Fine-Fit: A Fine-grained Gym Exercises Recognition System

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***Abstract*—Gym exercise recognition can help people to monitor and supervise their personal exercise progress. Although previous works have already recognized gym exercises by using wearable or external sensors, they failed to cover the recognition of activities at a finer level which means to identify exercises that perform similar activities but are significantly different in muscle firing. These finer level exercises, defined as fine-grained gym exercise in this paper, can cause completely different training effects to exercisers including muscle strength building, muscle circumference shaping, etc. The goal of this work is to propose a novel fined-grained gym exercise recognition system, namely Fine-Fit, which is aiming to provide more detailed sports information useful in monitoring exercises, assessing non-standard actions, and avoiding muscle injury as well. The unique design of Fine-Fit is to use a single source sensor (accelerometer) to sense the body movement and the corresponding muscle vibration simultaneously (Single Source Multi-view Sensing method, SSMS) for high accurate fine-grained exercise recognition. Besides, Fine-Fit proposes a novel feature, namely Muscle Recruitment Energy Coefficient (MREC), particularly for fine-grained exercise classification. MREC implicitly reflects the correlation of elastic potential energy and the corresponding moving distance of muscles and it is able to improve the accuracy of identification effectively. The preliminary results demonstrate that Fine-Fit can recognize fine-grained gym exercises of push-ups and barbell curls with different bearing weights and hands distances at 91% precision and Fine-Fit enhances activity recognition to a fine-grained level.**

***Index Terms*—activity recognition, wearable sensors, accelerometer, mechanomyography (MMG)**

I. Introduction

People nowadays have been paying more attention to daily gym exercises for the purpose of improving their physical fitness. Gym exercise recognition can help people to monitor and supervise their personal exercise progress.

Gym exercise recognition is a category of human activity recognition (HAR). In all categories of wearable HAR system, there are two kinds of signal that are commonly used: inertial sensor signal, and physiological signal. Several papers used inertial sensor signal, such as accelerometer, to recognize different kinds of activity [1, 2]. Weichao Guo et al. [3] used physiological signal, EMG and MMG to identify the hands motion. Tapia et al. [4] combined data from accelerometers and a heart rate monitor to recognize activities. **Although existing HAR systems including gym exercise recognition systems combine inertial sensor signal and physiological signal for activity recognition, they need to add another sensor source so that the cost and weight of the whole wearable network have also increased.**

In the prior works of gym exercise recognition, Heli et al. used a single accelerometer to identify 36 different gym exercises with over 96% accuracy [5]. myHealthAssistant classified gym exercises from three accelerometers by using a Bayesian classifier and achieved 92% accuracy [6]. Kai Kunze et al. attempted to recognize gym exercises through accelerometers and gyroscopes which is focus on eliminating the influence of sensor displacement and orientation by combining the two sensors [7]. Although previous works have already recognized gym exercises at high accuracy, they failed to cover the recognition of activities at a finer level which means to identify exercises that perform similar activities but are significantly different in muscle firing. These finer level exercises are defined as fine-grained gym exercises in this paper. For example, barbell curls with the wide grip, narrow grip, and shoulder grip are different in distance between hands, resulting in different biceps firing rate. Besides, decline push-ups has a greater bearing weight than standard push-ups and its triceps firing is higher.

Fine-grained exercises are non-ignorable in gym fitness, because they can cause completely different training effects including muscle strength building, muscle circumference shaping, etc. to exercisers. For example, for exercises with different bearing weight, if we use repetition maximum(RM) as an indicator, 15-20RM is mainly for developing strength endurance, 6-12RM for increasing muscle circumference and 1-5RM for increasing muscle strength [8]. Fine-grained gym exercises recognition can provide intelligent and opportune information, such as monitoring the exercises progress and repetition numbers, assessing non-standard actions to make more ideal fitness effect, and locating and predicting fatigue muscle to prevent muscle injury as well. **However, prior works failed to recognize these fine-grained gym exercises.**

The goal of this work is to propose a novel fined-grained gym exercises recognition system, namely Fine-Fit. Fine-Fit is a scalable and wearable system for detecting different fine-

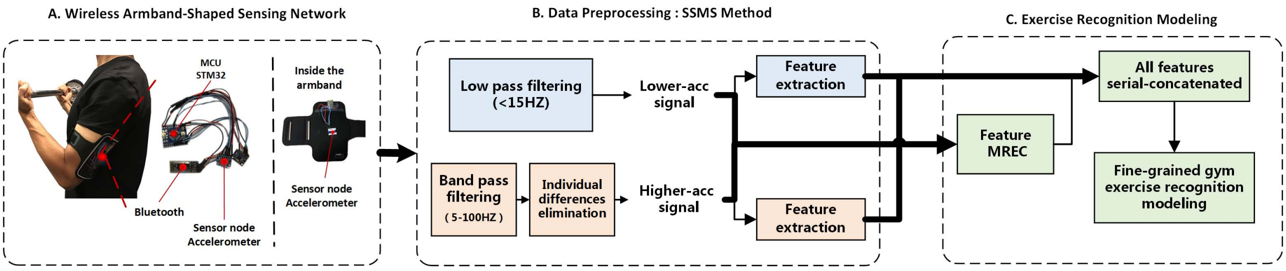

Fig. 1. Figure shows the overview of Fine-Fit system: first, the signal is collected through the sensor node fixed on the corresponding muscle and transmitted wirelessly to the backend computer through Bluetooth. Then the signal is preprocessed by the SSMS method to obtain two-view signal. Finally, the features epsextracted from the signals and a new feature MREC are serially concatenated for exercises recognition.

grained gym exercises and it senses inertial and physiological information simultaneously by only using a single unobtrusive, non-invasive source sensor (accelerometer). The preliminary results have demonstrated that Fine-Fit achieves average 91% accuracy in identifying fine-grained gym exercises.

The contributions of this work are as follows:

1.Single Source Multi-view Sensing (SSMS): Fine-Fit system is able to sense body movement and muscle vibration information with only a single source sensor, an accelerometer. These two kinds of information can make up for each other's shortcomings in recognition and lead to an improvement of final recognition accuracy.

2.Muscle Recruitment Energy Coefficient (MREC) feature: Fine-Fit system proposes a new feature MREC which implicitly reflects the correlation of elastic potential energy and the corresponding moving distance of muscles. We have proved through experiments that MREC can improve the accuracy of recognition effectively.

II. Fine-Fit System Overview

In this paper, our Fine-Fit system tries to tackle the problem of detecting fine-grained gym exercises using a single source accelerometer. Fine-Fit includes a front-end acquisition hardware (wireless armband-shaped sensing network) and two main back-end processing modules (data preprocessing module and exercise recognition modeling module). The workflow of Fine-Fit is shown in figure 1.

A. Wireless Armband-Shaped Sensing Network

First, Fine-Fit relies on the front-end acquisition hardware for collecting signals from the detected muscle.

At present, the exercises in our experiment are mainly the action of upper limbs. Thus, we designed a wireless armband-shaped sensing network for sensing signals of the muscle which is easy to wear and does not affect exercises. The sensor node of the network is small enough (2cm $\times$ 1.5cm) and contains triple axis accelerometers as in figure 1. It should be noted that the sensor node is just fixed on the center of the muscle which is measured when wearing the armband. The accelerometers we selected are MPU6050 which is accurate to $\pm$10 G with tolerances within 2%. Moreover, the data collected by the different sensor nodes are sent to a micro control unit stm32, and stm32 transmits them to a backend computer wirelessly through Bluetooth for gym exercise recognition.

B. Data Preprocessing

After the signal is collected and transmitted to the background, signal preprocessing is performed.

In the data preprocessing module, by adopting different frequency ranges, the accelerometer signal can be divided into two kinds of signals. The first is body movement signal with lower frequency ranges(lower-acc), and the second is muscle vibration signal with higher frequency ranges(higher-acc). After that, These two signals will extract features separately for the purpose of building a classification model for recognition. We call this method Single Source Multi-view Sensing (SSMS) and will describe it in detail in Section III.

C. Exercise Recognition Modeling

In the last module, we will build the classification model for recognition.

The exercise recognition modeling requires corresponding motion features. To better describe the correlation of elastic potential energy and the corresponding moving distance of muscles, we propose a novel feature MREC. In order to make full use of all the motion features, we serially concatenate MREC and the features extracted from the two signals in the data preprocessing module, which means connecting all the features end to end. Finally, Given all the features, Fine-Fit will build the classification model to recognize the fine-grained gym exercises. In the experiment, the classifier algorithm we chose is random forest because of its highest precision.

III. Single Source Multi-view Sensing(SSMS)

In the Fine-Fit system, the core idea is that we can get two-view information with only a single source. We call it Single Source Multi-view Sensing(SSMS) method. The single source sensor is an accelerometer and the two-view information are obtained by adopting different frequency ranges. The lower frequency range signal is the body movement signal and the higher frequency range signal is the muscle vibration signal. To the best of our knowledge, we are the first one to combine the advantages of these two signals for fine-grained gym exercises recognition in all studies.

A. Lower-frequency Body Movement Signal(Lower-acc)

The lower-acc has been widely used in HAR system for coarsely detecting body movement. Prior works have shown that this information can be modeled by signals at and below 15HZ frequency [1]. Thus, we can get the lower-acc signal through low pass filter.

B. Higher-frequency Muscle Vibration Signal(Higher-acc)

The higher-acc signal is also called mechanomyography (MMG) in many researches. In the physiology of skeletal muscles, muscle fibers are the vital part of skeletal muscles, which can contract and relax to enable movement in response to electrical impulses from the central nervous system [9]. Under muscular contraction, intrinsic mechanical vibrations occur due to friction and slide between the muscle fibers and the vibrations generate displacements on the skin surface.

This kind of muscle vibration signal can be detected using several types of transducers including piezoelectric contact sensors, microphones and accelerometers [10]. But the most popular sensor among researchers is the accelerometer. There are many studies that use accelerometers to acquire muscle vibration signals and demonstrate the effectiveness of the signal [9, 11]. Thus, we obtain the muscle vibration signal by placing an accelerometer on the muscle we interested and the accelerometer will be held on the most central of the muscle by sports armband. The frequency range of higher-acc [12, 13] is between 5HZ and 100HZ, which is higher than the lower-acc on average and we can obtain it through a band pass filter.

Because of the diversity in muscle quality of different people, the max contraction magnitude of some people may be higher than others when doing the same gym exercise, which means that the level of maximum voluntary contraction varies from people to people. Thus, all the higher-acc signal will be normalized by individual MVCs.

C. Feature Extraction

To enable the recognition of gym exercises, raw data have to pass through the process of feature extraction. After that, in our experiment, all the features will be serially concatenated to make full use for classification model building.

Features of the above two kinds of information are calculated using a fixed sliding window approach with 50% overlap on the filtered data stream separately. The fixed window is 4s because the average completion time of an action in the experiment is 3s, and the sliding window needs to include at least one complete action. A 50% overlap method is used for smooth transitions from one feature instance to the next [9].

TABLE I
FEATURES OF SMSS

Lower-acc	Higher-acc
mean	standard deviation
standard deviation	cosine correlation
frequency-domain energy*	mean power frequency gradient*
frequency-domain entropy*	power spectral density*
	frequency-domain entropy*

The specific features of the two signals are shown in table I. The features in the table who have a star behind are the frequency-domain features and all the features are extracted from three axes of the accelerometer. The usefulness of these features has been demonstrated in prior work [11, 14].

D. Multi-View Fusion

In SSMS, the lower-acc information represents macroscopic movement of muscle and the higher-acc information represents the microscopic vibration of muscle. Thus the meaning of the combination is to consider the physical information and physiological information at the same time.

When people do gym exercises, muscles have macroscopic movement and microscopic vibration simultaneously. The macroscopic movement can be detected by lower-acc which will distinguish the coarse-grained gym exercises and part of fine-grained exercises such as the barbell curls with different hands distances. However, it does not work for some exercises that have different bearing weight as the body movement is almost the same. In this case, we need to rely on the higher-acc information. When the bearing weight becomes larger, a larger number of muscle fibers contract to help this work so that the amplitude of the higher-acc signal becomes bigger.

Thus, we hope to combine the advantages of the both signals to make better recognition.

IV. MUSCLE RECRUITMENT ENERGY COEFFICIENT(MREC)

In this section, we propose a new feature, namely muscle recruitment energy coefficient (MREC), particularly for fine-grained exercises classification. MREC implicitly reflects the correlation of elastic potential energy and the outer moving distance of muscles.

When we do push-ups and place the Fine-Fit node on the triceps, the macroscopic view of triceps is that it generates movement relative to the ground and the microscopic view is that the length of muscle fibers changes. When the upper body is rising in push-ups, the triceps shortens and contracts. During the process of muscle contraction, ATP breaks down quickly and releases energy which is elastic potential energy to store in the muscle fibers. When the muscle contracts more adequate, there is more elastic potential energy stored. It is similar to the spring movement, if the external force is greater, the elastic potential energy is bigger. So when we do decline push-ups, the elastic potential energy stored in triceps is larger than standard push-ups. The consumption of internal elastic potential energy in muscle will help the muscle move relative to the ground macroscopically and complete various gym exercises [15].

In the dynamics model of the spring, the elastic potential energy is proportional to the square of the distance as shown in equation 1. However, it should be noted that the elastic potential energy in muscle is not generated once, which is different from the spring. The elastic potential energy of muscle is generated continuously with the constant consumption of

ATP when we maintain our exercise. Based on these theories, we make the following assumptions:

$$W = \frac{1}{2}kx^2 \tag{1}$$

- The vibration signal on the surface of the skin propagates in three directions.
- Like the spring, the square of the cumulative distance of muscle vibration is a kind of approximate energy which we call a-energy. a-energy is not an exact elastic potential energy of muscle, but these two values have a positive relationship.
- In different exercises, a-energy per muscle moving distance is different.

By the first assumption, the common role of three directions can be calculated as

$$a_h = \sqrt{a_{hx}^2 + a_{hy}^2 + a_{hz}^2} \tag{2}$$

Where a_{hx},a_{hy},a_{hz} are the higher-acc signal of x, y ,z axis.

Based on all assumptions, MREC is calculated in equation 3. The numerator of the equation is the value of a-energy as in the second assumption. When we perform different fine-grained gym exercises, the firing rate and recruitment level of the corresponding muscle are different, so the value of the elastic potential energy that muscle needs to maintain is different. There is a positive correlation between the elastic potential energy and a-energy which means that the larger the value of elastic potential energy, the larger the value of a-energy. The denominator is the outer moving distance of muscle where a_{lx},a_{ly},a_{lz} are the lower-acc signal we collected from x, y, z axis. Because the energy consumption inside the muscle helps the muscle to produce an outer moving distance, forming an action, and it is obvious that the value of elastic potential energy is also related to the value of the outer moving distance, we normalize the value of the outer moving distance to eliminate the difference caused by personal habits and physical factors.

$$MREC = \frac{s_h^2}{s_l} = \frac{\left(\int_{t1}^{t2} v_h(t)dt\right)^2}{\int_{t1}^{t2} v_l(t)dt}$$

$$v_h(t) = \int_{t1}^{t2} a_h(t)dt \quad v_l(t) = \int_{t1}^{t2} a_l(t)dt$$

$$a_l = \sqrt{a_{lx}^2 + a_{ly}^2 + a_{lz}^2} \tag{3}$$

We hope to use MREC to reflect the difference of cumulative elastic potential energy per muscle distance in different exercises. The experimental results will show in section V-D. MREC and features extracted from SSMS will be serial concatenated to build the classification model for recognition.

V. Experiment and Evaluation

In this section, we evaluate the effectiveness of the Fine-Fit system and describe the details of our experiments.

A. Experiment Setup

We selected a group of 17 healthy participants, 10 males and 7 females, including long-term fitness enthusiasts and fitness beginners, to participate in our designated exercises. All the subjects participated voluntarily.

There were two main types of fine-grained exercises in our experiments, actions with different hands distances and different bearing weights. The exercises that we evaluated Fine-Fit on, worked the triceps and biceps muscles. The triceps exercises contained a group of push-ups and the biceps exercises contained a group of barbell curls. It should be noted that each group of exercises only contains one muscle because we want to highlight that the accuracy of our classification results are from the effectiveness of the SSMS and MREC methods, rather than the fusion of multiple muscle information.

TABLE II
The Differences Between Push-ups Group

	Position of Feet		**Distance Between Hands**		
	40cm from the ground	on the ground	shoulder width	20cm laterlly from the shoulder	hands form a diamond shape
SS		√	√		
SW		√		√	
SD		√			√
DS	√		√		
DW	√			√	
DD	√				√

TABLE III
The Differences Between Barbell Curls Group

	Weight of Hands		**Distance Between Hands**		
	light-rod	15-20RM of barbell	shoulder width	1.5 times shoulder width	a fist width
NB		√	√		
WB		√		√	
RB		√			√
NL	√		√		
WL	√			√	
RL	√				√

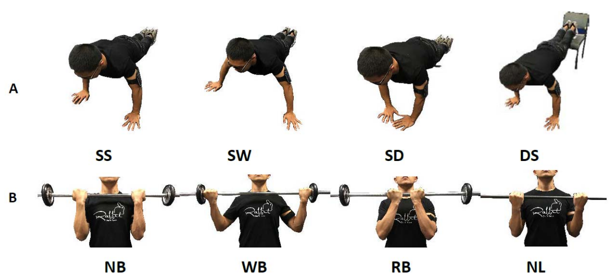

Fig. 2. Figure shows some typical actions in our experiment.

The first group of exercises was push-ups, the specific fine-grained movements included standard shoulder-width(SS), standard wide-width(SW), standard diamond(SD), decline shoulder-width(DS), decline wide-width(DW) and decline diamond(DD). The position of feet in decline push-ups was higher than the standard push-ups, which is equivalent to increase the bearing weight. The second group was barbell curls. The specific fine-grained movements included neutral grip barbell(NB), wide grip barbell(WB), narrow grip barbell(RB), neutral grip light-rod(NL), wide grip light-rod(WL), narrow grip light-rod(RL). The weight of the barbell we selected is 15-20RM. We chose it to ensure that the collecting data is not too small, and try to avoid injury of subjects. The light-rod movement was replacing the barbell with a lightweight rod. It is a special form of barbell curls with light bearing weight and some fitness beginners may try to train in this way. The differences of actions are shown in Table II and Table III separately, and some typical actions are shown in figure 2.

All subjects cleaned the muscles with alcohol first and the node was placed on the center of the muscle so that the measured signal was stronger. For comparison, we also measure electromyography(EMG) signals simultaneously. In addition, all subjects selected the experimental exercises according to their body conditions and the experiment interval was at least 2 days to avoid muscle injury.

We took all the data extracted by all subjects as samples to ensure that the fine-fit is robust to personalized characteristics, which means that it has strong generalization ability. The classification algorithm was random forest as we found it has the highest precision through experiment.

B. Fine-Fit Recognition Results and Discussion

We compared the precision and recall results between Fine-Fit and other three kinds of signal: single lower-acc signal, single higher-acc signal and EMG signal. The experimental results are shown in figure 3.

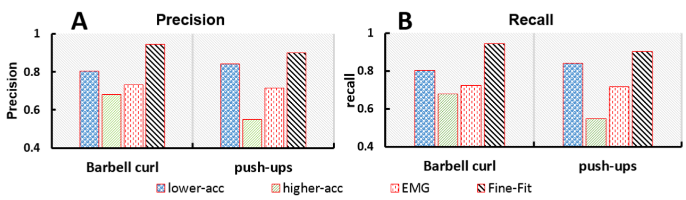

Fig. 3. recognition results of Fine-Fit vs single lower-acc, single higher-acc and EMG. A is the precision result and B is the recall result, they all show that Fine-Fit has the best results.

Results showed that all four methods can perform fine-grained gym exercises recognition with more than 50% precision and recall. However, Fine-Fit achieved the best precision and recall with more than 91% on average because Fine-Fit combined the advantages of both lower-acc and higher-acc signal. EMG was a physiological signal similar to MMG which do not have the information of macroscopic muscle movement, and the precision of exercises recognition was not high.

C. SSMS Evaluation

In order to find the advantages and characteristics of the lower-acc and the higher-acc signal in fine-grained gym exercise recognition, we took barbell curls as an example to find their recognition emphasis for different bearing weights and hands distances exercises in figure 4.

The table on the left side of the figure represented the confusion matrix after probability calculation with accuracy. Each row represented the actual label and each column represented the predicted label. So all values in the NB row represented the proportion of samples whose actual label is NB and be classified as Label NB, WB, RB, NL, WL, and RL. The results were also visualized with a histogram on the right of the figure. The top table and histogram were the classification results of the lower-acc signal, the middle were higher-acc signal, and the bottom were Fine-Fit.

The figure showed that lower-acc signal has a better recognition results for barbells curls with different hands distances. It was because the motion direction of the accelerometer that attached to the muscle surface has changed. However, for exercises with different bearing weight, there were some confusions because the two exercises may have the same macroscopic movement. It sholud be noted that these different bearing weight exercises can also be roughly recognized for some people because of their obvious biceps bulge when barbell curling. The higher-acc signal was opposite to the lower-acc signal. When doing gym exercises with different bearing weights, muscle recruitment level varied greatly, thus the frequency and amplitude of the higher-acc signal were different. On the contrary, the signal differences caused by the action with different hands distances were small so that the classification effect is poor. Fine-Fit combined the advantages of the two signals to make a fusion and it had the best recognition result.

D. MREC Evaluation

We evaluated the contribution of all features using random forest algorithm and listed the top 5 features in the table IV. Results showed that the MREC ranks second. In addition, we also compared the precision of fine-grained gym exercises classification with or without MREC in figure 5. Recognition precision was improved by 4% on average when adding MREC features. All of these proved the correctness of our assumptions in section IV.

The results demonstrate that when we do different fine-grained gym exercises, the energy maintained inside the muscles was different for per moving macroscopic distance.

VI. Conclusions

In our work, we proposed the Fine-Fit, a novel fine-grained gym exercises recognition system. Fine-Fit is a wearable system that relies on a single source, accelerometer, to sense both lower-frequency body movement signal and higher-frequency muscle vibration signal simultaneously. By leveraging the advantages of two signals and a new MREC feature which was proposed by us based on the muscle physiology principle, Fine-Fit was able to perform fine-grained gym exercise recognition.The experimental results demonstrated that Fine-Fit can accurately recognize fine-grained gym exercises of push-ups and barbell curls with different bearing weights and hands distances at 91% precision on average and Fine-Fit enhanced activity recognition to a fine-grained level.

Lower-Acc signal

Actual Label(AL)	Predicted Label (PL) NB	WB	RB	NL	WL	RL
NB	0.80	0.02	0.03	0.13	0.01	0.01
WB	0.03	0.77	0.03	0.02	0.14	0.01
RB	0.06	0.03	0.78	0.01	0.00	0.12
NL	0.17	0.03	0.03	0.69	0.04	0.04
WL	0.02	0.13	0.00	0.05	0.77	0.03
RL	0.02	0.01	0.15	0.04	0.03	0.75

Higher-Acc signal

AL \ PL	NB	WB	RB	NL	WL	RL
NB	0.74	0.09	0.10	0.01	0.03	0.03
WB	0.14	0.77	0.06	0.01	0.01	0.02
RB	0.16	0.06	0.76	0.01	0.02	0.01
NL	0.01	0.04	0.03	0.64	0.12	0.16
WL	0.04	0.03	0.02	0.22	0.60	0.09
RL	0.05	0.04	0.04	0.17	0.09	0.61

Fine-Fit

AL \ PL	NB	WB	RB	NL	WL	RL
NB	0.96	0.01	0.02	0.01	0.00	0.00
WB	0.02	0.97	0.00	0.00	0.01	0.00
RB	0.05	0.01	0.94	0.00	0.00	0.00
NL	0.00	0.01	0.00	0.94	0.02	0.02
WL	0.00	0.01	0.00	0.04	0.94	0.01
RL	0.00	0.02	0.00	0.06	0.02	0.90

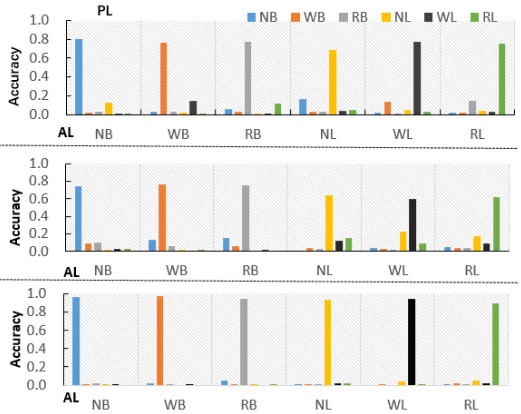

Fig. 4. The table is the confusion matrix after probability with accuracy calculation and the histogram is a graphical representation of the table on the left. The top table and histogram indicate that lower-acc signal is easily confused on exercises with different bearing weight, the middle show that higher-acc signal is easily confused on exercises with different hand distances, The bottom show that Fine-Fit overcomes the shortcomings of the above two signals.

TABLE IV
FEATURES OF SMSS

Contribution ranking	Feature vector
1	frequency-domain energy of lower-acc Z
2	MREC
3	standard deviation of higher-acc Y
4	mean of lower-acc Z
5	standard deviation of Lower-acc Y

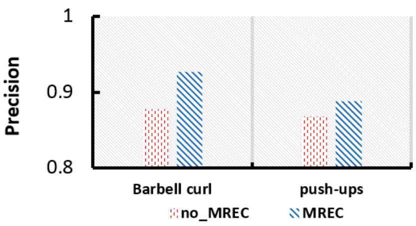

Fig. 5. Figure shows in push-ups and barbell curls, the precision results with MREC is improved compared to the results without MREC.

For future work, we will first focus on the more reasonable and accurate physical meaning for MREC based on the current assumptions. Secondly, since the muscle vibration signal is weak and hard to collect, we will contribute on better hardware design and signal processing methods.

ACKNOWLEDGMENT

The paper is supported by the National Natural Science Foundation of China (NSFC) under Grant No.61672498, the National Key Research and Development Program of China under Grant No.2016YFC0302300.

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