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Short communication

Does force myography recorded at the wrist correlate to resistance load levels during bicep curls?

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ABSTRACT

Resistance strength training is a proven method to improve bone density and muscle strength. A solution capable of automatically detecting the resistance force level exerted by a user from a wrist-based device can offer great convenience to the trainee and hence facilitate a better training outcome. In this short communication, we present our investigation aimed at exploring if force myographic (FMG) signals recorded at the wrist can predict the relative resistance levels that are associated with different weights. Specifically, we investigated the Spearman's correlations between the wrist FMG signal features and the dumbbell weights during a bicep curl exercise. 10 volunteers were recruited to perform a total of 100 curl actions, which included both the hammer and regular curls while the wrist FMG signals were being recorded. Three sets of weights ranging from 0.2 lb to 8 lb were used. For the hammer curls, a median correlation coefficient of 0.92 with an interquartile range (IQR) of 0.03 was obtained. For the regular curls, a 0.94 median correlation with a 0.02 IQR was obtained. We also used the data from the first 36 curls to generate a classifier model and applied it onto the rest of the data. An averaged validation accuracy of 88% was obtained. The results of this study showed the potential use of wrist FMG signal to detect different levels of the load during exercises; such information could potentially be used as feedback in fitness, sports, and rehabilitation activities.

1. Introduction

Resistance strength training is proven to be an effective route to improve bone density, increase muscle strength, and lower the risk of injuries during activities of daily living (Pollock et al., 2000). Like any other exercise, proper monitoring of the training is needed in order to train safely and efficiently. Currently, devices like "Strenx" by GymWatch, "PushBand" by PUSH, and "Wristband 2" by Atlas Wearables provide strength training feedback to the users, but they require the users to manually enter the weight of the training equipment. The need to manually input training parameters is inconvenient, and the user may forget to change the setting, which can result in an inaccurate feedback. Alternatively, the strength intensity can be detected from the point of contact by inserting force sensors into a pair of exercise gloves. However, due to frequent contact between the glove and the equipment, the hygienic and wear-and-tear aspects of the device makes it less suitable for monitoring daily exercise.

An alternative way to extract the strength intensity information is by monitoring the muscle activity using surface myography (sEMG) (Koskimaki and Siirtola, 2016; Mokaya et al., 2015; Yang and Hunt, 2014). However, the quality of the sEMG signal is often influenced by electrical interference and change of skin condition such as sweat and temperature (Castellini et al., 2014; Chowdhury et al., 2013). Therefore, this approach is less suitable for prolonged use during exercises. Other than the sEMG approach, we can use a technique named force myography (FMG) to decipher the muscle movement information (Wininger, 2008). FMG detects the movement of the muscle by attaching multiple pressure sensors with a preloaded force against the surface of the limb. Various pressure patterns can be registered during the different limb movements. Since the sensors register mechanical signals, FMG is less subjected to electrical interference and the change of skin conditions when comparing to sEMG.

The majority of the FMG research use signals extracted from the bulk of the forearm to detect upper extremity activities. These signals can be used to predict the movements of the hand, wrist, forearm, and elbow (Jiang et al., 2016; Xiao and Menon, 2017a, 2014; Zhou et al., 2016), as well as to predict grasping force with fixed arm postures (Ravindra and Castellini, 2014; Wininger, 2008).

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Yet, the placement of the sensors in these studies does not provide the same convenience as afforded by wrist-based devices. Currently, the majority of the fitness tracking devices are in the form of wrist watches or straps. The wide acceptance of such a form factor has already made the wearable technology market a multi-billion-dollar industry (Düking et al., 2016). A wrist-based device that can automatically detect the resistance force level exerted by a user can offer great convenience to the trainee and facilitate a better training outcome.

Compared to forearm FMG, the wrist FMG has received less attention within the research community. The wrist mainly consists of muscles, tendons, and bones; it does not have a comparable muscle mass to the bulk region of the forearm. Nevertheless, studies have shown wrist FMG can be used to detect some hand gestures (Dementyev and Paradiso, 2014; Jiang et al., 2016), and to count grasping action (Xiao and Menon, 2017b). Yet, it is unclear whether there exists a relationship between the wrist FMG signals and the individual-based resistance force levels during upper limb movements. When a user is picking up an object, some muscles and tendons of the forearm will contract to generate the grip force and the force to maintain the wrist positions. The heavier the object, the higher the tension within the muscle and tendons will be. Based on this idea, we hypothesized the existence of a high correlation (e.g., >0.8) between the wrist FMG signal features and the weight of the object. Using machine learning algorithms, the wrist FMG can be used to predict the relative load level for a user. Therefore, in this paper, we investigate the association between the wrist FMG pattern features and the relative load levels during bicep curl actions using dumbbells with different weights.

2. Methods

2.1. Experiment overview

An experiment was designed to collect wrist FMG data from participants while performing bicep curls, i.e., hammer curls and regular curls, with dumbbells of different weights. For the hammer curl, the user's forearm should maintain in a neutral position throughout the action; for the regular curl, the user's forearm should maintain in a supinated position. These two types of curls were included in the analysis as the forearm position was shown to have a large effect on the FMG pattern. The collected FMG were classified according to the different curl actions and the corresponding loads. For this experiment, ten healthy adults (6 males and 4 females with age between 21 and 42) participated after providing informed consent.

2.2. Experimental setup

Before the experiment, each participant was asked to sit in front of a table with different dumbbells on top of it. A research assistant then helped the participant to don a custom built FMG strap onto the wrist. The strap, see Fig. 1, consisted of with 8 force sensing resistors (FSR) for capturing FMG signals, an inertial measurement unit (IMU) for detecting movement information, a microcontroller for data acquisition, a Bluetooth transceiver for sending data to a personal computer, and a battery for powering the device.

Three dumbbell weights were considered in this experiment: 0.2 lb, 3 lb, and 8 lb. The 0.2 lb dumbbell was used to represent a sham scenario, and it was built with a lightweight hollow cylinder. The heaviest dumbbell was selected to be 8 lb with consideration of the capability of both male and female participants who were not experts in weight training exercise. For all the three dumbbells, the middle sections were modified to have the same diameter such that the shape of the hand would be consistent while grasping.

2.3. Experimental procedure

Once the FMG strap was donned, the participant was asked to pick up a dumbbell from the table, and then to perform different sets of bicep curl actions. The definition and execution sequence of the action sets are listed in Table 1. The first 36 sets followed a trend in which the load increased one by one within the same category of the bicep curls and the action types. The rest of the 64 sets had a mixed order of the curling types and the dumbbell weights. The sets with the increasing trend were designed for the ease of the preliminary data inspection. Meanwhile, the mixed order was intended to reduce the inherited experimental bias due to the predictable trend. The mixed order was not randomized as we wanted to ensure a volunteer did not need to lift the 8 lb dumbbell successively for more than 4 repetitions. As the objective of this study was to investigate the potential use of wrist FMG to detect resistance load level only, we intentionally designed the protocol in such a way that the effect of fatigue was controlled.

2.4. Data processing and analysis

Once the data were collected, the FMG signals were first scaled to have a global maximum value of "1". The 8 FMG signals were then linearly interpolated into 16 channels to capture spatial relations between the adjacent channels. This step explicitly increased the amount of information at the input level for the classification purpose. The assumption was that with more information, a more accurate model could be generated by the classification algorithm. With the help of the captured videos and IMU data, the FMG signal associated with each bicep curl was then manually identified and saved into a data frame. Seven statistical features associated with the magnitudes of each channel within a frame were computed. The features were the values of the zeroth to the fourth quantiles, the interquartile range, and the full range. Also, the length of the signal within each frame was captured, as the time to move a heavy object versus a light one may relate. Therefore, a total of 8

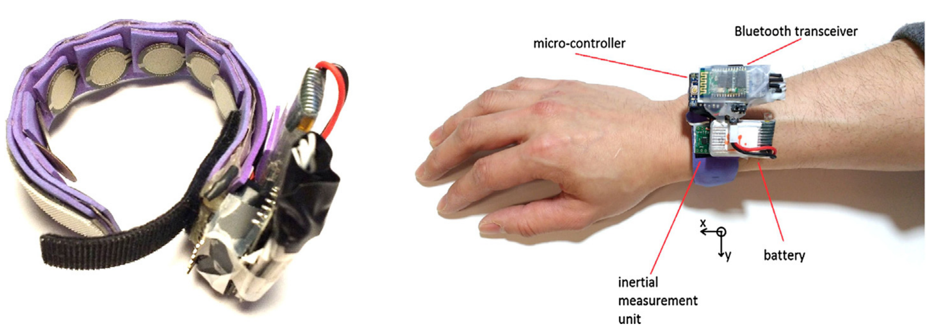

Fig. 1. FMG strap and its placement.

Table 1
Experimental protocol.

Set ID	Curling type	Dumb-bell weight	Action type	Number of bicep curl actions	Set ID	Curling type	Dumb-bell weight	Action type	Number of bicep curl actions
1	Hammer	0.2	Intermittent	3	13	Hammer	0.2	Intermittent	6
2		3		3	14	Regular	0.2		7
3		8		3	15	Hammer	8		3
4	Regular	0.2		3	16	Regular	8		4
5		3		3	17	Hammer	3		5
6		8		3	18	Regular	3		6
7	Hammer	0.2	Continuous	3	19	Hammer	0.2	Continuous	7
8		3		3	20	Regular	8		4
9		8		3	21		0.2		5
10	Regular	0.2		3	22	Hammer	8		4
11		3		3	23		3		6
12		8		3	24	Regular	3		7
			Total	36				Total	64
								Overall	100
	Number of hammer curl		49		Number of regular bicep curl			51	

Note: The intermittent actions required the participant to complete one curl action followed by at least 3 s of pause. The continuous type required the participant to perform multiple bicep curl actions without any pauses.

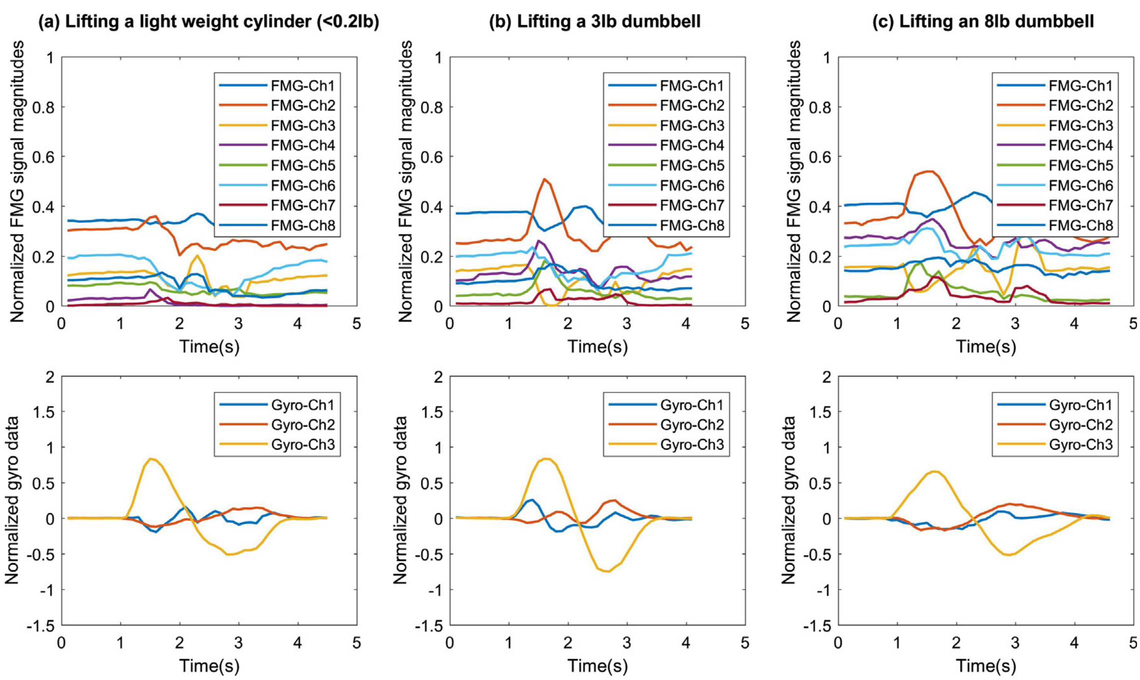

Fig. 2. An example of the FMG data during the hammer curl actions.

feature sets were analyzed for their correlation for the hammer and the regular curl actions.

Spearman's Rho was used to analyze the correlation between the weight of the dumbbell and each feature. Spearman's Rho is a non-parametric test to examine the relationship of two variables using a monotonic function (Best and Roberts, 1975). To note, this test assesses the monotonic relation between the variables, it does not suggest if the relationship is linear or not. For the quantiles feature, there were 16 channels associated with it. However, not all FMG signals were expected to have a strong correlation with the weights. Some FSRs might not even be in contact with the skin in some instance. Therefore, we only used the largest coefficient among the 16 feature channels to evaluate the association.

In addition to the correlation analysis, we examined the ability to use the wrist FMG signals to predict the curling action type and the corresponding weights simultaneously using the supervised classification approach. We separated the entire feature set of each individual's data into two parts; the first 36 feature frames were used as the training set, and the rest of the 64 frames were used as the validation set. We applied principal component analysis (PCA) to reduce the number of input features and then classified the filtered feature set with linear discriminant analysis (LDA).

3. Results

An example of the collected FMG and gyro data for lifting the different weights during hammer curl actions is shown in Fig. 2. The top row shows the normalized FMG and the bottom one shows the corresponding gyro data. The third channel of the gyro indicates the angular velocity of the elbow joint in the vertical plane. The angular position of the elbow can be approximated from the gyro plot. For instance, the elbow was fully extended with zero velocity at the beginning and the end of the plot. When the velocity reached the maximum or minimum, the elbow was at approximately 90 degrees. The zero-crossing between the two peaks signified the elbow was at a fully flexed position. When there was a change in velocity, there was a change of FMG pattern. There were clear distinctions of the FMG patterns between a lightweight curl action and the other two. Between the 3 lb and 8 lb curl actions, the majority of the channels exhibited similar trends with different magnitudes in this example. The FMG patterns among the participants were different; therefore, we focused on the association within each individual's data only.

The boxplots in Fig. 3 show the strength of association between the FMG features and the resistance load levels computed from the 10 participants' data. The first boxes of the two plots showed a mild correlation between the time to complete a bicep curl action and the weights. However, the values of the correlations were significantly lower than the ones of the FMG features based on the Kruskal-Wallis test with post-hoc analysis ($p \ll 0.01$). Within the FMG features, the 3rd-quartile feature has one of the highest median values, i.e., 0.92 with an interquartile range (IQR) of 0.02 and 0.94 with an IQR of 0.03 for the hammer and the regular curl, respectively.

Fig. 4 shows the classification results against different numbers of principal components (PC). For the training set, the averaged accuracies increased as the number of PC increased and reached 100% with the first 12 components. However, the accuracies of the validation set were lower. They steadily increased as the number of PC increased to 7 (88% ± 6%), and then remained at a similar level. These results showed that the LDA classifier was fully capable of separating the training set pattern but tended to overfit the data, which resulted in lower validation accuracies.

We also ran the same analysis without interpolating the FMG signals. We found the interpolated data did not affect the correlation analysis, however, it had slightly but not statistically significantly better maximum validation accuracies (i.e., within 1% of improvement for both curl actions) when it was compared to the non-interpolated version.

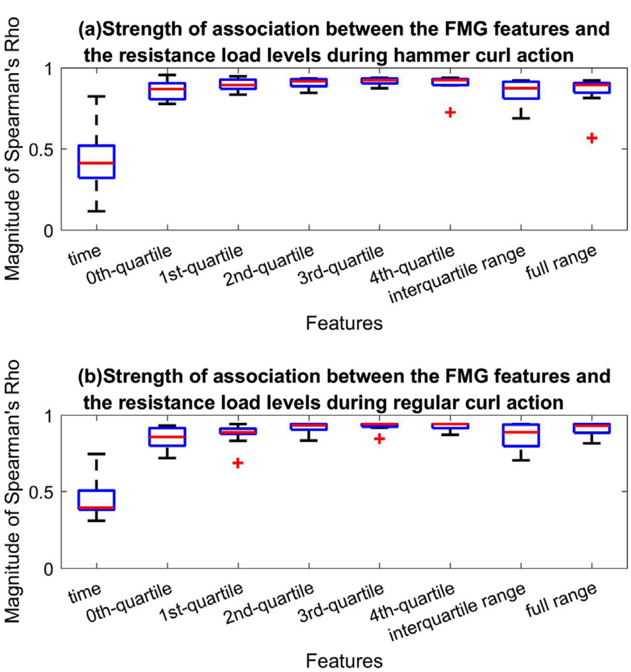

Fig. 3. Strength of association between the FMG features and the resistance load levels of 10 individual's data.

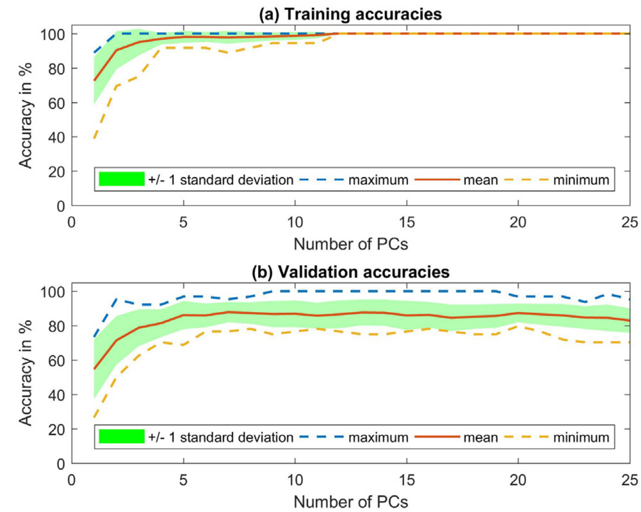

Fig. 4. Classification results of the 10 participants' data using different numbers of principal components.

4. Discussion

This preliminary study investigated the correlation between wrist FMG signals and the relative load levels. The high correlations showed the potential for using wrist FMG to predict the load level with machine learning. For instance, using the basic LDA algorithm on the features extracted from the 16 interpolated signals, a minimum 85% average accuracy was obtained. This accuracy was comparable to the ones of commercial wrist-based pedometers which had a range of accuracies from 84% to 99.9% (Ehrler et al., 2016; Husted and Llewellyn, 2017).

We recruited 10 healthy participants for the study, even though each participant performed 100 bicep curls, the amount of data collected was still small. The small data size was one factor that contributed to the overfitted phenomenon. For developing more robust algorithms in the future, more data will be needed. We also should collect more data from participants with different physical characteristics and longer data collection sessions.

The use of FMG with supervised machine learning approach for predicting resistance force levels also has its own limitations. Firstly, the model trained with one individual cannot be transferred to the other as the FMG pattern is quite unique to a user. Secondly, FMG can only predict relative resistance levels of an individual, but it cannot reveal the absolute force level in its current form. Thirdly, as an indirect measure of the force level, the force range is limited by the maximum stiffness of the muscle and tendons. There is a point in which no further change of FMG pattern can be observed with an increasing weight. The current study showed wrist FMG could be used to predict load level up to an 8 lb dumbbell, a future study should examine the full applicable range of the proposed method. Fourthly, our hands and wrists can perform many complicated actions and these actions may affect FMG patterns. Therefore, the fusion of IMU data should be considered as we can use such data to condition the FMG signals. For instance, we can first use an IMU to identify the different type of curl actions based on the forearm position; and then select the corresponding model to extract the force information. These IMU data can also allow us to compute elbow joint moment for a more in-depth dynamic analysis. Finally, the physical condition of the users can change from time-to-time due to the result of exercise or other factors such as aging or disease. To make accurate predictions, adaptive learning using unsupervised or a semi-supervised scheme should be considered.

5. Conclusion

This study investigated the correlation between wrist FMG features and three levels of loads for hammer and regular bicep curl actions with 10 healthy individuals. We obtained high correlation values (>0.90) for some FMG features and a good averaged validation accuracy (88%) using LDA. Overall, this study shows the wrist FMG can predict resistance force levels during dynamic movements and its potential to augment the functionality of the current wrist based smart device for fitness applications.

Acknowledgements

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Conflict of interest

The Principal Investigator, Carlo Menon, and members of his research team have a vested interest in commercializing the technology tested in this study, if it is proven to be successful and may benefit financially from its potential commercialization. The data are readily available upon request.

References

Best, D.J., Roberts, D.E., 1975. Algorithm AS 89: the upper tail probabilities of Spearman's rho. Appl. Stat. 24, 377. https://doi.org/10.2307/2347111.

Castellini, C., Artemiadis, P., Wininger, M., Ajoudani, A., Alimusaj, M., Bicchi, A., Caputo, B., Craelius, W., Dosen, S., Englehart, K., Farina, D., Gijsberts, A., Godfrey, S.B., Hargrove, L., Ison, M., Kuiken, T., MarkoviÄ, M., Pilarski, P.M., Rupp, R.R., Scheme, E., Marković, M., Pilarski, P.M., Rupp, R.R., Scheme, E., 2014. Proceedings of the first workshop on Peripheral Machine Interfaces: going beyond traditional surface electromyography. Front. Neurorobot. 8, 22. https://doi.org/10.3389/fnbot.2014.00022.

Chowdhury, R.H., Reaz, M.B.I., Ali, M.A.B.M., Bakar, A.A.A., Chellappan, K., Chang, T. G., 2013. Surface electromyography signal processing and classification techniques. Sensors (Basel) 13, 12431–12466. https://doi.org/10.3390/s130912431.

Dementyev, A., Paradiso, J.A., 2014. WristFlex. In: Proceedings of the 27th Annual ACM Symposium on User Interface Software and Technology – UIST '14. ACM Press, New York, New York, USA, pp. 161–166. https://doi.org/10.1145/2642918.2647396.

Düking, P., Hotho, A., Holmberg, H.-C., Fuss, F.K., Sperlich, B., 2016. Comparison of non-invasive individual monitoring of the training and health of athletes with commercially available wearable technologies. Front. Physiol. 7, 71. https://doi.org/10.3389/fphys.2016.00071.

Ehrler, F., Weber, C., Lovis, C., 2016. Influence of pedometer position on pedometer accuracy at various walking speeds: a comparative study. J. Med. Internet Res. 18, e268. https://doi.org/10.2196/jmir.5916.

Husted, H.M., Llewellyn, T.L., 2017. The accuracy of pedometers in measuring walking steps on a treadmill in college students. Int. J. Exerc. Sci. 10, 146–153.

Jiang, X., Merhi, L.-K., Xiao, Z.G., Menon, C., 2016. Exploration of force myography and surface electromyography in hand gesture classification. Med. Eng. Phys. 41. https://doi.org/10.1016/j.medengphy.2017.01.015.

Koskimaki, H., Siirtola, P., 2016. Accelerometer vs. electromyogram in activity recognition. ADCAIJ Adv. Distrib. Comput. Artif. Intell. J. 5, 31.

Mokaya, F., Lucas, R., Young Noh, H., Zhang, P., 2015. MyoVibe: vibration based wearable muscle activation detection in high mobility exercises. Proc. 2015 ACM Int. Jt. Conf. Pervasive Ubiquitous Comput., 27–38 https://doi.org/10.1145/2750858.2804258.

Pollock, M.L., Franklin, B.A., Balady, G.J., Chaitman, B.L., Fleg, J.L., Fletcher, B., Limacher, M., Pina, I.L., Stein, R.A., Williams, M., Bazzarre, T., 2000. Resistance exercise in individuals with and without cardiovascular disease : benefits, rationale, safety, and prescriptionan advisory from the committee on exercise, rehabilitation, and prevention, council on clinical cardiology. Am. Heart Assoc. Circul. 101, 828–833. https://doi.org/10.1161/01.CIR.101.7.828.

Ravindra, V., Castellini, C., 2014. A Comparative analysis of three non-invasive human-machine interfaces for the disabled. Front. Neurorobot. 8, 1–10. https://doi.org/10.3389/fnbot.2014.00024.

Wininger, M., 2008. Pressure signature of forearm as predictor of grip force. J. Rehabil. Res. Dev. 45, 883–892. https://doi.org/10.1682/JRRD.2007.11.0187.

Xiao, Z.G., Menon, C., 2017a. Performance of forearm FMG and sEMG for estimating elbow, forearm and wrist positions. J. Bionic Eng. 14, 284–295. https://doi.org/10.1016/S1672-6529(16)60398-0.

Xiao, Z.G., Menon, C., 2017b. Counting grasping action using force myography: an exploratory study with healthy individuals. JMIR Rehabil. Assist. Technol. 4, e5. https://doi.org/10.2196/rehab.6901.

Xiao, Z.G., Menon, C., 2014. Towards the development of a wearable feedback system for monitoring the activities of the upper-extremities. J. Neuroeng. Rehabil. 11, 2. https://doi.org/10.1186/1743-0003-11-2.

Yang, J., Hunt, A., 2014. Real-time auditory feedback of arm movement and Emg in biceps curl training to enhance the quality. SoniHED Conf. Sonification Heal. Enviromental Data, 1–7.

Zhou, B., Sundholm, M., Cheng, J., Cruz, H., Lukowicz, P., 2016. Measuring muscle activities during gym exercises with textile pressure mapping sensors. Pervasive Mob. Comput. https://doi.org/10.1016/j.pmcj.2016.08.015.