Development of Sensorised Resistance Band for Objective Exercise Measurement: Activities Classification Trial

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***Abstract*— Resistance bands are often used in resistance training programs for older adults. Despite their widespread use, there is a lack of objective assessment of the actual strength, speed and precision of the movements during these exercises. Therefore, this paper presents the development of a sensorised resistance-band and a preliminary trial of activities classification by using artificial intelligence. The results show that in the preliminary trial, the classification accuracy of 4 different activities reached over 96% using accelerometer data only. A future study will be based on the sensorised resistance band to quantify resistance band exercises objectively in elderly people.**

***Keywords*— Resistance band; Activity classification; Dementia treatment; Artificial Intelligence;**

I. Introduction

Ageing is a complex process that may lead to a decline in physical functions. These age-related changes affect a broad range of functions, such as muscular, cardiovascular, pulmonary-functions, body composition and physical functional capacities, which, cumulatively, could impact on the preservation of activities of daily living and independence in older adults [1], [2]. In general, a decrease in muscle functionality, that can compromise muscle mass and regional adiposity, muscle strength, and motor control, is considered one of the most important physiological changes during the ageing process [3]. This decrease is involved in the pathogenesis of frailty and disability that leads to a decrease in autonomy in activities of daily living [4]–[6], increasing the risk of falls, and consequent risk of morbidity and mortality [4], [7]. However, muscle strength can be improved in older adults through strength training exercises [8], [9].

One of the most frequently used approaches to strength exercise is progressive resistance training using weight resistance devices. Previous studies showed that the use of weight resistance devices improved muscle strength, power, functional skills and muscle mass in older adults [1], [3], [10]–[12]. Resistance band training is a specific training that could be defined as progressive strength training where the workout is against an external force that is increased as strength increases [3]. Considering the older adults population, with some untrained or with frailty (i.e. older adults with functional limitations of. muscles and joints), may be not able to use the necessary weight to produce positive muscle adaptation, due to a general physical inability, and decrease in motor control. Moreover, a gym-based resistance training program, based on free weights, isokinetic machines or other weight machines, could be not feasible as a long-term method for providing personalised strength training to the older adult population. Resistance-training programmes using resistance bands or tubing (e.g. Thera-Bands) to enhance their strength may offer a safe, inexpensive, and practical method for older adults [13].

In general, the quantification of the resistance bands exercises is limited to the number of repetitions and total time. Because of the variable loading patterns of resistance bands (greater stretch produces greater resistance), it is fundamental to quantify the exact strength, intensity and speed used to identify the volume and intensity of training [14]. This is fundamental to optimally assign tailored training programmes to the older adults. Resistance bands could be too weak or too hard, and consequently the execution and the effect of the prescribed exercise may be negatively affected.

The problem above could be solved with wearable sensing technology, which continually assesses exercise even after the patients has left the hospital [15], [16]. The type, frequency and intensity of exercise can then be assessed by using the data. By sharing the exercise information with the doctor, the doctor can also assess the patient remotely.

However, for elderly people or people with dementia, the wearable sensors are too complex to operate [15]. Instead of putting sensors on the body, we are sensorising the environment; in this case, the handle of resistance band. The first device we built for this objective is called WBR-SH1 [17]. The WBR-SH1 is integrated with multiple sensors which objectively measure motion and force data. However, there are a few limitations with it: A) the motion sensors are placed inside the handle, and the handle is rotated freely while doing exercises, which makes it difficult to identify the direction of resistance band; B) battery life is not sufficient for real-life experiments; C) the connection between the handle and the sensor board is weak; D) it is not possible to synchronise the data of the two handles.

This paper presents the development of the new sensorised resistance band WBR-SH2, aimed at overcoming the above-mentioned limitations, and its preliminary evaluation for the classification of exercises using TensorFlow [18].

II. Materials and Methods

The role of the WBR-SH2 was to collect raw data of multiple on-board sensors and send these to Android phones in real-time. All calculations are done by computer afterwards.

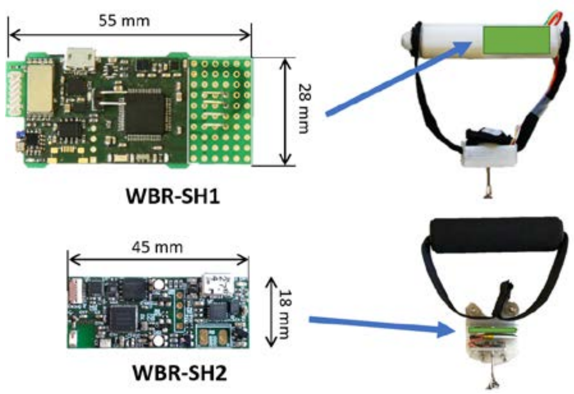

Figure 1. Sensor positioning difference in WBR-SH1 and WBR-SH2.

The new electronic board is shown in Figure 1. The most significant change is moving the motion sensor from the handle to the box in between the resistance band and handle.

TABLE I. Specification of WBR-SH Devices

Labels	WBR-Sensorised Handle	
	WBR-SH1	***WBR-SH2***
Size	55 x 28 mm	45 x 18 mm
MCU	STM32F405	NRF52832
Sensor	9-Axis Motion sensor, Barometer, Loadcell	9-Axis Motion sensor, Barometer, Loadcell
Resolution	Motion sensors 16bit, Loadcell & Barometer 24bit	Motion sensors 16 bit, Loadcell & Barometer 24bit
Power	153 mA	22 mA / Idle 100uA
Battery	1300 mAh	300mAh
Battery Life	8 hours	12 hours continuous acquisition; 90 days Idle
Wireless	Bluetooth 4.2, sub-1G	Bluetooth 5
Max Over Air Data Rate	500Hz	800Hz (single device), 500Hz (double devices)[b].
Storage	MicroSD card[a].	16 MBytes Flash
Weights	120g incl. Battery	32g incl. Battery
Visual Feedback	None	RGB LEDs
Sensor Position	Motion sensor within handle, loadcell is attached on resistance band	Motion sensor and loadcell attached on resistance band

a. Supports up to 32GBytes SDHC.

b. The maximum data rate is also limited by receiver's Bluetooth hardware and configuration.

The board integrates a Cortex M4F Bluetooth 5.0 SoC (System on Chip) NRF52832, a USB power management circuit; the load cell driver is connected to the board through an extension connection. The WBR-SH2 is always power-on but will enter idle mode while disconnected from the Smartphone, thus extending the battery life up to 90 days. The comparison between WBR-SH1 and WBR-SH2 is shown in TABLE I, with the green highlight showing the improvement.

A. *Experiment*

1) *Experimental protocol*

The Couch Potatoes for Cognition [19] programme is produced by Loughborough University specifically for elderly and people with dementia, and it consists of 4 types of low-intensity resistance band activities (Figure 2), each consisting of 20 repetitions followed by 1 minute of rest to avoid accumulation of fatigue. These activities are mainly focussed on improving upper body muscle strength, as a previous study proved that training of upper body strength will slow down the process of memory decline [20]. Subjects are asked to sit on a chair while they are doing the activities, to minimise the chances of falling.

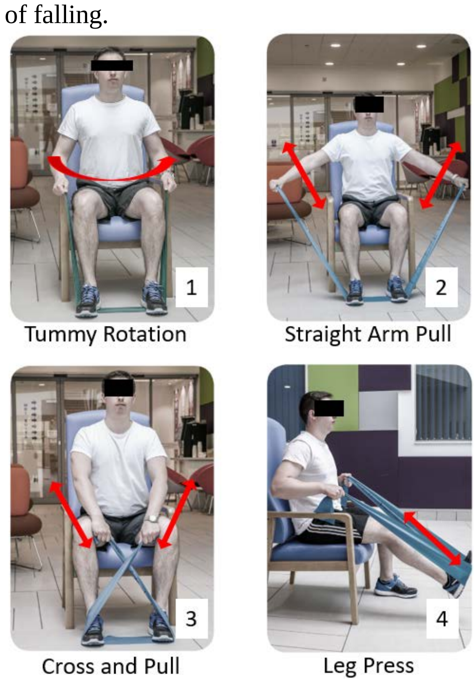

Figure 2. Couch Potatoes for Cognition; the red arrows show the direction of the movments in each activity.

Six healthy male volunteers (23yo to 40yo, all right handed) participated to the preliminary experiment. The experimental protocol involving human subjects was approved by the Loughborough University Ethics Committee (R17-P143).

2) *Experimental setup*

Before doing the exercises, both WBR-SH2 sensors were calibrated and synchronized. The participants followed the experimental protocol and used two WBR-SH2s instead of the regular handles. During the exercises, both WBR-SH2s sent the raw data to an Android phone (Xiaomi Mi6), in which the data was recorded and tagged manually from the start of each activities to the end.

B. *Data Pre-processing*

1) *Raw data frame*

During the experiment, all data was collected at frequency f = 100Hz and stored in a CSV file for further processing. Available data was from 3-Axis accelerometer, 3-Axis gyroscope, 3-Axis magnetometer, barometer, and loadcell. In this preliminary paper, only accelerometer data is used. Each frame consists of 3-Axis acceleration data from both left hand and right-hand sensors. No filtering of raw data is required while using the Convolution Neural Network (CNN) [18].

2) *Overlapping windows*

Most activity classification methods use windows technique to split data into small segments [21]. In the data processing, an overlapping windows technique is used to segment the raw data. Each segmented data length 2.5 seconds (250 frames) with 2/3 window overlapping [21]. An example is shown in Figure 3.

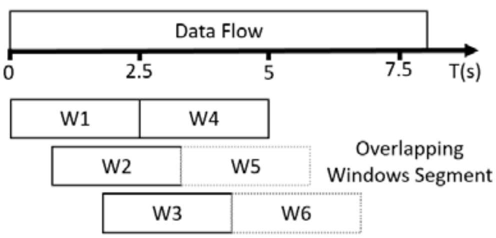

Figure 3. Overlapping windows segment.

3) *Sensor position switching*

Each frame consists of 2 sets of acceleration data coming from the two handles. To remove the differences between right and left (which are not relevant for the classification presented in this paper), raw data is duplicated and the position is switched in the segmentation process. This generates another set of segmented data. Both segmentations are put into the same neural network for training. Figure 4. shows the segmented raw data and the position-switched data.

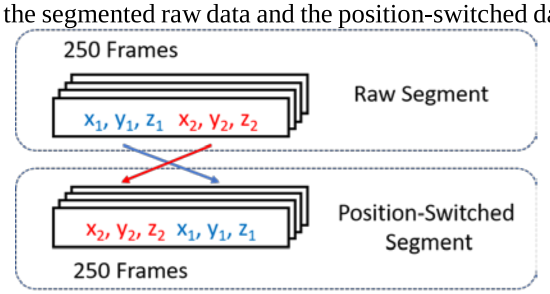

Figure 4. Position-switched segment.

4) *Neural network architecture*

The CNN architecture, implemented on TensorFlow 1.4 with Python 3.6, is shown in Figure 5. The training dataset and testing dataset are randomly picked from the segmented data with a ratio of 60% and 40%, respectively. Since the training data is randomly picked from the same dataset, the training of the neural network was performed several times to evaluate the stability. Each training was stopped at the 20th epochs, and the accuracy and confusion matrix were stored.

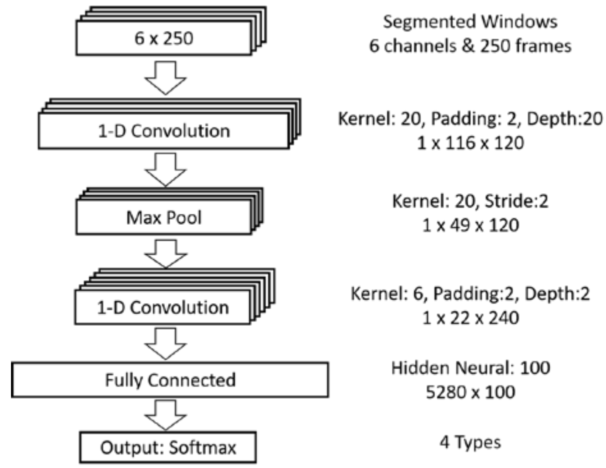

Figure 5. Convolution Neural Network Architecture.

III. Experiment Result

A. *Data distribution*

The total length of the recorded data is 143,940 frames, equivalent to 1439.4 seconds. After pre-processing, 3,190 segments of data are generated (including both raw data and position-switched data segments). Due to the natural differences between each activity, the data distribution is not equivalent. The total data distribution is shown in Figure 6.

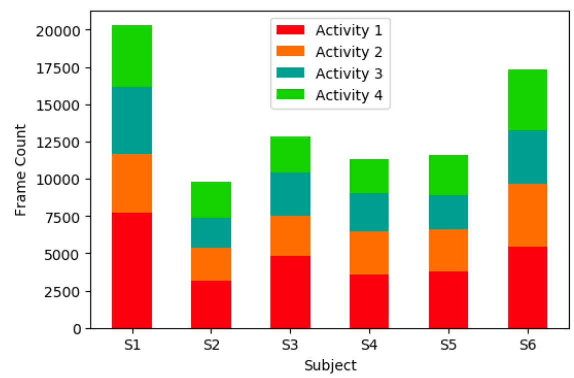

Figure 6. Data distribution. Data is collected from 6 subjects number from S1 to S6. Each subject did 4 different types of activities following Couch Potatoes instruction.

B. *Learning accuracy*

After 12 times training, the mean training accuracy and testing accuracy is plotted in Figure 7. The standard error of the testing accuracy is 0.9%.

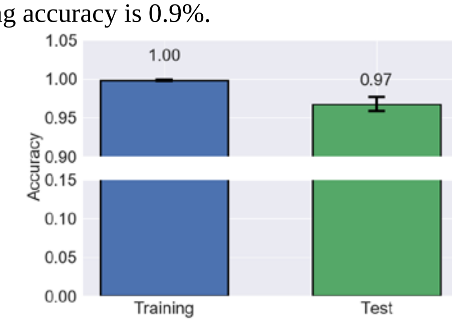

Figure 7. Average accuracy after 12 times of training.

C. Confusion Matrix

The Confusion Matrix is shown in TABLE II. Since the dataset for training and testing is randomly chosen from the same dataset, each time of training will produce a different network and result. TABLE II. shows the average value in each block after 12 times training.

TABLE II. CONFUSION MATRIX AFTER 12 TIMES TRAINING

		Test Activity Types			
		A1	***A2***	***A3***	***A4***
Train Activity Types	***A1***	335	5	4	0
	A2	3	185	9	0
	A3	3	5	199	0
	A4	1	0	3	200

IV. CONCLUSION

This paper presented the development of a sensorised resistance-band and a preliminary trial of activities classification by using artificial intelligence. The preliminary experiments show that the WBR-SH2 can be used as replacement equipment of the traditional resistance band handle for data collections. In the preliminary trail, the classification of CNN is accurate enough while only the acceleration data is analysed. However, the size of data set and types of activities are small, and the results may be limited. The further works is using other onboard sensors together to evaluate the exercise quantity in different types of activity with elderly people in both the lab-environment and home-environment.

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