Comparing the Placement of Two Arm-Worn Devices for Recognizing Dynamic Hand Gestures

Kathrin Kefer
University of Applied Sciences Upper Austria
Softwarepark 11
4232 Hagenberg, Austria
kathrin.kefer@fh-hagenberg.at

Clemens Holzmann
University of Applied Sciences Upper Austria
Softwarepark 11
4232 Hagenberg, Austria
clemens.holzmann@fh-hagenberg.at

Rainhard Dieter Findling
University of Applied Sciences Upper Austria
Softwarepark 11
4232 Hagenberg, Austria
rainhard.findling@fh-hagenberg.at

ABSTRACT

Dynamic hand gestures have become increasingly popular as an input modality for interactive systems. There exists a variety of arm-worn devices for the recognition of hand gestures, which differ not only in their capabilities, but also in the arm positions where they are worn. The aim of this paper is to investigate the effect of placement of such devices on the accuracy for recognizing dynamic hand gestures (e.g. waving the hand). This is relevant as different devices require different positions and thus differ in the achievable recognition accuracy. We have chosen two positions on the forearm: on the wrist and right below the elbow. These positions are interesing as smartwatches are usually worn on the wrist and devices using EMG sensors for the detection of static hand gestures (e.g. spreading the fingers) have to be worn right below the elbow.

We used an LG G Watch worn on the wrist and a Myo armband from Thalmic Labs worn below the elbow. Both are equipped with three-axis accelerometers, which we used for gesture recognition. Our hypothesis was that the wrist-worn device would have a better recognition accuracy, as dynamic hand gestures have a bigger action radius on the wrist and therefore lead to bigger acceleration values. We conducted a comparative study with nine participants that performed eight simple, dynamic gestures on both devices. We tested the 4320 gesture samples with different classifiers and feature sets. Although the recognition results for the wrist-worn device were higher, the difference was not significant due to the substantial variation across participants.

CCS Concepts

•Human-centered computing → Gestural input; Mobile devices; •Computing methodologies → *Machine learning;*

MoMM '16, November 28-30, 2016, Singapore, Singapore
© 2016 ACM. ISBN 978-1-4503-4806-5/16/11...$15.00
DOI: http://dx.doi.org/10.1145/3007120.3007146

Keywords

Gesture recognition; Hand gestures; Accelerometer; Sensor placement; Arm-worn devices

1. INTRODUCTION

Hand gestures are becoming increasingly popular as an input modality e.g. in cars or for home entertainment systems. However, most gesture recognition systems rely on cameras, which can be affected by poor lighting conditions or by obstructions that limit the range in which gestures can be used [1, 8]. These problems can be circumvented by reading gesture information directly from arm-worn devices.

One example of such a device is Thalmic Labs' Myo armband[1]. Compared to wrist-worn devices like activity trackers or smartwatches, it not only allows to detect dynamic gestures with its inertial measurement unit, but also static gestures (poses) with the hand [11] by using electromyography sensors, which read electrical signals from the muscles in the forearm to detect hand poses. This offers a wide range of gesture inputs to interactive systems, without the limitations of camera-based technologies.

One constraint, however, is the placement of the device. In order to read muscle signals properly from the forearm, the Myo device has to be wrapped around the forearm just below the elbow. While this placement is a necessity for detecting hand poses, we expect it to have a negative effect on the detection of dynamic hand gestures. Because of the lower action radius, accelerations get lower the closer the sensing device is worn to the rotary joint (elbow). Investigating the effect of placing an arm-worn device such as the Myo right below the elbow is relevant for interactive systems which use both static and dynamic gestures for their input.

Summing up, we expect the recognition accuracy of a device worn right below the elbow to be significantly lower than that of a wrist-worn device. The main contribution of this work is to test this hypothesis by comparing the Myo armband with a state-of-the-art smartwatch, the LG G Watch[2]. We limited our work to three-axial acceleration data, gyroscope and compass were not used for gesture recognition.

We used a set of eight simple gestures that have already been used in previous research (e.g. [5], [7] and [9]). The eight different gestures, which are shown in Figure 1, are waving left, waving right, waving up, waving down, drawing

[1] https://www.myo.com/
[2] http://www.lg.com/us/smart-watches/lg-W100-lg-watch

a square, drawing a triangle, and drawing a circle clockwise and counterclockwise with the right hand in the air.

2. RELATED WORK

2.1 Gesture Recognition Using Arm-Worn Devices

Much previous research on gesture recognition used accelerometers. Often devices were used which are held in the hand. Examples are the papers of Wu et al. [15], where the Nintendo Wii controller with its built-in accelerometer was used to distinguish 12 gestures, or the paper of Hwang et al. [6], where an Android smartphone was used as a gesture input device. However, in contrast to our work, the devices were held in the hand and not worn on the wrist or on the forearm of the user, like we do in our approach.

In other related work, wrist-worn devices were used for gesture recognition. However, to the best of our knowledge, none of them compared different accelerometer positions on the user's forearm. For example, Rekimoto [14] used a gesture detection unit which was mounted on the user's wrist and recognized hand gestures by capacitively measuring wrist-shape changes and forearm movements.

A gesture recognition system that used a smartwatch and its built-in accelerometer sensor to assist people with visual impairments was proposed by Porzi et al. [13]. In the work of Chen et al. [2], gestures with a smartwatch were used to enhance a wide range of interactive tasks on a smartphone.

In our work, we recognize gestures both with a smartwatch and a device strapped to the arm below the elbow joint simultaneously, in order to investigate which placement leads to a higher gesture recognition accuracy.

2.2 Placement of Accelerometers for Gesture Recognition

The placement of accelerometers was subject of research mainly in the field of activity recognition so far. Cleland et al. [3] conducted a study about the optimal placement of accelerometers for the detection of everyday activities like walking, sitting, lying, standing, and walking up and down stairs. They found that the hip was the best single location to record and classify the data, and that the simultaneous use of two sensors instead of one increased the accuracy.

The activity recognition accuracy for different accelerometer locations was also investigated by Olguin and Pentland [12]. They tested eight different common activities like walking, performing hand movements or sitting, using wireless accelerometers placed on the wrist, the left hip and the chest. The best recognition results were achieved with the simultaneous use of all three sensors. In both projects, the wrist was the only considered sensing location on the arm.

Another study on the accelerometer placement for fall detection as well as the recognition of postures that may be the result of a fall was done by Gjoreski et al. [4]. They tested nine placements of up to four sensors. The arm was not considered for a sensor placement in this work.

The related projects mentioned above examine the placement of accelerometers in the context of activity recognition. The sensors were placed all over the body and not on different positions on the arm, which is the scope of our work. To the best of our knowledge, there has been no research about the optimal sensor placements on the forearm for gesture recognition based on acceleration data.

3. IMPLEMENTATION DETAILS

We prototypically implemented an Android-based system for recognizing the gestures shown in Figure 1. The whole process can be split up into four steps, which will be described in more detail below: *sensor data collection*, *preprocessing*, *feature extraction* and *feature normalization*.

For the sensor data collection, a smartwatch (LG G Watch) and a gesture armband (Thalmic Labs' Myo armband) were chosen. For preprocessing, feature extraction and normalization, R[3] was chosen due to its comprehensive data analysis features. We used the Weka machine learning library[4] for the experimental part of this work because of the high number of implemented classifiers and feature filters.

3.1 Sensor Data Collection

To record the gestures with the Myo armband and the LG G Watch, an Android application was developed which runs on smartphones with Android version 4.3 or higher. To collect the acceleration data from the two supported input devices, a Bluetooth connection to the smartphone and its application is required. Using the Myo SDK, the connection to the Myo armband is established using Bluetooth 4.0 and the accelerometer data from the Myo is delivered via a callback method in the smartphone application.

For the Android Wear smartwatch, a dedicated application was implemented, which receives a start/stop command for data recording from the smartphone. The collected data is then sent to the mobile phone application via the established Bluetooth connection. The acceleration data from both devices is collected in a data strcucture until the gesture is finished, whereupon the raw acceleration data for all three axes and from both devices is stored in two csv-files on the smartphone's internal storage. The Myo armband delivers its data with a fixed sampling frequency of 50Hz, the sampling frequency of the Android Wear smartwatch was set to 50Hz in the application, but it can slightly vary due to the Android-internal sensor implementation.

3.2 Preprocessing

The preprocessing of this data includes two steps to smooth the acceleration data and to normalize the length of all gestures for a device. As smoothing function, a running median of odd span (the *runmed* method in R) was used with a width of 11 samples per window (corresponds to 220 ms).

For the gesture length normalization, the maximum length of all recorded gestures of a device was chosen to avoid loss of information for single gestures. The acceleration samples of each gesture were then interpolated, which resulted in 300 samples (6 seconds) for the Myo and to 421 samples (8.42 seconds) for the LG G Watch data using R's *approx* method.

3.3 Feature Extraction and Selection

Based on several existing works on gesture recognition with a three-axis accelerometers [5, 10, 16], a set of proven features was chosen. We selected a relevant subset with the *CfsSubsetEvaluation* and *BestFirst* algorithm using cross-validation with 10 folds as provided by the Weka Explorer. The basic features are calculated from a window that contains all accelerometer data belonging to one single gesture.

Due to the interpolation of the raw acceleration data, the

[3]https://www.r-project.org/

[4]http://www.cs.waikato.ac.nz/ml/weka/

Table 1: Set of features that were used for the classification. All features marked with a belong to the subset selected for the Myo armband, and those marked with b belong to the subset selected for the Android Wear smartwatch.

No.	Feature	Description
1	Mean Magnitude	The mean over all magnitudes.
2^a	Minimum Magnitude	The lowest of all magnitudes.
3	Maximum Magnitude	The highest of all magnitudes.
$4-6^{a,b}$	Range	The acceleration value range for each axis.
$7-9^a$	Mean	The mean value of the acceleration values for each axis.
$10-12^b$	Mean Absolute Deviation	The mean over all absolute deviations for each axis.
$13-15^a$	Root Mean Square	The mean over all squared accelerometer values for each axis.
$16-18^b$	Variance	The variance of the accelerometer values for each axis.
19	Mean Variance	The mean over the accelerometer value variances.
20^a	Magnitude Variance	The variance of the magnitude values.
21-23	Standard Deviation	The standard deviation of the accelerometer values for each axis.
24	Mean Standard Deviation	The mean over the accelerometer value standard deviations.
25	Magnitude Standard Deviation	The standard deviation of the magnitude values.
$26-28^{a,b}$	Peaks	The number of times an accelerometer values is higher than the mean for each axis.
29	Magnitude Peaks	The number of times a magnitude is higher than the Mean Magnitude value.
30^a	Mean Peaks	The mean over the accelerometer value peaks for each axis.
$31-33^a$	Mean Peak Values	The mean over all peaks values for each axis.
$34-36^{a,b}$	Correlation Coefficients	The correlation coefficient between two axes.
37-39	Energy	The energy of the accelerometer values for each axis.
$40-42^b$	Frequency Range	The frequency range for each axis.
$43-45^{a,b}$	Mean Frequency	The mean over the frequency values for each axis.
$46-48^{a,b}$	Frequency Peaks	The number times a frequency value is higher than the Mean Frequency for each axis.
$49^{a,b}$	Mean Frequency Peaks	The mean over the frequency peaks for each axis.
$50^{a,b}$	Gesture Duration	The number of accelerometer data values for a gesture.
$51-..^{a,b}$	Accelerometer Data	Every 50th raw acceleration value that was additionally normalized and centred. The exact number of acceleration values depends on the length of the original gesture.

window size is fixed to 300 samples for the Myo armband and 421 samples for the LG G Watch. The feature set shown in table 1 with more than 50 features was chosen as the basis for the feature extraction and the subsequent selection step.

3.4 Feature Normalization

In order to get better results and more accurate recognition accuracies especially for the k-Nearest Neighbour classifier (which is impacted by data that is not normalized), the whole feature set calculated during the feature extraction was additionally centered and scaled to the mean of the data being 0 and the standard deviation being 1.

4. EXPERIMENT

4.1 Participants

We conducted a comparative study with nine voluntary participants (2 female, 7 male). Their ages varied from 22 to 55 years (*mean*=31; *SD*=11.71) and all of them were right-handed. None was familiar with gesture recognition or with the eight gestures. Six of the participants were IT-students or programmers, three participants had no IT-background.

4.2 Apparatus

As gesture recording devices, the latest version of Thalmic Lab's Myo armband was used and as Android Wear smartwatch a LG G Watch W100 with Android Wear version 5.1.1 was chosen. For the Android smartphone application, Android Studio 1.4 was used as development environment. A Google Nexus 5x smartphone with Android version 6.0 was used as gesture recording device. For the preprocessing, feature extraction and normalization, R version 3.2.3 was used, for the experiment evaluation Weka version 3.6.13 was used.

4.3 Procedure

The participants were asked to perform the eight simple, dynamic gestures shown in figure **??** with both devices simultaneously for data collection. The recorded accelerometer data was first filtered and interpolated. Afterwards, the basic feature set shown in table 1 was calculated and normalized and then used for the evaluation.

At the beginning of each session, the gestures and how they should be performed was explained to each participant. For the data collection, the participants were equipped with the Myo armband and the LG G Watch on the right arm, and they were told which gesture to perform next and when to start. As starting position, the outstretched arm, being held orthogonal to the body and parallel to the floor, was defined. Starting from this position, each gesture was trained and performed 30 times by each of the nine participants as shown in Figure 1. This resulted in a total of 2160 gesture samples from each device.

4.4 Design

In order to test our hypothesis that the wrist-worn device (LG G Watch) has a better recognition accuracy that the one worn below the elbow (Myo armband), we evaluated the recognition accuracies using 4 different classifiers: k-Nearest Neighbour, J48 decision tree, Random Forest and Bagging. First, we evaluated the recognition accuracies with all features using 10-fold cross-validation with 10 repetitions. Second, we conducted a leave-one-subject-out cross-validation in which a single participant is repeatedly (for each participant) left out from the training data and used for testing

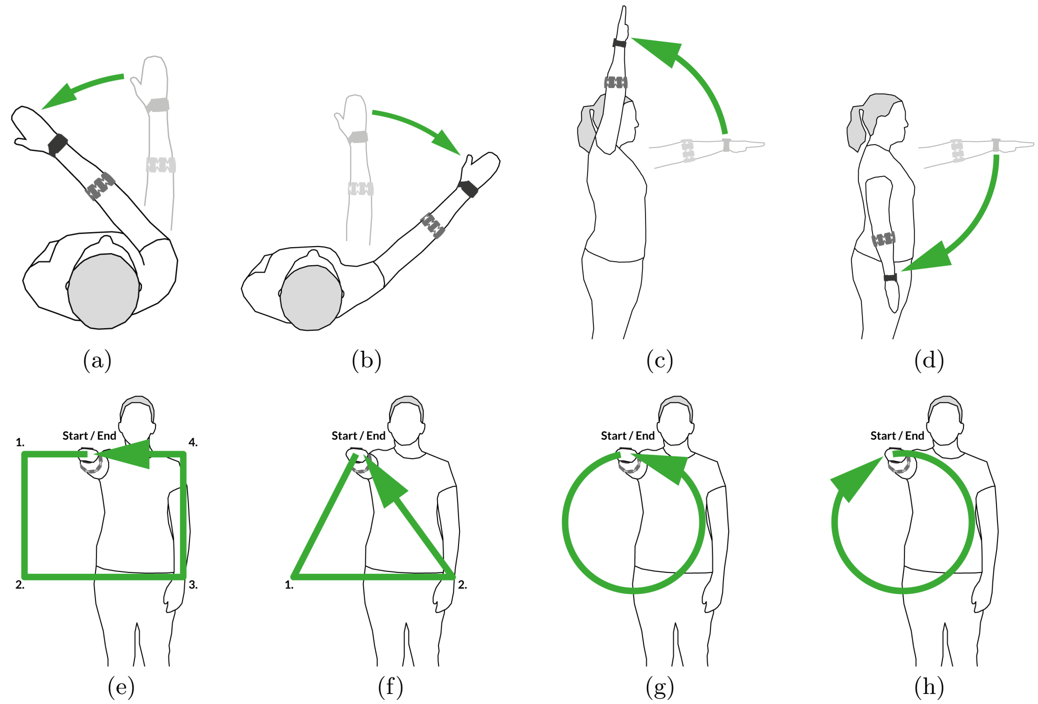


Figure 1: Visualization of how each gesture was performed by the participants: Waving (a) left, (b) right, (c) up and (d) down, as well as drawing (e) a square, (f) a triangle, (g) a circle clockwise and (h) a circle counterclockwise.

only, as the results are more generalizable. Moreover, we conducted the training for all features as well as for the selected features highlighted in table 1.

5. RESULTS AND DISCUSSION

The evaluation and classification of gestures was done with the Weka machine learning software on a PC. The bar chart Figure 2 shows the recognition accuracies for each device, classifier, feature set and evaluation type; the error bars represent the standard deviations. The results for 10-fold cross-validation with 10 repetitions are, as expected, better than for the leave-one-subject-out cross-validation, and that the deviation of the results is much lower.

The Myo armband achieves between 92.1% and 98.2% mean recognition accuracy for the different classifiers and therefore performs slightly better than the LG G Watch, which achieves between 86.5% and 96.2% with the 10-fold cross-validation and all features. Considering only the selected features (Tab. 1) changes the mean recognition accuracies by just $\pm 1\%$. This is a good result for using just one third (for the Myo armband) respectively one half (for the LG G Watch) of the original feature set consisting of more than 68 features for the Myo armband and 77 features for the Android Wear smartwatch.

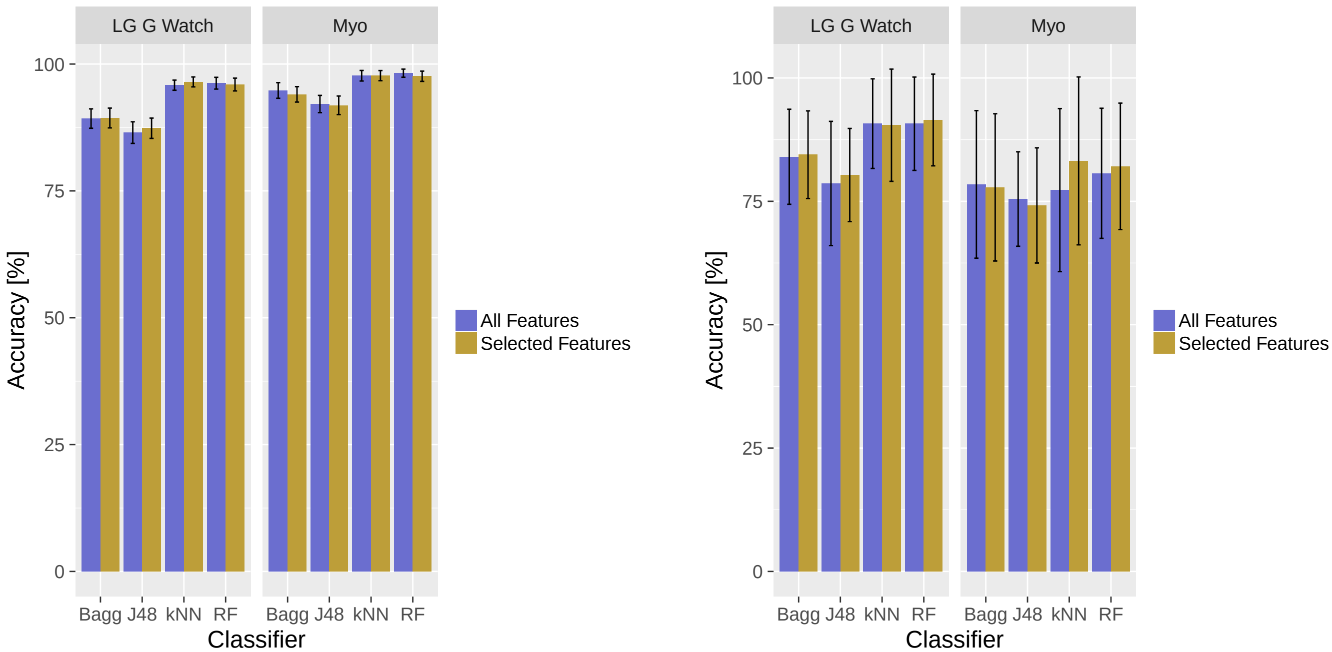
For the selected features subset, we tested the statistical significance for the best 10-fold cross-validation result for each device, being Random Forest for the Myo and kNN with k=1 for the smartwatch. The mean accuracy for the Myo was 97.6%, which was slightly more than the mean accuracy of 96.5% observed for the LG G Watch. The difference was statistically significant ($t99 = 15.5$, $p < 0.001$).

The results for the leave-one-subject-out cross-validation case with all features show that the LG G Watch performs better than the Myo armband with every classifier (90.7% for the LG G Watch compared to 80.7% for the Myo armband classified with Random Forest). Considering only the selected features increases the mean recognition accuracies of the Myo armband by up to $\sim$5%, whereas for the LG G Watch there is a maximum increase of $\sim$2%.

For the selected features subset, we tested the statistical significance for the best leave-one-subject-out cross-validation result for each device, being kNN with k=1 for the Myo armband and Random Forest for the LG G Watch. The mean accuracy for the Myo armband was 83.2%, which was more than 8% lower than the mean accuracy of 91,5% observed for the LG G Watch. However, as there were substantial variation across participants, the difference was not statistically significant ($t8 = -1.3$, ns).

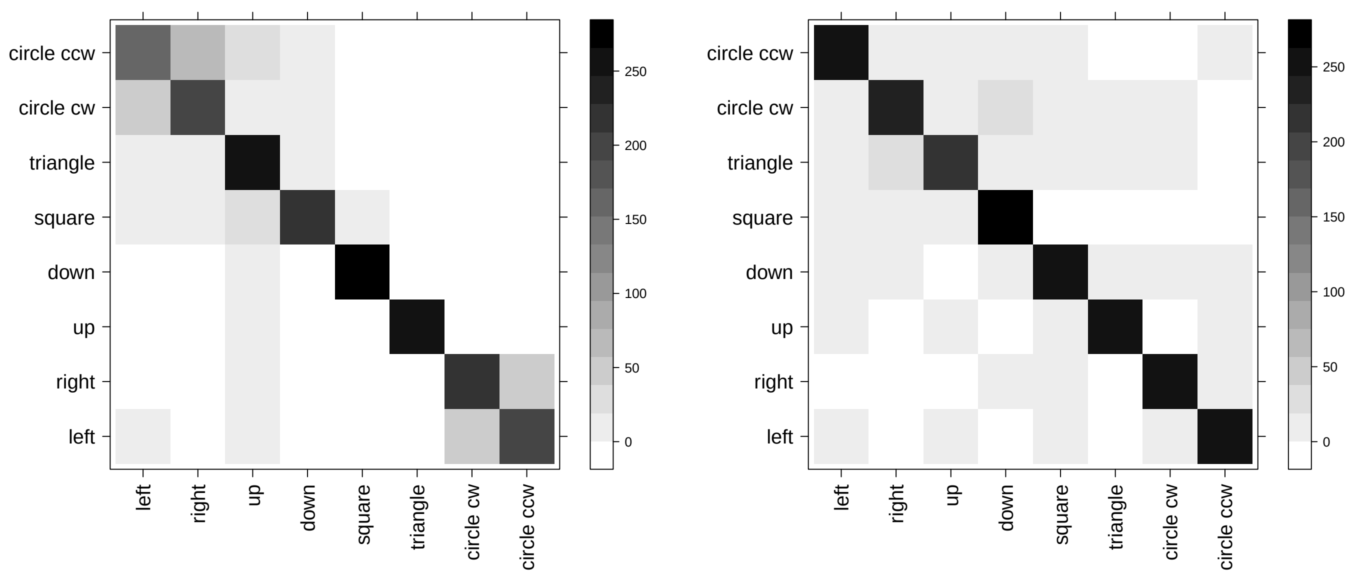
For this reason, we have to reject our hypothesis. For both the 10-fold cross-validation and the leave-one-subject-out cross-validation, the recognition accuracies for the wrist-worn device (LG G Watch) were not significantly better than for the arm-worn device (Myo armband).

Finally, Figure 3 visualizes the confusion matrices for the leave-one-subject-out cross-validation with only the selected features and the best classifiers (kNN with k=1 for the Myo armband and Random Forest for the LG G Watch). For the Myo armband, it can be seen that the waving left gesture was often confused with the waving right gesture and the circle clockwise with the circle counterclockwise gesture, whereas the square and triangle gestures were recognized almost without any error. With the LG G Watch, these four gestures were recognized and differentiated better.



(a) (b)

Figure 2: The recognition accuracies for the Myo armband and for the LG G Watch for each classifier and for all features as well as for the selected features. The evaluation was done with (a) 10-fold cross-validation with 10 repetitions and (b) with leave-one-subject-out cross-validation.



(a) (b)

Figure 3: The confusion matrices with leave-one-subject-out cross-validation for (a) the Myo armband and (b) the LG G Watch, each using the best classifier (kNN for the Myo and Random Forest for the LG G Watch) with the selected features only.

6. CONCLUSIONS

In this work we compared the placement of two wearable devices, an LG G Watch worn on the wrist and a Myo armband from Thalmic Labs worn right below the elbow, concerning the recognition of dynamic hand gestures. We implemented an Android-based system for simultaneously collecting sensor data from both devices. In a study with nine participants, we collected 2160 gesture samples from each device. The data was filtered and normalized, features were extracted, relevant features were selected and normalized, and they were classified using k-Nearest Neighbour, J48 decision tree, Random Forest and Bagging classifiers. We evaluated the recognition accuracy with 10-fold cross-validation with 10 repetitions and with leave-one-subject-out cross-validation.

Our assumption was that the wrist-worn device would have a significantly better recognition accuracy due to its bigger action radius. Using the set of selected features only and an evaluation with leave-one-subject-out cross-validation, whose results are more generalizable than those for the 10-fold cross-validation, the recognition accuracy for the LG G Watch was more than 8% higher than for the Myo armband. Although this supports our hypothesis we had to reject it, as the difference was not signification due to the substantial variation across participants.

A possible cause for the non-significance is the used set of fairly simple gestures. Moreover, the gestures were characterized by large hand movements, which is why the acceleration values measured below the elbow were still big enough to distinguish the gestures well. Therefore, an interesting item of future work would be the investigation of recognition accuracies with a larger number of gestures and with more complex gestures. This would include less sweeping gestures as well as gestures with rotations of the forearm.

7. ACKNOWLEDGEMENTS

This work has partially been carried out within the scope of the project *InterPlayces* funded by the Austrian Research Promotion Agency (FFG) under contract number 850843. This work has partially been carried out within the scope of *u'smile*, the Josef Ressel Center for User-Friendly Secure Mobile Environments, funded by the Christian Doppler Gesellschaft, A1 Telekom Austria AG, Drei-Banken-EDV GmbH, LG Nexera Business Solutions AG, NXP Semiconductors Austria GmbH, and Österreichische Staatsdruckerei GmbH.

8. REFERENCES

[1] Lingchen Chen, Feng Wang, Hui Deng, and Kaifan Ji. 2013. A Survey on Hand Gesture Recognition. In *Proc. of the 2013 International Conference on Computer Sciences and Applications (CSA '13)*. 313–316.

[2] X Chen, T. Grossman, D. J. Wigdor, and G. Fitzmaurice. 2014. Duet: Exploring Joint Interactions on a Smart Phone and a Smart Watch. In *Proc. of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, New York, NY, USA, 159–168.

[3] I. Cleland, B. Kikhia, C. Nugent, A. Boytsov, J. Hallberg, K. Synnes, S. McClean, and D. Finlay. 2013. Optimal placement of accelerometers for the detection of everyday activities. *Sensors* 13, 7 (2013), 9183–9200.

[4] H. Gjoreski, M. Lustrek, and M. Gams. 2011. Accelerometer Placement for Posture Recognition and Fall Detection. In *Proc. of the 7th International Conference on Intelligent Environments*. Washington, DC, USA, 47–54.

[5] N. Helmi and M. Helmi. 2009. Applying a neuro-fuzzy classifier for gesture-based control using a single wrist-mounted accelerometer. In *Proc. of the 2009 IEEE International Symposium on Computational Intelligence in Robotics and Automation*. 216–221.

[6] K. Hwang and J. M. Lee. 2013. An Implementation Experience of Accelerometer-based Gesture Recognition with Android Smartphone. *International Journal of Advancements in Computing Technology* 5, 12 (2013).

[7] J. Kela, P. Korpipää, J. Mäntyjärvi, S. Kallio, G. Savino, L. Jozzo, and D. Marca. 2006. Accelerometer-based Gesture Control for a Design Environment. *Personal and Ubiquitous Computing* 10, 5 (2006), 285–299.

[8] J. J. LaViola. 1999. *A Survey of Hand Posture and Gesture Recognition Techniques and Technology.* Technical Report. Providence, RI, USA.

[9] J. Liu, L. Zhong, J. Wickramasuriya, and V. Vasudevan. 2009. uWave: Accelerometer-based personalized gesture recognition and its applications. *Pervasive and Mobile Computing* 5, 6 (2009), 657–675.

[10] T. Marasovic and V. Papic. 2011. Accelerometer-based gesture classification using principal component analysis. In *Proc. of the 19th International Conference on Software, Telecommunications and Computer Networks*. 1–5.

[11] S. Mitra and T. Acharya. 2007. Gesture Recognition: A Survey. *IEEE Transactions on Systems, Man, and Cybernetics, Part C* 37, 3 (2007), 311–324.

[12] D. O. Olguin and A. S. Pentland. 2006. Human activity recognition: Accuracy across common locations for wearable sensors. In *Proc. of the 10th IEEE International Symposium on Wearable Computers*. 11–13.

[13] L. Porzi, S. Messelodi, C. M. Modena, and E. Ricci. 2013. A Smart Watch-based Gesture Recognition System for Assisting People with Visual Impairments. In *Proc. of the 3rd ACM International Workshop on Interactive Multimedia on Mobile and Portable Devices*. ACM, New York, NY, USA, 19–24.

[14] J. Rekimoto. 2001. GestureWrist and GesturePad: Unobtrusive Wearable Interaction Devices. In *Proc. of the 5th International Symposium on Wearable Computers), 8-9 October 2001, Zurich, Switzerland*. IEEE Computer Society, 21.

[15] J. Wu, G. Pan, D. Zhang, G. Qi, and S. Li. 2009. Gesture Recognition with a 3-D Accelerometer. In *Ubiquitous Intelligence and Computing*. Lecture Notes in Computer Science, Vol. 5585. 25–38.

[16] Yinghui Zhou, Lei Jing, Junbo Wang, and Zixue Cheng. 2012. Analysis and Selection of Features for Gesture Recognition Based on a Micro Wearable Device. *(IJACSA) International Journal of Advanced Computer Science and Applications* 3, 1 (2012).