Reducing Uncertainty in User-independent Activity Recognition
A Sensor Fusion-based Approach

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Abstract: In this study, a novel user-independent method to recognize activities accurately in situations where traditional accelerometer based classification contains a lot of uncertainty is presented. The method uses two recognition models: one using only accelerometer data and other based on sensor fusion. However, as a sensor fusion-based method is known to consume more battery than an accelerometer-based, sensor fusion is only used when the classification result obtained using acceleration contains uncertainty and, therefore, is unreliable. This reliability is measured based on the posterior probabilities of the classification result and it is studied in the article how high the probability needs to be to consider it reliable. The method is tested using two data sets: daily activity data set collected using accelerometer and magnetometer, and tool recognition data set consisting of data from accelerometer and gyroscope measurements. The results show that by applying the presented method, the recognition rates can be improved compared to using only accelerometers. It was noted that all the classification results should not be trusted as posterior probabilities under 95% cannot be considered reliable, and by replacing these results with the results of sensor fusion -based model, the recognition accuracy improves from three to six percentage units.

1 INTRODUCTION

Human activity recognition using inertial sensors is a widely studied area of pattern recognition. One reason for this is that it can be applied to many different types of application, including health monitoring; targeted advertising; home automation that anticipates the user's needs; and self-managing system that adapts to user's activities (Lockhart et al., 2012).

For many applications, especially the ones made for smartphones, human activity recognition should be accurate but light as well to save the battery. For this reason, in most of the studies activity recognition is based on the measurement of one sensor only as it is known that the more sensors are used the higher the battery consumption is (Zappi et al., 2008). Typically, this sensor is an accelerometer as it is shown that they do not only produce more accurate results than other sensors but they are also more energy efficient ((Shoaib et al., 2015), (Otebolaku and Andrade, 2013)), This is problematic, as it is also shown that sensor fusion-based methods provide higher recognition accuracies than the methods based on only one sensor (Shoaib et al., 2014), (Maurer et al., 2006), (Ward et al., 2006). What is even more problematic, is that sometimes accerometer-based user-independent recognition models do not work as accurately as they should and the classification results contain a lot of uncertainty. The reason for this kind of behavior can be that recognition conditions are challenging in some way and these conditions cause untypical measurements. For example, sensor placement can differ from the placements used in the training process (Roggen et al., 2013), the person that uses the activity recognition application moves differently than an average person (Albert et al., 2012), or environmental conditions are non-typical (Altini et al., 2014). In addition, it has been noted that recognition rates in real-life conditions are often much lower than in laboratory conditions (Ermes et al., 2008).

Many of these problems can be solved if user-dependent models are used instead of user-independent as these are found to be more accurate (Weiss and Lockhart, 2012). However, the problem with user-dependent models is that they require personal training data from the user, and therefore, they cannot be used out-of-the-box. This makes them unusable, or at least difficult to be used, in applications which are aimed for masses. Therefore, the recognition of activities accurately and unobtrusive in challenging condition calls for novel approaches.

The increase in battery consumption means that

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often it is not possible to classify instances 24/7 using sensor fusion -based model. Luckily there are some previous studies where sensor fusion is applied so that all the sensors are not used constantly. For instance, in (Zappi et al., 2008) sensors in multiple body positions were used, however, in order to save energy the number of used sensors was decided dynamically. It was noted that the number of sensors can be reduced without significant effect to the recognition accuracy. In our study, multiple types of sensors are used but only in one body location. This was also the case in (Wang et al., 2010), where a smart and energy-efficient way to deploy the sensors of a mobile phone to recognize activities was presented. The method presented in the study uses minimum number of sensors needed to detect user's activity reliably and when activity changes, more sensors are used to detect the new activity. By using this smart sensor selection, the battery life was improved by 75%. Altini *et. al.* (Altini et al., 2014) present another method to use sensor fusion in a smart way. The study presents a method to personalize user-independent walking speed estimation model. In the study, sensor fusion is used as it is noted that user-independent walking speed estimation model based on accelerometer data is not accurate when walking in unconstrained conditions. In the study, sensor fusion is used to automatically calibrate models by combining accelerometer and GPS data to find a person-specific offset to be used with a user-independent estimation model. The offset is determined by comparing walking speed estimation at a treadmill to speed measured by the GPS outdoors. By using this method, it was possible to reduce the root mean square error from 25% to 39% depending on walking speed.

In this study, a method to improve classification accuracy in challenging conditions is presented. In the study, conditions are considered challenging when the classification results contain a lot of uncertainty which means that posterior probability of the classification result is not above some threshold. This study is divided into two parts: firstly, it is studied when classification results using accelerometer data cannot be considered reliable. This is based on the posterior probalities of the classification results. Although there are some activity recognition studies using posterior probabilities (for instance semi-supervised approach proposed in (Hachiya et al., 2012)) the way they are applied in this article is new. In the second part of the study, a novel sensor fusion-based user-independent method to recognize activities accurately in situations where classification results are unreliable is presented. It is known that sensor fusion increases the energy consumption, and therefore, reduces the battery life. For this reason, the method presented in this study uses several sensors in the activity recognition process only when necessary. Experiments are done using two data sets: daily activity data set collected using the sensors of a mobile phone, and tool recognition data set collected using a sensor box specially designed for research usage.

The paper is organized as follows: The used methods and data sets are explained in Section 2. The main contributions of this study are presented in Section 3, where it is studied when classification results are reliable, and in Section 4, where a method to reduce uncertainty of the classification result is presented. Experiments are in Section 5. Finally, the conclusions are in Section 6.

2 DATA COLLECTIONS AND METHODS

In this study, two data sets were used: daily activity data set and tool usage data set. With both data sets sliding window technique was used to obtain real-time results. This means that, the signals from the sensors were divided into equal-sized smaller sequences, also called windows, and then classified based on the features extracted from windows. Moreover, to reduce the number of misclassified windows, the final classification was done based on the majority voting of the classification results of three adjacent windows. Therefore, when an activity changes, a new activity can be detected when two adjacent windows are classified as a new activity. While both data sets used 3 second windows, the features extracted from them were decided data set-wise.

2.1 Daily Activity Data

The data were collected using a Nokia N8 smartphone running Symbianˆ3 operating system. N8 includes a wide range of sensors: a tri-axis accelerometer and magnetometer, two cameras, GPS, a proximity sensor, microphones and an ambient light sensor. The used sampling frequency was 40Hz, which is much less than the maximum sampling frequency of most phones. This enables the same sampling frequency to be used with any smartphone, where the maximum frequency of the accelerometer is at least 40Hz, making recognition less phone model dependent (Siirtola and Röning, 2012).

The classification models used in this study were trained based on the activity data collected from seven healthy subjects. The subjects were carrying five phones at the same time. They were located at *trousers' front pocket*, *jacket's pocket*, *at backpack*, *at brachium* and one *at the ear*. The participants performed five different activities: *walking*, *running*, *cycling*, *driving a car*, and *sitting/standing*. The reason for selecting these activities for the study is that normal everyday life consists mainly of these five activities. Moreover, data were collected when a phone was laying *on the table*. Therefore, six activities were recognized. What makes this data set challenging is that it was collected outside laboratory, and therefore, the conditions were not always optimal. For instance, at places the used roads were bumpy making signals difficult to analyze. The total amount of the data collected was about fifteen hours. The data are introduced in more detail in (Siirtola and Röning, 2013).

In this study, daily activities are recognized body position -independently and orientation independently as well. For this purpose, the effect of gravitation was eliminated in the pre-processing phase by combining all three acceleration channels as one using square summing. This way orientation independent magnitude acceleration signal was obtained. The same was done to magnetometer signals as well. However, it was noted that the orientation of the phone has some limitations. For example, the screen or the back of the smartphone is always against the user's leg when the phone is in the trousers' pocket. Therefore, it was tested if features extracted from a signal where two out of three acceleration and magnetometer channels were square summed, would improve the classification accuracy. From these signals calibration independent -features were extracted (Siirtola and Röning, 2013). Three types of features were extracted from these signals: statistical, time domain and frequency domain features, and these included variance, minimum, maximum, different percentiles and crossings, sums and square sums of values below/above some percentile and sums of sequences of the FFT signals. Altogether 120 features were extracted from acceleration signals, as well as, from magnetometer signals and the used window size was 120 observations, which is 3 seconds as the sampling rate was 40Hz.

2.2 Tool Usage Data

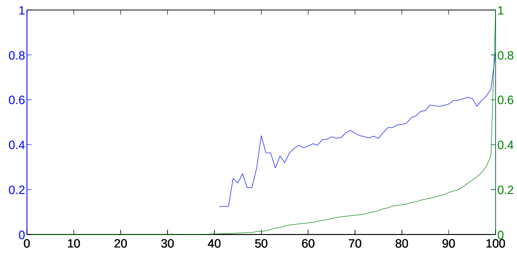
The tool recognition data set was collected using a mobile SHAKE sensor, it is equipped with a 3D accelerometer, a 3D gyroscope, a 3D magnetometer and two proximity sensors. However, in this study only accelerometer and gyroscope data were used. The data were collected from five study subjects and the task was to assemble a wooden drawer. The sensor was attached to the both wrists of the subject but in this study only the data from right wrist were used. The data set contained seven activities: *usage of screwdriver*, *hammering*, *usage of spanner*, *attaching small tips*, *tapping*, *adjusting drawer legs* and *using power drill*. The activities performed in this data set were not common to all the persons from whom the data were collected. Therefore, the data contains a lot of variation between study subjects which increases uncertainty in the classification process. The data are introduced in more detail in (Huikari et al., 2010).

Unlike daily activity data set, data for tool usage activities were collected from only one body position as the location of the sensor was fixed as wrist. Therefore, it the features extracted from the data do not necessary need to be orientation independent. In this case, features were extracted from each axis of 3D accelerometer and 3D gyroscope signals. However, in addition magnitude acceleration and gyroscope signals were also obtained using square summing and features from these were extracted, as well. Three types of features were extracted from these signals: statistical, time domain and frequency domain features, and these included variance, minimum, maximum, different percentiles and crossings, the sums and square sums of values below/above some percentile, the sums of the sequences of FFT signals and correlations between different channels. Altogether 99 features were extracted from acceleration signals, as well as, from gyroscope signals, and the used window size was 300 observations which is 3 seconds as the sampling rate was 100Hz.

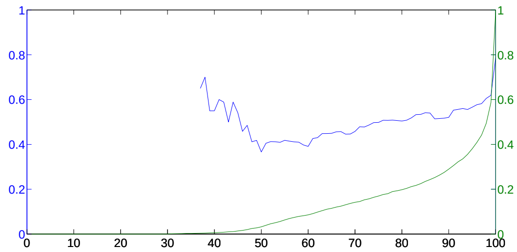
2.3 Feature Selection and Classification

The feature selection method and classifiers applied to both data sets were the same. In order to achieve the highest possible recognition rates, the most descriptive features for each model were selected using a sequential forward selection (SFS) method (Devijver and Kittler, 1982).

The main contribution of this study is to present a method to recognize activities reliably when the analyzed data can contain untypical measurements. As this method is not dependent on the used classifier, in this study only two classifiers were compared. Because of good experiences in our previous studies (Siirtola and Röning, 2012; **?**), it was decided to use QDA (quadratic discriminant analysis) and LDA (linear discriminant analysis) as a classifier. QDA is a classification method that finds a quadratic surface, that separates the classes best in the feature space (Hand et al., 2001). LDA works differently as it uses a linear decision surface to separate classes.

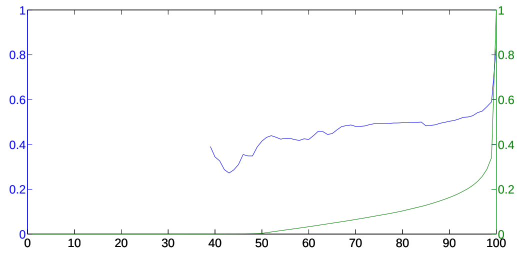


(a) QDA

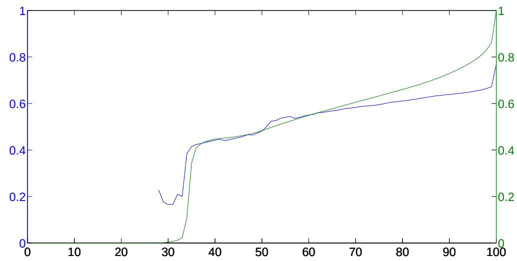


(b) LDA

Figure 1: The effect of posterior probability on the recognition accuracy with tool usage data set. In the figure, *x*-axis is the posterior probability in percentages, the blue curve shows the recognition accuracy of such classification results where posterior probability is below the value defined by *x*-axis. In addition, the green curve shows how many percentages of the data set have posterior probability below the value defined by *x*-axis. In the upper figure classification is obtained using QDA, and in the lower using LDA.



(a) QDA



(b) LDA

Figure 2: The effect of posterior probability n the recognition accuracy with daily activity data set. In the figure, *x*-axis is the posterior probability in percentages, the blue curve shows the recognition accuracy of such classification results where posterior probability is below the value defined by *x*-axis. In addition, the green curve shows how many percentages of the data set have posterior probability below the value defined by *x*-axis. In the upper figure classification is obtained using QDA, and in the lower using LDA.

3 ACTIVITY RECOGNITION IN CHALLENGING CONDITIONS - IS THE CLASSIFICATION RESULT RELIABLE?

In this study, it is presented a method to improve classification in situations where the classification result cannot be considered reliable. Therefore, at first it need to be studied when models are not reliable. Here result is not considered reliable when it contains a lot of uncertainty which means that posterior probability of the classification results is not above some threshold. As mentioned in the previous section, this can be for example a consequence of a misplaced sensor, non-typical environmental condition, or a movement style different to an average person. This threshold is for instance dependent on the used classifier, the number of classes, and types of activities.

In Figures 1 and 2 it is shown how posterior probability is related to classification accuracy when classification is performed using statistical and time domain features extracted from acceleration data and classification is done using QDA and LDA. In the figure, *x*-axis is the posterior probability in percentages, the blue curve shows the recognition accuracy of such classification results where posterior probability is below the value defined by *x*-axis. In addition, the green curve shows how many percentages of the data set have posterior probability below the value defined by *x*-axis. Based on these figures it can be concluded that higher the posterior probabilities are more likely to produce higher recognition accuracy. While this finding is quite obvious, it is more interesting to see how already a small change in posterior probability can have a massive impact to recognition accuracy. For instance, with tool usage data one percentage drop in posterior probabilities, from 100% to 99%, with LDA causes recognition accuracy to drop from 78.7% to 61.9% and with QDA from 81.3% to 64.8%. This means that the posterior propability of the classification result need to be really high to be reliable. On the other hand, as shown in the figure by the green curve, there are not many classification results with posterior propability under 95%. The only exception is daily activity recognition using LDA. In that case, there is

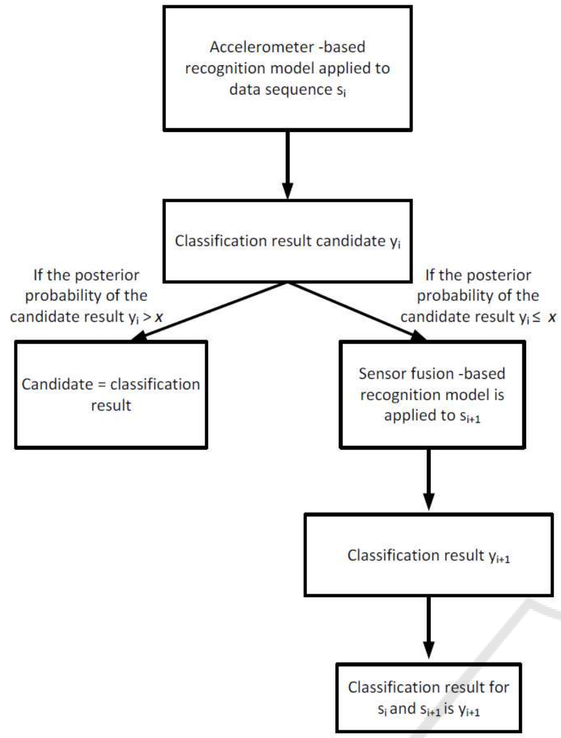


Figure 3: The presented method consists of two recognition models: one using only accelerometer data and other based on sensor fusion. The sensor fusion-based model is only used when the classification result obtained using an accelerometer-based model is known to be unreliable.

a lot of results with posterior propabilities under 40%. However, also in this case there is a huge difference in recognition accuracies (10 percentage units) when the posterior propability drops from 100% to 99%. In addition, according to the figures, the recognition accuracy for observations with the posterior propability 95% is around 50%. It is decided in this study, that observations under this threshold cannot be considered reliable. Therefore, 95% posterior is in this study considered as the threshold for reliable classification.

4 BUILDING MORE RELIABLE RECOGNITION MODELS - A SENSOR FUSION-BASED APPROACH

The idea of the study is to improve user-independent activity recognition in challenging condition using sensor fusion. The basic idea of the proposed method is presented in Figure 3. The method consists of two models: one accelerometer-based that is used in normal conditions, and another model to recognize activities when the candidate results provided using an accelerometer-based model are unreliable. The purpose is that most of the time the recognition is based on this model as it is low power consuming. The method also contains another model that uses data from several sensors and a lot more features than the first one. This model is only used when the candidate recognition result obtained using the first model is not reliable, meaning that the posterior probability of the results is not high enough.

Let us assume that the purpose is to classify a sequence of windows $\{s_1, \ldots, s_i, \ldots s_k\}$ using the method presented in this paper. When window s_i is studied, in the first place it is classified using the accelerometer -based user-independent classification model and candidate y_i as a class label of this window is obtained. If the posterior probability of this classification is above some predefined threshold, the classification can be considered reliable. However, if the posterior probability is not above this threshold, the classification cannot be considered reliable. In this case, the sensors used by the sensor fusion model are switched on and the next window y_{i+1} is classified using the more complex sensor fusion -based model, and the class label y_{i+1} obtained using it is considered as a class label to windows s_i and s_{i+1}.To keep the battery consumption low, after classifying s_{i+1} all the sensors expect accelerometer are switched off and s_{i+2} is again classified using accelerometer -based model.

As it can be seen from Figure 3, one classification using a sensor fusion model effects to the labels of two windows. Therefore, in this study the number of classifications using the sensor fusion-based model is not equal to the number of results obtained using the fusion model.

In the experiment section it is studied how much the proposed method improves the recognition accuracy using the threshold defined in Section 3.

5 EXPERIMENTS

The presented human activity recognition for challenging conditions is tested with two data sets, and therefore, this experiments section comprises two parts: daily activity recognition and tool usage recognition. In both cases, the recognition is done using QDA and LDA as a classifier and features are selected using SFS. Moreover, to obtain reliable user-independent results, the training was performed using the leave-one-out method, so that each person's data in turn was used for testing and the rest of the data were employed for model training.

Table 1: The recognition rates for daily activity data sets using models based on acceleration and sensor fusion.

Data set / Model	**Accelerometer**	**Sensor fusion**
Daily activity / QDA		
Accuracy	83.7%	89.7%
Daily activity / LDA		
Accuracy	76.9%	80.7%

5.1 Daily Activity Recognition

Daily human activities were recognized using following features: an acceleration-based model used only statistical and time domain features while the sensor fusion based method used statistical, time domain and frequency domain features extracted from acceleration and magnetometer signals.

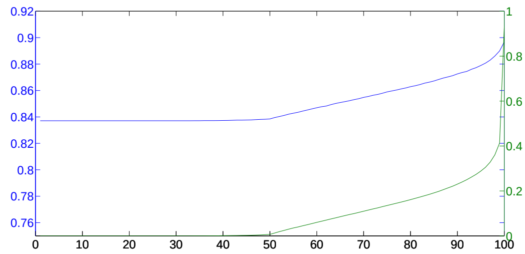
5.1.1 Results

The classification results are shown in Table 1. However, the purpose of this study is to show how sensor fusion can be used to improve the classification rates in challenging conditions. In this study, conditions are considered challenging if the posterior probability of the recognition result provided by the accelerometer-based model are not high enough. In Figure 4 it is shown how differently chosen posterior thresholds affect the recognition rates.

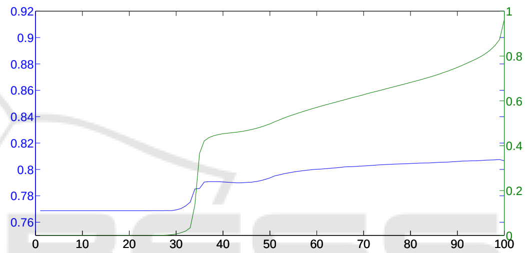
5.1.2 Discussion

The results in Table 1 show that sensor fusion, acceleration and magnetometer in this case, improves the recognition rates of daily human activity data set significantly, six percentage units using QDA and four using LDA. This came as no surprise, as more sensors mean more data and features, which of course makes classification easier.

The results shown in Figure 4 are more interesting. It is shown in this figure, that in order to obtain recognition rates that are almost as high as the ones obtained using only a sensor fusion-based model, it is not necessary to classify each window using a sensor fusion-based model. In fact, with QDA already by replacing a fifth of the accelerometer-based classification results with sensor fusion-based classification improves the recognition rate by over three percentage units (83.7 % vs. 86.8%). Note that, for example, if the posteriors of a tenth of classifications are below the threshold it means that actually a fifth of the results are replaced by the sensor fusion -model as the class label given to windows s_i and s_{i+1} is the same. Moreover, if candidate recognition results with posterior propabilities under 95%, as suggested in Section 3, are replaced with sensor fusion -based results



(a) QDA



(b) LDA

Figure 4: Results using daily activity data set. The blue curve shows the total recognition accuracy where accelerometer-based classification results are replaced by the results of the sensor fusion model when the posterior probability of accelerometer model is below the value defined by *x*-axis, the green curve shows how often classifications were obtained using sensor fusion-based model. In the upper figure classification is obtained using QDA, and in the lower using LDA.

as suggested in Section 3, it means that around 29% of the classifications are based on this models results when using QDA. In this case, the improvement in detection accuracy is over four percentage units (83.7 % vs. 87.9%).

LDA seems to behave differently as there are a lot of classifications with low posterior probabilities. This means that sensor fusion model needs to apply in his case more often. In this case, when results with posterior probabilities under 95% are replaced with sensor fusion -based results, the detection accuracy improves almost four percentage units (76.9% vs. 80.7%). However, this would mean that 80 percentage of the classification should be obtained with sensor fusion -based model making the suggested approach less energy efficient.

Table 2: The recognition rates for tool usage data sets using models based on acceleration and sensor fusion.

Data set / Model	Accelerometer	Sensor fusion
Tool usage / QDA		
Accuracy	81.3%	85.0%
Tool usage / LDA		
Accuracy	78.7%	85.6%

5.2 Tool Usage Recognition

Tool usage activities were recognized using following features: an acceleration-based model used statistical and time domain features, and a sensor fusion method used statistical, time domain and frequency domain features extracted from acceleration and gyroscope signals.

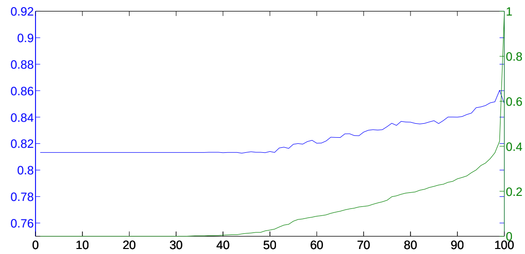
5.2.1 Results

The classification results are shown in Table 2. In the case of the proposed method, a sensor fusion-based method is used when the posterior probability of the class label obtained using accelerometer-based is below some threshold. In Figure 5 it is shown how differently chosen posterior thresholds affect the recognition rates.

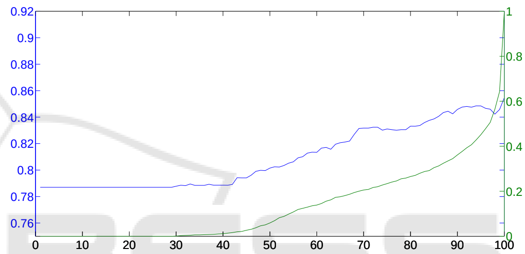
5.2.2 Discussion

The results shown in Table 2 show that sensor fusion consisting of accelerometer and gyroscope data improves the detection rates of tool usage recognition. This improvement seems to be approximately as big as the one obtained with daily activity data set. However, it was expected that this improvement is bigger in the case of tool usage data as it is claimed in the previous studies, such as (Shoaib et al., 2014), that gyroscope is a more accurate sensor to be used in activity recognition than magnetometer that was used with daily activity data. However, it is possible that in this case there was no much room for improvement, and therefore, the improvement gained by combining accelerometer and gyroscope is not as high as the improvement achieved combining accelerometer and magnetometer with daily activity data set. Moreover, in this study the same features were extracted from each sensor. These features are the ones commonly used with accelerometer data. Therefore, it should be studied in more detail what kind of features should be extracted from gyroscope and magnetometer data to achieve the highest possible recognition rates.

In Figure 5 it is shown how the combination of accelerometer and sensor fusion-based models improves the recognition accuracy compared to using only a accelerometer model. Also in this case, the proposed method improves the detection accuracy. With QDA, improvement is well over three percentage unit when 31% of the candidate recognition results, the ones with posterior propabilities under 95%, are done using the sensor fusion -base method (81.3% vs. 84.8%). Similarly with LDA this improvement is over six persentage units (78.7% vs. 84.9%), and means that 45% percentage of results are obtained using the sensor fusion-based model.



(a) QDA



(b) LDA

Figure 5: Results using tool usage data set. The blue curve shows the total recognition accuracy where accelerometer-based classification results are replaced by the results of the sensor fusion model when the posterior probability of the accelerometer model is below the value defined by *x*-axis, the green curve shows how often classifications were obtained using sensor fusion-based model. In the upper figure classification is obtained using QDA, and in the lower using LDA.

6 CONCLUSIONS

In this study, a novel sensor fusion-based method to recognize activities accurately when the results provided by the traditional accelerometer-based model contain a lot of uncertainty was presented. The method uses two recognition models: one using only accelerometer data and other based on sensor fusion. However, as the sensor fusion-based method is known to consume more battery than an accelerometer-based, sensor fusion is only used when the candidate recognition result obtained using accelerometer-based model is known to contain too much uncertainty and can be considered as unreliable. This reliability is measured based on the posterior probabilities of the classification results. The method is tested using two data sets: daily activity data sets collected using accelerometer and magnetometer, and tool recognition data set consisting of data from accelerometer and gyroscope measurements.

In the first part of the article it is studied when results can be considered reliable. This is different to the most activity recognition studies where reliability of the results is not questioned. Reliability is studied using two classifiers: QDA and LDA. It was noted that the recognition accuracy for observations with posterior probability 95% is around 50%. Therefore, it can be concluded that when posterior probability is below 95%, the model is not reliable, and the threshold for reliable classification was set to 95%. However, it should be further studied with multiple classifiers and data sets how this threshold could be decided using some metrics.

In the experiment section, the proposed method is applied to two data sets. It is shown that when 95% threshold is used, the results improve significantly. For instance, using QDA improvement is over four percentage units with daily activity data set and over three percentage units with tool usage data set. In addition, in most cases 95% threshold means that well under half of the results are replaced with the results of the sensor fusion based model. Which again means that less than 25% of the instances are classified using the sensor fusion model. However, improvements can be achieved already using the sensor fusion-based model less frequently. For instance, in the case of daily activity recognition, setting the threshold for posterior probability so that a fifth of accelerometer-based classification results are replaced with sensor fusion-based classification, improves the recognition rate by over three percentage units (83.7 % vs. 86.8%) when QDA is used. In addition, it is likely that the recognition rates of sensor fusion-based models can be further improved as in this study the same features were extracted from each sensor. However, in order to obtain the highest possible benefit from sensor fusion, the special characteristics of each sensor should be studied, and extract different types of features from different sensors based on these.

Future work includes experiments with multiple data sets in order to test the method with different kind of activities. In addition, the presented method should be tested in real-time. For instance, it could be implemented into a smartphone to be tested in real-life conditions. Moreover, at this point, the method uses two user-independent models, however, more models based on different sensors could be trained, and create a model that uses more than two models and selects the model to be used using some metrics.

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