Recognition of Human Activities and Falls by Analyzing the Number of Accelerometers and their Body Location

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ABSTRACT

This paper presents an approach to activity recognition and fall detection using wearable accelerometers placed on different locations of the human body. We studied how the location and the number of wearable accelerometers influence on the performance of the recognition of the activities and the falls. The final goal was to build a machine learning model that can correctly recognize the activities and the falls using as few accelerometers as possible. The model was evaluated on a public dataset consisting of more than 850 GB of data, recorded by 17 people. In total we evaluated 15 combinations of four accelerometers placed on the belt, the left ankle, the left wrist and the neck. The results showed that the neck and the ankle accelerometers proved sufficient to correctly recognize all the activities and falls with 94.2% accuracy. Each of the sensors used individually achieved 94.02% and 93.4% accuracy respectively.

KEYWORDS

activity recognition, fall detection, wearable sensors, machine learning

1 INTRODUCTION

According to United Nations World Population Prospects 2019, by 2050, one in six people in the world will be over the age of 65 [1]. As people are getting older, their risk for falls also increases. Falls are a major public health problem in elderly people often causing fatal injuries. It is important to assure that injured people receive assistance as quickly as possible. Because of this, building a good fall detection system is of a big importance to help medicine solve this problem.

The field of Human Activity Recognition (HAR) and fall detection has become one of the trendiest research topics due to availability of low cost, low power consuming sensors, i.e., accelerometers. The recognition of human activities has been approached in two different ways, namely using ambient and wearable sensors [2]. In the former, the sensors are fixed in predetermined points of interest on the body of the subject, so the inference of activities entirely depends on the voluntary interaction of the users with the sensors. In the latter, the sensors are attached to the user.

This paper presents a machine learning approach to activity recognition and fall detection using wearable accelerometers placed on different locations of the human body. The goal of the paper is to study how the location and the number of wearable accelerometers influence on the performance of the recognition of the activities and the falls. This study is of practical importance of such systems, i.e., to build a machine learning model that can correctly recognize the activities and the falls using as few accelerometers as possible.

2 RELATED WORK

A considerable amount of work has been done in human activity recognition for the last decade where a lot of studies aim to identify activities based on data obtained from accelerometers as sensors widely integrated into wearable systems [3][4].

Researchers have reported high accuracy scores in detecting activities when investigating the best placement of the accelerometer on the human body [5][6][7]. Increasing the number of sensors increases the complexity of the classification problem. For these reasons, a number of studies have investigated the use of a single accelerometer. However, doing so generally decreases the number of activities that can be recognized accurately [8]. Consequently, one of the major considerations in activity recognition is the location or combination of locations of the accelerometers that provide the most relevant information.

In [5] the authors study the best location to place accelerometers for fall detection, based on the classification of postures. Four accelerometers were placed at the chest, waist, ankle and thigh. Statistical features were calculated for each axis of the accelerometer in addition to the magnitude. Results indicated that one accelerometer (chest or waist) by itself was not enough to sufficiently classify the activities (75%). There was, however, a significant improvement in classification accuracy achieved by combining the accelerometer at the chest or waist with one placed on the ankle (91%). Following the work described in [5] we explore this approach using different dataset while investigating all possible sensor placement combinations.

* Both authors contributed equally to this research.

Information Society 2020, 5–9 October 2020, Ljubljana, Slovenia

3 ACTIVITY RECOGNITION

3.1 Dataset

In this research we used the UP-Fall Detection dataset, which is publicly available [9]. The dataset contains 17 Subjects that are performing 11 activities. Each activity is performed 3 times. The activities performed are related to six simple human daily activities and five human falls showed in Table 1. These types of activities and falls are chosen from the analysis of those reported in literature [10][11]. All daily activities are performed during 60 s, except jumping that is performed during 30 s and picking up an object which it is an action done once within a 10-s period. A single fall is performed in each of the three ten seconds period trials.

Table 1: Activities performed in the Dataset

Activity ID	Description	Duration (s)
1	Falling forward using hands	10
2	Falling forward using knees	10
3	Falling backwards	10
4	Falling sideward	10
5	Falling sitting in empty chair	10
6	Walking	60
7	Standing	60
8	Sitting	60
9	Picking up an object	10
10	Jumping	30
11	Laying	60

In order to collect data from young healthy subjects without any impairment, is considered a multimodal approach for sensing the activities in three different ways using wearables, context-aware sensors and cameras, all at the same time. However, of our particular interest is how acceleration data can be used for the recognition of activities. The analyzed data is obtained from accelerometers placed on ankle, neck, wrist and belt. This way we created 15 different

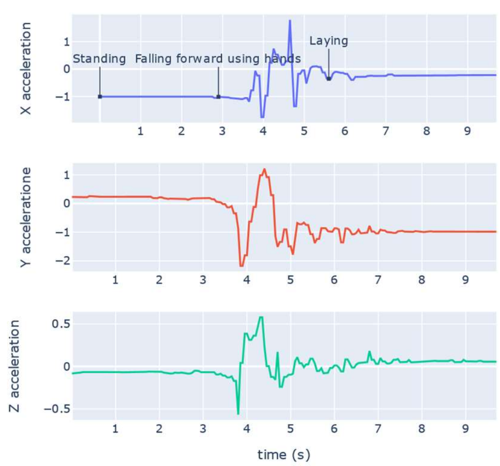

Figure 1 Raw Data from 3-Axis Accelerometer

datasets representing every combination of these sensors to show the importance of the placement of the accelerometer.

In our research the sampling rate of the sensor is 18 Hz, which means 18 samples are provided every second. In Figure 1**Error! Reference source not found.** the raw data from 3-axis accelerometer is shown from person who is performing three activities: standing, falling forward using hands and laying.

3.2 Feature Extraction

Feature extraction is really important step in the activity recognition process in order to filter relevant information and obtain quantitative measures that allow signals to be compared. In our research we used statistical features to create the feature vectors. All the attributes are computed by using the technique of overlapping sliding windows [5].

Because the final sampling frequency of our accelerometers was 18 Hz, we chose a window size of 18, which is one second time interval. We decided for one-second time interval because in our target activities there are transitional activities (standing up and going down) that usually last from one to four seconds. Statistical attributes are extracted for each axis of the accelerometer.

The feature extraction phase produces 36 features (summarized in Table 2) from the accelerations along the x, y, and z axes. The first three features (Mean X/Y/Z,) provide information about body posture, and the remaining features represent motion shape, motion variation, and motion similarity (correlation).

Once the features are extracted (and selected), a feature vector is formed. During training, feature vectors extracted from training data are used by a machine learning algorithm to build an activity recognition model. During classification, feature vectors extracted from test data are fed into the model, which recognizes the active.

Table 2: Overview of the extracted features. The number of features is represented with #

Feature name	#
Mean (X, Y, Z)	3
Standard deviation (X, Y, Z)	3
Root mean square (X, Y, Z)	3
Maximal amplitude (X, Y, Z)	3
Minimal amplitude (X, Y, Z)	3
Median (X, Y, Z)	3
Number of zero-crossing (X, Y, Z)	3
Skewness (X, Y, Z)	3
Kurtosis (X, Y, Z)	3
First Quartile (X, Y, Z)	3
Third Quartile (X, Y, Z)	3
Autocorrelation (X, Y, Z)	3

3.3 Methods

Machine learning approach was used for the activity recognition. In this study, the machine learning task is to learn a model that will be able to classify the target activities (e.g. standing, sitting, falling, etc.) of the person wearing accelerometers. For this purpose, we used 4 different machine learning algorithms: Random Forest, Support Vector Machine, k-Nearest Neighbors and Multilayer Perceptron.

The Random Forest (RF) classifier, like its name implies, consists of a large number of individual decision trees that operate as an ensemble. The fundamental concept behind RF is the low correlation between any of the individual constituent models protecting each other from their individual error.

The Support Vector Machine (SVM) method has also been broadly used in HAR although they do not provide a set of rules understandable to humans. SVMs rely on kernel functions that project all instances to a higher dimensional space with the aim of finding a linear decision boundary (i.e., a hyperplane) to partition the data.

The k-Nearest Neighbors (k-NN) is a supervised classification technique that uses the Euclidean distance to classify a new observation based on the similarity (distance) between the training set and the new sample to be classified.

The Multilayer Perceptron (MLP) [12], is an artificial neural network with multilayer feed-forward architecture. 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 MLP is efficient in non-linear classification problems, including human activity recognition. Brief study of MLP and other classification methods is shown in [13][14].

4 EXPERIMENTS

4.1 Evaluation Techniques

To properly evaluate the models, we divided the data into train and test using leave-one-person-out cross-validation. With the leave-one-person-out each fold is represented by the data of one person. This means the model was trained on the data recorded for 16 people and tested on the remaining person's data. This procedure was repeated for each person data (17 times) and the average performance was measured.

Four evaluation metrics are commonly used in activity recognition: the recall, precision, accuracy and F-measure. We have analyzed the accuracy score, which shows how many of the predicted activities are correctly classified.

4.2 Results

For the first experiment we compared 4 ML models using the ankle accelerometer - shown in Figure 2. We used the ankle accelerometer because our initial studies showed that it performs the best. Random Forest showed the best results with 92.92% of accuracy. Therefore, it was used for further experiments.

Table 3 shows the comparison of activity recognition accuracy using 4 accelerometers placed on ankle, belt, neck and wrist. It shows how the number and placements of accelerometer can affect the recognition of particular activities.

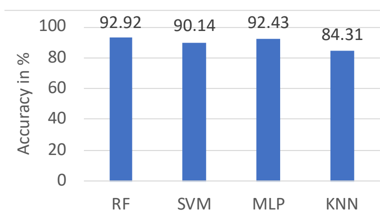

Figure 2: Comparison of different algorithms using Ankle Accelerometer

Placing the accelerometer on the belt can distinguish sitting, standing or jumping, but distinguishing different kind of falls that include some transitions, like standing, falling and then laying is a problem. Adding one accelerometer on the neck, can slightly improve the results, but still cannot recognize correctly the falls. Combination of neck and ankle accelerometer proved best results with 94.2% accuracy. On the other hand, an accelerometer on the ankle can distinguish walking, standing and laying, but has problems with picking up an object and also recognizing the falls. Most of the fall activities are recognized as standing or laying. By combining

Table 3: Comparison of activity recognition accuracy using different number of accelerometers (1, 2, 3 or 4) placed on ankle, belt, neck and wrist

Activities	Ankle	Belt	Neck	Wrist	Ankle+ Belt	Ankle+ Neck	Ankle+ Wrist	Belt+ Neck	Belt+ Wrist	Neck+ Wrist	Ankle+ Belt+ Neck	Ankle+ Belt+ Wrist	Ankle+ Neck+ Wrist	Belt+N eck+ Wrist	Ankle+ Belt+ Neck+ Wrist
Falling forward using hands	57.9	64.4	75.1	63.0	63.2	73.6	60.3	71.7	63.2	70.1	69.5	63.1	72.7	71.1	73.5
Falling forward using knees	72.6	81.4	76.2	55.7	76.4	77.7	61.2	77.6	68.6	64.5	77.9	75.8	75.0	72.4	78.7
Falling backwards	69.4	68.7	71.4	52.4	71.7	75.0	64.4	70.6	56.6	62.2	71.7	67.0	70.5	63.9	69.1
Falling sidewards	63.6	67.3	69.7	42.5	66.8	74.8	58.1	67.3	53.4	57.4	70.0	68.3	70.3	62.1	70.4
Falling sitting in empty chair	56.8	68.3	75.6	48.7	65.8	71.4	52.8	70.6	58.3	67.3	73.5	60.4	69.6	70.0	71.7
Walking	98.6	96.6	99.2	94.2	98.9	98.6	98.9	96.6	98.5	98.7	98.8	99.0	98.6	98.6	98.8
Standing	96.6	91.4	69.6	92.8	97.7	97.1	91.9	93.1	93.5	96.8	98.3	98.2	97.8	97.9	98.2
Sitting	90.2	66.4	95.0	85.2	75.9	84.5	80.6	83.9	68.4	87.6	71.4	72.3	79.9	85.5	76.8
Picking an object	67.7	73.0	86.8	43.3	76.0	88.0	63.0	82.1	71.3	82.9	87.7	74.1	87.0	82.1	86.8
Jumping	99.7	99.8	99.9	99.2	99.8	99.8	99.7	99.8	99.8	99.9	99.8	99.8	99.9	99.9	99.8
Laying	95.7	92.1	89.4	96.8	96.7	98.2	94.6	97.04	89.3	97.5	98.2	97.5	98.4	97.4	98.2

this sensor with neck accelerometer, the algorithm can distinguish each of the discussed activities.

Because of situation like this, we decided to compare the results using different number of accelerometers and different body placements. The idea is to use as few sensors as possible to maximize the user's comfort, but to use enough of them to achieve satisfactory performance.

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Activity	1	2	3	4	5	6	7	8	9	10	11
1	73.6	0.0	1.3	0.7	0.9	0.4	12.2	0.0	0.0	0.0	11.0
2	0.0	77.7	0.0	1.6	0.4	0.4	4.3	0.0	0.0	0.0	15.6
3	0.3	0.0	75.0	3.5	1.2	0.0	7.8	0.0	0.0	0.0	12.2
4	0.0	0.0	3.3	74.8	1.5	0.5	9.7	0.0	0.0	0.0	10.3
5	0.4	1.5	2.1	5.4	71.4	0.0	9.3	0.0	0.0	0.0	10.0
6	0.0	0.0	0.0	0.0	0.1	98.6	1.3	0.0	0.0	0.0	0.0
7	0.1	0.1	0.0	0.0	0.0	0.4	97.1	1.9	0.3	0.0	0.2
8	0.0	0.0	0.0	0.0	0.0	0.0	11.0	84.5	0.1	0.0	4.5
9	0.0	0.0	0.0	0.0	0.0	0.5	10.6	1.0	88.0	0.0	0.0
10	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	99.8	0.0
11	0.1	0.1	0.2	0.1	0.2	0.0	0.7	0.3	0.0	0.0	98.2

Figure 3: Confusion matrix for Neck and Ankle Accelerometer

We must make a trade-off between correctly detecting simple activity and specific fall. The results showed that neck and ankle accelerometers are best suited for fall detection with overall accuracy of 94.19%. The confusion matrix for neck and ankle accelerometers is shown in Figure 3. The most false positive predictions for fall activities are predicted as laying. Also, very small percent of the non-fall activities are predicted as falls, which dismiss the false alarms for falls.

5 CONCLUSION

In this paper we presented an approach to human activity recognition and how location and number of sensors can impact on the process of HAR. Our aim was to build a model who can correctly recognize and classify the fall activities using small number of accelerometers, but still can obtain high accuracy scores. With one accelerometer placed on the ankle or the neck we got high accuracy scores, but by combining these two sensors the model can classify the falls more precisely.

The main input to our system is the data from the inertial sensors. Because the data is sensory, additional attributes are calculated. This process of feature extraction is general and can be used in similar problems. Next, the algorithms for the final tasks of activity recognition and fall detection are designed and implemented using the data from the ankle accelerometer. We used a machine learning approach for solving the problem of activity recognition. We evaluated the models and Random Forest showed best results. Then, we compared the best model on different data, and we got the conclusion that the data from ankle and neck sensors was sufficient for human activity recognition and fall detection process with accuracy of 94.2%.

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