MuscleSense: Exploring Weight Sensing using Wearable Surface Electromyography (sEMG)

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ABSTRACT

Strength training improves overall health, well-being, physical appearance, and sports performance.There are four major factors that affect training efficacy in a training session: exercise type, number of repetitions, movement velocity, and workload. Prior research has used wearable sensors to detect exercise type, number of repetitions, and movement velocity while training. However, detecting workload remains constrained to instrumented exercise equipment, such as smart exercise machines or RFID-tagged free weights.This paper presents MuscleSense, an approach that estimates exercise workload by using wearable Surface Electromyography (sEMG) sensors and regression analysis. We evaluated the accuracy of several regression models and the effects of sensor placement through a 20-person user study. Results showed that MuscleSense achieved an accuracy of 0.68kg (root mean square error, RMSE) in sensing workload using both forearm and arm sensors and support vector regression (SVR).

CCS CONCEPTS

• **Human-centered computing → Empirical studies in ubiquitous and mobile computing**.

KEYWORDS

Biosensing; Fitness; Health; Sports; Strength training; Wearables; Machine learning; Electromyography (EMG)

ACM Reference Format:
Chin Guan Lim, Ching-Yi Tsai, and Mike Y. Chen. 2020. MuscleSense: Exploring Weight Sensing using Wearable Surface Electromyography (sEMG). In *Fourteenth International Conference on Tangible, Embedded, and Embodied Interaction (TEI '20), February 9–12, 2020, Sydney, NSW, Australia.* ACM, New York, NY, USA, 9 pages. https://doi.org/10.1145/3374920.3374943

TEI '20, February 9–12, 2020, Sydney, NSW, Australia

ACM ISBN 978-1-4503-6107-1/20/02…$15.00
https://doi.org/10.1145/3374920.3374943

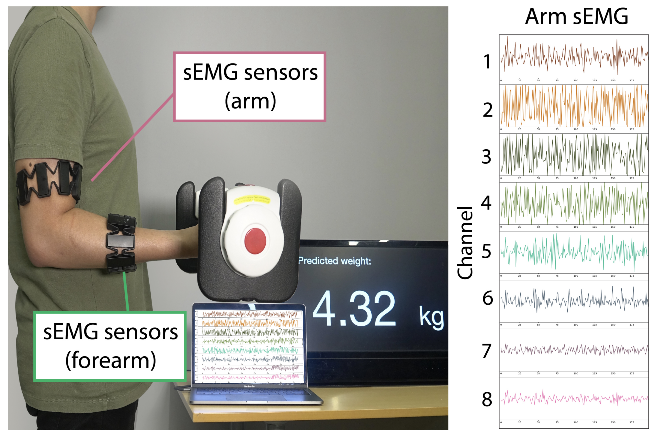

Figure 1: MuscleSense senses exercise weights using wearable sEMG sensors. The chart on the right shows the signals from sEMG sensors on the upper arm, from Channel 1 to Channel 8.

1 INTRODUCTION

Strength training improves overall health, well-being, physical appearance, and sports performance. The World Health Organization (WHO) specifically recommends that *"muscle-strengthening activities should be done involving major muscle groups on 2 or more days a week"* in order to improve cardiorespiratory and muscular fitness, bone health, and to reduce the risk of depression [35].

There are four major factors that affect training efficacy in a training session: exercise type, number of repetitions, movement velocity, and workload. Prior researchers have used sensors to track the type of exercise [24, 32, 39], number of repetitions [10], and movement velocity [27, 33, 34].

Workload sensing is essential to strength train because progressive overload, a gradual increase of stress placed upon our body during training, is fundamental to maintaining and advancing training goals and to avoid over-training [25]. However, detecting workload remains constrained to instrumented exercise equipment such as smart exercise machines and RFID-tagged free weights [16].

This paper explores a new, wearable approach to workload sensing. By sensing the user instead of exercise equipment, it works across all types exercises and exercise equipment, including machines, free weights, body-weight exercises [20] (e.g push-ups, street workout [41], and TRX [44]), and resistance bands [3] that are elastic and provides variable workload.

We present MuscleSense, an approach that uses wearable surface electromyography (sEMG) sensors and machine learning to sense workload while training. sEMG measures nerve impulse during muscle contraction and is related to the intensity of contraction. Our prototype consists of two 8-channel wearable sEMG sensors mounted on a user's arm and forearm. Sensor readings are streamed over Bluetooth and regression models are used to estimate the workload in real-time. We conducted a 20-person user study to compare the accuracy of 4 regression methods: 1) support vector regression with linear kernel, 2) random forest regression, 3) extra tree regression, and 4) multi-layer perceptron regression with lbfgs solver, and to evaluate the effects of multiple sensor locations and fatigue.

Our contributions are as follows:

- We proposed a machine learning approach that uses wearable sEMG sensors to sense workload using personalized regression models.
- We evaluated the effects of sensor placement, showing that using sensors from multiple locations improves accuracy.
- We compared the accuracy of 4 regression models, and showed that support vector regression with linear kernel achieved RMSE of 0.68kg for training data (1kg interval) using sensors on both arm and forearm. The accuracy is within the interval of weights of machines and free weights which normally range from 5 lbs (2.26 kg) to 2.5 kg[1, 29], making it usable in real world strength training scenarios.

2 RELATED WORK

Our work is closely related to 1) training assisting systems and 2) surface electromyography (sEMG).

Training assisting system

Several training guidelines [13, 17, 40] have been proposed to emphasize the importance of overloading and progressive overloading of program variables targeting certain parts of the body. The variables include training intensity (workload), training volume (number of sets and repetitions), exercise selected (the type of exercise), rest interval between each set, training frequency and velocity of contraction (movement velocity) [26]. Rest interval usually affect by exercise selected whereas training frequency does not change in a training session, while the others often change. Therefore it is essential to note down the type of exercise, number of sets and repetitions, movement velocity, and workload.

There have been a great number of studies that employ different types of sensors, including inertia sensors [27, 33, 34], RFID readers [11, 16], GPS [38] to assist exercise. Some of them have been deployed on smartphones [32, 39] to identify the type of exercise. Chang et al. [10] used two accelerometers at the user's hand and waist to recognize exercise type and count repetitions of free weight exercises, while Khurana et al [24] used a camera at the gym to detect, recognize and track simultaneous exercises. Sports companies such as Nike, Under Armour and Garmin, have introduced their own fitness mobile phone applications to track user's training activities.

Tonal [42] is a fitness system that combines training equipment and guidance, tracks full-body workout but limits the type of exercises and is expensive. Interferi [22] could track lifted weights of 0, 6, 9, 12, 15 lbs from acoustic interferometry at a fixed posture. The tracking of workload or training weights used is very important as it associates with training intensity [19]. MuscleSense supports weight sensing using a different approach, and also takes into account the fatigue emerged during a training session.

Surface Electromyography and Force

Surface Electromyography (sEMG) is a technique for collecting the electric signal from muscles using electrodes on the skin. In previous works [45], it is stated that EMG signals will still be produced regardless of direction and sense of strength. Hence, predicting the force of different exercise is indeed possible, even in isometric exercises.

Becker et al. [5] used a regression model to estimate the force, as the mean of absolute values over all EMG channels has a high correlation to real force values. Choi et al. [12] pointed out that multiple muscles have non-linearity with the force instead and sEMG is significantly dependent on an individual's neuromuscular factors. There are also a few works that estimate hand or finger forces using artificial neural networks (ANN) [2, 31], suggesting that ANN is sufficient to estimate force from sEMG signals. We adopted their methods, sensing training workload using sEMG signal through machine learning models. We tried various models to investigate which model perform the best under our approach.

Generally, EMG amplitude and spectrum is affected by fatigue and the generation of muscular force [28]. EMG signal median frequency would decrease and the signal power spectrum would shift toward lower frequencies while fatigue [14]. The change in intramuscular pH value would alter conduction velocity thus changing the amplitude of EMG signal [6, 7]. As mentioned, the EMG signal is also affected by a decreased capacity for physical work (generation of force) during fatigue [4]. The actual influence of fatigue while measuring force using sEMG signal remains unexplored, our work intends to also examine how fatigue would affect workload sensing, as muscle fatigue normally happens in strength training.

Body Sensor(s) Data Prediction

Body sensor data are widely used in predicting daily activities. Truong et al. [43] introduced CapBand, an ultra-low power capacitive sensing wearable armband to detect small skin deformations to predict 15 hand gestures. Tomo [46], a low-cost system using Electrical Impedance Tomography (EIT) could read cross-sectional impedances between electrodes on wrist or arm skin to predict user's hand gesture. Fan el al. [18] applied support vector machine on forearm electromyography data from different forearm muscular activity while grasping objects to predict 15 different objects.

Prior research shows that body sensor data, in particular sensors at wrist and arm are useful and could be utilized to predict various activities at a comparatively low cost.

Our method to recognize workload through surface electromyography (sEMG) from wearable armband could be applied to both free weight exercise and machines.

3 PHYSIOLOGY OF MUSCLE CONTRACTION

To choose a good training feature for our approach, we did some background research on the physiology of muscle contraction.

A single muscle cell in muscle tissue contains lots of myofibrils. Each myofibril is made of many sarcomeres attached end-to-end and bundled together. Sarcomeres are the minimum muscle contraction units, concist of two types of myofilaments, which are actin filament and myosin filament. The contraction of the muscle is a decrease in the gap between these two types of myofilaments. There are three main substances required in the contraction process: 1) the presence of nerve impulse, which could trigger the beginning of a contraction 2) Ca^{2+} ion, which reveals the myosin-binding sites on actin so that the myosin head could be attached to 3) the energy, which is usually Adenosine triphosphate (ATP) that allows the myosin to crawl along the actin filament. Absent of any substance would cause muscle contraction to stop. The measurement of nerve impulse is electromyography (EMG) which is directly related to how much the muscle is contracted.

There are two components to measure EMG (one of quantification of muscle contraction) that is nerve conduction study and needle EMG. Nerve conduction study places several electrodes on the surface of the skin to measure the sEMG while the needle EMG inserts a needle into muscle tissue to evaluate muscle activity when at rest and when contracted. The measurement of sEMG has limited assessments of muscle activity. sEMG also cannot reliably discriminate between discharges of two adjacent muscles. However, it is less invasive and still provide sufficient information to be used in our approach validated through a prototype.

4 FIELD STUDY

We did a 30-person field study at a local gym to further understand users' training and recording habit as well as how important is the weight used in their training. The users are given several questions, for examples "Why do you workout?", "How often do you workout?", "What is the exercise you selected?", "Do you record any information about your training? If yes, how do you record it?", "Have you ever forgot the weight or repetition of your exercise?", their respective answers are recorded. Out of 16 male and 14 female, which consists novice who just started training for few months and veteran trainers who have been working out for over ten years, 19 would remember the training variables including weights, repetitions, and set numbers, 6 would record the information using phone application, 1 would record using pen and paper and the rest do not remember or record any details. In the 5-Likert-scale rating on the importance of recording to training, up to 83.3% of participants rated it as important to very important. 26 out of 30 people had experience of forgetting the exercise information leading them to use the wrong weight or waste time on finding out what weight they should use, hence there are needs to help them record it. One of the participants quoted, "It is very ineffective to not record what we did in a training, as it is hard to know how could we progress. Moreover, it might be very dangerous or time-consuming if we used the wrong weight."

The field study showed the importance of recording variables, especially workload which motivates our approach MuscleSense. Thus, a convenient way to sense weight while training is essential to aid in recording the weights used. The rest questions in this field study helped in designing our system and study tasks.

5 SYSTEM DESIGN AND IMPLEMENTATION

We decided to make our approach more robust and scalable, thus we augment user with sensors rather than augmenting weights with sensors.

Device

The Myo [9] is an off-the-shelf wearable armband with consumer-grade wireless sEMG sensors. It consists of eight electromyographic (EMG) sensors (200Hz sample rate) and IMU (50Hz sample rate) with a 3D gyroscope, 3D accelerometer, and magnetometer. The amplitude of the Myo EMG signal is limited between -128 and 127 arbitrary Myo unit. The sample rate and amplitude limitation of Myo suggest that it is not suited to record high-quality sEMG signal data but it carries sufficient information for hand movement classification [37]. Hence, we used Myo in our study, considering it is affordable by most people and should be capable to satisfy our device requirement. However, using a commercial product bear some limitations. (1) The Myo can only be stretched to a radius of around 6cm. (2) The sEMG data provide by the Myo is processed and thus the dynamic range of EMG signal is limited.

Sensor Placement

We considered the potential positions of sensor placement in various facets: (1) It should be able to fit into the Myo, that is the parameter of the part should be less than 35cm or the diameter should be less than 6cm. (2) It should contain active muscles used in training. (3) There should be enough pressure to push the electrodes to the skin. (4) Current positions of wearable devices.

Thus, we chose the wrist, arm, and forearm as possible candidates. The wrist was then removed although it is where an everyday wearable device for example watches and armbands commonly located at. From the aspect of human anatomy, part beneath the skin at wrist contains mostly tendon which might provide spurious signals due to cross-talk. The sensors at the wrist may pick up signals induced by surface friction, thus it was removed after validation that it is futile to be used in sensing workload in a pilot study.

Bicep and tricep brachii located at arm are part of the main muscles of the upper body, they are also the most common muscles exercised in weight training directly or indirectly. The forearm is the default working area of Myo, it could provide EMG signals from fingers which are undoubtedly the most common muscles we use daily. Moreover, the muscles at forearm (brachioradialis) act as synergists muscle while we grasp an object, such as a dumbbell in weight training. Hence, we used a setup using 2 Myos to investigate the effects of sensor placement and the feasibility to use respective sEMG signals to sense workload at two positions: arm and forearm.

Signal Processing and Smoothing

The Myo streams raw EMG data of eight channels at the rate of 200Hz and IMU data at a rate of 50Hz. The raw EMG data has gone through a notch filter to avoid power grid interference, the data are in arbitrary Myo units (a.u.) which is -128 127 signed integer. There is no official translation from a.u. to volts (V) or millivolts (mV).

Our interest is on the moving weighted average amplitude of EMG signal [30], thus we tried two methods to smooth the sEMG signal after the signal is rectified. One which used a Butterworth band-pass filter of [10Hz, 100Hz], and then smoothed with a low pass filter of 10Hz. Another technique we tried is the Bayesian filtering [21] for sEMG based on Markov process. The final results after Bayesian filtering are more stable and contain fewer jitters thus was chosen, although it is non-linear and takes more time to process. Actual equation of our smoothing is as below:

$$rectified\_sEMG = abs(sEMG - \overline{sEMG})$$
$$smoothed\_sEMG = Bayesian(rectified\_sEMG))$$

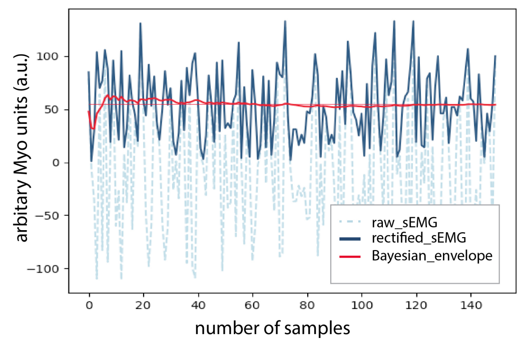

Figure 2: The sEMG data of a channel in a Myo. The light blue dashed line (raw_sEMG) is the raw sEMG data. The dark blue line (rectified_EMG) is the rectified sEMG data. The red line (Bayesian_envelope) is the smooth sEMG data using Bayesian Filtering envelope.

Our signal processing results could be seen in Figure 2.

Machine Learning and Cross Validation

We demonstrated the feasibility of MuscleSense through a proof-of-concept implementation using machine learning.

Prior work shows that Multilayer Perceptron Artificial Neural Network (MLPANN) provide a good estimation of hand force in isotonic condition [31].

Since EMG signal can be affected by some causative intrinsic factors such as electrode-skin interface, muscle-fibers diameter, the number of muscle fibers, the distance between skin-surface and muscle-fiber, and the amount of non-muscle tissue compared to active muscle fibers, which vary by personal physiological difference [15, 23]. We only used a personal model for our machine learning implementation.

The machine learning is implemented in Python 3.7 using the Scikit-learn package. We chose regression over classification based on the following consideration: (1) Workload is ordinal instead of nominal, each of the classes (weight) are closely related (2) Regression allows interpolation and extrapolation, granting the system ability to sense smaller units and unseen value(weights), which is quite important as users may use workload differ from the training weights

We would then test and compare 3 sets of features, with data from a channel being a feature:

(1) 8 channels sEMG data from arm Myo
(2) 8 channels sEMG data from forearm Myo
(3) 8 channels sEMG data from arm Myo + 8 channels sEMG data from arm Myo

Each feature is series of average smoothed sEMG signal amplitude for a single time window from a channel. The timestamps are used to synchronize data from different Myo if needed. Myo provide data of all channels simultaneously every 0.05 seconds.

We also compared a series of regression models. The parameters of the regressions was decided through trial and errors process.

- Support Vector Regression (SVR) using Linear Kernel (auto gamma, C=1.0, epsilon = 0.2)
- Random Forest Regression (number of estimators = 200)
- Extra Tree Regression (number of estimators = 200)
- Multi-layer Perceptron Regression ('lbfgs' solver)

The model is validated using leave-one-repetition-out and leave-one-round-out cross-validation. The R^2 and root mean square error (RMSE) in each fold is then averaged.

6 USER STUDY

We conducted a user study to collect sEMG data for evaluating the accuracy of our method, to validate that our approach is feasible.

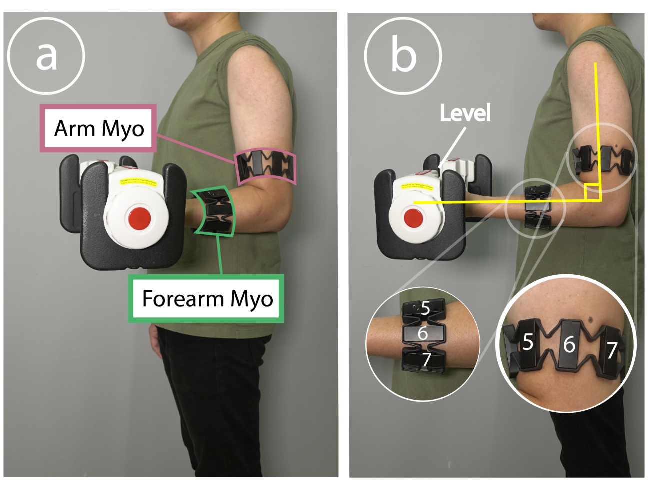

Figure 3: a) Device setup uses 2 Myo. A Myo is on arm, the other Myo is on forearm. b) The task of our user study, a 90°elbow flexion static hold for 3 seconds. The enlarged portion showed the number of channel of arm Myo.

Participants

We recruited 20 participants (10 females, 10 males) with diverse cultural backgrounds and ages ranging from 19 to 30 (mean 24.1, SD 3.3). We included 2 (1 females, 1 male) participants that do not involve themselves in any sports and 3 (2 females, 1 male) participants that do exercises which are not strength training to verify that our approach is appropriate for not only gym enthusiast but also regular user. One of the 20 participants is a female gym trainer.

Setup

The study is conducted in an indoor open space, with all surrounding obstacles removed before the study. In the study, participants are required to wear two Myos on the arm he/she preferred as shown in Figure 3a.

(1) The first Myo is worn on the arm, with Channel 4 (the channel with the Myo's icon) locate above the belly of bicep brachii.
(2) The second Myo is worn at the forearm, with Channel 4 facing upward while palm faces upward.

Experimental Design

There are several considerations during the design of our study.

Task. Restricted by the maximum diameter Myo can fit in, we chose single-sided bicep curl, a common exercise.

In this exercise, participants lift up a dumbbell from the front of the thigh (concentric, biceps contract, triceps relax), stop at the front of their shoulders and then slowly return the dumbbell (eccentric, biceps relax, triceps relax) to the initial position. The agonist muscles are biceps brachii, while the antagonist muscle is triceps brachii. Only forearm move during the exercise, the position of the arm should be idle. The muscles at fingers and forearm are also involved while participants hold the dumbbell.

In order to remove the impact of changes in force due to motion, we modify our task into dumbbell static hold at 90 °elbow flexion as shown in Figure 3b. The static hold is very similar to bicep curl at 90°elbow flexion, thus it could be extended to bicep curl by using the sEMG signal at a certain angle. Although static hold is an isometric exercise that measures in maximum voluntary contraction (MVC) while bicep curl is an isotonic exercise which measures in one repetition max (1RM), MVC and 1RM are correlated [36].

We chose 3 seconds duration for the static hold in order to provide sufficient data for training.

Procedure. Before the study starts, participants would estimate their 1RM through their weight of 5RM to 8RM to decide what is the maximum weight they are lifting [8]. Participants are given instructions on study procedures and

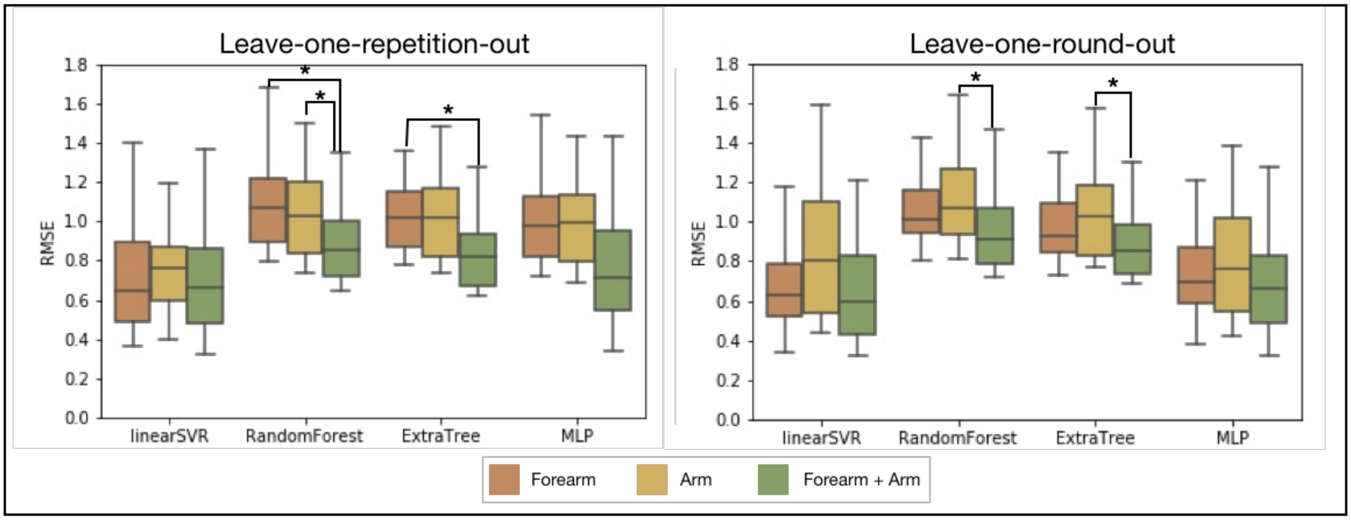

Figure 4: The boxplot of Root Mean Square Error (RMSE) of leave-one-repetition-out and leave-one-round-out cross-validation in kilogram (kg). The black * represents a statistically significant difference between RMSE of different feature set using the same regression model. The blue * represents a statistically significant difference between RMSE of leave-one-repetition-out (non-fatigue) and leave-one-round-out (different fatigue) scenario.

precautions of the task while warming up for the study task using the 1kg dumbbell. The precautions include but are not limited to try to only use your biceps, do not swing the dumbbell while holding, do not hold your breath, do not over flex your muscles and others. The study conductor would then demonstrate the task to the participant.

Participants would perform the task (static hold) for 3 seconds in a set of 3 repetitions for each weight for 3 rounds. The weights are in a range of 1kg to 75% of participants' respective 1RM, in a 1kg interval. The maximum weights used ranged from 4kg to 19kg (mean= 8.85kg). The order of weights is randomly shuffled. 5 seconds rest is given between repetitions, while 30 seconds rest is given between weights and 2 minutes rest is given between rounds. If the participant couldn't finish all repetition of a certain weight, the weight and following weight that are heavier in current and subsequent rounds are skipped. The angle of wrist, forearm, and shoulder are controlled, thus the postures of a participant would be as identical as possible for all repetition.

We choose a repetition of three and weight up to 75% of 1RM (N) as a result of our pilot that this would provide a good balance of fatigue and the ability to complete most of the weights.

Every round would contain a maximum of 3 repetitions * N weights, providing up to 9 * N trials of task per participant in 3 rounds, with N be their respective study maximum weight. The study lasts up to 2 hours depends on the weights the participant is lifting.

While performing the task, the sEMG signals, orientation, gyroscope, accelerator data of all Myos are sent to the computer using Bluetooth adapter at their respective sample rate which is 200Hz for sEMG and 50Hz for others.

Noted that in every round, the participants are always more fatigue than the previous rounds but we do not try to quantize the fatigue level because the cognition of fatigue is different from person to person.

7 RESULTS

We present our results in leave-one-repetition-out and leave-one-round out cross-validation. The leave-one-repetition-out cross-validation uses one of the repetition from a single round as test data and the other two repetitions as training data. The outcomes for each fold would then be averaged to produce a result for each round, followed by averaging the results from each round to get each participants' result.

The leave-one-round-out cross-validation uses all (3) of the repetitions from a round as test data and the rest repetition from the other two rounds as training data. The results for each fold would then be averaged to produce a result for each participant. Since our user study is a task of 3 repetitions in 1 set for each weight for 3 rounds, both of the cross-validations are 3-fold cross-validation. All of the regression models use 8 features which are average smoothed signal's amplitude in a sliding time window of 0.5s from 8 channels of a Myo with the exception of the model that uses a combination of data from the arm Myo and the forearm Myo which has 16 features (channels).

The outcomes we obtained is the R^2 and the calculated root mean square error (RMSE, in kg). R^2 describes how well the regression model is fitted and the root mean square error describes how far is the estimated value away from the actual value.

Our cross-validation results can be seen at Figure 4. All regressions provide an average R^2 of over 0.80 for all feature sets, thus they all provide a quite good fit. From the results of the Wilcoxon rank-sum test, there is a significant difference between RMSE of forearm+arm Myo feature sets and the other two (forearm Myo p=0.029 and arm Myo p=0.024) using random forest regression in leave-one-repetition-out. There is also a significant difference between RMSE of forearm+arm Myo feature sets and forearm Myo using extra tree regression ($p=0.041<0.05$). For the case of leave-one-round-out cross-validation's RMSE, there is a significant difference between RMSE of forearm+arm Myo feature sets and arm Myo ($p=0.018<0.05$) using random forest regression, while a significant difference between RMSE using extra tree regression of forearm+arm Myo feature sets and arm Myo ($p=0.015<0.05$) is present.

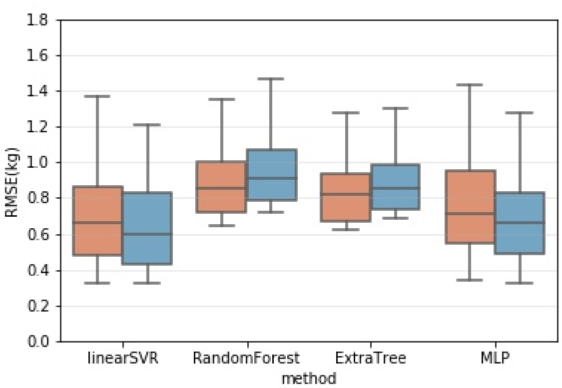

Figure 5: The comparison of RMSE of leave-one-repetition-out (non-fatigue) and leave-one-round-out (different fatigue) scenario using Forearm+Arm sEMG sensors.

Generally, our approach is robust to fatigue as shown in Figure 5. Although there isn't a significant difference between feature sets found in all regression models using statistical tests, we could see that the average RMSE of multiple sensors is always better than single sensor. Thus, multiple sensors should be used if possible but single sensors would still work fine.

It is also quite vivid that arm's RMSE in leave-one-round-out cross-validation is worse than in leave-one-repetition-out, although there is no statistically significant difference. This suggests that the agonist (arm) muscles' sEMG signal do affect by fatigue, as a larger variation is observed while we use data across rounds in cross-validation. Although synergistic (forearm) muscle may not provide direct sensing, its sEMG signal is correlated with the task and do not suffer severely from fatigue gained in training.

Training with a larger interval

We modify our training and testing data to better compare with Interferi's results. In a leave-one-weight-out cross-validation using weights interval of 2kg, our approach archived RMSE of 0.801 kg using linear kernel SVR and sEMG sensor at forearms. The RMSE is around 44% of the interval (2kg), while Interferi's is 53% (1.36kg interval).

8 DISCUSSION

Although our user study task is constrained (fixed motion and velocity) while we validate our approach using 90°elbow flexion static hold, our results suggested that sEMG signal from synergistic muscle could be used. Muscles at the forearm, functioning as synergistic muscles, are used in most strength training exercise and thus our approach is feasible for other exercises that involve grasping an object, regardless of free weights or a constant weight workload.

In our study, we try to investigate the effect of fatigue in different rounds of strength training, using the assumption that participants do not become more fatigue in a single set which differs from the actual scenario. We do notice that some weight orders, for example, 1kg workload before 5kg while 10kg (maximum weight) workload before 4kg would make the sEMG signal of 4kg and 5kg harder to differentiate. The effect of fatigue in a single set would be further investigated in our future work.

Although the Myo has limited signal dynamic range, it could still provide a quite good prediction of workload. The circular arrangement of sEMG sensors allows the surrounding muscles to provide information, so the sEMG sensors may not able to be positioned directly on the muscle; however, additional signal channel calibrations are needed to make sure that the sensors could match the channel position of training data.

Our approach's resulting lowest RMSE is 0.683kg, which is not significantly larger than the interval of 1kg; although it does not provide excellent results in predicting workload in our study, a lot of training equipment has a larger weight interval, such as 5 lbs (2.26 kg) which means it might work fine in an actual training scenario. Still, we would refine our approach in the future to strengthen its capabilities to sense workload at a finer measure.

9 CONCLUSION

In this paper, we proposed MuscleSense, an approach sensing training weights in strength training using wearable surface Electromyography. Our user study results demonstrated that our approach is feasible, predicting workload at adequate accuracy and error. Our results suggest that a similar system could choose multiple sensors at primary and supportive muscles for the best results, primary muscles for non-fatigue tasks and supportive muscles for fatigue tasks.

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