A Hybrid Hierarchical Framework for Gym Physical Activity Recognition and Measurement Using Wearable Sensors

Jun Qi, Po Yang, *Member, IEEE,* Martin Hanneghan, Stephen Tang and Bo Zhou

***Abstract*—Due to the many beneficial effects on physical and mental health and strong association with many fitness and rehabilitation programs, physical activity (PA) recognition has been considered as a key paradigm for internet of things (IoT) healthcare. Traditional PA recognition techniques focus on repeated aerobic exercises or stationary PA. As a crucial indicator in human health, it covers a range of bodily movement from aerobics to anaerobic that may all bring health benefits. However, existing PA recognition approaches are mostly designed for specific scenarios and often lack extensibility for application in other areas, thereby limiting their usefulness. In this paper, we attempt to detect more gym physical activities (GPAs) in addition to traditional PA using acceleration, A two layer recognition framework is proposed that can classify aerobic, sedentary and free weight activities, count repetitions and sets for the free weight exercises, and in the meantime, measure quantities of repetitions and sets for free weight activities. In the first layer, a one-class SVM (OC-SVM) is applied to coarsely classify free weight and non-free weight activities. In the second layer, a neural network (NN) is utilized for aerobic and sedentary activities recognition; a hidden Markov model (HMM) is to provide a further classification in free weight activities. The performance of the framework was tested on 10 healthy subjects (age: 30 ± 5; BMI: 25 ± 5.5 kg/m^2; body fat: 20.5 ± 5.4), and compared with some typical classifiers. The results indicate the proposed framework has better performance in recognizing and measuring GPAs than other approaches. The potential of this framework can be extended in supporting more types of PA recognition in complex applications.**

***Index Terms*— Internet of things, physical activity recognition, free weight training, wearable sensors**

I. Introduction

According to WHO, physical activity (PA) is defined as any bodily movement produced by skeletal muscles that requires energy expenditure. Physical inactivity has been identified as the fourth leading risk factor for global mortality causing an estimated 3.2 million deaths globally[1]. Thus doing regular physical exercise has become extremely significant for human healthcare [2]. The applications of recognizing PA can promote a healthier lifestyle and potentially provide substantial reduction in healthcare costs. A number of studies over the last few decades have focused on the research of delivering accurate and robust PA recognition solutions with wearable devices/sensors (e.g. accelerometers and gyroscopes) [3]–[6].

Traditional PA recognition techniques have more focal points on the exercises of repetitive movement such as *walking*, *running* and *cycling*, etc. or static actions such as *standing*, *sitting* and *lying*[4], [7]–[9]. In clinical and rehabilitation fields, work has been carried out on methods for transitional activity detections such as *stand-to-sit*, *sit-to-lie*, etc. [10][11][12]. Also, in recent years, customer PA tracking devices/apps have been released in the fitness market [13]–[16]. Unfortunately, tracking and detecting weight training is mostly excluded in the existing studies/products. The American Heart Association (AHA) [17], the American College of Sport Medicine (ACSM) [18] and the American Association for Cardiovascular and Pulmonary Rehabilitation (AACVPR) [19] have declared that weight training has been considered an important modality for human healthcare and developed guidelines for various groups from elderly people, patients with chronic diseases to healthy sedentary and physically active adults [20]. Furthermore, a survey has shown [21] that an increasing number of people become gym members in recent years with fitness membership hitting nine million in UK alone last year (approximately 14% of the population). The significance of aerobic exercises and weight training are generally approved both in medical communities and public societies. Moreover, automatically tracking and recording each workout provides systematic support to increase the repetitions progressively which is especially essential for frequent weight trainees, as manually recording is not only time consuming and tedious but would affect one's exercising schedule.

During the last decade, nevertheless, sensing and monitoring weight training has only contributed a limited amount of research [22]–[24]. The reason is that first compared with routine PA especially like *walking* and *sitting*, weight training is less frequently performed by each person each single day. Second, there is a massive variety of training activities as well as various measures of performance which is a tedious task to select and collect. More importantly, the separation of sets of free weight exercise from non-free weight activity is an important issue since the duration of the activity of each set is short and the states of activity are continuously changing, while a whole exercise commonly consists of three to five sets with

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The authors are with the Department of Computer Science, Liverpool John Moores University, L3 3AF, UK (e-mail: j.qi@2015.ljmu.ac.uk; poyangcn@gmail.com).

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non-free weight activities in between. In other words, such activity is composed of several atomic activities such *as sitting, lying, lifting, standing*, thus makes it more difficult to identify. These composite activities cause traditional standalone machine learning methods to fail to identify patterns efficiently and accurately. Due to the diversity and complexity of PA in weight training, the accuracy and performance of these devices with using traditional PA recognition and classification approaches are relatively low. Thus, tedious and time-consuming manual recording is still widely used in gym environment. One essential issue leading this phenomenon is that the majority of PA recognition and monitoring approaches lack of extensibilities and scalabilities. The workflow of these studies is much identical by following steps from data collection, feature selections to algorithms training. There has been some trade-off between recognition accuracy and types of PA. The approaches designing for certain cases have limited extension and scalability in supporting more types of PA in other cases. It lacks of some general methodologies potentially integrating existing PA works into an extendable and scalable framework with less effort in supporting more activities and different applications.

In this work, we attempt to target at this issue by design a hybrid hierarchical gym physical activity (GPA) recognition and measurement framework (GPARMF) aiming at re-constructing two main specific-sensor based PA methods into an effective hybrid solution for general GPA recognition and measurement. The framework involves more GPA category recognitions and implements sets and repetitions counts for each weight training activity using two wearable sensors. Due to the training machine limitations, we only consider free weights with barbells and dumbbells, as it is regarded as the most effective strength training way for healthcare and muscle mass[25]. The framework is composed of two layers. In the first layer, a one-class support vector machine (OC-SVM) classifier is applied to separate free weight (i.e., bench press, deadlifts or squats) and non-free weight activities (i.e., walking, running or sitting). In the second layer, a hidden Markov model (HMM) is utilized to provide a fine grained classification in free weight activities, using a neural network (NN) for classifying non-free weight. In contrast to existing studies that either simply recognize aerobic exercises and static postures [4], [7]–[9] or merely focus on weight training activities [22]–[24], this work covers all three categories of PA with extensibility and scalability to integrate more PA types for example from simple PA (i.e., repetitive movements: walking or running) to complex PA (time-series-based changing PA: anaerobic exercises or free weights). Additionally, by achieving high recognition accuracy, almost all studies classify weight training activity with only one set signals data in a controlled environment while in practice, people typically perform different activities between sets within a whole weight training program. Thus, our training data samples are collected from 10 healthy subjects by each exercise rather than each set in which the former contains much more uncertain activity combinations that haven't been resolved to date.

To summarize, this paper has the following contributions:

- A novel two-layer sensor fusion based physical activity recognition framework GPARMF, is proposed for effectively recognizing and classifying free weight and non-free weight gym physical activities. This framework is capable of accurately separating and recognizing free weight and non-free weight GPAs.
- During GPARMF, an OC-SVM classifier is designed to coarsely classify free weight and non-free weight exercises. Also, a neural network (NN) model is utilized for aerobic and sedentary activities recognition; a hidden Markov model (HMM) is to provide a further classification in free weight activities.
- A throughout experimental evaluation on practical gym environment with heterogeneous devices is carried out. Intensities of free weight exercises are measured through counting repetitions and sets with normalized. The results show that the proposed framework has better performance in recognizing and measuring GPAs than other standalone approaches

The paper organized as follows: Section II presents the latest work on PA and free weight activity recognition. Section III describes our GPA recognition framework and data processing algorithms. Section IV gives details of our implementation of the framework, and conclusions and further work are presented in Section V.

II. Related Work

Many PA recognition approaches and systems using acceleration information have been explored during the last few decades for healthcare use. Essential points rely on machine learning classifications such as neural networks (NN) [26][27], support vector machines (SVM)[28][29] and decision trees (DT) [30][31], etc. These studies are dedicated to tracking human routine PA like aerobic exercises (i.e., walking, running, cycling, etc.), and sedentary activities (i.e., sitting, lying, etc.). Weight training especially free weight activity recognition using wearable sensors, as a new PA tracking field, only has limited research. Chang et al. [32] is the pioneer in the last decade to use tri-axial accelerometers to recognize weight training exercises. The study not only tracked repetition numbers but also compared HMM and naïve Bayes on nine exercises showing that recognition accuracy of HMM is over 90%, outperforming naïve Bayes. Later on, Pernek et al. [33] evaluated upper body exercise recognition accuracy with SVM using different numbers and placement of sensors, features, sliding window and classifiers and concluded that a two second window length with 50% overlap yields the highest exercise recognition. Hausberger et al. [34] assessed three single time-series approaches, namely dynamic time wrapping (DTW), HMM and SVM, applied on seven weight training exercises and concluded DTW provided the highest accuracy with over 99% recognition. DTW also shows satisfying results in the study [35] with only a mobile phone as the sole sensing device. The platform is able to classify free weight activities, set and repetition counts and provide feedback to the user.

The studies above achieve outstanding experimental results in diverse approaches and functionalities, including some extraordinary recognition results and thorough user demands [34][35]. However, they are all conducted in a controlled environment, which means each activity is predefined with only

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one pattern. Additionally, most work uses repetitions of signal datasets that cut out from the whole free weight activity or only count repetition numbers. Yet there are more diverse performances within one activity especially among sets in free weight exercises. Thus segmenting free weight from non-free weight within uncontrolled environments is a problem that has not been explored to date. To cope with this problem, we built a two-layer framework to recognize and measure GPAs, shown in fig.1. In the first layer, we attempt OC-SVM [36] which adapts a traditional binary SVM to a one class situation to set apart non-free weight and free weight activities. The algorithm has been widely applied in anomaly detections [37] and unbalanced labelling data [38]. We adopt this due to the unbalanced training samples of the two classes in realistic scenarios.

DTW is a template-based dynamic programming matching technique for efficiently matching two time-series signals [39]. However, when it comes to different patterns of activity with transient free weight activity within all sets and other PAs that may take a longer time and contain more uncertainties, it needs a large number of templates for a variety of patterns and also fails to match undefined templates. Hence, in the second layer of our framework, another time-series approach, HMM, is presented to resolve the free weight activity recognition issue. HMM is a probabilistic sequence model that describes a process of mapping a sequence of observations to a sequence of hidden states. It has been successfully applied in speech recognition [40], gesture recognition [41] and activity recognition [42], etc. We chose HMM because it is a spatio-temporal model that is capable of handling undefined patterns which is suited to a variety of free weight performances. HMM requires high computational expense and large number of training samples, thus to balance the feasibility and efficiency, neural networks (NN) have been designed to recognize non-free weight activities in this layer. Whilst the NN is not able to detect free weight from all GPAs, it gives the best performance in classifying traditional PA types [26][27]. Subsequently, GPA measurement approaches with wearable sensors of accelerometers are also offered in GPARMF through counting the numbers of sets and repetitions for free weight exercises.

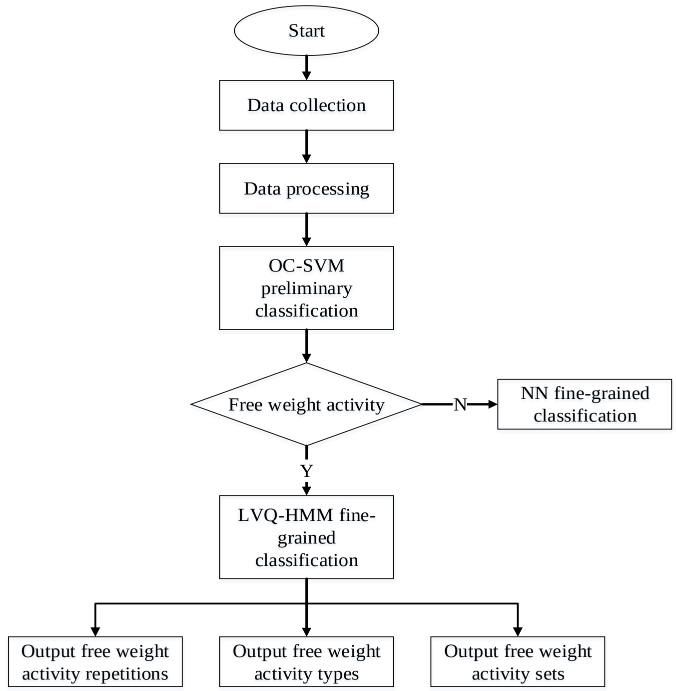

Fig.1 flow chart of GPARMF

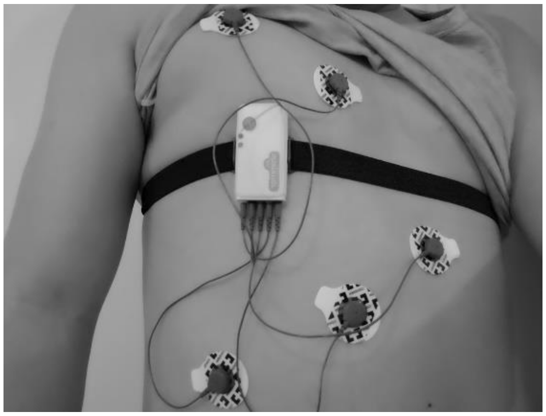

Fig.2. a subject performs free weight activities with ECG attached

III. Proposed Framework

The GPARMF consists of two recognition steps: preliminary classification and fine-grained classification, as shown in fig.3. Acceleration data are firstly collected from the sensing layer before features are extracted and selected through time and frequency domains. OC-SVM is exploited to roughly distinguish free weight and non-free weight activities. In the second classification step, HMM is used to classify free weight exercises and NN is used to classify aerobic activity and static postures to obtain the concrete activity results. The repetitions and sets are also measured in the framework through given thresholds and heartbeat fluctuations. The whole procedure is presented in Fig.1.

A. Data Collection

The goal of our data collection is to implement GPA recognition and intensity measures of free weight activities based on realistic data in natural training conditions. A total of 10 healthy subjects (7 males, 3 females; age: 30 ± 5; BMI: 25 ± 5.5 kg/ m^2; body fat: 20.5±5.4) took part in the data collection process. Four of the subjects are professional trainees that have continuously trained for 2 to 5 years. Others are untrained people engaging in sedentary desk jobs. The subjects were asked to place two Shimmer3 wireless wearable sensors [43] on wrist and chest respectively, shown in fig.3. As reported in the study [8] that the chest is closer to the center of body mass and thus is an ideal measurement position especially for sedentary activities, whilst the heartbeat also can be obtained. Arm movements play an important role in most activities, thus we select a sensor put on the wrist to increase recognizer accuracy. The sensor sampling rates are 50Hz which is higher than basic requirements (20Hz is sufficient to infer ambulation activities [44]). Yet considering the short duration of each set of free weight exercise and heart rate, we decided to use 50Hz for data collection. The sensors were connected and the signals were

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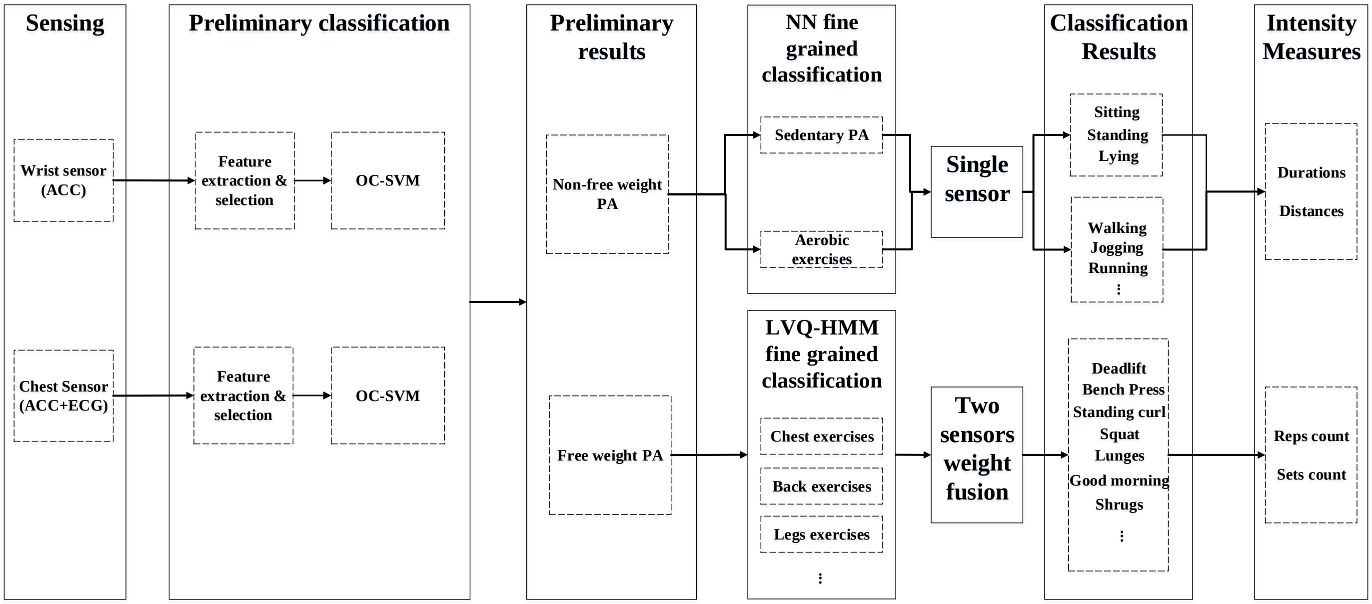

Fig.3 proposed gym physical activity recognition approach (ACC-accelerometer, ECG- Electrocardiogram; LVQ: learning vector quantization; HMM-hidden Markov model)

TABLE 1. TYPICAL GYM PHYSICAL ACTIVITIES IN CATEGORIES

Activity class	Activity name	Activity category	Muscle groups	Posture
A1	Bench press	Free weight	Chest	Lying
A2	Squats	Free weight	Legs	Standing
A3	Lunges	Free weight	Legs	Standing
A4	Bend-over rows	Free weight	Back	Standing
A5	Deadlifts	Free weight	Back	Standing
A6	Good morning	Free weight	Back	Standing
A7	Shrugs	Free weight	Shoulders	Standing
A8	Front raises	Free weight	Shoulders	Standing
A9	Overhead extensions	Free weight	Triceps	Lying
A10	Curls	Free weight	Biceps	Standing
A11	Walking	Aerobic	None	Standing
A12	Jogging	Aerobic	None	Standing
A13	Running	Aerobic	None	Standing
A14	Cycling	Aerobic	None	Sitting
A15	Ascending	Aerobic	None	Standing
A16	Rowing	Aerobic	None	Sitting
A17	Sitting	Sedentary	None	Sitting
A18	Standing	Sedentary	None	Standing
A19	Lying	Sedentary	None	Lying

stored on an Android mobile phone (Nexus 6P) via Bluetooth.

Furthermore, rather than controlled lab settings, the dataset are collected in the user's real training environment (i.e., gym), so each free weight set is in terms of a RM (repetition maximum) principle which is the most weight a subject can lift for a defined number of exercise movements, so that it truly reflects the heartrate change and duration of the free weight exercises. Each subject first performed six types of aerobics (walking, jogging, running, cycling, ascending, and rowing) and three types of static postures (sitting, standing, and lying) for 5 minutes each and repeated three times. And then does ten types of typical and important free weight movements selected for the human main muscle groups: chest, legs, back, shoulders, triceps and biceps, as presented in table 1. Each free weight activity was performed as the intensity of light (8-12 RM), Medium (6-8 RM), high (4-6 RM) and extremely high (2-4 RM)[45], and repeated three times, so 12 sets in total per subject.

B. Data Processing

The goal of our data collection is to implement GPA recognition and intensity measures of free weight activities based on realistic data in natural training conditions. A total of 10 healthy subjects (7 males, 3 females; age: 30 ± 5; BMI: 25 ± 5.5 kg/ m^2; body fat: 20.5±5.4) took part in the data collection process. Four of the subjects are professional trainees that have continuously trained for 2 to 5 years.

1) Pre-processing

In the preprocessing stage, we first apply a straightforward metric called signal magnitude vector (SMV) that directly processes acceleration signals from three axes $x(i), y(i), z(i)$ respectively, shown in Eq. (1), which provides a measurement of the degree of activity intensity. We then smooth the metrics through Savitzky Golay filters [46]. Fig. 4(a) shows three-axis raw signals of six types of aerobic exercise. Fig.4 (b) shows raw signals of *deadlifts*, *squats* and *bench press*. Fig. 4(b) shows a whole period of standing curl activity after SVM and smoothing processing.

$$\mathrm{SMV} = \sqrt{x_i^2 + y_i^2 + z_i^2} \quad (1)$$

2) Feature extraction and selection

Feature extraction is a crucial procedure for GPA recognition since any classification method can be appropriately selected if the features are robust. Time domain and frequency domain features are extracted from each accelerometer axis, and R waves are extracted from ECG for heartrate calculation. The extracted features are presented in table 2.

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ECG is exploited to measure one's heart rate for sets tracking. As free weight activities are normally performed within a very short time, an individual's heartbeat would dramatically fluctuate during this period. When one set finished, he/she may have a break and prepare for the next set. During the break time, one would perform different activities, such as *walking*, *standing*, *sitting*, etc. Detecting and distinguishing short time activities within such a large random activity with motion sensors is a difficult task. However, there is an inevitable relation between intensity and heartbeat, and an individual's heart rate undergoes regular changes when performing the activities. During and a short time after the activity, heartbeat will be dramatically increased, and tends to be stable during the break regardless of types of movement. As such, we adopt ECG for sets calculation. The ECG signals are firstly detrended and filtered, then we find R wave peaks which are used to calculate heartbeat every minute in terms of Eq. (2)

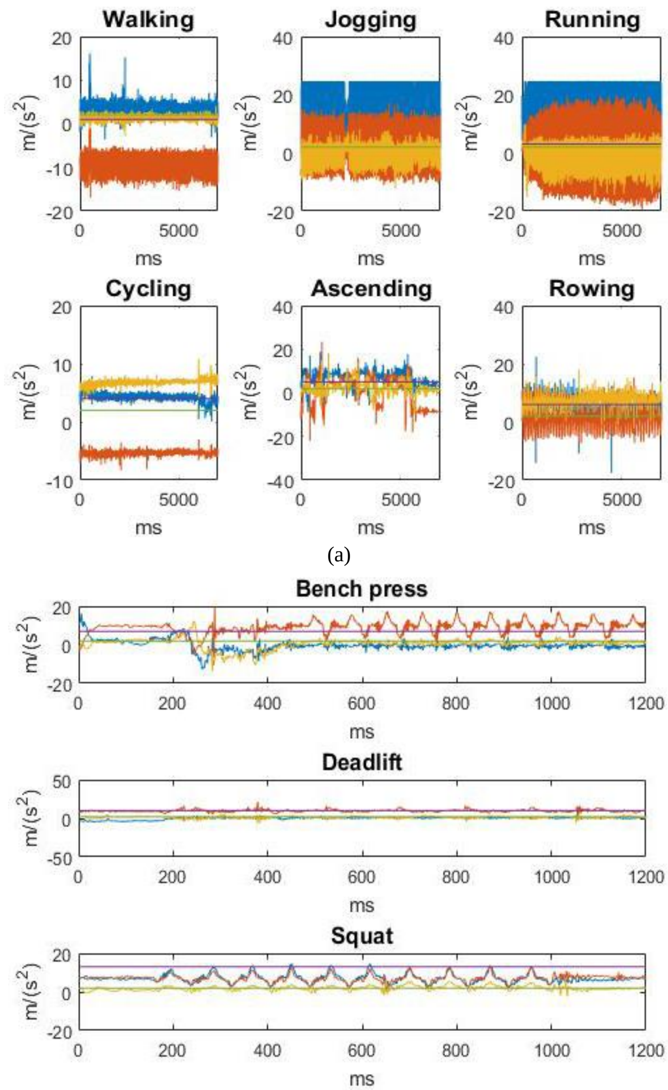
$$Heartbeat(i) = \frac{sampling\ rate \times 60}{R\_wave\ (i+1) - R\_wave\ (i)} \qquad (2)$$

TABLE 2. FEATURE EXTRACTION CATEGORY AND EXTRACTED FEATURES FOR FINE GRAINED CLASSIFICATIONS

Category	Extracted features
Time domain	Mean, standard deviation (SD), covariance, variance, min, max, correlation, root mean square (RMS), signal magnitude vector (SMV)
Frequency domain	FFT energy, entropy
Biometrical domain	R wave

C. Preliminary classification with OC-SVM model

As free weight exercises are instant and intensive compared with other PAs such as *walking* and *sitting*, the first step in the framework is to distinguish free weights from non-free weight activities. This is a typical issue of binary classification if the non-free weight activities are denoted as positive samples, and the free weights are negative samples. However, there are only small portions of free weight activity volumes within our GPA dataset owing to the fact that our data collections are from real training scenarios, in which rest periods between sets vary from 30 seconds to five minutes depending on training levels. Normally, it takes 2.5 to three minutes to recover from a set of intense exercise [47]. On the contrary, the weight training period of a set is around one minute or less. Also when mixed with other free weight samples are difficult to capture for binary classification. Therefore, OC-SVM is designed in the first level of GPARMF. We use support vector domain description (SVDD) such as that proposed by Tax et al. [36] to separate non-free weight and free weight activities. Instead of a conventional OC-SVM that finds a hyperplane to separates target samples from the origin using maximum separation, our algorithm maps all target samples which are non-free weight activity features into high dimensional feature space through a radial basis function (RBF) kernel function and computes the surface of a minimal hypersphere with all positive samples. The outliers are the regions with densities lower than the given threshold is then classified as free weight activities. Fig.6 shows a hypersphere of two datasets. The dots inside the circle are target samples, and the dots falling outside the circle are outliers.



(a)

(b)

Fig.4.Raw tri-axial accelerometer data of free weight activities on the wrist (top to bottom: bench press, deadlift and squats)

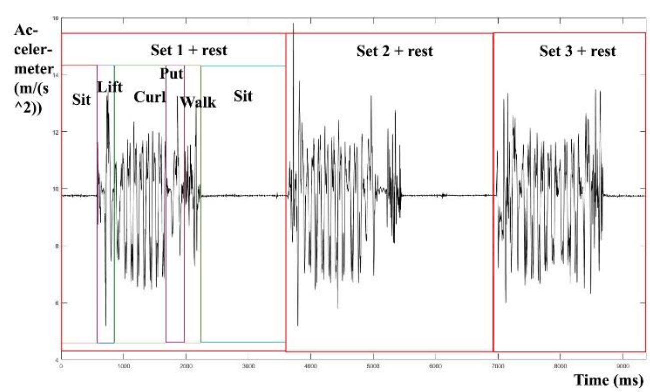


Fig.5 three sets of standing curl

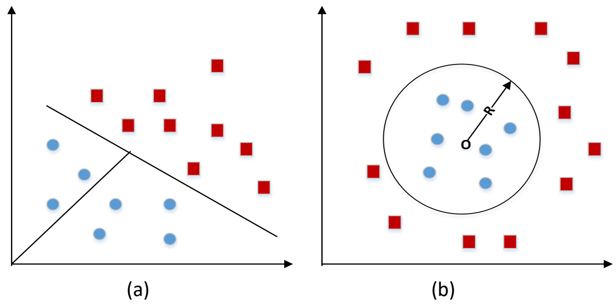


Fig.6 (a) the hyperplane separates with maximum margin target samples from the origin by mapping all targets of dots to the upper side of the hyperplane and dots in outliers to the lower side. (b) Support vector domain description (SVDD) which the target samples are surrounded by hypersphere.

Let $A_{nw} = \{a_{nw1}, a_{nw2} \cdots a_{nwm}, m \in R\}$ as non-free weight positive samples, and x as the centre of hypersphere, R as the radius, so the optimal form that involves positive samples is:

$$\min(R^2 + \frac{1}{vl}\sum_{i=1}^{l} \xi_i) \tag{3}$$

Subject to:

$$\|\phi(a_{nwi}) - x\| \leq R^2 + \xi_i \ \ (\xi_i \geq 0; i \in m) \tag{4}$$

Where a_{nwm} is the i^{th} non-free weight training pattern, m is the total number of training patterns, and $\xi = [\xi_1, \cdots, \xi_i]$ is the vector of the slack variables, which is to optimize the function margin to be convergent.

In the GPARMF, we assume that frequency of arm swings is slower in performing free weight than non-free weight activities. And arm movements are presented the way of up and down in most of free weights, while they are back and forth in aerobics and static or irregular movements in sedentary situations. Hence to differentiate the two classes, the interval of signal peaks, height of peaks and variance are adopted to set the threshold, and we have the following rules:

$$if\ f_i(x) > y, then\ x \in \{free\ weight\};$$
$$if\ f_i(x) < y, then\ x \in \{non - free\ weight\} \tag{5}$$

Where $f_i(x)$ is the SVM decision function and y is the threshold defined by Eq. (6)

$$y = d_i + m_i + v_i \tag{6}$$

Where d_i, m_i and v_i are the distance between peaks, height of peaks and variance computed from all decision function values in terms of Gaussian distribution.

D. Free weight classification with HMM

A free weight activity is composed of different postures and activities in orders. For example, when an individual performs the activity bench press, he/she would first lie to the bench, and then lift and hold the barbell, next to press, and repeat pressing, after that, put back the barbell and keep laying or sitting up. (Described as a series activities: lie->hold barbell->press->... (Repeat pressing)-> put back barbell->sit to rest->…). To build the recognizer, there are two stages: 1) the training stage, and 2) the recognizing stage.

1) Training stage

In this stage, representing the combination of postures and activities with a series of sequences means it is essential to use a HMM approach. As a HMM is a collection of finite states connected by transitions, let $\lambda = (A, B, \pi)$ be a free weight activity recognition model, as it is shown in fig.7, where A is the matrix of activity state transitional possibilities, denoted as $A = \{A_{i,j}\}$, where $A_{i,j}$ is the activity state transition from state i to state j. B is the matrix of emission possibilities, denoted as $B = \{B_{i,j}\}$. And π is the vector of the initial probabilities state n. Observation sequence $O = \{O_1, O_2 \cdots, O_t\}$ is the input observation state from accelerometer's signals at time t. And hidden state is denoted as $I = (i_1, i_2, \cdots i_t)$, the set of time is $T = (t_1, t_2, \cdots t_m)$.

Training a HMM is the procedure of maximizing the probability of the observation sequence $P(O|\lambda)$, where

$$P(O|\lambda) = \sum_I P(O|I, \lambda) P(I|\lambda) \tag{7}$$

And then Baum-Welch algorithm is employed for building a free weight activity HMM. Let $(O, I) = (o_1, o_2, \cdots, o_t, i_1, i_2, \cdots i_t)$ be all states, $\hat{\lambda} = (\hat{A}, \hat{B}, \hat{\pi})$ be the re-estimation from $\lambda = (A, B, \pi)$, so to obtain the maximum log-likelihood, we have

$$argmax \sum_{i \in I} log P(O, I; \lambda) P\left(I \middle| O; \hat{\lambda}\right) =$$
$$argmax \sum_{i \epsilon I} \log P(O, I; \lambda)\, P\left(I, O; \hat{\lambda}\right) = argmax \hat{L}(\lambda, \hat{\lambda}) \tag{8}$$

Where

$$P(N, O; \lambda) = \prod_{i=1}(\pi_{i_1} B_{i_1}(O_1) \prod_{t=2}^{T} A_{i_{t-1} i_t}(O_t) B_{i_t}(O_t)) \tag{9}$$

And Eq. (8) and Eq. (9) give

$$L\left(\lambda, \hat{\lambda}\right) = \sum_{i \epsilon I} log \pi_{i_1} P\left(I, O; \hat{\lambda}\right) +$$
$$\sum_{i \epsilon I} \sum_{t=2}^{T} log A_{i_{t-1} i_t} P\left(I, O; \hat{\lambda}\right) +$$
$$\sum_{i \epsilon I} \sum_{t=2}^{T} log B_{i_{t-1} i_t} P\left(I, O; \hat{\lambda}\right) \tag{10}$$

After applying Lagrange multipliers, the three factors in the model are:

$$\pi_j = \sum_{i=1}^{I} P(i_1 = i | O; \hat{\lambda}) \tag{11}$$

$$A_j = \frac{\sum_{t=2}^{T} P(i_{t-1} = j | \hat{\lambda})}{\sum_{t=2}^{T} P(i_{t-1} = j | \hat{\lambda})} \tag{12}$$

$$B_j = \frac{\sum_{t=1}^{T} P(i_t = j | \hat{\lambda}) I(i_t = j)}{\sum_{t=1}^{T} P(i_t = j | \hat{\lambda})} \tag{13}$$

Since a HMM training only receives discrete variables, the features need to be quantified into observation symbols. To improve the reliability and accuracy of the training, all samples in our dataset are labelled, which are also represented as fixed length within each time window, hence a learning vector quantization (LVQ) neural network [48] is adopted for the continuous observation densities. A HMM model of free weight activity consists of a range of atomic activities which are

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labelled as subclass for LVQ training, and then the extracted features are input as training vectors for assigning to individual classes.

Due to the complexity of free weight exercises, in order to improve its performance, we use both wrist and chest accelerometers to assess them. The results are derived from two sensor fusion, each of which is given a weight, and the final fusion will be a summation of the sensor's Gaussian distributions based on each atomic activity, and one sensor dominates in both. For example, in the activity *bench press*, the chest sensor in the first atomic activity (*lying*) is assigned a larger weight (say 0.9), and in the second atomic activity (*holding barbell*), wrist sensor is initialized a larger weight than chest sensor, as it is an arm movement. Likewise, in the next movement (*pressing*), the wrist sensor is also a larger weight. As such, the combination from two sensors with discriminant weight during the HMM training procedure can provide more accurate outcome than a single one. The training procedure is presented in fig.7.

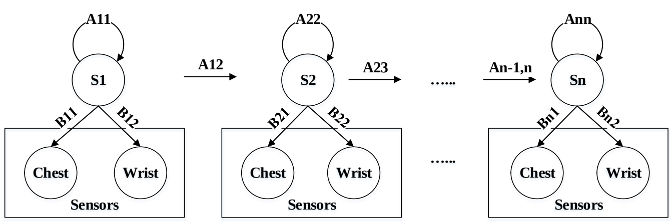


Fig.7 HMM structure in GPARMF

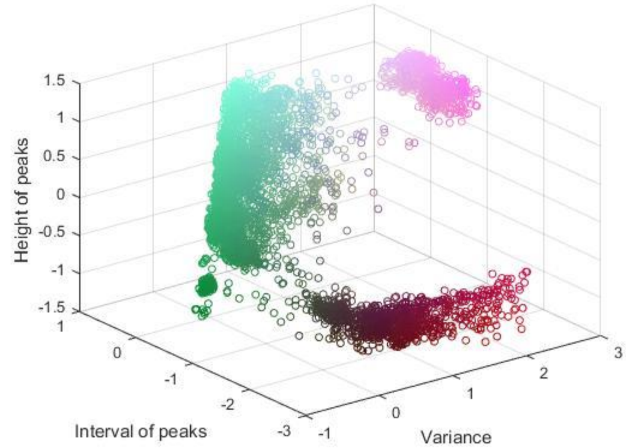


Fig.8 distribution of features of interval of peaks (pink), height of peaks (green) and variance (red) from tri-axial accelerometers of GPAs

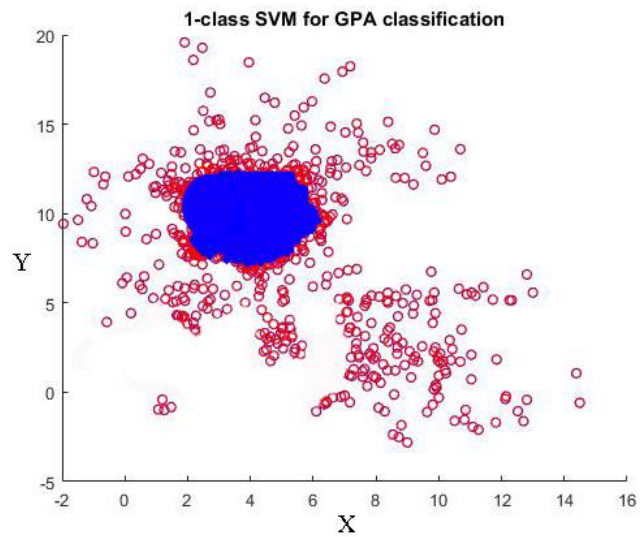


Fig.9 distribution of free weight and non-free weight activities using OC-SVM

2) Recognizing stage

In the recognizing phase, the free weight activities are embedded in a range of input streams. Finding the start and end points is the key issue. The Viterbi algorithm is used in this phrase to find the most likely observation sequence at time *t* defined as Eq. (14)

$$\delta_t(i) = maxP(i_t = i, i_{t-1}, \cdots i_1, o_t, \cdots o_1|\lambda) \quad (14)$$

As such, we can find the most optimal possibility and classify it in the corresponding activity class.

IV. EXPERIMENTAL EVALUATION

A. GPA preliminary classification

We first evaluate OC-SVM performance in GPARMF. The threshold is set from three features which are peaks of distance, variance and mean whose distribution is presented in fig.8. The classification result is shown in fig.9, where the blue part is non-free weight activity features and hollow circle dots falling outside the circle are free weight activity features. The classification accuracy is up to 85% in this layer.

B. GPA fine-grained classification

After separating free weight and non-free weight classes, we first evaluate nine non-free weight activities (6 aerobics and 3 static states) with a NN. In order to match the activity patterns, data sets are segmented as results in consecutively activated sensors on the subject's body. Such data sets are broken down with temporal series using a time window. In the GPARMF, the sliding windows are segmented into a fixed temporal length of one second with 50% overlapping.

Due to the large number of features, dimensionality is very high with redundant information that may cause high computational complexity for the next classification procedure. Thus, we select some features using a typical dimension reduction approach principal component analysis (PCA) which reduces data dimensionality by projecting a dataset onto a lower dimensional space but keeping the most information within the datasets. In our implementation, the dimension is reduced from to 1×88 to 1×36 for each window size after using PCA.

Three layers (input, hidden and output layer) feedforward NNs are explored for the aerobic and sedentary activities classification. To build three NN models, we only make use of feature vectors from accelerometer data of wrist as input layers, 18 neurons assigned within the hidden layer and 9 neurons in output layer in terms of aerobic and sedentary activities listed in table 1. The accuracy of the NN model is evaluated by 10-

fold cross-validation. The classification results are compared with decision tree (DT), k-nearest neighbors (KNN) and hidden Markov model (HMM) and shows that the neural network gives the best performance as shown in the orange line in fig.10. The precision in NN in A1 to A9 are 95.2% on average.

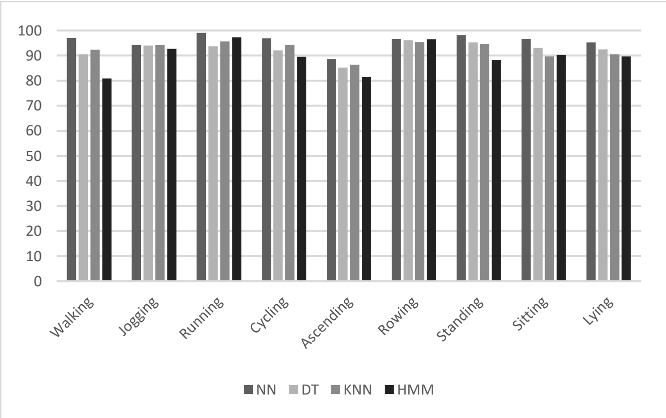


Fig.10 Comparison of accuracy of four recognizers in non-free weight activities with only wrist accelerometer (NN: neural network; DT: decision tree; KNN: k-nearest neighbors; HMM: hidden Markov model)

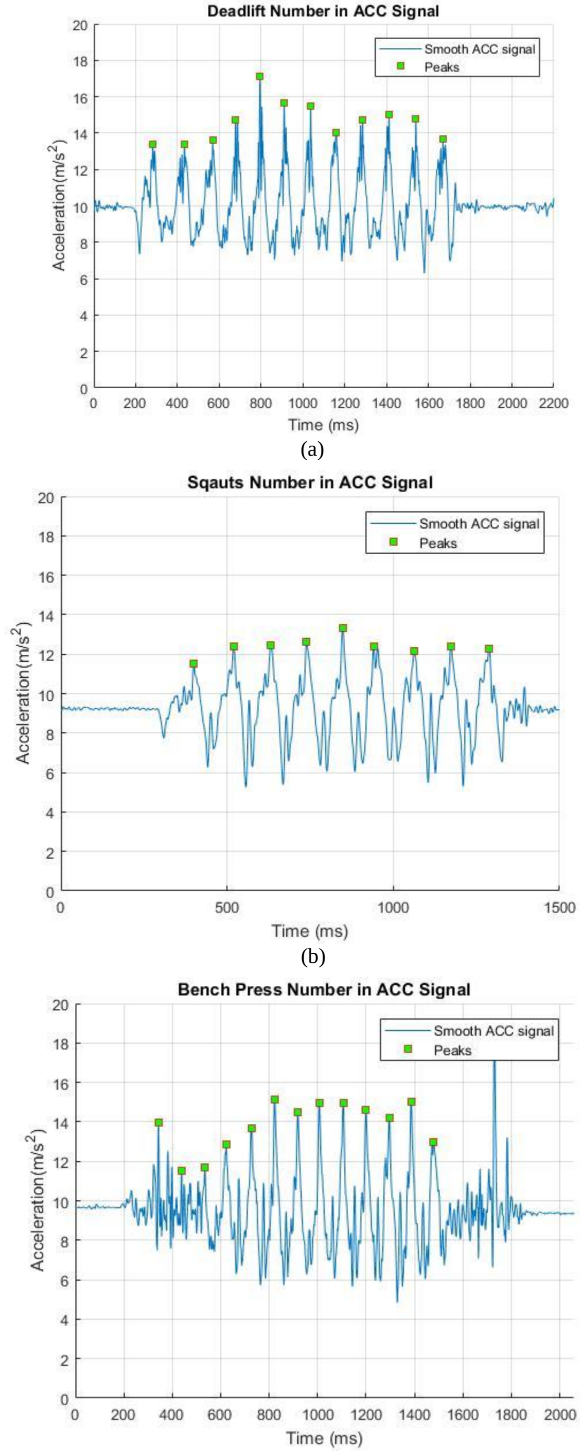
C. GPA measurements

(1) Free weight repetition calculation

A rep (or repetition) is a single movement of any exercise. We tracking the number of reps by finding peaks of the accelerometer signal in each activity set. To do so, we need to 1) smooth the raw accelerometer data; 2) standardize the axis value; 3) define the threshold in each set's signal including minimum height of the peak and distance between two peaks. We use vertical and horizontal thresholds to define the peaks. With the majority of sets' data we collected, the peaks are at least 20% higher than start point vertically, and distance between two peaks is 1000 millisecond minimum. Results are shown in fig.11, where (a) is deadlift peaks and (b) is squat peaks marked in green solid circle dots.

(2) Free weight intensity and set calculation

Four intensity levels (low, medium, high, extremely high) are measured with Shimmer ECG electrons when the subject is performing a deadlift. To calculate heartrate per minute, finding out the R-R interval is essential. The threshold is set through the minimum distance of two peaks and minimum height of smoothed and detrended signals. Fig.12 (a) presents the R-R intervals in triangle dots. And fig.12 (b) shows the heartrate changing states when doing free weight exercises. As we can see, in low and medium intensity, the activity is performed longer and the subject's heartrate increases slowly. The heartrate is up to 128 beat/min in low intensity at 10s point, while it is 148 beat/min at 10s. However, in the activities of high and extremely high intensity, the heartrate increase dramatically and reach to highest point at 7s and 5s respectively in the first set. With the heartrate changing status during the activity, as such, it is also clear that the subject has done two sets in this case shown in the fig.12 (b).



(c)

Fig. 11 one set of a free weight activity repetition calculates (a) deadlift numbers; (b) squat numbers; (c) bench press numbers

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TABLE 3 CLASSIFICATION RESULTS IN GPARMF

Class	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19
Precision	97.0	94.2	99.1	96.9	88.6	96.6	98.2	96.7	95.3	89.6	90.2	89.6	90.4	82.6	82.4	88.4	82.6	92.4	91.4
Recall	95.2	98.6	91.7	95.1	94.2	98.6	97.0	95.2	91.2	80.5	88.5	82.4	88.2	81.2	78.8	82.5	82.8	90.5	93.0
F-Measure	96.1	96.3	95.3	96.0	91.3	97.6	96.5	92.2	92.6	88.6	92.2	88.6	91.2	89.8	80.5	88.6	76.5	88.8	86.2

TABLE 4 COMPARISON OF PRECISION (P), RECALL (R) AND F-MEASURE (FM) OF DIFFERENT CLASSIFIERS IN FREE WEIGHT TRAINING RECOGNITION (DTW: DYNAMIC TIME WRAPPING; NN: NERUAL NETWORK; GMM: GAUSSIAN MIXTURE MODEL; HMM: HIDDEN MARKOV MODEL)

Classifier	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19
DTW	P: 66.3 R: 70.5 FM: 72.4	P: 70.6 R: 71.5 FM: 80.4	P: 80.6 R: 80.5 FM: 78.6	P: 80.5 R: 82.2 FM: 85.3	P: 70.5 R: 77.3 FM: 78.5	P: 74.3 R: 79.5 FM: 76.4	P: 81.2 R: 80.1 FM: 85.7	P: 75.4 R: 81.5 FM: 79.0	P: 85.4 R: 81.2 FM: 82.5	P: 81.3 R: 76.5 FM: 85.0
NN	P: 81.3 R: 85.5 FM: 80.2	P: 85.3 R: 88.5 FM: 90.3	P: 81.4 R: 75.5 FM: 78.3	P: 85.9 R: 88.8 FM: 86.7	P: 75.4 R: 77.5 FM: 80.6	P: 69.8 R: 71.2 FM: 77.4	P: 75.6 R: 78.9 FM: 80.5	P: 71.3 R: 74.0 FM: 70.8	P: 80.2 R: 81.5 FM: 74.9	P: 82.4 R: 85.5 FM: 86.7
GMM + HMM	P: 72.5 R: 75.2 FM: 75.8	P: 75.4 R: 79.4 FM: 75.6	P: 83.5 R: 82.4 FM: 88.9	P: 91.5 R: 90.6 FM: 89.8	P: 80.6 R: 80.5 FM: 85.6	P: 79.4 R: 80.8 FM: 82.2	P: 85.4 R: 82.3 FM: 80.6	P: 78.3 R: 79.4 FM: 80.5	P: 88.7 R: 90.8 FM: 92.0	P: 89.8 R: 91.2 FM: 85.6
LVQ + HMM	P: 89.6 R: 80.5 FM: 88.6	P: 90.2 R: 88.5 FM: 92.2	P: 89.6 R: 82.4 FM: 88.6	P: 90.4 R: 88.2 FM: 91.2	P: 82.6 R: 81.2 FM: 79.8	P: 82.4 R: 88.8 FM: 80.5	P: 88.4 R: 82.5 FM: 88.6	P: 82.6 R: 82.8 FM: 76.5	P: 92.4 R: 90.5 FM: 88.8	P: 91.4 R: 93.0 FM: 86.2

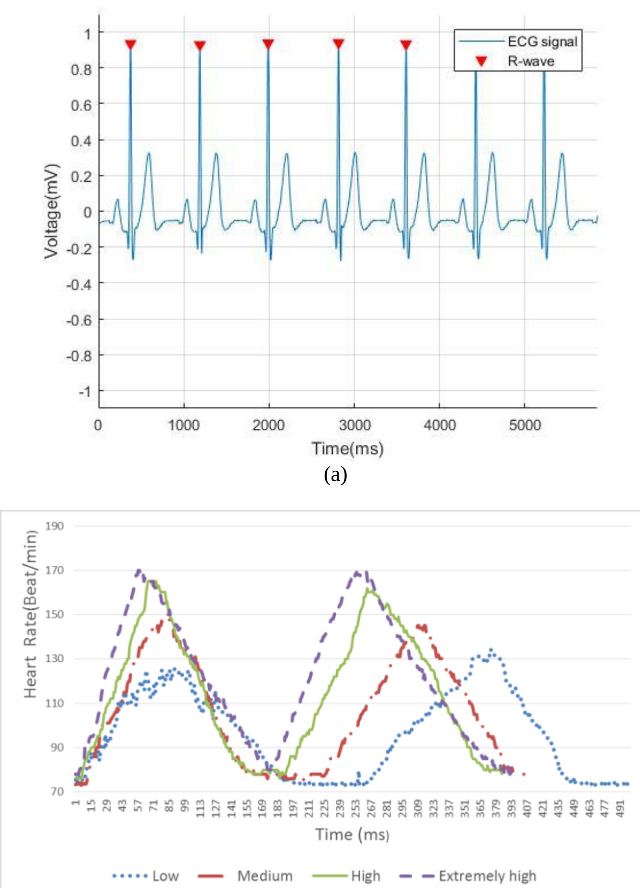

Fig.12 Heartrate per minute using ECG (a) finding R-R intervals; (b) two sets of a free weight activity with low intensity (8-12RM) in blue line, medium intensity (6-8 RM) in red line, high intensity (4-6 RM) in green line and extremely high intensity (2-4 RM) in purple line.

V. CONCLUSION

Regular doing GPA is essential for human healthcare. There are a number of studies that contribute to the field physical activity recognition and monitoring. However, there are still a large range of activity types have not been explored. In this work, with accelerometers and ECG, we build a gym physical activity recognition and measurement framework (GPARMF) that is capable of classifying 19 gym physical activities including free weights, aerobic and sedentary activities. The framework is divided into two layers based on the non-free weight boundary. A one-class support vector machine (OC-SVM) is applied in the first layer to separate free weight and non-free weight activities in light of a given threshold, and in the second layer, a neural network (NN) and hidden Markov model (HMM) is adopted to classify non-free weight and free weight activities respectively. In addition, learning vector quantization (LVQ) is used to quantize feature vectors for continuous input to the HMM, which gives the better performance than a conventional Gaussian mixture model (GMM) and other classifiers. Furthermore, GPARMF, based on the repetition maximum (RM) principle, evaluates intensity of free weight exercises with changing heartrate within a user's natural environment. It is also capable of calculating repetitions and sets for each free weight exercise. In the next stage, we intend to collect more subject data and further improve the accuracy of the framework and evaluate more GPAs including further types of free weight exercises.

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