IoT for Movement Recognation and Prehabilitation Support System

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***Abstract*--With more than a decade of research and development, the Internet of Things (IoT) and Cyber-Physical Systems (CPS) are both promising solutions for various novel healthcare applications. This proves significant for supporting data collection on human movement detection and recognition. The paper discusses a novel concept of the IoT for healthcare applications. The focus is on the follow-up of prehabilitation programs that are essential for pre-operative patients. The solution caters for a flexible approach that benefits both supervised and unsupervised prehabilitation programs. This paper describes the overall system architecture considering a distributed computation model that includes the wearable sensors, the access points and the edge or cloud-related computing. The model can act as a baseline for a digital twin that could follow up the prehabilitation program implementation of a preoperative patient and offer the necessary information relevant to recommendations and alerts.**

Keywords— IoT, Prehabilitation, Wearable sensor device, smart movement monitoring

I. Introduction

Major surgery is associated with a significant deterioration in quality of life[1]. Physical fitness and level of activity are considered important factors for patients undergoing major abdominal surgery[2]. Prehabilitation is an emerging concept and can be defined as the process enabling patients to withstand the stressors associated with surgery though augmenting functional capacity[3]. There are two main prehabilitation models currently used on patients undergoing major surgery: supervised and unsupervised programmes[4]. Both programmes share key prehabilitation elements such as a time frame of four to six weeks and the implementation of physical exercise (i.e. walking, running, cycling, cross trainer, rowing, treadmill, step up, leg press, and staircase ascending/descending). Type and intensity of the physical activity, time of each activity, frequency, and auxiliary factors such as bedrest all have impact on the prehabilitation program. Patients who are involved in the supervised programme usually perform the prescribed physical exercises under the direct supervision of a healthcare professional. This type of prehabilitation is usually limited to those individuals who live in close proximity to a hospital [5]. The home-based prehabilitation programme (unsupervised) offers flexibility for patients to perform the prescribed activity in their home or a community centre or gymnasium [6]. Another advantage of the home-based programme is that it overcomes geographical barriers so that patients living outside the region may access services that would not typically be available to them due to the distance and time required to travel to the referral centres[6, 7]. Despite being home-based, unsupervised prehabilitation programmes often include prescribed physical exercises that are similar to those used in a supervised prehabilitation programme [8]. One of the key problems with unsupervised prehabilitation programmes is that there is minimal direction and advise on exercise progression from a health professional resulting poor compliance and failure to achieve key prehabilitation goals.

Currently, most established prehabilitation programs are run in key medical centres, and a significant number of patients undergoing major surgery are unable to attend these programs because of obstacles such as limited number of resources, geographical isolation, work commitments, and long waiting lists[6, 7]. Telehealth has the potential to address this health disparity and improve health outcomes [9] by providing an alternative for those who are unable to travel due to caring or work commitments, conflicting clinical appointments, or treatment-related symptoms [10, 11]. A mixed mode prehabilitation programme supported by the use of IoT could be a viable option for those who are unable to visit the physiotherapy clinic on a regular basis [12]. The mixed mode gives patients the option of performing physical activities at the physiotherapy centre, at home, or in the gym. By recruiting key elements from both existing prehabilitation programmes (supervised and unsupervised), this model has integrated the advantages of both existing prehabilitation programmes while minimising the disadvantages [12]. Furthermore, the use of IoT and a cloud-based integrated solution allows the program's integrity to be monitored through data collection, analysis, and timely interaction.

The aim of this paper is to provide an overview of the IoT system implementation based on the integration of wearable sensor devices (WSD), a mobile internet access device or gateway, and edge or cloud backup tools that can help with advanced analysis such as movement recognition and long term monitoring of preoperative prehabilitation programs. Transparency of key events to the patient, caregiver and health providers are described throughout the design.

This paper is organised as follows. Section II will provide a brief introduction on prehabilitation programmes and their associated challenges. Section III presents the activity recognition challenges and smart monitoring. A mixed mode prehabilitation program supported by IoT CPS case study is then discussed in IV. Finally, conclusions are made in Section VI.

II. IoT Architecture Supporting the Mixed Mode Prehabilitation Model

Figure 1 shows the three main components of the IoT solution. These are the wireless wearable device, the smart mobile access point or gateway, and the remote cloud. These three main components which host the distributed software and generated data for supporting the mixed mode prehabilitation model. The first component is the wearable device that is attached to the patient and collects movement data. It has to be active over the specific duration of data collection. This is normally during the daytime where individuals undertaking prehabilitation perform activities of daily living and specifical prescribed exercises. Preliminary analysis of the nature of data and possible event recognition may significantly help support communicating the information with the upper level. In general, most of its processing is relevant to short term data collection.

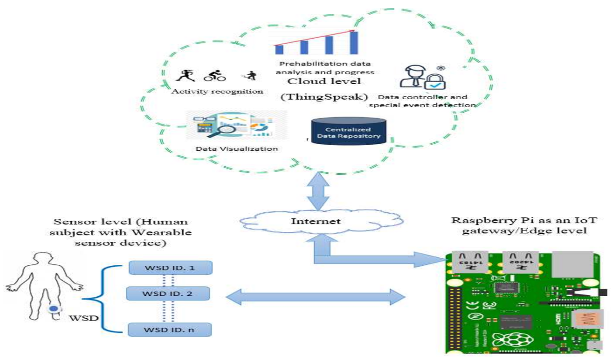


Figure .1. Main physical components of the IoT system that host the operational software and generated data.

The second compoent is the smart mobile access point. This covers the connectivity of the wearable device with the cloud through the internat and supports the medium term data management and processing. This may relate to a single user with a single or multiple sensing points on the same user, but could also involve a small group of users like members of family, rest home residents, or even a section of a public gym. Usage duration might be from few houres to a whole day. The mobile access point might be available at a given location within a residential buiding but is portable enough to accompanied the user if they move to different loactions. It should allow for delay tolerance and opportnistic connectivity.

The third component is the cloud level (Thinkspeak). At the cloud level there is more involved data management and processing over the prehabilitation program lifetime. This should be the centre for the overall operation and includes basic level data management and processing as well as interaction interface between users and IoT system. At the more involved level it performs system and prehabilitation program modelling and virtualization that facilitate operational cross-checking and facilitate some level of expertise intelligence.

A. *Werable Sensor Device WSD*

The WSD shown in figure 2 a and b is the front-end component of the IoT cyber-physical system and is responsible for sensing the movement and capturing raw data from the user. The architecture of the WSD for human physical activity consists of five main functionalities (see Figures 2.a, and 2.b), namely movement sensing, timestamped data acquisition and calibration, data compression and feature recognition, data storage, and data communication. Further information about each of these functions is describe in our previous works [12, 13] . The WSD size, power consumption, computation functionality requirements, data storage, and communication requirements are all examined in this design.

Figures. 2. a. the combinations of Microduino boards with 3.7DC battery, b. final WSD inside 3D printed box.

a b

The WSD is attached to the patient's ankle [13] and it's small size and light weight are the key features that need to be considered. In this study, the Microduino stack (sensors, microcontroller, and other supporting boards) were used to offer the flexibility for testing the various combinations of hardware and software functional components. We have investigated the effects of different operational modes on the energy consumption of the wearable device using a ½ AA rechargeable battery of 700 mAh at 3.7V. The current consumption can be reduce by 20% (see details in the table 1) which allows the battery to function the WSD continuously for 22 hours at full operational mode. This covers the full day comfortably.

TABLE 1. COMPARISON BETWEEN NORMAL AND OPTIMISING OPERATION MODE. SNO= SENSOR NUMBER

S. No	Sensing Board	Idle Mode Current(mA)	Operational Mode Current (mA)	Optimized Mode Current(mA)
1	Core RF	22	22-24	22
2	10 DOF	0.01	0.02-0.06	0.03
3	SD card	1.5	5-7	4.46
4	NRF24	2.8	11.3-13.5	4.925
5	RTC	0.032	0.05-0.1	0.07
Total Current Consumed		**26.3mA**	**38.37-44.66 mA**	**31.475 mA**

Long term storage of data is considered within the WSD, and our previous work found that storing the raw and processed Fast Fourier Transform (FFT) every four seconds [13] was the most acurate and efficient way of storing data (see Figure 3). This was chosen for two reasons. Firstly, the time spent on storage of both processed and raw data is only slightly more than the that used on raw data alone with no significant effect on the processing. Secondly, storing raw data provides a long-term back up for both researcher and healthcare staff to use for further analysis.

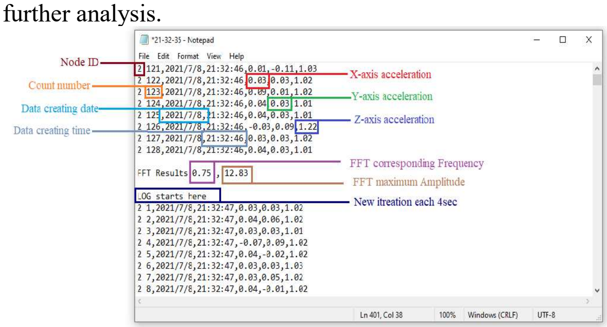


Figure. 3. The long-term storage pattern in the WSD SD card.

As discussed in previous works [13] the128Hz sampling frequency of the 3D accelerometer data was chosen to detect the movement frequencies during physical activity for elderly people. A four-second duration is the minimum data-collection window at this sampling rate, enabling accurate frequency analysis and movement identification without any distortions in information gathering. Our previous work found that increasing the duration of the window did not reduce the power consumption and nor affect the signal quality. However, increasing the duration of the data-collection window led to missing some data during the collection process. Furthermore, an increase in the time gap between each data transmission to the upper level (gateway) will reduce data traffic and increase the number of serving nodes, and the latency of activity recognition will be longer, and the performance of the system for the activity recognition will reduce.

Different scenarios were examined to optimise the four-second data transmission of raw 512 (XYZ data), filtered 128 sampled data (XYZ-DC offset) epochs, and processed FFT data (Amplitude and Frequency) to the gateway. The best-case scenario was sending fully processed data (FFT amplitude and frequency data) every four seconds, which resulted in minimal loss of data during transmission from WSD to the Gateway (RPi). Another advantage of transmitting the processed amplitude and frequency data every four seconds is the lower minimal data transmission rate of 250 kbps for the NRF24L0 radio transmitter (Tx) device. This lower transmission rate enabled an increase in the Tx range and reduced the traffic at the front-end radio NRFL0 receiver (Rx). This also enhanced the overall Tx/Rx performance by offering spare time for the Tx in case there was no acknowledgement received from the Rx.

B. *IoT gateway*

Raspberry Pi (Rpi) has been selected as an example gateway and edge computing device in this IoT system. The main reason for selecting the RPi as an IoT gateway is that it is a single board computer with a full operating system [14]. In this study two types of RPi were used: the Raspberry pi 3B (RPi3B) as a base station gateway; and the Raspberry pi Zero W(RPiZW) as a mobile gateway (see figure 4 a and b).

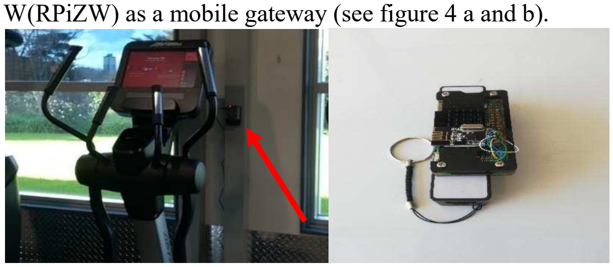


Figure. 4. a. RPi3B as base station gateway, b. RPiZW as a portable gateway.

The light weight and reasonably small size of the RPiZW and WSD have been designed for comfort and ease for the participants. The gateway features have been designed to support the prehabilitation program in terms of physical activity recognition, time period of each activity, and activity intensity level. The gateway is able to handle multiusers (WSD) simultaneously, enable the storage of short-term and long term raw and processed data, perform real-time processing and transmitting data to the cloud, cover the discontinuity transmitting data (Internet disconnections). The use of smart monitoring and activity detection techniques were considered in this design as well.

The gateway code was designed and implemented to support the mixed mode prehabilitation programme in terms of multi-sender (WSD) data receiving and analysis, activity recognition, short-term data repository, detecting the key elements and boundaries of the mixed mode prehabilitation model, and calculating the accumulated time and gain and then sending. The whole processed data can be transmitted to the cloud TS for further analysis as shown in Figure 5 below.

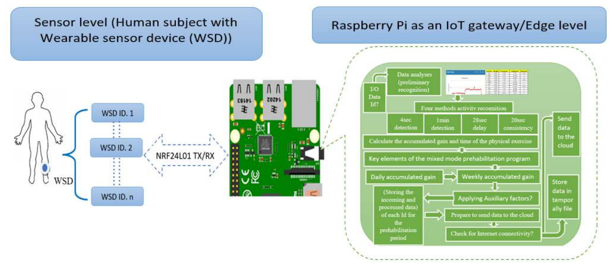


Figure. 5. Gateway architecture and feature for handling and processing multi-sender WSD data.

The first feature ?? of the gateway is the process that prepares the receiver for the incoming data. During this stage, all the data buffers and basic parameter variables are initialised, the data queue is constructed, and the data output filename is made according to the current date. The naming of the file according to the data enables a new file to be made for each instance that data logged. This is done to avoid losing complete set of data in the case where a file is corrupted, or if the gateway fails to send processed data to the cloud. The second feature of the gateway is related to ensuring that data is not lost due to the Internet connection issues. When the database is storied in the local list, the script moves forward by opening the 'not synced' data, which might have accumulated because of the Internet disconnection during the physical activity session (e.g., outdoor physical activity). Once the comma-separated values (CSV) file is opened, all the data, along with their original timestamps, are loaded in the queue (see Figure 6). This process allows the system to maintain the timestamp and the sequencing of the data.

	A	B	C	D	E	F	G	H	I	J
1	Node Id	Date	Time	Amplitude (m/s^2)	Frequency (Hz)	Code of activity Recognition	Accumulated Time of each WSD	Accumulated Gain of Each WSD	ThingSpeak API Key	ThingSpeak channel ID
2	2	2021-08-04	19:21:33	14.38	0.75	11	0.01333	0.00335	0G6PAH7KD	51383
3	0	2021-08-04	19:21:33	12.93	1.5	2	2.13333333	0.0536	233TUBX2W	4957
4	3	2021-08-04	19:21:35	0.07	0.25	0	0.66666667	0	PO66I4OX5	20023
5	1	2021-08-04	19:21:36	22.87	1.75	7	1.53333333	0.0132	HYV4OWYE6	6247
6	0	2021-08-04	19:21:37	14.21	1.5	2	0.1333	0	233TUBX2W	4957
7	2	2021-08-04	19:21:38	17.82	0.75	11	0.02666	0.005025	0G6PAH7KD	51383
8	1	2021-08-04	19:21:39	22.77	1.75	7	1.6	0.0264	HYV4OWYE6	6247
9	3	2021-08-04	19:21:40	0.08	3	0	0.73333333	0	PO66I4OX5	20023
10	0	2021-08-04	19:21:41	15.22	1.5	2	2.26666667	0.00165	233TUBX2W	4957
11	2	2021-08-04	19:21:42	15.27	0.75	11	0.03999	0.0067	)G6PAH7KD	51383

Figure. 6. Full details of accumulated data per channel stored in 'not synced' CSV file in case of lost Internet connectivity.

The third feature of the gateway is re-establishing Internet connectivity. To achieve this, the data stored in the CSV file is uploaded first followed by the uploading of the live feed of data. This script uses threading and makes two threads for multiprocessing. The first thread is for the handling of the incoming data from the WSD, all recognition techniques, the logging of the data, and the storing of the data in CSV file. The second thread is for uploading the available data to the cloud TS, as shown in Figure 6. Once the Internet connectivity is confirmed, the basic header of the data is constructed in the form of a string, and the main buffer is initialized. In the queue, the data are gathered from different nodes, and thus, it is necessary that the system can sort the data according to different nodes so that the data can be sent to their respective channels. Once this sorting is done, and the main buffer list is constructed with the data of all nodes, uploading is performed. The upload performed here is a bulk upload in which the system can upload 900 data frames in a single request (see Figure 7). Any two consecutive bulk upload requests for the same channel should be separated by a time frame of 15 seconds, otherwise, the server will reject the data.

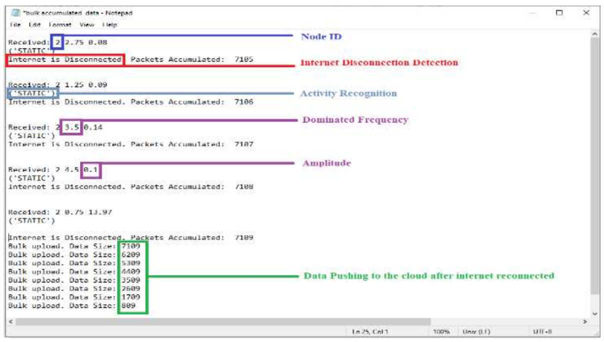


Figure. 7. Full details of accumulated data per channel stored in ‘not synced’ CSV file in case of lost Internet connectivity.

The fourth feature that is the multi-node receiver the Python script is made for receiving the data from the WSD using the NRF24 module. The protocol used to transmit the data is ‘NRF24_Network’. In this protocol, each WSD is given a node ID address, as shown in Figure 8. After receiving the data, scripts are checked for any false values. If the data received follow the syntax and range of real or acceptable data, then they are processed further by the program, otherwise, a ‘none acknowledged’ message is sent to the WSD for sending the data again.

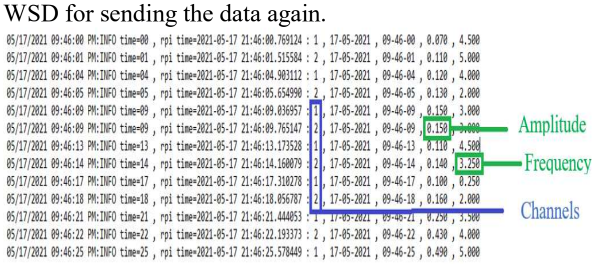


Figure. 8. Raspberry Pi logfile showing the TX/RX time, node ID, amplitude, and frequency.

C. Cloud ThingSpeak Platform

Gateway processed data will be sent to the TS using the HTTP protocol, along with the amplitude and frequency extracted from the WSD. The TS application is used for storing, retrieving, and analyzing live data from different sensors. It is treated as a platform for aggregating and processing the sensor data using MATLAB software for further data analysis and visualization. An additional feature that the TS can perform is “Thing Tweet”, which includes programming the TS channel for limited value. When a value exceeds the limit, an automatic Tweet alerts the user or healthcare support. All these features, including visualizing the real-time incoming data from the gateway, have been used in this design to support the mixed mode prehabilitation program (see Figure 9). Using the information available inside the cloud repository and utilizing the processed data and activity information, a presentation is created (see Figure 9). The first two plots (a and b) symbolize the compressed parameters (i.e., maximum amplitude, corresponding frequency), while the third and fourth graphs (c and d) represent the accumulated time and gain.

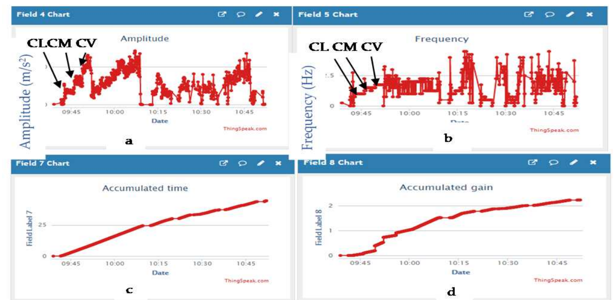


Figure. 9. Cloud data visualisation for both WSD data (a and b) and gateway processed data (c and d)

III. Activity Recognitions Challenges and Smart Monitoring

To validate the data collection from the participants a special technique has been developed to recognize the different physical activities [12]. The technique used for the recognizing the common prehabilitation physical activities prescribed for participants undergoing major abdominal surgery has been described in our previous works [12, 13]. Accordingly, three distinct database types were subjected to the same techniques for movement outlier detection and correction. The first category is the personalized database which contains training data taken from the same individual while engaging in a number of physical activities typically used in prehabilitation programs. Reference identifiers extracted from these training data were then used for the methods of activity recognition [12]. The second database type is based on multiple categories attained from exercise performed by participants who could be classified into groups (i.e., age, level of fitness). Each group has a common database. At this stage the categorization has been based on the span of the Fast Fourier Transform (FFT) dominant frequency and associated acceleration ranges.

The third type of database used is a general database (non-personalized) that covers all ages and conditions, which was developed from physical activity information gathered from multiple participants and patients. A common value for each physical activity was calculated from the group data and compiled in a shared (non-personalized) database and then utilized as a point of reference for new users when they begin undertaking various physical activities.

Analysis was performed on four participants of each age group who conducted the same physical activities on the same pieces of fitness equipment three times in the same environment.

Figure 10 depicts the four participants (P1, P2, P3, and P4) conducting treadmill (TM), cycling (C), rowing (RO), and cross trainer (CT) at varied intensities (Low (L), Moderate (M), and Vigorous (V)) on different days. In the initial session all participants performed the same four activities, and their performance data was stored in the system as a reference for each participant (personalized database). The precision percentages of the activity recognition for the same person ranged from 70% in TM to more than 95% in CL and CT activities.

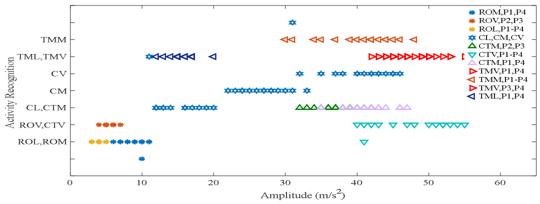


Figure. 10. Personalised activity recognition from four participants performing the same activity at varying times.

A categorised database could be created based on age group, fitness level, and on any health-related factors could be common with a certain group of people. Table 2 shows the comparison between activity recognition percentages in personalised, categorised and non-personalised database of eight different physical activities. Table 2 shows high percentages of activity recognition for the personalised database in comparison with the other databases. While the non-personalised database recorded lower percentages of activity recognition.

TABLE 2. THE PERCENTAGE OF RECOGNITION OF EACH ACTIVITY FOR PERSONALISED, CATEGORISED, AND NON-PERSONALISED DATABASES.

Physical activity	Personalised (%)	Categorised (%)	Non-personalised (%)
Cycling	94	88.5	85
Cross Trainer	90.5	80.7	76
Rowing	90	84	81
Leg Press	90	81	78
Treadmill walking	82	69	67
Walking	73.5	58	56
Staircase	30-45	28-38	25-35
Step Up	35-45	31-41	25-35

Figure 11 shows the histogram of activity recognition of eight prebailition activities using the three different databases.

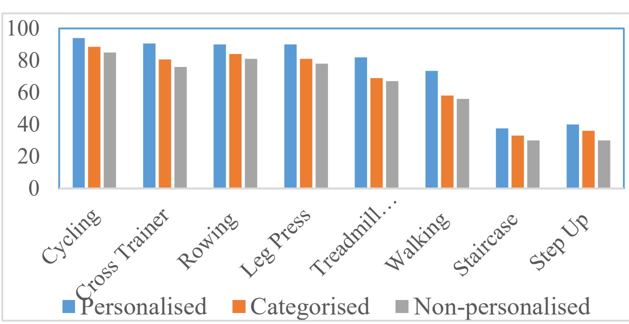


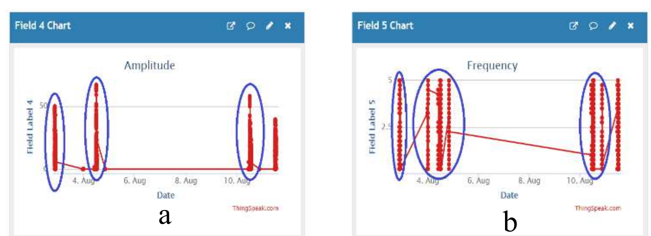
Figure 11. Activity recognition of eight prehabilition exercises based on different types of database.

IV. MIXED MODE PREHABILITATION PROGRAM SUPPORTED BY IOT CPS CASE STUDY

Three participants completed the mixed mode prehabilitation program. This included one elderly abdominal cancer patient waiting for surgery and two middle-aged healthy people. The patients conducted three sessions within ten days (two sessions in the gym and one outdoor session). The total accumulated time was approximately 140 minutes with varying intensity levels. The outdoor activity only involved walking at varying intensities. Nonetheless, the other two participants continued for two weeks, doing six sessions (three sessions per week equating to a total of 100-130 minutes of exercise time). This consisted of three sessions of 45-60 minutes at the gym (cycling, treadmill, cross trainer, and rowing) at varying intensity levels, and three 30 to 45 minute sessions in outdoor environments walking at varied intensities. The portable RPiZW and WSD (Figure 12) were given to all three participants, and the RPiZW was joined to a local internet connection. Specific TS channels were assigned to each participant, preventing data from being mixed up with other participants.

Figure. 12. RPiZW, WSD, Strip Band, and USB Charger Cable.

The preliminary data for the first and second participants were available during the first AUT physiotherapist lab session test, while the data for the third participant was not accessible. Therefore, the personalised database was used for the first and second participants, whereas the shared database was a reference for the activity recognition for the third participant. Figures 13 a and b show the TS visualisation of the three physical activity sessions in detail for the first participant. Figures 14 a to d demonstrate more detailed data from one session conducted in the gym, illustrating the amplitude, frequency, accumulated time, and gain. Figures 14 e and f display the digital values of accumulated time and gain for the various physical activities in the same session.



Figures 13. a. Amplitude and b. frequency for three sessions at different dates and time, respectively.

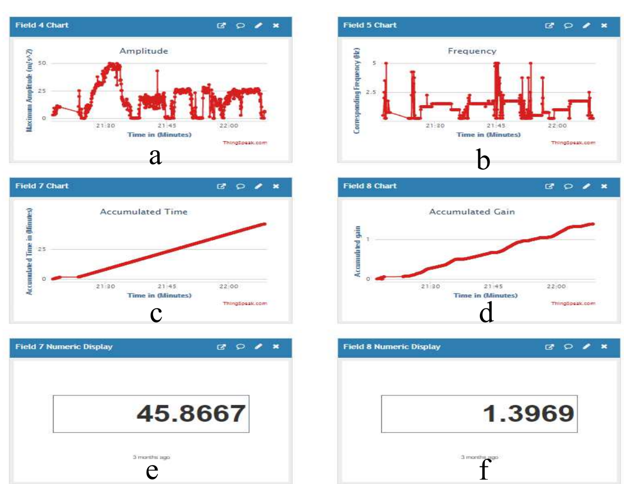


Figure 14. a. amplitude, b. frequency, c. accumulated time, and d. accumulated gain credit with numeric displays of a single exercise session.

The above figures demonstrated that the system was able to attain data from the different activities, store and analyse the offline data in the gateway and pushed the data to the cloud once the internet was reconnected again (for example, when the participant returned home). The system recognised 82% of the actual activities that were performed in the gym, while this value was around 68% for outdoor activities (walking in varying intensities) due to the overlapping between walking and some other activities. The results were about the same for the second participant (83% at the gym and 65% recognition for outdoor walking). However, the results of the third participant with a shared database varied for different activities. For example, there was 95% recognition for the cycling, 78% for rowing and leg press, and less than 65% recognition for the cross-trainer, outdoor and treadmill walking. These lower scores were primarility due to the overlapping between these activities. Physical efforts were not recognised only if the results of the amplitude and frequency analysis did not correspond to any database value. Therefore, the overlapping among physical activities would reduce the system performance from the point of specific activity recognition. This in turn would underestimate the total efforts, including accumulated gain and time.

Figure 15 indicates the mixed mode prehabilitation program results for the three participants. The percent of the ideal gain for the three participants were 78%, 72%, and 68%, respectively. These percent values show that the design and application of the IoT remote monitoring system supported a mixed mode prehabilitation program. Moreover, the target gains also doubled when the personalised database fed the system, and the patient performed the prescribed physical activities.

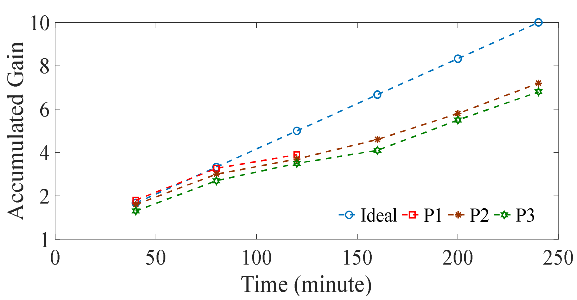


Figure 15. Accumulated gain for the three participants for a two-week mixed-mode prehabilitation programme. Note the blue line represents the ideal or prescibed credit gain.

V. Conclusion

The developed IoT system demonstrated the ability to support a mixed mode pre-rehabilitation program. The use of wearable technology accompanied by smart gateway allow collection of movement data for both supervise and unsupervised exercises. The proper utilization of computational resources at the wearable sensor, the access point age computing and cloud/fog enable the smooth and transparent flow of data, information, and events. This in turn can motivate the patient and enable the health provider to deal with exercise engagement and assess the condition more accurately. While this prehabilitation exercise tool has developed using a dedicated smart gateway, the use of cell phone may be considered as more practical smart access device.

This approach should minimise the prehabilitation barriers for people living in a remote areas where limited resources and support are available. Furthermore, the findings of the prehabilitation exercise intervention show how personalisation and non-personalisation logical analysis of movement dynamics affect alignment with reality. For seven activities, the system was able to recognise more than 70% of personalisation data while the percentages were considerably less (55%) for non-personalisation data.

Ethical Approval

this study, was approved by the Auckland University of Technology Ethics Committee (AUTEC reference number 19/212).

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