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INTELLIGENT PERSONAL HEALTH DEVICES CONVERGED WITH INTERNET OF THINGS NETWORKS

JAMES J. KANG
Deakin University
jkang@deakin.edu.au

HENRY LARKIN
Deakin University
henry.larkin@deakin.edu.au

Smartphone technology has become more popular and innovative over the last few years, and has led to the prevalence of wearable devices embedded with body sensors for fitness tracking and various smartphone features. Internet of Things (IoT), which can interact with wearables and personal sensor devices (PSDs), is emerging with technologies such as mobile health (mHealth), the cloud, big data and smart environments like smart homes. It may also provide enhanced services utilising health data obtained from physiological sensors. When these sensors are converged with IoT devices, the volume of transactions and traffic are expected to increase immensely due to the increased demand of health data from the IoT network. These additional demands will affect the existing mHealth services. Health service providers may also demand more data to enhance their services such as real-time monitoring and actuation of sensors alongside the existing monitoring of traffic. Both of these situations can cause rapid battery consumption and consume significant bandwidth. Some PSDs are implanted on or inside the body, and may require invasive surgical operations to replace batteries, such as for a heart pacemaker. It is therefore crucial to save and conserve power consumption in order to reduce the frequency of such procedures as well as health data transmission when needed. There has not yet been any research into managing and controlling data processing and transmission to reduce transactions by applying intelligence onto body sensors. This paper provides a novel approach and solution to reduce data transactions in sensors and allow for the transfer of critical data without failure to medical practitioners over IoT traffic. This can be done via an inference system to transfer health data collected by body sensors efficiently and effectively to mHealth and IoT networks. The results from the experiments to reduce bandwidth and battery resources with heart rate sensors show a possible savings in resource usage of between 66% and 99.5%. Battery power can be saved by 3.14 Watts in the experiments if the transmission of a single 1KB data point is reduced, and by 7.47 Watts if the transmission of 628 data points totalling the size of 120KB is reduced. The accuracy of data inference between the originally sensed data and the data transmitted after inference can be maintained by up to 99% or more. Such savings have the potential of making always-on mHealth devices a practical reality. This research contributes a low-overhead approach to mHealth sensors by inferring the processing and transferring of data.

Key words: Body sensors; WBAN; IoT; mHealth; Personal sensor device (PSD); Body sensor network (BSN); Activity Recognition (AR)

1 Introduction

The rapid popularity of smart devices such as wearables have led to an increasing demand for health related services and applications along with emerging technologies such as the Internet of Things (IoT), big data and the cloud. For example, sensors can monitor the cardiovascular system using electrodes on the chest for electrocardiography (ECG). Implantable medical devices such as pacemakers can have smart functions to communicate wirelessly with external devices [1]. In addition, fitness tracking devices and smart watches are being popularised for the use of health status monitoring and services, which can connect and provide IoT applications.

As a result, industries such as the healthcare industry are embracing mobile technology to support and integrate with these technologies to provide secured and efficient services demanded by other networks. This has resulted in new applications such as mobile health (mHealth) converged with IoT. Furthermore, health service network operations will want to manage their customers' devices to provide better managed services as well as physicians, who will want to access their patients' device for real-time monitoring or actuation when needed.

All these demands will cause additional transactions and workloads on wireless personal area networks (WBAN) consisting of personal sensor device (PSD) and smart devices such as smartphones, which will consequently affect the performance and battery power of PSDs such as physiological sensors and wearables. Current PSDs neither profoundly interact with IoT networks nor intelligently provide data to health networks. Instead, they are passive and simply provide sensed data on a regular basis or on demand due to typical sensors having hardware and size limitations. However, this is now being changed due to the introduction of smartphones interacting with wearables, allowing sensors access to more powerful resources and a greater capacity to provide health information demanded by wellbeing requests. As sensors interacting with IoT devices to use health data is a new area of demand, there have not been many works done on how to efficiently transfer sensor data to external networks. It is to be expected and envisaged that traffic and transactions of data requests to PSDs will be enormously increased by IoT networks, as Gartner forecasted that 20.8 billion 'things' will be connected to IoT by 2020 [2].

This paper proposes an inference system in sensors to determine and ensure whether it can manage data between PSD networks (e.g. WBAN) and external networks (e.g. IoT or healthcare), such that critical information is always transmitted. This includes designing, implementing and verifying intelligent functions on sensors to provide inferred decision making on what and how to transfer data to requestors[a]. For example, sensors can prioritise transactions differently from physicians or a smart light-bulb with quality of service (QoS) by using algorithms which use processed information analysed by big data in a cloud monitoring centre.

As the contribution, sensors will process and transmit sensed data intelligently and be able to provide an optimised data transfer mechanism controlling workload and traffic. Sensors should also provide real-time tracking of mHealth user's health status and future predictions of their wellbeing such as alarming of health conditions to caregivers before a dangerous health situation occurs. This is possible when a PSD is intelligent enough to send a warning message to the patient's doctor or caregiver by checking and inferring from the pre-defined threshold database, and prioritising this task to other IoT traffic. Furthermore, these sensor data can be utilised along with activity recognition (AR) data which currently uses accelerometer devices in order to enhance the accuracy of situation determination for alarming. Figure 1 shows both existing and new interfaces between mHealth and IoT networks.

[a] Requestors are those who request health data of sensors such as caregivers in mHealth and IoT devices.

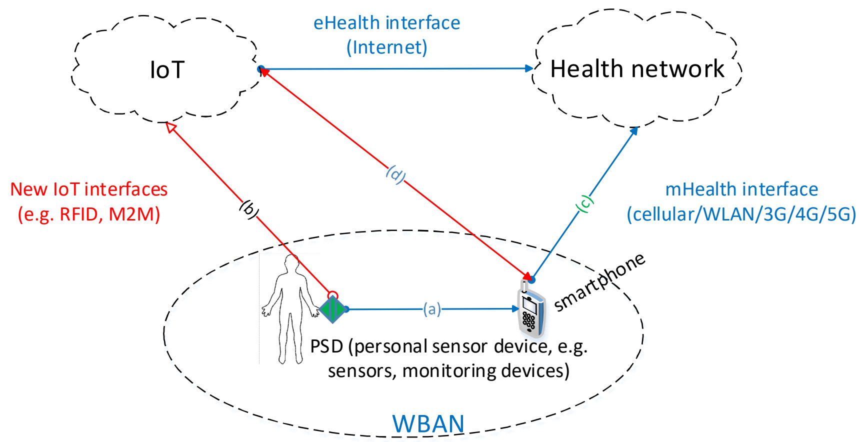


Figure 1 Interfaces of Health and IoT network from WBAN. Interface (b) and (d) are new while (a) and (c) are already existent. A PSD can be any device with sensor functions attached on or inside a body to collect health data

1.1 Research Motivation

Little research has been conducted between mHealth and IoT due to the limitations and constraints of PSD hardware resources such as battery power and computational capacity as they are equipped on or implanted on the body [3]. In recent times, the innovation of wearable devices has changed the direction of the industry and the wearables market. Apple launched the Apple Watch in mid-2015 and other major players such as Samsung and Google also developed or made plans to develop similar products. These mobile devices are powerful and well integrated with smartphones and smart devices, providing ease to communicate with IoT for its smart functions and powerful resources (i.e. CPU, memory, interfaces, battery and apps). It is obvious that sensors and monitoring devices will be equipped with more capacity to better handle the problems of additional traffic that burdens PSDs.

Infectious diseases such as the Middle East Respiratory Syndrome (MERS) and the Zika virus affect human health and quality of life in many countries. The World Health Organization (WHO) reports that the global case count for MERS was 1,651 laboratory-confirmed cases as of 10 March 2016, including 590 deaths with a fatality rate of 36% since the first cases were reported in September 2012 [4]. In the Republic of Korea, the MERS outbreak resulted in 186 infected people, including 38 deaths. This emerging epidemic nearly paralysed the country resulting in 2208 school closures, 16000 people quarantined for health monitoring and over 100,000 scheduled tourists cancelling their trip from nearby countries. It took 6 weeks to bring the disease under control [5]. This case could have been better managed with mHealth monitoring system converged with IoT as the disease has symptoms of fever and coughs that may be monitored by sensors during quarantine. Infected patients visited several hospitals for medical shopping and visited other places during the self-quarantine period at home. The government had no information of their movements other than to call them on a daily basis to manually ask about their symptoms and location. Pandemics are regarded as a national security that may cause more casualties, especially during a time when globalisation allows for disease to spread widely and more rapidly than in the past. Thirty four percent of all deaths worldwide are now attributable to infectious disease, while war only accounts for 0.64 percent of deaths [6]. When a case requires the monitoring of a large volume of people and geographic area such as a city or across borders, it may cause network congestions from a continuous stream of data. Thus it will be crucial to minimise the size of data from personal sensor devices when transmitting to the monitoring centre (MC). It is vital to consider how best to handle the prioritisation of traffic between sensors and IoT devices and between sensors and the MC.

As the merging of IoT traffic with existing mHealth traffic will create additional transactions, it is also required to manage and control PSDs of which functions such as registration, device status, traffic measurements, software updates and battery checks are essential. This requirement will be an additional burden to PSDs which generally have limited resources to be carried by a human body. It is proposed to implement intelligent functions on PSDs and smart devices to provide inferred decision making on what and how to transfer data to requestors. These tasks need to consider and reflect QoS and security requirements into the inference system to adopt smart algorithms when making a decision, along with taking into account information processed and analysed by big data in the cloud monitoring centre. Figure 2 illustrates an example of the data flow of inference and its application e.g. prediction of health status. Health data received from the sensor are processed and resent to the same sensor based on the knowledge base built and maintained by the sensor for future decision making. Another example is that the sensor uses the information of past requests received and stored from an IoT device so that it can decide the priority of what information to transfer and how often.

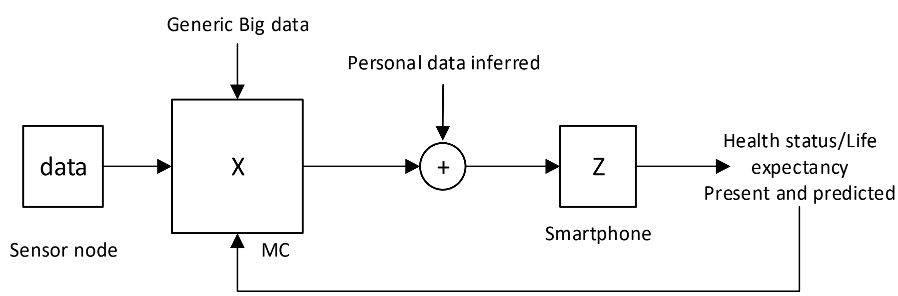


Figure 2 Data inference flow for an application. Monitoring Centre (MC) collects and creates meaningful information to feed back to sensors, which continuously adjusts the thresholds and utilises the results for inference

1.2 Research Problems

There are major problems envisaged in the mHealth domain with the convergence of mHealth with IoT technology and networks [7, 8].

- Sensors are currently passive and are programmed to transfer data on a scheduled basis without discerning the situation of priority or the importance of the data. This may cause battery power issues which is a constraint for functionality, actuation and urgent monitoring function.
- Currently, sensors are not managed by a network operation, and work in isolation for tasks such as device registration and status monitoring [9]. This includes an alarm for low battery levels and malfunctions, security attacks and statistics. When this function has been implemented, it will cause additional transactions and increase the burden to PSDs.
- Personal sensor data volume will increase significantly for sensors to provide health information to IoT networks (e.g. additional data demanded from IoT devices) [10]

- There is no functionality or intelligence on PSDs to manage and control the external demand, which will overload the device capacity and eventually malfunction with risks of being a target of attack.

1.3 Research Approach and Methodology

In order to experiment and assess the result, we undertook an extensive set of testing to obtain test data from a real human subject. The outcome of the experiments is in the form of measurements, such as efficiency and accuracy comparing the original data with the processed data from the inference system. Therefore the quantitative data analysis is used for testing and assessing the solution including various types of data, i.e. nominal, ordinal, interval and ratio [11]. Whilst there is no definite figure for validating the research problems from the results, experiments show how accurate and efficient the solution is against the original data volume in terms of bandwidth and battery power consumption. For example, sensors assess the data request to see whether they are from a caregiver terminal or an IoT device (nominal), the captured data to see whether they are in a normal or an abnormal range (ordinal) as well as the frequency of data transfer decided (interval). This is done prior to sending out the personal sensor data such as heart pulse rate (ratio) to the requestor.

The solution is verified by experimental testing of the sensor data and analysing the results both with and without implementation of the inference system.

- Testing: Test environment and network topology, test data, test tools, end to end testing, integration and interoperability testing, entry/exit criteria
- Evaluation: Show amounts of battery power saved after the inference, efficiency rate, and descriptive result record for further analysis. Accuracy and efficiency are used to evaluate the results of inferences
- Proof of Success: Compare test results with and without the solution applied followed by a result review process. The outcome will be shown using an efficiency and accuracy rate to show how efficiently the solution works to reduce data transmission and bandwidth to save battery power

To create and analyse test data and set out the criteria for verification, it is planned to adopt the concept of the experimental design method originally formed by Fisher [12] and Kirk [13], which may be suitable to this project for the variability of individual health data. Therefore, the following calculations are proposed to be used in analysing the results to assess the outcome of inference system with efficiency and accuracy along with bandwidth and battery power savings, which is the ultimate goal. Whilst efficiency is generally defined to show the ratio between the actual output and the effective or designed capacity (or input and output ratio of energy), the main concern is to know how much capacity can be saved against the volume of transferred data. Thus, a new equation is proposed as shown in Equation 1 below to define how efficiently the data are transmitted by defining the difference of sensed data and transferred data against the actual transferred data volume.

$$\text{Efficiency Rate (ER)} = \frac{\text{No of Sensed data} - \text{No of Transferred data}}{\text{No of Transferred data}}$$

Equation 1 Efficiency Rate

To calculate the SR, data savings are measured from the total volume of the original data points versus the total of screened (reduced) data points. Whilst ER or SR can show how much data are saved or reduced, it does not represent how accurately the data have been produced and transmitted. To determine how closely the transmitted data is compared to the original data, it is required to calculate the accuracy rate (Ar) as shown in Equation 3 below.

$$\text{Savings Rate (SR)} = \frac{\text{No of Sensed data} - \text{No of Transferred data}}{\text{Number of Sensed data}} \text{x100}$$

Equation 2 Savings Rate

$$\text{Accuracy Rate (Ar)} = \frac{\text{Sum of original DPs} - \text{Sum of differences}}{\text{Sum of original DPs}} \text{x100}$$

Equation 3 Accuracy Rate (%)

2 Current Practice and Related Research Works

Sensors have traditionally been passive devices. Smart sensors are now being deployed but wearables are limited in the role of biomedical sensors nodes. Instead they are mainly used for monitoring and capturing physiological data such as in accelerometers, gyroscopes and pedometers. Therefore, it is hard to find literature regarding the empowerment of PSDs with intelligence, as intelligence is yet to be implemented on PSDs. There are few ‘inference’ related works found in the IoT domain [14] but not in the emerging areas of PSD or mHealth networks. However, there have been many solid approaches and works done in the IoT network domain.

As a by-product of the solution, there can be an application of using the result of big data analysis and processing for a personalised life expectancy that can be estimated on an individual basis. Therefore, literature on prediction algorithm and mechanisms are searched and reviewed to see how this research will affect the industry. Whilst there are many research works found regarding life expectancy of a country, region, race or on a disease basis, there have been no works done on regarding this metric at a personal level basis. In this regard, [7] was published with a novel idea of tracking and predicting a personal health status for individuals as well as intelligent functionality of inference systems in sensor nodes to interface IoT networks.

In addition, activity recognition is essential to determine the status of alarms before transmitting sensed data to requestors in order to minimise false alarming. Thus, this area has been included in the search.

There have been much research in inferencing body activity monitoring, conserving battery power, processing sensed data and improving efficiency network protocols. Haghighi et al [15] proposed a situation-aware mobile health monitoring framework to monitor health conditions using an algorithm of activity recognition classifier. They identify health status by utilising health data such as heart rate with other vitals, which we also suggest to use multiple data for inferencing. However this solution is processed outside of sensor networks, which is crucial in case of emergency, e.g. real-time alarming. Furthermore, developing individual thresholds would be a key information and our solution proposes enhanced alarm notification in real-time by a user feedback system.

Whilst there are many works on improving sensor networks to process data such as using middleware in a new global sensor network infrastructure [16], improving routing protocols or acquisition of reading and modelling the accuracy of the sensor reading using algorithms [17], there have been little works performed in trying to minimise the data sampling and transmission from the sensors. Jara et al [18] presented an interconnection framework for mHealth and IoT which makes continuous remote monitoring for vital signs. Borodin et al [19] suggested applications design from multi sources for health care monitoring systems such as ECG and Heartrate monitors which require interfaces between patient terminals and IoT. They discuss how to collect and transfer health data to MC, however, they do not show how those monitoring devices can interface to other networks such as IoT.

Wearable sensors have been developed and have increased significantly in number in the last few years, requiring the consideration of techniques on how the data are treated and processed. Accordingly, there have been many methods and algorithms used to analyse data from wearable sensors and physiological monitoring devices capturing vital signs in healthcare services including anomaly detection, prediction, diagnosis and decision making [20]. A Bayesian model has been used for averaging to develop a high-accuracy prediction analytic method for a large-scale IoT application [21], however, this method cannot be applied to mHealth data as the volume size and nature of the data are quite different between mHealth and IoT networks. IoT networks involve a huge number of devices over the Internet whilst mHealth is a personal body network.

Privacy is key to the security of mHealth. Kang and Adibi [22] comprehensively surveyed a range of security protocols and mechanisms for mHealth as confidentiality of health data is a priority concern. It was discovered that many works have already been done in areas of authentication, authorisation, key management and hash technologies. However, a light-weight security with a well-secured measure is required to transfer health data when it needs to communicate with IoT networks, which will request health data for their own purpose and are beyond the control of mHealth networks. This requires thorough security to protect mHealth devices as well as the privacy of users.

In conclusion, it was found that there have been many works done in the area of sensors, IoT, WSNs, WBANs, mHealth, eHealth, network security, inference logic and system, remote monitoring, network management system, communication protocols, prediction of situation and applications. However, there is very little work which focuses on implementing intelligence on personal sensor networks and its enhancement with intelligence and its integration with IoT, and traffic control of sensor devices when it is overloaded.

3 Implementation

Our proposed system focuses on an inference system embedded in the sensor itself to make a decision on how best to transmit sensed data through discerning situations and optimising data.

3.1 Situation Determination

There are existing techniques such as [15] to determine a situation, which is required for alarm notification in our inference system. Depending on the requestor such through WBAN or machine to machine (M2M) protocol, sensor nodes will wake up when a request arrives. When data are captured by sensors, it is calculated to work out the actual value to be used to produce the health status value. Inferred value can be obtained by applying thresholds such as low, normal, and high for blood pressure, and other data such as male/female, age, disease related, body weight, exercise tolerance and the individual's overall health condition [23]. They are used along with the weighting of the attribute which is the portion of which it affects the health status. The outcome of the inferring process is to calculate a personalised range of normal thresholds for each attribute and to compare it with generic information, such as an individual's personal blood pressure range (85/55 – 110/70 mmHg) to the generic range (90/60 – 120/80 Hg) of the specific group the user belongs to. When data are captured by sensors, it is calculated to work out the actual value to be used to produce the health status value. As shown in Table 1, each data type has its own activity defined by a medical professional. These values are used to determine an activity along with other data types to determine a situation. Utilising the prescribed data, an individually developed health status can be calculated for each data type as shown in Table 2. Data types can be each of the sensed data such as blood pressure (e.g. 140/90 mmHg), heart rate pulse (e.g. 97 bpm) and Body Mass Index (BMI) (e.g. 24 = 170cm/70kg). Table 2 shows an example of how the weighted value can be used to calculate a situation activity when there is a mixed outcome based on each application. Points are the input to the result using a calculation table which can be prepared by physicians or scientists. Thus, the outcome in this case will be 'running' activity, i.e. 39R (running) over 33W (walking) as 39 is larger than 33.

By combining various data, it is possible to determine a situation or activity as physiological data are related to each other. When a user is running for instance, heart rate increases, body temperature goes up [24] and respiration rate also rises.

Figures in Table 1 and Table 2 are given arbitrarily, and should be designated by a physician in a real world application depending on the context of its usage. The weighting for Table 1 is defined based on the attributes and is multiplied with the inferred value to result in the points.

Table 1. Situation determination to define the threshold of the activity from each type of data

Data type	Sleeping	Resting	Walking	Running	Weighting
BP	<110/70	120/75	130/80	145/100	4
HR	<60	60-100	101-149	>150	5
BT	33	33.4	35.5	36.9	2
RR	<12	13-18	19-30	>30	6

Table 2. Situation and Activity calculated from a mixed outcome using points to get results based on a pre-defined table

Attributes	Data measurement and calculation			
	Sensed Data	Inferred activity	point	result
BP	145/100	5.5 (Running)	4	22+R
HR	85	3.0 (Walking)	5	15+W
BT	40	8.5 (Running)	2	17+R
RR	20	3.0 (Walking)	6	18+W

In order to improve the accuracy of the determination, existing activity recognition (AR) sensors such as an accelerometer can be used together with physiological data. Whilst the AR sensors indicate the status of activity motion such as sitting, standing, walking, running or dancing, they do not show the level of activity, such as the degree of tiredness. Furthermore, the accuracy of the activity relies on the sensor location which may be untrue when misplaced. To enhance the quality of content, physiological data and AR sensor data can be used together to assess the situation.

3.2 Optimisation of Sensed Data

The inferred value obtained by the situation determination is used to represent how the attribute locates the overall status of the individual's health. When comparing data from multiple sensors it may not give much option to discern due to discrepancies as shown in Figure 3, which was taken from an hour of walking while wearing two devices, i.e. sensor device 1 for heart rate and sensor device 2 for heart rate, along with skin temperature sensors on the same wrist. This discrepancy could be accounted for by averaging the values from the different data sources. When the number of sensors increases to more than two devices, it becomes more difficult to determine how to handle the data. For example, when sensed data from various sensors for body temperature are different and some of them are not consistent with the rest of the data, it needs to be inferred to decide whether the specific data should be ignored.

3.3 Alarm Generation

An alarm notification is generated when the battery level is lower than a pre-defined threshold, or data are out of the normal ranges. When sensed data are out of the normal range as shown in Table 3, it needs to be verified against the situation of whether they are normal or abnormal as the activity will determine the normality. For example, a heart rate of 170 will be normal when the user is in exercise mode whilst it will be alarming if it was captured during sleep. The alarm notification can be improved by using feedback from the user to optimise the accuracy of alarm determination [25].

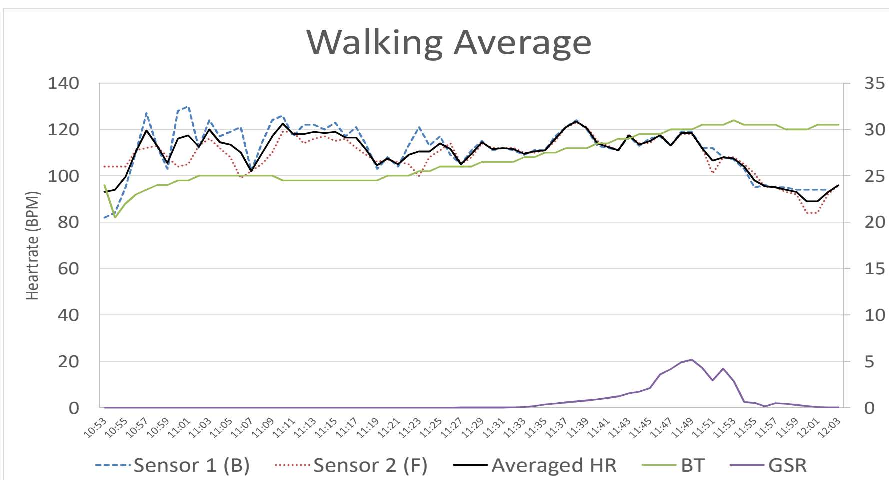


Figure 3. Data discrepancy of two heart rate sensors, which are averaged as well as body temperature.

3.4 Data Transmission

The outcome of previous inferences provides user priority, optimised data, validity of sensed data, alarming and the content of message for transmission. In order to transmit the data, sensors calculate the frequency of transmission such as whether to transmit immediately or after a delay, periodically or with increased intervals, and to ignore the request and do nothing if required. When the sensed data does not change often, it is likely that the user is in a reasonably stable condition without many motion changes, and the data can be transmitted less instead of transmitted regularly as originally scheduled. In this case, the intervals between each data transmission can be lengthened to reduce the battery consumption.

For alarming, a threshold table (Table 3) is used as suggested by a medical practitioner for a general purpose. Values are customised for individuals by their physicians and the table shows an example only.

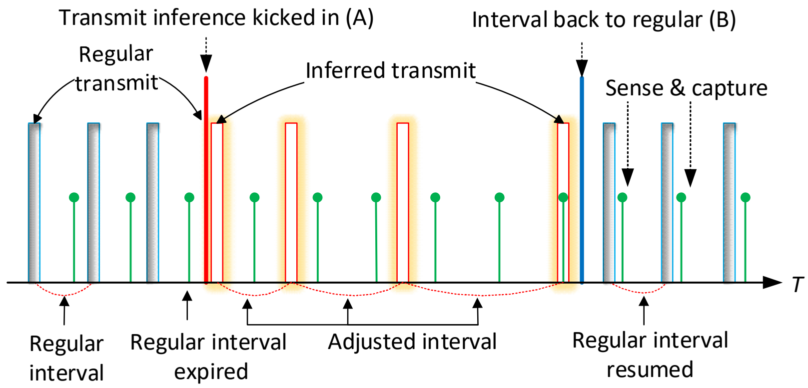


Figure 4. Data transmission interval with inference applied.

Table 3. Alarm Threshold of Sensed Data

Data type	Acceptable		Warning		Severe		Critical	
	Low	High	Low	High	Low	High	Low	High
BP	91	169	90	170	80	185	65	220
HR	51	139	50	140	40	180	32	210
BT	34.1	37.9	34	38	32	40	30	42
RR	11	29	10	30	8	36	6	45

Figure 4 depicts how the frequency of data transmission is adjusted based on the data transmission inference algorithm. After a pre-defined period of data transmission without a change in the data based on the threshold table, e.g. 5 consecutive regular transmissions, the time interval algorithm kicks in at (A) starting with the 5th frame. The interval is extended until it reaches the set time or the sensor captures a range criteria changed data depending on whichever comes first, before returning to the regular scheduled cycle at (B). To apply a non-linear interval time, the equation below can be used for instance as it is a design requirement.

$$Interval\ Time(ITx) = a_0 + \sum_{n=1}^{K}\left(\frac{n(n+1)}{2}\right) + IT\ (x-1),$$

$$where\ x > 0, a_0 = default\ minimum\ delay\ time, K = each\ interval\ value$$

For example where $a_0 = 30$, the interval time will be (31, 65, 105, 160, 225) for each interval period of K.

4 Verification and Discussion

HR data are used for collection over a period of short (2 hours) and long (24 hours) observations tested repeatedly over a few weeks before taking samples for experiments. More data and increasing the frequency of capturing will increase the accuracy in averaging and increases the credibility of the outcome. As heart rate sensors are popular and practical to collect data, it is used in this experiment. A heart rate sensor has been attached on the wrist for 24 hours and the tester moved with various motions including resting, walking, jogging, running, sitting and sleeping. The sensor device collects data every second during exercise mode and every five seconds as a function of a general mode.

There are various algorithms to apply to get the final data and transmission, and how it is applied depends on the design requirements. For example, when the data are captured during sleeping, the body temperature is unlikely to change often and the transfer interval algorithm will significantly reduce the number of transmissions. However, physicians may request not to apply the inference for a certain period of time in order to obtain a pure observation of their patient's health status.

Whilst this paper proposes to use physiological data along with AR information to provide enhanced information, it is difficult to measure the effectiveness as it can vary depending on how they design and use AR along with this solution. Thus this simulation focuses on how much it can reduce the transactions of sensors to transfer data to smartphone as it directly affects the battery and bandwidth capacity. In this case, the efficiency rate and savings rate (percentage of eliminated data prior to data transmission) are used as in Section 1.3. The result in the body temperature simulation is a 2000% improvement. In other words, battery life can be extended by 20 times and an implanted device does not need to have its battery replaced for instance. As previously discussed, it depends on the design requirements, however it surely demonstrates how the solution can improve the resource capacity.

Two sampling intervals, i.e. every second and minute, and various percentage variances have been used to process the collected data. Figure 5 depicts HR patterns based on activities which show that BPMs are around 80 or below during resting, and around 140 or below during walking. Running status is shown as having a BPM above 140. After inferring, data were reduced by 62% with an efficiency rate of 1.68, as according to equations (2) and (1) respectively. Results show that the larger the inference variance rate (roughness) applied, the higher the efficiency rate. For example, a variance rate of 10% reduced the data transactions by 99 percent of the original sensed data volume, and this is good enough to identify heart rate zones of Peak (over 141 BPM), Cardio (over 116 BPM), Fat Burn (83 BPM) with a customised zone setting of the tester with 167/60 BPM. Sampling interval affects the quality of data and there are significant differences to consider between the sampling intervals, that is, data obtained per second are 60 times the volume of data obtained per minute. Furthermore, beacons play a key role in optimising data as it provides a framework of the data shape. Sometimes, beacon DPs alone can be good enough to represent the original data. In case of short interval data, removing duplications can be quite useful to reduce the original data and can be used as a baseline itself for further inferences. In addition, the sensing interval can be significant for sensible cases. In conclusion, testing has verified that inferring data processing saves bandwidth and battery power significantly.

There are two ways to transmit sensed data from sensors to requestor networks, i.e. Store and forward, or Cut-through [26]. When transferring HR data by the store and forward method for example, the data is fragmented into 1460 bytes (payload) to be formed into a frame including headers (1514 bytes) since the data (2800 KB before compression) is larger than the maximum frame size. There are in total 448 packets directly exchanged between the sensor and the smart device. Among these, 180 packets have been transmitted from the sensor to the smart device, and 268 packets received (mainly for acknowledgement) at the sensor. Data are compressed before transmission. Battery consumes more power during radio transmission than in receiving or standby mode. For simulation purposes, the figures below are used for discussion [27].

Knowledge assumption:

- 1 micro ampere is consumed for standby
- 10 milli ampere are used for data receiving
- 25 milli ampere are used for transmission

Table 4. Outcome of Inference Efficiency after applying different variance rates

Inference Var (%)	**1**	**2**	**3**	**4**	**5**	**10**
Efficiency Rate	1.8	3.9	6.8	14.2	25.2	257
Savings Rate (%)	65	80	88	93	96	99

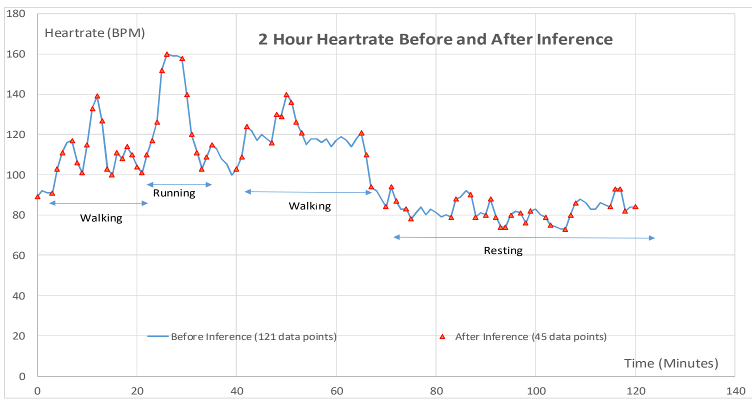


Figure 5. Hourly sensed data every minute with activities and their inference results obtained from the original sensed data.

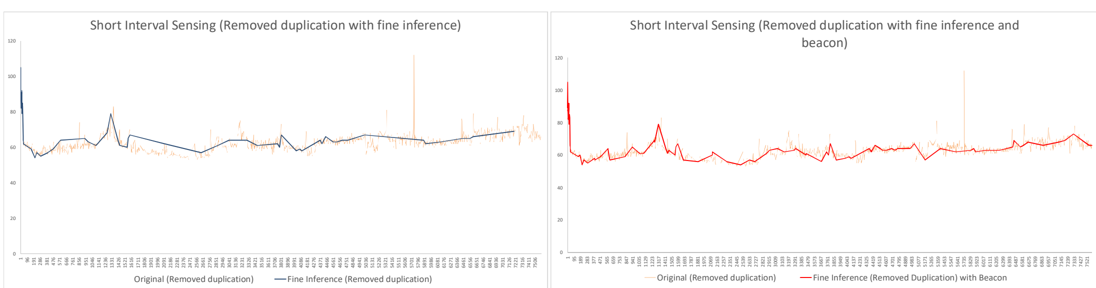


Figure 6 Inferring original data without (left) and with (right) beacons

When inferring, beacons are very important to improve the accuracy of inferred data. As shown in Figure 6 when a fine inference is applied (baseline DP: 1308, inferred DP: 69) without beacons (left figure), the result is very rough (i.e. less accurate). However, when beacons are applied in addition to the inference (right figure), it corrects for the roughness and the accuracy improves significantly with a minimal increase in sampling data (baseline DP: 1308, inferred DP: 107).

To transmit 2800 KB data in a simulation by store and forward method, it consumes 3130mA (2680mA for receiving + 4500 mA for transmission), which affects the power consumption directly (e.g. P=VI) as each type of battery may have different voltage types. When sensed data are transmitted in real-time without storing, the number of transmissions directly affect the power consumption and therefore the power is significantly affected if the frequency of transmission is decreased. There are many packets exchanged to establish a communication before and after the transmission even to transmit a single data point. Results show a possible power savings when sensor data have been inferred and reduced for the transmission accordingly. For example, in the case of zinc-carbon or alkaline type batteries, they produce around 1.5 volts per cell and 3.14 W (i.e. 2090mA x 1.5V) of power can be saved when a transmission of single data of HR is reduced by the inference system.

Table 5 Summary of Data processing for long/short interval for resting and exercise modes

Test data	Walk minute	Sleep minute	Walk second	Sleep second
Mode	Exercise	Rest	Exercise	Rest
Interval	Long	Long	Short	Short
Efficiency	1.8	3.8	8.8	14.7
Savings (%)	45	73.6	88.7	93.2
Accuracy (%)	99.98	99.1	98.2	98.62

In summary, the table below shows the result of data processing for exercise and resting modes as well as short and long interval sensing times. Generally, a higher data savings implies a better efficiency, and a lower accuracy. This result can be compared with before applying the inference. Battery power can be saved by 2090 mA x1.5V for a single data point transmission reduced, and 4980 mA x 1.5V for 120KB size of data reduced. Saving resource capacity resulted in reduced transactions in sensors which can allow additional capacity to be reserved for high priority transactions.

Informed consent from all human subjects were obtained prior to the experiment, and comply with ethical clearance codes such as the Australian 'National Statement on Ethical Conduct in Human Research' [28].

5 Conclusion

It is expected that body sensors will be overloaded and will consume battery quickly when they connect to the IoT network due to the additional traffic and transactions that will be demanded. This paper tries to address this problem by considering how to determine whether a resource constrained sensor in a WBAN can provide data to external networks consistently and reliably regardless of the traffic load. As a solution, we proposed to implement intelligence on body sensors by applying an inference system to reduce unnecessary transactions and save resources. Three intelligent functions are implemented, i.e. 1) requestor analysis 2) data processing and situation decision making 3) data transmission. These are done using 'captured data' analysis and a pre-defined data threshold which is prescribed and provided by physicians for their patients. Experiment results showed that this solution is far more efficient and effective than other methods, e.g. up to 99.5% reduction of the original data. However, it remains a design aspect with regards on how to program and optimise this system with medical practitioners who will determine the level of detail of data they require. Moreover, IoT networks may need a single datum from sensors even though they simply request bulk data without 'thinking', and therefore it is the role of sensors to be 'smart' in discerning 'things' and inferring data.

References

[1] D. Bragg, M. Yun, H. Bragg, and H.-A. Choi, "Intelligent Transmission of Patient Sensor Data in Wireless Hospital Networks," in *AMIA Annual Symposium Proceedings*, 2012, p. 1139.

[2] R. v. d. Meulen. *Gartner Says 6.4 Billion Connected "Things" Will Be in Use in 2016, Up 30 Percent From 2015* [Newsroom Press Release]. Available: http://www.gartner.com/newsroom/id/3165317, [Accessed: 22 June 2016]

[3] S. Adibi, "An application layer non-repudiation wireless system: A cross-layer approach," in *World of Wireless Mobile and Multimedia Networks (WoWMoM), 2010 IEEE International Symposium on a*, 2010, pp. 1-2.

[4] Australian Government Department of Health. *Middle East Respiratory Syndrome (MERS). Important information for health professionals and the general public on MERS.* Available: http://www.health.gov.au/internet/main/publishing.nsf/Content/ohp-mers-cov.htm, [Accessed: 2 October 2016]

[5] The Korean Society of Infectious Diseases and Korean Society for Healthcare-associated Infection Control Prevention, "The Same Middle East Respiratory Syndrome-Coronavirus (MERS-CoV) yet Different Outbreak Patterns and Public Health Impacts on the Far East Expert Opinion from the Rapid Response Team of the Republic of Korea," *Infection & Chemotherapy,* vol. 47, pp. 247-251, 2015.

[6] J. Evans, "Pandemics and national security," *Global Security Studies,* vol. 1, pp. 100-109, 2010.

[7] J. J. Kang, S. Adibi, H. Larkin, and T. Luan, "Predictive data mining for Converged Internet of Things: A Mobile Health perspective," in *Telecommunication Networks and Applications Conference (ITNAC), 2015 International*, 2015, pp. 5-10.

[8] J. J. Kang and H. Larkin, "Inference of Personal Sensors in the Internet of Things," *International Journal of Information, Communication Technology and Applications,* vol. 2, 2016.

[9] G. Fortino, R. Giannantonio, R. Gravina, P. Kuryloski, and R. Jafari, "Enabling Effective Programming and Flexible Management of Efficient Body Sensor Network Applications," *IEEE Transactions on Human-Machine Systems,* vol. 43, pp. 115-133, 2013.

[10] J. J. Kang, T. Luan, and H. Larkin, "Data Processing of Physiological Sensor Data and Alarm Determination Utilising Activity Recognition," *International Journal of Information, Communication Technology and Applications,* vol. 2, p. 24, 2016-09-24 2016.

[11] B. J. Oates, *Researching information systems and computing*. London SAGE, 2006.

[12] R. A. Fisher, *The design of experiments*, 7th ed. Edinburgh: Oliver & Boyd, 1960.

[13] R. E. Kirk, "Experimental design," *Sage handbook of quantitative methods in psychology,* pp. 23-45, 2009.

[14] D. W. Cheun, "A Framework for Controlling Internet of Things Devices and Inference with Contexts," PhD, Soongsil University, 2012.

[15] P. D. Haghighi, A. Perera, M. Indrawan-Santiago, and T. M. Huynh, "Situation-aware mobile health monitoring," in *Proceedings of the 11th International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services*, London, United Kingdom, 2014, pp. 248-256.

[16] K. Aberer, M. Hauswirth, and A. Salehi, "Infrastructure for Data Processing in Large-Scale Interconnected Sensor Networks," in *2007 International Conference on Mobile Data Management*, 2007, pp. 198-205.

[17] M. A. Osborne, S. J. Roberts, A. Rogers, S. D. Ramchurn, and N. R. Jennings, "Towards real-time information processing of sensor network data using computationally efficient multi-output Gaussian processes," in *Proceedings of the 7th international conference on Information processing in sensor networks*, 2008, pp. 109-120.

[18] A. J. Jara, M. A. Zamora-Izquierdo, and A. F. Skarmeta, "Interconnection Framework for mHealth and Remote Monitoring Based on the Internet of Things," *Selected Areas in Communications, IEEE Journal on,* vol. 31, pp. 47-65, 2013.

[19] A. Borodin, Y. Zavyalova, A. Zaharov, and I. Yamushev, "Architectural approach to the multisource health monitoring application design," in *Open Innovations Association (FRUCT), 2015 17TH Conference of*, 2015, pp. 16-21.

[20] H. Banaee, M. U. Ahmed, and A. Loutfi, "Data mining for wearable sensors in health monitoring systems: a review of recent trends and challenges," *Sensors,* vol. 13, pp. 17472-17500, 2013.

[21] X. Zhu, K. Fang, and W. Yongheng, "Predictive Analytics by Using Bayesian Model Averaging for Large-Scale Internet of Things," *International Journal of Distributed Sensor Networks,* pp. 1-10, 2013.

[22] J. J. Kang and S. Adibi, "A Review of Security Protocols in mHealth Wireless Body Area Networks (WBAN)," in *International Conference on Future Network Systems and Security 2015*, Paris, France, 2015, pp. 61-83.

[23] L. J. Vorvick, "Vital signs," *U.S. National Library of Medicine,* 2015.

[24] C. L. Lim, C. Byrne, and J. K. Lee, "Human Thermoregulation and Measurement of Body Temperature in Exercise and Clinical Settings," *Ann Acad Med Singapore,* vol. 37, pp. 347-53, 2008.

[25] J. J. Kang, T. H. Luan, and H. Larkin, "Alarm Notification of Body Sensors Utilising Activity Recognition and Smart Device Application," presented at the Proceedings of the 14th International Conference on Advances in Mobile Computing and Multi Media, Singapore, Singapore, 2016.

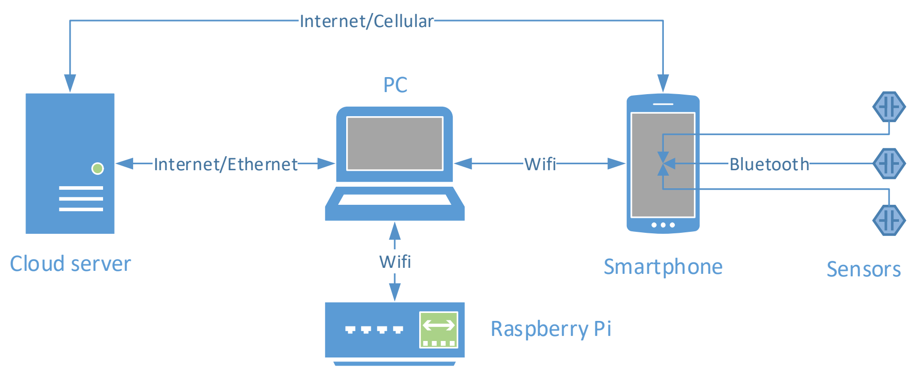
[26] B. M. Bass, D. R. Henderson, E. H.-C. Ku, S. J. Lemke, J. M. Rash, L. B. Reiss*, et al.*, "Simultaneous cut through and store-and-forward frame support in a network device," ed: Google Patents, 2000.

[27] M. Brain. *A Typical Mote - How Motes Work*. Available: http://computer.howstuffworks.com/mote4.htm, [Accessed: 15 June 2016]

[28] NHMRC, "National Statement on Ethical Conduct in Human Research (2007) - Updated May 2015," ed: Australian Government National Health and Medical Research Council, 2015.

Appendix: Test environment and network topology

Test Network Topology for sensed data capture, transfer and export is as below. Cloud servers are in production network provided by Intel and Fitbit, which collects sensed data via the PT and provides export functions to the PC when requested for data processing. Testing devices include Fitbit Charge HR sensors (Accelerometer, Gyrometer, and always-on heart-rate sensor), Basis Peak sensors (Motion/steps, Heart rate, Calories, Sleep tracking, Skin temperature), Samsung Galaxy Note 4 smartphone and Raspberry Pi3.



Raspberry Pi3 port configuration is as below.