Accelerometer vs. Electromyogram in Activity Recognition

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ABSTRACT

In this study, information from wearable sensors is used to recognize human activities. Commonly the approaches are based on accelerometer data while in this study the potential of electromyogram (EMG) signals in activity recognition is studied. The electromyogram data is used in two different scenarios: 1) recognition of completely new activities in real life and 2) to recognize the individual activities. In this study, it was shown that in gym settings electromyogram signals clearly outperforms the accelerometer data in recognition of completely new sets of gym movements from streaming data even though the sensors would not be positioned directly to the muscles trained. Nevertheless, in recognition of individual activities the EMG itself does not provide enough information to recognize activities accurately.

1. Introduction

The wearable sensor market is currently one of the most rapidly growing area in consumer electronics. The global market for wearables is estimated to reach $34 billion by 2020 (CCS Insight, 2016) and to almost $70 billion by 2025 (Weinswig, 2016). In research perspective, this has enabled that mobile sensors based recognition (activities, gestures, symptoms, diagnosis) to become one of the fastest developing areas of machine learning. The remarkable progress in the actual sensor development including improved memory and battery properties has making possible to measure human physiology 24/7, and more importantly with such accurate readings that has previously been possible only in laboratory settings.

The overall wearable sensors based human activity recognition process includes a data set collected from the activities wanted to be recognized, preprocessing, segmentation, feature extraction and selection, and classification (Bulling et al., 2014). By now the activity recognition approached include for example, daily activity recognition (Banos et al., 2012; Zhang and Sawchuk, 2013) and it has been used in various sport sector applications (Chang et al., 2007; Siirtola et al., 2011). It has also been utilized for manufacturing industry purposes like in monitoring of assembly tasks (Stiefmeier et al., 2008; Koskimäki et al., 2009).

One of the problems of activity recognition is that to recognize *n* activities, training data must be collected from at least *n*-1 activities (Siirtola, 2015). The remaining activity could be recognized based on the assumption that if the performed activity was not recognized as one of the *n*-1 from which training data was collected, it

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must be the one from which training data was not available. Nevertheless, in practice the streaming data consists also plenty of data not interesting from application specific point of view, and that cannot be collected inclusively. This so called as null-data or "other activities" makes the decision if there actually is a novel activity or should it be considered to belong null-class a challenging task.

Thus in this article the problem studied for unseen activities is that how to recognize them as activities instead of belonging to the null-class. Moreover, in this study, a new sensor is introduced to be used to solve the problem in gym setting. The gym activity recognition makes a quite unique problem into the activity recognition area while the gym exercises mostly consists of repetitive movements. How to recognize different gym activities based on acceleration sensors have been studied, for example, in (Chang et al., 2007; Muehlbauer et al., 2011; Morris et al., 2014). In (Chang et al., 2007) there were no null-data collected thus making the research simpler but in (Muehlbauer et al., 2011; Morris et al., 2014) both a segmentation approach was used as a solution to decide beforehand if gym activity is performed against the null-data. Nevertheless, in both cases the segmentation is optimized based on the existing activities (the leave-one out approach is used as person independent approach) and there are no information of the generalization of the segmentation to novel gym sets. Moreover, the few studies considering the unseen activities are also completely different to ours. In (Cheng et al., 2013), for example, they are concentrating to recognize the actual gym exercises based on semantic attributes (e.g. dumbbell curl consist of arm down and arm curl actions) and there are no null-data in the study.

On the other hand, electromyogram (EMG) is used to measures muscles to see the power needed to perform certain gym exercises (Holviala et al., 2012). Nevertheless, to be able to do that EMG device has to be positioned directly on the muscle to be measured. Thus although it could sound trivial to use EMG to recognize the actual gym exercises from the other activities the approach where sensors are not positioned to the actual trained muscle or changed between the exercises makes the study novel. While the EMG-sensors are attached in the forearm of the user in this study the movement of individual fingers also effect to the tension of the forearm muscles making the approach more challenging.

As an extension to the authors' previous article (Koskimäki and Siirtola, 2016), in this article also the possibility to use the EMG signals to the user-independent (UI) activity recognition is studied. In this approach the null data is discarded and the basic leave-one-person-out cross-validation is used using acceleration information, using EMG information, and using combination of both.

This article is organized as follows: Section 2 introduces the sensors used as well as the data collection procedure. The methods related to the activity recognition process including feature extraction, feature selection, classification and leave-one-out cross-validation are described in Section 3. The results for both scenarios 1) unseen activities and 2) UI activity recognition are covered out in Sections 4 and the discussion of the findings is carried on in 5. The whole study is concluded in Section 6.

2. Sensors and Data Collection

The data were collected using a Myo Armband (Myo, 2016). Myo includes 8 EMG sensors and a nine-axis IMU containing three-axis gyroscope, three-axis accelerometer, three-axis magnetometer (Figure 1). 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

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Figure 1: Myo Armband.

Muscle group	Exercises
Triceps	Close-Grip Barbell Bench Press, Bar Skullcrusher, Triceps Pushdown, Bench Dip / Dip, Overhead Triceps Extension, Tricep Dumbbell Kickback
Biceps	Spider Curl, Dumbbell Alternate Bicep Curl, Incline Hammer Curl, Concentration Curl, Cable Curl, Hammer Curl
Shoulders	Upright Barbell Row, Side Lateral Raise, Front Dumbbell Raise, Seated Dumbbell Shoulder Press, Car Drivers, Lying Rear Delt Raise
Chest	Bench Press, Incline Dumbbell Flyes, Incline Dumbbell Press, Dumbbell Flyes, Pushups, Leverage Chest Press
Back / lats	Seated Cable Rows, One-Arm Dumbbell Row, Wide-Grip Pulldown Behind The Neck, Bent Over Barbell Row, Reverse Grip Bent-Over Row, Wide-Grip Front Pulldown

Table 1: Gym exercises, more details can be found from (Koskimäki and Siirtola, 2014).

located at the right forearm positioned so that the IMU was on the top of the forearm while the EMG sensors located evenly distributed around the arm. In this study the frequency of 50 Hz were used in data collection. The recognition was done based on EMG and accelerometer data, and therefore, gyroscope and magnetometer data were not used.

The actual data were collected from 10 persons and from 30 different gym exercises, each of them consisting a set of 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). While the data set was gathered as a continuous signal, the data set constituted also data between every exercise set 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 of which 77 percent was considered as null-data.

The difference between EMG and acceleration signals are shown in Figures 2 and 3. In both cases the same

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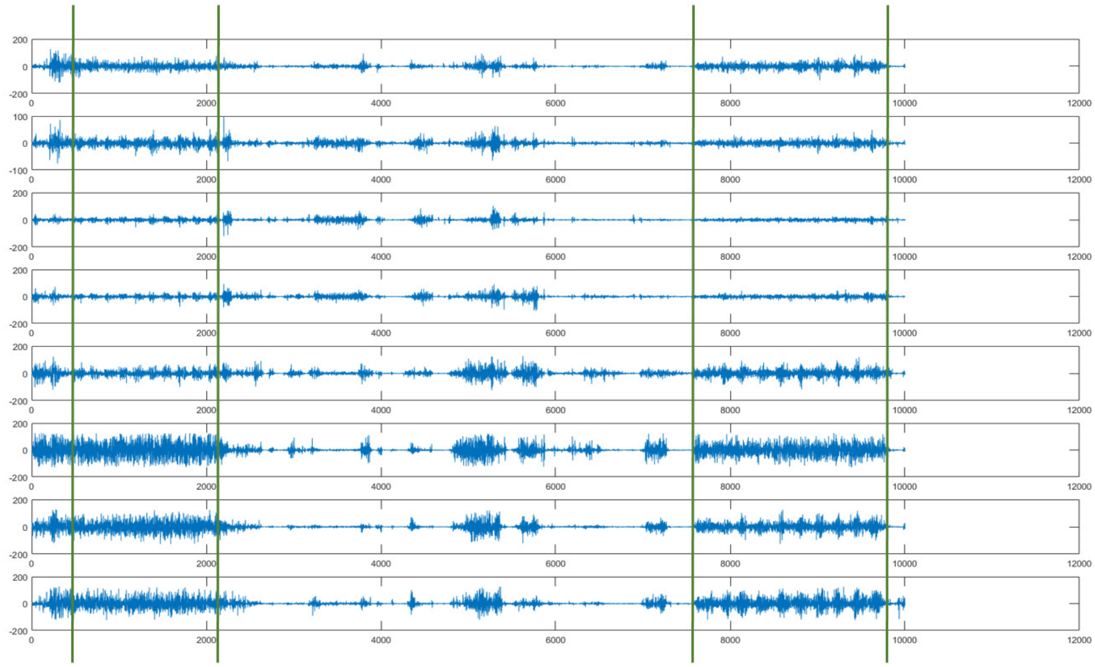

Figure 2: 8 channels of EMG signals corresponding to two different gym exercises (separated between vertical lines) and null-data between the exercises.

time interval is shown including data from two different gym exercises and null-data between the exercises. It can be noted that during exercises there is periodical movement in each of the three acceleration channels. However, in the case EMG periods are not visible in all of the channels, and also in these channels they are more difficult to see than in the case of accelerometer data. In addition, when signal from two different activities are compared, it can be seen that with accelerometer data signals are different while with EMG there are much less differences. When null-data interval is studied, it can be seen that accelerometer signals contain a lot more non-periodical movement than EMG signals. Therefore, it would seem that periodical exercises are easier to detect from accelerometer data than from EMG while EGM seems to be more suitable in recognizing null-data.

3. Methods

The EMG signals were pre-processed with two different ways: 1) all the eight EMG signals were summed up as a single signal, or 2) different channels were summed with the values of adjacent EMG signals (the EMG signal 1 consisted of sum of signals 8, 1 and 2; and signal 2 of signals 1, 2 and 3, etc.). For acceleration signals, no

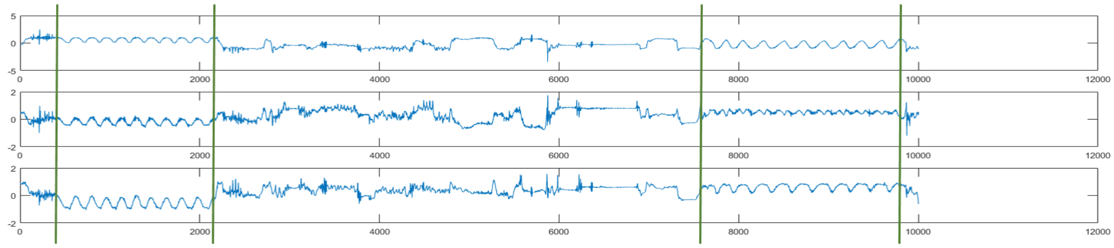

Figure 3: 3 acceleration signals (x,y,z) corresponding to two different gym exercises (separated between vertical lines) and null-data between the exercises.

Data set	Feature type	Features
Acc	Statistical features	std, mean, min, max, median, percentiles (5, 10, 25, 75, 90, 95), zero and mean crossing
	Frequency domain	FFT sums (1:2, 1:5, 6:10, 10:15), squared sum using all channels
	Haar wavelets	sums of wavelet decompositions using different bookkeeping vectors
	correlation	autocorrelation and cross-correlation
EMG	Statistical features	std, mean, min, max, median, percentiles (5, 10, 25, 75, 90, 95)
	Sums	sums of data value over 25, 50, 100, 150 and 200
EMG sum	Statistical features	std, mean, min, max, median, percentiles (5, 10, 25, 75, 90, 95), zero and mean crossings
	correlation	autocorrelation

Table 2: Features calculated from acceleration data, EMG signals (channels summed with adjacent channels (EMG), or channels summed altogether (EMG sum)).

pre-processing was done.

After the pre-processing the continuously measures signals were divided into segments using the sliding window method, where window length of two seconds with a slide of 0.5 seconds between two sequential windows was used. For every of the windows, features were calculated including statistical values for all the signals and for acceleration also frequency domain and correlation features were calculated (Table 2). The amount of features for acceleration signals were 219, for 8 channels of EMG 128 and for summed EMG channel 19.

In this article, the best features to recognize unseen activities were chosen using sequential forward selection (SFS) and minimum Redundancy Maximum Relevance Feature Selection (mRMR). With SFS the best features

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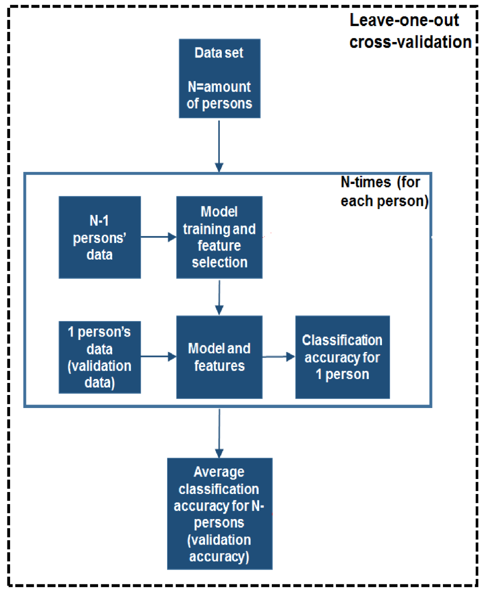

Figure 4: Leave-one-out cross-validation.

were selected one at a time using the classification accuracy of the model in question as a selection criteria (Devijver and Kittler, 1982). However, the selection was not stopped at local minimum but it was allowed to choose until "the best features" included all the features. On the other hand, with mRMR the feature selection was done model independently by selecting features having the highest correlation to the classification variable but locating far from each other (Peng et al., 2005). With mRMR the amount of features was decided before hand as signal-wise based on a preliminary test with all the data. The recognition of individual activities was done using all the features, and therefore, feature selection was not used.

The classifiers used in this study were the parametric linear discriminant analysis (LDA), quadratic discriminant analysis (QDA). The LDA and QDA model the class-conditional densities parametrically as multivariate normals (Duda et al., 2012). 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. Moreover, it has been shown in practical activity recognition applications the simplest methods can outperform the more sophisticated methods (Koskimäki, 2015).

To compare the results leave-one-person-out cross-validation was used (Figure 4). The idea is to divide the data set into as many data sets that there are persons in the data. With every iteration one person's data is used as validation data while the data from the N-1 person are used in the model training. The person-wise accuracies achieved during these N iteration are then used to to calculate the average user-independent classification rate.

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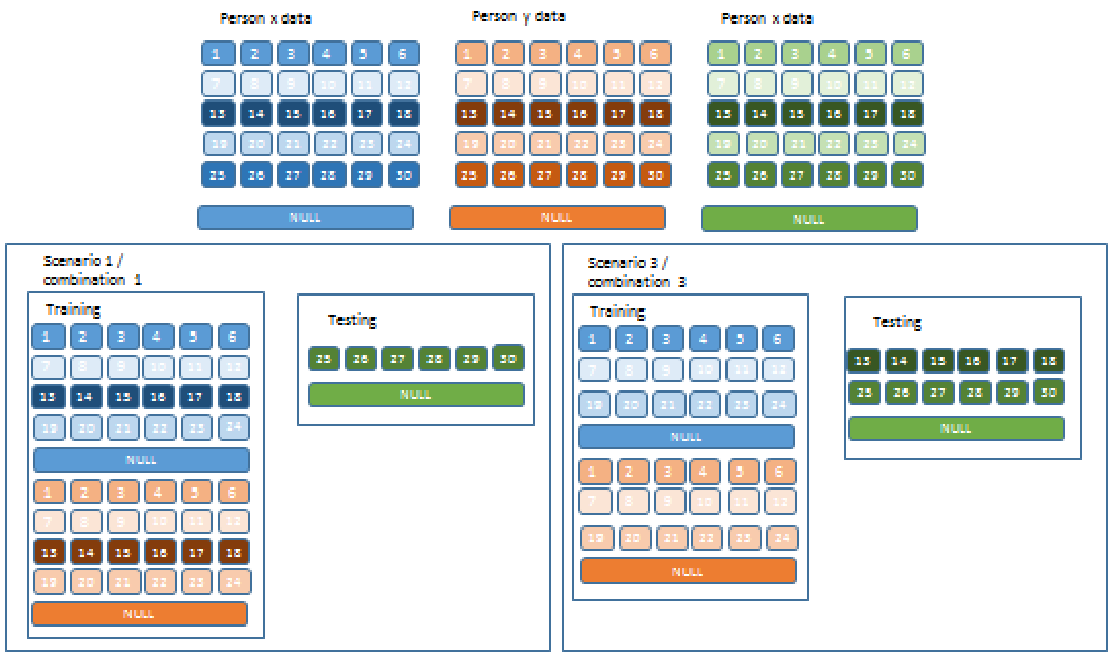

Figure 5: Two scenario examples for case of data from three persons. The training data includes data from the persons as well as gym activities not used for testing. In the study all the combinations are went through.

4. Results

4.1 Recognition of unseen activities

The model generalization to new exercises were studied by selecting suitable subsets of activities into training and testing under leave-one-person-out cross-validation schema. In addition to that, to study the recognition of unseen activities also data from certain exercises were deleted simultaneously. Nevertheless, instead of the traditional version where a single activity is deleted at a time the deletion in this article is done muscle-group specifically in four scenarios.

In practice this means that for every person at a time, in scenario 1, every set of exercises (6 exercises) at a time and the null-data were used as testing data while the other 4 sets of exercises (24 exercises) and the null-data from the remaining 9 persons were used for training (see Figure 5). In scenario 2, the same procedure was done by using two sets (12 exercises) for testing and three sets (18 exercises) for training, in scenario 3 using three sets (18 exercises) for testing and two (12 exercises) for training and in scenario 4 using four sets (24 exercises) for testing and one (6 exercises) for training. Thus the classification becomes more and more difficult between

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Feature selection	Classifier	Scenario	Signal				
			ACC	EMG	EMG sum	ACC+EMG	ACC+EMG sum
mRMR	LDA	1	77.7	85.2	82.7	83.2	**84.2**
		2	74.8	81.1	82.3	81.8	82.6
		3	69.9	76.2	81.9	76.3	77.8
		4	62.2	70.4	81.3	70.3	71.6
	QDA	1	68.6	77.0	84.0	81.4	83.4
		2	66.5	77.2	**84.0**	80.8	81.3
		3	64.0	78.5	**83.8**	75.2	76.6
		4	59.7	77.5	**83.2**	70.1	65.2
SFS	LDA	1	85.2	88.2	83.0	89.9	88.1
		2	83.1	88.2	83.1	89.5	87.7
		3	82.3	88.0	83.1	**88.6**	87.0
		4	79.3	87.7	83.0	**88.2**	85.7
	QDA	1	84.7	87.8	85.3	**90.1**	89.8
		2	83.9	87.8	85.2	**89.6**	89.1
		3	83.9	87.8	85.1	88.5	87.5
		4	77.5	87.5	84.7	87.8	86.5

Table 3: Average recognition rates using mRMR and SFS feature selection methods with both LDA and QDA classifiers using acceleration data, EMG signals (channels summed with adjacent channels (EMG), or channels summed altogether (EMG sum)), or a combination of the signals.

scenarios. In every scenario, all the combinations are gone through and the results are shown as an average of every person and of those combinations (6, 10, 10 and 6 combinations, respectively). Moreover, the average is shown as an average of class-wise averages preventing the massive amount of null-data to skew the results.

The results in Table 3 clearly show that the accuracies achieved with mRMR feature selection method are remarkably different from the SFS results. The only accuracy staying over 80 percent through the four scenarios is the accuracy achieved when using features calculated from the summed EMG-signal. Naturally, the reason for that is that there were not so many features to be selected (19 original features). Nevertheless, when using the summed EMG-signal and QDA, over 83 percent accuracies were achieved even when only movements targeted to single muscle groups were used as training data (scenario 4) which is over 20 percentage units higher than the accuracy achieved using acceleration signal (62.2%).

On the other hand, when considering the results achieved with SFS feature selection a more higher accuracies overall can be seen. The first obvious remark also with this case is that EMG signals contained more generalizable information than the acceleration signals. From the scenario 1 to scenario 4 only 0.6 percentage units drop was shown while within the acceleration signals a drop of 6 percentage units is seen between the scenarios, in addition to the 3 percentage units lower accuracy already in the first scenario (LDA). Moreover, by combining the acceleration information with EMG-information, it can be seen that no remarkable improvement in overall accuracies is achieved at least in the scenarios 3 and 4.

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Data set	Acceleration	EMG	Acceleration and EMG
All the data	55.8	12.4	58.7
Every second exercise	72.0	21.5	75.9
Every sixth exercise	86.1	41.0	85.9

Table 4: Recognition rates when using all the exercise data (30 classes), using every second exercise data (15 classes) and when using only one exercise per muscle group (5 classes).

4.2 Recognition of the individual activities

To test the information comprised by acceleration and electromyogram signals the null data was removed manually from the data set. Due to the high variety of gym exercises used in data collection (the recognition is in most studies based only on nine or ten exercises) three different sets of the whole data set was used. In the first case, all the data was used including data from 30 exercises of which some were highly overlapping (e.g. Spider Curl vs. Concentration Curl). In the second case the amount of activities were dropped to half deleting every second activity (15 classes, 3 activities per muscle group). The third case is the simplest one, including only one activity per muscle group and altogether 5 classes.

From the results presented in Table 4 can be seen that the recognition rate, 55.8% using only accelerometer and 58.7% using combination of accelerometer and EMG, is really low when all 30 are recognized. The detection accuracy is especially low when the recognition is based only on EMG data (12.4%). Therefore, the collected data set does not include enough information to detect all 30 exercises reliable. Reducing the number of classes to 15 improves the recognition accuracy, 72.0% using only accelerometer and 75.9% using combination of accelerometer and EMG, but still the rates are quite low. Again, it can be seen that individual activities cannot be detected using only EMG (21.5%). After reducing the number of classes to 5, the recognition rates are already pretty good (86.1% using only accelerometer and 85.9% using combination of accelerometer and EMG), except if only EMG data is used (41.0%). What is noticeable is that based on the results of Table 4, it can be noted that when individual activities are recognized, EMG data does not provide any added value to the accelerometer data as the combination of EMG and accelerometer data does not improve the detection rates significantly compared to using accelerometer only.

5. Discussion

When the aim was to recognize unseen activities, the results showed that the EMG signals contained more generalizable information than the acceleration signals. While the acceleration signals still coped the problem when there can be assumed to be at some level similar information in the training set, the more novel the new activity is the more difficult it is classified using the acceleration. This is quite surprising while the gym exercises contained sequential movements (repetitions) which are in acceleration signal based studies considered to separate the activity from the null-data. Nevertheless, as stated before, in previous studies the optimization of segmentation is based on the known activities which can affect to the results.

From the feature selection point of view an interesting remark was that the mRMR feature selection itself had

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a notable negative effect on the generalization results. This can be explained that with the SFS the features were selected based on results achieved for the testing data, in practice, telling the feature selection method that we do not want to optimize the training data classification but the testing data classification. For mRMR no information of the actual problem was introduced. Nevertheless, it has been already show that the recognition rates are biased in SFS while the same data is used for selecting the features and validating the features (Koskimäki, 2015). Thus by using SFS the unseen activities are not unseen but already used in model optimization. Although the difference between the accuracy of EMG and acceleration signals with SFS is so apparent that it cannot be caused by this bias, the more reliable overall results are those achieved with mRMR which clearly favored EMG-data.

EMG-data was useful when unseen activities were recognized. However, when the task was to recognize individual activities, the situation was different. In this case, the combination of EMG and accelerometer did not provide any added value compared to using only accelerometer. In addition, when only EMG data was used in the recognition process, the recognition accuracy was really low. The reason for this this can be seen from Figure 2, EMG signals are not different in different exercises. In addition, movement caused by exercise is visible only in some signal channels, not in all. Therefore, when the aim is to recognize individual activities, the recognition should not be based on EMG data, instead accelerometers are advised to be used.

In this study, all the activities were targeted to upper body muscles which still leaves the question "how the results generalize in the cases of lower body muscles workouts" open. For example, there are lower body muscles targeted gym equipments where hands are positioned into stationary handles causing the acceleration to fall behind. Nevertheless, interesting would be seen, if the adherence of the handles would be enough to EMG-signals to contain the information of exercise time. Also interesting would be to know if lactic acids effect to the EMG signals.

6. Conclusions

In this article, the generalization of acceleration signals information was compared with EMG signals in novel events at gym activity recognition. It was shown that when the aim is to recognize unseen activities even non-optimally positioned EMG-sensor will outperform the accelerometer information; the most dissimilar new activities can be extracted from null-data with 10 to 20 percentage unit higher accuracy by using EMG signal. Naturally, more accurate results could be achieved by using optimally located EMG sensor but this was considered non-practical in real world usage while the end-user cannot be obligated to change the sensor location between every gym set. However, the situation is totally different when the aim is to recognize individual activities. In this case, accelerometer-sensor outperforms EMG-signal. In fact, even the combination of EMG and accelerometer does not provide any added value compared to using only accelerometer.

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