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A Hybrid Hierarchical Model for Accessing Physical Activity Recognition towards Free-living Environments

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Abstract—**Driven by the new revolution in healthcare, the importance of understanding Physical Activity (PA) in the uncertain, dynamic, free-living environments has been drawing growing attention. However, there is a lack of holistic investigation on how to improve the accuracy of PA recognition in free-living environments using cost-effective wearable devices with feasible algorithms. In this paper, we design a two-layer hybrid hierarchical model for accessing and evaluating cost-effective wearable intelligence approaches for PA recognition in free-living environments. The hypothesis of this model first suggests utilising less-attached on-body consumable wearables like belt and wristband devices, and then building up a PA dataset collected in free-living environments like an elderly home, hospital, office and gym. The model is then defined with components of lightGBM (LGB) and Artificial Neural Networks (ANN) for coarse and fine-grained classification, parameters of achieving high recognition rate including time window sizes, features and activation functions. The experimental results indicate that our model has superior ability over other state-of-the-art algorithms in classifying three typical types of PA (dynamic, sedentary, and transitional) with an average accuracy up to 84%. Specifically, our model performs good results of PA recognition with the ageing populations including 5 Mild Cognitive Impairment (MCI) and 17 Parkinson's disease (PD) patients.**

Keywords — Physical activity recognition; artificial neural networks; wearable device; healthcare

I. INTRODUCTION

The innovative opportunities in the forthcoming years of revolution of healthcare enable advanced cutting-edge information and communications technology (ICT) and applications that can provide cost-effective and pervasive personal healthcare services for people in daily free-living environments. Physical Activity (PA) [1] has been gaining importance on a range of clinical healthcare applications. The design and development of innovative and effective technologies [2, 3] for supporting long-term monitoring, recognition and analysis of people's daily PA, intensities and their associated parameters have been drawing much attention over the last decades. These technologies bring great benefits to many current healthcare cases and applications including early diagnosis and treatment and rehabilitation, etc.

Among a myriad of ICT applications dealing with PA monitoring and recognition, many studies [4]-[6] show that traditional approaches of leveraging advanced on-body wearable sensors, extraction of reliable features and classification algorithms can provide relatively high accuracy of PA recognition and their associated parameters in many controlled environments. These techniques have great potential on healthcare services [7]. A typical procedure of these studies is composed of three stages: (1) to select and place multiple wearable sensors [8] on different positions of human body for acquiring different the PA from different types of users and related signal data; (2) to extract distinguished and reliable features [9] ultimately from the acquired multi-modal signal data; (3) to use advanced machine learning or classification algorithms [10] to classify different types of PA. Thus, towards conventional PA recognition approaches in controlled environments, their performance heavily depends on the factors like data quality and sensitivity of wearable devices, reliability of selected features and performance of training algorithms.

However, in free-living environments, low-cost and easy-to-use wearable devices with embedded inertial sensors (e.g., mobile phone or wrist band) have been widely becoming daily necessities. Traditional PA recognition approaches suffer from low accuracy and weak robustness of objectively qualifying PA in free-living environments due to many restrictions. The first limitation is that there are fewer wearable devices (i.e., less-attachment) that are attached to people in free-living environments, because in reality most people only take one wearable product. It is extremely hard to achieve good physical activity recognition rate (PAR), when compared a data collected in labs. Some studies have more coarse and fine-grained classification, parameters of achieving high recognition rate including time window sizes, features and activation functions. More specifically, we have concentrated on evaluating parameters of three pre-defined categories containing over 15 PA types through our designed hierarchical framework: repetitive dynamic PAs (DPA), sedentary PAs (SPA) and transitional PAs (TPA). Notably, DPA and SPA are detected directly by using ANN; TPA is processed by the combination of LBM and ANN. The procedure includes time window sizes, while features and activation functions are evaluated under different types of activities. We evaluate our proposed model with data collected in free-living environment with 4 datasets in a gym, home, office and hospital, and participants include Mild Cognitive Impairment (MCI) patients, Parkinson's disease (PD) patients and healthy students and staff at university for the purpose of improving robustness of the model. The experimental results with average accuracy of up to 84% indicate that our model has superior ability over state-of-the-art algorithms [12-14] in classifying three typical types of PA (dynamic, sedentary and transitional) collected by belt and wrist devices in free-living environments.

The remainder of the paper is structured as follow: Section II describes the methodology. Section III presents the results of experiment. Finally, the discussion and conclusion are given in Section IV and Section V.

II. Methodology

There are five steps in the PAR structure, as shown in Figure 1, which collects accelerometer and gyroscope signals from one or more wearable devices over the participants' body. The data will be then transmitted through Bluetooth or Zigbee to be processed. As the raw data usually contain redundant information, the data is first be pre-processed through filter and absolute maximum normalization, and subsequently divided into time windows. Key features extracted from the signals are time-domain and frequency-domain, as such, it can provide useful and robust representation for the learning stage. Due to the high dimensional space produced by the two wearable devices with four sensors, we use a series of dimensionality reduction methods. The learning step eventually classify these features into different basic PA types, and finally outputs the recognized activities.

We propose a hierarchical PAR model that includes two layers. Two wearable devices with embedded accelerometer and gyroscope are exploited for data collection. As ANN has great performance on repetitive signals classification such as DPA and SPA but suffers from TPA, we separate the recognition procedure into two steps. In layer 1, feature set 1 from peak amplitude, width of peaks, mean, standard deviation and Fast Fourier Transform (FFT) are extracted for coarse classification of DPA, SPA and TPA. Then feature set 2 which covers entropy, correlation, root mean square, etc. of each 3D axis in both time domain and frequency domain are extracted and then LGB is applied on TPA for feature reduction and further fine-grained classification. Eventually, ANN is utilized for the final 15 types of PA recognitions. The proposed framework will be explained in detail in the next sub-section.

A. Data Collection

We use Shimmer3 Inertial measurement units (IMU) to collect data, as shown in Figure 2. The sampling rate of the sensors is 204 Hz. The PAs are categorized into 16 dynamic, sedentary and transitional, presented in Table II, from 10 healthy participants and 5 MCI patients at a lab. Two sensors are placed on the wrist and waist. Each dynamic and sedentary PA is performed for 1 minutes, and the duration of each transitional PA is 3 to 5 seconds for 10 repetitions (Table I). We used video recordings to label PA types. The participants were not asked to perform each PA as a certain position but based on their how they would normally do them in their casual, daily lives. Dataset shown in Table I is from Shimmer devices and placement of the body. We also found data on daily activities of 17 Parkinson's patients [15] downloaded from the Internet. The dataset of gym PA detection is from our previous work [16]. Table I shows a variety of activity data collected from people of different ages and levels of health (including fitness enthusiasts in their 30s, regular people in their 20s, people over 50 with mild cognitive impairment and those diagnosed with Parkinson's disease) in four different environments (gym, classroom, housing, outdoor). A mobile phone (Samsung Galaxy S6) was connected to the shimmer devices via Bluetooth.

B. Data Preprocessing

We exploit 3D linear accelerometer and 3D gyroscope data on wrist and waist positions. Temporal segmentation and feature extraction are the crucial steps to process signal data. The sensory dataset is broken down with temporal series by sliding time windows. The minimum time point of the peak and the width of peaks in transitional PA is 5s; thus, in our hierarchical framework, ten-second window length with no overlapping is applied in the first layer. In the second layer, the window size is segmented to 50, 100 and 200 samples respectively with 50% window overlapping.

The datasets are broken down with temporal series using time windows and then sliding window is applied for feature extractions. A straightforward metrics signal magnitude vector (SMV), presented in the formula (1), is used to directly process signals of 3D inertial sensor and provides a measurement of the degree of activity intensity.

$$\mathrm{SMV} = \sqrt{x_i^2 + y_i^2 + z_i^2} \tag{1}$$

Tilt angle (TA), presented in the formula (2), and refers to the relative tilt of the body in space. It is defined as the angle between the positive z-axis and the gravitational vector g and is calculated according to

$$\mathrm{TA} = \arccos(\mathrm{z}) \tag{2}$$

C. Features Extraction

Time domain features involve root mean square (RMS), magnitude, covariance, variance, min, max, etc. for example, the standard deviation is to stabilize the sensory data and the mean is to remove redundant information. Additionally, Frequency domain includes Fast Fourier transform (FFT) and spectral entropy (SE) in this work.

In the first layer, with two sensors of on the wrist and waist, dynamic, sedentary and transitional PA are coarsely classified. The features are extracted from peaks, width of every two peaks, mean and standard deviation. Also, FFT are also applied to with reconstructed component and the frequency with maximum peak components.

In the second layer, in order to estimate the feature performance for further fine-grained recognition, two feature sets from four sensors placed on the people's wrist and waist are selected for further comparisons. The first set is 16 basic

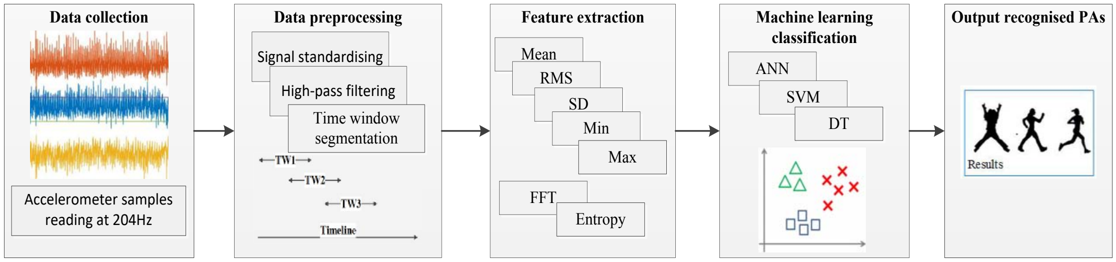
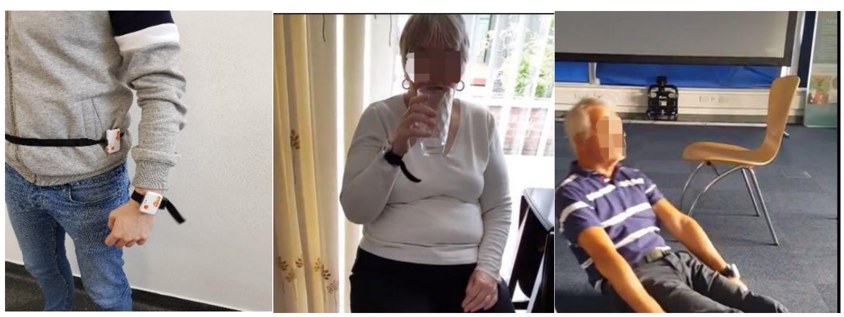


Figure 1. 5 steps of sensor-based PAR procedures

TABEL I DATASET DESCRIPTION

GYM		HEALTH		MCI		PD	
Serial number	Activity name	Serial number	Activity name	Serial number	Activity name	Serial number	Activity name
A1	Squat-light	B1	Pick up	C1	Bend-stand	D1	Standing
A2	Walk	B2	Drink	C2	Circle	D2	Walking straight
A3	Jog	B3	Open	C3	Close	D3	Walking while counting
A4	Run	B4	Close	C4	Downstairs	D4	Stairs up
A5	Cycle	B5	Walk	C5	Drink	D5	Stairs down
A6	Up	B6	Upstairs	C6	Lie	D6	Walking through a narrow passage
A7	Row	B7	Downstairs	C7	Lie-to-sit	D7	Finger to nose – right arm
A8	Bench-light	B8	Sitting	C8	Open	D8	Finger to nose – left arm
A9	Dead-light	B9	Standing	C9	Pick up	D9	Repeated arm movement – right arm
\	\	B10	Lying	C10	Place down	D10	Repeated arm movement – left arm
\	\	B11	Stand to sit	C11	Sit to lie	D11	Sit to stand
\	\	B12	Sit to lie	C12	Sit to stand	D12	Drawing and writing on a paper
\	\	B13	Lie to sit	C13	Standing	D13	Typing on a computer keyboard
\	\	B14	Sit to stand	C14	Stand to bend	D14	Assembling nuts and bolts
\	\	B15	Bend-stand	C15	Stand to sit	D15	Take a glass of water and drink
\	\	B16	Circle	C16	Stairs up	D16	Organizing sheets in a folder
\	\	\	\	C17	Walk	D17	Folding towel
\	\	\	\	\	\	D18	Sitting



(a) (b) (c)

Figure 2. PA data collection with the two wearable devices from (a) healthy participants in controlled and uncontrolled environments; (b) MCI patients in an uncontrolled environment; and (c) MCI patients in a controlled environment

time domain features and 4 frequency domain features; while the second set is 66 time domain and 12 frequency domain features. Feature details are shown in the Table II, where x, y, z represent three axes of inertial sensors.

D. LGB-based Feature Selection

As hundreds of features are extracted from multiple sensors, a new feature space to project the data is needed to maximize class separability as well as to avoid overfitting in the learning process. As such, LGB are used and compared to reduce the dimension of our feature set. LGB is performed on a fast, distributed, high-performance gradient boosting framework based on a decision tree algorithm and thus to obtain feature rankings for transitional PA. The LBM algorithm can produce better results than any existing boosting algorithms.

Let the training set $X = \{(x_i, y_i)\}$, LGB can find an approximation $\hat{f}(x)$ to a certain function *f(x)* to minimize the value to a loss function *L(y,f(x))* as the formula (3)

$$\hat{f}(x) = argminE_{y,X}L(y, f(x)) \quad (3)$$

And then integrates the regression trees functions $\sum_{t=1}^{T} f(X)$ to the model as shown in the formula (4).

$$f_T(X) = \sum_{t=1}^{T} f_T(X) \quad (4)$$

III. RESULTS OF PROPOSED FRAMEWORK

As the calibrations vary from different participants, *we* selected the 5Hz to 25Hz bandpass filter to smooth the raw signals and then standardise them by removing DC components. Outliers are consequently removed through standard deviation.

Figure 3. presents the preprocessed signal waveforms from three axes respectively in the *Bend-over-to-stand* of the wrist sensor during one window length. The top three subfigures are the x, y, z axis data from the accelerometer after preprocessing and the bottom subfigure presents the SMV waveform.

In our two-layer framework and because ANN suffers from the performance of TPA, we firstly separated PA as three main categories with 5 features, and then applied ANN directly on DPA and SPA. The TPA dataset (Figure 3.) is organized by LGB with the feature importance ranking. Our proposed model is compared with the latest deep learning algorithms [17, 18] and new machine learning algorithms [19, 20] such as lLGB) [19]. Overall, our proposed model has greater performance than SVM, DT and ANN. LSTM [20], the deep learning algorithm, is not applied to the active datasets we collected and only performs well on individual datasets. The GYM dataset has fewer kinds of activities, and the amount of data for each activity is relatively large. Besides, the activity type of the GYM dataset is simple, so it shows a high accuracy rate with LSTM. The HEALTH and PD datasets have more types of activities than the GYM dataset, and the data corresponding to a single activity is reduced, resulting in a low accuracy rate when using LSTM. The three MCI datasets had the lowest classification accuracy, because these datasets had many active categories and too small data sizes. CNN [18] has almost the same effect as LSTM. In this CNN model, every sample is a matrix with the size of 32 (batch sizes) ×3 (X, Y, and Z axis data) × 600 (data of three seconds). After the first convolution layer, the data size obtained is (32, 16, 600). The output data size of the first max-pooling layer is (32, 16, 120), and the output data size of the second convolution layer is (32, 32, 118). After the last max-pooling, the data size obtained is (32, 32, 40).

In these datasets, the overall effect of traditional SVM [21] and DT algorithm is better than LSTM. Clustering algorithm KNN [23] has a high classification accuracy for data containing only a few people, and its performance decreases by 10% when the number of users increases. The accuracy of LGB for different datasets is relatively uniform, but the overall accuracy is not as good as our model, and XGB [20] has poor training effect for a small amount of data. The specific results are as displayed in Table III and Figure 4.

IV. Discussion

From different conditions, people, devices, and optimised algorithms of the recognition accuracy, we can safely conclude that the PA recognition with a small number of wearable devices in the uncontrolled environment within different categories of participants are not fully and successfully resolved. This is mainly because there are many uncertainties and issues in an uncontrolled environment. Some other investigations also show that the recognition accuracy would drop significantly when out data is collected in such non-controlled environments. Whether the traditional learning algorithms can be effectively applied in larger scales within such conditions is still challenging now.

In this work, we have collected sensor data both in lab and home environments from healthy participants and MCI patients, simulating wearable placements in the fully uncontrolled environment using two sensors on the wrist and waist. A typical machine learning approach ANN was firstly evaluated. The results show that it is robust in repetitively dynamic and sedentary PA but it suffers especially from transitional PA. The results show that ANN has the best experimental results on SPA and DPA but it is not suitable for TPA. Therefore, a recognition hierarchical framework was proposed with two layers. In the first layer, with amplitude of peaks, width of peaks, mean, stand deviation and FFT, DPA, SPA and TPA are coarsely classified. Then, in the second layer, the repetitive DPA and SPA movements are further fine-grained classified with LGB and ANN. Our potentially guide the application of our model into other real-world PA recognition scenarios, where the focus is on using few wearable devices. For instance, for people who can use a wristband and/or belt device daily in their homes (an uncontrolled environment), our model can enhance the number of recognized PA types and accuracy of their intensity.

TABEL II EXTRACTED FEATURE SETS

(Std: standard deviation; Corr: correlation; rms: root mean square; var: variation; FFT: Fast Fourier transform; Se: spectral entropy; s: signal magnitude vector; a: tilt angle; Ac_mean: mean of autocorrelation coefficient)

Category	Feature sets in layer 1	Feature sets 1 in layer 2	Feature sets 2 in layer 2
Time domain	Peak points (s), Peak width (s), mean(s), Std(s)	Min(x,y,z,s), Max(x,y,z,s), Mean(x,y,z,s), Std(x,y,z,s)	Mean(x,y,z,s,a), Max(x,y,z,,a), Min(x,y,z,s,a), Std(x,y,z,s,a), Corr(xy,xz,xs,yz,ys,zs), Rms(x,y,z,s,a), Var(x,y,z,s,a) Ac_mean(x,y,z,s,a) Ac_max,Ac_min,Ac_std (x,y,z,s,a) Skewness (x,y,z,s,a) Kurtosis(x,y,z,s,a)
Frequency domain	FFT(s)	FFT(x,y,z,a)	FFT(x,y,z,s), Se(x,y,z,s) Entropy (x,y,z,s)

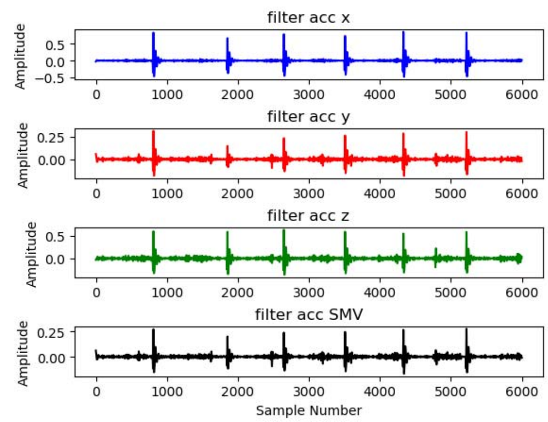


Figure 3. Accelerometer data of *Bend-over-to-stand* from the waist sensor: X axis (1st subfigure), Y axis (2nd subfigure), Z axis (3rd subfigure) and SMV (4th subfigure) after filtering, standardizing and outlier removal.

V. Conclusion

In order to improve the quality of life of a person who suffers with chronic diseases and maintain fitness for active healthy people, pervasive technologies for self-care can achieve related behaviours. However, with the revolution in

TABEL III

Dataset	Our model	LSTM[20]	CNN[18]	SVM[21]	DT[22]	KNN[23]	LGB[19]	XGB[20]
GYM	0.88	0.79	0.8	0.83	0.76	0.84	0.81	0.87
HEALTH	0.81	0.47	0.48	0.76	0.62	0.69	0.83	0.84
MCI	0.81	0.26	0.31	0.75	0.59	0.81	0.80	0.68
PD	0.84	0.58	0.66	0.81	0.71	0.74	0.81	0.80
Average	0.84	0.53	0.56	0.79	0.67	0.77	0.81	0.80

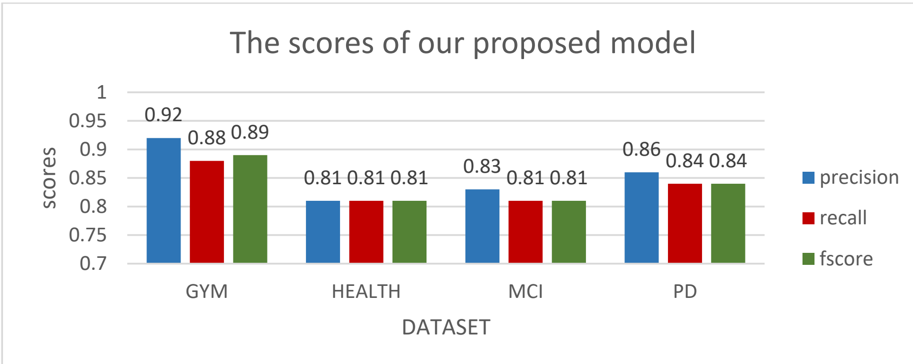


Figure 4. The scores of precision, recall, f-score of our proposed model

healthcare, it is questionable whether the traditional machine learning approaches can tackle such uncertain and practical conditions. In this paper, just by using two wearable devices on the waist and wrist and 20 healthy participants and MCI patients, we developed a hierarchical recognition framework with two feature sets, feature reduction and classification methods LGB and ANN. We then compared and evaluated the performance of two feature sets and four-time window sizes on three ANN activation functions, both in lab and non-controlled environments, respectively. The results show that the proposed framework have satisfactory performances especially in uncontrolled conditions and when few wearable sensors are used by different types of users and in various scenarios.

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