Experimental Analysis of Artificial Neural Networks Performance for Physical Activity Recognition Using Belt and Wristband Devices

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Abstract— **Physical activity (PA) is widely recognized as one of the important elements of personal healthy life. To date, as the development of wearable sensing technologies, it is possible to utilize wearable devices and machine learning algorithms to efficiently and accurately monitor PA types, intensity and its associated human pattern for many health applications. But there is a trade-off between less-attachment of wearable devices and achievement of high accuracy in existing PA recognition studies. This paper attempts to investigate possible utilisation of Artificial Neural Networks (ANN) achieving high recognition accuracy of PA using less-attachments of wearable devices. Following a four-steps designed experimental protocol, we collect the real activities dataset with only belt and wristband devices from 10 healthy subjects at home and gym environment. The parameters of typical PA recognition with ANN including time window sizes, features and activation functions are evaluated under 24 different subjects of activities. The experimental results indicate that ANN dealing with belt and wristband data can achieve satisfactory PA recognition results in dynamic and sedentary activities but suffers from transitional activities in both environments.**

Index Terms — Physical activity recognition, artificial neural networks, wearable device, healthcare

I. Introduction

As one of the most representative indicators to personal health and well-being, effective Physical Activity (PA) measure has been posing great significance on a wide range of clinical practice and health applications. Understanding, recognition and analysis of PA types, intensity and its associated human behaviour patterns enable great benefits to many healthcare cases, including diagnosis and treatment of chronic diseases, self-rehabilitation programme, and fitness maintenance. Thus, a large number of innovative ICT enabled techniques [1]–[3] recently have been studied in this field, aiming at providing cost-effective solutions for automatically recognizing various types of PA and accurately measure their intensity and associated parameters. These techniques have demonstrated some great potential on benefiting healthcare services like clinical intervention to elder and chronically ill people [4], or sports training progression to physically active people [5].

Regarding training algorithms for PA recognition studies, researches have been exploring supervised learning algorithms [6] for processing data from a variety of wearable sensors, including motion sensors, mobile phone and smart watch with imbedded accelerometer and gyroscope. Typical supervised learning algorithms here include support vector machine (SVM) [7], hidden Markov model (HMM) [8], Decision trees (DT) [9], Artificial Neural Networks (ANN) etc. Among these algorithms, owning to strong capabilities of dealing with non-liner classifications, ANN classifier has provided an effective approach in PA recognition and prediction with model complex patterns. It is a parallel and distributed information structure that consists of artificial neurons and connections. Especially, ANN performs better performance on larger datasets than other machine learning algorithms.

While these technologies can recognise over twenty different activity subjects with accuracy up to 98%, their experimental results are mostly evaluated under laboratory environment. Also, the achievement of outstanding recognition accuracy usually requires sufficient number of wearable sensors being attached on human body. The adoption and utilisation of existing work may hardly provide accurate state detection and monitoring with moderate complex implementation in an uncontrolled environment like human daily life. Thus, there is a trade-off between less-attachment of wearable devices and achievement of high accuracy in existing PA recognition studies. Especially, considering the real-world fact that most people only take one wearable product, it is extremely hard to achieve good PA recognition accuracy as the one in labs [10]–[12]. The motivation of the work in this paper is to investigate the possible solution of achieving high recognition accuracy of PA using less-attachments of wearable devices. Assuming that belt and wrist devices are most commonly used wearable products, we have mainly considered the cases of using these two wearable devices in home-based PA recognition. Then, we focus on evaluating and analysing performance of ANN algorithms under these cases.

In this work, we have concentrated on evaluating parameters of typical PA recognition using ANN including time window sizes, features and activation functions are evaluated under different subjects of activities. we have data collection in semi-natural environment of daily living environment. The accelerometer data are collected through Shimmer wearable sensors from the wrist and waist of 15 healthy subjects who stay physically active, and age between 24 to 36 years old. But each accelerometer's performance is validated separately. We validate the ANN models' performance with only one accelerometer from each sensor

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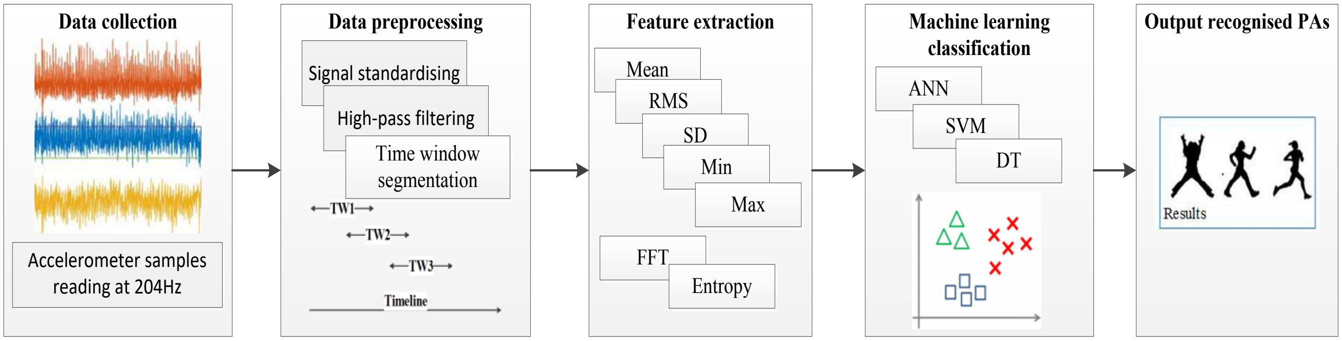

Figure 1. Sensor-based PAR procedures using machine learning approaches

and present comparisons four different time window sizes, two PA datasets of daily PA and gym PA, three activation function combinations of ANN from each sensor.

The remainder of the paper is structed as follow: Section II describe the data collection procedures. Section III gives the data collection procedure. Section IV presents the overview of data processing approached used in this paper. And Section V illustrates the results and analysis of ANN. Finally, discussion and conclusion is given in Section VI and Section VII.

II. Evaluation Methodology

Five steps are involved in PAR structure, as shown in Figure 1. The general system collects information from wearable sensing devices from one or more different parts of the subject's body and then the signals transmit through a middleware such as Bluetooth or Zigbee. These wearable devices are embedded with accelerometer, gyroscope, pressure sensors, magnetic field sensors etc. Among this data, accelerometer and gyroscope play significant roles in PAR sensing. As the raw data usually contain redundant information, the data will first pre-processed through standardising and filtering, and subsequently divided into overlapping or non-overlapping time windows. Key signal features using time-domain, frequency-domain or other techniques are collected in the feature extraction phase in order to provide more useful and robust representation. The activity classification/clustering step eventually categorizes these features into different basic PA types. And finally output the recognised activities.

III. Data Collection

We use Shimmer3 IMU units for PA data collection, shown in figure 2. The frequency rate of the wearable sensors is 204 Hz which is 15 dynamic, sedentary and transitional, as presented in table1, are collected from 15 healthy subjects. Two sensors are placed on the wrist and waist. Each PA is performed 1 minutes and repeated 10 times. Videos are recorded for the purpose of labelling PA types. The subjects were not asked to perform PAs as a certain position but their own casual daily activity habits. Dataset 2 shown in table II is from our previous work of gym PA detection [13] by using the same devices and placement.

A Samsung Galaxy S6 was used to connect to the shimmer devices via Bluetooth. An Android application called Multi Shimmer Sync Evaluation was used to connect the devices

Figure 2. Wearable sensors setup for PA data collection

TABLE I. Activity Types and Categories

Activity	Activity name	Activity category
A1	Picking Up and down Object	Dynamic
A2	Taking a Drink of Water	Dynamic
A3	Opening a door	Dynamic
A4	Closing a door/cupboard	Dynamic
A5	Walking	Dynamic
A6	Walking upstairs	Dynamic
A7	Walking downstairs	Dynamic
A8	Sitting	Sedentary
A9	Standing	Sedentary
A10	Lying	Sedentary
A11	Stand-to-Sit	Transitional
A12	Sit-to-lie	Transitional
A13	Lie-to-sit	Transitional
A14	Sit-to-stand	Transitional
A15	Bend over-to-stand	Transitional

TABLE II. Typical Gym Physical Activities in Categories

Activity class	Activity name	Activity category
B1	Walking	Dynamic
B2	Jogging	Dynamic
B3	Running	Dynamic
B4	Cycling	Dynamic
B5	Ascending	Dynamic
B6	Rowing	Dynamic
B7	Bench press	Transitional
B8	Deadlift	Transitional
B9	Squats	Transitional

and collect data. This application allows for the streaming and logging of data from multiple devices. Shimmer devices can be configured using the application.

IV. Data Processing

A. Feature extraction

Sensor datasets are broken down with temporal series using time windows and then sliding window is applied for feature extractions. The window size is segmented to 20, 50, 100 and 200 samples respectively with 50% window overlapping.

Two feature sets are extracted for further comparisons. the first set is 19 basic time domain features and 1 frequency domain features; and the second set is 32 time domain and 8 frequency domain features, including mean, max, min, standard deviation, root mean square, Fast Fourier transform and spectral entropy from each axis respectively.

B. Training and validation

ANN classifiers are adopted to train PAR model. It consists of interconnected artificial neurons structured into three parts: input layer, hidden layer and output layer. The lines between the nodes indicate the flow of information from one node to the next. The input layer comes from vectors of PA feature, sequentially duplicated and sent to all of the hidden nodes.

We applied three different activation function combinations in ANN such as ReLU, ReLU6 and ELU. Validation is made use of 10-fold cross-validation method that the datasets are randomly dividing into 10 groups and the first fold is exploited as a validation whilst rest 9 folds are for training.

V. Results and analysis

ANN classifier's performance is tested in four different time window sizes which are 0.1s, 0.25s, 0.5s and 1s. The results shown in figure 3. the accuracy is weakly increased with the time window increasing. While larger time window size tends to improve classification efficiency, however, recall is not significantly decreased with the window length increasing the result on the wrist overperforms the waist achieving 70% on average. Whilst recall of the waist has slightly increased with larger time window size.

The ANN classifier is consisted of 15 hidden nodes and feature set 1 and set 2 as utilised as the input vectors to the layer of neurons. Three activation function combinations are evaluated in this work. Our results show that 18 more extracted features in the feature set 2 produce a lightly higher classification accuracy than feature set 1 with 1.2% average. In particular, when only the sensors mounted on the wrist, the accuracy of the recognition of the feature set 2 is 9% higher than the accuracy of the feature set 1. The movement of the wrist is larger than that of the waist, so the sensor feature set of the wrist is more valuable, and the recognition accuracy can be greatly improved after more feature extraction.

However, in the selection of the number of features of the sensor at the waist, the recognition accuracy only changes slightly. All ANN models generally perform well on dynamic activities (A1 to A7) and sedentary activities (A8 to A11) with only one accelerometer mounted on wrist or waist respectively. In the table V the feature set, the results of wrist in activation function of ReLU6+softplus produce the highest accuracy on both dynamic and sedentary PAs. And in the

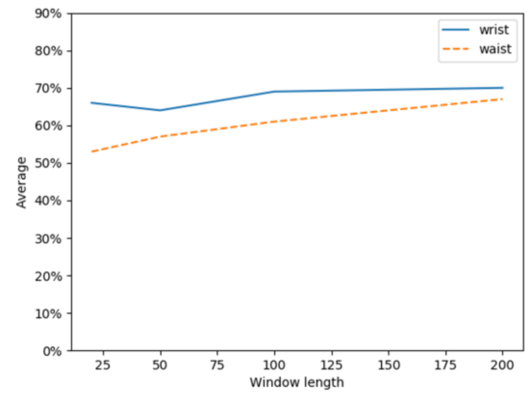

Figure 3. Average recall of 15 PAs from wrist and waist

TABLE III. Accuracy of three activation functions of feature set 1 of dataset 1

Activation function	ReLU+softmax		ReLU6+softplus		ELU+sigmoid	
Feat set 1	wrist	waist	wrist	waist	wrist	waist
A1	0.55	0.62	0.56	0.65	0.57	0.35
A2	0.83	0.65	0.63	0.73	0.70	0.86
A3	0.56	0.61	0.67	0.53	0.69	0.68
A4	0.70	0.47	0.62	0.56	0.78	0.42
A5	0.52	0.49	0.52	0.56	0.59	0.52
A6	0.64	0.70	0.55	0.70	0.59	0.66
A7	0.68	0.81	0.69	0.77	0.68	0.73
A8	0.98	0.98	0.99	0.98	0.98	0.98
A9	0.98	0.95	0.98	0.92	0.97	0.86
A10	0.99	1	0.98	1	0.98	0.99
A11	0.16	0.22	0.16	0.29	0.21	0.19
A12	0.60	0.73	0.62	0.74	0.38	0.61
A13	0.44	0.35	0.35	0.27	0.44	0.44
A14	0.18	0.23	0.22	0.31	0.28	0.19
A15	0.66	0.51	0.42	0.37	0.50	0.46
Average	0.68	0.68	0.66	0.68	0.68	0.65

TABLE IV. Accuracy of three activation functions with feature set 2 of dataset 1

Activation function	ReLU+softmax		ReLU6+softplus		ELU+sigmoid	
Feat set 2	wrist	waist	wrist	waist	wrist	waist
A1	0.76	0.77	0.70	0.72	0.67	0.77
A2	0.77	0.67	0.76	0.55	0.85	0.67
A3	0.81	0.67	0.79	0.53	0.66	0.50
A4	0.58	0.71	0.60	0.66	0.45	0.75
A5	0.85	0.45	0.86	0.39	0.83	0.30
A6	0.85	0.68	0.41	0.75	0.83	0.79
A7	0.86	0.88	0.91	0.87	0.84	0.90
A8	0.99	0.95	1	0.97	1	0.95
A9	0.95	0.97	0.87	0.98	0.92	0.96
A10	1	0.96	1	0.99	1	0.95
A11	0.33	0.24	0.33	0.31	0.54	0.31
A12	0.76	0.49	0.78	0.36	0.83	0.59
A13	0.63	0.40	0.68	0.42	0.58	0.28
A14	0.38	0.33	0.3	0.20	0.30	0.16
A15	0.67	0.49	0.53	0.35	0.72	0.40
Average	0.79	0.70	0.73	0.67	0.77	0.68

TABLE V. ACCURACY OF THREE ACTIVATION FUNCTIONS WITH FEATURE SET 2 OF DATASET 2

Activation function	**ReLU+softmax**		**ReLU6+softplus**		**ELU+sigmoid**	
Feat set 2	wrist	waist	wrist	waist	wrist	waist
B1	0.92	0.92	0.89	0.95	0.88	0.94
B2	0.92	0.96	0.94	0.97	0.97	0.73
B3	0.91	0.95	0.93	0.93	0.94	0.96
B4	0.9	0.95	0.92	0.96	0.92	0.99
B5	0.83	0.97	0.75	0.96	0.83	0.96
B6	0.96	0.97	0.95	0.99	0.95	0.99
B7	0.53	0.72	0.6	0.85	0.78	0.84
B8	0.9	0.03	0.79	0.67	0.91	0.6
B9	0.56	0.02	0.56	0.43	0.41	0.38
Average	0.89	0.9	0.88	0.94	0.9	0.9

the table V of feature set 2, also the wrist presents the best performance on both PA categories but with the activation function of ELU+sigmoid. On the other side, each accuracy results from table V overperform ta ble IV on the dynamic and sedentary PAs.

However, ANN suffers from transitional activities which the accuracy is lower than 50% on average from three tables. The reason leading to this might be transitional PAs are time-sequence-changing-based signals that a series of simple actions (e.g., sitting, standing, bending) are comprised within such PA. We also validate ANN performance in a gym dataset using feature set 2, the results are shown in table VI that it has great recognition rate in six dynamic PA, three transitional activities of free weight exercises, nevertheless, are incapable to classify properly.

VI. DISCUSSION AND CONCLUSION

Our work mainly has two contributions. Firstly, we have evaluated PA recognition in home-based environment through a typical machine learning approach ANN and found that ANN has the best experimental results on sedentary and dynamic PAs but maybe not suitable for transitional ones. The second advantage of our work is that we demonstrate how to select the parameters of ANN for achieving best performance in PA recognition. These findings will potentially guide the application of ANN techniques into many real-world PA recognition scenarios with the need of less-attachment of wearable devices. For instance, towards persons who can uses wristband and belt device in daily living environment, ANN algorithms can enhance the number of recognized PA types and accuracy of their intensity.

However, the work still has much space to be improved. First, there might be a trade-off between computational cost and recognition rate due to the high dimension features of the fusion, as well as uncertainties of lifelogging monitoring (e.g., one device running out the battery), which may not be appropriate for long-term free-living PA monitoring, thus how to improve machine learning algorithms' performance in PAR with only one wearable device becomes essential. Second, there are also other supervised learning algorithms and feature selection schemes available for further study. We will continue evaluate other algorithms for future study.

ACKNOWLEDGEMENT

This work was supported in part by Natural Science Foundation of China (NSFC) under the Grant No.61876166 and 61663046; Yunnan Applied Fundamental Research Project under the Grant No.2016FB104; Yunnan Provincial Young Academic and Technical Leaders Reserve Talents under the Grant No.2017HB005; Program for Yunnan High Level Overseas Talent Recruitment; Program for Excellent Young Talents of Yunnan University.

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