3-Axial Accelerometers Activity Recognition

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Abstract. Activity Recognition is a typical classification problem. The goal is to detect and recognize everyday activities of a person. This paper presents our approach to measurements and classification of a person's movements. This is done by using two 3-axis radio accelerometers attached to the person's body and by reconstruction and interpretation of the user's behavior. We compared two machine learning algorithms (J48 and Random Forest) and various attributes characterizing the user's behavior in order to obtain accurate classification of the behavior into predefined classes - activities.

Keywords: Activity Recognition, 3-axial Accelerometers, Attributes, Activities, Instances, Machine Learning, Classifiers.

1 Introduction

Activity Recognition is becoming a very popular research topic. There are a lot of projects and useful applications being build, aiming at nursing older people [6, 8]. Most of them belong to the area of ambient assisted living and are trying to make the everyday life easier, simpler and safer. The essential part in these applications is the activity recognition module. There are applications that aim to recognize activities and find macro and micro level irregularities. Macro level covers more general and longer periods of activities like recognizing the pattern of walking and alarming if something is wrong with the walking signature. On the other hand, micro level activities represent every single movement and gesture of the person. Recognizing these activities is a very interesting and challenging field, and therefore they are the goal of our research.

Activity recognition can be formulated as machine learning, classification problem. In the narrow sense it can be seen as a pattern recognition problem [1, 2, 5]. Therefore good attributes that describe the person's behavior are crucial for the classification techniques to be applied. There are lots of projects using different attributes

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(features), starting from traditional attributes like: mean, variance, correlation [1, 3, 4] to more complex that transform the data in frequency domain [2].

Our goal was to detect and recognize every single movement the person makes. Other researchers are using windows, window sizes and overlapping windows of the data [1, 2, 5]. With this approach, every instance cannot be classified, but a group of instances (one window) are classified together. The disadvantage of this approach is that short activities like going down and standing up cannot be recognized.

For the needs of the research described in this paper, two 3D accelerometers were used. A 3-axial accelerometer is a sensor that provides the projections of the acceleration vector along three axes: x, y and z. The 3 projections and the timestamp are the raw data that we get from the sensors. Using the raw data we extracted some features that are later used for the machine learning and the classification techniques. Some of the attributes are the traditional features that are used for acceleration activity recognition like: mean, standard deviation, root mean square, etc., but there are also some features that measure the direction and the movement of the person.

We tried to distinguish and recognize 7 activities: *Standing, Sitting, Lying, On all fours, Sitting on the ground, Standing up,* and *Going down*. We decided to include walking into *standing*, so *standing* can be a static or a dynamic activity. Some very quick activities like *going down* and *standing up* were also included. These two activities are very difficult to separate and recognize using just acceleration sensors, because they happen very fast and we don't have as many instances as we have for *lying* for example.

The classification techniques used for this research are: J48 (Weka's implementation of C4.5) and Random Forest. These were the techniques yielding the best results, after analyzing several options in the open source library Weka.

2 Data Collection

The data needed for training the classifiers was retrieved using two 3-axial accelerometers. One of them was positioned on the chest and the other on the right ankle of a person. It is important to state that the same results would have been achieved even if the second accelerometer was placed at the left ankle instead of the right ankle.

The raw data consisted of the following attributes: timestamp, acceleration along x axis, acceleration along y axis and acceleration along z axis. The data in the raw state is insufficient in the recognition process, so we calculated and extracted other attributes that can help in the classification.

The accelerometers frequency of sending data was 5Hz, so 5 measurements per second were obtained. Other researchers try to combine the data and use windows to recognize the activities [1, 2, 5]. With this approach every single data (instance) measured cannot be recognized and classified. Instead, this approach classifies bigger windows of instances (ex. 50 instances together as one action). The advantage is that noise is eliminated, but on the other hand, information is lost. From our point of view this method can be very useful when the aim of the project is recognizing longer activities. We couldn't use it because we are also interested in short activities like *going down* and *standing up*. With our approach we tried to recognize every instance that was coming from the accelerometer. Perhaps this is a more difficult task, because we tried to detect every single instance, even if they are very quick and do not last long (ex. *going down*). In fact, that was the aim of this research. We collected the data in order to recognize these 7 activities:

1. *Standing*
2. *Lying*
3. *Sitting*
4. *On all fours*
5. *Sitting on the ground*
6. *Going down*
7. *Standing up*

The data that we collected was separated in two scenarios. Each of them contained all seven activities. The first scenario was longer and had around 7000 instances and was used for building the classification model. The second one was shorter and was used for testing and analyzing the results. The process of collecting the data, building the model and classification is presented in Figure 1.

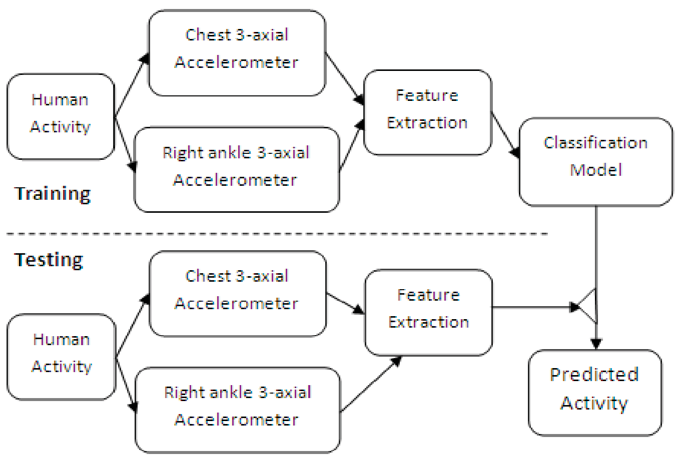

Figure 1. The activity recognition process used in this research.

3 Feature Extraction

Once raw data was obtained, 14 features (attributes) were extracted from it. We used both the 6 raw data attributes (3 attributes per accelerometer) and the extracted features in our classification procedure. Eventually, before building the model, we summed up to 20 features that describe each activity. Some of the features that we extracted from the raw data are the traditional features used in activity recognition, like: mean [1, 7], standard deviation [1, 3, 7], root mean square.

When calculating the mean we used 7 acceleration values (instances). Since from the accelerometers we obtained 5 acceleration values in one second (5 Hz), 7 values corresponds to 1.4 seconds worth of activities. The value 7 was chosen so that the delay in the data is minimized, but the necessary information is still present. The attribute is good for distinguishing long lasting static activities from fast and transitional activities. We used four mean attributes in the model: mean value of the acceleration along 3 axes (x, y, and z) and mean value of the length of the acceleration vector. Very similarly, root mean square and standard deviation are calculated too. The only difference is in calculating the standard deviation attribute. After analyzing this feature we decided just to use the standard deviation for the length of the acceleration vector.

The next two attributes that we used are the lengths of the acceleration vectors for the two accelerometers. This is an attribute very simple for computation, but very useful for machine learning. It is used in the computations of some of the other attributes.

Another very useful feature is the direction of the acceleration. In fact, the direction of the acceleration is the angle between the acceleration vector and one of the axes.

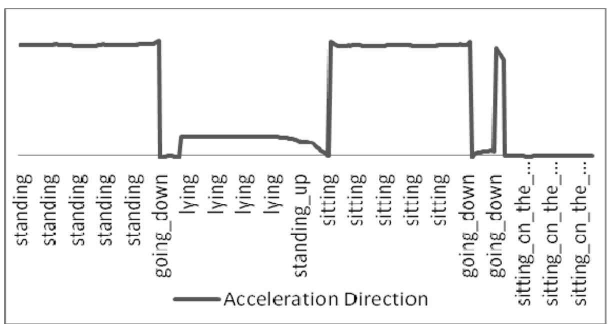

Figure 2. The direction of the acceleration vector

Using this attribute it is very easy to distinguish between activities that have different direction of acceleration (lying on the bed and standing, or lying and sitting on the ground). The attribute and its values on different activities are shown in Figure 2.This attribute is simply computed as an angle between two vectors:

$$\cos\alpha = \frac{acc\_y}{\sqrt{acc\_x^2 + acc\_y^2 + acc\_z^2}} \tag{1}$$

Another feature that is used only for the chest accelerometer is the *change of differences of the lengths of the acceleration vectors*. The mathematical definition of this attribute is:

$$\sum_{i=0}^{n} |len_{i+1} - len_i| \tag{2}$$

This attribute is good in detecting the movement of the person. The value of *n* is chosen to be 15. That means that 15 past instances are used when we decide if the person is moving or not. If we take in consideration that the hardware sending data frequency is 5 Hz (5 instances per second), the conclusion is that we use the last 3 seconds of the person's measured activities. The value is chosen to be 15 after series of tests and analyzing the results.

We also calculated an additional boolean (true/false) attribute that completely uses the value of the *change of differences of the lengths of the acceleration vectors* attribute. Actually we just compared a threshold value to the value of the previous attribute and if it is above the threshold, the boolean attribute will be *true*, otherwise *false.*

4 Building the Models

The activity recognition classification algorithm should recognize the accelerometer signal pattern corresponding to every activity. We should emphasize that every activity has its own pattern that is more or less different than the others [1]. We formulate the activity recognition problem as a classification problem where classes correspond to activities. A test instance is a set of acceleration attributes collected over a time interval and post-processed into a single example instance. The decision, which classifiers to use in our research was made after evaluating the results in the Weka toolkit. We managed to achieve the best results with J48 and the Random Forest classifier. J48 is an open source Java implementation of the C4.5 algorithm in the Weka data mining tool.

When building the model we used a very long scenario containing approximately 7000 instances. We tried to have an equivalent distribution of the class activities. However, some activities are very quick compared to others (ex. standing up vs. lying) and do not happen as often in real life. Therefore it was not possible to have equal number of instances of every activity.

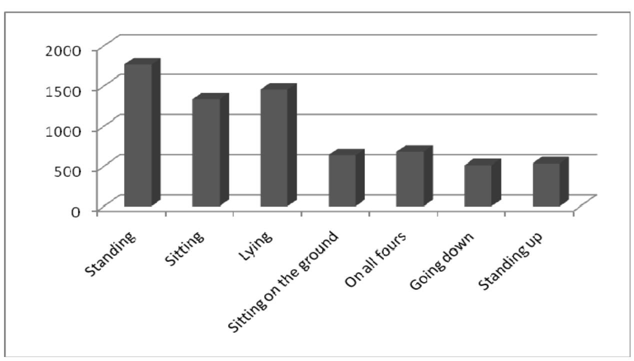

Figure 3. The distribution of the activities instances used in building the classification model.

Naturally, we used a different scenario for testing the model. The difference in the testing scenario was that the activities were shorter and contained fewer instances. The final distribution of the instances is shown in Figure 3.

5 Tests and Results

In the models that we used, there are 20 attributes (6 raw data, 14 extracted) and one class attribute. We should also mention that the class attribute was labeled manually by watching the video/scenario and analyzing the data. That caused the accuracy percentage to have a variation of 2-3%, especially for short activities. Therefore, successive activities (ex. *standing->going down->lying*) probably have some instances misclassified at the beginning and at the end of each activity. We assumed that the best way to present our results is by using confusion matrix and percentage accuracy for each classifier. The results that we got by building the model and testing the data in Weka are shown in *Table 1* and *Table 2*:

Table 1. Confusion Matrix for J48 Model and percentage accuracy

J48		**Predicted Class**							
		Standing	Going d.	Sitting	Stan. up	Lying	Sit on g.	On all 4's	%
Actual Class	Standing	**772**	3	2	31	0	0	0	95,5
	Going d.	28	**30**	1	15	9	0	3	34,9
	Sitting	30	6	**42**	42	0	0	0	35
	Stan. up	16	18	3	**75**	10	2	46	44,1
	Lying	0	1	0	0	**442**	0	70	86,2
	Sit on g.	1	0	32	1	0	**170**	1	82,9
	On all 4's	0	2	0	0	0	0	**67**	97,1
				Overall accuracy					**81**

Table 2. Confusion Matrix for Random Forest Model and percentage accuracy

Random Forest		**Predicted Class**							
		Standing	Going d.	Sitting	Stan. up	Lying	Sit on g.	On all 4's	%
Actual Class	Standing	**786**	0	0	22	0	0	0	97,3
	Going d.	37	**18**	1	16	2	0	15	20,2
	Sitting	26	9	**79**	0	0	0	0	69,3
	Stan. up	10	16	4	**70**	7	3	61	40,9
	Lying	0	4	0	0	**471**	0	40	91,5
	Sit on g.	0	0	16	4	1	**184**	0	89,8
	On all 4's	0	1	0	0	0	0	**68**	98,6
				Overall accuracy					**85**

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It is obvious that Random Forest gives better results in almost every activity. Actually it is worse only in short and transitional activities like *going down* and *standing up*. Another interesting fact that we can notice is that sitting is very often misclassified with standing, which is because the direction of the accelerometers is almost the same in both activities. As a result 23 % of the sitting instances are misclassified with standing. Similarly, *lying* is misclassified with *on all fours* because when the person is lying on the stomach, the directions of the accelerometers are the same as when he is *on all fours*.

In conclusion we can state that better results are achieved on longer activities (*standing*, *lying*, *sitting on the ground, on all fours*) and worse on transitional, short activities (*going down, standing up*). That is because the accelerations are not that drastic ex. when the person is going down, so it is easy for machine learning to misclassify with other activity (ex. standing - walking). The overall accuracy is 81% with J48 and 85 % with Random Forest and that is a good start for a research in this field, where we try to classify every single instance that we get from the sensors.

6 Future Work

The first issue that needs to be addressed in our future work is the problem that we have while distinguishing *standing* and *sitting*. This problem can be easily solved by putting one more accelerometer on the thigh. By doing this, *standing* and *sitting* will have completely different direction of the acceleration vector and can be easily recognized.

Also adding one more hardware component (not necessarily accelerometer) can improve the results and make the system more efficient.

Another aspect that could be improved is adding detection of falling among the classes being classified. This can be an excellent improvement if our activity recognition is used as a part in an e-health application.

The machine learning algorithms used can be improved, particularly the classifiers. One approach that could be used is combing the best classifiers, in a voting process. Several meta-level classifiers and techniques can be used [1]: bagging, boosting etc.

7 References

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