Feature Engineering for Activity Recognition from Wrist-worn Motion Sensors

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Abstract: With their integrated sensors, wrist-worn devices, such as smart watches, provide an ideal platform for human activity recognition. Particularly, the inertial sensors, such as accelerometer and gyroscope can efficiently capture the wrist and arm movements of the users. In this paper, we investigate the use of accelerometer sensor for recognizing thirteen different activities. Particularly, we analyse how different sets of features extracted from acceleration readings perform in activity recognition. We categorize the set of features into three classes: motion related features, orientation-related features and rotation-related features and we analyse the recognition performance using motion, orientation and rotation information both alone and in combination. We utilize a dataset collected from 10 participants and use different classification algorithms in the analysis. The results show that using orientation features achieve the highest accuracies when used alone and in combination with other sensors. Moreover, using only raw acceleration performs slightly better than using linear acceleration and similar compared with gyroscope.

1 INTRODUCTION

Mobile phones' ubiquity and the rich set of sensors available on these devices make them a suitable platform for human activity recognition (Incel et al., 2013; Bulling et al., 2014). More recently, wrist-worn devices, such as smart watches are also emerging as an alternative for activity recognition. Wrist-worn devices have the advantage of capturing wrist, hand and arm movements compared to the smart phones which are usually carried in pockets and bags. Moreover, the smart phones may not always be attached to the user's body, such that it can be left on a desk, while the wrist-worn devices are usually attached to the user unless removed.

While other sensors, such as GPS, microphone, can also be used for activity recognition, motion or inertial sensors available on wrist-worn devices, such as accelerometer, gyroscope, are among the most effective sensors for activity recognition. They can easily capture the user's movements and in fact activity recognition using inertial sensors has been an active field of research (Avci et al., 2010; Bulling et al., 2014; Lane et al., 2010; Shoaib et al., 2015b). These sensors also have the advantage of consuming less battery power compared to other resource-hungry sensors, such as GPS.

In this paper our aim is to analyse the performance of activity recognition with different set of features for activity recognition from wrist-worn motion sensors, particularly the accelerometer. The main idea is to analyse how much a wrist-worn device move, change its orientation and rotate and how these changes can be used to recognize the activities of a user. For this purpose, we categorize the features to be extracted from raw accelerometer data into three classes: motion features, orientation features and rotation features. Features from the magnitude of acceleration are used as the motion-related features, whereas features from the individual axes of the accelerometer are utilized to compute the orientation-related features. Additionally, instead of using gyroscope for rotation information, we extract rotation-related features, namely pitch and roll, from the acceleration readings. The main motivation is to explore the effectiveness of an only-accelerometer solution.

In order to investigate the effectiveness of these features both alone and when fused together, we use a dataset (Shoaib et al., 2016) collected from ten participants. A Samsung Galaxy S2 phone was used to emulate a smart watch and was placed on the wrist of the participants. The sampling rate was 50Hz. In

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total, 13 activities were performed: eating, typing, writing, drinking coffee, smoking, giving a talk, walking, jogging, biking, walking upstairs, walking downstairs, sitting and standing. Although some activities can easily be captured by a wrist-worn device, such as eating, typing, some are more challenging to detect by such a device, such as sitting, standing. The second category of activities are usually used in the studies for activity recognition with mobile phones.

In the initial tests, we show how the recognition performance can be increased with the use of orientation and rotation-related features besides the motion-related features using only the accelerometer. In the next round of tests, the use of linear acceleration is investigated compared to the accelerometer and in the last round, instead of computing rotation features from accelerometer, gyroscope is used for extracting rotation related features. The aim is to compare the performance of an acceleration-only approach with using extra sensors. In all the tests, performance of different classifiers such as, decision tree, naive Bayes and random forest is also compared. Our results show that using orientation features achieve the highest accuracies when used alone and in combination with other sensors. Moreover, on average the random forest classifier performs the best compared with other classifiers. Using only raw acceleration performs better than using linear acceleration and similar compared with gyroscope. The following lists the main highlights of this paper:

- We extract pitch and roll features from the accelerometer. The use of these features were investigated for activity recognition from smart phone sensors in (Incel, 2015; Coskun et al., 2015), but not from wrist-worn sensors.
- We categorize the set of features into three categories: motion related features, orientation-related features and rotation-related features. We analyse the performance of activity recognition using motion, orientation and rotation information both alone and in combination.
- We focus on activities that can be recognized from wrist-worn sensors, such as eating, smoking, and also activities, such as walking, running, that are typically recognized by smart phone sensors placed in the pocket. This makes our dataset more challenging and different from those that only utilize wrist-related activities.
- We analyse the performance of accelerometer-only solution and compare its performance with different classifiers.

2 RELATED WORK

Feature engineering is an important part of the activity recognition process. In recent years, it has been studied extensively in the context of physical activity recognition as summarized in various survey studies (Lane et al., 2010; Bulling et al., 2014). However, most of the studies focus on the recognition of simply physical activities at the pocket position. For example, the authors in (Figo et al., 2010) studied extensively various time and frequency domain features which are suitable for running on smartphones. They compared various features using their computation and storage complexity and described their suitability for mobile devices. However, they evaluate all these features using a threshold based mechanism with only three activities such as walking, jumping, and running. Moreover, this study used only one accelerometer in the right jeans pocket position. Similarly, the authors in (Kwapisz et al., 2011) also investigated various features for simple seven physical activities at the pocket position.

Some of the studies also investigated various features at the wrist position. However, they also mainly focused on the simple physical activities. For example, the authors in (Maurer et al., 2006) compared various features on multiple body positions including wrist using a decision tree classifier. However, they only evaluated seven simple physical activities. Moreover, they used only accelerometer. Previously, we also investigated various time and frequency domain features for the wrist position, however, it was done only for seven simple physical activities (Shoaib et al., 2014).

We have previously studied the recognition of simple and complex activities at the wrist position, however, it was done using only two simple time-domain features: mean and standard deviation (Shoaib et al., 2016; Shoaib et al., 2015c). Moreover, the main focus of that study was to evaluate the effect of increasing window size and combining sensor data from pocket position with the wrist position on the recognition performance of various activities. We also did not consider any features based on pitch and roll. In this study, we extend our previous work by exploring an extended set of features for both simple and complex activities at the wrist position as described in Section 1.

3 METHODOLOGY OF FEATURE ENGINEERING

3.1 Dataset Details

The dataset was collected from ten participants with an age range: 23 to 35. All participants were given two mobile phones (Samsung Galaxy S2) during data collection. One was located in in their right trousers' pocket. In order to emulate a smart watch or a wrist-worn device, the other phone was located at their right wrist. While in our previous work (Shoaib et al., 2016), we investigated the fusion of data from both phones, in this paper we only use the data collected from the phone located at the wrist. Our aim is to analyse the performance of wrist-worn devices with these activities. Data was sampled at 50 Hz from the phone's accelerometer, its (virtual) linear acceleration sensor and its gyroscope.

In total, 13 activities were included in the dataset. Seven activities (walking, jogging, biking, walking upstairs, walking downstairs, sitting and standing) were performed by all the participants with a duration of 3 minutes per activity. Seven of the participants also performed the activities of eating, typing, writing, drinking coffee and giving a talk with a duration of 5-6 minutes. Smoking data was collected from six of the participants, where each of them smoked one cigarette while standing, since not all the participants were smokers. More details of the dataset can be found in (Shoaib et al., 2016).

3.2 Feature Extraction

In this paper, our aim is to analyse the classification performance with different feature sets, namely the motion features, orientation features and rotation features. The raw acceleration readings include both the dynamic (due to movement of the phone) and static acceleration (due to gravity) values and it is not possible to separate them when the phone is moving without using gravity readings. However, in this study, instead of using computing the exact orientation of the phone, we try to detect the changes in the acceleration readings in the individual axes.

The magnitude of acceleration (square-root of the sum of the squares of readings in each accelerometer axis) is utilized for the extraction of motion features. From the raw acceleration readings, the following motion features are computed over a time-window of 20 seconds:

- **Mean:** The average value of the magnitude samples over a time window.
- **Variance:** Average of the squared differences of the sample values from the mean value over a time window.
- **Root Mean Square (RMS):** The root mean square is the square root of the sums of each data over a window, divided by the sample size.
- **Zero-Crossing Rate (ZCR):** The number of points where a signal crosses through a specific value corresponding to half of the signal range. In our case, the mean of a window is utilized.
- **Absolute Difference (ABSDIFF):** Sum of the differences from between each magnitude sample and the mean of that window divided by the number of data points. This feature was utilized in (Alanezi and Mishra, 2013) for individual acceleration axis to enhance the resolution in capturing the information captured by data points.
- **First 5-FFT Coefficients:** the first 5 of the fast-Fourier transform coefficients are taken since they capture the main frequency components.
- **Spectral Energy:** Square sum of spectral coefficients divided by the number of samples in a window.

The readings from each of the 3-axis of the accelerometer are used for the computation of orientation features. The following features are extracted from each accelerometer axis such that in total 12 features are computed:

- Standard Deviation: Square root of variance.
- Root mean square (RMS)
- Zero-crossing rate (ZCR)
- Absolute Difference (ABSDIFF)

The rotation features are computed from the changes in the pitch and roll angles. The rotational information can be extracted from the gyroscope or orientation sensor on Android phones, however this requires the use of other sensors and the orientation sensor was deprecated in Android 2.2 (API level 8). In our previous work (Incel, 2015; Coskun et al., 2015), we extracted pitch and roll information from the acceleration readings. In Equation 1 and Equation 2, it is given how the pitch and roll values are computed respectively. In the equations x, y and z represent the accelerometer readings in the 3-coordinates, whereas g is the gravitational acceleration, i.e., 9.81 m/s^2:

$$\beta = \frac{180}{\Pi}.tan^{-1}(y/g, z/g) \quad (1)$$

$$\alpha = \frac{180}{\Pi}.tan^{-1}(x/g, z/g) \quad (2)$$

Using the pitch and roll values, the following rotation-related features are extracted such that 12 more features are extracted:

- Mean
- Standard Deviation: Square root of variance.
- Root mean square (RMS)
- Zero-crossing rate (ZCR)
- Absolute Difference (ABSDIFF)
- Spectral energy

In total, 35 features are extracted from the accelerometer readings. Similar to raw acceleration readings, the same set of features are extracted from linear acceleration readings. In order to evaluate the performance of rotation features extracted from gyroscope we extract Standard-deviation, RMS, ZCR and ABSDIFF of three axes, resulting in 12 features(discussed in Section 4.3).

4 PERFORMANCE EVALUATION

In this section, we present the results obtained by following the methodology explained in Section 3.

We used Python programming environment for preprocessing the data and feature extraction. For the classification phase, we used Scikit-learn (Version 0.17), which is a also Python-based machine learning toolkit (Pedregosa et al., 2011). Three classifiers, which are commonly used for practical activity recognition, are utilized: Naive Bayes, decision tree and random forest (Shoaib et al., 2015b; Shoaib et al., 2015a). All the classifiers were set in their default mode. For the decision tree, Scikit-learn uses an optimized version of the CART (Classification and Regression Trees) algorithm.

In the classification phase, we used 10-fold stratified cross-validation without shuffling. In this validation method, the whole dataset is divided into ten equal parts or subsets and at each iteration, nine of these parts are used for training and one part for testing. The window size was selected as 20 seconds since in our previous work (Shoaib et al., 2016), it was shown that larger window sizes achieve higher accuracies with activities where wrist movements dominate and are less-repetitive.

4.1 Recognition with Accelerometer

In this section, we present the results obtained by using raw acceleration readings and discuss how motion, orientation and rotation features perform when both used alone and in combination. We also compare the recognition performance of different classification algorithms, namely naive Bayes, decision tree and random forest.

In Figure 1, the results of experiments using decision tree classifier are presented. In this test, the aim is to analyse different combinations of features in detail.The y axis represents the accuracy values. Although the accuracy values range between zero and one, in the text, we mention the accuracies in terms of percentages, for the ease of reading.

When the results of individual sets of features are analysed (only motion, only orientation, only rotation), in general using only orientation features achieves the highest accuracy for most activities with a few exceptions. For example, the motion features perform better for walking, biking, walking downstairs and rotation features for sitting, smoking and eating.

For various combinations of different feature sets, such as motion and orientation (MO), motion and rotation (MR) and orientation and rotation (OR), the combination of motion and orientation features (MO) achieves the highest accuracies for different activities. Compared with the single sets of features, the combination of feature sets performs better for drinking coffee, talking, smoking, eating and walking downstairs. For other activities, either motion or orientation features perform better, except sitting where rotation features achieve the highest accuracy. When all feature sets are used together (MOR), accuracies either remained the same, or decreased in few cases. It could be that adding rotation features increased the confusion rate between activities. Only exception is the sitting activity, where rotation and motion-rotation features (MR) achieve the best results.

The average accuracy for all activities is 69% for motion features, 78% for orientation, 76% for rotation, 81% for motion-orientation, 79% for motion-rotation, 79% for orientation-rotation and 77% for motion-orientation-rotation combinations. Overall, using motion and orientation features achieves the highest accuracy on average. We achieve the highest accuracy for biking and jogging and lowest accuracy for walking, walking upstairs and downstairs, because these activities were confused with each other. An example confusion matrix for Random Forest classifier using motion-orientation features is given in Table 1. Additional sensors, such as pressure, can be used in differentiating these activities or they can be combined into a single activity if possible.

In Figure 2, results with naive Bayes classifier are presented. Compared with decision tree results given in Figure 1, accuracies for all the activities have in-

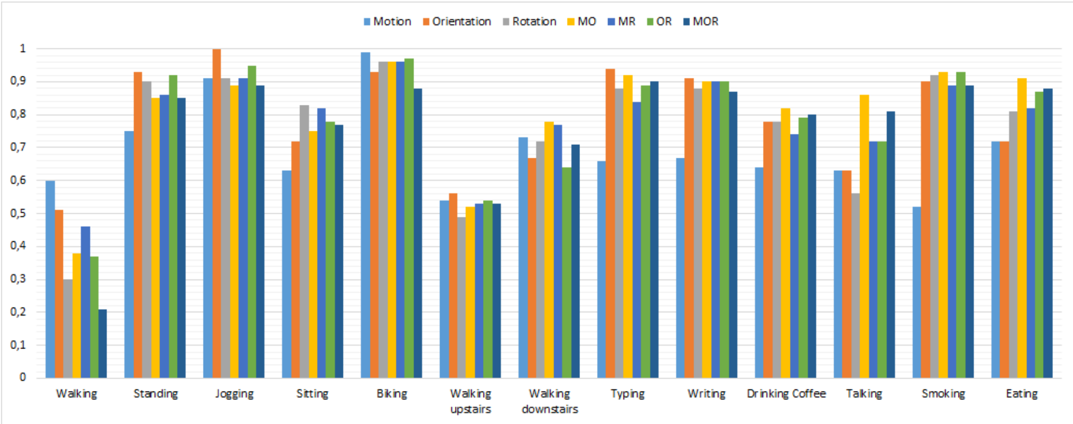

Figure 1: Recognition performance of accelerometer with different feature combinations using decision tree classifier (M:Motion, O:Orientation, R: Rotation).

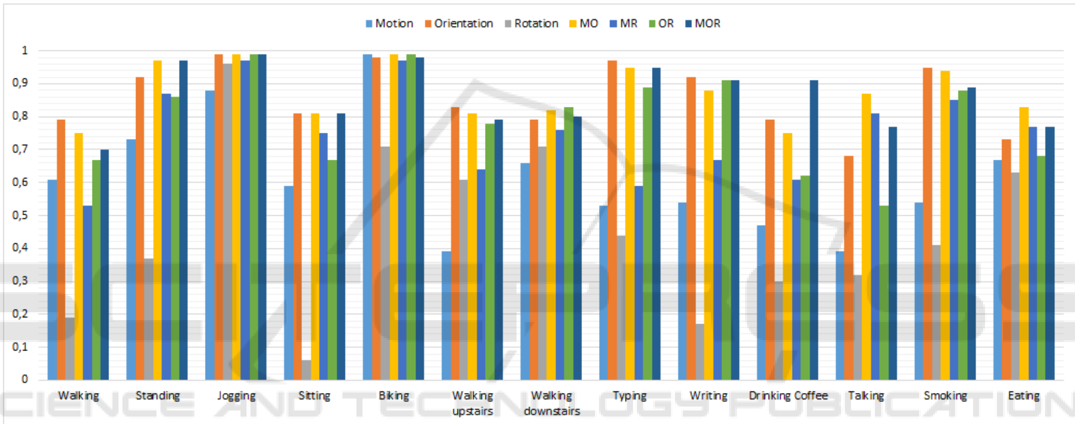

Figure 2: Recognition performance of accelerometer with different feature combinations using Naive Bayes classifier (M:Motion, O:Orientation, R: Rotation).

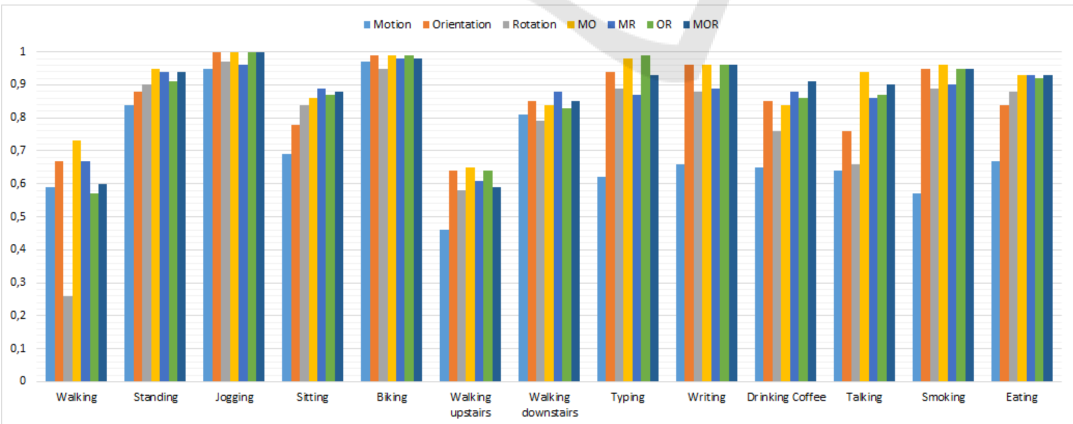

Figure 3: Recognition performance of accelerometer with different feature combinations using Random Forest classifier (M:Motion, O:Orientation, R: Rotation).

creased except for eating and sitting activities. Particularly, walking, walking upstairs and downstairs activities are recognized with higher accuracies. Similar to the decision tree results, the orientation features are the dominant set of features in achieving high accuracy. Walking, walking upstairs, typing, writing

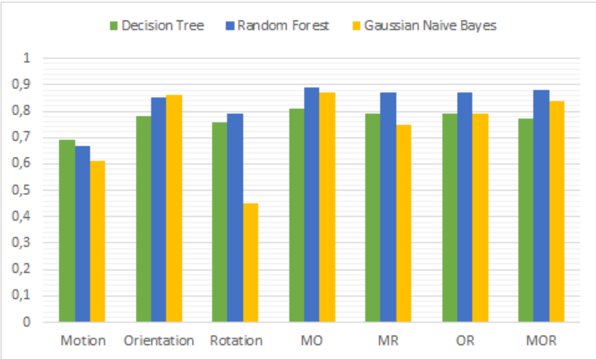

Figure 4: Comparison of Decision Tree, Naive Bayes and Random Forest in terms of average accuracy (M:Motion, O:Orientation, R: Rotation).

and smoking are recognized with the highest accuracy when only orientation features were used. The highest average accuracies for all the activities are computed as 86% with motion features and 87% with motion-orientation features.

In Figure 3, the results of the experiments using random-forest classifier are presented. In particular, the maximum average accuracy is achieved with motion and orientation features which is 89%. This is higher compared with other classifiers where maximum average accuracy is 81% for decision tree with motion-orientation features, and 87% with naive Bayes classifier again using motion-orientation features. In Figure 4 we present a comparison of the classifiers in terms of their average performance.

In general, random forest achieves the highest accuracies for most of the activities. However, naive Bayes achieves higher accuracies for walking and walking upstairs activities. As mentioned, these activities are confused with each other and an example confusion matrix is given in Table 1 using motion-orientation features.

4.2 Recognition with Linear Acceleration

In this section, our aim is to analyse the performance with linear acceleration readings instead of using raw acceleration. The accelerometer sensor on Android phones, measures the gravitational acceleration, if the device is stationary or its speed does not change. If the phone is accelerating, it measures the combination of the gravitational acceleration and the acceleration due to movement and this acceleration due to movement, is named as the “linear acceleration”. We only provide the results with the random forest classifier in this section due to space limitation. We also experimented with the other two classifiers, however random forest achieved the highest accuracies similar to raw acceleration results.

The results are given in Figure 5. When we compare these results with the results obtained with raw acceleration, given in Figure 3, we see that results are either the same or slightly lower with linear acceleration. Particularly, the walking activity is recognized with 64% accuracy using motion features with linear acceleration whereas it is recognized with 73% accuracy using raw acceleration with motion-orientation features, which results in 9% lower accuracy. Computing linear acceleration readings generally consumes more battery power and may not be preferred in real-time, continuous-running applications of activity recognition (Incel, 2015).

4.3 Recognition with Acceleration and Gyroscope

In this section, we aim to analyse whether gyroscope should be used for extracting rotation features. As mentioned we extracted features from pitch and roll values which were computed from raw acceleration readings. Hence, in this section we extract rotation features from gyroscope and use them either in combination with motion and orientation features extracted from raw acceleration or alone. We replace the twelve rotation features extracted from acceleration with the twelve features extracted from the individual axes of gyroscope: Standard-deviation, RMS, ZCR and ABSDIFF. The evaluation is performed with the random forest classifier.

Results are given in Figure 6. In general, using only rotation, i.e. the gyroscope, performs worse than using combinations of features. Compared with the results obtained with raw acceleration, given in Figure 3, most of the activities are recognized with a similar accuracy. However, sitting, walking upstairs and downstairs are recognized with 4%, 12% and 9% higher accuracies compared with raw acceleration. The average accuracy considering all the activities is around 90% when using motion-rotation or motion-orientation-rotation features, which was 88% when motion-orientation-rotation features are calculated from raw acceleration. Although an accelerometer-only solution provides an efficient solution, gyroscope can compute exact rotation information, compared to using accelerometer for computing pitch and roll values. However, the average performance with only acceleration solution is still acceptable with 89% accuracy using motion-orientation features.

Table 1: Confusion Matrix with Random Forest using motion-orientation features, in %.

	Walk	Stand	Jog	Sit	Bike	Walk Up-stairs	Walk Down-stairs	Type	Write	Drink	Talk	Smoke	Eat
Walk	**72.22**	0	0	0	0	23.33	4.44	0	0	0	0	0	0
Stand	0	**92.22**	0	0	0	0	0	0	0	2.22	2.22	3.33	0
Jog	0	0	**100**	0	0	0	0	0	0	0	0	0	0
Sit	0	0	0	**84.44**	0	0	0	1.11	4.44	7.78	0	0	2.22
Bike	0	0	0	2.22	**97.78**	0	0	0	0	0	0	0	0
Walk Up-stairs	23.33	0	0	0	0	**64.44**	12.22	0	0	0	0	0	0
Walk Down-stairs	2.22	0	0	0	0	11.11	**84.44**	0	0	0	2.22	0	0
Type	0	0	0	0	0	0	0	**97.78**	1.11	1.11	0	0	0
Write	0	0	0	0	0	0	0	1.11	**97.78**	0	0	0	1.11
Drink	0	1.11	0	10	0	0	0	0	0	**83.33**	1.11	1.11	3.33
Talk	0	0	0	0	0	0	0	0	0	0	**93.33**	2.22	4.44
Smoke	0	0	0	0	0	0	0	0	0	1.11	0	**98.89**	0
Eat	0	0	0	0	0	0	0	0	0	3.33	0	0	**96.67**

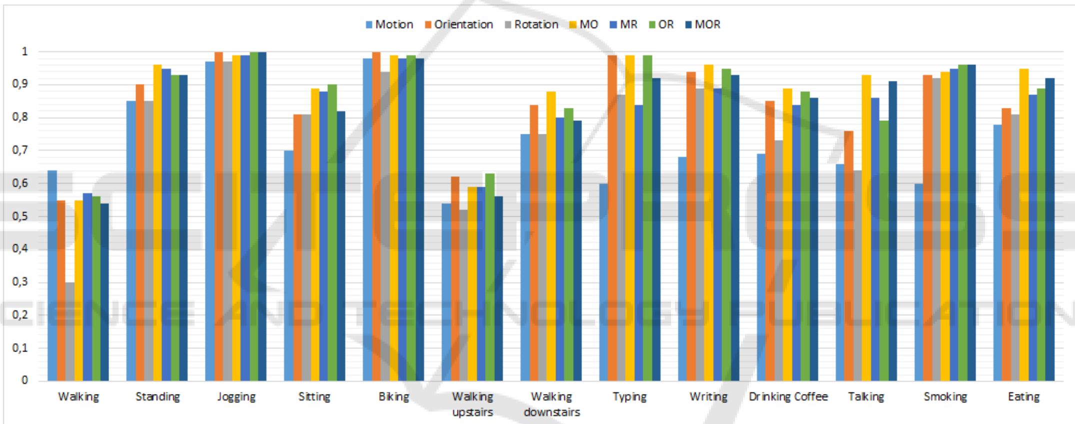

Figure 5: Recognition performance of linear accelerometer with different feature combinations using Random Forest classifier (M:Motion, O:Orientation, R: Rotation).

Figure 6: Recognition performance of acceleration and gyroscope with different feature combinations using Random Forest (M:Motion, O:Orientation, R: Rotation).

5 CONCLUSION AND FUTURE WORK

In this paper, the main motivation is to evaluate the performance of activity recognition with wrist-worn devices using inertial sensors and particularly analyse the performance with different feature sets. We categorize the set of features into three classes: motion related features, orientation-related features and rotation-related features and we analyse the performance using motion, orientation and rotation information both alone and in combination. We utilize a dataset collected from 10 participants with thirteen activities and use decision tree, naive Bayes and random forest classification algorithms in the analysis. The results show that using orientation features achieve the highest accuracies when used alone and in combination with other sensors. However, the combination of all features (motion, orientation and rotation) does not usually improve the results. Considering the average accuracies, random forest classifier achieves the highest performance. Additionally, using only raw acceleration performs slightly better (89%) than using linear acceleration and similar compared with gyroscope. Hence, our results show that using an accelerometer only solution can perform as well as using linear acceleration or using both an accelerometer and gyroscope. The main advantage is that an acceleration-only solution consumes less battery power and this is an important factor for real-time, continuous-running applications.

We are currently collecting a dataset using smart watches and particularly focusing on the recognition of smoking. As a future work, we plan to apply the same methodology to the new dataset. Moreover, we aim to apply feature selection methods and reduce the number of features used and analyse the battery consumption on a smart watch.

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