MyoGym - Introducing an Open Gym Data Set for Activity Recognition Collected Using Myo Armband

Heli Koskimäki
Pekka Siirtola
Juha Röning

Biomimetics and Intelligent
Systems Group
University of Oulu
PO Box 4500
90014 University of Oulu
Finland

heli.koskimaki@oulu.fi
pekka.siirtola@oulu.fi
juha.roning@oulu.fi

UbiComp/ISWC'17 Adjunct , September 11–15, 2017, Maui, HI, USA

ACM 978-1-4503-5190-4/17/09...$15.00
https://doi.org/10.1145/3123024.3124400

Abstract
The activity recognition research has remained popular although the first steps were taken almost two decades ago. While the first ideas were more like a-proof-of-concept studies the area has become a fruitful soil to novel methods of machine learning, to adaptive modeling, signal fusion and several different types of application areas. Nevertheless, one of the slowing aspects in methodology development is the burden in collecting and labeling enough versatile data sets. In this article, a MyoGym data set is introduced to be used in activity recognition classifier development, in development of models for unseen activities, in signal fusion, and many other areas not yet known. The data set includes 6D motion signals and 8 channel electromyogram data from 10 persons and from 30 different gym exercises, each of them consisting a set of ten repetitions. The benchmark results provided, in this article, are in purpose made straightforward that their repetitiveness should be easy for any newcomer in the area.

ACM Classification Keywords
I.5.4. [Pattern recognition]: Applications; H.1.2. [Information Systems]: User/Machine Systems

Author Keywords
Activity Recognition; Wearable Sensors; Electromyogram; IMU; Open Data; Gym Exercises.

Introduction

Human activity recognition is a research area where wearable sensors based information is used to recognize human activities. The overall activity recognition process includes a data set collected from the activities wanted to be recognized, preprocessing, segmentation, feature extraction and selection, and classification [9]. For example, activity recognition is used in recognizing daily activities [4, 28], in sport sector [22, 10] and in monitoring of assembly tasks [26, 16].

Sidefigure 1: Myo sensor

One of the most time consuming step in activity recognition research is the data collection phase. Although, there currently are several open data sets [1, 20, 5, 3, 25, 6, 7, 8, 24, 19, 27, 11] many of those are based merely on IMU data and more versatile data sets would be needed to renew the approaches. In this article, an open data set collected using Myo sensor, providing accelerometer and gyroscope data as well as 8 channel electromyogram data, is introduced. The data set is collected as streaming data from gym exercises, but unlike in previous studies [10, 22, 21] the amount and the similarity of the gym exercises is in purpose exploded to provide more challenging data set. In addition, the gym data provides fruitful environment when considering the problem of handling activities belonging to the null-class.

While the IMUs are commonly used in activity recognition the electromyogram (EMG), on the other hand, is mainly used to measures muscles to see the power needed to perform, for example, certain gym exercises [14]. Nevertheless, to be able to do that EMG device has to be positioned directly on the muscle to be measured while with Myo this was not possible. Thus the sensors are not positioned to the actual trained muscle but they are kept in the same location throughout the data collection. Moreover, while the EMG-sensors are attached in the forearm of the user the movement of individual fingers also effect to the tension of the forearm muscles which should be noted in future studies.

By now the introduced data set has been used when studying how to recognize unseen activities as gym activities instead of belonging to the null-class [18] and to study if EMG-data provide benefits in actual activity recognition [17]. Nevertheless, the articles just scratch the surface and in both the angular velocity information is totally left out. On the other hand, in a distinct study not related to MyoGym data set [29] Myo sensor has also been used as a reference sensor to textile pressure mapping sensors in a gym setting.

In this article, all the MyoGym data set provided sensor data are combined and a benchmark recognition results are presented. The data set is available through [2] as a raw signals and labels for every data point, as well as feature vectors and their labels as introduced in this article.

Sensors and Data Collection

The data were collected using a Myo Armband [23]. Myo includes 8 electromyogram (EMG) sensors and a nine-axis IMU containing three-axis gyroscope, three-axis accelerometer, three-axis magnetometer (magnetometer data not available within data set). It is developed for gesture recognition purposes and thus meant to be worn in a forearm of the user. In our study, the Myo was located at the right forearm positioned so that the IMU was on the top of the forearm while the 8 EMG sensors located evenly distributed around the arm (Sidefigure 1). In this study the frequency of 50 Hz were used in data collection.

The actual data were collected from 10 persons and from 30 different gym exercises, each of them consisting a set of

Table 1: Exercises and their class labels.

Class	Name	Muscle group	Posture	One-arm, both or alternate	Equipment
1	Seated Cable Rows	Middle Back	Seated	Both	Cable
2	One-Arm Dumbbell Row	Middle Back	Bent Over	One-arm	Dumbbell
3	Wide-Grip Pulldown Behind The Neck	Lats	Sitting	Both	Cable
4	Bent Over Barbell Row	Middle Back	Bent Over	Both	Barbell
5	Reverse Grip Bent-Over Row	Middle Back	Bent Over	Both	Barbell
6	Wide-Grip Front Pulldown	Lats	Sitting	Both	Cable
7	Bench Press	Chest	On back	Both	Barbell
8	Incline Dumbbell Flyes	Chest	Seated inclined	Both	Dumbbell
9	Incline Dumbbell Press	Chest	Seated inclined	Both	Dumbbell
10	Dumbbell Flyes	Chest	On back	Both	Dumbbell
11	Pushups	Chest	On hands & knees	Both	Own weight
12	Leverage Chest Press	Chest	Seated	Both	Machine
13	Close-Grip Barbell Bench Press	Triceps	On back	Both	Barbell
14	Bar Skullcrusher	Triceps	On back	Both	Barbell
15	Triceps Pushdown	Triceps	Standing	Both	Cable rope
16	Bench Dip / Dip	Triceps	Weight on hands	Both	Own weight
17	Overhead Triceps Extension	Triceps	Standing	Both	Barbell Plate
18	Tricep Dumbbell Kickback	Triceps	Bent Over	One-arm	Dumbbell
19	Spider Curl	Biceps	Sitting	Both	E-Z Curl Bar
20	Dumbbell Alternate Bicep Curl	Biceps	Standing	Alternate	Dumbbell
21	Incline Hammer Curl	Biceps	Seated inclined	Both	Dumbbell
22	Concentration Curl	Biceps	Seated	One-arm	Dumbbell
23	Cable Curl	Biceps	Standing	Both	Cable Bar
24	Hammer Curl	Biceps	Standing	Alternate	Dumbbell
25	Upright Barbell Row	Shoulders	Standing	Both	Barbell
26	Side Lateral Raise	Shoulders	Standing	Both	Dumbbell
27	Front Dumbbell Raise	Shoulders	Standing	Alternate	Dumbbell
28	Seated Dumbbell Shoulder Press	Shoulders	Seated	Both	Dumbbell
29	Car Drivers	Shoulders	Standing	Both	Barbell Plate
30	Lying Rear Delt Raise	Shoulders	On stomach	Both	Dumbbell
0	NULL				

ten repetitions. The exercises were mostly done using free weights, and for every upper body muscle group, data from six different exercises were collected (Table 1, the names of the exercises are consistent with the names provided in [13]). All the test subjects were asked to act as normal as they can through the whole data collection period and they were allowed to freely select the weights they used. While the data set was gathered as a continuous signal, most of the data set comprised of data between distinct exercise sets in which the subject moved around at the gym, changed weights, stretched or just stayed still (null-data). Altogether, there were more than 11 hours of data

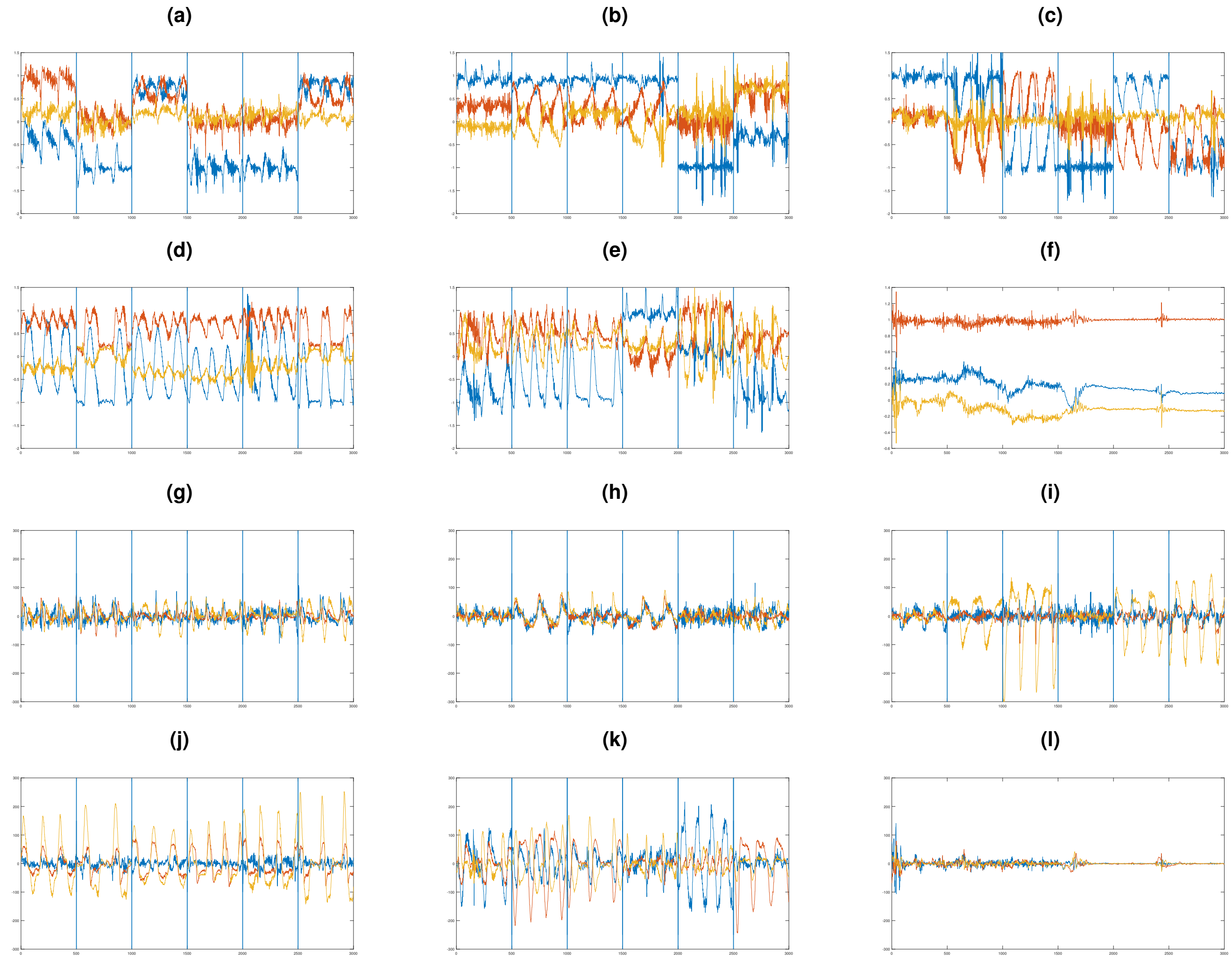

Figure 1: 10 second long 6D motion signals from exercises a) 1-6, b) 7-12, c) 13-18, d) 19-24, e) 25-30, f) 99 (x=blue, y=red and z=yellow) and g) 1-6, h) 7-12, i) 13-18, j) 19-24, k) 25-30, l) 99 (x=pitch, y=roll and z=yaw).

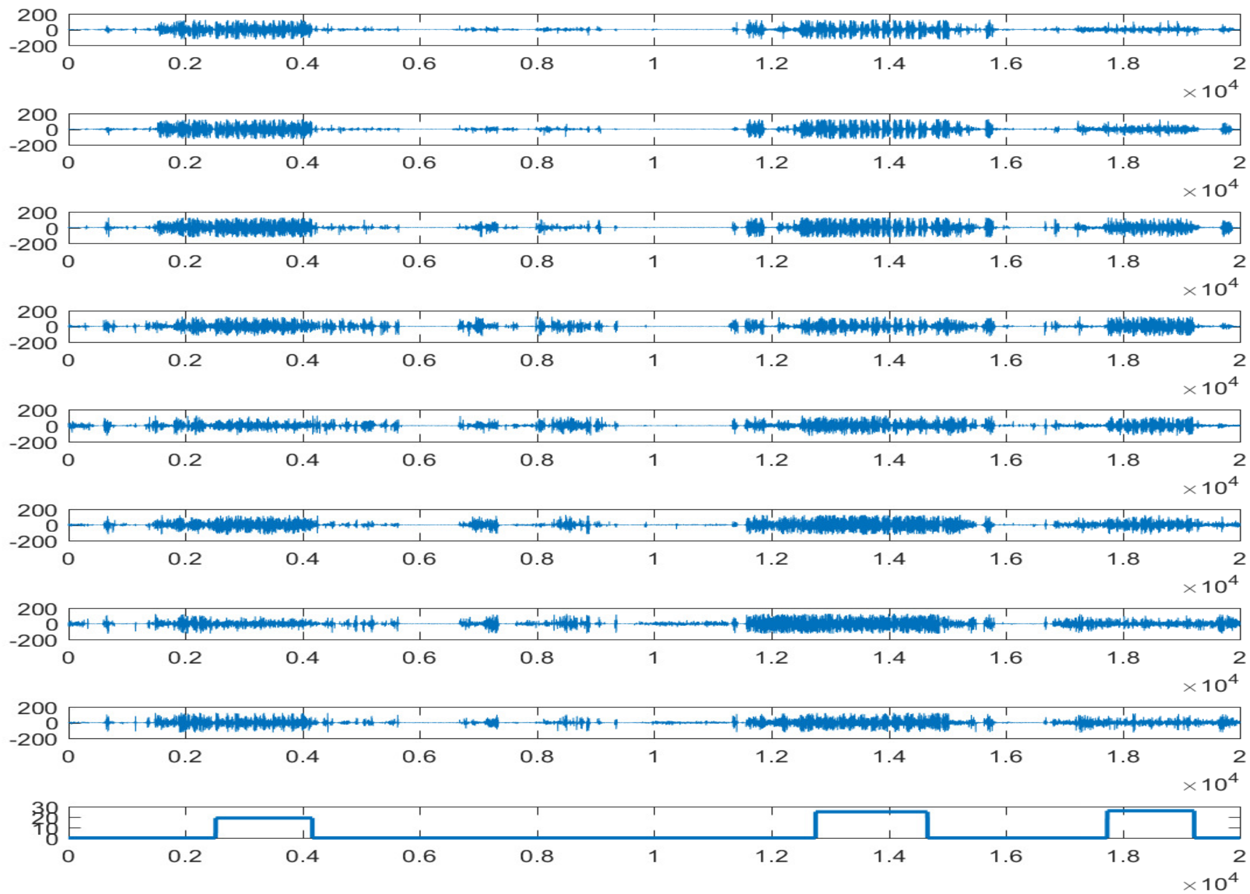

Figure 2: 8 channel EMG signal and the corresponding class labels at bottom (classes 19, 25 and 26, respectively).

Table 2: Features calculated from acceleration and gyroscope data and from EMG signals. As Hjort parameter the mobility parameter (i.e. the square root of the ratio of the variance of the first derivative of the signal) was used.

Sensor	Features
Acc	Hjorth parameters, std, mean, max, min, prctiles (5, 10, 25, 50, 75, 90 and 95), zero and mean crossings, FFT sums (1, 1-5 and 6-10), entropy, and correlation between channels
Gyro	Hjorth parameters, std, mean, max, min, prctiles (5, 10, 25, 50, 75, 90 and 95), zero and mean crossings, FFT sums (1, 1-5 and 6-10) and entropy
EMG	std, mean, max, min, prctiles (5, 10, 25, 50, 75, 90 and 95), sum of values larger than 25, 50 and 100

(2017041x17 double vector) of which 77 percent was considered as null-data. Figure 1 show examples of 6D motion signals for all the different exercises. From every exercise there is selected a 10 second representative, from a single person showing approximately 3 repetitions from an exercise. To save space the exercises targeted to same muscle group are illustrated in the same subfigures although it has to me remembered that in MyoGym data set there is always null-data between exercises. In Figure 2 it is shown the real streaming signal while the figure illustrated the 8 EMG signals collected during 3 different exercises (19, 25 and 26) as well as from null-data in the between.

Feature Extraction

To make results straightforward in this study, all the sensor data was kept unprocessed. A sliding window method with a window length of 4 seconds and a slide of a second was utilized to divide the streaming data into suitable segments for feature extraction.

The features extracted included mostly basic statistical and time-domain features presented in Table 2. Altogether 57 acceleration, 54 angular velocity and 112 EMG -based features were extracted.

The final feature set, nevertheless, did not include all the features, but best features were selected using sequential forward selection (sfs) method.

At this point, it has to be noted that in feature extraction at maximum 48 windows achieved a NaN value in calculation (e.g. in Hjorth parameters) but because they consisted only observations from null-class they were just removed from feature matrices. After this, the final data set included altogether 40 253 windows and 223 features.

Classification Results

The achieve the recognition results presented leave-one-person-out cross-validation was used. Although, it is shown to add a bias to the results when using simultaneously with sfs feature selection [15] it is widely adopted in activity recognition studies and thus also used in the paper.

Two different classifiers were used to report the results: linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA). The LDA and QDA model the class-conditional densities parametrically as multivariate normals [12]. In practice, QDA separates classes using nonlinear decision boundaries while LDA uses linear decision boundaries. Both of the methods are fast to train, easy to implement and the memory requirements are small thus making them well-liked in practical applications and devices.

Table 3: The average classification accuracy for different sensor combinations and amount of features selected using LDA and QDA classifiers.

Sensors	Classifier	Accuracy	# features
All	LDA	71.6	55
Acc + gyro	LDA	67.8	52
Acc + EMG	LDA	68.5	54
Gyro + EMG	LDA	44.7	89
Acc	LDA	62.0	35
Gyro	LDA	37.7	36
EMG	LDA	20.7	14
All	QDA	66.0	32
Acc + gyro	QDA	62.4	19
Acc + EMG	QDA	62.6	14
Gyro + EMG	QDA	45.1	33
Acc	QDA	58.7	11
Gyro	QDA	39.9	23
EMG	QDA	19.1	17

In Table 3 there are shown the accuracies of every individual sensor and with different combinations using both LDA and QDA classifiers. The accuracies are calculated as class-wise averages for one person at a time which are then averaged to achieve the final average accuracy. Moreover, in the table it is shown how many features were selected in which case.

As a result it can be seen, not surprisingly, that the best accuracy was achieved when using all the sensors available with LDA classifier. Nevertheless, the actual accuracy is not as high as many times reported in activity recognition studies. This, however, was already intended when selecting the very similar gym exercises to the data set. Interesting aspect in the sensor combination is that although the EMG sensors alone seem to have very poor separation capability when using them combined with acceleration data they do provide more accurate recognition than gyroscope data. Nevertheless, the acceleration data is the one containing the most information.

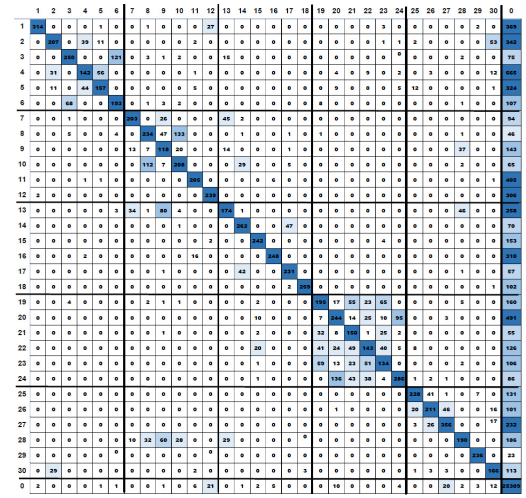

Figure 3: Confusion matrix of LDA classification using all the sensor information.

The actual classification confusion matrix is shown only in the case of the highest accuracy achieved when using data from all of the sensors and LDA in classification. These results can be seen as Figure 3. From the matrix the first clear remark is that the null-data (class 0) is the one mixing the results the most. While in many open activity recognition sets, especially considering daily activities, all the data is meaningful, when there are actually data that can contain almost everything it will harm the recognition accuracies. Another remark from the table is that the classes mixing the most do contain data from exercises of the same muscle group. In the most of the cases there are two classes mixing with each other like classes 3 (Wide-grip pulldown behind the neck) and 6 (Wide-grip front pulldown), 8 (Incline Dumbbell Flyes) and 10 (Dumbbell Flyes) but with biceps almost all the exercises are mixing with each other. These exercises are of course very similar, nevertheless, all these exercises include subtle changes although their separation is not trivial.

Discussion

As noted earlier, the purpose of this article was to present MyoGym data set including EMG sensor data not yet openly available for activity recognition at this extent. Authors do admit that when extracting more suitable features and optimizing the classifier a slight improvement for the overall accuracy can be achieved but on the other hand the LDA has been shown to outperform many more sophisticated methods in real world activity recognition. Thus the authors anticipate that to actually make remarkable improvements to the classification accuracies more versatile approaches are required.

One solution anticipated is based on novel signal fusion approaches. In the article, the most straightforward approach was selected and the signal fusion was only approached by combining features calculated from different signals with a single classifier. An interesting aspect would be to see which sensors would perform the best when using separate classifiers for the most similar exercises or do the signal fusion reveals time points when the actual separation can be done.

On the other hand, the data set can be used for other purposes than just to improve classification processes, including for example segmentation and unseen activity recognition. In [18] it was already shown that the EMG sensor performs the best when considering separation of unseen activities from null-data. In the article, for one person at a time in the most complicated scenario only data from a single muscle group (6 exercises) and null-data was used for training while the remaining four sets (24 exercises) were used to test if a novel data point was null-data or exercise data. When comparing this to the current state-of-the-art, e.g. [22, 21], where the separation of exercise and null-data is mainly approached using segmentation and moreover, using segmentation optimized based on the existing activities the data set has plenty to offer.

Nevertheless, although the data set can be used in segmentation, in this article any segmentation method to remove the null-data before the actual activity recognition was not used. However, it has to be noted that even removing the null-data before the activity recognition do not improve the classification accuracies remarkably. With this data set the accuracy when removing the null-data but otherwise using the same procedure (sfs feature selection, leave-one-person-out LDA classification and class-wise averaging) the accuracy achieved is only 75.7 percents i.e. 4 percentage units higher than with null-data.

Conclusion

In the activity recognition area the collection and labeling the data is one of the most time consuming steps and in the most cases it slows down the methodology development. The gym data recognition have been in high interest in null-data point of view but also semantic approaches have been developed utilizing the data. One of the disadvantages, nevertheless, has been that the data collected actually includes in many cases easily separable exercises. With the data set introduced in the article this is not the case. The classes are highly similar and their distinction requires novel approaches in signal fusion side but also in classifier development. Moreover, novel segmentation approached for null-data removal can be tested using the data set provided.

Acknowledgments

The authors would like to thank Academy of Finland for funding this work (Decision 257468, Postdoctoral Researcher project: Mobile Sensors and Behavior Recognition in Real-world). Moreover, authors acknowledge their gratitude to all the volunteers in data collection.

REFERENCES

1. 2017. Algosnap data set. http://crowdsignals.io/. (2017). Accessed: 2017-05-04.
2. 2017. MyoGym Open data. http://www.oulu.fi/bisg/node/40364/. (2017). Accessed: July 7th 2017.
3. D. Anguita, A. Ghio, L. Oneto, X. Parra, and J. Reyes-Ortiz. 2013. A Public Domain Dataset for Human Activity Recognition using Smartphones.. In *ESANN*.
4. O. Banos, M. Damas, H. Pomares, A. Prieto, and I. Rojas. 2012. Daily living activity recognition based on statistical feature quality group selection. *Expert Systems with Applications* 39, 9 (2012), 8013–8021.
5. O. Baños, M. Damas, H. Pomares, I. Rojas, M. Tóth, and O. Amft. 2012. A benchmark dataset to evaluate sensor displacement in activity recognition. In *Proceedings of the 2012 ACM Conference on Ubiquitous Computing*. ACM, 1026–1035.
6. O. Banos, C. Villalonga, R. Garcia, A. Saez, M. Damas, J. Holgado-Terriza, S. Lee, H. Pomares, and I. Rojas. 2015. Design, implementation and validation of a novel open framework for agile development of mobile health applications. *Biomedical engineering online* 14, 2 (2015), S6.
7. B. Barshan and M. Yüksek. 2014. Recognizing daily and sports activities in two open source machine learning environments using body-worn sensor units. *Comput. J.* 57, 11 (2014), 1649–1667.
8. B. Bruno, F. Mastrogiovanni, A. Sgorbissa, T. Vernazza, and R. Zaccaria. 2013. Analysis of human behavior recognition algorithms based on acceleration data. In *Robotics and Automation (ICRA), 2013 IEEE International Conference on*. IEEE, 1602–1607.
9. A. Bulling, U. Blanke, and B. Schiele. 2014. A Tutorial on Human Activity Recognition Using Body-worn Inertial Sensors. *ACM Comput. Surv.* 46, 3, Article 33 (Jan. 2014), 33 pages. DOI: http://dx.doi.org/10.1145/2499621
10. K. Chang, M. Chen, and J. Canny. 2007. Tracking Free-Weight Exercises. *UbiComp 2007: Ubiquitous Computing* (2007), 19–37.
11. R. Chavarriaga, H. Sagha, A. Calatroni, S. Digumarti, G. Tröster, J. Millán, and D. Roggen. 2013. The Opportunity challenge: A benchmark database for on-body sensor-based activity recognition. *Pattern Recognition Letters* 34, 15 (2013), 2033–2042.
12. R. O. Duda, P. E. Hart, and D. G. Stork. 2012. *Pattern classification*. John Wiley & Sons.
13. Exercise list. 2017. https://www.bodybuilding.com/exercises/. (2017). Accessed: 2017-07-07.
14. J. Holviala, W.J. Kraemer, E. Sillanpää, H. Karppinen, J. Avela, A. Kauhanen, A. Häkkinen, and K. Häkkinen. 2012. Effects of strength, endurance and combined training on muscle strength, walking speed and dynamic balance in aging men. *European Journal of Applied Physiology* 112, 4 (2012), 1335–1347.

15. H. Koskimäki. 2015. Avoiding Bias in Classification Accuracy - a Case Study for Activity Recognition. *IEEE Symposium on Computational Intelligence and Data Mining* (2015).

16. H. Koskimäki, V. Huikari, P. Siirtola, P. Laurinen, and J. Röning. 2009. Activity recognition using a wrist-worn inertial measurement unit: a case study for industrial assembly lines. *The 17th Mediterranean Conference on Control and Automation* (2009), 401–405.

17. H. Koskimaki and P. Siirtola. 2016. Accelerometer vs. Electromyogram in Activity Recognition. *Advances in Distributed Computing and Artificial Intelligence Journal* (2016).

18. H. Koskimäki and P. Siirtola. 2016. Recognizing Unseen Gym Activities from Streaming Data-Accelerometer Vs. Electromyogram. In *Distributed Computing and Artificial Intelligence, 13th International Conference*. Springer International Publishing, 195–202.

19. J. Kwapisz, G. Weiss, and S. Moore. 2011. Activity recognition using cell phone accelerometers. *ACM SigKDD Explorations Newsletter* 12, 2 (2011), 74–82.

20. D. Micucci, M. Mobilio, and P. Napoletano. 2017. UniMiB SHAR: a new dataset for human activity recognition using acceleration data from smartphones. *arXiv preprint arXiv:1611.07688v2* (2017).

21. D. Morris, TS. Saponas, A. Guillory, and I. Kelner. 2014. RecoFit: Using a Wearable Sensor to Find, Recognize, and Count Repetitive Exercises. *Proceedings of ACM CHI* (2014).

22. M. Muehlbauer, G. Bahle, and P. Lukowicz. 2011. What Can an Arm Holster Worn Smart Phone Do for Activity Recognition? *15th Annual International Symposium on Wearable Computers (ISWC)* (2011), 79 – 82.

23. Myo. 2016. `https://www.myo.com/`. (2016). Accessed: 2015-10-30.

24. A. Reiss and D. Stricker. 2012. Introducing a new benchmarked dataset for activity monitoring. In *Wearable Computers (ISWC), 2012 16th International Symposium on*. IEEE, 108–109.

25. M. Shoaib, S. Bosch, H. Incel, O.and Scholten, and P. Havinga. 2014. Fusion of smartphone motion sensors for physical activity recognition. *Sensors* 14, 6 (2014), 10146–10176.

26. T. Stiefmeier, D. Roggen, G. Tröster, G. Ogris, and P. Lukowicz. 2008. Wearable Activity Tracking in Car Manufacturing. *IEEE Pervasive Computing* 7, 2 (2008), 42–50.

27. M. Zhang and A. Sawchuk. 2012. USC-HAD: A Daily Activity Dataset for Ubiquitous Activity Recognition Using Wearable Sensors. In *ACM International Conference on Ubiquitous Computing (Ubicomp) Workshop on Situation, Activity and Goal Awareness (SAGAware)*. Pittsburgh, Pennsylvania, USA.

28. M. Zhang and A. A. Sawchuk. 2013. Human Daily Activity Recognition With Sparse Representation Using Wearable Sensors. *Biomedical and Health Informatics, IEEE Journal of* 17, 3 (May 2013), 553–560.

29. B. Zhou, M. Sundholm, J. Cheng, H. Cruz, and P. Lukowicz. 2017. Measuring muscle activities during gym exercises with textile pressure mapping sensors. *Pervasive and Mobile Computing* 38, Part 2 (2017), 331 – 345.