# Exploring the use of accelerometer for assisting weight lifting exercise

Nour Alhuda Albougha ,Brahim Benaissa and Sozo Inoue

**Abstract** One of the most important aspects of professional athleticism and rehabilitation is muscle activation. Although sport tracking technologies are advancing rapidly, existing technologies and devices for detecting muscle performance are still out of common users' hands, due to their complexity, invasive nature and high cost. However, sensor equipped devices are getting widely available, which opens the door to alternative solutions using software. In this work we explore the possibility of using accelerometer data for muscle performance in a weightlifting exercise. By investigating a predefined common weightlifting exercise, we exploited a correlation between the acceleration and the lifted weights using a simple RBF prediction method, in a real experiment where data obtained from three participants. The obtained results show that the weight could be predicted in acceptable accuracy for each individual, based on acceleration data.

## 1 Introduction

Doing exercises regularly and correctly is essential to keep the body healthy and able to maintain life tasks efficiently. The advances in wearable sensors, as well as computational breakthroughs of the last decade, made sport exercise more efficient, and pushed our athletic achievement forward. Through sophisticated software we are

Nour Alhuda Albougha
Graduate School of Life Science and Systems Engineering Kyushu Institute of Technology, Kitakyushu, Japan., e-mail: bougha.nour-alhuda403@mail.kyutech.jp

Brahim Benaissa
Graduate School of Life Science and Systems Engineering Kyushu Institute of Technology, Kitakyushu, Japan. e-mail: benaissa.brahim776@mail.kyutech.jp

Sozo Inoue
Graduate School of Life Science and Systems Engineering Kyushu Institute of Technology, Kitakyushu, Japan. e-mail: sozo@brain.kyutech.ac.jp

now able to track step count [15], [18], [3], velocity [26], [11], [13], [28], physiological signs like heart rate [17], [10], muscle activation [4], [23], breathing [22], [29], although some of the mentioned technologies are currently available for professionals only, due to the complexity of use and high cost [1]. That requires several sensors placed in multiple positions on the body, and technician supervision. The Privacy issue is also raised in vision-based technologies [16], [30].

The quality of the exercise is one of the important aspects of professional athleticism. In weight lifting sports, the exercise focuses on one region with one or a set of muscles. The athlete is required to be precise in the way the weight is lifted, in terms of the body pose, speed exercise of execution, and the manner of taking the charge [35], [27], [6].

The professional trainer ' s job is to ensure the highest quality of the exercise through instructions and comments, But it has been proven in several sport domains that sensor technologies can bring new insights and detailed information forward [2], [9], which will help improve the performance, as well as making such abilities available for larger population of people in health and amateur sport domains. In general, there are several devices that help to track sport performance using different body parameters during exercise such as heart rate [17], [10], gait detection [37], [8], [19], [31], and others. Muscle performance is an important measurement that can give good vision of the muscle progress based on the exercise.

Many researches targeted the muscle performance during exercises and explored techniques such as LPT sensors that measure the displacement and velocity of an object [14], [21], [20], [34], electromyography sensors (EMG) [7], [32] which consists of electrodes placed on the skin overlying the muscle by measuring the electrical signals of nerves, and controlling the contraction of the muscles. Inertial sensors such as accelerometer and gyroscope, that measure motion and orientation, are used in order to detect muscle activation in several studies, whether by a combination of sensor types [24], [33] or like a combination of EMG with inertial sensor [12]. On the other hand, some studies use a network of one type of sensor [25]. Another category of studies overcome the issue of convenience by using vision and tracking systems like Video and motion capture [36], the latter is used to calculate the joint flexion angles and estimate the muscle effort.

Due to the technical complexity of these methods, existing technologies are not widely adopted. In this study we want to explore the potential of an approach, of weight lifting exercises, that rely on data obtained from only one accelerometer positioned on a non-invasive spot of the weight itself, specifically a dumbbell. The final goal of this study is to achieve an approach that determines exercise quality based on accelerometer data in the case of predetermined weightlifting exercise (Fig.1). The first step is described in this paper, where several weightlifting exercises have been performed by 3 subjects. The collected data was then used to establish a relationship between the different weight values and the measured acceleration data. We assume at this stage that the weightlifting exercise is done in the right way in which all the force is generated from one muscle. We chose the biceps exercise because of its biomechanical characteristics that are favorable for this study.

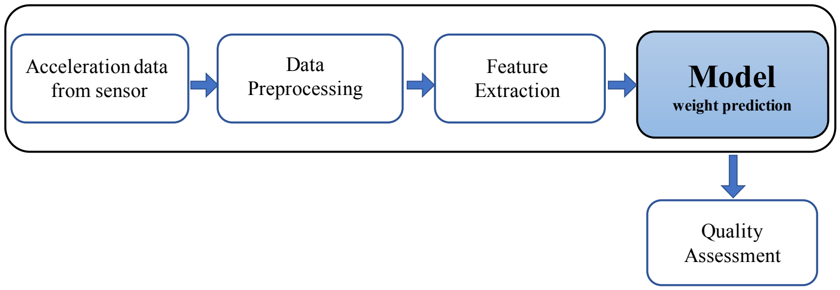



Fig. 1: Flow chart of weight prediction and quality assessment

# 2 Method

## 2.1 Weightlifting exercise

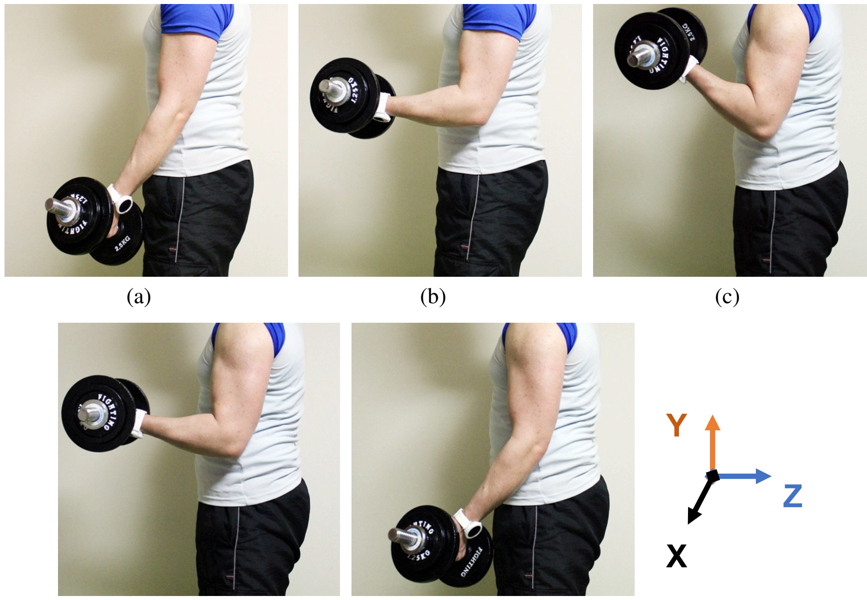
To achieve our goal of detecting a specific muscle force, we selected the Unilateral Dumbbell Biceps Curl exercise the specification we used, adapted from [5], was the following: (1) Stand solidly upright; (2) Feet should be shoulder-width apart; (3) Shoulders should be down; (4) Curl the dumbbell in an upward arc. Curl the dumb-bell to the top of the movement when your biceps is fully contracted; (5) Elbows pointing directly down and return to the start position. And for our purposes we requested to make sure that the palms facing up from the start till the end of the exercise, as demonstrated in Fig.3 .

Three volunteers participated in this experiment. The participants were males in the thirties with different levels of sport habits. The participants were aware that the maximum weights will be used in the experiment and were requested to inform about fatigue, difficulties or possible feeling of bad condition to rest or stop the experiment. We used one wearable triaxial accelerometer sensor embedded in Ticwatch[1] (Fig.2). In our experiment the watch was fixed on the weights to limit the axis movement or change in direction between subjects.


Fig. 2: Acceleration axes directions of Ticwatch

The experiment was made in the laboratory environment over three different sessions using 10 different weights ranging between [1,12.5] Kg with intervals of 1-1.5 Kg. Each weight exercise was made for 5 repetitions with a short period of rest between different weights. We define the beginning of the repetition as when the user starts to lift it and the end as when it reaches the initial position again. The acceleration data was acquired at 100Hz sample rate (1297 in 12.882 secs). All data

[1] https://www.mobvoi.com/ca/pages/ticwatche2




(a) (b) (c)

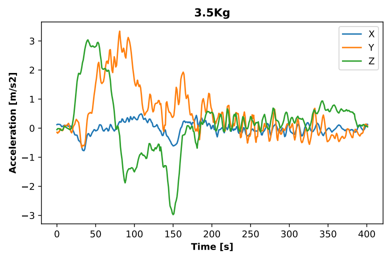
(d) (e) (f) Device's axes directions during performed exercise

Fig. 3: Demonstration of performed exercise (Unilateral Dumbbell Biceps Curl exercise)

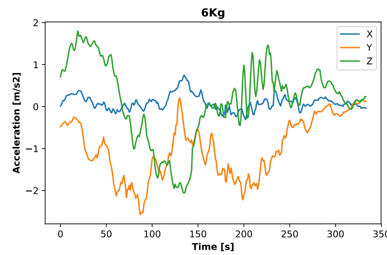
were streamed to a smartphone paired with the watch using Android application installed on both the wearable device and smartphone. Then it was streamed to a computer for the remaining off-line processing and analysis.

## 2.2 Data Analysis

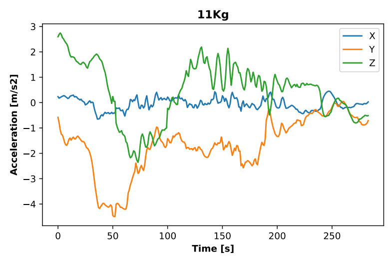
By using one accelerometer sensor for a limited exercise, and analyzing the acceleration data, we observed that the accelerometer signal is different for each weight, especially in the weights higher than 2 kg, which can be exported to distinguish each weight value based on the accelerometer signal. The following figures in (Fig.4) show the accelerometer signal for weights 3.5, 6 and 11 kg respectively. The x axis values are much more stable than the Y and Z axis values, and this behavior is occurring in all weight values. On the other hand, the considerable change in the Y and Z axis follow the same patterns across weights but reach different values. We observe in the Y axis a shift from high acceleration from positive to negative values, as for the Z axis the acceleration values are close in different weights but the period of the patterns increases as the mass get heavier.




(a)




(b)




(c)

Fig. 4: Raw acceleration data for one repetition weightlifting exercise of Subject2 with 3.5 ,6 ,11Kg weight values.

These observations are present in all participants and for different exercise takes. This solidifies the idea that this behavior is linked to the exercise itself and not to the participants, although we should mention that the participants were healthy and with close body proportions. This behavior might well likely be related to the arm lengths and other physiological measures. The effect of muscle fatigue is also highly related to the way the weight is lifted. In this experiment the participants took the exercise 5 times on the same day, weight may reflect on the accelerometer signals, but according to the data analysis the change is not considerable enough, probably due to weight charges that are not relatively high with 12.5 kg maximum.

### 2.3 Weight-acceleration model with RBF kernel

The Radial basis functions method is used in this paper, this method is chosen because first it respects the objective of our work, which is simplifying the sport tracking technology and allowing it to be used in less complex manner, due to its ability to be computationally low cost and can be handled in a smartwatch. It can also be flexible and personalized to each user, based on their data, as it does not require large data set to make good predictions, as long as the problem is simple enough.

Based on the earlier observation, and with respecting of the exercise constraints, the observed behavior is favorable to RBF method. We went forward to build a model that linked between accelerometer signals, during a weightlifting exercise, and lifted weight value. In this first step we want to examine the potential of this relationship by predicting the weight value using an acceleration signal. This approach assumes that the relationship between the weight and the measured acceleration can be expressed as follows:

$$W = C.A \tag{1}$$

where A is the matrix of acceleration database, and W is the matrix that contain the corresponding lifted weights. The matrix C denotes the coefficient matrix that holds the relation. RBF of in this work help determine the Weight for an unknown acceleration signal. It is a function whose value depend on the distance between points.

Considering that A is the quantity of data. each data point is written in vector form with 3 spacial dimensions. Moreover, these vectors constitutes the data matrix A. While G is the matrix of the normalized signal values, and it represent the RBF effect of each sample point on all the other points.

$$G = \begin{bmatrix} g_1(\left|a^1 - a^1\right|) & \dots & g_1(\left|a^j - a^1\right|) & \dots & g_1(\left|a^M - a^1\right|) \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ g_i(\left|a^1 - a^i\right|) & \dots & g_i(\left|a^j - a^i\right|) & \dots & g_i(\left|a^M - a^i\right|) \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ g_M(\left|a^1 - a^M\right|) & \dots & g_M(\left|a^j - a^M\right|) & \dots & g_M(\left|a^M - a^M\right|) \end{bmatrix} \tag{2}$$

the Acceleration matrix is then represented by G(A)

$$W = C.G(A) \tag{3}$$

The matrix C, which collects the interpolation coefficients, is calculated as:

$$C = W.G(A)^{-}1 \tag{4}$$

by calculating the matrix C, the offline model construction phase is done. In order to do weight prediction for a measured signal a, a vector g(a) should be calculated, and the weight is estimated using the following equation:

$$w(a) = C.g(a) \tag{5}$$

Where w(a) is the weight value corresponding to the measured acceleration signal. C the interpolation matrix calculated in the offline stage. Initially introducing acceleration signals for each weight as an input and once the model is built, tests are made using an acceleration vector that is not included in the input data, and predict the weight equivalent to that signal. Each participant got a dedicated model, and test for each participant is made on their own models.

Several RBF functions have been used to test the accuracy of predictions, this paper presents the results obtained by the following function.

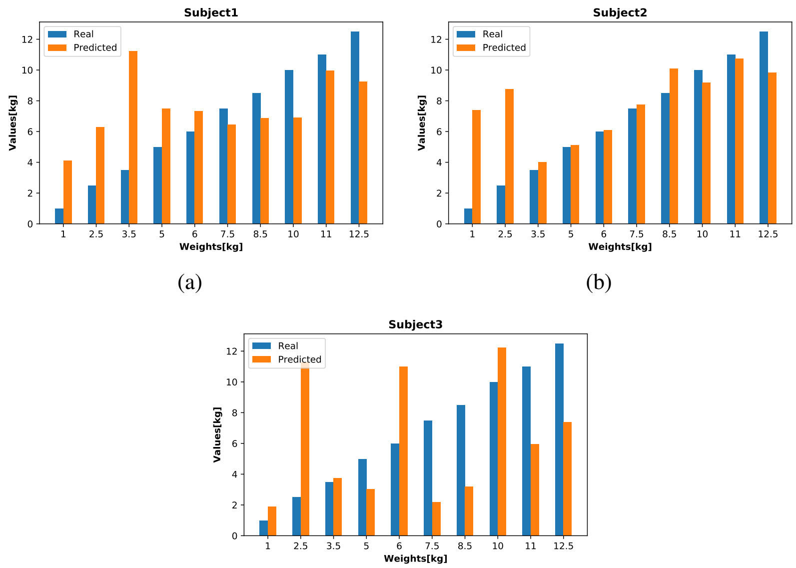
$$g(a) = \sqrt{||a - a_i||^2} \tag{6}$$

# 3 Results

## 3.1 Raw Acceleration

At the first stage, several models were tested by combining accelerations form X, Y and Z axes. The accuracy obtained from these models varied greatly, where the X axis corresponded to the worst accuracy for all weight values, followed by the Y axis while the Z acceleration reflected the best accuracy. The combination between axes did not help improve the accuracy further. The figures (a), (b) and (c) in Fig.5 compares the predicted weights for three participants to the real weights using the Z axis acceleration data. We observe initially that the highest error value occurs in the weights lower than 3 kg. and best lowest errors are in the medium weights.

We also observe that the predictions for the third participant are not as precise as the first two participants, which brings the issue of performance based on individuals. This will be the study of the next step which will be the exercise quality assessment based on accelerometer data.



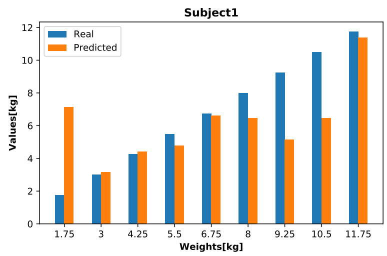

(a) (b)

(c)

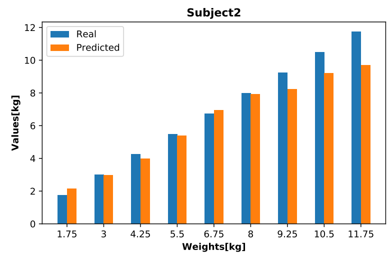
Fig. 5: Weight prediction from Z axis raw acceleration data using RBFs for three subjects

## 3.2 Average Acceleration

We attempted to improve the accuracy of the prediction by filtering and feature extraction techniques, in this section we present the results issued of models where the acceleration data is used in the average form . The average of the five repetitions for each weight per one session for each participant was taken as input of the model ,and prediction was made for different weights of the in-between values as shown in (Fig.6). The most obvious observation in this case is that accuracy in low weight values has drastically improved and the prediction appears to be more stable than in the case of raw acceleration data. We notice that the estimated value does not exceed the real value in most predictions, which might be caused by a bias. Results for subject three are improved as well.




(a)

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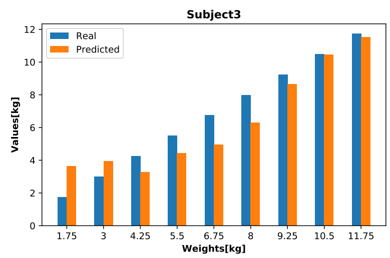


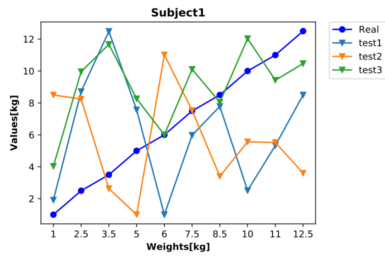

(c)

Fig. 6: Weight prediction from average acceleration data of (X,Y,Z) axes using RBF network for three Subjects

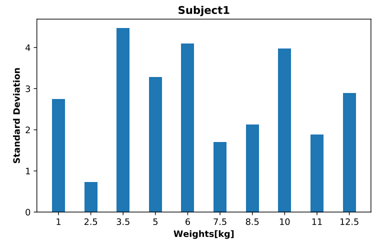
## 3.3 First Phase of Acceleration signal data

After observing the raw acceleration data pattern , we noticed that the first phase of the signal represent the most considerable part of the motion . In order to benefit from this observation in improving the prediction and since the Z axis reflected the best prediction results as discussed earlier ,we fed the model with the average of the first phase of Z axis values of each repetition for each weight value .

The created model for each subject was tested using leave-one-out cross validation , where one repetition for each weight was randomly selected for the test from all the performed sessions and the rest repetitions were used as training data .Even though this approach showed some improvement in prediction of the lowest and highest weights in some tests as shown in (a,c,e in Fig.7), it resulted in some bad results for the in-between weights which indicated that the previous approach of using the full Z axis data showed more accurate results.The accuracy was acceptable in most tests, however the standard deviation calculated for the tests ranged in [0.4 ,4.5] (b,d,f in Fig.7) indicating the instability of prediction values.




(a)

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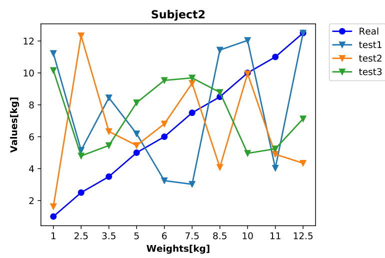


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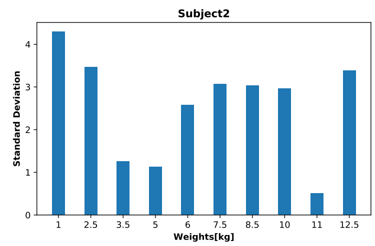


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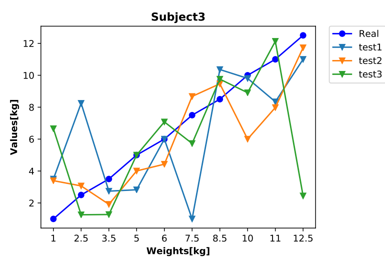
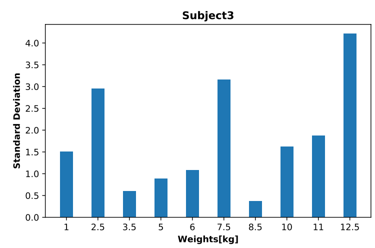


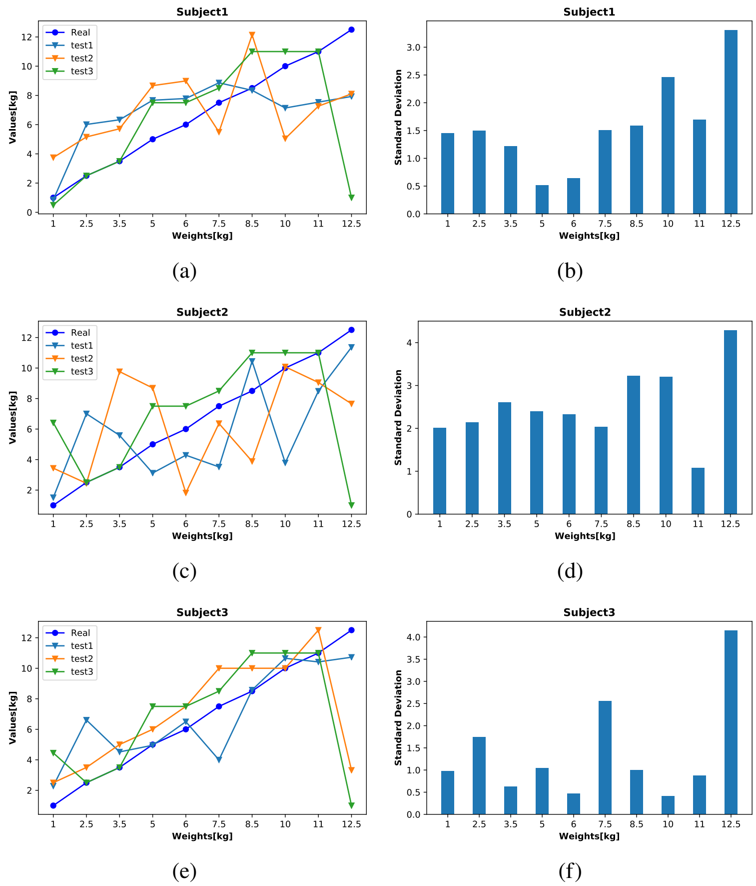

(e)




(f)

Fig. 7: Weight prediction from average first phase of each repetition using Z axis acceleration data only, using RBF network for three Subjects with calculated Standard Deviation

We also applied the approach of using the first phase on X,Y and Z axes acceleration data to get the average of each repetition values and tested the corresponding model for each subject by leave-one-out cross validation over the sessions. The prediction values showed improvement in most of the tests especially for the in-between weight values , while in some tests it resulted in bad prediction for the lowest and highest weight values .The standard deviation also showed a slight improvement for all subjects' models and ranged in [0.5,4.3] but still represent an instability of the prediction (Fig.8).




(a) (b) (c) (d) (e) (f)

Fig. 8: Weight prediction from average first phase of each repetition using (X,Y,Z) axes acceleration data , using RBF network for three Subjects with calculated Standard Deviation

Finally , more tests were applied using average the full signal of three acceleration data axes (X,Y,Z) over the three performed sessions as input for training the models and tested to evaluate the stability of the created models .This approach showed the best accuracy for all weight values and the standard deviation was significantly improved for most of the subject ranging mostly in [0,1.5] indicating the stability of the prediction models. (Fig.9).

In all results, we notice that the outcome for subject 3 are in most of the time better than those for subject 1 and subject 2. Based on the different data segments we used, it seems that there is something specific about the way the weight is lifted that let the acceleration data less stable thus reduce the accuracy of the prediction. Because the data that is used to construct the model has a lower degree of correlation.

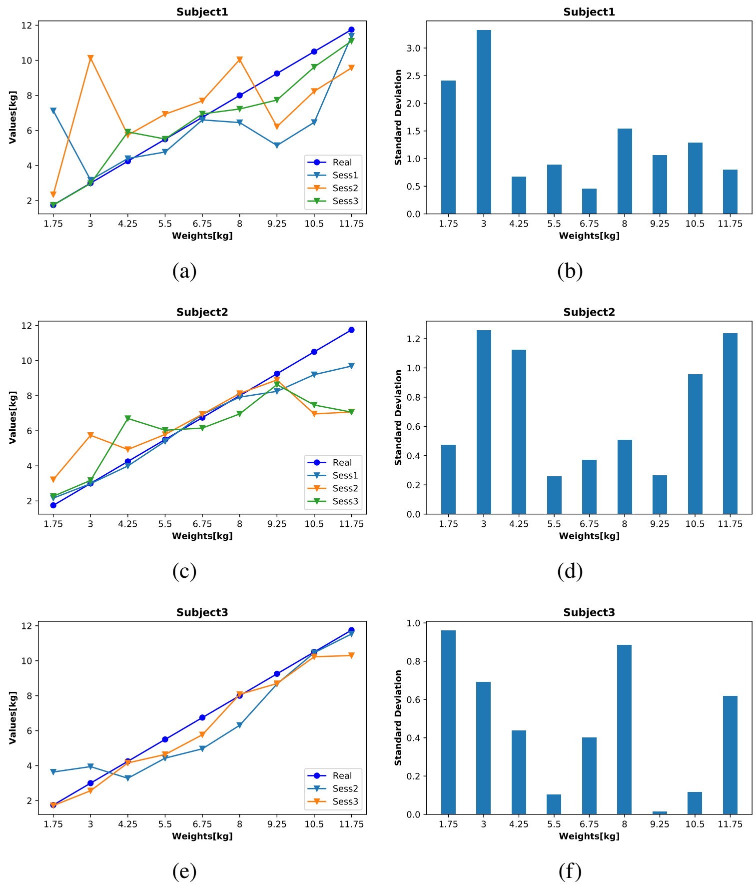



Fig. 9: Weight prediction from average acceleration data of (X,Y,Z) axes using RBF network for three Subjects with calculated Standard Deviation

Based on this observation, we may assume that by reversing the operation, starting from a known weight, we can create a way to determine the quality of the exercise, using the relationship between the weight value and the acceleration shape plus an incorporated data of good quality exercise. which we will focus on in our next step of this research.

## 4 Conclusion

In this position paper we described the motivation of our work and the need for a simple approach that makes weightlifting assessment technology available for common people, and explored the possibility to link between the acceleration during a weightlifting exercise and the value of lifted weight.

The observation made during a real test showed that this approach can be promising, and we started by examining the predictability of this relationship using an RBF kernel. The results obtained varied in accuracy depending on the weight value and on the participants, but in most cases showed that the accelerometer data in a constrained exercise can be exploited further to develop an assessment approach.

For all participants, the accuracy of prediction is high. This result cannot be practically useful on itself as it is easier to directly measure the weight than to measure the acceleration in our daily experiences. But this opens the possibility of a tracking technology, by providing this ability to a smart system along with the exercise type.

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