Improved Activity Recognition by Using Enriched Acceleration Data

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ABSTRACT
Sensors embedded in smartphones are an essential component for activity recognition. Even though the accelerometer is the most widely used sensor, the highest recognition accuracies are obtained when using data collected from multiple sensors. However, the use of multiple sensors has an adverse impact on the energy consumption of power-limited devices such as smartphones. In this paper, we present a new method to improve the recognition accuracy of physical activities by using only the accelerometer. We utilize a low-pass filter to split the acceleration data into a low- and a high-frequency component. These components provide a new set of features, which can be used as a complement to the raw acceleration to reduce the number of sensors needed to recognize physical activities. After evaluating our method for a public dataset, we found that our approach represents an average of up to $16\,\%$ increase in the recognition accuracy over the raw acceleration data, outperforming even widely used combinations such as the raw acceleration plus the gyroscope. The highest accuracies are obtained when using a cut-off frequency in the interval $[0.001 - 0.05]$ Hz as well as a combination of the acceleration with its low-frequency component.

Author Keywords
Activity Recognition; Acceleration; Low-Pass Filter

ACM Classification Keywords
I.2.1. Artificial Intelligence: Applications and Expert Systems

INTRODUCTION
In the past few decades, significant improvements in the field of activity recognition have been made [5, 12]. Physical activities such as walking, sitting, running or standing can be recognized by using different kinds of sensors. Early approaches used accelerometers attached to the body for many applications such as the recognition of physical activities [9, 14], the recognition of complex activities [3, 13], fall detection [4, 15, 17] or posture recognition [7, 8]. Recently, to further improve the recognition accuracy of physical activities, the combination of sensors including accelerometers, gyroscopes, and magnetometers has been also investigated [6, 16]. Wu et al. reported in [23] an improvement of $\sim 10\%$ for individual activities, when using the accelerometer and the gyroscope in combination. In [20], Shoaib et al. investigated the influence of an accelerometer, a gyroscope, and a magnetometer as well as their combinations on the recognition accuracy for different activities. They showed that the combination of an accelerometer and a gyroscope improved the recognition accuracy of physical activities. Dernbach et al. developed a smartphone-based activity recognition approach by combining acceleration and gyroscope data to recognize not only physical activities, such as sitting or running, but also complex activities, such as cooking, cleaning, and taking medication [6]. Recently, Khan et al. utilized an accelerometer, a pressure sensor, and a microphone to recognize a set of 15 activities. They examined the most relevant features of each sensor and discussed the influence of the smartphone position on the recognition accuracy [10]. Although these publications encourage the combination of several sensors for activity recognition, the use of multiple sensors has a negative influence in the energy consumption of smartphones [11]. In this paper, we propose a new method to improve the recognition accuracy of physical activities by using only the accelerometer sensor. Instead of collecting additional data from other physical sensors, such as the gyroscope or the magnetometer, we use a low-pass filter to split the acceleration data into a low- and a high-frequency component. This additional data can be used, in combination with the raw accelerometer, to increase the recognition accuracy of physical activities. We refer to the combination of raw acceleration with its low and high-frequency components as *enriched acceleration data*. An evaluation using a public dataset shows that our approach improves the average recognition accuracy by $\sim 3.5\%$, while for single activities this represents an increase of up to $\sim 16\%$. This outperforms the combination of raw acceleration and gyroscope data and other combinations. We also found that the highest improvements are obtained in the region of low cut-off frequencies, namely, $[0.001 - 0.05]$ Hz. To the best of our knowledge, there are no publications on using filtered signals with such cut-off frequencies for activity recognition.

This paper is organized as follows. In the following section, we describe our method. Then, we describe how to apply our

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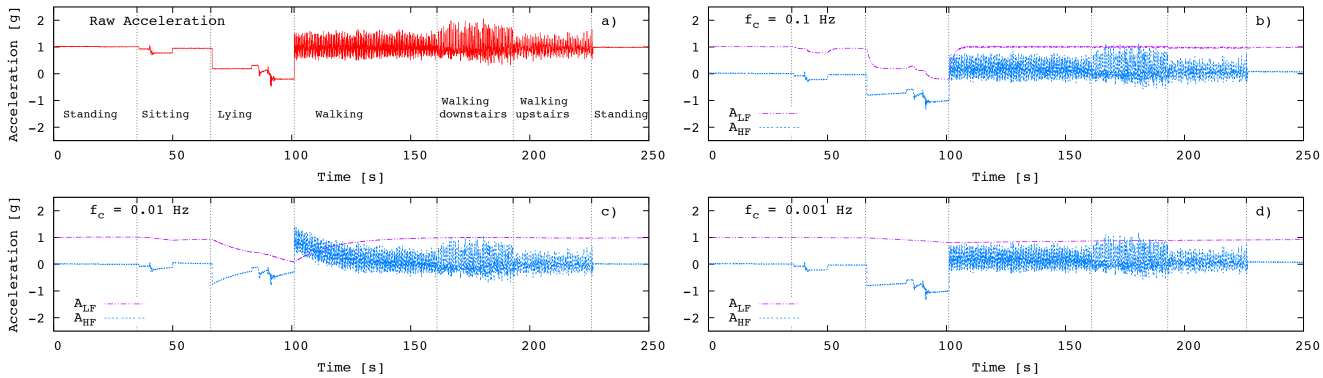

Figure 1. The raw acceleration signal (red line) from a subject performing physical activities (a), compared to the same signal filtered with a cut-off frequency f_c of (b) 0.1 Hz, (c) 0.01 Hz and (d) 0.001 Hz, respectively.

method for activity recognition using a public dataset. In Section *Results*, we present our main findings and finally, in the last section, we present our conclusions.

ENRICHED ACCELERATION DATA

To increase the recognition accuracy of physical activities, we use *enriched acceleration data*. This enriched data contains the raw acceleration from the sensor together with a Low-Frequency (LF) and a High-Frequency (HF) component. To derive these additional signals, we use a Butterworth Low-Pass Filter (LPF). The low-frequency signal can be directly obtained after applying the LPF. To compute the HF component (A_{HF}) we subtract the LF-Acceleration (A_{LF}) from the raw acceleration (A) as

$$A_{HF} = A - A_{LF}. \tag{1}$$

To investigate the effect of the filtering we use cut-off frequencies in the interval $[0.001 - 0.99]$ Hz. The response of the original signal A to the filtering can be observed from Figure 1. Figure 1.a shows the original accelerometer data from a subject performing physical activities (red line). In Figures 1.b-d, we plot the HF and LF signals for three different cut-off frequencies $f_c = 0.1$ Hz, 0.01 Hz, and 0.001 Hz, respectively. The LF components (purple lines) are obtained after applying a Butterworth low-pass filter to the original data. Once we have the LF component, we can compute the HF component (blue lines) by using Equation 1. From Figure 1.b, we can observe that a cut-off frequency of $f_c = 0.1$ Hz removes a significant part of the high-frequency signal in the raw acceleration data (purple line). By decreasing the cut-off frequency to a value of $f_c = 0.001$ Hz we can completely remove the high-frequency signal in the raw acceleration, which can be seen in Figure 1.d (purple line).

EVALUATION

We evaluate our approach by using the *Human Activity Recognition (HAR) dataset* [1]. The dataset includes inertial sensor data (e.g. accelerometer and gyroscope) from 30 subjects sampled at 50 Hz. Each person was asked to perform six activities *walking, walking up and downstairs, sitting, standing, and lying*, while wearing a smartphone (Samsung S2) on the waist. To recognize this set of physical activities we use four different types of classification algorithms,

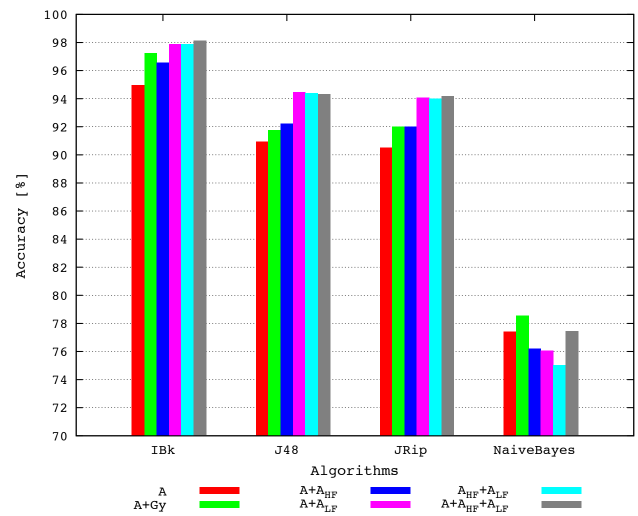

Figure 2. Recognition accuracy for different algorithms. A: Acceleration, Gy: Gyroscope, A_{HF}: High-Frequency Acceleration, A_{LF}: Low-Frequency Acceleration

namely, a *Lazy learner*, a *Decision Tree*, a *Rule-based*, and a *Bayesian* classifier. More precisely, we used the algorithms [*IBk*, *J48*, *JRip*, and *Naive Bayes*] implemented in the WEKA toolkit [22]. These standard algorithms have been widely used for activity recognition [3, 19]. To evaluate the performance of these algorithms we randomly split the dataset into two subsets. The first subset contains 70 % of the data and is used to train the classifier while the remaining 30 % is used as test data. This process was repeated 50 times to calculate the mean values and their corresponding standard deviations.

Features

Feature extraction is done by using the sliding window approach. As different window lengths have an influence on the classification accuracy [2], we evaluate different lengths ($\omega_1 = 0.64$ s, $\omega_2 = 1.28$ s, and $\omega_3 = 2.56$ s) with an overlap of 50 %. For a better comparison with previous works, we used a set of standard statistical features containing: mean, standard deviation, variance, maximum, minimum, information entropy, and energy.

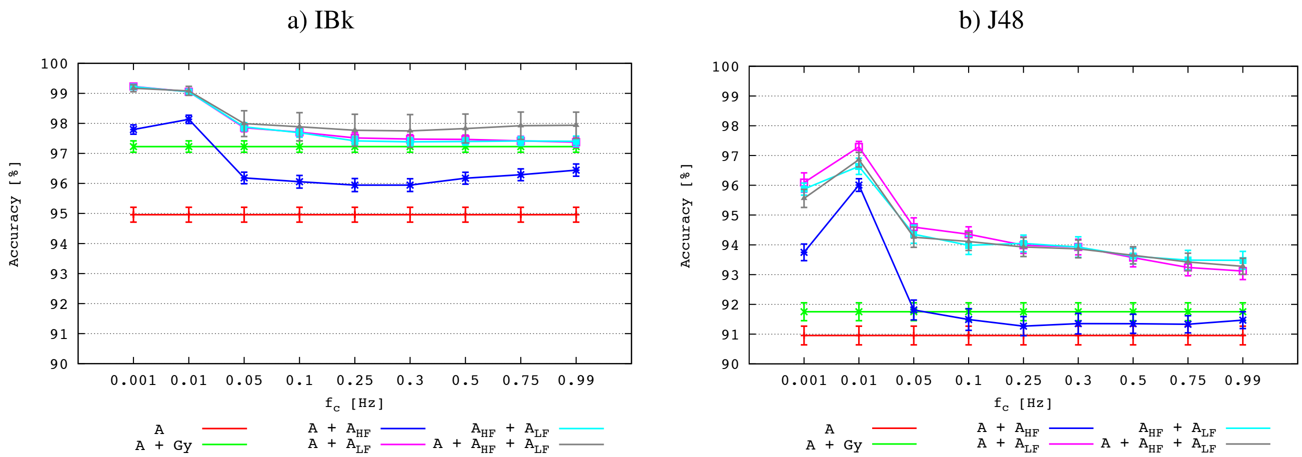

Figure 3. Recognition accuracy with respect to the cut-off frequency f_c for the algorithms: a) Ibk and b) J48. A: Acceleration, Gy: Gyroscope, A_{HF}: High-Frequency Acceleration, A_{LF}: Low-Frequency Acceleration.

Activity	A	$A + Gy$	$A + A_{HF}$	$A + A_{LF}$	$A_{HF} + A_{LF}$	$A + A_{HF} + A_{LF}$
Lying	99.92	99.92	99.94	99.92	99.90	99.93
Sitting	96.21	95.77	96.64	97.29	96.96	96.88
Standing	96.17	95.63	96.58	97.22	97.00	96.81
Walking	82.35	85.96	85.75	91.25	91.32	91.44
Walking-Downstairs	84.06	84.68	85.49	88.67	88.64	88.47
Walking-Upstairs	82.43	84.41	84.71	89.40	89.46	89.42

Table 1. Precision for the different activities when using the J48 algorithm. The highest accuracies are obtained when using enriched acceleration data.

RESULTS

In Figure 2, we plot the classification accuracy of the four classifiers. We compare the accuracy obtained when using only the raw acceleration (red bars) with the accuracy obtained by using enriched acceleration data. To allow a better comparison with earlier approaches, we also include the combination Acceleration + Gyroscope (green bars). The results show that the classification accuracy improves when using enriched acceleration data. In particular, the combinations of $A + A_{LF}$, $A_{LF} + A_{HF}$, as well as the combination $A + A_{LF} + A_{HF}$ perform better than the raw acceleration alone or even the combination of accelerometer and gyroscope $A + Gy$. This is not the case for the Naive Bayes classifier, where the highest accuracy is obtained when using $A + Gy$. This might be due to the fact that the new set of features used for classification, which arise from the same signal, are not independent. This fact contradicts the assumption of conditional independence, established by the Naive Bayes classifier. However, the Naive Bayes classifier shows more than $10\,\%$ lower accuracy than the IBk, the J48, and JRip algorithm. This is independent whether using enriched acceleration data or any other combination.

The highest accuracies are obtained by the IBk algorithm, which achieves an accuracy of $\sim 95\,\%$ using only the raw acceleration. When using our approach the recognition accuracy improves up to $3.5\,\%$ for all algorithms, except for the Naive Bayes. The accuracy of the combinations, that use filtered data are obtained by averaging over the different cut-off frequencies in the interval $[0.001 - 0.99]$ Hz.

Figure 3 shows the recognition accuracy of the algorithms with respect to the cut-off frequency that was used to derive the LF and HF components. For each cut-off frequency, we plot the corresponding error bars. We can observe that by using the enriched acceleration data the classification accuracy increases for all cut-off frequencies. The highest accuracies are obtained by the IBk algorithm, which classified the activities with an overall accuracy of $\sim 99\,\%$ for $f_c = 0.01$ Hz. However, the highest improvements are obtained when using the J48 and the JRip algorithm with an average gain of up to $\sim 6\,\%$. From Figure 3, we can see that the highest improvements are obtained with cut-off frequencies in the range of $[0.001 - 0.05]$ Hz. We can also observe that in this region, the size of the error bars decreases, showing the robustness of our method.

Since the IBk algorithm already showed high accuracies when using the raw acceleration and the Naive Bayes does not benefit from our approach, we focus only on the algorithm that profits the most by using our approach. Table 1 shows the precision of each activity for the J48 classifier. From this table, we can observe that the highest accuracies (filled cells) are obtained when using enriched data. The walking activity benefits the most from our approach, with an average gain of up to $9\,\%$. As mentioned above, the highest improvements are obtained for the lowest cut-off frequencies. Therefore, in Fig-

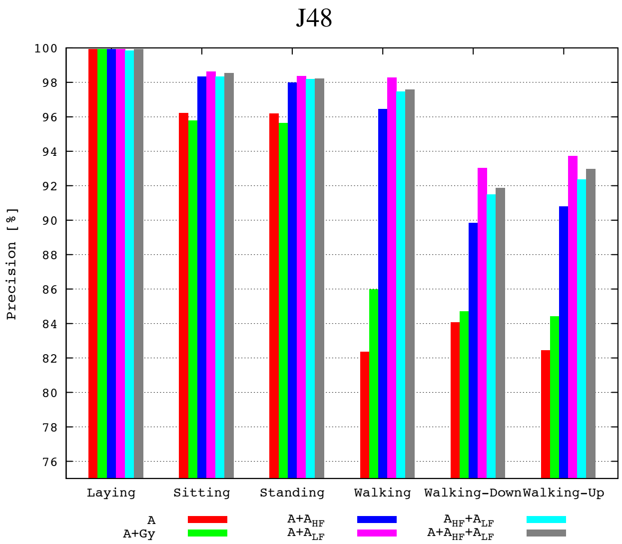

Figure 4. Precision for the different activities when using the J48 algorithm and a cut-off frequency of $f_c = 0.01$ Hz. A**: Acceleration,** Gy**: Gyroscope,** A_{HF}**: High-Frequency Acceleration,** A_{LF}**: Low-Frequency Acceleration.**

Algorithms	Signal Set	Window Length ω_1	ω_2	ω_3
J48	A	90.95	92.66	92.37
	$A+Gy$	92.20	93.44	92.91
	$A+A_{HF}$	94.46	95.13	94.23
	$A+A_{LF}$	94.33	94.92	94.13
	$A_{HF}+A_{LF}$	94.38	94.95	94.08
	$A+A_{HF}+A_{LF}$	91.75	92.45	91.60
	Average	93.20	94.07	93.35

Table 2. The influence of the window lengths $\omega_1 = 0.64$ s, $\omega_2 = 1.28$ s, and $\omega_3 = 2.56$ s to the recognition accuracy. The window length $\omega_2 = 1.28$ s provides the highest recognition accuracies. Accuracies are given in [%].

ure 4 we plot the precision of each activity using the J48 algorithm and a cut-off frequency of $f_c = 0.01$ Hz. By using this parameter, we increase the recognition rates of the activities walking, walking downstairs and walking upstairs between 8 % to 16 %. Since the J48 algorithm employs the information gain of the features to select the main nodes when building the decision tree, the improvement in the classification accuracy is caused by an increased information gain due to the low-frequency and high-frequency components. To verify this hypothesis, we calculated the information gain of the new features. The results showed that the features computed from LF and HF components contribute to the information gain.

The effect of the window length in the recognition accuracy of the J48 classifier is presented in Table 2. From this table, we can see that the window length parameter has an influence on the recognition accuracy. The highest variations are of about ~ 3 %. The window length $\omega_2 = 1.28$ s results in the best classification accuracies.

Author	Algorithm	Features	Accuracy %
Anguita et al. [1]	SVM	561	89
Romera et al. [18]	OVO	561	96
	OVA	561	94
	K-NN	561	90
Silva et. al [21]	J48	37	86
This work	IBk	48	99
	J48	48	97
	JRip	48	97
	NaiveBayes	48	84

Table 3. Recognition accuracy of several works using the *HAR using smartphones dataset* [1]. SVM: Support Vector Machine, OVO: One vs One, OVA: One vs All, K-NN: K-Nearest Neighbor.

In Table 3 we present previous results based on this dataset. Anguita et. al [1] and Romera-Paredes et. al [18], obtained an accuracy of ~ 89 % and ~ 96 %, respectively, when using a set of 561 features derived from the Gravity, the Linear Acceleration and the Gyroscope. The former employed a Multiclass Support Vector Machine (SVM) while the latter used a One-vs-One (OVO) Multiclass Support Vector Machine. Recently, Silva et al. [21] used a reduced feature vector, containing 37 features, and the J48 algorithm to classify the six activities in the same dataset. They report a classification accuracy of ~ 86 %. As we can see from this table, by using enriched acceleration data we achieve higher accuracies than those reported in previous works.

CONCLUSION

In this paper, we present a new approach to improve the recognition accuracy of physical activities. Instead of combining data from multiple physical sensors, we use only accelerometer-derived data. To extract additional data from the accelerometer we use a Butterworth low-pass filter with a cut-off frequency in the range $[0.001 - 0.99]$ Hz. As a result of the filtering, we obtain a High-Frequency (HF) and a Low-Frequency (LF) component from the acceleration. Our results show that for the IBk, J48, and JRip algorithm, the use of enriched data helps improving the classification accuracy independent of the cut-off frequency. The highest accuracy results are obtained when using a cut-off frequency in the interval $[0.001 - 0.05]$ Hz. The highest accuracies are obtained when using the combination *Acceleration + LF Acceleration*, which even outperforms widely used combinations such as *Acceleration + Gyroscope*. When using this combination, the precision of the activities shows an improvement of up to 16 %. Although direct comparison with previous approaches is a difficult task, we can conclude from our results that by using our approach we achieve accuracies higher than the ones reported in previous works using a smaller set of features and only one physical sensor.

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