LPWAN Wearable Intelligent Healthcare Monitoring for Heart Failure Prevention

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Philip A. Catherwood
School of Engineering
Ulster University
Shore Rd., N'abbey
Co.Antrim, BT370QB
p.catherwood@ulster.ac.uk

Joseph Rafferty
Sch. of Computing & Mathematics
Ulster University
Shore Rd., N'abbey
Co.Antrim, BT370QB
j.rafferty@ulster.ac.uk

Stephen McComb
CHIC Innovation Centre
Ulster University
Shore Rd., N'abbey
Co.Antrim, BT370QB
sj.mccomb@ulster.ac.uk

James McLaughlin
School of Engineering
Ulster University
Shore Rd., N'abbey
Co.Antrim, BT370QB
jad.mclaughlin@ulster.ac.uk

This paper presents an advanced long-range low-power Internet of Things wearable temperature sensor to evaluate and predict the likelihood of a heart failure event in high-risk patients. Initial trials have validated the potential of long-range long-term personalized community-based monitoring with smart intervention decision making. The intelligent device implements machine learning to understand the user's activities of Daily Living (ADL) and their environment; using this information coupled with their body temperature allows the system to evaluate and predict the likelihood of a heart failure event. The solution is based upon the European 868 MHz LoRaWAN standard. As Ulster University roll out a regional LoRaWAN "Things Connected" network across Northern Ireland (owned by Digital Catapult, UK) the embryonic solution will be tested on a larger scale for both home based monitoring as well as patients undertaking daily living activities.

Cardiac, Heart failure, Intelligent, Intervention, Internet of Things, LPWAN, Machine learning

1. INTRODUCTION AND LITERATURE REVIEW

A new generation of solutions are becoming essential to address growing healthcare shortages due to a global ageing population [1], an increase in chronic conditions [2], global health economics, and increasing need for earlier diagnosis and predictive analysis. Current monitoring techniques are inherently inconvenient to patients and clinicians and fail to meet increasing demand. However, practical telehealth monitoring has been proven to reduce Emergency Room visits by 15%, emergency admissions by 20%, bed days by 14%, and mortality rates by 45% in the general population [3]. Particularly, remote monitoring has been proven to have predictive value in early detection of heart failure decompensation [4].

Artificial Intelligence (AI) and the Internet of Things (IoT) promise to be disruptive technologies in every sector of society, with healthcare being a key interest. The IoT market is predicted to be worth USD 661.74 billion by 2021 and a $15.7 trillion potential contribution to the global economy by 2030 from AI [5]. Remote healthcare has been an on-going topic of interest [6] and IoT devices offer potential for remote health monitoring of patients living with chronic diseases including cardiovascular diseases (CVD) [7] which is the leading cause of death worldwide [8].

The Internet of Things (IoT) can play a defining role in enabling unobtrusive portable solutions for long-term remote patient monitoring, offering an Internet of Medical Things (IoMT) [9]. IoT-enabled remote healthcare has the potential to expedite the return home of patients after hospitalisation. LoRaWAN a key emerging long range wireless technology, operates in the license-free Industrial Scientific and Medical (ISM) radio band at 868 MHz (EU) and 915 MHz (N. America) and boasts three layers of encryption for its transmissions and up to 25Km operational distances [10, 11]; it has been previously trialled for e-Health applications to address the cost of hospital stays [12, 13].

This wireless enabling technology is particularly attractive as it can facilitate any type of home or region, particularly those without suitable cell phone coverage, broadband connections, or even a basic landline [14], and offers subscription-free long-range monitoring to deliver significant financial and time savings over long hospital stays, or frequency home visits or clinic appointment.

2. DEVELOPMENTS TO DATE

Presented is an autonomous LoRaWAN medical patient monitoring system under development that can be worn for a few days at a time to monitor patients are risk of heart failure while they continue

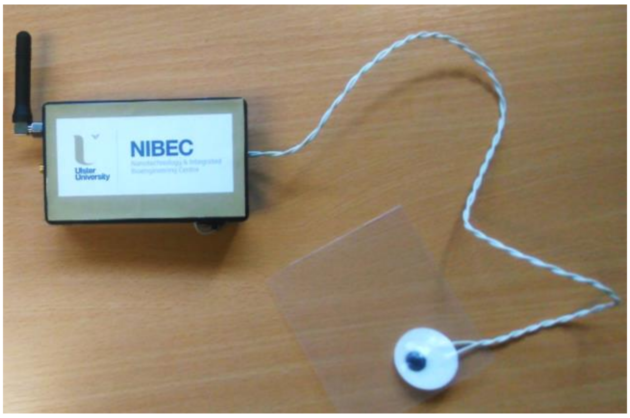

Figure 1: *Wearable LPWAN smart monitor*

with their daily living activities following release from hospital. The developed research was created to understand the disruptive potential of the innovation which will better inform the international technical community. The wearable LoRaWAN device measured patient's skin temperature, ambient room temperature (significant for elderly wellbeing and heart failure prediction [15]), and patient location using a u-Blox GPS chip (to rapidly locate patients in the event of illness or a fall). The device also reported system parameters such as received signal strength, signal to noise ratio, and the battery level of the device. The device has a 14-bit digital accelerometer (MMA8451Q, 3-axis) to detect if the wearer has suffered a fall. The device was designed to transmit this variety of information via the LoRaWAN network for testing purposes, although in practice this information may not be regularly transmitted except as part of communications when the system predicts increasing risk of a cardiac event. The created device is depicted in Figure 1 shows the housed system with an external thermistor bead skin temperature sensor encapsulated in disposable foam with a skin-adhesive surface on one side.

Table 1: *Raw data from device*

Recording		Body temp. (degC)	RSSI (dBm)	SNR	Ambient temp. (degC)	Battery level (%)	Location
15th Feb.	AM	35.5	-63.0	7.8	21.4	61	54°41'15.08"N, 5°52'41.37"W
	PM	34.9	-55.0	8.6	20.5	60	54°41'15.78"N, 5°52'42.91"W
16th Feb.	AM	35.8	-47.6	7.1	20.5	60	54°41'15.38"N, 5°52'41.66"W
	PM	35.1	-76.7	11.2	7.5	58	54°41'09.81"N 5°53'04.92"W
17th Feb.	AM	35.0	-37.1	12.4	18.6	58	54°41'15.25"N, 5°52'41.32"W
	PM	35.7	-41.4	10.6	21.9	56	54°41'15.66"N, 5°52'41.48"W
18th Feb.	AM	36.1	-83.8	5.2	14.2	56	54°37'47.43"N 5°55'04.39"W
	PM	35.4	-52.9	9.0	20.7	55	54°41'16.01"N 5°52'43.16"W
19th Feb.	AM	34.8	-86.2	6.2	8.3	54	54°41'49.31"N 5°57'08.64"W
	PM	35.9	-68.4	9.4	21.5	54	54°41'13.87"N 5°52'46.09"W
20th Feb.	AM	35.8	-77.7	8.7	23.1	51	54°41'17.45"N 5°52'50.25"W
	PM	35.4	-82.3	6.8	21.8	50	54°42'02.91"N 5°53'11.14"W
21st Feb.	AM	34.8	-47.7	10.1	18.3	49	54°41'14.68"N 5°52'42.65"W
	PM	35.1	-86.4	5.4	6.9	49	54°37'47.21"N 5°55'03.54"W

The system gathers data from the ambient temperature sensor (itself a key indicator of heart failure risk), GPS location, accelerometer data (to evaluate movement, activity levels, falls, waking/sleeping behavioural patterns, etc.) and skin temperature and uses the information to determine per-defined risk levels using a proprietary algorithm. The system also analyses general patterns of environmental change cross-referenced with the various sensor data. This allows the system to make an educated decision on the level of risk. We consider future iterations will allow this risk level to be set depending on the patient's medical prognosis, their personal living arrangements (e.g. living alone, remote location living, a home without heating, etc.) as well as more advanced algorithms to compensate for other chronic conditions such as dementia.

With regards to the radio transmission portion of the solution testing in an anechoic chamber (located at Ulster University, Shore road) revealed that the wearable device's signal strength experienced additional shadowing attenuation of between -5 to -45dB depending on facing towards or away from the gateway respectively. This is partially due to natural body effects (propagating through bone, muscle, etc. at 868 MHz is more difficult than propagating through air) as well as losses due to antenna detuning effects when an antenna is positioned on the human body (a future iteration will also develop an intelligent RF tuning balun to compensate for the wearer's unique biological makeup). Despite these additional signal attenuations we discovered all the signals were still suitably received over a 12 Km radius from the LoRaWAN gateway, with patient location accuracy of better than 3m and skin temperature readings in line with commercial temperature monitors.

3. PROTOTYPE TRIAL AND CHALLENGES

A short validation trial was conducted using a device wearer with no known history of heart failure risk. The raw data was transmitted to assist with validation of the system (Table 1) and results show that each of the measurements were correctly recorded and robustly received at the local gateway and relayed to the secure server for inspection. With the new network in Northern Ireland it was observed that transmissions can be received on 3 or more gateways which offers robust communication through redundancy. Over a 7 day period the system monitored the range of sensors at its disposal (transmitting raw data to prove the veracity of the long range telemetry aspect) and the gathered data was used to understand the potential of the decision-making solution. While the system can highlight low temperature as a sole indicator of potential risk the authors believe cross-correlation with the other data will reduce the chances of false positives (a nuisance to clinical staff and patients) or false negatives (potentially fatal). For example, if the air temperature sensor records a low value yet the accelerometer indicates that the user is walking to the shops (GPS verified) as part of their daily routine whilst presenting a healthy skin temperature range then an alarm to the clinician is unwarranted. Conversely, if the patient is in their home and both ambient temperature and skin temperature are dropping then an intervention is required. This is additionally true if behaviour patterns (based on the accelerometer and GPS) have notably changed. This can be pre-programmed into any patient monitoring system and the machine learning for the individual patient can increase the accuracy of intervention information to be patient-specific.

A number of challenges have been identified that require addressing to further develop the system. It is understood that a large volume of controlled testing will be required to develop a mass of data to initially train the system; following this the system will then need to be trialled with closely monitored heart failure patients to understand whether the system can learn quickly enough based on controlled training data and incoming data from it new environment. Typically the patient will need monitored for a number of weeks to a number of months; for those patients requiring shorter term observation it will need to be understood how quickly the system can learn and adapt to the temporal environment to avoid false positives or negatives. It is however recognised that this is the common challenge facing intelligent machines for healthcare monitoring and a key obstacle to overcome before such devices are trusted by clinicians and patients alike.

The machine learning-based analytical models could be augmented by creating a database from clinical trial data. This database would store curated and high quality labelled data. This database would provide suitable data to produce an initial, functional, model for classification of conditions. Thus, this clinical data would address aspects of the cold start problem common to machine learning-based solutions.

Subsequent works will evaluate models produced by a range of supervised machine learning algorithms and techniques, such as Naïve Bayes [16], Recurrent Neural Networks [17], Support Vector Machines [18] and Decision Trees [19]. Through this experimental evaluation a single or ensemble [20] of supervised machine learning models will be adopted into the final solution – as dictated by performance. Initially this experimental evaluation will occur using graphical tools such as Weka [21], R-studio [22] and TensorFlow [23] Following this evaluation, appropriate solutions will be integrated into the final solution via libraries, such as Neuroph [24], TensorFlow or PyTorch [25].

As dictated though future experimental evaluation, problem complexity and required use cases, federated learning [26], [27] may be adopted, ideally via Open Neural Network eXchange (ONNX) models [26].

During field trials we highlighted an issue with the ranges possible with LoRa. We have confirmed that 20+ Km between a device and the gateway is easily achievable in rural areas and over bodies of water, and that 5+ Km in suburban and urban is regularly achievable without issue. During testing however we found that a few areas of Belfast city obtained no signal despite the gateway-device separation distance being less than 2 Km. While this was found to be the exception rather than the rule it does highlight that planning of gateway locations is necessary through the use of empirical testing [16] coupled with computer modelling of signal coverage as is now customary with cell phone base station deployment.

Future work includes further development of the machine learning aspect of individual user's long term patterns of behaviour as well as to develop a more user friendly graphical user interface at the clinical end (current data is displayed in Base-64). Overall we believe these investigations will have a material impact on future remote healthcare provision and consider LoRaWAN to be an essential technology to deliver future services.

4. FUNDING

This work was funded by Invest Northern Ireland (Connected Health Innovation Centre) and Digital Catapult, UK (Things Connected Programme).

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