IoT based Testbed for Human Movement Activity Monitoring and Presentation

Akash Gupta, Khalid-Al-Naime and Adnan-Al-Anbuky
School of Engineering, Computer and Mathematical Sciences, Auckland University of Technology, Auckland, New Zealand

Keywords: Internet of Things (IoT), Activity Monitoring, Wearable Sensor, Testbed, Remote Monitoring.

Abstract: Rehabilitation or Prehabilitation are vital healthcare practices that allows people to recover their muscle strength and return to their normal daily life activities or be ready for operating on respectively. Each type of injury or operation would require its own specific movement activities that need to be conducted over a predefined supervised or unsupervised program. Tracking, recording and monitoring the daily movement activities can significantly help in follow up the correct implementation of a predefined program. The recent advancement in digital health could be leveraged upon in benefiting the above indicated processes. Internet of Things (IoT) is the technological revolution that allows objects to be interconnected, related movement activities to be tracked and online gathering of real time and history data to be collected. This in effect should offer the possibility of converting regular rehabilitation into a smart rehabilitation care. This paper proposes a generic IoT based testbed using three layered solution for human activity movement monitoring. These are wireless sensing layer, the local processing and internet access layer and remote cloud service layer. Functionality for each of these layers are explored and tested based on hip fractured rehabilitation use cases. Experimental results reflect the ability to drive the system in a software defined mode for accommodating different use cases.

1 INTRODUCTION

With an unprecedented advancement in IoT, numerous services and prototypes have been developed and proposed (Dang, Piran et al. 2019). Integrating IoT with healthcare can help significantly in reducing the cost, enrich user experience and improve the quality of life (Salunke and Nerkar 2017). However, it possesses a lot of growing challenges like data storage, management, latency, constrained resources, exchange of data between the devices, mobility, security , network connectivity, ubiquitous access and system performance (Buyya and Srirama 2019). In fact, different multi-layer IoT based architectures have been proposed by many researchers that include the sensing, networking, service and the user interface layer (Kowal, Kuzio et al. , Lee and Lee 2015, Farahani, Firouzi et al. 2018).

A wearable IoT architecture for home based and personalised healthcare services is proposed by (Kumari, López-Benítez et al. 2017) based on edge computing. In their work, the system architecture component is composed of the wearable human activity tracking device comprising of many different sensors like 9-axis motion sensors, responsible for data collection, storage and processing. Edge computing device is used for storage, processing and for communicating information to the cloud. Cloud computing and other analytical services are used for real time visualisation of subject data. Their architecture provides an explanation as how each of these device functions in formulating a complete system. However, the system lacks technical detailed explanation about the frequency of data acquisition, different types of storage available, data communication frames and protocols by providing examples. The paper has given examples as how their architecture could be suitable for clinical practises. However, there is no discussion on real-life testing on any of the application to see what challenges the system can offer and how the researchers can benefit at each level while addressing application requirement.

(Cabra, Castro et al. 2017) have presented a work-in-progress IoT approach for deploying WSN applied to the environmental monitoring of temperature and

Gupta, A., Khalid-Al-Naime, . and Adnan-Al-Anbuky, .
IoT based Testbed for Human Movement Activity Monitoring and Presentation.
DOI: 10.5220/0009347800610068
In *Proceedings of the 6th International Conference on Information and Communication Technologies for Ageing Well and e-Health (ICT4AWE 2020)*, pages 61-68
ISBN: 978-989-758-420-6

humidity within hospitals or clinic laboratories. The work aimed at developing an IoT architecture capable of autonomously sensing the environmental conditions and providing to the user real-time remote monitoring. The authors have structured their architecture based on three layers starting with the node layer based on WSN, the local management layer, and the cloud-based layer for remote monitoring. In their approach, the sink module receives all the data sent by different sensing nodes based on MTM-CM5000-MSP module then sends to the local PC in which it can be sent to the cloud. The information of data packets is ID node, humidity and temperature values. From the findings, node layer factors like data packet size, sampling rate etc. have not been presented in detail.

However, the current focus is now shifting towards two different types of IoT architecture i.e. centralised and decentralised approach. In the centralised approach, the operational and computational processes are placed within the cloud. All the involved devices forward the data to the cloud before any decision making can take place. This may lead to challenges in handling the unnecessary increase in the traffic and load of resources (Verma, Kawamoto et al. 2017). Whereas in the decentralised approach, utilizing the other layers of the architecture for distributing the computational and decision-making capabilities from the cloud to the edge and fog layer represented by the end and intermediate devices (gateway) respectively. This can lead to significant reduction in the transferred data, thus decreasing the communication delay (Mocnej, Seah et al. 2018). However, this concept has not been employed to cloud based WSN and can be of great interest while proposing and implementing the layered architecture by considering the computation process to be done in the various spots of the network.

This paper attempts to underline and address all the competent functions involved in IoT based testbed architecture for human activity movement monitoring. The concept could support many different healthcare monitoring applications. Moreover, the paper also validates the proposed architectural functionality at each level by considering the case of hip fracture rehabilitation movement activity monitoring.

2 HUMAN ACTIVITY MOVEMENT MONITORING SYSTEM

The architecture for the proposed human movement activity monitoring IoT testbed is illustrated by Figure 1. The design is based on three main layers. These are Wireless Sensing layer, Gateway layer and Cloud layer. Each layer has its own unique role in the overall movement monitoring process.

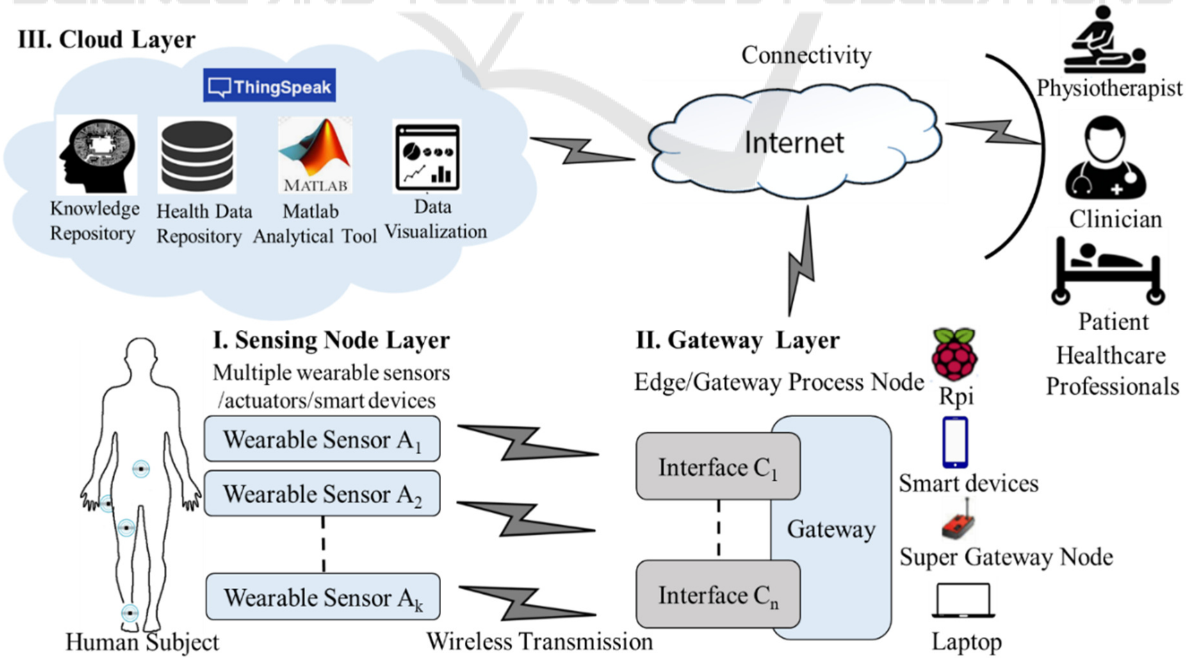

Figure 1: Activity movement monitoring testbed design.

The wearable sensors report to a gateway through embedded protocol(s) such as Bluetooth, Wi-Fi or ZigBee. Other customized protocol may also be facilitated. The rate of data acquisition and reporting could be configured to suit the application. This may involve one or more sensing types and the gateway may handle one or more wireless sensors. These may relate to multiple users or multiple wearable sensors on the same subject. Both wearable sensor and gateway offers the role of communicating the data. They could be involved in edge computing and backup storage. Hence, this could be handled as generic solution.

Alternatively the two network components (wearable sensor and the gateway level) could be driven as a software defined functions. This could be done by utilising the two components for data processing, compression and some level of activity recognition. It will significantly help in relieving the cloud from detailed signal processing and in reducing the data size. At the Cloud, real-time and history data will be managed. Visualization modelling and more involved processing take place. The Cloud facilitates the key interaction with the various types of users including the subject, health service providers such as caretaker, physiotherapist, clinician etc.

2.1 Wearable Sensor Function

The wearable sensor function can be seen by Figure 2. It involves four key functionalities for offering a software driven configurable system.

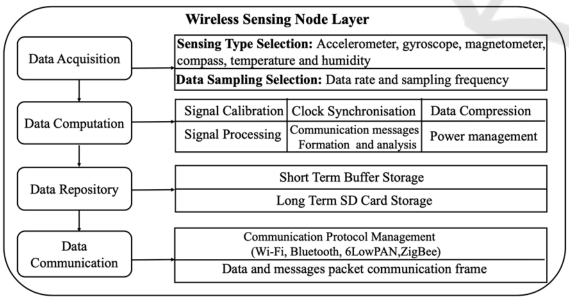

Figure 2: Wearable sensing node layer involved components.

First, data acquisition that is responsible for sensing type selection (such as accelerometer, gyroscope, magnetometer, compass, temperature and humidity), data sampling selection (such as data rate and sampling frequency). Second, data computation that encompasses signal calibration, signal processing, data compression, communication messages formation and analysis, clock synchronisation, operational modes and power management. Third is data repository for short term buffer at main memory and long-term back storage (SD card). Last is the communication which involves data and messages frames and communication protocol management.

In this research, a wearable monitoring device prototype is designed based on Microduino system. The main components involved are Microduino CoreRF, SD card, Real Time Clock, and Microduino nRF board holding the Nordic nRF24Lo1+ transceiver, Microduino 10 DOF sensor board comprising MPU6050 that contains triaxial accelerometer and gyroscope, magnetic field strength (HMMC583L) and barometer sensor (BMP180). A Microduino Real time clock for capturing the human subject activity movement event period and Core RF processor for computational purposes. The device is battery powered through a rechargeable battery.

Figure 3 shows the proposed wearable device and its placement at ankle location along with the device components stack. Ankle location is selected as favourable location for recognising post hip-fracture rehabilitation movements activities (Gupta, Al-Anbuky et al. 2018). Moreover, commercial fabric strip is tailored based on the wearable sensor design to make it comfortable for the user wearing the sensor.

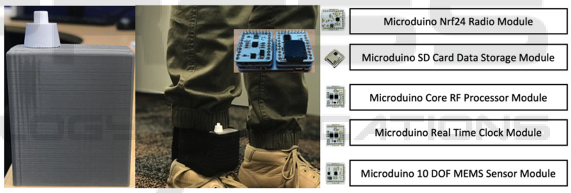

Figure 3: Wearable device placed on the right ankle and its components stack.

Among all the available sensors within the proposed device, only triaxial accelerometer sensor is used in this article which is responsible for sensing real-time human activity data. The data is collected at a sampling frequency of 128 Hz. It offers four different ranges of acceleration ±2g, ±4g, ±8g, ±16g where g is the acceleration due to gravity in m/s^2. Acceleration range of ±2g is considered sufficient for appreciating ambulatory activities (Gupta, Al-Anbuky et al. 2018).As part of testing, data is collected for a time period of two hours where different set of post-operative hip-fracture rehabilitation activities like lying on stomach , lifting thigh upwards, slow and fast walking are performed in an ad-hoc manner only during the first five minutes and for the remaining time the device is in static state to investigate the operational reliability and continuity in data collection.

Two storage space has been provided within a wearable device. A circular buffer has been used for short term storage of the continually processed data whereas SD card is used as a long-term storage purpose here. Firstly, it can be used for long-term storage of the continuous raw activity accelerometer data. SD card of 16GB was used in this research which can store data for around 10 days when run continually for 24 hours a day. However, any size SD card can be used for extending the longevity of the data storage depending on the application need. Secondly, the availability of the data can help researchers or clinicians for carrying out further detailed intelligent computational analysis. Also, it act as a backup in the event of misconnection of connectivity to the gateway and the cloud.

The screenshot and trend of the sample or unfiltered activity data stored in the SD card can be seen from Figure 4 and 5. Figure 4 sample the unfiltered type of activity data stored in the SD card i.e. node id, date, timestamp and 3 axis (x, y and z axis) accelerometer readings.

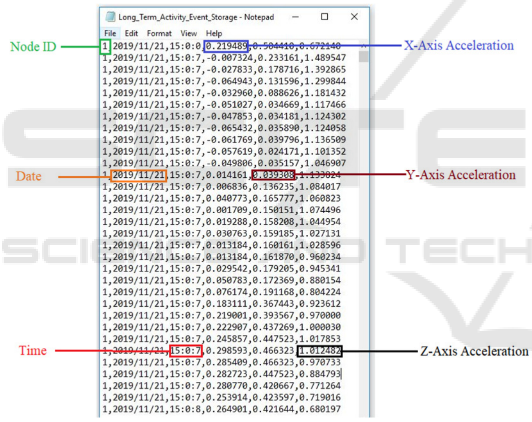

Figure 4: Sample activity movement SD stored data.

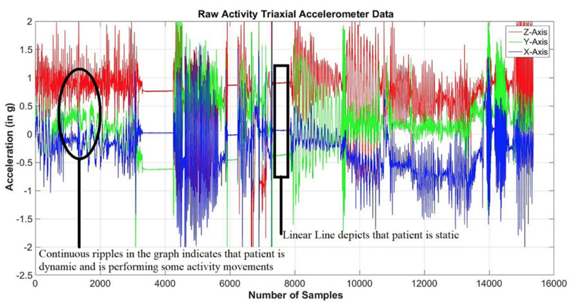

Figure 5: Sample trend of the activity movement data.

Whereas in Figure 5, the continuous ripples portray that human subject is dynamic and is performing some type of activity movements. However, there are scenarios when the accelerometer data is steady at fixed value which means that subject is static (exercise no movements).

After capturing the raw activity data, one option is to then subject the raw data to filtering methods. This is done by combining all the three axis samples, taking the mean, removing the DC offset and taking average of every four samples, down-sizing the sampling rate to 32 Hz (Gupta, Al-Anbuky et al. 2018) to comply with the 20 Hz suggested for everyday activities by (Sharma, Purwar et al. 2008).

In order to establish a communication between the wearable device and gateway node different communication protocols can be used for instance Wi-Fi, Bluetooth and ZigBee. However, for data packet transmission and reception, Nordic nrf24 chipset has been used that works on an enhanced shock burst protocol. It supports three air data rate i.e. 250kbps, 1Mbps and 2 Mbps and is suitable for ultra-low power wireless applications.

For preliminary testing purpose, point to point communication is established for transmission of data packet once every four seconds from the wearable node to the gateway. A portable Raspberry Pi attached with a Microduino nrf24 radio module is acting as a gateway here.

The transmission of radio data packet from node to the gateway takes place at a data rate of 250kbps. It has a 5 byte radio pipe address for transmission and reception, 2 byte for node id, 2 byte for packet transmission id for packet trace, 2 byte for date, 2 byte for time and 4 byte for the processed data as portrayed in Figure 6. In total, one reading has a data packet size of 12 byte and 128 such reading are send to the gateway layer accommodating a total of 1536 byte of data.

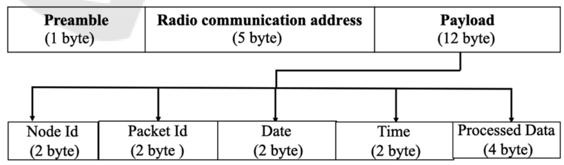

Figure 6: Data packet communication frame.

Considering the radio packet transmission in mind, analysing the energy consumption and how long the wearable device would last is essential. This is done by studying the device in idle mode and that of fully functional. As the Microduino hardware can run on 3.3 V, the wearable nodes are powered by a ½ AA rechargeable battery of 700 mAh at 3.7V where the cut-off voltage is 2.75 V. This is a random selection of the battery so that the device can almost cover a day. The current in idle and operational (op) mode of each module can be seen from Table 1.

Table 1: Current consumption of the node components.

S.no	Sensing Board	Idle Mode Current (mA)	Operational Mode Current (mA)
1	Core RF	22	22-24
2	10 DOF	0.01	0.02-0.06
3	SD card	1.5	5-7
4	Nrf24	2.8	3-4.5
5	RTC	0.032	0.05-0.1
Total Current Consumed		**26.3 mA**	**30-36 mA**
Total Power Consumed		**97.4 mW**	**111-132 mW**

From the practical measurement of the device, a total current of 26.33 mA and between 30-36 mA in idle and operating mode is used by the device. Whereas, a total power consumption of 97.4 mW and between 111-132 mW has been used for both the modes.

However, a slight fluctuation in the current is observed during transmission and reception and the variation is mostly between 30-36 mA. This could be due to several reasons for example when the data is stored in the SD card, it draws more current. Based on our calculations and as shown by Table 1, battery capacity is sufficient to collect, store and transmit data continuously for a time period of 20 hrs and needs to be recharged using a USB cable when human subject is going to bed.

2.2 Gateway Function

A portable Raspberry Pi is attached with a Microduino nrf24 radio module and the functionalities involved at the gateway layer is represented in Figure 7.

There are four key functionalities involved. First is the wearable device communication interface. This relate to the protocol used and act as the protocol convertor. It will help receiving the data through wireless and pass it through serial communication. Example for a gateway could be a raspberry pi, smartphone or laptop. Second is the incoming data from the wearable device and locally processed data storage and management. This can be short term storage available within the main memory (1GB RAM), long-term storage at SD card (16 GB) and data can be managed using database like SQL and MongoDB. Third is the computational capability analysed locally at gateway layer like signal processing, data aggregation and priority before connecting to the cloud and transmitting using internet protocols like TCP-IP, 6LowPAN, Cellular.

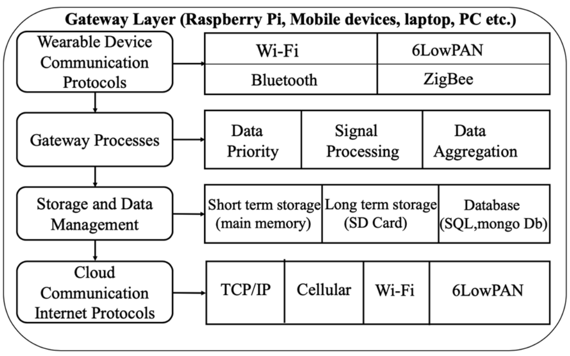

Figure 7: Gateway layer involved components.

In this research, the main purpose of making the device portable is to allow subject to carry it anywhere and with ease if they move out of the allocated residence. The radio module used is attached serially to raspberry pi for data reception using serial peripheral interface (SPI).

A complete packet of 128 pieces of data is received regularly (representing the 4 second data acquired by the wearable sensor) by Raspberry Pi (Rpi) . This data packet is stored continually in the SD card residing within Rpi in form of a text file. The screenshot of the data packet received at raspberry pi is shown in Figure 8. Here “1” represents the node id, “0” is the packet track count that increments by 1 whenever the new packet is received. This is to keep a track which packet has been received or lost during the transmission. 2019/11/21 represents the date and “15:0:12” represents the time and “-1.6545” represents the processed data at wearable sensor node level.

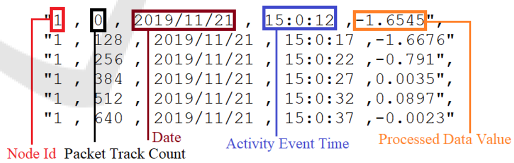

Figure 8: Wearable sensor processed data packet format received at Raspberry Pi.

The representation of the wearable sensor processed/filtered data vs the one minute activity time period event stored in the raspberry pi is represented in Figure 9. In contrast to the raw graph as shown in Figure 5, the graph below is smoother and consistent due to cleaned pre-processing. Moreover, based on the ripples observed at different point in the graph marked with different coloured circles, indicates subject has performed different types of activity movements instead of being static all the time. Red circle indicates that subject was static whereas other different circles portrays different sets of activities that cannot be recognised on the basis of this data. Therefore, it is difficult to discriminate the activities based on the wearable sensor processed data and require further data compression. Compressing of the data acquired by the wearable sensor taken place by Raspberry Pi gateway using FFT based signal processing as discussed by (Gupta, Al-Anbuky et al. 2018).

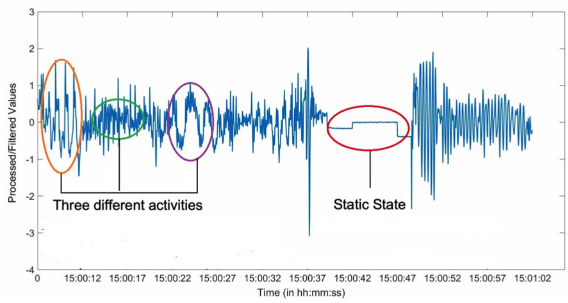

Figure 9: 1-min filtered values vs activity time period event plot received at the Raspberry Pi.

The process identifies the dominant amplitude and the corresponding frequency of the maximum amplitude (Cf_{MA}) for each of the 4 seconds data batch. The timestamp is associated with the end time of that sampling snap. In fact, the final compressed long-term data is stored in the Rpi SD card in form of a text file due to following reasons. First, to validate the data packet loss. Second in case of connectivity to the cloud is lost but the activity recognition data can still be recovered. The screenshot of the FFT process data packet format is shown in Figure 10:

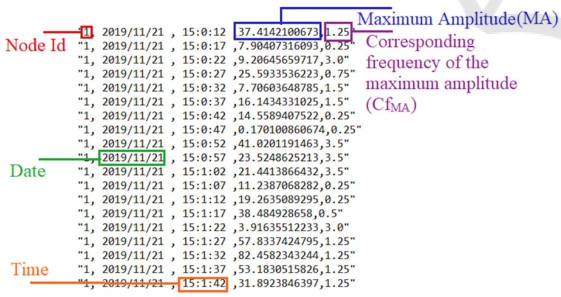

Figure 10: Gateway FFT based signal processing data packet.

Each activity threshold condition is set based on the if-else condition for a user as depicted by (Gupta, Al-Anbuky et al. 2018) in table: Activity classification overall summary at the ankle location. Therefore, activity recognition is performed at gateway level based only on maximum amplitude and corresponding spectrum. On recognising an activity, maximum amplitude, corresponding spectrum and the recognised activity code is sent to the cloud. Here, the recognised activity code is a number that ranges from 0-8 and is respectively identified as static state, slow walking, fast walking, leg movement, lifting thigh upwards, swinging leg to a side, lying on back, lying on stomach and unrecognised activity. For example, if a recognised activity is slow walking, the gateway will send a value 1 to the cloud. The visualisation of all these data is represented in Figure 13. Moreover, communication between the Raspberry Pi and ThingSpeak cloud platform is established using TCP-IP internet protocol.

The research investigated power consumption of the portable device theoretically based on the information available from the datasheet. In this research, gateway device is powered by two AA battery of 2500 mAh (equivalent to 5000 mAh) at 3.6V. The recommended input voltage for Rpi is 5V with a ±5% tolerance. This means the voltage could be supplied between 4.75-5.25V. Table 2 represents the current and power consumption of the Rpi3 when it is in idle mode versus to its fully operational mode.

Table 2: Current and power consumption of the Rpi3 in idle and operation modes.

Raspberry Pi3	Current Consumption (mA)	Power Consumption (W)
Idle Mode	260	1.3
Storing/opening File from SD Card	285	1.425
Operational Mode	670	3.35

If we consider the fully operational mode current consumption of Rpi3. The calculations shows that battery capacity is sufficient to collect, store and transmit data continuously for a time period of only 7 hrs. Considering that the battery power is only needed when the subject is outdoor, the 7 hours should be sufficient to cover the data collection time before recharging again.

2.3 Cloud Function

The key involved functions within the cloud layer are represented in Figure 11. At cloud layer, the "ThingSpeak" open source IoT based platform has been used. This platform provides the capability of collecting and storing the data in real time and allows for developing IoT based processing and visualization for the application. Importantly, Matlab data tools are available to process, elaborate and analyse the data further. The data is transmitted from the Raspberry Pi using HTTP protocol to the ThingSpeak cloud. The data is stored in the ThingSpeak cloud (in JSON, XML and CSV format)

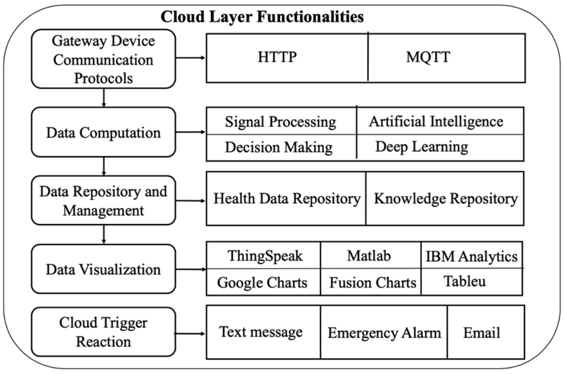

Figure 11: Cloud layer involved components.

repository across six different fields (Field 1: Node Id, Field 2: Date, Field 3: Time, Field 4: Maximum Amplitude, Field 5: Spectrum with Peak Intensity, Field 6: Preliminary Recognition ID).

Utilising Matlab analytical tools provided within ThingSpeak for computational purpose, a human subject activity monitoring track vs time visualisation has been created (refer Figure 12) from the data available within the cloud repository.

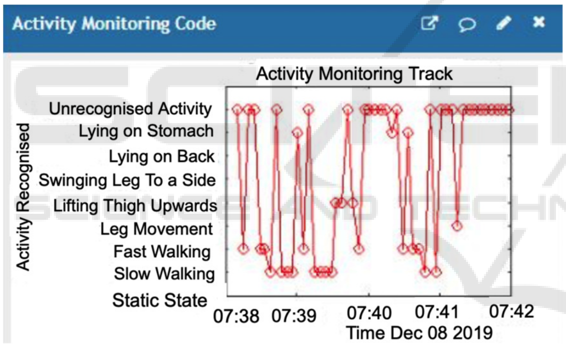

Figure 12: Activity monitoring track Vs time using Matlab analytical tools.

This plot provides the overall view of the different type of activity movements performed (represented by red coloured circles) by a subject vs time. Findings shows that patient has performed lifting thigh upwards, lying on stomach, slow and fast walking whereas some of the activities was not recognised. The approach we used at this stage is simply rule-based approach using the FFT outcome. There are areas of overlap among activities and further and more involved recognition approach is needed.

3 TESTBED PERFORMANCE

This section reflects the testbed performance by considering the examples of activities related to post-operative hip fracture rehabilitation activity movement as a use case.

Hip fracture is a common incident among older adults and results in poor outcomes. Although, many rehabilitation programmes are available that focus on improving the physical functionality, mobility and help in returning back to their daily life routine activities. But, the effectiveness of the program is still uncertain (Pol, ter Riet et al. 2019). In fact, most of the rehabilitation occurs when the patient has been discharged from the hospital and is living independently or in rehabilitation homes. As a result, healthcare professionals lacks real time precise data of the daily functioning of the patient activity movements. This prevents the person to achieve their personalised and realistic goals. This is due to the non-existence of remote activity movement monitoring system using wearable sensors that can track patient's activity movement levels in long-term (Pol, ter Riet et al. 2019).Therefore, by addressing it, the gap can be filled.

For hip fracture rehabilitation monitoring, the activities that need to be recognised are similar to the ones proposed by (Gupta, Al-Anbuky et al. 2018). These are leg movement (while sitting), lifting thigh upwards, swinging leg to a side, lying on back and stomach, slow and fast walking and static state i.e. sitting and standing. Patients are advised to perform these activity movements at least two times a day by repeating each movement 5 to 10 times (Buyya and Srirama 2019). We make use of the proposed testbed architecture in designing and implementing the complete system at each layer. As part of our preliminary testing, a healthy young individual was asked to perform few activities like slow and fast walking, lifting thigh upwards and lying on stomach in any order and based on their comfortability.

Findings shows that the testbed was successful in implementing the functionalities at each layer and based on the activity movement data collected and analysed. No concerns with the data storage across different layers has been observed. The system was able to recognise some of the performed activities in real time that can be seen from Figure 13. The rule based approach used is limited at this stage and require further support through either additional sensing or more involved deep learning.

Apart from that, further research work is required to enhance the testbed functionality so that system can be implemented on large scale like hospitals, rehabilitation home etc. This include establishment of multiple wireless sensor connectivity, multiple sensor sending data to gateway and then to cloud, investigate packet loss, data drop rate when multiple sensors are involved, investigate what is the suitable number of sensors that can accommodate with a single gateway in establishing secure connectivity and in data transmission and reception, how to optimize data traffic and process, overall system communication performance, more involved activity movement recognition with the use of machine and deep learning. Also, how the system can be personalised and adaptive to a particular subject automatically.

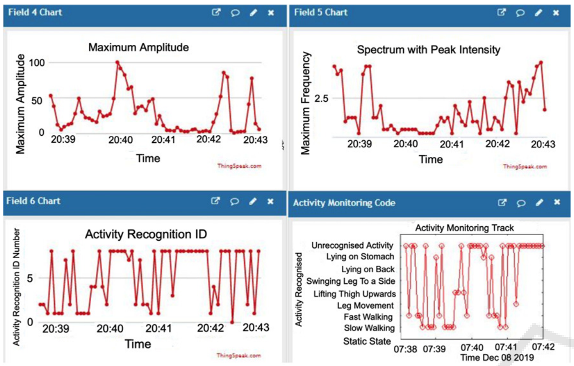

Figure 13: Data presentation of maximum amplitude, corresponding frequency of the maximum amplitude, activity recognition ID and activity monitoring track.

4 CONCLUSIONS

This paper proposed a generic IoT test-bed architectural design for human movement activity monitoring. The design is driven towards modular structure that allow both hardware and software modules to be tested and can be applied to wide range of healthcare applications. The paper implemented the proposed testbed functionality pragmatically by considering post-operative hip fracture rehabilitation activity movement recognition as one of the use case. Experimental results represent that the system was able to implement the testbed functionalities across all layers and also in recognising most of the activities. Further involvement will look into testing the performance measures on activity classification recognition accuracy, users acceptability and usability of the proposed device. It will also look into the compliance of the system with IIOT or Industry 4.0 direction and ability for software defined infrastructure.

REFERENCES

Buyya, R. and S. N. Srirama (2019). Fog and edge computing: principles and paradigms, John Wiley & Sons.

Cabra, J., D. Castro, J. Colorado, D. Mendez and L. Trujillo (2017). An IoT approach for wireless sensor networks applied to e-health environmental monitoring. 2017 IEEE International Conference on Internet of Things (iThings), 21-23 June 2017, Exeter, UK, 10.1109/iThings-GreenCom-CPSCom-SmartData.2017.91

Dang, L. M., M. Piran, D. Han, K. Min and H. Moon (2019). "A Survey on Internet of Things and Cloud Computing for Healthcare." Electronics 8(7): 768.

Farahani, B., F. Firouzi, V. Chang, M. Badaroglu, N. Constant and K. Mankodiya (2018). "Towards fog-driven IoT eHealth: Promises and challenges of IoT in medicine and healthcare." Future Generation Computer Systems 78: 659-676.

Gupta, A., A. Al-Anbuky and P. McNair (2018). "Activity Classification Feasibility Using Wearables: Considerations for Hip Fracture." Journal of Sensor and Actuator Networks 7(4): 54.

Kowal, J., A. Kuzio, J. Mäkiö, G. Paliwoda-Pękosz, P. Soja and R. Sonntag "ICT Management for Global Competitiveness and Economic Growth in Emerging Economies (ICTM)."

Kumari, P., M. López-Benítez, G. M. Lee, T.-S. Kim and A. S. Minhas (2017). Wearable Internet of Things-from human activity tracking to clinical integration. 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), IEEE.

Lee, I. and K. Lee (2015). "The Internet of Things (IoT): Applications, investments, and challenges for enterprises." Business Horizons 58(4): 431-440.

Mocnej, J., W. K. Seah, A. Pekar and I. Zolotova (2018). "Decentralised IoT architecture for efficient resources utilisation." IFAC-PapersOnLine 51(6): 168-173.

Pol, M. C., G. ter Riet, M. van Hartingsveldt, B. Kröse and B. M. Buurman (2019). "Effectiveness of sensor monitoring in a rehabilitation programme for older patients after hip fracture: a three-arm stepped wedge randomised trial." Age and ageing.

Salunke, P. and R. Nerkar (2017). "IoT driven healthcare system for remote monitoring of patients." International journal for modern trends in science and technology 3(6): 100-103.

Sharma, A., A. Purwar, Y.-D. Lee, Y.-S. Lee and W.-Y. Chung (2008). Frequency based classification of activities using accelerometer data. 2008 IEEE international conference on Multisensor Fusion and Integration for Intelligent Systems, IEEE.

ThingSpeak. "ThingSpeak." Retrieved 12 December 2019, from http://www.thingspeak.com

Verma, S., Y. Kawamoto, Z. M. Fadlullah, H. Nishiyama and N. Kato (2017). "A survey on network methodologies for real-time analytics of massive IoT data and open research issues." IEEE Communications Surveys & Tutorials 19(3): 1457-1477.