest. Inability to record moving objects in a long distance, dependence on surface texturing and occlusion problem in cluttered environment represent other negative aspects of the Kinect. Also, cost of processing and storing images are relatively high compared to wearable sensors. Recently, hybrid solutions based on the use of both wearable sensors and vision-based systems are developed. In this study, activity recognition of physical daily living activities will be limited to the use of inertial wearable sensors. The use of video based systems will not be addressed.

Figure 1. Graphical illustration of a remote health monitoring scheme built on wearable sensors.

In the following, the whole process of activity recognition is described, starting from sensors' placement, followed by data pre-processing and ending with data classification. Performances of different classification algorithms are compared using a real dataset.

In section 2, sensor's placement over the human body is discussed and different combinations are compared in terms of activity recognition classification rates. In section 3 data pre-processing including feature selection and extraction is also discussed. This step has significant importance on the quality of the learned models. Thus, data pre-processing represents preparation of features that later are supposed to be used as inputs into the classifier. Some classification techniques are described in section 4. In the last section human activity recognition is conducted where raw data end features extracted from inertial sensors are used. Well known classifiers in both contexts supervised machine learning (k-Nearest Neighbors (k-NN), Support Vector Machines (SVM), Supervised Learning Gaussian Mixture Models (SLGMM) and Random Rorest (RF)) as well as unsupervised machine learning (K-means, Gaussian Mixture Models (GMM) and Hidden Markov Model (HMM)) are compared in terms of their correct classification rates. Unlike other recent research works [5], [7] done in the same context of this study; in this paper, only acceleration data are used in the classification process and also comparative results of unsupervised machine learning based algorithms are shown and analyzed.

2. Wearable sensors' placement

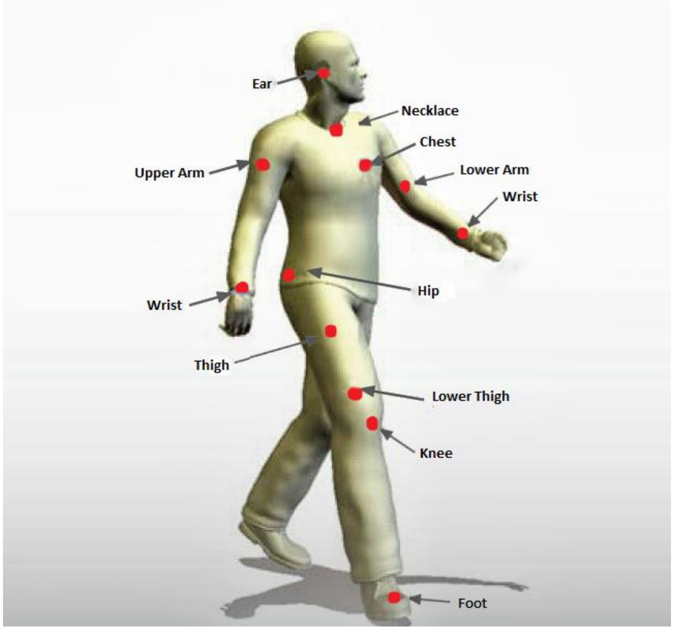
The placement of wearable sensors problem is related to the locations where the sensors are placed and how are attached to those locations. However, the wearable sensors placement has a direct effect on the measurement of bodily motions [8] but the ideal location of the sensor for particular applications is still subject of debate [9]. As shown in Figure 2, wearable sensors can be placed at different parts of the human body. In particular, the sensors are usually placed on the sternum [10], lower back [11], and waist [12]. Waist-placement of the wearable sensors can better represent the most human motion since it is close to the center of mass of the human body [13].

Various studies have combined multiple accelerometers attached at different locations of the body (See Table 1). The majority of these studies highlight that placing many sensors can become weighty for the wearer, leading thus to focus on determining the minimum number of sensors as well as their relevant placement while ensuring an accurate activity recognition. This accuracy indeed decreases with the number of wearable accelerometers. As observed in Table 1, accuracy levels of 83% to 100% for recognition rates have been obtained on human activities [14], [15], [11], [16].

Cleland et al. [9] reported their investigation on everyday activities such as walking, jogging on a motorized treadmill, sitting, lying, standing, stairs ascent and descent. The data were obtained from six sensors placed on different locations on the body (the chest, left hip, left wrist, left thigh, left foot and lower back). The obtained results show that the sensor placed on the hip provides the best measures to recognize most of everyday activities used in their studies.

Other researchers investigated optimal placement of accelerometers for human activities recognition. Gjoreski et al. [17] have studied the optimal location of accelerometers for fall detection. Four accelerometers have been placed at the chest, waist, ankle and thigh. The authors indicate that the best accuracy rate was achieved by combining sensors placed at the chest or the waist and the ankle. Chamroukhi et al. [18] have also evaluated the impact of the number of the sensors and their location on the accuracy of the human activity recognition. The best results have been obtained for configuration with three sensors located at the chest, thigh and ankle. These results demonstrated that the human activity recognition could be significantly improved by combining accelerometers located on both the upper and lower parts of the body.

Figure 2. Graphical illustration of wearable sensors placement.



According to Karantonis [12], Mathie [15], Parkka [14] and Yang [19] data acquired from the sensor placed on the waist gives pertinent informations on many activities such as sitting, standing, walking, lying in various positions, running, stairs ascent and descent, vacuuming and scrubbing. Other accelerometer's placements such as on wrist, chest, hip, lower back, thigh and trunk have also used to identify lying, sitting, walking, running, cycling, working on a computer, etc. [11], [16], [20], [21].

As for recognition of typing, watching TV, drinking, stairs ascent and descent, Pirttikangas et al [22] use wrists, thigh and necklace as relevant placement of sensor on the body.

Table 1. Review of studies on accelerometer placement for human activity recognition.

Reference	**Placement of Accelerometers**	**Detected Activities**	**Average (%) of Classification Accuracy**
Karantonis et al, 2006 [12]	Waist	Walking, Falling	90.8%
Mathie, 2004 [15]	Waist	Falling, Walking, Sitting, Standing, Lying	98.9%
Yang et al, 2008 [19]	Wrist	Walking, Running, Scrubbing, Standing, Working at a PC, Vacuuming, Brushing teeth Sitting	95%
Pirttikangas, 2006 [22]	Thigh, Necklace, Wrists	Typing, Watching TV, Drinking, Stairs Ascent and Descent	91.5%

Parkka, 2006 [14]	Wrist, Chest	Lying, Sitting, Walking, Rowing And Cycling	83.3%
Olguın, 2006 [20]	Wrist, Chest, Hip	Sitting, Running, Walking, Standing, Lying, Crawling	92.13%
Bonomi, 2009 [20]	Lower Back	Lying, Sitting, Standing, Working on a Computer, Walking, Running, Cycling	93%
Yeoh, 2008 [16]	Thigh, Waist	Sitting, Lying, Standing And Walking Speed	100%
Lyons, 2005 [21]	Thigh, Trunk	Sitting, Standing, Lying, Moving	92.25%
Gjoreski, 2011 [17]	Thigh, Waist, Chest, Ankle	Lying, Sitting, Standing, All Fours, Transitional	91%
Chamroukhi, 2013 [18]	Chest, Thigh, Ankle	Stairs Ascent and Descent, Walking, Sitting, Standing Up, Sitting on the Ground	90.3%
Bayat et all, 2014 [23]	pocket, Hand	Slow Walking, Fast Walking, Running, Stairs-Up, Stairs-Down, and Dancing	91.15%
Moncada-Torres, 2014 [24]	Chest, Thigh, Ankle	16 activities of daily living	89.08%
Gupta et all 2014 [25]	Waist	walking, jumping, running, sit-to-stand/stand-to-sit, stand-to-kneel-to-stand, and being stationary	98%
Garcia-Ceja et all, 2014 [26]	Wrist	long-term activities (Shopping, Showering, Dinner, Working, Commuting, Brush Teeth)	98%

Raj et al. [27] classify the human daily activities such as walking, running, stairs ascent/descent, or driving a vehicle using watch with an embedded tri-axial accelerometer. Wrist-worn accelerometer can also be used to estimate sleep duration [28] and activity levels during sleep [29]. Ankle-attached accelerometers are able to efficiently estimate steps, travel distance, velocity and energy expenditure [14] ,[30]. Accelerometers placed at the top of the head have been also used for measuring balance during walking [31].

Sensors attachment to the human body involves fixing sensor directly to skin [10], [32] as well as using straps, pant belts and wristbands [28], [31], [33]. Wearable devices can also be integrated into clothing [34]. In order to avoid relative motion between the human body and the sensors, this latter should be correctly attached to the human body. Otherwise, the vibration or displacement of the wearable systems causes interference signal and thus the measurement accuracy deteriorates.

New technological advancements and the advent of smartphones in our daily lives offer new opportunities for daily living human activities research. Recently, many systems have been proposed to recognize daily living human activities using data acquired from mobile phones [23], [35]. Accelerometer data collected with a wrist-watch was used by Garcia-Ceja et al [26] to segment long-term activity. An overview of studies according to combinations of sensors placement for human activity recognition is given in Table 1.

3. Pre-processing

Data pre-processing is one of the most important step in data mining process. It consists of filtering data, replacing the missing and outlier's values and extracting/selecting features.

To extract features from raw data, windowing techniques are generally used. These techniques consist of dividing sensor signals into small time segments. Segmentation and classification algorithms are then applied respectively to each window. Three types of windowing techniques are usually used: sliding window, where signals are divided into fixed-length windows, event-defined windows, where pre-processing is necessary to locate specific events which are further used to define successive data partitioning and activity-defined windows where data partitioning is based on the detection of activity changes. The sliding window approach is well-suited to real-time applications since it does not require any pre-processing [1].

3.1 Features Computation

Human activity recognition from inertial data is generally preceded by the feature extraction step. Signal characteristics such as time-domain and frequency-domain features are widely used for feature calculation. Time-domain features includes mean, median, variance, skewness, kurtosis, range, etc. Peak frequency, peak power, spectral power on different frequency bands and spectral entropy are generally included in the frequency-domain features. Some of the common time-domain and frequency-domain features used for human activity recognition are presented in the following.

3.1.1. Time-domain features

Mean ($\bar{x}$) denotes the sample mean of data over the sliding window. The mean is generally used in order to pre-process raw data. It allows to remove random spikes and noise from sensor signals. In human activity recognition, mean of accelerometer data is generally used to discriminate different postures. Using the signals of vertical acceleration component, standing and laying postures can be efficiently differentiated.

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{1}$$

With *n* and x_i represent window length and the ith data value respectively.

Variance (s^2) is another important feature used in human activity recognition. It is defined as the signal variance around the sample mean into the window. Variance over window of length *N* can be expressed as follow:

$$s^2 = \frac{1}{N-1}\sum_{i=1}^{N} (\boldsymbol{x_i} - \bar{x})^2 \tag{2}$$

Median ($\tilde{x}$) is the numerical value separating the higher half of a data sample from the lower half. By arranging the sliding window elements *y* in increasing order, the median over window of length *N* can be expressed as follow:

$$\tilde{x} = \begin{cases} y_{\frac{N+1}{2}} & \text{if N is odd} \\ \frac{1}{2}\left(y_{\frac{N}{2}} + y_{N+\frac{1}{2}}\right) & \text{if } N \text{ is even} \end{cases} \tag{3}$$

The range is the difference between the maximum and the minimum sample values over the sliding window. In the case of human activity recognition it is mainly used to discriminate walking from running activity [36].

Bouten et al. [37], applied integral method to offer estimation of energy expenditure using a inertial sensor. The author used the total Integral of Modulus of Accelerations (IMA). This metric is referred to the time integrals of the moduli of accelerometer signals (equation (4)), where a_x, $a_{\boldsymbol{y}}$, $a_{\boldsymbol{z}}$ denote the orthogonoal components of accelerations, *t* denotes time and *N* represents the window length.

$$IMA_{tot} = \int_{t=1}^{N} |a_x|\, dt + \int_{t=0}^{N} |a_y|\, dt + \int_{t=0}^{N} |a_z|\, dt \tag{4}$$

Other time-domain features such as Zero-Crossings Correlation-Coefficient root mean square,...etc are used in [38].

3.1.2. Frequency-domain features

Discrete Fourier Transform (DFT) is used to compute frequency spectrum of the discrete data signal *x*. The DFT is specified as follows [39]:

$$X(f) = \sum_{i=0}^{N-1} x_i\, e^{-j2\pi f i/N} \tag{5}$$

Where X denotes the frequency spectrum, f the f^{th} Fourier coefficient in the frequency domain and N the length of the sliding window.

Equation (5) can be rewritten using complex form as follows:

$$X(f) = \sum_{i=0}^{N-1} a_i + jb_i \tag{6}$$

With $a_i = x_i \cos(\frac{2\pi f i}{N})$ and $b_i = x_i \sin(\frac{2\pi f i}{N})$.

One of the most important frequency-domain feature used for human activity recognition is Power Spectral Density (PSD). This feature has been used by [40] to recognize activities such as walking, cycling, running and driving. PSD can be computed as the squared sum of its spectral coefficients normalized by the length of the sliding window:

$$P(f) = \frac{1}{N} \sum_{i=0}^{N-1} a_i^2 + b_i^2 \tag{7}$$

Peak frequency represents the frequency corresponding to the highest computed power spectrum density over the sliding window. The peak frequency has been used in several studies related to activity recognition [38], [40], [41].

The entropy is another feature that is widely used in human activity recognition [42]. Generally, this feature helps to discriminate between activities that having the same PDS but different patterns of movement [41]. Entropy can be formulated as follows:

$$H(f) = \frac{1}{N} \sum_{i=0}^{N-1} c_i \log(c_i)\,, c_i = \frac{\sqrt{a_i^2 + b_i^2}}{\sum_{k=0}^{N-1} \sqrt{a_i^2 + b_i^2}} \tag{8}$$

The DC component is another important feature also used in human activity recognition [41] . It represents the PDS at frequency $f = 0$ Hz. It can be formulated as the squared sum of its real spectral coefficients normalized by the length of the sliding window:

$$DC = \frac{1}{N} \sum_{i=0}^{N-1} a_i^2 \tag{9}$$

Other frequency-domain features based on wavelet analysis are also used in human activity recognition. For more informations reader is invited to see [38], [43], [44].

3.2. Feature Selection

Feature selection consists of selecting a subset of relevant features from the original feature set [45]. To differentiate between samples, classification algorithms need representative features. The presence of redundant or irrelevant features can reduce the classification performance. Therefore, the so-called "the curse of dimensionality" occurs when the number of input features increases and the performance of classifier decreases. Therefore, the selection of a reduced number of features which have optimal discriminative power between classes has an essential importance in data mining. Feature selection not only allows to improve the classification results but also to reduce the complexity and the computation time of the machine-learning algorithms. The feature selection process is generally defined as a search process to find a relevant subset of features from the original set.

Liu et al. [46] categorize the feature selection algorithms in a three-dimensional framework: a search strategy, which can be complete, sequential or random; an evaluation criterion, which can be categorized as a filter, wrapper or hybrid; and a data mining task, which can be a classification or clustering task [46]. In the literature, several authors categorize the feature selection algorithms into three categories: filter methods [47], [46], wrapper methods [48], [49] and hybrid methods [50], [51]. The filter methods operate directly on the dataset and provide weights or a ranked set of selected features. These approaches exploit the intrinsic properties of the features without involving any classifier because the selection process is independent of the classification process. Unlike the filter methods, the wrapper methods include the classification task that evaluates subsets of variables using their predictive accuracy through, e.g., cross validation of the learning data. These methods often yield better results than the filter methods. Finally, the hybrid methods use the internal parameters of the machine-learning algorithm to select the most relevant subset of features. These methods are nearly similar to the wrapper methods because they combine the selection process with the learning algorithm without any validation step.

For more details of using feature selection methods in human activity recognition problems, related work can be found in [52], [53].

3.3. Feature extraction

Combination of original features is an alternative way of selecting a subset of relevant features. This technique consists of combining the original features set to define a new relevant features set. In other words, feature extraction is the transformation of high-dimensional data into a meaningful representation of reduced dimensionality. The main advantages of feature extraction is that it facilitates classification and visualization of high-dimensional data.

The most popular technique for feature extraction is the principal component analysis (PCA) [54]. PCA is linear technique that consists of transforming the original features generally inter-correlated into new features mutually uncorrelated. These new features are so-called principal components. The main idea behind PCA is to remap the original features into low dimensional space in which the principal components are arranged according to their variance (from largest to lowest). The principal components that contribute to very low variance are omitted.

Linear Discriminant Analysis (LDA) also extracts features through a linear transformation. LDA is closely associated to principal component analysis (PCA) since these two methods try to find linear combinations of variables which best represent the data [55]. LDA method projects the original features points into new space of lower dimension, which maximizes the between-class separability while minimizing their within-class variability unlike PCA does not take into account any difference in classes.

Independent component analysis (ICA) [56] is another feature extraction technique commonly used on non-Gaussian data. This technique was initially developed to provide solution to a problem known as Blind Source Separation (BSS). ICA searches for projections of original features such that the probability distributions of the projected data are statistically independent. The ICA algorithm aims at finding independent components, such as the original features can be expressed as a linear combination of those components.

Another feature extraction method used in data mining is Factors Analysis (FA). In FA method, the original features can be grouped according to their correlation, however, FA represents each group of features that are highly correlated but have small correlations with features in other groups by a factor.

For more details of using feature extraction methods in human activity recognition problem, related works can be found in [57], [58], [59], [60].

4. Classification techniques

The features extracted/selected from the raw sensor data are used as inputs of the classification algorithms. In case of human activity recognition, the patterns of input data are associated to the considered activities (classes). In general, the classification task requires learning a decision rule or a function associating the inputs data to the classes. There are two main directions in machine learning techniques: supervised and unsupervised approaches [56], [61], [62]. Supervised learning approaches for classification such as artificial neural networks [61], Support Vector Machines (SVM) [63], require entirely labeled activity data. The unsupervised learning approaches, such as those based on Gaussian Mixture Models (GMMs), Hidden Markov Models (HMMs) [64] allow to infer automatically the labels from the data.

In the following sections, we briefly describe the classification techniques used in this study (GMMs, k-Nearest Neighbors (k-NN), SVMs, Random Forests (RFs), K-means and HMMs), as well as other techniques that are widely used in human activity recognition such as multilayer perceptron, naive Bayes, hierarchical classification ...

4.1. k-Nearest Neighbors

k-Nearest Neighbors (k-NN) [56], [62] is a supervised classification technique that can be seen as a direct classification method since it does not require a learning process. It just requires the storage of the whole data. To classify a new observation, the K-NN algorithm uses the principle of similarity (distance) between the training set and new observation to classify. The new observation is assigned to the most common class through a majority vote of its k nearest neighbors. The distance of the neighbors of an observation is calculated using a distance measurement so-called similarity function such as Euclidean distance.

Foerster et al. [65] were the first to apply the k-NN classification to discriminate between nine activities using time-domain features obtained from three uni-axial accelerometers. In [66] Foerster and Fahrenberg combine k-NN with a hierarchical decision to scheme to recognize nine activities using frequency-domain features. This approach has proven to be more efficient, in terms of classification accuracy, compared to the k-NN.

Other studies based on k-NN for human activity recognition have also shown a high level of accuracy and satisfactory segmentation results [67], [18].

4.2. Support Vector Machines

Support Vector Machines (SVM), introduced by Vapnik [63], is a classifier derived from statistical learning theory. This known machine learning technique minimizes an empirical risk (as a cost function) and at the same time, maximizes the margin between the so-called separating hyperplane and the data.

In their standard formulation, SVM are linear classifiers. However, non-linear classification can be achieved by extending SVM by using kernels methods [68]. The key idea of kernels methods is to project the data from the original data space to high dimensional pace so-called feature space by using a given non-linear kernel function. A linear separation in the resulting feature space can then be achieved thanks to Cover's theorem [69].

Huynh and Schiele [70] combined SVM and multiple eigen-spaces approach in order to enhance the standard naive Bayes classifier (see section 4.7) with small numbers of training data. Krause et al. [71] considered the recognition of eight common activities using SVM and observed better achievement of frequency-domain features compared to time-domain features.

Doukas and Maglogiannis [72] and Zhang et al.[73], [67] applied SVM techniques to discriminate between falls and other activities. A microphone and tri-axial accelerometer are used to identify falls and two activities: walking and running. The range of recognition rates attains 84-96%.

4.3. Random forests

Random Forests (RF) [74] consists of a combination of decision-trees. It improves the classification performance of a single-tree classifier by combining the **b**ootstrap **agg**regat**ing** (bagging) method and randomization in the selection of partitioning data nodes in the construction of decision tree. The assignment of a new observation vector to a class is based on a majority vote of the different decisions provided by each tree constituting the forest.

In [75], the authors proposed a classification methodology to recognize from acceleration data different class of motions, like driving a car, being in a train, and walking, by comparing different machine learning techniques (Random Forests, SVM and Naive Bayes). The authors show that Random Forest algorithm provides the highest average accuracy outperforming the SVMs and Naive Bayes.

4.4. Gaussian Mixture Models

A Gaussian Mixture Model (GMM) is a probabilistic approach, generally used in an unsupervised classification. Unlike standard probabilistic models based on approximating the data by a single Gaussian component density, GMM uses a weighted sum of finite Gaussian component densities. The parameters of GMM (the proportions, the mean vectors and the covariance matrices of the Gaussian components) are estimated using the expectation-maximization (EM) algorithm [76]. Using constructed features for human activity recognition, it is possible to learn separate GMMs for different activities. The data classification can then be performed by selecting the GMM with the highest posterior probability. The GMM has been applied in several studies for human activity recognition [77], [78].

4.5. K-means

K-means is a well-known unsupervised classification technique that allows to cluster n objects into k classes. K-means clustering minimizes the distortion measure or by equivalence the total intra-cluster variance as cost function [86]. This consists in iteratively finding the clusters centroids, and then assigning the data according to their distance (e.g., Euclidean) to the cluster centroids, until convergence. Regarding the use of the K-means for human activity recognition, the reader can refer to [79] , [80].

4.6. Markov Chains and Hidden Markov Models

A Markov chain represents a discrete time stochastic process covering a finite number of states where the current state depends on the previous one [18]. In the case of human activity recognition, each activity is represented with a state. A Markov chain is well adapted to model sequential data and is often used in a more general model that is the Hidden Markov Model (HMM).

The HMM assumes that the observed sequence is governed by a hidden state (activity) sequence. Once the HMM is trained, the most likely sequence of activities can then be determined using the Viterbi algorithm [81].

Lester et al. [82], [83] use the HMM as a part of a two-stage classification for differentiating between numerous daily activities. The HMM is trained using the posterior probabilities of the decision stump in order to take advantage of the results from the discriminatively trained classifier (decision stump), as well as reduce the complexity of the HMM.

HMMs have also been used as a part of unsupervised learning algorithms for human activity recognition studies [57], [84], [85] , [86] , [87]. In this studies, an HMM with GMM emission densities was developed using the HMM toolbox [88].

The next section provides a brief summary on other useful techniques which have been used for human activity recognition.

4.7 Other classification techniques used in activity recognition

In order to define a given activity, a threshold-based classifier compares different features to a predefined threshold, generally fixed by the user. This approach is sufficient to identify static postures, for instance standing, sitting and lying [89], [90]. Threshold-based classification has been also used to classify postural transitions [10], [91]. However, this classification method is sensitive to the chosen thresholds values.

A number of studies have shown that combing different threshold rules improves fall detection accuracy. For instance, in [92], three threshold-based rules are used for angular velocity, angular acceleration and orientation features. Obtained results demonstrated that falls can be differentiated from everyday activities with 100% accuracy. In [90], authors combined acceleration thresholds with a measure of change in orientation for fall detection.

Another paradigm for human activity recognition is the one of fuzzy logic methods. Fuzzy logic takes its origin from fuzzy sets theory. It shows a big potential for activity classification problems. However, fuzzy logic need employing methods for constructing proper membership functions as well as the combination and the interpretation of fuzzy rules. Besides, only a few studies showed good classification accuracy in fall detection.

The multilayer perceptron (MLP) [93], is an artificial neural networks with multilayer feed-forward architecture and is in general based on non-linear activations for the hidden units. The MLP minimizes the error function between the estimated and the desired network outputs, which represent the class labels in the classification context. Several studies show that a MLP is efficient in non-linear classification problems, including human activity recognition.

Another well-known supervised classification technique, which is a probabilistic approach, is the Naive Bayes classifier. The naive Bayes approach is popular due to its effortlessness and ease of implementation. In tis approached the input features are assumed to be independent. However, conditional likelihood function for each activity can be expressed as the product of simple probability density functions. For human activity recognition, the naïve Bayes approach shows equivalent (similar) accuracy level than other classification methods. The studies presented in [94] and [95] show that sometimes naïve Bayesian approach outperforms the other classification approaches, while in [84] the obtained classification accuracy when using naïve Bayes approach is not high.

Hierarchical classification scheme builds binary decision structure, which consists of numerous consecutive nodes. Relying on the input features, binary decision is made at each node. The discrimination between activities is achieved based on the decision results. Making decisions at each node requires manual supervision and analysis of the training data making this approach very time consuming. Time-domain features are used in [96] to classify four different activities. Each activity is fully recognized (100%) using accelerometers placed on chest, wrist, shank and thigh. Similarly, single collected from accelerometer placed on waist is used in [97] to identify four static and five dynamic activities. In [14] and [98] a threshold-based hierarchical classification scheme is applied to discriminate different dynamic activities. In addition, in [98] the performances of the hierarchical approach are compared to those of other standard classification techniques. In [15] probabilistic methods and signal morphology techniques are combined for making classification decision at each node. The authors show that this approach is sufficient for discriminating between large range of postures, activities and postural transitions. The idea of using an additional node identifying abnormal peaks in the accelerometer signal is performed in [12] for fall detection.

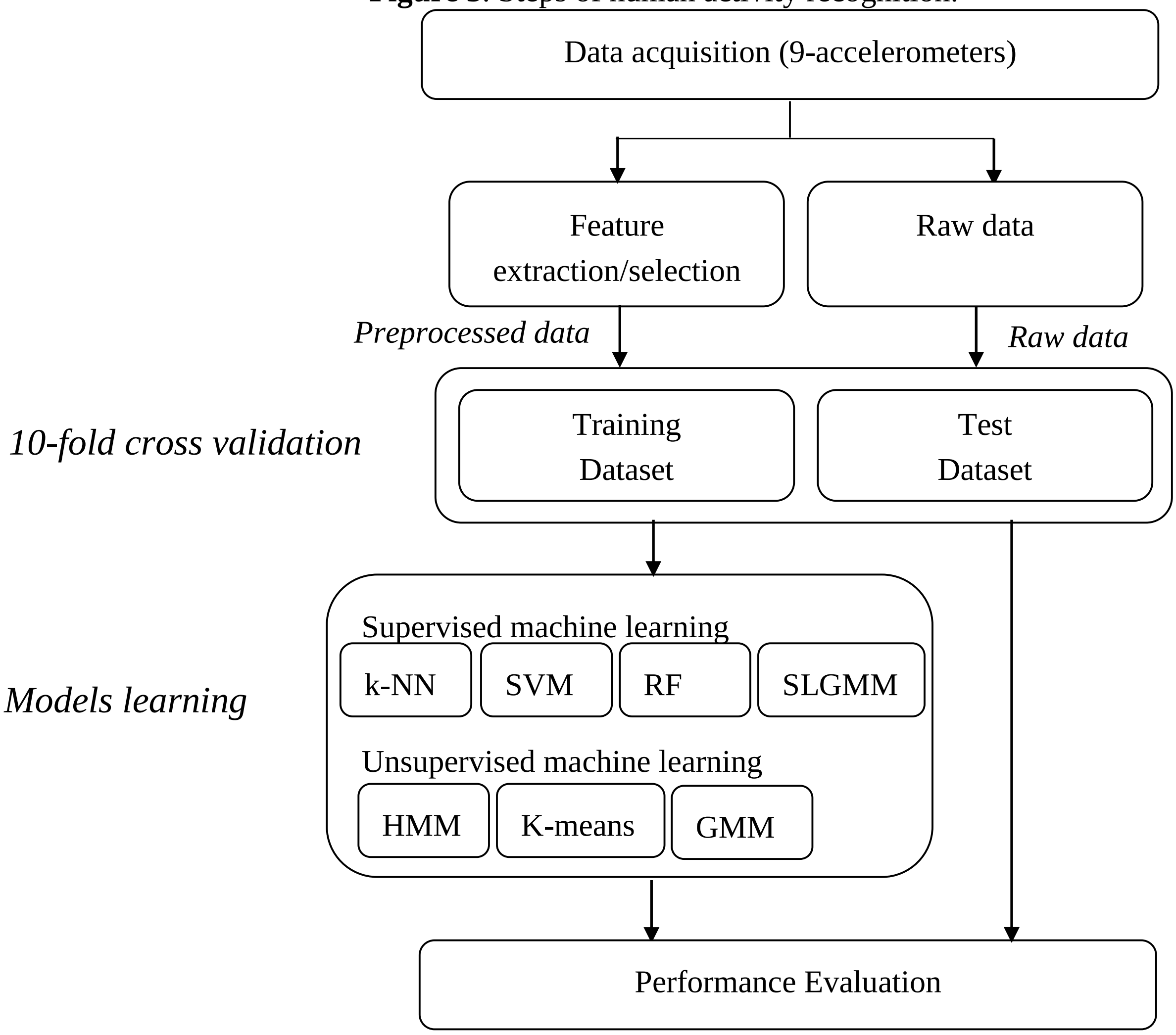
5. Experimental results

In this section we present and discuss the experimental results obtained on a real dataset using standard supervised and unsupervised machine learning approaches. In this comparative study, two cases are considered:

1) using raw data
2) using features extraction and selection.

Figure 3 summarizes the steps of the used methodology.

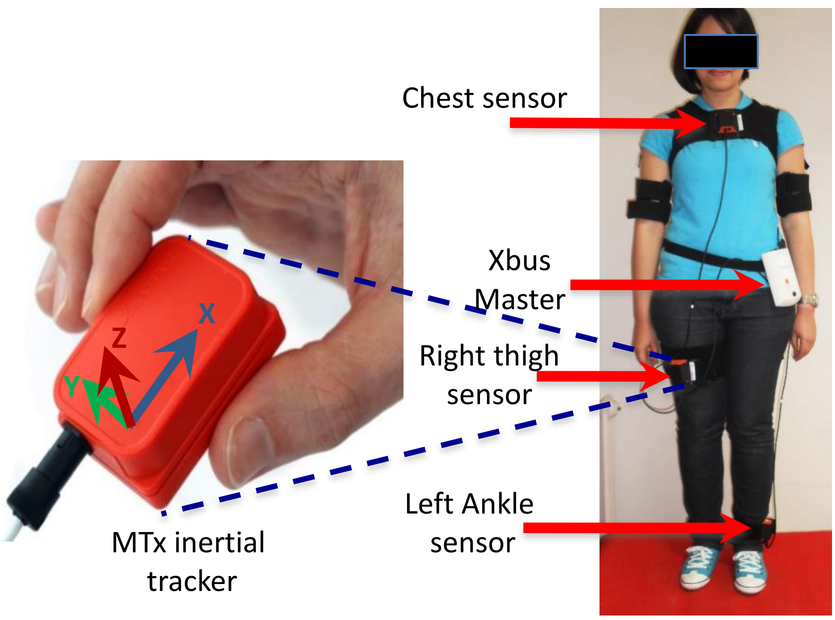
Figure 3. Steps of human activity recognition.



5.1. Data acquisition

In this study, human activities are estimated using three MTx 3-DOF inertial trackers see figure 4. This sensor was developed by Xsens technologies. Each MTx unit is equipped with a tri-axial accelerometer measuring the acceleration in the 3-d space. The sensor placement is achieved to ensure capturing all dynamic changes when performing daily physical activities while optimizing the number of sensors. The choice of sensor placement results from a tradeoff between the number of sensors to be used and their key locations on the human body. In this study, the sensors are placed at the chest, the right thigh and the left ankle as shown in Figure 4. In addition to these sensors central unit called Xbus Master to which theMTx unit are connected is placed at the belt level of subject. This central unit ensures the acquisition and the recording of raw data coming from the inertial units through via a wired link and transfers the acquired data to a computer via Bluetooth wireless link. This sampling frequency of this system is 25 Hz which is sufficient to measure the daily physical human activities [37]. For more details about the experiment the reader is invited to see [18].

Figure 4. MTx-Xbus inertial tracker and sensors placement.



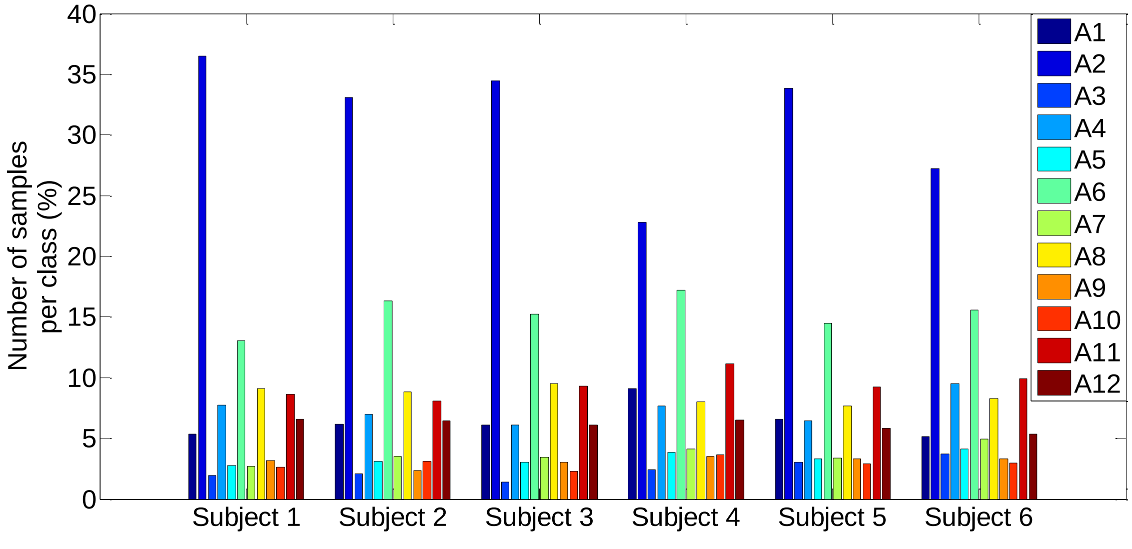
Data are collected at the LISSI Lab/University of Paris-Est Creteil (UPEC). Six healthy subjects with different profiles (mean age: 26 years old, mean weight 65 kg) have participated in the experiments. The subjects are given instructions to perform activities in their usual manner without specific constraints. A total of twelve activities were performed by each subject. The different activities and their descriptions are given in Table 1. The data are manually labeled by an independent operator.

Table 1. Description of the considered activities.

Activity reference	Description
A1	Stair descent
A2	Standing
A3	Sitting down
A4	Sitting
A5	From sitting to sitting on the ground
A6	Sitting on the ground
A7	Lying down
A8	Lying
A9	From lying to sitting on the ground
A10	Standing up
A11	Walking
A12	Stair ascent

The dataset is composed of six sequences where each sequence is performed according to the following sequential activities order: A2 A1 A2 A3 A4 A5 A6 A7 A8 A9 A6 A10 A2 A11 A2 A12. Figure 5 shows the number of samples in each class (each activity corresponds to a class) for each sequence. We can notice that the different classes are not equidistributed. The transition activities A3, A5, A7, A9, A6 and A10 are weakly represented, compared to other activities. In can also be noticed that the majority of sequences are composed of standing activity (about 32% of all dataset).

Figure 5. Representation of the number of samples in each class for each sequence



In this study, two approaches of machine leaning (supervised and unsupervised machine leaning techniques) are used in order to recognize twelve human activities. Four supervised machines learning techniques namely: k-NN, SVM, SLGMM and RF and three unsupervised machine learning techniques namely: K-means, GMM and HMM are compared in terms of performances of human activity recognition. Two cases are considered in terms of input data:

- Raw dataset
- Feature set extracted/selected from raw data.

5.2. Classifier parameters tuning

The hyper-parameters for each algorithm are set as follows.

5.2.1. Supervised machine learning techniques

• In this study LIBSVM toolbox [99] is used to implement a nonlinear SVM model with a radial basis function kernel. The hyper-parameters C and γ are estimated using a grid search method. The optimal values are C = 2 and γ = -5.

• In the case of the RFs algorithm, the only parameter to tune is the number of tree is adjusted by varying the number of trees from to 1 to 100 and determining the one providing the best accuracy rate. The best number of trees is 20.

• For the SLGMMs, a mixture of 12 diagonal Gaussians is used. The mean and covariance matrix for each Gaussian is estimated during the training phase.

• For the k-NN method, since the best choice of k depends on the data, the optimal value of k is obtained by varying k from 1 to 20. The best accuracy is obtained for k = 1.

5.2.2. Unsupervised machine learning techniques

• In this study, HMM with GMM emission probabilities is developed using the HMM toolbox [88]. However, two hyper-parameters are tuned: the number of states and the number of mixtures. First, as we have twelve activities to recognize, the number of state is set to be 12 with ergodic topology. Then, number of mixtures are varied from 1 to 4. Based on the best accuracy rate, the states are modeled with a mixture of 2 diagonal Gaussians.

• In the case of the K-means algorithm, the only parameter to estimate is the number of cluster which correspond to the number of activities (k=12).

• In the case of the GMM algorithm, as in the case of the K-means algorithm, the only parameter to estimate is the number of mixture which correspond to the number of activities. A mixture of 12 diagonal Gaussians is used.

The dataset were divided into a training set and a test set according to a 10-fold cross validation procedure. For the supervised approaches, the classifiers are trained in a supervised way. In the test step, the class labels obtained for the test data are compared to the ground truth and the classification error rates are computed. In the case of the unsupervised approaches, the models are trained in an unsupervised way from only the raw data. The class labels are not considered in the training process, but are only used to evaluate the classification performances. In the test step, since the approaches act in an unsupervised way, the class labels obtained for the test set are matched to the true labels (ground truth) by evaluating all the possible matchings; the matching providing the minimum classification error rate is selected [18].

5.3. Evaluation

To evaluate the classifiers performances, the accuracy measure is used. This metric, commonly used in machine learning algorithms measures the proportion of correctly classified examples. In a binary classification problem, the accuracy is defined as follows:

$$\text{Accuracy} = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \tag{10}$$

where T_p (true positives), T_n (true negatives) represent the correct classifications of positive examples and negative examples, respectively. F_p (false positives) represent the incorrect classification of negative examples class into the positive class; and F_n (false negatives) are the positive examples incorrectly classified into the negative class.

Using accuracy as a performance measure assumes that the data are balanced between classes. In unbalanced datasets, accuracy is particularly highly biased to favor the majority class. Regarding the dataset used in this study, class frequencies are not well balanced since the number of samples of transitions activities are too small compared to the number of samples of others activities see (Figure 5). Thus the following evaluation criterions are consider: the average of the accuracy rate (R) and its standard deviation (std), F-measure, recall and precision as classifier evaluation criteria.

The F-measure is defined as the combination of two criteria, the precision and the recall which are defined as follows:

$$\text{precision} = \frac{T_p}{T_p + F_p} \tag{11}$$

$$\text{recall} = \frac{T_p}{T_p + F_n} \tag{12}$$

The F-measure is calculated as follows:

$$\text{F\_measure} = \frac{(1 + \beta^2).\,\text{recall}.\,\text{precision}}{\beta^2\ \text{recall} + \text{precision}} \tag{13}$$

Where β is a weighting factor that controls the degree of importance of recall/precision. This parameter is positive real number. In this study to β is set to 1 to give the same importance to recall and precision.

5.4. Results and discussion

5.4.1. Case 1: raw data

The results obtained in the case of raw data are given in Table 3 and Table 4. Table 3 summarizes the performances obtained with the supervised approaches. It can be observed that the correct classification rates obtained with different techniques are higher than 84%. k-NN algorithm gives the best results in terms of global correct classification rate and its standard derivation, F-measure, recall, and precision followed by RF then SVM and at last the SLGMM algorithm gives the worst results.

Table 4 summarizes the obtained results with the different unsupervised learning approaches. Compared the unsupervised classifiers K-means and GMM, the HMM approach gives the best results in terms of global correct classification rate and its standard derivation, F-measure, recall, and precision. These results can be explained by the fact that the HMM approach takes into account the temporal aspect of the data used in this study.

Table 3 and Table 4 show that supervised approaches outperform unsupervised approaches. However, unsupervised approaches show very encouraging results mainly in the case of HMM. Since these performances are obtained without any labeling which is time consuming.

Table 3. Performances of the supervised algorithms using raw data.

	Accuracy ± std	F-measure	Recall	Precision
k-NN (%)	**96.53±0.20**	**94.60**	**94.57**	**94.62**
RF (%)	94.89±0.57	82.87	82.28	83.46
SVM (%)	94.22±0.28	90.66	90.98	90.33
SLGMM (%)	84.54±0.30	69.94	69.99	69.88

Table 4. Performances of the unsupervised algorithms using raw data.

	Accuracy ± std	F-measure	Recall	precision
HMM (%)	**80.00±2.10**	**66.67**	**65.02**	**66.15**
K-means (%)	68.42±5.05	49.89	48.67	48.55
GMM (%)	73.60±2.32	57.68	57.54	58.82

5.4.2. Case 2: features extraction and selected

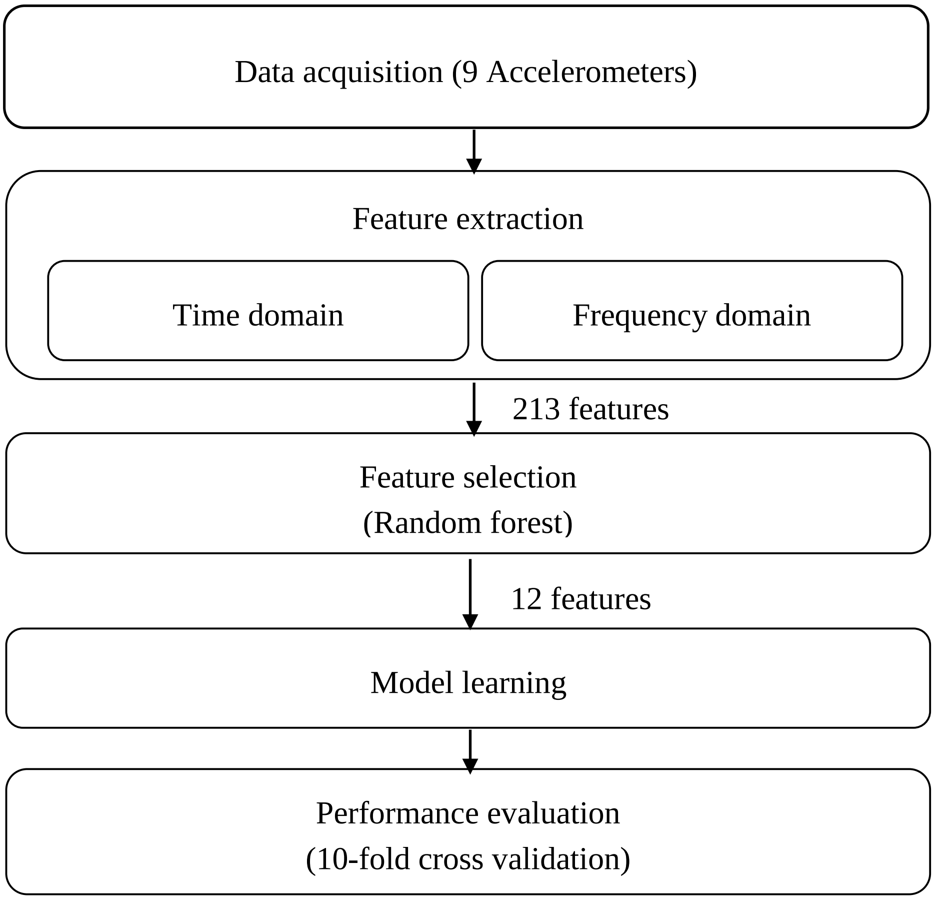
In order to improve the results presented above a preprocessing step consisting of features extraction and selection is performed. Nine accelerometrics signals are acquired from three MTX and for each signal the following time and frequency domain features are calculated:

- Eleven time-domain features are extracted, namely: mean, variance, median, interquartile rang, skewedness, kurtosis, root mean square, zero crossing, peak to peak, crest factor and rang.
- Six frequency-domain features are extracted, namely: DC component in FFT spectrum, energy spectrum, entropy spectrum, sum of details coefficient of wavelets, sum of squared details coefficients of wavelets, energy of detail wavelets coefficients and energy of approximation wavelets coefficients.

In addition the correlation coefficients of axis and mean and variance of the norm of each MTX are calculated. Thus, a set of 45 correlation coefficients, 6 mean and variance of the norm of each MTX are calculated.

A total of 213 (9*11+9*7+45+6) characteristics are calculated for each sliding window of size of 25 samples (1 second) with 80% of overlapping. The choice of the window size aims to ensure the statistical significance of the calculated features. The choice of window overlapping is mainly due to the good characterizing of transition activities which are ephemeral. In our case, the transition activities takes about 2 seconds, thus using windows of 25 samples without overlapping lead to extract features with just 2 samples which are insufficient to characterize these transitions. After the step of feature extraction, a process is performed to find a minimal subset of features that are necessary and sufficient to well characterize the different activities. As described above, finding the best subset among all features is carried out by feature selection procedure. In this study, a wrapper approach based on random forest feature selection algorithm [74] is used to select the best features among the extracted ones. This algorithm reorders features according to their percentage of relevance. A set of 12 features representing more than 80% of relevance are selected as input of classifiers. Figure 6 describes the different steps of activities recognition using selected features.

Figure 6. Steps of activity recognition using features extraction and selection.



The results obtained using the supervised approaches on extracted/selected features are reported in Table 5. The correct classification rates obtained with different techniques are greater than 85%. Similarly to the case of raw data, k-NN algorithm gives the best results in terms of correct classification rate and its standard derivation, F-measure, recall, and precision followed by RF then SVM and at last SLGMM. As shown by these results, a significant improvement for some algorithms can be found (an average improvement of 3% with a slight reduction of std is observed for k-NN and RF). In the case of SVM and SLGMM, a slight improvement about 1% can be observed on the correct rate. Regarding F-measure, recall and precision, an average improvement of 10% and 4% is observed for respectively SVM and SLGMM.

The obtained results using unsupervised machine learning techniques in the case of selected features are reported in Table 6. These results show an improvement in terms of correct rate classification, F-measure, recall and precision. Besides, in the case of HMM, an improvement of 3% of global rate with slight reduction of std (about 0.8%) can be observed while F-measure, recall and precision are increased about 3%. Improvements can be noticed for the GMM. In the case of K-means, it can be observed an improvement of 4.53% and 3.53% of global correct rate classification and recall, respectively with a decrease of 3% of std. A slight improvement about 0.4% and 2.67% can also be observed on F-measure and precision respectively.

Finally, even though improvements in terms of performances are observed when using the selected features as input of different algorithms, the feature extraction/selection step requires implementing additional models and routines, to extract/select optimal features. Furthermore, the feature extraction step requires an additional computational cost which can be penalizing in particular in the perspective of real time applications.

Table 5. Performances of the supervised algorithms using extracted features.

	Accuracy ± std	F-measure	Recall	precision
k-NN (%)	**99.25±0.17**	**98.85**	**98.85**	**98.85**
SVM (%)	95.55±0.30	93.02	93.15	92.90
RF (%)	98.95±0.09	98.27	98.24	98.25
SLGMM (%)	85.05±0.57	73.44	74.44	73.61

Table 6. Perforamnces of the unsupervised algorithms using extracted features.

	Accuracy ± std	F-measure	Recall	precision
HMM (%)	**83.89±1.30**	**69.19**	**68.27**	**67.74**
K-means (%)	72.95±2.80	50.29	52.20	51.22
GMM (%)	75.60±1.25	65.00	66.29	64.30

6. Conclusion

We have presented an overview of different classification techniques, which have been used in the studies of human activity recognition from wearable sensor data. This paper describes the whole structure of recognition detection process (from data acquisition to classification). First, we have dealt the problem of wearable sensor's properties and placement in terms of acquisition of appropriate data for human activity recognition. Next, we have dealt the feature extraction in both domains, time and frequency domain. Then we have discussed the feature computation, the feature selection and feature extraction. After that we have conducted comparison literature review between various supervised and unsupervised learning approaches used for classifying daily physical activities. Finally we have presented a comparative study on the obtained results using well known supervised and unsupervised machines learning approaches (k-Nearest Neighbors, Gaussian Mixture Models in both cases supervised and unsupervised approaches, Support Vector Machines, Random Forest, k means and Hidden Markov Models) on real dataset. Both, raw data and extracted/selected features are used as input of classifiers. The different classification approaches are compared in terms of the recognition of twelve activities (including static, dynamic and transition activities) using data from a three MTx 3-DOF inertial trackers placed at the chest, the right thigh and the left ankle.

We have seen that supervised approaches when using raw data or extracted/selected features are more accurate than unsupervised approaches, yet the latter are more computational efficient and don't require any labels (unsupervised classification techniques are able to directly create models from unlabeled data either by property estimation or discovering similar groups).

The obtained results with the real dataset show the effectiveness of the k-NN approach which gives the best results compared to other methods. RF and SVM give almost the same results slightly better in the case of RF especially when using extracted/selected features. Concerning SLGMM algorithms, it gives lowest results in the case of supervised approaches. In the case of unsupervised approaches, HMM gives the best results, flowed by GMM and K-means. The main advantage of the HMMs approach compared with other techniques is that the statistical model used in the HMMs includes both the sequential aspect and the temporal evolution of the data. Except HMM, Other algorithms treat data as several realizations in the multidimensional space without taking into the consideration possible dependencies between the activities.

We have also seen that the extracted/selected features allow improving the classification accuracy at the expense of computation time which can be penalizing in particular for a perspective of real time applications.

This work can be extended in several directions. The combination of classifiers is quite promising approach. When several classifiers are applied to the same dataset they generate different decision boundaries, by which they are able to display different patterns. Thus, merging the classification techniques can give complementary decisions and advance the accuracy level.

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