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Strength Training: A fitness application for indoor based exercise recognition and comfort analysis

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***Abstract*— Mobile and Wearable health applications are playing a key role in monitoring user fitness data. Current Wearable devices like Fitbit, Jawbone, and Samsung Gear provide solutions for outdoor fitness activities. However a lot of people prefer to do indoor exercises but there are limited auto activity tracking solutions. Existing solutions are not concentrated on the ease at which a user is able to perform an exercise. This work provides automatic indoor exercise recognition for both in gym and home usage scenarios. Activities under consideration are Biceps curl, Chest fly, Row, Push up, Sit up, Squat and Triceps curl. Accuracy of 95.3% and 99.4% is achieved for activity recognition and repetition count respectively. Along with activity recognition this work targets at analyzing comfort and measuring calorie burnt during the exercise. We introduce Comfort factor, which is the state of physical ease during workout. Comfort factor is predicted using the relation devised between Resting Heart Rate (RHR), Maximum Heart Rate (MHR), Real-time heart rate value and hand tremor at exercise exhaustion limit of the user. With this comfort factor, user can decide whether to go for more weights or reduce weights in weight training activities.**

Keywords—Exercise tracking; Activity recognition; Workout detection; Comfort analysis

I. Introduction

A. Motivation

The Centers for Disease Control and Prevention recommends that all adults should get at least 30 minutes of moderate-intensity aerobic activity five days a week and muscle-strengthening activities two or more days per week [1]. It is customary to go to gym for doing muscle-strengthening activities and use various equipment. While doing so, people find it difficult to track activities manually.

Having spoken about the importance of workout in daily life, it's also important to know your limit during any workout. Overdoing exercise can lead to injuries, and may end up erasing all the benefits that physical activity can have. According to the article in the Time-Health, Journal of the American College of Cardiology researchers say that people who push their bodies too hard may undo the benefit of exercise [2].

To solve above problems, we developed an application which detects activity, counts number of repetitions, predicts user's comfort factor and measures calorie burnt.

B. Prior Works

Smartphones and Wearables are ubiquitous and becoming more and more sophisticated, with ever-growing computing, networking, and sensing powers. This has been changing the landscape of people's daily life and has opened the doors for many interesting data mining applications in the realm of indoor fitness.

The recent trend in activity recognition is towards sport activities like swimming and gym exercises [3]. Google Fit application for smart-watches [4] identifies the number of repetitions count for an exercise only after manually selecting the activity. Samsung Health application for wearable [5] detects a workout automatically but it is limited to outdoor activities. Also these applications do not provide any information on what is the user's ease of doing exercise. There are some studies which concentrates on wearable sensor based gym exercise recognition like [6] and [7]. The results achieved in these studies are quite promising but there is no talk about the user's ease of doing those activities.

II. Proposed System

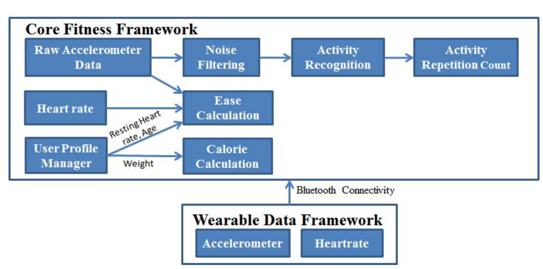

Fig. 1. Architecture.

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Architecture of the proposed system is depicted in Fig. 1. Core fitness framework is explained in below subsections:

A. Data Collection

Around 850 hours of data were collected for training purpose from 78 different volunteers (53 males and 25 females). Consent was taken from all the participants to collect their data and use for experimental purpose. Volunteers were allowed to wear the smart watch on any of the wrists. The Heart Rate Monitor (HRM) belt was tied around the chest. They were instructed to perform each activity multiple times along with some random movements. The mean age and mean weight of volunteers was 33.4 years and 72.2 Kgs with standard deviation of 9.6 and 22.1 respectively.

We collected 3-axial linear acceleration data without gravity from Samsung Gear S3. The smart watch collects the data at 25 Hz sampling frequency and sends to Samsung Galaxy Note5 smartphone. At the same time, with HRM belt, heart rate data was collected and sent to the same smartphone. We mapped the heart rate and accelerometer data based on the timestamp. At the end of each set, all the volunteers provided the annotated comfort value on the scale of 1 to 10; 1 being lowest and 10 being highest exhaustion during the workout. User's RHR value is taken from Samsung Health application.

B. Noise Filtering

For activity recognition and cycle count calculation, signal should be noise free. We tried various noise filtering algorithms like DFT (Discrete Fourier Transform), STFT (Short Time Fourier Transform) and Wavelet transform [8] on the accelerometer signal. After initial analysis on our data, we found that wavelet transform was best suited as the signal can be analyzed at different frequencies and at different time resolutions. For our experiment we used a Morlet wavelet.

As activity recognition and repetition count is calculated at real-time, raw signal is processed dynamically. The wavelet is scaled along the time axis to provide the frequency bands of interest by convolving it with the raw signal at a particular moment. Based on our analysis on the training datasets, we divided noise into 4 levels, each of which corresponds to a particular frequency. Thus, we found that there are 4 relevant frequency bands as shown in Table 1. The noise level is decided depending on the number of slope changes in 50 continuous trained data points. Slope change occurs when 2nd accelerometer value is lesser/greater than 1st and 3rd value in 3 consecutive data points. More the slope changes, more the noise in the signal.

TABLE I. FREQUENCY LEVELS FOR VARIOUS NOISE LEVELS

Number of slope changes (50 data points)	>24	20-24	12-20	<12
Wavelet Frequency (Hz)	0.15	0.25	0.40	0.80

C. Activity Recognition

The system detects Biceps curl, Chest fly, Squats, Push up, Row, Sit up and Triceps curl activities. Activities outside the scope of these movements are recognized as random exercises. For the development of the system, initially 24 features were derived from each 2 seconds sample window of the training data. Among these features, 14 were selected based on their significance and computational efficiency.

TABLE II. FEATURE CATEGORIZATION

Derived Features	
Pair Wise Correlation	Correlation between x and y component of acceleration
	Correlation between y and z component of acceleration
	Correlation between z and x component of acceleration
Dominant Axis	Standard deviation of the signal along the x component of acceleration.
	Standard deviation of the signal along the y component of acceleration.
	Standard deviation of the signal along the z component of acceleration.
Pair Wise Dominant Axis Factors	Multiplication result of standard deviation of x and y component of acceleration signal.
	Multiplication result of standard deviation of y and z component of acceleration signal.
	Multiplication result of standard deviation of z and x component of acceleration signal.
	Absolute Difference between standard deviation of x and y component of acceleration signal.
	Absolute Difference between standard deviation of y and z component of acceleration signal.
	Absolute Difference between standard deviation of z and x component of acceleration signal.
Stillness Factor	Standard deviation of the resultant of the tri-axial acceleration signal.
Signal Time Period	Time period of the tri-axial resultant acceleration signal

Initially, we used off the shelf J48 decision tree, K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) for the activity recognition using the features shown in Table 2. However, a Deep Neural Network (DNN) classifier system yielded the most accurate result with these features. The accuracy comparison is shown in Table 3.

TABLE III. COMPARISION OF ACTIVITY CLASSIFICATION ACCURACY

Classification Algorithm	**J48**	**KNN**	**SVM**	**DNN**
Accuracy (%)	72	77	83	95

Classifier Structure Configuration: We divided the datasets into 60:20:20 ratio for training, cross validation, and testing purpose. Based on the result from the cross validation data, our system is configured with 2 hidden layers and 0.03 learning rate. The hidden layers consist of 10 and 8 units respectively. We used WEKA Machine Learning library [9] for this training phase.

D. Activity Repetition Count

From the training dataset, we noticed that, amplitude and noise is not constant for the entire signal. Amplitude of the signal is less and noise is more when exercise pace is slow as depicted in Fig. 2. Amplitude varies for different exercises even after maintaining same pace as depicted in Fig. 3.

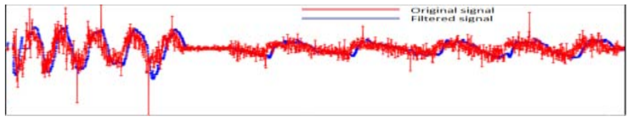


Fig. 2. Same exercise with varying pace.

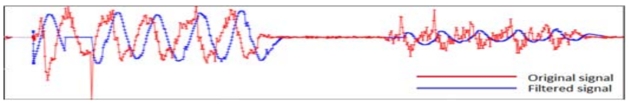


Fig. 3. Biceps curl and Chest fly exercises with same pace

Hence we need threshold for amplitude to detect valid cycles in the signal. This threshold should be different for different noise levels and different exercises. We observed from training dataset that amplitude value more than |15| is a false spike. Hence in each workout, various thresholds are tried for positive peak and negative peak from 0 to |15| with increments of 0.005 and root mean square error is identified for cycle count. 10 threshold values (t1 to t10) with least root mean square error is noted. Average of these 10 threshold values are tabulated in Table 4. When user is performing exercise, valid cycle is determined if amplitude of peak/valley is between ±2 standard deviation of average values mentioned in Table 4. Then amplitude of current valid cycle is stored as t1. Existing t1 to t9 is shifted one position and t10 is removed. This way system always updates with user's movement.

TABLE IV. AVERAGE POSITIVE AND NEGATIVE PEAK VALUES

Activity	Biceps curl	Chest fly	Squat	Push up	Row	Sit up	Triceps curl
Average +ve Peak	3.42	5.19	10.23	0.18	8.35	1.35	3.26
Average -ve Peak	4.26	5.06	12.36	0.10	9.41	2.14	4.01

In our experiment, we observed that user can do max 2 cycles per second and minimum 0.2 cycles per second for selected workout types. This means, our required filtered signal should consist of frequency only in 0.2 – 2Hz range. Frequency above this range is considered as noise and below this range is considered as unwanted data. Peaks and Valleys which matches threshold for recognized activity are considered as valid cycles in waves. By following this approach, we are able to achieve better accuracy for repetitive count calculation.

E. Calorie Calculation

For calories calculation (1), we have used the predefined MET [10] value for the recognized activity along with weight of the user and the activity duration.

$$CalorieBurnt = MET * Weight(kg) * time(Hours) \quad (1)$$

F. Comfort Factor

The comfort factor depicts a user's ease of doing an activity over the time. Noise is a major entity in calculating Comfort factor. As user gets tired, tremor increases which results in more noise in the signal. Depending on the noise level in the signal and user's heart rate, comfort factor is predicted on the scale of 1 to 10. Methods used for comfort factor calculation are described in detail below.

1) Comfort factor calculation using exercise Time period variance: The system finds out the comfort factor of the user during each set. We observed that comfort factor is directly proportional to the peak to peak magnitude but inversely proportional to the time period of the cycle. So, we derived a feature periodicAmplitudeFactor as in (3) to make a wider separation of this feature for a user's comfort level during an exercise.

$$peakToPeak = positivePeak - negativePeak \quad (2)$$

$$periodicAmplitudeFactor = \frac{peakToPeak}{timePeriod} \quad (3)$$

If a user is not comfortable during the workout, periodicAmplitudeFactor varies otherwise it almost remains the same over the entire set. For each set, we determine the Comfort factor as in (4) by calculating the variance of this periodicAmplitudeFactor.

$$Ease\ factor = variance(periodicAmplitudeFactor) \quad (4)$$

However, in the case of gradual increase of a user's exercise movement, variance may not be the best candidate as the comfort indicator. So, we analyzed the pattern of the periodicAmplitudeFactor variation after each set to find continuous positive gradient points for sliding window of 4 consecutive cycles. Proposed System rates user's comfort level by observing previous comfort factor for the relevant exercise with same weights. Meanwhile, the system will store the current observations for future comfort measurement.

2) Comfort factor calculation using hand Tremor and Heart rate variation relation: We observed that comfort of an exercise is more dependent on the muscle tiredness rather than only physical exhaustion and heart rate variation. When there is muscle tiredness, some mild but undesired periodic involuntary tremor starts in the exercising hand. From this observation, we devised a relation between user's heart rate and exercise hand tremor factor at the exercise exhaustion limit. This provides a user's comfort of performing an exercise after each set. We calculated A_{sum} (sum of three axes values) from the collected 3-axial acceleration data. Derived features are explained below.

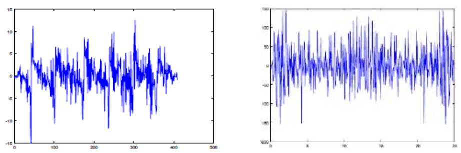
a) Heart Rate Factor during tremor (HRF_{tremor}): We used A_{sum} for the tremor signal analysis. We extracted the frequency representing the tremor or shake from the signal. We identified the Tremor frequency using wavlet transform from numerous numbers of exercise trials. This frequency lies between around 5Hz – 9 Hz as shown in Fig. 4(a) and Fig. 4(b). During the tremor we captured the Average Heart rate ($HRtremor$) value. By incorporating Resting Heart Rate (RHR), Maximum Heart Rate (MHR) and $HRtremor$; Heart Rate Factor value is calculated as in (5). RHR and age is taken from the user's profile data.

$$\mathrm{HRFtremor} = \frac{\mathrm{HRtremor} - \mathrm{RHR}}{\mathrm{MHR} - \mathrm{RHR}} \quad (5)$$

b) Noise Ratio Factor (NRF): Using SNR (Signal to Noise ratio) value, we derived the Noise Ratio Factor (NRF) as in (6).

$$NRF = \frac{1}{1+SNR} \tag{6}$$

NRF provides noise power component present in the signal for each workout set. This factor increases as user becomes uncomfortable during exercise.



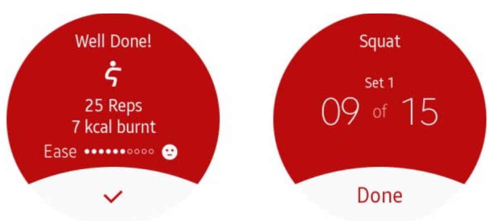
(a) (b)

Fig. 4. Time and frequency response of signal (A_{sum}) with tremor.

We annotated the ease on scale of 1-10 and derived a multinomial logistic regression model using HRF_{tremor} and NRF. When we generalized the real data using our model, we observed average Root Mean Square error of 1.93.

III. RESULT

Beta version of the proposed system without activity recognition is already released in Samsung Tizen gear app store as Strength Training. Fig. 5 depicts the screenshots of the strength training application in Gear S3 smartwatch. Fig. 5(a) shows squat workout completed with 25 repetitions and 7 Calories are burnt with 60% ease. Fig. 5(b) shows user performing set 1 of squat exercise.



(a) (b)

Fig. 5. Screenshots of Tizen Strength Training application from Samsung Gear S3 Smartwatch.

The results from DNN classifier for activity recognition are tabulated in Table 5. First column represent the activities performed by user. Header row indicates activities detected by our system. Table 6 represents the repetition count and accuracy obtained from the algorithm.

TABLE V. CONFUSION MATRIX FOR ACTIVITY RECOGNITION

	Biceps curl	Chest fly	Row	Push up	Sit up	Squat	Triceps curl	Random
Biceps curl	956	0	1	0	0	0	25	18
Chest fly	3	948	0	1	0	3	0	45
Row	0	3	954	6	0	1	1	35
Push up	5	0	2	912	0	1	0	80
Sit up	0	0	0	1	957	0	13	29
Squat	0	0	4	0	0	987	0	9
Triceps curl	20	0	0	1	0	0	961	18

When user completes the exercise, ease of the user is taken in the scale of 1 to 10. Root mean square error is calculated using user given comfort value and algorithm calculated value. Average RMS for all the participants for each of the exercise is tabulated in Table 7.

TABLE VI. REPEATATION COUNT FOR VARIOUS EXERISES

Activities	Biceps curl	Chest fly	Row	Push up	Sit up	Squat	Triceps curl
Actual count	1000	1000	1000	1000	1000	1000	1000
Calculated count	994	999	989	979	998	1000	999
Accuracy (%)	99.4	99.9	98.9	97.9	99.8	100	99.9

TABLE VII. COMFORT FACTOR VERIFICATION

Activities	Biceps curl	Chest fly	Row	Push up	Sit up	Squat	Triceps curl
Root Mean Square error	1.69	2.25	2.03	1.58	1.34	2.85	1.83

IV. CONCLUSION

Sensor analytic challenges in indoor fitness equipment are quite unique as variations in sensor data are very limited. In depth analysis of sensor data by applying techniques like threshold adapter is required to improve the repetition count accuracy. We could achieve accuracy of over 99% for exercise count and 95% for exercise recognition with the techniques employed. Our comfort factor calculation algorithm does not perform very well when a user intentionally varies the speed of exercise movements and hence comfort prediction accuracy is around 75%. As a future work, we will improve ease prediction accuracy by incorporating further feature sets. Also, this method can be extended to include more indoor exercises.

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