SPHERE in a Box: Practical and Scalable EurValve Activity Monitoring Smart Home Kit

James Pope, Ryan McConville, Michal Kozlowski, Xenofon Fafoutis,
Raul Santos-Rodriguez, Robert J. Piechocki and Ian Craddock
Digital Health Engineering, University of Bristol, UK
Email: {james.pope, ryan.mcconville, m.kozlowski, xenofon.fafoutis,
enrsr, r.j.piechocki, ian.craddock}@bristol.ac.uk

***Abstract*—Non-invasive, environmental monitoring is being successfully utilised to improve health care outcomes for patients while allowing them to more safely and comfortably live in their homes instead of health care facilities. This promises to reduce costs and ease the health care burden for many countries globally. However, these systems are still in early stages of research and only highly skilled researchers and engineers can successfully deploy them. The difficulty in deploying these systems prevents their mass use and potential cost savings motivating research interest in smart homes in a box (SHiB). In this paper we present the *EurValve Activity Monitoring Kit*, a minimalist activity monitoring system that can be deployed in a home by the patient and still obtain valuable lifestyle and activity level information for medical clinicians. We describe the design of the system and how it is being used in the H2020 EurValve Project. The initial results show that the system is easily deployed and yet still effective for non-invasive sensing for activity classification and localisation.**

I. Introduction

Ageing populations are putting demands on already strained health care systems in many nations throughout the world [14], [16], [20]. Governments are investing research into finding solutions to reduce health care costs. A promising approach is to allow patients that do not need immediate health care but still require monitoring to live at home [23], [7]. These patients can be monitored using sensors placed around their homes and non-invasively on their body. Research continues on smart homes for health care regarding the cost benefits and quality. These smart homes for health care systems typically require a team of skilled engineers and researchers to install and train patients on how to use the system [9], [8]. Additionally, some use very expensive components such as high resolution video cameras. The difficulty and cost in deploying these systems remain an obstacle in scaling these systems, for example, to more than several hundred homes.

To address scalability for smart homes, recent research has suggested that a "smart home in a box (SHiB)" can be designed at a much lower cost. "CASAS: Smart Home in a Box" [8] uses relatively low cost components (e.g. passive infra-red, magnetometers) and could potentially be installed by a user. While the accuracy of the data provided by the system was degraded, the research showed that the CASAS system still provided sufficient information for a particular use case. However, this system still required over 40 sensors to be installed requiring several hours to deploy for healthy individuals.

Fig. 1. EurValve Activity Monitoring Kit.

This paper details a SHiB for individuals with a health condition, specifically heart issues. The patients are awaiting heart valve surgery and are living at home with periodic visits to the hospital for monitoring. While at the hospital, the medical clinicians obtain accurate measurements but have no visibility of the patient's activity while they are living at home. Providing clinicians with this activity information is of vital interest. The system must meet the following qualitative design requirements. The system should:

- Be relatively low cost;
- Be easily installed by patients;
- Be easily used by patients;
- Provide adequate data for activity recognition.

The research question can be summarised: Can a system be designed that is low cost, easy to install/use by patients and still provide sufficient information for clinician decision making? Note that the smart homes considered in the research are not meant for active medical alert purposes; these smart home systems are passive and meant to provide longer term information.

We propose the EurValve Activity Monitoring Kit, a subset of the Sensor Platform for Healthcare in a Residential Environment (SPHERE) System [21], that aims to meet these requirements. In this paper we provide evidence that the kit is low cost and easily installed/used by patients. We also show that the EurValve kit provides useful information that we believe can be used by clinicians to help determine the time and type of procedure to perform. The kit is shown in Figure 1.

The kit uses a single low cost, wrist worn wearable (hereafter simply referred to as *wearable*), that provides accelerometer data. However accelerometer data alone may lead to ambiguities. For example, it may be difficult to distinguish between showering and washing dishes using only accelerometer data. Previous research [22], [15] suggests utilising the user's location to better determine the activity, generally termed *context aware activity recognition*. The kit uses this approach by placing anchor wireless devices (denoted *gateways*) placed around the patient's home. These gateways can be used to determine the room the patient is located. The wearable sends periodic wireless transmissions and nearby gateways receive the data along with the received signal strength indicator (RSSI). Though the RSSI is noisy it is correlated with distance and can be used for room level localisation [10]. This is demonstrated in Section IV. This room level localisation information, separate from accelerometer data, can be used to determine certain activities such as the number of room transfers.

The design of the kit was driven by a particular use case on the EurValve Project [1]. In the near future the kit will be used to monitor the activities of a group of 60 heart surgery patients. The patients will be monitored over two week periods before the surgery, immediately after the surgery, and several months after the surgery. The goal is to provide medical clinicians with continuous activity information during these periods. Currently the clinicians only have activity information collected during hospital visits and from patient reported questionnaires and lose visibility while patients wait/recover at home. The clinicians have indicated that room level localisation and a limited set of activities (e.g. walking, sitting, sleeping) are sufficient. The kit will provide less biased, quantitative activity measures compared to information obtained from questionnaires.

During installation, the patients will perform predetermined activities in various rooms to provide a small amount of training data. During this short training period, the data will be annotated by simply placing the wearable on a gateway (using the combined RSSI and accelerometer measurements to produce a unique signature). Due to the limited training data, more advanced machine learning techniques will have to be employed.

The data collected by the kit is analysed offline using various machine learning algorithms. Though experiments with heart patients has yet to occur, this paper presents several preliminary experiments demonstrating that room-level localisation and limited activities can accurately be inferred using the kit. The contributions of this paper are enumerated as follows:

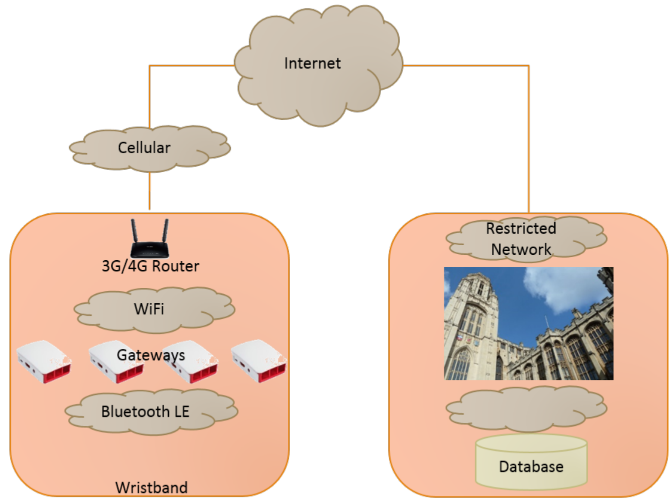

Fig. 2. EurValve Activity Monitoring Design.

- We present the challenges and the design of a low-cost smart home in a box that is able to provide adequate data for activity recognition in the context of monitoring the rehabilitation of heart surgery patients in their home environment.
- We demonstrate evidence of ease of installation and use of our kit.
- We conduct three separate experiments using the kit deployed in different scenarios.
- Via data analysis and machine learning we show preliminary evidence of feasibility of context-aware activity recognition using limited data.

The rest of the paper details the kit's components, including the wearable and gateways. Preliminary data collection and analysis is then presented. Finally, lessons learned, future work, and conclusion are provided.

II. Related Work

The research and reports provided in [14], [16], [20] describe various ageing populations around the world, the impact on health care systems, and potential solutions. All of these publications cite activity as a key component to provide health care for these ageing populations.

Zheng, et al. [23], provides an overview of unobtrusive sensing and wearable technologies. Clifton, et al. [7], suggest combining wearable data with clinical data for predictive monitoring.

Kasteren, et al. [19], present a sensor system for activity recognition in a home setting, however, do not consider context. Cook, et al. [8], propose a Smart Home in a box to address scalability suggesting that users should be able to install / use the system. Perera, et al. [17], provide a survey of IoT systems for several application areas including smart homes. Agoulmine, et al. [3], propose U-Health, a ubiquitous smart home using unobtrusive monitoring to assist the elderly.

Afonso, et al. [2], evaluate the performance of Bluetooth Low Energy in high data rate body sensor networks analytically showing goodput for various connection parameters. The authors also compare their model with several commonly used devices.

III. System Design

The EurValve Activity Monitoring Kit was developed as a subset of the SPHERE system [21]. Figure 2 depicts an overview of the kit operating at a patient's home and the communication networks involved between kit components and the University of Bristol (UBRIS). The kit costs approximately £350. The kit is comprised of the following components:

- 1 × Router
- 4 × Gateways
- 1 × Wearable

The kit monitors physical activity using the wearable's inertial sensor and provides indoor room-level localisation using the gateways. The router provides a cellular link to access network time protocol (NTP) servers, reports system monitoring information, and transmits collected data from the gateways to the UBRIS database.

The wearable communicates with the gateways using Bluetooth Low Energy (BLE) advertisement packets. The advertisement packets are sent 5 times per second and contain 3D acceleration samples (25Hz). The gateways within range receive the advertisements and save the data to a daily log file (on an SD card) along with the RSSI. Each gateway will have an RSSI value that can be roughly correlated with distance.

The gateways communicate with the router using WiFi (2.4 GHz band). The gateways routinely test the WiFi connection and each night will attempt to copy the collected data to the UBRIS database.

Each of the components are detailed in the following sections along with design considerations.

1) Router: The Router is commercial hardware [18]. It provides a WiFi access point for the Gateways and a 3G/4G cellular link to the Internet. The WiFi/Cellular link provides the following:

- Access to NTP servers
- One-way communication from the participant's home to the UBRIS network
- Daily status

It is assumed that the patient's location has cellular coverage. To minimise cost and complexity the gateways do not have a real-time clock. However it should be noted that without correction they will not have an accurate time and thus incorrectly time stamp the data. As this is not desirable they are configured to use Internet NTP servers to get and maintain the correct time. The router provides access to the Internet and NTP servers.

The gateways record a daily log file that they attempt to transfer to the UBRIS database each midnight. The gateway communicates with the router via WiFi and the router relays its information via the cellular connection to the Internet and finally to the UBRIS database.

This mechanism provides fault tolerance for the event of a Gateway's SD card failing when deployed in a patient's home.

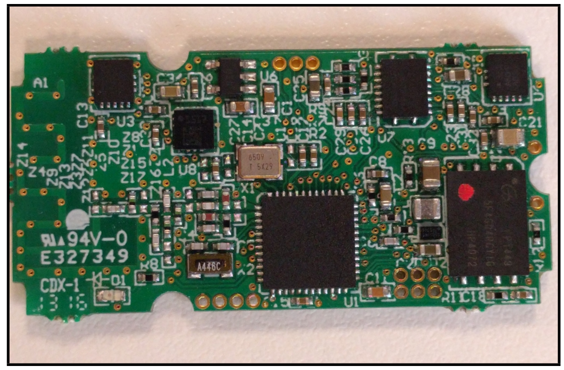

Fig. 3. EurValve Wrist Worn Wearable PCB.

While the kit uses high quality SD cards, SD card failures are not uncommon. The Router allows the data to be backed up to the UBRIS database each night. In case of a failure, the Gateway's current daily log file will be lost. However, previous log files for that Gateway can be recovered from the database.

Finally, the Router's WiFi/Cellular link provides a mechanism that can be used to ensure the system is functioning properly each day. Using the link, the gateways report system information to UBRIS once an hour. Also, the absence of daily log files from the Gateways would be an indication that a problem has occurred.

2) Gateway: The gateways are based on the Raspberry Pi 3, Model B. They are equipped with a BLE radio and a WiFi radio. Each Gateway's operating system and data are stored on a local SD card (8 GB for the OS and 8 GB for data). After booting, the gateways query an NTP server on the Internet to get the correct time and then start listening for BLE advertisement packets from the wearable. As each packet is received, the following steps occur:

1) The packet is decrypted;
2) The RSSI value is appended to the data;
3) The data is timestamped;
4) The data, timestamp and RSSI are appended to the daily log file.

Each midnight, each gateway stops recording, compresses and encrypts the daily log file. The Gateway then attempts to send the compressed/encrypted file to the database. Note that the compressed/encrypted file remains on the Gateway's SD card until the end of the experiment.

The gateways can handle data from multiple wearables and store the data so that each user can be analysed separately. Thus the kit can currently accommodate additional wearables without any modification.

While the accelerometer data received by each gateway will be identical the RSSI value is expected to be different for the same received advertisement packet. The RSSI value will be used to assist in determining the room the patient is located and therefore useful for activity classification.

3) Wearable: The SPHERE wearable [11], shown in Figure 3, incorporates a CC2650 (a System-on-Chip that integrates a Cortex-M3 processor and a BLE radio), an ADXL362

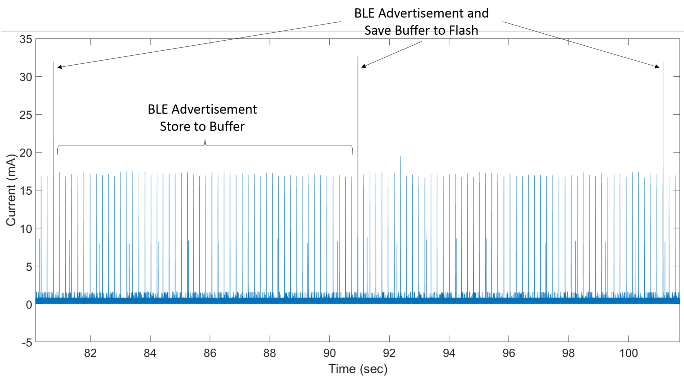

Fig. 4. EurValve Wearable Energy Usage.

acceleration sensor, and a 4 Mbit flash (GD5F4GQ4xC). The accelerometer is configured to sample at 25 Hz with 8-bit samples between ± 4 g. Every 200 milliseconds a BLE advertisement packet is sent with 5 of the acceleration samples. The flash has 2048 blocks. Each block has 64 pages. Each page can hold 4 kB of data. Overall, the flash can hold up to 512 MB of data.

The PCB (Printed Circuit Board) is powered by a Li-Po (Lithium-Polymer) battery that can be wirelessly charged when placed on a Qi charger. The PCB along with the battery are together in the enclosure with accompanying wearable (shown in Figure 1 with the charger). Wireless charging was chosen to aid ease of use.

The device stores the transmitted packet's payload (20 bytes containing 5 triaxial samples and the sequence number) to a temporary memory buffer (50 payloads equivalent to 1 kB) and then saves that buffer to flash. Thus, the flash is activated, written to, and deactivated every 10 seconds. Each day 8.64 megabytes are stored to flash.

The data is stored on the wearable to ascertain activities outside the house. Though localisation is no longer possible (assuming the gateways in the house are no longer in range), the acceleration data can still provide activity information, such as steps taken [5] and physical activity levels [4].

The data stored to the wearable's flash can be retrieved in BLE *connected* mode. However, optimistic BLE goodput rates are approximately 8 kilobytes per second [2]. Current experimental rates are approximately 3 kilobytes per second. This was determined using the wearable as the peripheral and an Android phone (Nexus 5X) as the central device. A Raspberry Pi 3 was also used as the central device with similar results. Assuming no loses, it would take approximately 18 minutes to download one day's worth of accelerometer data. To download two weeks would require over 4 hours. Considering practical transmission rates and loses, this approach will require an excessive amount of time (another non-wireless approach would be to use UART). Employing compression may certainly bring this within a reasonable amount of time. The compression would have to have little to no memory overhead, require little computation, and provide a good compression ratio (e.g. 5:1).

A. Wearable energy usage

The energy usage of the system was determined by using the Texas Instruments INA226 Power Monitor. The system is powered using a 3.7 V battery with 100 mAh capacity. The wearable was configured to operate as a peripheral in the *connectable advertising* mode. Figure 4 shows the current usage over roughly a 20 second period.

In Figure 4 the average current is shown to be approximately 210 uA. Note that this is the energy usage of the entire system, including the radio/microcontroller, accelerometer, and flash. Based on these parameters the system can last for an estimated 20 days (100 mAh / 0.210 mA). A longevity experiment confirmed this analysis where the wearable lasted for approximately 23 days before ceasing to operate.

The wearable takes about 45 minutes to charge from a completely empty battery. However, if partially charged, it only takes around 20 minutes to become fully charged.

B. Security

There are several security layers applied to the collected data, including data transfer and data storage. All security operations are standardised / widely accepted and the implementations used are based on commonly used hardware and software.

The wearable encrypts the accelerometer data in the BLE advertisements using AES-128 (Advanced Encryption Standard) encryption with a pre-shared key on the wearable and each gateway. Gateways decrypt the accelerometer data and store the data along with RSSI to a log file.

Each day the gateways compress and encrypt the log file using a hybrid symmetric / asymmetric scheme. A 128-bit message authentication code (MAC) is produced over the compressed log file. A randomly selected 128-bit key along with a 128-bit initialisation vector (IV) are generated and used to AES encrypt the compressed log file.

Each kit has an RSA 2048-bit public key. The MAC, key, and IV are encrypted using the public key and appended to the encrypted log file. The private keys to decrypt the files are securely stored at UBRIS.

IV. Preliminary Results and Analysis

Three experiments were conducted using the EurValve Activity Monitoring kit. The primary purpose of these experiments was to validate the kit and determine how well room level localisation and activity recognition could be performed using the data collected. Significant training data and annotations were available for these experiments. This will not be the case for the planned EurValve deployments where we will only have a short duration of training data from the patients. However, these results show that this approach is feasible using limited anchor points and limited data.

A. Ease of Installation and Use

For the following experiments, the EurValve Activity Monitoring kit was installed by 5 healthy individuals who had no

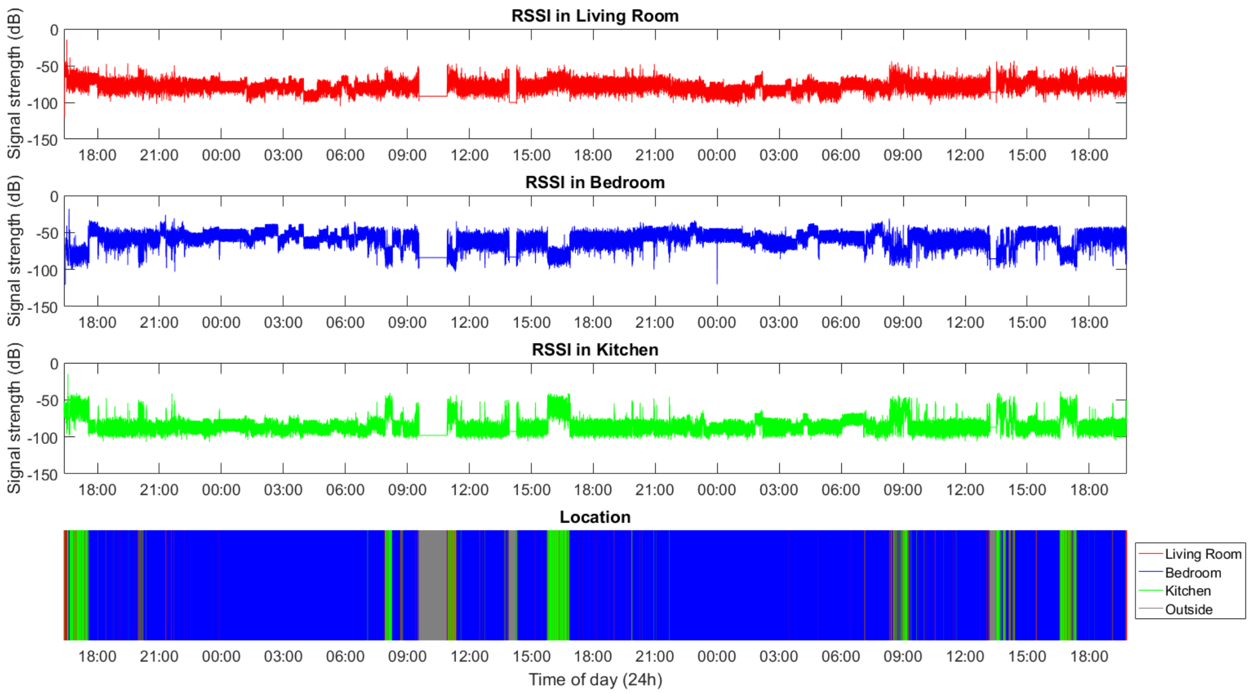

Fig. 5. Experiment 1: RSSI measurements can be leveraged for room-level localisation. The top three graphs plot the RSSI as observed in the Living Room, Bedroom and Kitchen, respectively. The bottom graph plots the room with the highest RSSI.

involvement in the development of the kit and no prior experience with installing it. All individuals successfully installed the kit in less than 10 minutes. Post-questionnaires verify its ease of installation and use. In particular, on a scale from 1 to 5, where 1 corresponds to *Very Easy* and 5 corresponds to *Very Difficult*, the users reported that the kit was easy to install ($\mu = 2$, $\sigma = 1$) and very easy to use ($\mu = 1$, $\sigma = 0$).

B. Experiment 1

The kit was installed in a flat (in this case only 3 Gateways were used) over a weekend. The researcher maintained a journal along with a video based system to annotate the data.

The RSSI for each Gateway is shown in Figure 5. The top graph in red is the living room Gateway's RSSI. The second graph in blue is the bedroom Gateway's RSSI. The third graph in green is the kitchen Gateway's RSSI. The bottom graph shows the result of a simple room localisation algorithm that selects the room with the highest RSSI. It can be seen that the absence of the wearable advertisements is also valuable information, as it indicates that the user is out of the flat.

Figure 6 shows a comparison of magnitude of the the acceleration (top graph) and the prediction of the output of a binary k-NN activity classifier (bottom graph). The classifier is configured to distinguish between two classes, namely activity and no activity. The results visualise behavioural patterns. For example, observe that the sleeping habits of the participant are apparent, while the classifier was able to successfully detect the disturbance of the participant's sleep at approximately 3 am during the first night. Furthermore, the output of the classifier can be used to calculate daily digests of the participant's activity levels that allow medical practitioners to quickly assess the rehabilitation of their patients by comparing them against the pre-surgery levels. Indicatively, the results presented in Figure 6 indicate that the user was active for 19% of the first day and 17% of the second day of the experiment.

C. Experiment 2

The kit was installed in a small flat (in this case only 3 Gateways were used) over a three day weekend. The researcher maintained a journal and after the experiment annotated the data. Note that this is an estimate of the "ground truth" label. The RSSI data was smoothed using a moving average. A logistic classifier (linear) was trained on a random sampling of 20% of the data. The remaining 80% was used for test data. An L2 penalty was used to ameliorate over-fitting. Table 1 shows the results of the training and test accuracy and compares against a majority classifier. The results demonstrate that the system is able to provide room-level indoor localisation with high accuracy ($> 92\%$), outperforming the majority classifier of Figure 5.

D. Experiment 3

In the third experiment the EurValve kit was installed in an office environment. All four of the gateways were utilised. One was placed by the office desk of the participant (a researcher), another by the desk of a colleague, around 10 meters away,

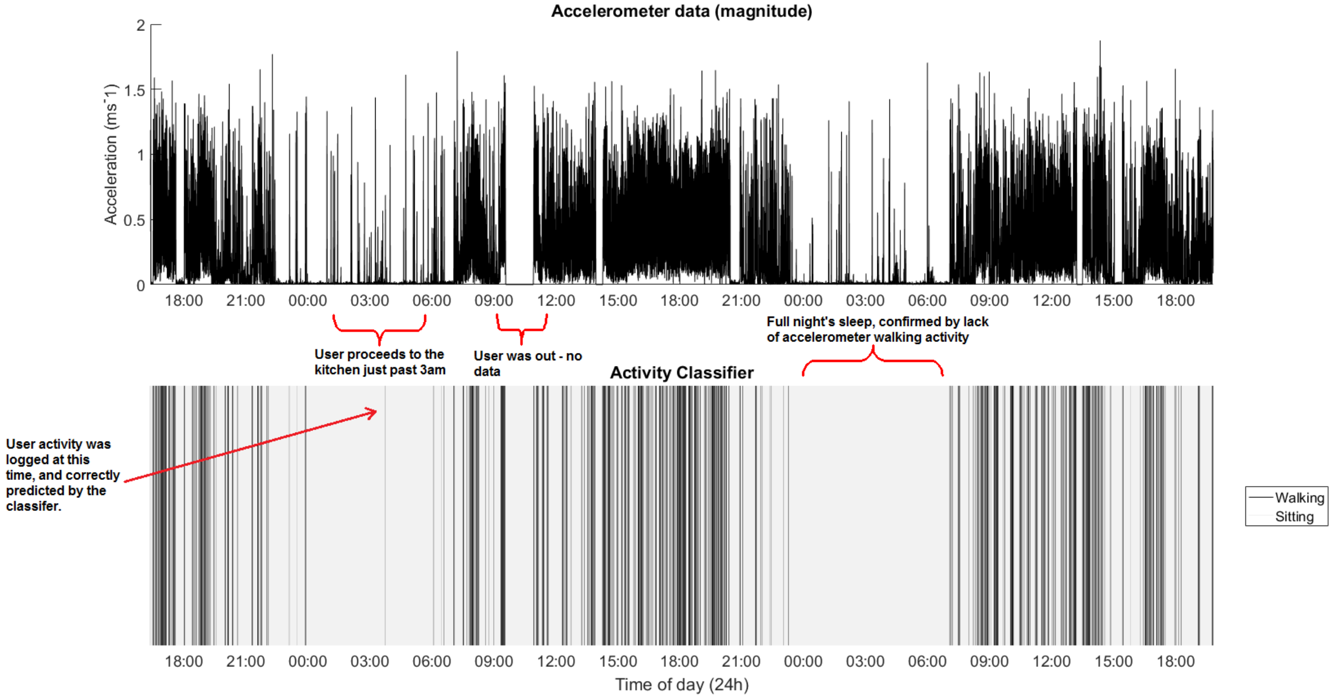

Fig. 6. Experiment 1: The magnitude of the acceleration (top) can be leveraged for determining the physical activity levels of the user. The binary activity classification results (bottom) are verified by the user diaries.

which is located close to the entrance of the office, a third within the office reception and the final in the kitchen. The layout and size of the office create what we expect to be one of the more challenging environments due to the close proximity of two of the gateways with no major objects such as walls in between. The RSSI values are averaged over a 5 second time window. The participant maintained a coarse journal of their movements around the office over the period of three days. Due to the setting the participant spent significant time by their desk, with, in order, less time spent in the kitchen, office entrance and reception. In fact, very little time was spent in the reception area, but due to the schematics of the office it requires passing in order to access other areas of the office, such as the kitchen.

The data used in localisation included the RSSI from each of the gateways and the accelerometer data from the wrist worn wearable. We will also explore whether that the inclusion of the accelerometer data would be beneficial to improving the localisation results, and we will show this empirically by trying each combination of the data sources.

TABLE I
EXPERIMENT 2: LOCALISATION CLASSIFICATION RESULTS

Room	Training Accuracy	Test Accuracy	Majority Classifier
Living room	0.932	0.928	0.690
Kitchen	0.930	0.929	0.688
Bedroom	0.953	0.952	0.700

TABLE II
F1 SCORE FOR A MAJORITY CLASSIFIER.

	Precision	Recall	F1-Score	Support
Desk	0.84	1.00	0.91	13941
Kitchen	0.00	0.00	0.00	1716
Reception	0.00	0.00	0.00	144
Office Entrance	0.00	0.00	0.00	769
Average / Total	0.71	0.84	0.77	16570

A number of machine learning algorithms were applied to the labelled data and their results are compared below. For each experiment stratified 10 fold cross validation was used in order to maintain the class imbalance characteristics. The Random Forest (RF) algorithm [6] was constructed with 10 estimators and balanced class weights. The MultiLayer Perceptron Neural Network (MLP) algorithm [13], [12] used the quasi-Newtonian limited-memory BFGS (L-BFGS) optimiser due to the relatively small dataset. The L2 regularisation term

TABLE III
F1 SCORE FOR A RANDOM CLASSIFIER.

	Precision	Recall	F1-Score	Support
Desk	0.83	0.25	0.38	13941
Kitchen	0.10	0.23	0.13	1716
Reception	0.01	0.20	0.01	144
Office Entrance	0.05	0.27	0.08	769
Average / Total	0.71	0.24	0.34	16570

was $1e^{-10}$ in order to better capture the minority classes in the imbalanced dataset. There were three hidden layers each with ten neurons and the rectified linear unit function was used.

Table IV and Table V highlight the ability for algorithms to learn how to localise a participant with a wearable using RSSI and the accelerometer. Due to the class imbalance the F1 score is calculated, which is the harmonic mean of the precision and recall. We note that the total reported in the tables are the F1 micro score. In order to show how effectiveness of the two algorithms they are compared with two baseline classifiers. Table II shows the results of a classifier which simply chooses the majority class each time, i.e. it will always predict the participant is at the desk. Table III shows the results of a classifier which simply chooses one of the four possible locations at random each time.

Figure 7 shows the mean F1 macro score for the stratified 10 crossfold validation of each algorithm. From this it is clear that both of the machine learning algorithms outperform the baselines with all tested combinations. Note that we chose to compare the performance of the F1 macro score rather than micro score in this figure. The macro score is computed over each class while the micro score is computed globally. Due to the class imbalance with this experiment the micro score would cause the larger class to dominate the smaller classes. Therefore we believe the F1 macro score, which takes into account the smaller classes, provides a better overview of the performance in this experiment.

Figure 7 also shows the performance of the algorithms using only RSSI data, and only acceleration data, as well as both combined. With just acceleration data considered, the performance of the MLP and RF achieve scores of 25% and 39% respectively. While out-preforming the baselines, acceleration is, as expected, a poorer feature for localisation than RSSI. With just the RSSI information considered, the performance increases to 55% for the MLP and 52% for the RF. Further, with both acceleration and RSSI information included, there is almost no significant change in performance of the approaches over RSSI alone. The RF loses 1% while the MLP has no change in accuracy. This is likely due to our experimental setup which has limited human behaviour actions compared to home settings, for e.g. most activity is sitting or walking with no lying down. A more thorough and complete experiment will be undertaken in a residential setting as part of the EurValve project.

Overall, it is clear that the combination of the EurValve system and machine learning is able to perform localisation more accurately than a random and majority classifier even on this challenging imbalanced dataset. A more thorough and detailed analysis will be carried out in the future after deployment of the system to participants. Nonetheless, these initial informational results provide further evidence of the potential of the EurValve smart home in a box system.

TABLE IV
F1 Score for a Random Forest classifier.

	Precision	Recall	F1-Score	Support
Desk	0.92	0.93	0.92	13941
Kitchen	0.56	0.53	0.54	1716
Reception	0.44	0.21	0.28	144
Office Entrance	0.45	0.51	0.48	769
Average / Total	0.86	0.86	0.86	16570

TABLE V
F1 Score for a MLP Neural Network classifier.

	Precision	Recall	F1-Score	Support
Desk	0.93	0.97	0.95	13941
Kitchen	0.77	0.58	0.66	1716
Reception	0.30	0.10	0.15	144
Office Entrance	0.60	0.60	0.60	769
Average / Total	0.90	0.90	0.90	16570

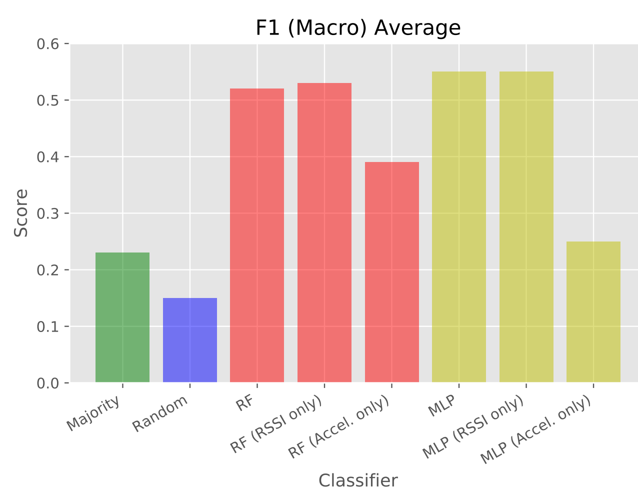

Fig. 7. A comparison of the average F1 macro scores across a stratified 10 fold cross validation.

V. Conclusion

In this paper we proposed a smart home in a box design that is low cost and relatively easy to install and use by patients. The kit was significantly constrained to meet these requirements. The number and types of sensors were limited to just an accelerometer and several anchor points. Given these constraints, the system was still shown to produce valuable data for activity recognition during controlled experiments. The wrist-worn wearable was shown to be energy-efficient lasting for three weeks without recharging easing the maintenance burden on patients. The paper also presented a number of challenges encountered while designing the system and potential solutions. In the future, the kit will be deployed with patients in less controlled environments and will present a more challenging data analysis problem.

Acknowledgement

This work was supported in part by EurValve (Personalised Decision Support for Heart Valve Disease), Project Number: H2020 PHC-30-2015, 689617. This work was also supported by the SPHERE IRC funded by the UK Engineering and Physical Sciences Research Council (EPSRC), Grant EP/K031910/1.

References

[1] "EurValve: Personalised Decision Support for Heart Valve Disease." [Online]. Available: http://www.eurvalve.eu/index.php/workpackage-4/

[2] J. A. Afonso, A. J. F. Maio, and R. Simoes, "Performance evaluation of bluetooth low energy for high data rate body area networks," *Wireless Personal Communications*, vol. 90, no. 1, pp. 121–141, 2016. [Online]. Available: http://dx.doi.org/10.1007/s11277-016-3335-4

[3] N. Agoulmine, M. J. Deen, J. S. Lee, and M. Meyyappan, "U-health smart home," *IEEE Nanotechnology Magazine*, vol. 5, no. 3, pp. 6–11, Sept 2011.

[4] S. Bosch, R. Marin-Perianu, P. Havinga, and M. Marin-Perianu, "Energy-Efficient Assessment of Physical Activity Level Using Duty-Cycled Accelerometer Data," *Procedia Computer Science*, vol. 5, pp. 328–335, 2011.

[5] A. Brajdic and R. Harle, "Walk detection and step counting on unconstrained smartphones," in *Proceedings of the 2013 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, ser. UbiComp '13. ACM, 2013, pp. 225–234. [Online]. Available: http://doi.acm.org/10.1145/2493432.2493449

[6] L. Breiman, "Random forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001. [Online]. Available: http://dx.doi.org/10.1023/A:1010933404324

[7] L. Clifton, D. A. Clifton, M. A. F. Pimentel, P. J. Watkinson, and L. Tarassenko, "Predictive monitoring of mobile patients by combining clinical observations with data from wearable sensors," *IEEE Journal of Biomedical and Health Informatics*, vol. 18, no. 3, pp. 722–730, May 2014.

[8] D. J. Cook, A. S. Crandall, B. L. Thomas, and N. C. Krishnan, "CASAS: A Smart Home in a Box," *Computer*, vol. 46, no. 7, pp. 62–69, July 2013.

[9] A. Elsts, G. Oikonomou, X. Fafoutis, and R. Piechocki, "Internet of things for smart homes: lessons learned from the sphere case study," in *Proceedings of the Global Internet of Things Summit*. IEEE, Jun. 2017.

[10] X. Fafoutis, E. Mellios, N. Twomey, T. Diethe, G. Hilton, and R. Piechocki, "An rssi-based wall prediction model for residential floor map construction," in *2015 IEEE 2nd World Forum on Internet of Things (WF-IoT)*, Dec 2015, pp. 357–362.

[11] X. Fafoutis *et al.*, "SPW-1: A low-maintenance wearable activity tracker for residential monitoring and healthcare applications," in *Proc. Int. summit on eHealth*, 2016, pp. 294–305.

[12] X. Glorot and Y. Bengio, "Understanding the difficulty of training deep feedforward neural networks," in *Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics*, ser. Proceedings of Machine Learning Research, Y. W. Teh and M. Titterington, Eds., vol. 9. Chia Laguna Resort, Sardinia, Italy: PMLR, 13–15 May 2010, pp. 249–256. [Online]. Available: http://proceedings.mlr.press/v9/glorot10a.html

[13] G. E. Hinton, "Connectionist learning procedures," *Artif. Intell.*, vol. 40, no. 1-3, pp. 185–234, Sep. 1989. [Online]. Available: http://dx.doi.org/10.1016/0004-3702(89)90049-0

[14] M. Illario, M. M. R. Vollenbroek-Hutten, D. W. Molloy, E. Menditto, G. Iaccarino, and P. Eklund, "Active and Healthy Ageing and Independent Living 2016," *Journal of Aging Research*, vol. 2016, no. 8062079, p. 3, 2016.

[15] Y. V. Mane and A. R. Surve, "CAPM: Context aware provisioning middleware for human activity recognition," in *2016 International Conference on Advanced Communication Control and Computing Technologies (ICACCCT)*, May 2016, pp. 661–665.

[16] L. Patterson, "Making our health and care systems fit for an ageing population: David Oliver, Catherine Foot, Richard Humphries. King's Fund March 2014," *Age and Ageing*, vol. 43, no. 5, p. 731, 2014. [Online]. Available: + http://dx.doi.org/10.1093/ageing/afu105

[17] C. Perera, C. H. Liu, and S. Jayawardena, "The emerging internet of things marketplace from an industrial perspective: A survey," *IEEE Transactions on Emerging Topics in Computing*, vol. 3, no. 4, pp. 585–598, Dec 2015.

[18] TP-Link. (2017, February) AC750 Wireless Dual Band 4G LTE Router, Archer MR200. [Online]. Available: http://uk.tp-link.com/products/details/cat-4691_Archer-MR200.html

[19] T. van Kasteren, A. Noulas, G. Englebienne, and B. Kröse, "Accurate Activity Recognition in a Home Setting," in *Proceedings of the 10th International Conference on Ubiquitous Computing*, ser. UbiComp '08. New York, NY, USA: ACM, 2008, pp. 1–9. [Online]. Available: http://doi.acm.org/10.1145/1409635.1409637

[20] World Health Organization, "Strategy and action plan for healthy ageing in Europe, 20122020," Regional Committee for Europe, 62nd Session, Tech. Rep., September 2012. [Online]. Available: http://www.euro.who.int/en/health-topics/Life-stages/healthy-ageing/publications/2012/eurrc6210-rev.1-strategy-and-action-plan-for-healthy-ageing-in-europe,-20122020

[21] P. Woznowski *et al.*, "SPHERE: A sensor platform for healthcare in a residential environment," in *Designing, Developing, and Facilitating Smart Cities: Urban Design to IoT Solutions*. Springer International Publishing, 2017, pp. 315–333.

[22] O. Yurur, C. H. Liu, and W. Moreno, "A survey of context-aware middleware designs for human activity recognition," *IEEE Communications Magazine*, vol. 52, no. 6, pp. 24–31, June 2014.

[23] Y. L. Zheng, X. R. Ding, C. C. Y. Poon, B. P. L. Lo, H. Zhang, X. L. Zhou, G. Z. Yang, N. Zhao, and Y. T. Zhang, "Unobtrusive sensing and wearable devices for health informatics," *IEEE Transactions on Biomedical Engineering*, vol. 61, no. 5, pp. 1538–1554, May 2014.