# MyoBuddy: Detecting Barbell Weight Using Electromyogram Sensors

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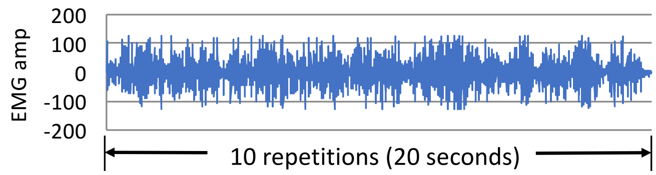
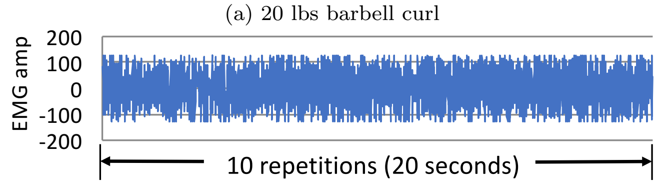
## ABSTRACT

Muscular dystrophy is a group of genetic diseases that cause the loss of muscles and hence weakening the muscle strength. A typical treatment for muscular dystrophy patients is routinely performing weight exercise to slow down the loss in muscles. Thus, we propose a system MyoBuddy to help both physical therapists and patients to keep track of the weights in workout activities based on electromyography (EMG) sensors embedded in Myo armband. In our study, we collect 102 sessions of EMG data from barbell bicep curl exercise with a range of weights from 20 to 70 lbs with a 10-pound increment. Both Support Vector Machine and Random Forest algorithms are explored to classify which weight of barbells are lifted. At the end, we achieve 77.1% classification accuracy on average.




(a) 20 lbs barbell curl




(b) 70 lbs barbell curl

Figure 1: Two traces of EMG signals measured from $4^{th}$ channel of Myo armband, each is measured when performing barbell bicep curl with a different weight.

## 1. INTRODUCTION

Muscle dystrophy is an umbrella term for genetic diseases whose major symptom is dramatic loss of muscle mass. According to an investigation by the Centers for Disease Control and Prevention, 1 out of 7,250 males aged 5 to 24 suffer from muscle dystrophy[1]. As of today (April 2017), there is no cure for muscle dystrophy. Steroids are used as major medical treatment for severe patients, however, steroids can disrupt normal hormone production or levels in a patient's body. Daily weightlifting routine is a natural and effective physical therapy to reduce the rate of muscle loss. To help physical therapists monitor the degree of muscle dystrophy, we propose a system called MyoBuddy that monitors and classifies the weights that patients lift during weightlifting exercises.

There are several infrastructure-based solutions for weight detection, for instance, attaching RFID tags on each weight or using computer vision techniques to identify numbers on the weights. However, the deployments of these methods are time consuming and require high installation cost. Moreover, since these techniques rely on external sensing facilities, users have little control how their weightlifting activities are monitored and stored, and hence user privacy becomes a concern. MyoBuddy, on the other hand, seeks for a single-point sensing approach that only requires users to wear a Myo armband [1]. Myo is composed of 8 electromyography (EMG) sensors, and each EMG sensor measures the change of electrical signals from skeletal muscles. These electrical signals allow MyoBuddy to distinguish the degree of muscle activation. Two time series of EMG data are demonstrated in Figure 1 when a user lifts two different weights. In both cases, EMG signals show high frequency, but when lifting a heavier weight, the amplitude of EMG sensor signals is larger.

Previous work has shown that detecting the weight lifted is challenging. In Zhou et al's work [20], only 43% accuracy is achieved where weights are grouped into 4 categories based on participants' body strength. In our work, MyoBuddy aims at achieving a high accuracy in weight detection and targets finer-grained weight recognition. In our experiment, we collected one week of EMG data when performing barbell bicep curl exercise from both authors[2]. By using machine learning models, Support Vector Machine (SVM) and Ran-

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[1] The source of the statistics: https://www.cdc.gov/ncbddd/musculardystrophy/research.html

[2] The data is collected from the authors and thus does not require approval from IRB.



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Figure 2: Myo Armband is composed of 8 units, each is equipped with an EMG sensor inward of the band. The numbers above the band show the channel identifier.

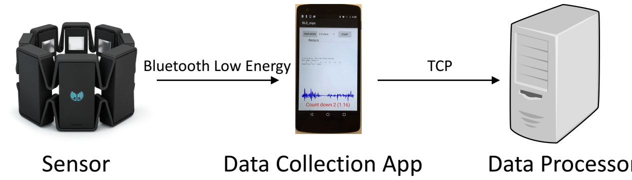



Figure 3: Overview of MyoBuddy system.

dom Forest, MyoBuddy can train a personal model which achieves up to 80% accuracy with four weight categories and 66% accuracy with six weight categories. We also create user-independent models that achieve 63% accuracy on average.

Our contributions in this work are:

- We develop a system to systematically collect and analyze workout data.
- We collect one week's worth of EMG data from two authors.
- We explore both user-specific and user-independent models and report their performance.

The rest of paper is organized as follows: We first discuss the background of EMG sensors and the Myo armband in Section 2. Then, we talk about related work in Section 3. In Section 4 and 5, we describe the details of our experiments and present an evaluation of our system. We mention the limitations of our work in Section 6. Finally, we provide possible extensions for future work and conclude our work in section 7.

The source code of data collection application, analysis software, and raw data can be found at:

https://github.com/nesl/MyoBuddy

# 2. BACKGROUND

**Electromyography Sensors (EMG).** Similar to electroencephalogram sensors (EEG), EMG sensors are used to capture the electrical activities of skeletal muscles. EMG sensor is made of electromyograph that can detect the biopotential of muscle cells. When a person needs to use his muscles, the neurons in the brain release electrical signals to control the movement, causing potential changes in muscle cells. The potential changes can be captured by an EMG sensor.

**Myo Armband.** Myo [1] armband is one of the cheapest commercial EMG sensors (∼\$200), and it features capturing hand gestures through analyzing the EMG and inertial (IMU) signals from a user. Myo armband, as shown in figure 2, consists of 8 pods, each pods equips an EMG sensor. The $4^{th}$ pod additionally contains a Bluetooth Low Energy hardware module and a 9-axis IMU. Each EMG sensor is made by noise filters and one quad precision op-amp. The theoretical sampling rate of each EMG sensor is 200 Hz[3].

[3] The expected sampling rate is clarified in this thread https://developer.thalmic.com/forums/topic/1945/

# 3. RELATED WORK

**Weightlifting tracking.** FitBit [9] and Nike+ [2] are commercialized devices that have abilities to track cardio exercise. Several previous researches discussed how the weightlifting activities can be sensed. MyoVibe [11] leverages mechanomyogram (MMG) sensors to sense muscle activation for session segmentation. Repetitions can be counted by processing inertial sensor signals [3, 14, 16] or observing the Doppler Effect from RFID sensors [10]. Prior work also explored exercise type recognition through machine learning algorithms [7, 20]. RecoFit [13] and myHealthAssistant [18] are complete systems which automate the weightlifting tracking process, including repetition counting and type detection. Burnout [12] exploits wearable sensors to quantify muscle fatigue index to prevent injury. Among aforementioned work, only Zhou *et al.* [20] tackles the weight usage detection. However, the accuracy of distinguishing four groups of weights in their work is only 43%. Our work aims at distinguishing different weights in a finer grained categories with a higher accuracy.

**Electromyography sensor.** Electromyography (EMG) sensor has been studied for more than two decades [8], and has been widely applied in medical domain for identifying neuromuscular diseases such as back pain [17] or muscle fatigue level [12]. In human-computer interaction domain, EMG sensor has been used for gaming [15], capturing hand gesture [1, 15], idenfication [19], and an controlling wheelchair [4]. Our work further extend the capability of EMG sensors for weight detection.

# 4. EXPERIMENT DESIGN

The system overview of MyoBuddy is shown in figure 3. A Myo armband measures EMG signals from users. A mobile phone application serves as a proxy to receive EMG data from Myo via Bluetooth Low Energy, and forwards the data to the server over TCP. All the computation and feedback are done in the server.

## 4.1 Data Collection Application

We implemented an Android application to receive and log EMG data from Myo armband through Bluetooth Low Energy (BLE). Our experimental sampling rate of EMG data in our application ranges between 130 and $170Hz$, which is close to the theoretical sampling rate of $200Hz$ stated by the manufacturer. The fluctuation in the data sampling rate is caused by crowded Bluetooth communication and stability. In fact, several other BLE devices were found in the experimental area.

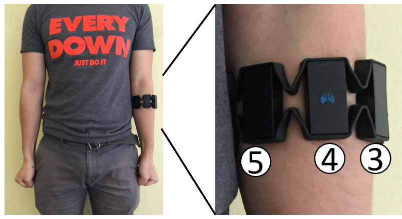



Figure 4: The left picture shows that the band should be worn on the middle of a left arm. The right picture shows the direction of the Myo armband. The Myo logo should point outward and align with the left thumb.

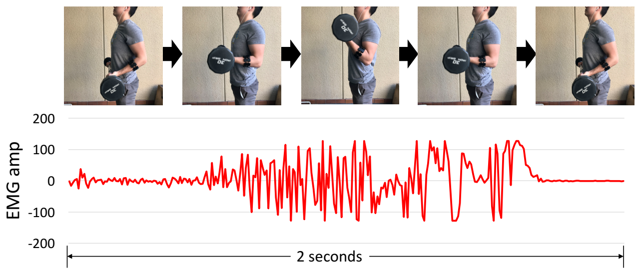



Figure 5: The motion of one repetition of the barbell curl exercise and its corresponding EMG data from one EMG sensor.

The packet format of EMG data from Myo is partially open-sourced by ThalmicLab[4]. Each packet contains two consecutive samples, and each sample includes 8 bytes, and each byte represents a EMG sensor reading whose value ranges from $-128$ to 127. The values indicate the relative bio-potentials, but the unit is not defined.

## 4.2 Experimental Procedure

Each EMG sensor in Myo senses electrical signals corresponding to the muscle groups the EMG sensor is attached to. To reduce ambiguity in data analysis, we described a fixed way to wear the Myo armband, i.e., the orientation and the position of the Myo armband with respect to the forearm is always the same when the device is worn. Figure 4 shows the expected way to wear a Myo armband. A user should wear the Myo device on her left forearm close to the elbow, with the logo (printed on $4^{th}$ EMG sensor) aligned with the center of the fist.

We chose barbell bicep curl as the exercise in our experiment[5]. Figure 5 presents the procedure of a standard barbell curl. Both authors tried their best to complete each barbell curl repetition in 2 seconds: 1 second for lifting the barbell and 1 second for returning to the start position. We define a *repetition* as one cycle of the barbell motion, and a *session* to be several consecutive repetitions. In our experiments, both authors performed a maximum of 10 repetitions per session. To minimize the impact of muscle fatigue in our experimental results, the authors rested for at least 1 minute between sessions.

[4]Myo armband Bluetooth packet format: https://github.com/thalmiclabs/myo-bluetooth/blob/master/myohw.h

[5]A standard barbell exercise is described in https://www.bodybuilding.com/exercises/main/popup/name/barbell-curl

| Items | User 1 | User 2 |
|---|---|---|
| # of sessions | 60 | 42 |
| # of repetitions | 593 | 409 |
| Weight range | 20-70 lbs | 20-50 lbs |
| # of different weights | 6 | 4 |
| Total length | 40.9 minutes | |

Table 1: Summary of dataset.

Because of the variation in each individual's body strength, the maximum weight the first author can lift is 70 lbs, and the second author can lift up to 50 lbs. Both authors performed barbell curls starting from 20 lbs to their respective limits, incrementing by 10 lbs in each experiment.

## 4.3 Weight Classification

The data processing server leverages machine learning algorithms for weight detection. Since EMG signals are time series data, MyoBuddy first segments the time series data and then extracts features in each window. We consider each window to be 2 seconds long because it includes a full-cycle of barbell bicep curl motion. Then, MyoBuddy computes several amplitude-based features in each window including absolute mean, variance, percentiles, and percentage of samples within certain ranges. All features are computed separately for the 8 channels of Myo device. We use Support Vector Machine (SVM) with RBF kernel [6] and Random Forest (RF) [5] as our learning classifiers.

# 5. EVALUATION

We collected 102 sessions of data over a week. Table 1 summarizes the characteristics of our dataset. We conduct several evaluation scenarios based on this dataset to analyze different aspects of our system, which is reported in the following subsections.

## 5.1 Personal Model

We first train a model for each person separately. To evaluate the sensitivity of our personal models to the weight increments, we selectively choose data points in our dataset based on predefined weight increments. For instance, in the 10-pound increment case, we keep the data points corresponding to 20 lbs, 30 lbs, up to the maximum weight each author can lift. Similarly, in the 20-pound increment case, we keep the data points corresponding to 20 lbs, 40 lbs, and 60 lbs, and discard the rest. For our analysis, we consider 10, 20, and 30-pound increment cases. The resultant datasets corresponding to each case are partitioned into 80% and 20% for training and testing data, respectively.

Figure 6 shows the classification accuracy of all repetitions. Generally, the performance of RF is better than SVM. One possible explanation that RF gives a better result is that it employs a better feature selection algorithm and leverages ensemble techniques which are more resilient to over-fitting. Moreover, since the weight range that Author 2 can lift is smaller and hence fewer classification labels, the overall classification accuracy of Author 2 is higher than Author 1.

Our classifier gets a higher accuracy when the weight increment increases. For Author 1, the classifier achieves higher than 80% in both the 20-pound and the 30-pound

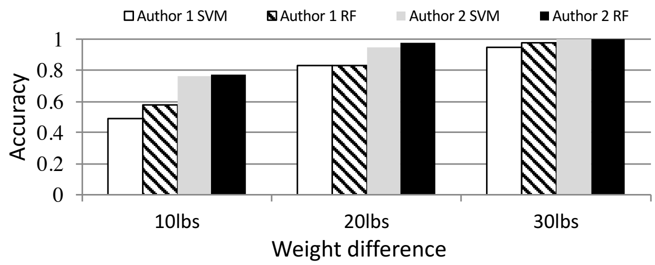



Figure 6: Repetition-level weight classification accuracy when applying SVM and RF algorithms

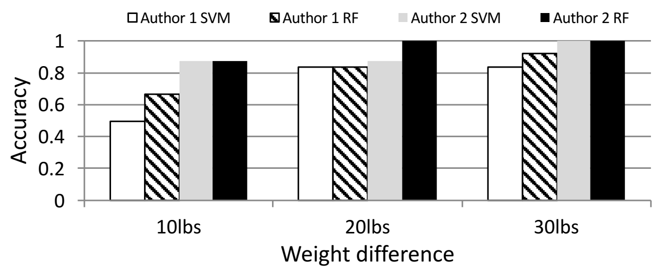



Figure 7: Session-level weight classification accuracy when applying SVM and RF algorithms

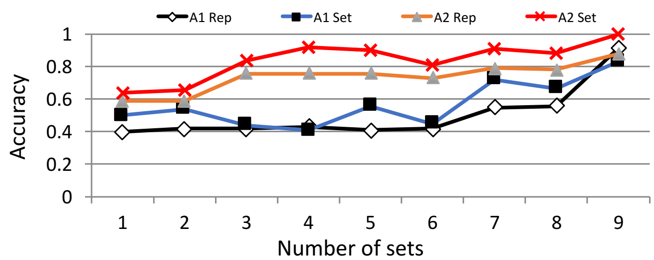
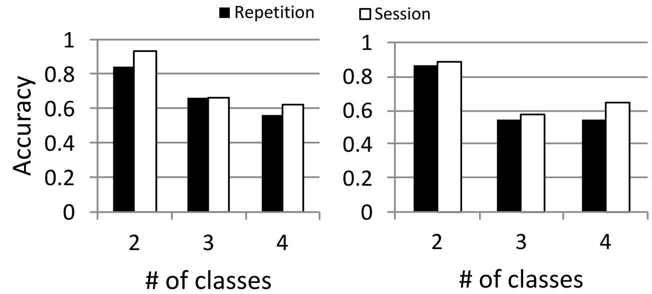



Figure 8: The accuracy increases when there are more number of sessions of each weight in the training set. We report both authors' (A1 and A2) repetition (rep) and session (set) accuracies.




(a) Author 1 → Author 2 (b) Author 2 → Author 1

Figure 9: Accuracy of user independent model. X → Y means we take X's data as the training set and apply on Y's data. Both repetition and session accuracy are reported.

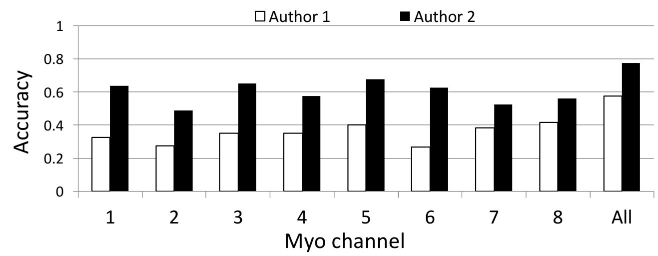



Figure 10: The repetition accuracies if we only consider one particular EMG channel from Myo.

increment case. The accuracy drops to slightly lower than 60% in the 10-pound increment case. On the other hand, for Author 2, the accuracy of 10-pound increment case is close to 80%, and is higher than 96% in both the 20-pound and the 30-pound increment cases.

We apply majority voting on estimated weights of all repetitions within a session because the weight within a session will not change. This session-level optimization strategy improves the accuracy to 68% for Author 1's 10-pound increment case. Figure 7 summaries the session-level weight classification accuracy.

### 5.1.1 *Training data size*

To determine the minimum amount of data to achieve an acceptable accuracy, we increment the training data size and evaluate the classification accuracy. Figure 8 summarizes the results. For Author 1, the accuracy does not converge until 9 sessions of all 6 weights are included in the training set. The accuracy for Author 2 achieves 82% in just 3 sessions of 4 weights. As a result, our model only needs a few sessions to achieve an acceptable accuracy, and will achieve better performance if more training data are provided.

## 5.2 User-Independent Model

Our application will be much more useful if we can train the classifier from one group of people and apply to other people. We simulate this situation by training on one author's data and applying the model on the other author. The EMG signals can differ a lot for two people lifting the same weight due to the difference in muscle strength. However, EMG signals have similar amplitude when both authors lift a weight close to their strength limits. Based on this observation, the weights are partitioned into 2 to 4 categories. Figure 9 demonstrates that when the result is binary (2-category case), both models can achieve an accuracy higher than 85%. However, when there are more weight categories, the accuracy drops to below 65%.

We also utilize Author 1's model without grouping any weight and apply it on Author 2's dataset. The prediction result is interpolated based on their weight limits, i.e., mapping 70 lbs to 50 lbs. The average predicted weight error is 5.2 lbs.

## 5.3 Muscle Groups Matter

To evaluate the necessity of the 8 EMG sensors in Myo, we simulate the situation by keeping the data from one EMG channel at a time for classification. Figure 10 shows the results that only one EMG sensor data is used. As we can see, the $5^{th}$ EMG sensor is the most significant channel because the greatest amount of force is exerted where the sensor resides. In contrast, the $2^{nd}$ EMG sensor gives the lowest accuracy because the muscles under it do not play a key role in bicep exercises. However, the accuracy of each EMG sensor does not drop dramatically compared to when all the 8 EMG channels are used, suggesting all the EMG sensors can sense activated muscles.

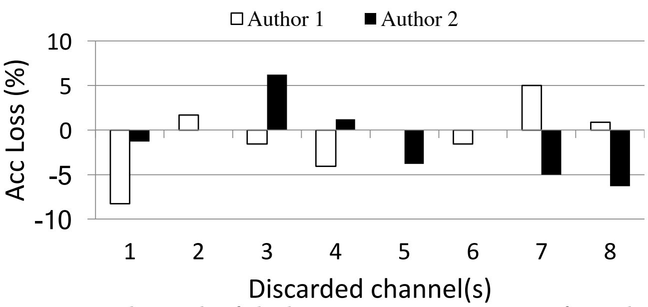


Figure 11: The result of the leaving-one-out experiment for each EMG channel. The y-axis presents the accuracy loss compared to the original personal models.

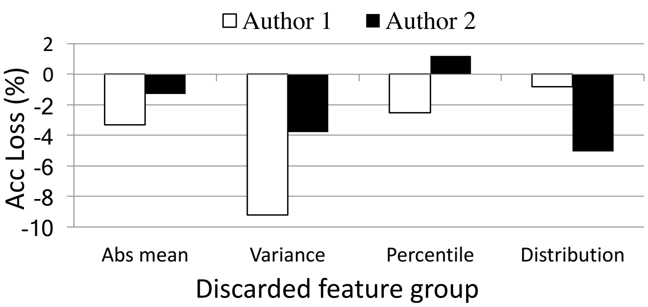


Figure 12: The result of the leaving-one-out experiment for features including absolute mean, variance, percentile, and percentage of samples within certain ranges (distribution). The y-axis presents the accuracy loss compared to the original personal models.

To examine the importance of each channel, we conducted a leave-one-out experiment for every channel. Figure 11 presents the accuracy loss when the data of one EMG channel is absent. The results show that none of the channels significantly affect the classification performance. In addition, the accuracy increases after removing the $1^{st}$ and $4^{th}$ channels because they cause noise in the model. After removing these two noisy channels, the accuracy can improve by 2.5% and 1.3% for Author 1 and Author 2, respectively.

## 5.4 Feature Analysis

Similar to the previous experiment, we conducted a leave-one-out experiment for the following feature groups: absolute mean, variance, percentiles, and percentages of samples within certain ranges, as mentioned in Section 4.3. Figure 12 shows that the accuracy increases the most when the variance feature is removed. The final accuracy increases to 66% and 80% for Author 1 and Author 2, respectively.

# 6. DISCUSSIONS AND LIMITATIONS

**Orientation of Myo.** One limitation of our experiments is that the Myo armband must be worn in a specific orientation on the forearm. However, this orientation can be automatically acquired using the built-in inertial sensors in Myo. Once the device orientation is measured, the angular difference between the measured versus expected orientation can be detected, and EMG data can be calibrated by shifting the EMG channels.

**Arm motion pace.** EMG measurements capture the electrical signals sent out from muscles, which is an indicator of how much force is being exerted. However, a person may use a different amount of force when lifting the same weight because of the pace of the motion. Generally, one needs to use more force to complete a workout session more quickly. Our experiment avoids this complication by constraining the duration of each bicep curl rep. However, this restriction could be removed by measuring the duration of each repetition from inertial sensors [14, 16].

**The sensing scope of workout.** In our study, we choose barbell bicep curl for our application evaluation. However, the methodology can be generalized to other workout activities as well, such as all upper body exercises because arms are always needed to coordinate for upper body exercises. In the future, the weight detection model should consider the workout type as a prior [7, 20] because the muscle activation can vary among different exercises.

# 7. CONCLUSION AND FUTURE WORK

We designed a practical system called MyoBuddy using EMG sensors to estimate the weights of the barbell exercise. Our results show that MyoBuddy can distinguish weights with a 10-pound increment with 73.4% repetition-level and 77.1% session-level accuracy.

Although we only collected one week of data from two authors, in the future, we plan to recruit more volunteers and to test our system in different weightlifting exercises such as tricep ropes, bench dips, etc. We further aim to migrate the data processing program to smartphone so that users can obtain real-time feedback and see the performance improvement. Our system has potential to enable different interesting applications, such as a tool for bodybuilders to track their weight limits and adjust their training plan accordingly.

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# 8. REFERENCES

[1] Myo Band. https://www.myo.com/.
[2] Nike+. http://www.nike.com/us/en_us/c/nike-plus.
[3] VimoFit. http://www.vimofit.com/.
[4] D. Andreasen and D. Gabbert. Electromyographic switch navigation of power wheelchairs. In *Annual conference of the rehabilitation engineering and assistive technology society of North America*, 2006.
[5] L. Breiman. Random forests. *Machine learning*, 45(1):5–32, 2001.
[6] C.-C. Chang and C.-J. Lin. Libsvm: a library for support vector machines. *ACM Transactions on*

*Intelligent Systems and Technology (TIST)*, 2(3):27, 2011.

[7] H.-T. Cheng, F.-T. Sun, M. Griss, P. Davis, J. Li, and D. You. Nuactiv: Recognizing unseen new activities using semantic attribute-based learning. In *Proc. 11th ACM MobiSys*, 2013.

[8] C. J. De Luca. The use of surface electromyography in biomechanics. *Journal of applied biomechanics*, 13(2):135–163, 1997.

[9] K. M. Diaz, D. J. Krupka, M. J. Chang, J. Peacock, Y. Ma, J. Goldsmith, J. E. Schwartz, and K. W. Davidson. Fitbit®: An accurate and reliable device for wireless physical activity tracking. *International journal of cardiology*, 185:138–140, 2015.

[10] H. Ding, L. Shangguan, Z. Yang, J. Han, Z. Zhou, P. Yang, W. Xi, and J. Zhao. Femo: A platform for free-weight exercise monitoring with rfids. In *Proc. 13th ACM SenSys*, 2015.

[11] F. Mokaya, R. Lucas, H. Y. Noh, and P. Zhang. Myovibe: Vibration based wearable muscle activation detection in high mobility exercises. In *Proc. ACM UbiComp*, 2015.

[12] F. Mokaya, R. Lucas, H. Y. Noh, and P. Zhang. Burnout: A wearable system for unobtrusive skeletal muscle fatigue estimation. In *Proc. 15th ACM/IEEE IPSN*, 2016.

[13] D. Morris, T. S. Saponas, A. Guillory, and I. Kelner. Recofit: Using a wearable sensor to find, recognize, and count repetitive exercises. In *Proc. 32nd ACM CHI*, 2014.

[14] B. J. Mortazavi, M. Pourhomayoun, G. Alsheikh, N. Alshurafa, S. I. Lee, and M. Sarrafzadeh. Determining the single best axis for exercise repetition recognition and counting on smartwatches. In *Proc. 11th IEEE BSN*, 2014.

[15] D. G. Park and H. C. Kim. Muscleman: Wireless input device for a fighting action game based on the emg signal and acceleration of the human forearm. In *International Symposium on Neural Networks. ISNN*, 2011.

[16] I. Pernek, K. A. Hummel, and P. Kokol. Exercise repetition detection for resistance training based on smartphones. *Personal and ubiquitous computing*, 17(4):771–782, 2013.

[17] A. E. Sandoval. Electrodiagnostics for low back pain. *Physical medicine and rehabilitation clinics of North America*, 21(4):767–776, 2010.

[18] C. Seeger, A. Buchmann, and K. Van Laerhoven. myhealthassistant: a phone-based body sensor network that captures the wearer's exercises throughout the day. In *Proceedings of the 6th International Conference on Body Area Networks*, pages 1–7. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), 2011.

[19] L. Yang, W. Wang, and Q. Zhang. Secret from muscle: Enabling secure pairing with electromyography. In *Proceedings of the 14th ACM Conference on Embedded Network Sensor Systems CD-ROM*, pages 28–41. ACM, 2016.

[20] B. Zhou, M. Sundholm, J. Cheng, H. Cruz, and P. Lukowicz. Never skip leg day: A novel wearable approach to monitoring gym leg exercises. In *Pervasive Computing and Communications (PerCom), 2016 IEEE International Conference on*, pages 1–9. IEEE, 2016.