Recognizing Hand-Specific Activities with a Smartwatch Placed on Dominant or Non-dominant Wrist *

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ABSTRACT
In this paper we analyze the possibility to use an accelerometer-equipped smartwatch to recognize hand-specific activities. We start with a large set of activities, and since many activities have a similar acceleration pattern, we gradually group semantically similar activities to find a tradeoff between the accuracy on one hand, and semantically understandable and useful activity groups on the other hand. Additionally, we compare the activity recognition in terms of the number of activities and accuracy when wearing a smartwatch on the dominant or non-dominant wrist. The preliminary results show that we can recognize up to seven groups of activities with the dominant, and up to five activity groups with the non-dominant wrist.

Categories and Subject Descriptors
D.3.3 [**Human-centered computing**]: Ubiquitous and mobile computing

Keywords
Activity recognition, wrist wearable, machine learning, accelerometers

1. INTRODUCTION
Activity recognition is an important module in person oriented intelligent systems, since most of the further reasoning or assistance to the user depends on the user's current or past activity. This dependency is highly significant in applications intended for the management of lifestyle and sports activities [6], as well as chronic diseases such as diabetes or chronic heart failure (CHF). In diabetes, the user needs to monitor two particular activities, the eating (which increases the blood glucose level) and exercise (which decreases the blood glucose) [1] and in CHF it is important to monitor the food intake (eating) as well as exercise in terms of its intensity and amount of rest [4].

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Due to importance of activity recognition and availability of accelerometer equipped wearables it is not surprising that the research area is very popular and partially also very mature. The maturity of the area is shown in the amount of applications and wearable devices dedicated to activity monitoring available on the market [2, 3]. However, these applications and devices mostly recognize three activities (walking, running and rest), which is insufficient for applications in which e.g., eating or any other hand-oriented activities are important.

In this paper we analyze and evaluate a possibility to use accelerometer equipped smartwatch to recognize a large set of hand-oriented activities. Since many activities have similar pattern we gradually group semantically similar activities into single activity to find a tradeoff between accuracy and semantically understandable activity groups. Additionally, we compare the activity recognition in terms of number of activities and accuracy when wearing a smartwatch on dominant or non-dominant wrist.

The paper is structured as follows. Section 2 presents the related work on activity recognition, Section 3 introduces the dataset and methods for preprocessing and training the models. The evaluation results are present in Section 4 and Section 5 concludes the paper.

2. RELATED WORK
Pioneers in activity recognition research studied use of single or multiple accelerometers attached to different locations on the users body. Attal et al. [5] reviewed the research done until 2015 and proved that number of recognized activities increases with the number of sensors attached to the users body. Since using one or more dedicated accelerometers was perceived as unpractical, the researchers started using devices that most people already have or will have in future, such as smartphones and wristbands.

Research on activity recognition with the smartphone mostly covers analysis of accelerometer signals without any knowledge of its orientation, thus recognizing only small fraction of activities (walking, running, rest, etc.) [11]. Martin et al. [10] was first to take varying orientation and location into consideration. Their approach requires use of all available smartphone sensors to estimate the location and normalize the orientation. In our recent research [8], we proposed a real-time method that normalizes the orientation, detects the location and afterward uses a location specific machine-learning model for activity recognition.

The research on activity recognition with wrist-worn devices has started with the accelerometer placed on a persons wrist [5]. Since this is the most comfortable placement of the sensor, the research became popular for recognizing sports activities [12] and common activities (sitting, standing, lying, walking, running) [7]. However, none of the research focused on recognizing hand-specific activities (e.g., eating, washing, hammering, etc.), which is the topic of this paper.

3. MATERIALS AND METHODS

3.1 Dataset

Dataset consists of data of 11 volunteers equipped with two smartwatches with accelerometer and a heart rate sensor (one on each wrist), performing a predefined scenario. Average accelerometer sampling rate was 48.2 Hz (± 4.4) for the left hand and 51.3 Hz (± 14.2) for the right hand.

The scenario contained 39 different activities, but not all were performed by each volunteer. Figure 3.1 presents the distribution of data in terms of number of instance and in terms of people performing the activity. We can observe that some activities were performed by one person only, which is insufficient for training the models and evaluating them using leave-one-subject-out approach. Omitting these activities left us with 30 activities, due to errors in data collection we also had to omit the mobile use, phone call, clapping, white board and rolling dice. This left us with 25 activities for further analysis.

3.2 Preprocessing

The goal of the preprocessing procedure is to combine the accelerometer and heart rate data received from the smartwatch into form suitable for further use with machine-learning algorithms (feature vectors).

The raw acceleration and heart rate data is first segmented into 2-second windows, each next overlapping by half of its size, from which we extract 90 acceleration features and 4 heart rate features. In brief, the raw acceleration data is first filtered (low-pass and band-pass) to remove noise and gravity. These data is afterward used for calculation of physical (e.g., velocity, kinetic energy, etc.), statistical features (e.g., the mean, variance, etc.) and features which use signal processing expert knowledge (e.g., number of peaks in a signal, etc.). The reader is referred to [8] for more details about the feature extraction. Once the features are extracted they are used to form a feature vector to be used for machine-learning.

3.3 Method

Activity recognition is set as a classification task, performed in real-time. The feature vector formed during the feature extraction (Section 3.2) is feed into a classification machine-learning model trained to recognize the activities.

The collected dataset contains data labeled with 25 activities for each wrist. To design the method efficiently we had to solve two challenges: (i) the difference in movement of dominant and non-dominant during the same activity (e.g.,

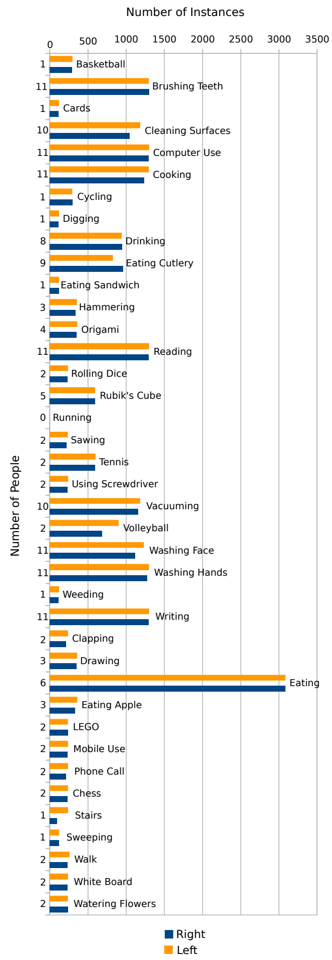

Figure 1: Number of instances per activity (y axis) and number of people performing the activity (x axis)

drinking, eating, writing, etc.), and (ii) similar hand movement when performing different activities. We decided to develop two classification models, one for each wrist according to dominance to solve the first challenge. For the second challenge we analyzed the possibility to semantically group the activities, thus achieve higher recognition accuracy but still keep the understandability of the classification result.

To select the machine-learning classification algorithm to be used for training the models, we have first evaluated the classification accuracy of five different machine-learning algorithms as implemented in Weka suite [9] (J48, SVM, JRip, Random Fores and Naïve Bayes) on the dataset with 25 activities. All experiments are done with Leave-One-Subject-Out approach (LOSO). As in our previous activity monitoring research, the Random Forest achieved the best results and was chosen for all further experiments.

Once the machine-learning algorithm was chosen we analyzed the possible grouping of the activities according to dominance. We started with the dominant hand, the grouping of which is presented in Figure 2. We start by gradually grouping the most similar activities together and evaluating

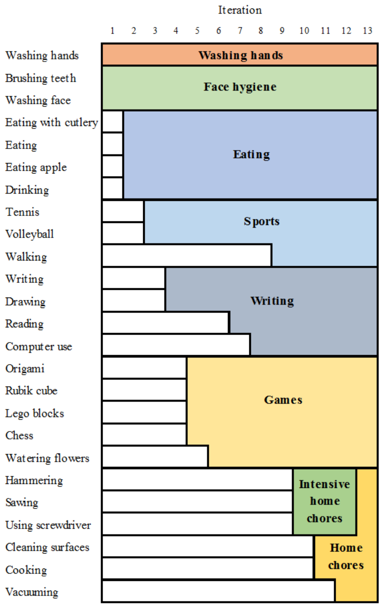

Figure 2: Grouping of activities when smartwatch is worn on a dominant hand.

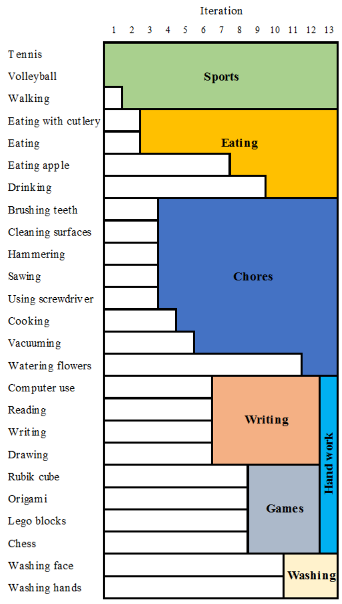

Figure 3: Grouping of activities when smartwatch is worn on a non-dominant hand.

the impact on accuracy. We first group the activities that seems the most similar. All upper hand movements used in face hygiene are grouped together, next are the eating activities, sports and activities similar to writing. The final three groups are the activities where the person plays games or the hand gesture is of low intensity. We also tried to group home chores by intensity in to low and intensive which turned out less accurate then if grouping all home chores together. With this approach we divided all 25 activities into 7 groups or classes to be recognized when smartwatch is worn on dominant hand. Results of each iteration is presented in Section 4.

The same approach was used to group activities to be recognized by non-dominant hand (Figure 3). We grouped the sports activities, eating activities, all chores activities together. The activities that were left were very similar in terms of non-dominant hand movement. We tried to distinguish between activities which are similar to writing and games activities, but this decreased the accuracy compared to grouping the two types of activities into single group (hand work). The last group of activities contain the washing activities. With this approach we divided all 25 activities into 5 groups or classes to be recognized when smartwatch is worn on non-dominant hand. The results of each iteration are presented in Section 4

Apart from evaluating the classification models for each wrist on dedicated grouping of activities, we have also evaluated the use of non-dominant hand activities grouping for training the dominant hand model and vice-versa. Both experiments were preformed in two ways:

- By using the machine-learning model trained for the specific wrist directly, namely Default approach (D)
- By smoothing the results using the majority classification in the 10-class sliding window, namely smoothing approach (S). The length of the window was selected arbitrarily.

The results are presented in Section 4.

4. EVALUATION

The goal of the evaluation was to analyze and compare the recognition of the activities according to the retrieved data from the smartwatch attached to the dominant or non-dominant wrist. Additionally, we wanted to evaluate and get an insight into type of activities that can be recognized in respect to the hand dominance. The evaluation was performed with Random Forest algorithm in leave-one-subject out (LOSO) manner on dataset presented in Section 3.1. The results are presented in Table 1.

First, we evaluated the use of acceleration and heart rate data retrieved from the smartwatch attached to the dominant wrist. We used the default approach (D) introduced in Section 3.3 to group the activities into seven classes. The increase in accuracy while gradually decreasing the number of recognized classes from 25 to seven is presented in Figure 4. As expected the accuracy increased with each subsequent grouping and we have finally settled for seven classes (Dominant wrist (D)). If we apply smoothing (Dominant wrist (S)) we gain 3 percentage points in accuracy. Finally, we evaluated the recognition of seven classes with non-dominant wrist data, which returned poor accuracy of 58% when default (D) method was used and 63.7% when smoothing was applied (Figure 4 Cross: Non-dominant wrist (S)).

The same approach was used to define the classes to be recognized with non-dominant hand. We first used the default approach (D) to group the activities which resulted in five final classes. The process of grouping and respective accuracy is presented in Figure 4 (Non-dominant wrist (D)). When smoothing is applied (Non-dominant wrist (S)) we gain 4 percentage points in accuracy. Finally, we evaluated the recognition of five classes with dominant wrist data, which as expected returned higher accuracy then with seven classes (76% when default (D) method was used and 84% when smoothing was applied (Figure 4 Cross: Dominant wrist (S)).

Table 1: Evaluation of activity recognition. The methods: D=default, S=smoothed.

Wrist (method)	Accuracy [%]	# classes
Dominant (D)	71	7
Dominant (S)	79	7
Cross: Non-dominant (D)	58	7
Cross: Non-dominant (S)	64	7
Non-Dominant (D)	70	5
Non-Dominant (S)	74	5
Cross: Dominant (D)	76	5
Cross: Dominant (S)	84	5

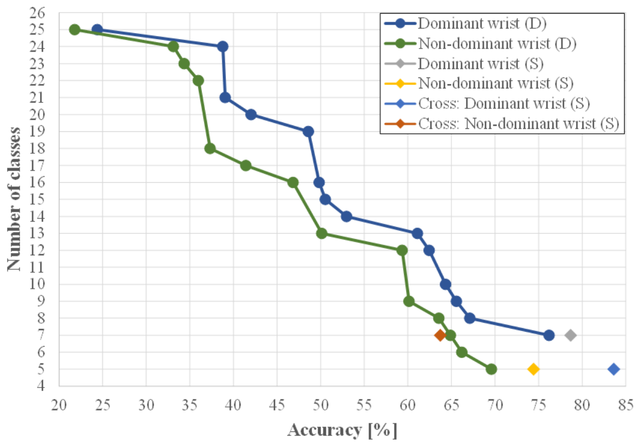

Figure 4: Accuracy.

5. CONCLUSION

We presented a feasibility study of recognizing hand-specific activities using data retrieved from smartwatch on dominant or non-dominant wrist. We start with large set of hand-specific activities and gradually decrease the number of activities by semantically grouping them together. The preliminary results show that we can recognize larger set of activity groups if we use data from the smartwatch worn on dominant wrist (7 activity groups) then using data from the smartwatch worn on non-dominant wrist (5 activity groups).

Since these are only preliminary results, which gave us a feasibility insight, we will need to repeat the data collection procedure to collect more samples of already recorded activities as well as record additional activities (e.g., sport-specific, home-chores specific, etc.). To achieve higher accuracy, we will also need to perform feature selection procedure and analyze which features are relevant for the task. Finally, we will need to merge the dataset with other datasets which contain non-hand-specific activities and probably design more complex algorithm to achieve good results.

6. ACKNOWLEDGMENTS

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7. REFERENCES

[1] American Diabetes Association. http://www.diabetes.org/food-and-fitness/. [Online; accessed September-2017].

[2] FitBit. https://www.fitbit.com/eu/home. [Online; accessed September-2017].

[3] Runkeeper. https://runkeeper.com/. [Online; accessed September-2017].

[4] P. A. Ades, S. J. Keteyian, G. J. Balady, N. Houston-Miller, D. W. Kitzman, D. M. Mancini, and M. W. Rich. Cardiac Rehabilitation Exercise and Self-Care for Chronic Heart Failure, 2013.

[5] F. Attal, S. Mohammed, M. Dedabrishvili, F. Chamroukhi, L. Oukhellou, and Y. Amirat. Physical Human Activity Recognition Using Wearable Sensors. *Sensors (Basel, Switzerland)*, 15(12):31314–38, 2015.

[6] S. Chatterjee and A. Price. Healthy Living with Persuasive Technologies: Framework, Issues, and Challenges. *Journal of the American Medical Informatics Association*, 16(2):171–178, 2009.

[7] S. Chernbumroong and A. S. Atkins. Activity classification using a single wrist-worn accelerometer. *2011 5th International Conference on Software, Knowledge Information, Industrial Management and Applications (SKIMA) Proceedings*, pages 1–6, 2011.

[8] B. Cvetković, R. Szeklicki, V. Janko, P. Lutomski, and M. Luštrek. Real-time activity monitoring with a wristband and a smartphone. *Information Fusion*, 2017.

[9] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten. The WEKA data mining software. *SIGKDD Explorations Newsletter*, 11(1):10, 2009.

[10] H. Martín, A. M. Bernardos, J. Iglesias, and J. R. Casar. Activity logging using lightweight classification techniques in mobile devices. *Personal and Ubiquitous Computing*, 17(4):675–695, 2013.

[11] M. Shoaib, S. Bosch, O. Incel, H. Scholten, and P. Havinga. A Survey of Online Activity Recognition Using Mobile Phones. *Sensors*, 15(1):2059–2085, 2015.

[12] P. Siirtola, P. Laurinen, E. Haapalainen, J. Röning, and H. Kinnunen. Clustering-based activity classification with a wrist-worn accelerometer using basic features. In *2009 IEEE Symposium on Computational Intelligence and Data Mining, CIDM 2009 - Proceedings*, pages 95–100, 2009.