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Wearable Technology for Hazardous Remote Environments: Smart Shirt and Rugged IoT Network for Forestry Worker Health

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ABSTRACT

This paper introduces the architecture and details of our wearable IoT solution for workplace health and safety in rugged outdoor environments. We focus on the specific requirements defined by the New Zealand forestry environment as it is the industry with the most fatalities and highest accident rate in New Zealand. Neither consumer-level products nor professional wearables have been found to be suitable for forestry conditions. Furthermore, forestry workplaces cannot rely on existing networking infrastructure, and due to their remote and rugged nature, no permanent setup is possible.

We describe the Hakituri project in which we integrate wearable devices, networking, data analytics, and a buddy system into a novel monitoring solution for worker health and safety. Our wearable IoT solution includes a dynamic network set-up, wearables suitable for forestry conditions, contextual rule-based data analytics, and real-time alerts. A wearable smart shirt carries sensors for collecting personal data from forestry workers, while further environmental sensors capture contextual data. The IoT network is set up for communication in unreliable and rugged outdoor environments. We explore a variety of setups to achieve the best quality outcomes for health and safety in the forestry domain.

1. Introduction

The forestry industry in New Zealand has one of the highest number of fatalities and serious injuries across the country.[1] While the specific forestry setting is unique, other outdoor-based and labour-intensive industries – such as mining, haulage, all-terrain farming and fishing – encounter similarly hazardous situations. This paper introduces the concept and details of our wearable IoT solution for rugged outdoor environments, such as those listed above, with special consideration of forestry-typical settings and requirements. Our research is informed by current health and safety considerations in the New Zealand forestry industry.

Our project aims to predict potential health hazards in outdoor work situations by using lightweight, wearable technology, relying on correlations between mental and physical fatigue (Hockey & Ebrary, 2013) and hazardous situations. Forestry work involves manual labour in combination with heavy machinery. As most forestry work places are situated in remote locations, the worker crews have to travel before dawn to their workplaces in varying forestry settings. Travel may take more than two hours each way, and work often involves long hours in remote settings without shelter. Workers engage in a number of activities which see them entering the forest in crews of two (e.g., for clearing out and harvesting), working on their own with heavy machinery, or in groups (e.g., silviculture activities). Hazardous situations arise during harvesting (using a mix of chain saws and heavy machinery), trucking and silviculture (manual planting of small trees), alongside travel hazards.

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[1]Forestry had a fatality rate of 56.73 per 100,000 workers in 2018. Forestry workers are 6 times more likely to be seriously injured and 22 times more likely to be fatally injured than in other NZ industries (Forestry New Zealand).

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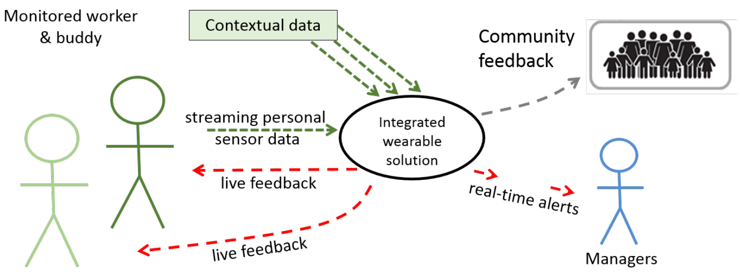


Fig. 1: Interactions in worker-focussed monitoring solution

The workplaces have no existing communication network structure that may be relied upon for worker health and safety monitoring, and due to their remote and rugged nature, no permanent setup is possible. In prior evaluations, we found that wearable consumer products do not provide sufficiently reliable data and typically restrict access to raw data (Bowen et al., 2015, 2017b). Professional devices predominantly focus on athletes or specific heath care situations, and were found to be too costly for use in forestry.

Our wearable IoT solution thus needs to include a dynamic network set-up and personal sensors attached to a wearable unit, in addition to environmental sensors for contextual data. From our previous research with forestry workers (Bowen et al., 2017a), we can identify hazard patterns, which are to be encoded into wearable devices (such as a Smart shirt, hat, or vest). The wearable sensors and control software are IoT components that need to communicate reliably within a rugged outdoor work environment. This communication is influenced by a number of factors not typically considered in city-focused IoT, such as weather, heavy machinery, safety clothing, environmental hazards and potentially rough handling. The workers' body-area network in collaboration with the IoT network therefore need to ensure communication in unreliable and rugged outdoor environments to enable health and safety monitoring of forestry workers.

Interaction in worker-focused monitoring solution.. Traditional real-time monitoring solutions typically incorporate direct lines of communication to health and safety personal and line managers (Bernal et al., 2017). It is well known that such a setup of close activity tracking potentially leads to resistance from monitored workers. The reasons are manifold, including resistance to workplace surveillance (loss of trust) (Botan, 1996) and potential data use for employee control beyond health concerns (Kortuem et al., 2007). Recent developments seem to confirm these concerns, as Australian workers may lose their employment over refusals to provide personal bio-metric data (Knaus). Therefore our project takes a different approach: instead of continually informing line managers and creating growing data collections about worker behaviour, our interaction concept relies on providing live feedback on each worker's health to themselves and their colleagues via a buddy system (see left in Figure 1) and, in aggregated form, to their family or wider community (see top right in Figure 1). Line managers will only be informed in case of emergency.

Dataflow between IoT components.. Our previous studies on worker fatigue monitoring (Bowen et al., 2017a) showed that in order to meaningfully analyse the data streams from the wearable device of each worker, contextual data from the work environment and worker tasks need to be taken into account. A high-level data flow between the IoT components involved in our worker health monitoring solution is shown in Figure 2. A set of sensors is attached to each worker's wearable unit — they communicate via a Body Area Network (Bluetooth network of wearable devices) with a body-worn processing unit, see left part of Figure 2.

Data is secured and processed for detection of longer term patterns in a base station (attached to the crew's truck), see middle of Figure 2. This communication is managed via a Rugged IoT network (RIoT). Data from further environmental sensors and beacons on other machinery is also transferred to the base station. This data supports local pattern matching for each worker by providing context data for the work day. Each worker's processing unit combines the streams of personal sensor data and incoming contextual data, together with information about personal base lines and work tasks, to match against patterns for fatigue. A probabilistic model then predicts the likelihood of the occurrence of hazardous situations caused by worker fatigue.

Alerts about situations that may give rise to heath and safety concerns are raised on a worker's unit (or phone)[2] and their safety vest. A worker is also presented with alerts for their linked colleague via the buddy system. Once the crew returns to the company, the base station data is uploaded for permanent storage, and aggregation of data for community displays, see right part of Figure 2.

Structure of the paper.. This paper describes the Hakituri project, in which we integrate wearable devices, networking, data analytics, and a buddy system into a novel monitoring solution for worker health and safety. It is structured as follows: we begin with a discussion of related work, which includes ethical considerations of worker monitoring, IoT networking, and wearables for health monitoring. The paper then outlines the data to be collected from the wearable device, in Section 3. In particular, we discuss the question of which data is measurable and which is meaningful to collect. This directly influences the design of the wearable device. In Section 4, we outline the overall architecture of the IoT solution developed within the Hakituri project and step through the details of its dataflow. We then describe the design of the wearable device for forestry workers and the processing unit that form together the wearable solution (see Section 5), as well as the RIoT network setup between workers and base station

[2]Most forestry workers are not permitted to carry mobile phones as these may introduce further complexity into already hazardous situations. Many forestry work places are out of phone reception. Some worker's—depending on the tasks—carry communication devices (e.g. CB radio) that may also be used in case of emergency.

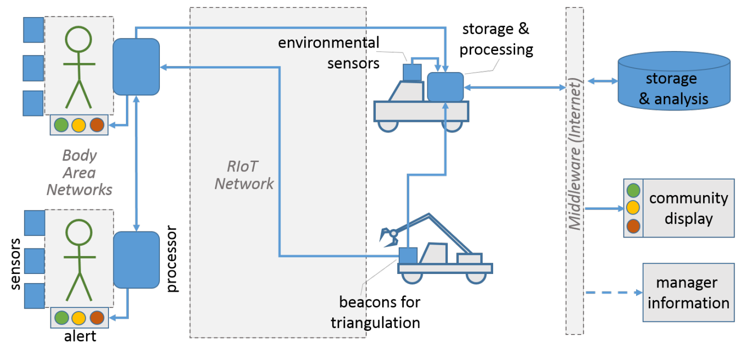


Fig. 2: High-level data flow between components

(see Section 6). Section 7 outlines a set of throughput and redundancy tests that were performed on the data transfer between the wearable solution and the base station. Finally, we briefly outline the elements of the system that go beyond the main focus of this paper, namely challenges for the contextual stream pattern matching, concepts of the buddy system for alerting workers and their family, and the server side communication (see Section 8).

2. Related work

Here we discuss a range or areas which contribute considerations of related work, such as ethics of workers monitoring, IoT-based monitoring for health care, and wearable devices for health monitoring.

2.1. Ethics of Worker Monitoring

Monitoring and tracking of workers is a concept that has not just been developed with the advent of wearable devices but has been used in a variety of ways since the early floor-walkers and punch-in time clocks. As with these early methods, it is well known that many forms of mechanised or digital monitoring of employees create tension between employers/managers and employees/workers (Botan, 1996). Irrespective of the motivations for the surveillance, workers may feel untrusted by their employers and be under the impression that this is likely to be the first step in other management interventions. Zammuto et al. (2007) acknowledge that IoT applications can make certain aspects of work processes visible and available for analysis, possibly to a larger audience. On the other hand, there is a managerial view that IoT will improve accountability in organisations, but Boos et al. (2013) warns that IoT similarly produces new accountability demands.

Kortuem et al. (2007) explored the organisational issues of industrial health and safety monitoring systems. They particularly considered the use of a vibration monitoring technique for reducing a condition called “Vibration White Finger" in industrial workers. They found that even in cases that were intended to keep workers healthy there was still a perception that such a system could be used to exert control over employees, for example by creating detailed logs of worker activities.

In recent years an increasing number of companies seek to promote the health of their workers by providing trackers for personal employee use to support this. For example, Target in the U.S have offered to provide FitBit trackers to all of their workers to increase awareness about healthier lifestyles.[3] In a similar manner, although with more focus on rewarding adherence, the oil company BP tracks step-counts of workers and offer lower health-care premiums to those who meet certain criteria.[4] One of the latest fitness trackers, Fitbit’s Inspire, is developed specifically for corporate employees and health insurance members,[5] seven million of which are already signed up to plans provided by employers, insurance or hospitals. We discuss the ethical and technical challenges of monitoring workers in greater detail in Bowen et al. (2017c).

2.2. IoT Applications for Health Monitoring

While wearable consumer products, such as smart watches and fitness trackers, are gaining popularity, they are often experienced as stand-alone end-user devices. On the other hand, the Internet of Things (IoT) is still predominantly discussed in terms of a network connecting objects in ‘smart’ homes and businesses, with most components being stationary or at least well connected within a stable network. Applications such as smart buildings, ambient intelligence, and smart health-care typically assume large-scale and stable computation and sensor constellations.

Even IoT applications that use dynamic sensor constellations typically make these assumptions. For example, for participatory sensing or mobile crowd-sensing activities (Jaimes et al., 2015; Capponi et al., 2019), members of the public place sensors in regions of interest. These are typically using well-established and stable urban computing environments. Similarly, some smart home applications are treated as an extension of a body area network, e.g., for health-care applications (Rahmani et al., 2018), which can rely on a stable network environment. In contrast, health

[3]http://www.cnbc.com/2015/09/16/targets-fitbit-offer-to-workers-may-miss-its-mark.html
[4]http://www.forbes.com/sites/parmyolson/2015/10/20/fitbit-employers-barclays-godaddy-wellness/#6170061b3baa
[5]https://techcrunch.com/2019/02/09/fitbit-inspire/

and safety in the forestry domain has a strong concern with the human body in hostile remote environments, where communication may require a body area network in interplay with a dynamic network to incorporate groups of sensors and workers.

IoT sensors and systems enable health care applications in electronic health care, mobile health care, and ambient assisted living. Most of these rely on remote monitoring and tracking of patients. In any case, even smart homes or hospitals need bridging points (gateways) for their IoT-based health-care systems: a communication structure connecting sensor infrastructure network and the Internet (Rahmani et al., 2018). Thus most frameworks for remote health monitoring employ a 3-tier architecture: a body area network of sensors, communication and networking, and a service layer (Hassanalieragh et al., 2015); or a sensing network, delivery network, and analysis network (Verma et al., 2017). Our situation differs as there is no reliable communication to a web-based service layer and decisions need to be made on streaming data within the body area network or the nearest hub.

2.3. Wearables for Health Monitoring

For a number of years, several simple wearable technology applications have been available, such as a T-shirt that visualises air quality monitoring results (Kim et al., 2010) or cycling helmets displaying heart-rate data (Walmink et al., 2014). In these cases, the sensing is instantly translated into the visualisation, without recording capability nor any links to the wearer's personal activity context. Mobile health (mHealth) applications employ mobile devices, often in a personalised manner, to improve health of their users. Many explored the use of consumer products for mobile health tracking, e.g., (Naslund et al., 2015; Bowen et al., 2015; Evenson et al., 2015; Xie et al., 2018) as well as the use of mobile apps (Firth et al., 2015; Wilhide III et al., 2016; Stoyanov et al., 2015). Commercial products are starting to move beyond watches into jewellery-like monitors, such as the Ōura ring,[6] the BellaBeat Leaf,[7] and the Kerv Ring.[8] A number of specialised devices have been explored for healthcare use, such as glasses for mental health monitoring (Vidal et al., 2012), wrist-worn devices to engage patients in physical activity (Batsis et al., 2019), a bracelet as visualisation for multiple applications (Fortmann et al., 2016), up to 'soft' IoT devices that aim to blend with the "wearer's personality" (Møller & Kettley, 2017). The typical options that are explored are accessories (such as head-mounted or wrist-worn devices), sensor patches, or eTextiles (Seneviratne et al., 2017). The importance of context, meaning of data, and support beyond the tracking/monitoring of people have been identified in several areas (Miyamoto et al., 2016; Lentferink et al., 2017; Bernal et al., 2017)

A large number of smart garments/eTextiles have come to market in recent years, such as Athos fitness gear,[9] OMsignal,[10] Myontec,[11] Cityzen,[12] Physiclo.[13] Most of these incorporate sensors and the collected data is sent to the user's smart phone (e.g., via Bluetooth). While there is a large array of health-care related technology proposals, not many are developed to be employed in real-life situations; while questions of technology adoption and acceptance are still being discussed (Li et al., 2016, 2019). Many researchers focus on the garment itself, assuming readily available communication infrastructures, or without consideration for practical usability (Wu et al., 2019). Many of these health-related applications use IoT architectures that are akin to smart-city proposals, e.g. (Domingo, 2012; Islam et al., 2015).

A number of projects explore wearable for occupational health and safety (Pavón García et al., 2018; Kamardeen, 2019), many of which are in conceptual or early design stages. One of a number of early prototypes is the Deep Vision Shield (Colombo et al., 2019), a helmet prototype with integrated sensors and display. During user testing, ergonomic considerations and comfort were identified as relevant criteria. Users also voiced concerns about possible loss of human skills and alertness. Safety++ similarly is an IoT safety interface prototype for the energy industry (Bernal et al., 2017). Different to our project, their approach assumes that accidents are often caused by workers' unsafe behaviours and lack of compliance with laws and regulation. They acknowledge that many systems focus solely on technological performance and neglect user needs. As part of the system, they include awareness and peer alert, both of which have similarities with our buddy system. Due to their assumptions about accident causes, they also include remote supervision and accident restriction.

Kritzler et al. (2015) explored the integration of sensors into workers' PPE gear (e.g., beacons into helmets and goggles), and the use of a smart watch for alerts. They target workers in construction sites, which are assumed to provide some basic communication infrastructure. As part of the evaluation it was noted that the chosen smart watch with LCD display and attachable beacons would not endure harsh industrial environments. A project similar to our wearable device in its focus on outdoor workers is the Australian Smart vest for construction workers (Edirisinghe & Blismas, 2015). The vest used an Arduino lilypad integrated with a 3.7V LiPo battery, on-board temperature sensor, and LEDs for alerting about overheating. In this example of wearable tech, the Arduino board is fully integrated: collecting data, analysing and alerting the user. However, the Arduino has only serial USB, which limits communication options. Their use of conductive thread, however, inspired our exploration of this option.

3. Data Considerations for Wearable Technology

Advances in lightweight sensors and wearable technologies means that there are increasing numbers of different types of data that can, in theory, be collected. Our primary concern is in ensuring that we have the right data (suitable for our needs) in a usable form (consistent, and with little noise). We categorise these properties as *Measurable* and *Meaningful*.

[6] https://ouraring.com/the-ring/
[7] https://www.bellabeat.com/
[8] http://kerv.com
[9] https://www.liveathos.com/
[10] http://omsignal.com.
[11] http://www.myontec.com
[12] http://www.cityzensciences.fr
[13] https://physiclo.com

For data to be measurable, it is not enough that there is some sensor or wearable technology that can capture that data, as it is often the case that the context of the person being monitored has a big impact on the technology. As an example, consider commercially available activity trackers. In our early experiments with forestry workers, when we just wanted to get an indication of their activity levels, we imagined that we could use such activity trackers fairly reliably to gather data such as step counts, hill climbing etc. However, initial lab-based experiments and subsequent pilot studies elicited a number of problems (Bowen et al., 2015), such as: inconsistency between devices worn by the same person (no correspondence between steps counted); activities such as driving over bumpy roads or walking on soft surfaces affecting step counts; wearable attributes of the device causing problems in a work domain (discomfort over a long working day, wrist-worn items catching on tree branches).

Although technology has continued to evolve and improve since our initial studies in 2015, we have found similar problems with more recent data-gathering technologies and this has been noted for other high-end solutions which often work well in one domain but cannot be generalised to different types of activities (Fox et al., 2017). For data to be measurable, therefore, means that there are sensors or wearable technologies that can collect the data reliably and accurately in an outdoor work setting, such as forestry. In addition, the technology must not be physically intrusive (obstruct work activities or be uncomfortable if used/worn for the entire working day). The technologies that collect the data must also be 'low maintenance' for the workers (not require constant attention) with a battery life that will span at least one full working day (including travel time to and from the work setting).

Meaningful data is data that we can use to understand relevant properties of the workers in our domain. More specifically it is combinations of data that meet this criteria. For example worker location can be captured using GPS, but by itself it is not meaningful (i.e, we do not learn anything useful from the data). However, in combination with other data, such as the location of machinery, it becomes meaningful, as with both pieces of data we can understand if a worker is potentially at risk of being struck by a piece of machinery. Again we must be careful with the choices we make here. It is not enough to use standard assessment techniques that have been proven meaningful in experimentation in a laboratory setting, such as Brisswalter et al. (1997); Williamson et al. (2011); Hockey (2013).

In an uncontrolled setting (such as an outdoor work environment) contextual factors can have a big impact on the meaning of the data and there may be uncontrollable variables that we are not aware of. For example, if we see a spike in the heart-rate of one of the workers we cannot infer anything from just this piece of information. If they are currently carrying a heavy piece of equipment up a steep incline then the sudden increase in heart-rate might be expected. However, if they are operating a piece of machinery and have been performing the same low-intensity physical activity for a period of time then this sudden increase may be concerning. Some examples of data that for our purposes are both measurable and meaningful (when combined or used with contextual information) are heart-rate, heart-rate variability, galvanic skin response, ambient temperature and body temperature. Combinations of these types of data may be used to infer worker fatigue and/or risk.

The final consideration we raise is that of the effect on the workers of being monitored and the ethics of collecting personal data in this way. There are a number of inherent challenges in collecting data in workplace environments (for a discussion of some of these see the collected papers of the Human Work Interaction Workshop (Human Work Interaction Workshop, 2015)). As mentioned in Section 2.1, workers may behave differently if they feel they are being observed (as in the Hawthorne Effect (McCarney et al., 2007)). They may become dissatisfied or suspicious of the monitoring process and how it might be used (Spitzmüller & Stanton, 2006; Chang et al., 2015), which may lead them to resist the process. Our goal is to be both evidence-based (as above) and ethical (Bowen et al., 2017b). The data that we collect will belong to the workers we collect it from, and will be used primarily to provide information to them, rather than as a management tool. This also has implications on the technology we use and the way we store the data, which we will discuss later in this paper. A more detailed discussion of the management of data ownership rights, particularly in a bi-cultural context, is provided in Judy Bowen (2019).

4. Hakituri Architecture and Dataflow

This section outlines the overall interplay between the project components within the Hakituri architecture and steps through its dataflow. Figure 3 shows the architecture of the Hakituri project. The upper part of the architecture contains the workers' wearable components (green colour) and those attached to the worker environment (green) or machinery (blue). The components shown in the middle layer, consisting of base station (orange) and additional sensors (green and blue), are attached to the crew's truck, and are therefore not in the immediate vicinity of the workers during their shift. The lower part of the architecture shows the web-based components for storage (grey) and visualisation for worker community (green) and management (blue), which are not part of the live streaming.

Wearable and body area network.. Sensors attached to a wearable unit (such as a Smart Shirt) for each forestry worker capture personal characteristics such as heart rate, heart rate variability and galvanic skin response. Together with contextual data about the worker's environment (such as environmental data as well as information about machinery near by), the stream of personal sensor readings is analysed for fatigue patterns. The system also takes into account information about other workers near by.

If a pattern is recognised that indicates a heightened probability for hazardous situations (for example, due to physical or mental fatigue or dehydration), an alert is sent to the worker to be shown on their wearable safety gear (e.g., their vest). The alert is also sent to the workers paired buddy (more on this concept in Section 8). All communication between worker units is done via Bluetooth.

Base station and RIoT network.. When the workers return to their trucks, for example, during break time or at the end of shift, all information from the wearable units is transferred to the base station via a local area network (LAN). The base station also collects further information from connected environmental sensors and information about machinery in the vicinity. We refer to this networking setup within the forestry environment as RIoT – Rugged Internet of Things. The base station holds the data from this working day, in addition to the more complex probabilistic model for the worker crew and complex event processing (CEP) rules for pattern recognition in stream processing. The new worker data is compared to the complex model, and necessary adjustments may be made to the local CEP at the wearable worker unit.

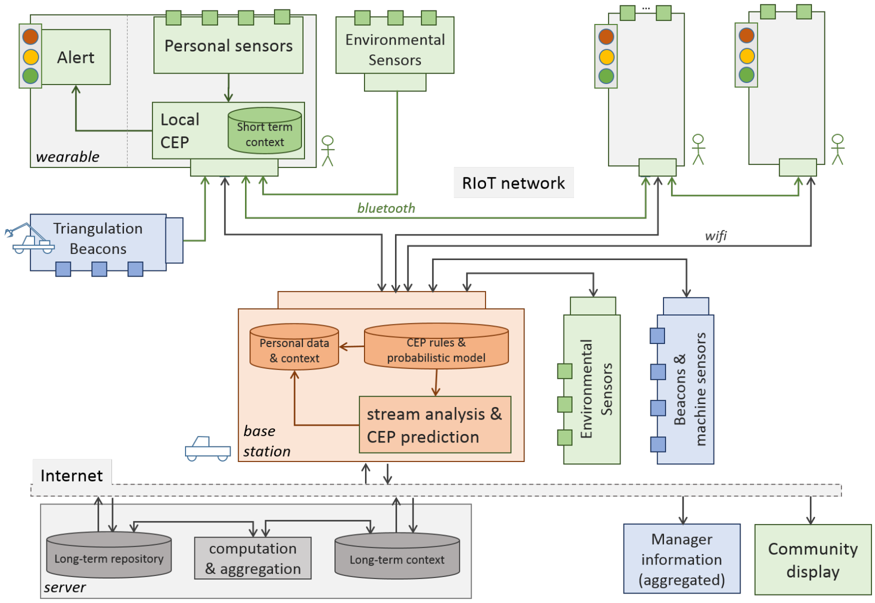


Fig. 3: Hakituri architecture and dataflow

Backend and visualisations.. Once the workers return to their home base at the company office (often up to 2 hours drive away from their remote work location in the forest), the base station will connect to the server for backup (both of worker data and context data) and long-term data pattern analytics. The managers may receive aggregated data about the work day (in addition to real-time alerts from the crew), while the workers' family and wider community receive information about the health and safety of their families.

5. Exploring the Wearable Device

We are interested in capturing sensor data from workers in forestry, such that we can predict (and avoid) hazardous situations that may arise due to fatigue. Mental fatigue affects a person's cognitive processes while physical fatigue affects a person's ability to perform physical actions. In forestry workers, the main cause of fatigue is likely to be long hours of physical work or mental concentration, as well as insufficient sleep (due to long hours and shift rotation patterns). It is well known that repetitive or boring tasks can cause a bigger impact of fatigue. We initially explored off-the shelf solutions (Griffiths et al., 2017) and found that these either do not provide sufficient data quality, or costs are too high for use in forestry.[14] Additionally, existing wearable solutions tend to be tailored toward athletes and are often purpose-built for single disciplines.

In response to this, custom-built wearable-technology solutions have become increasingly common. **?**, for example, developed a wearable prototype that monitors patients' rehabilitation progress after experiencing knee injuries. Although there are differences between the application for their device (i.e. monitoring knee injuries) and the application for ours (i.e. monitoring fatigue in forestry workers), there are several similarities around requirements. For example, it is important, when developing wearable technology, to design devices that are non-intrusive, compact, and washable.

The design of our wearable device is somewhat limited by the hardware available at reasonable cost to be suitable for usage in forestry. In addition to being cost-appropriate, for use in forestry conditions the wearable devices need to be:

- non-intrusive for workers (i.e., not impeding forestry tasks),
- comfortable to wear during extended physical exercise,
- reasonably light-weight when including sensors and hardware,
- compact (i.e., not introducing heath and safety risks due to catching on tree branches),
- durable (able to withstand harsh outdoor conditions),
- repairable, allowing long-term use,
- personalised to the physiological baselines of the worker (and identifiable), and
- washable and suitable for daily use (i.e., removable battery and circuits)

The data that is captured needs to be reliable to be useful for real-time data analysis. The wearable design can be split into a number of considerations: the physical design of the wearable garment (shirt, vest, hat), the sensor placement, the placement of the circuit boards with sensors attached, and the design of the software.

[14] Commercial products are, for example, Ambiotex, Hexoskin and Garmin.

5.1. Sensor Placements and Wearable Garment Design

As discussed in Section 3, the sensor data needs to be meaningful in order to be worth collecting from the workers. Here we will discuss our use of heart rate, heart rate variability and galvanic skin response sensors in the wearable. First we consider placement of sensors.

Heart rate variability.. HRV is the variation in timing between heart beats. A low HRV indicates a decreased variability between heart beats, which means that the body is under stress.

The placement of a heart rate sensor on a wearable is influenced by two factors. Firstly, sensors using optical readings require good blood perfusion, that is blood to be prominent in the outer skin layers. Secondly, any movement of the body part with the sensor can disrupt the reading of the sensor and thus create motion artefacts (i.e, misreadings). As a consequence, the upper arm is under normal circumstances a suitable place for the HR sensor as there is typically limited movement and good blood perfusion. However, for forestry workers operating chain saws or planting saplings, this may not apply. The ear is a similarly good location due to high blood perfusion, however, sensors would have to use earbuds. The forehead is another suitable position due to high blood perfusion and less motion artefacts than in the ear. While many wearable consumer products that use optical sensors are affixed to the wrist, this is not a suitable location for reliable measuring of heart rate and heart rate variability due to motion artefacts. Finally, legs are not suitable for HR measurements due to low blood perfusion.

An alternative sensor type for HRV uses electrocardiography measures (ECG); these need to be placed on the chest for best results. In commercial designs, these are often embedded in chest straps that are uncomfortable to wear over long time periods. Again, movement can disrupt the reading of the sensor and thus create motion artefacts.

Galvanic Skin Response.. GSR is a change in electrical properties of the skin, which reflects the activity of the sympathetic nervous system and thus provides a parameter for assessing the sympathetic nervous activities associated with stress and emotion (Majumder et al., 2017). In order to measure the electrical resistance, a constant voltage needs to be applied and the skin conductance calculated based on the current flow. A Galvanic Skin Response Amplifier applies a small voltage through the skin which cannot be perceived by humans. However, rising GSR levels might also be related to a rise in temperature, heavy physical work or other external factors. In other words, the GSR change patterns can be related to contexts that are mostly hidden and must therefore be carefully considered to make GSR readings themselves useful and meaningful (Bakker et al., 2011). The GSR sensor can detect when a person is exercising and how much exertion is being performed. The GSR sensor can be used alongside other physiological data to determine if a person is becoming fatigued. Bakker et al. (2011) also used GSR for detecting stress levels.

As Galvanic Skin Response measures the activity of the sweat glands, the optimal position for GSR sensors would be a place with a high density of sweat glands. van Dooren et al. (2012) explored the correlation between GSR sensor readings and 16 different locations of the body. They found that fingers, foot and forehead were the best locations to obtain good GSR readings. While these are ideal locations, they are not the most practical for a forestry worker. The next best positions were shown to be shoulders, wrist, neck, chest and calf. For forestry workers, shoulders and chest would be suitable positions as they provide good contact and are least intrusive.

Wearable garment design. If sensors are being physically disturbed or their contact with the skin is interrupted while a reading is taken, this might result in noisy data (i.e., introducing gaps or peaks). Both of these are likely issues when gathering data from forestry workers as manual labour involves over the head movement or walking and bending to plant saplings (silviculture). We considered the suitability of possible garments: vest, hat, harness, and shirt:

Vest: The workers are wearing PPE safety vests, and the unit and sensors could be easily attached to the vest. However, none of the possible sensor placements (as discussed above) are in easy reach from a vest. On the other hand, suitable placements on the vest are not close enough to the skin and readings would be affected by the vest's physical movement. These considerations ruled out the vest for data capturing. However, we are exploring the use of the vest for alerting workers, e.g., via light strips attached to the reflection bands.

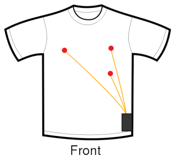
Hard hat: The workers are wearing hard hats, so sensors could be placed inside hat straps on the forehead. However, attaching the processing unit also to the hard hat is not practicable: it cannot be placed inside the hat due to its size, and placement on the outside would potentially create a hazard. A hybrid approach that combines sensor placements within the hard hat and a processing unit that is located in the vest or shirt is feasible, but the involvement of two separate garments is detrimental.

Harness: a harness might be well suitable to carry both the sensors and the processing unit. However, it would have to be worn next to the skin to support best sensor placement. Our initial tests found harnesses to be too uncomfortable to be worn for extended periods.

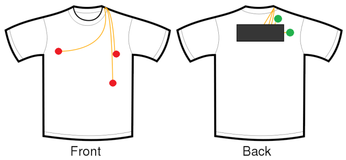
Shirt: use of a shirt (similar to an athlete's compression shirt) is well suited for forestry conditions to ensure prolonged sensor contact with skin. It combines the positive aspects of a hat and a harness in terms of sensor attachment, without the discomfort. Furthermore, the shirts do not introduce any additional health and safety risks. We conducted a participatory study using a smart shirt with a forestry crew, and worker feedback was very positive. While the workers reported being aware of wearing the shirt at the start of the first day of the study, by the end of the second day they reported that they had become accustom to it and no longer noticed that they were wearing it. More information about this study can be found in **?**.

We selected the placement of the GSR and HR monitor probes onto the shirt based on the observations outlined above. Shirt Concept 1, shown in Figure 4a is similar to the commercial Hexoskin[15] smart shirt concept with a waist-mounted pouch for the electronics unit. On evaluation,

[15] https://www.hexoskin.com/

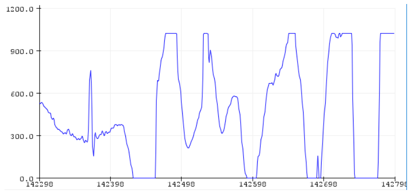


(a) Shirt Concept 1

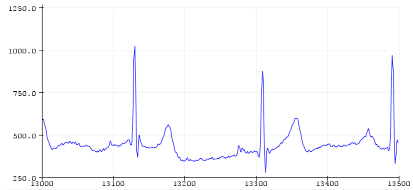


(b) Shirt Concept 2

Fig. 4: Shirt concepts: pouch (grey), wires (yellow), HR sensor (red) and GSR sensor (green)



(a) Unsuitable sensor placement



(b) Improved sensor placement

Fig. 5: Heart rate readings

this concept was found to be suitable for patients at a hospital setting or medical centre, but is limiting for a person who is physically active. Furthermore, this concept placed the pouch where forestry workers have the belts for their PPE gear. Finally, the pouch placement makes it liable to be caught on trees, branches or work tools.

Shirt Concept 2, shown in Figure 4b uses a back-mounted pouch for the electronic unit, thus moving them out of the way from where the forestry workers might interfere with them. Mounting the pocket on the back also allows the lengths of wires used to be shorter, lowering the probability for gear to become caught or damaged. However, for machine operators in forestry, this design may uncomfortably interfere with the back rest of their seat. A neoprene cover may mitigate some of the effects but further research is needed.

The HR monitor has three sensors placed on the body: one for HR measurements and two to check contact with the person. The GSR sensor needs a single sensor only. For HR and HRV readings, we first attached optical sensors to a number of places in reach of a compression shirt. Through a series of tests we had to conclude that we were not able to identify any placements that could provide reliable readings and would not be disturbed by forestry worker movements. We then switched to ECG sensors, which have to be placed on the chest. The initially used contacts for placing the ECG heart rate monitor on the skin were single-use sticky pads that were found to be very sensitive to movement of the body. Our initial placements of the pads on the chest were unsuitable as they were too close to the shoulders and led to interrupted readings when moving/working (see Figure 5a).

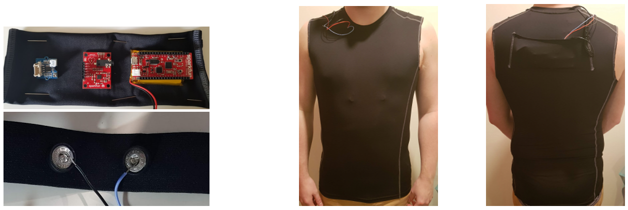
For the current prototype, we cut two of the ECG connectors off their pads and soldered them into a 5cm section of a soft strap (which was originally designed for use with the Polar H7 heart rate monitor), see Figure 6a, bottom. The remaining sensor needs to be placed elsewhere on the body. Using this strap allows for movement whilst getting valid heart rate readings (see Figure 5b). In Ziekow et al. (2019) we explored a machine-learning approach to QoS management of potential data gaps and peaks caused by physical movement of the sensors. Finally, one other consideration that had to be taken into account when developing this device is the affect that perspiration will have on the readings. Forestry is a physical job, which would result in workers sweating throughout the day. While light-based heart rate monitors are negatively affected by sweat, both the ECG and GSR sensors are not. Both ECG and GSR use electrical activity. The introduction of sweat is an advantage for both as the conductivity of sweat means that both readings are amplified. Figure 6b shows the compression shirt prototype with a back pouch and the improved sensor placement.

The shown prototype is using wires for connectivity, but the final shirt uses conductive thread. The benefit of the conductive thread is that components can be connected without adding pressure to the shirt and the worker, and reduced likelihood of entanglement. These thread wires can remain in the shirt during washing, and only the hardware would need to be removed. Tests show that the impact of water and salt on the conductivity of the thread is minimal.

5.2. Processing Unit with Body Area Network

The body-worn processing unit is a micro-processor that has the capacity to connect to both analogue and digital sensors, as well as provide communication to external network elements. Two iterations of this component have been developed. The first focused on communication with the smart shirt sensors. The second extended the first and incorporated greater data storage (for caching collected data) and processing power (for pattern matching), and added a focus on communication with the base station.

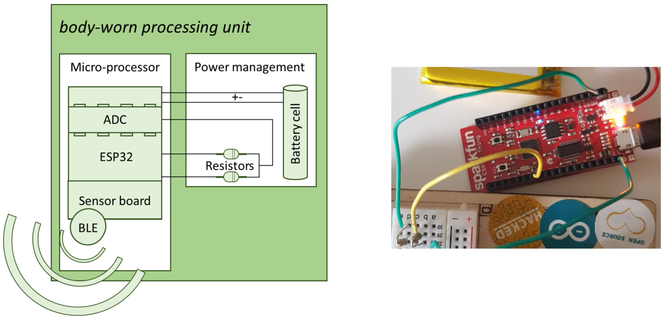
First iteration: communication with the smart shirt sensors. Figure 6a (top) shows the hardware elements for the first iteration of the processing unit. This iteration used the Sparkfun ESP32 board (right), the HR monitor board (middle) and the GSR sensor board (left). While for testing purposes we attached female headers to both ESP32 and HR monitor board (as seen in the figure), the communication between sensors and the ESP32 uses low energy Bluetooth (forming the body area network). The pouch also houses the lithium-ion polymer battery for the ESP32 (yellow



(a) Processing unit in pouch (top), connectors on strap (bottom)

(b) Front of shirt (with sensors), back of shirt (with pouch)

Fig. 6: Smart Shirt prototype



(a) Components

(b) Prototype

Fig. 7: First iteration of the body-worn unit

pack under the ESP32), which is a rechargeable battery that uses polymer electrolyte technology. Not shown in Figure 6a are the cables for power supply.

Figures 7a and 7b show the simple layout of the hardware elements for the first iteration of the processing unit. The micro-processor Sparkfun ESP32 board has a built-in sensor board, analogue-to-digital converter (ADC), and Bluetooth 4.0 capability (BLE). The processing unit manages the data collection from the sensors, self-diagnosis of battery levels, as well as the communication between the board and any external units. For data collection, the HR monitor needs three connectors on the ESP32. The GSR sensor needs a single connection on the ESP32. The ESP connectors (pins) used for both types of sensor readings need to be capable of receiving analogue data.

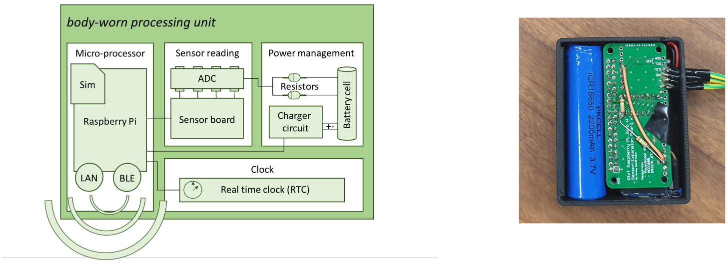
To ensure reliability of the unit, the status of the battery powering the ESP32 needs to be monitored. The ESP32 allows maximum input of 3.3V, and the Lithium Polymer (LiPo) Battery output is specified at 3.7V (1200mAh), but may be higher. In our tests, we discovered that a fully charged battery provides up to 4.2V. We also found that the minimum operating voltage of the micro-processor board was 3.00V. We also observed the typical discharge pattern for LiPo batteries: after starting at the observed $\tilde{4}$.2V (for the top 20% charge), the charge plateaus around 3.7V (for the next 65%) and then drops sharply below 3.0V (in the last 15% charge) (IBT Power, 2017). This non-linear battery drain necessitated that we include a function to observe the battery status (as a simple timer would not suffice). As the ESP32 board does not have built-in battery level readings, a voltage divider was used to determine the battery level. For our prototype, we decided to include a simple warning once the battery voltage drops. For long-term use, the lifespan of the battery also needs to be considered.

The processing unit software collects the data readings from sensors in a multi-threaded manner (using Python with Zerynth IDE). The GSR sensor provides a stream of sensor readings, while the HR sensor provides readings of both heart rate and intervals between successive heartbeats (RR intervals). To distinguish between the HR and RR values in a data stream, we use flags to indicate which data type is being sent (using a byte array) each time data is transmitted. HRV is calculated using these data streams.

For this first iteration, all external communication with the base station and other external sensors was also managed via Bluetooth. More details about the wearable unit and details about further experiments are presented in Exton.

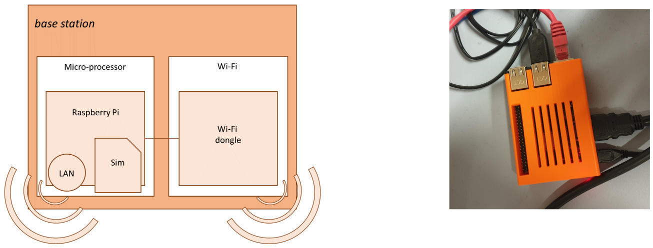
Second iteration: data storage & transfer to base station. The second iteration of the body-worn processing unit focused more strongly on data storage and processing power, see Figures 8a and 8b. As such, a Raspberry Pi was used for the micro-processor, rather than the Sparkfun ESP32 board that was used in the first iteration. Although the Raspberry Pi provides more data storage (32GB versus 448KB) and more processing power (512MB versus 520KB), it does not include a built-in sensor board and analogue-to-digital converter, instead these components were added into the layout of the body-word unit. Additionally, in this second iteration of the processing unit, we added a clock to support the ordering and timing of transferring sensor data to the base station. The resulting device thus consists of: (1) a micro-processor, (2) sensor reading hardware with ADC, (3) power management, and (4) a clock.

The micro-processor is a Raspberry Pi Zero W, and is used to store sensor data and send it to the base station when it is within range (more about this later). The Raspberry Pi includes a SIM card with 32 gigabytes of storage, 802.11n Wireless LAN (local area network), and Bluetooth 4.0. The sensor reading hardware consists of a sensor board and analogue-to-digital converter, which are used to connect to and measure sensor data. The sensor board connects external sensors to the Raspberry Pi. When hard wiring sensors, as opposed to using Bluetooth, it has the capacity



(a) Components (b) Prototype

Fig. 8: Second iteration of the body-worn unit



(a) Components (b) Prototype

Fig. 9: Base station

to support up to seven analogue sensors and up to 63 digital sensors. The analogue-to-digital converter allows the Raspberry Pi to measure readings from analogue sensors, which is achieved by measuring voltage, so long as it is in the range of 0 to 3.3V. Power management for the unit includes a battery cell, battery charger circuit and two high value resistors. The battery cell is again a lithium-ion polymer battery (LiPo). The battery charger circuit handles charging the battery cell and converts the 2.7 to 4.2V of the battery to 5V for the Raspberry Pi. The high value resistors are used to split the voltage from the battery in half, bringing it within range of the analogue-to-digital converter. This, in turn, allows the battery to be treated like another analogue sensor, allowing the unit to measure battery voltage. Finally, the unit includes a real time clock (RTC), which is used to keep track of time when the Raspberry Pi is powered off and supports the data transfer to the base station.

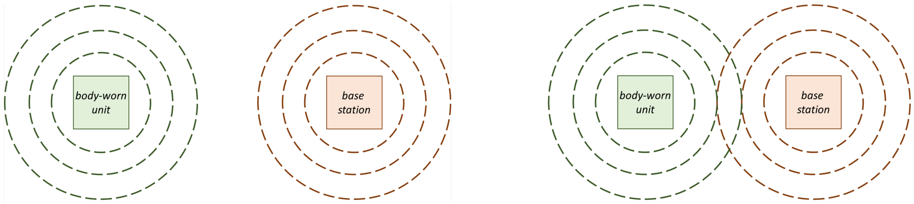
6. RIoT Networking Components

The body-worn processing unit measures data from any connected sensors (and the battery) and transfers the data to the base station, whenever it is within range.

The base station itself is made up of two components: (1) a micro-processor and (2) a USB Wi-Fi Dongle, see Figures 9a and 9b. The base station uses a Raspberry Pi 3B+. While the Raspberry Pi Zero Wireless (used in the processing unit) is designed for embedded applications and wearable technology, the Raspberry Pi 3B+, used in the base station, is faster and features strong connectivity, including dual-band 2.4GHz and 5GHz wireless LAN. This allows the base station to act as the RIoT Network. The base station uses the Raspberry Pi's internal Wi-Fi adaptor to provide a Wi-Fi access point to the wearable devices, creating a local area network. The USB Wi-Fi Dongle then provides a connection to any accessible external Wi-Fi networks, allowing the sensor data to be sent to the server for back-up and long-term data pattern analysis, as mentioned later in Section 8.3.

The body-worn unit and base station can be in one of two states, as shown in Figure 10. They can be either: out of range of each other (Figure 10a), or they are within range and are able to communicate with each other (Figure 10b). The former is the typical situation when a workers is engaged in harvesting or silviculture, while the latter applies for machine drivers and during break time and at the end of day. For the former situation, any sensor data that is being measured by the body-worn unit is stored in it's micro-processor, using its 32 gigabytes of storage on the SIM card. For the latter, once the processing unit is within range of the base station's local area network, it can begin asynchronously sending live sensor data, and sending any data that has been cached in storage. Each data point that is sent over the local area network includes a unique ID that is associated with both the sensor's ID and an incremental count that updates each time a measurement is read. This ID is used to ensure no data is lost when transferring between the processing unit and the base station.

Contingencies have been built into both the processing unit and the base station. First, the body-worn processing unit will not mark data points as 'sent' until it has received a 201 success record back from the base station. In the case where a success record is not received, the processing unit will resend the data every two seconds. Further to this, the base station will check if any data is missing every 60 seconds. As the data IDs include an incremental count, the base station is able to check whether any data points are missing, and if necessary, request that they be resent.



(a) Outside of range (b) Within range

Fig. 10: Communication between the wearable unit and base station

The base station runs an Apache web server using WSGI (Web Server Gateway Interface). It includes an SQLite database for storing the data points and a Flask[16] front-end web application, which uses REST APIs to add new sensors and make the sensor data available for viewing and exportation. The web application can be accessed by any device (smartphone, laptop, etc.) that is within range of the local area network, or connected to Wi-Fi so long as the base station is also connected. SSH is also possible when the base station is connected to an external network connection.

7. Throughput, Redundancy, and Battery Testing

When evaluating the robustness of the SmartVest, there are three main areas where failures or faults could occur. First, when the body-worn unit and the base station are within range of each other, the body-worn unit sends data to the base station by sending small packets in real time at high frequency. Second, when the body-worn unit and the base station are not within range of each other, the body-worn unit collects the data, then uses a bulk transfer to send the packets once the body-worn unit and base station reconnect. Third, when being used on-site in the forestry industry, the body-worn unit will need to stay active for the duration of a full workday. Any issues with battery consumption could cause a critical failure.

In this section, we outline a series of tests that we conducted. We evaluate the throughput when data is being sent at high frequency in real time, we evaluate the redundancy that has been built into the body-worn unit and base station for bulk transfers, and we evaluate the average battery consumption of the body-worn unit. The components that were used for the tests are as follows:

- Body-worn unit: Raspberry Pi Zero W
- Base Station: Raspberry Pi 3B+
- Private Network: Wavlink Nano Wi-Fi Adapter

The network testing tool iPerf3[17] was used to evaluate throughput and packet loss. From this we determined the bandwidth, the maximum throughput, and the packet drop rate of the network. Redundancy tests were conducted using a comparison of the databases stored on the body-worn unit and the base station. In order to determine the theoretical best performance, we evaluated the setup with a single client connected to the base station at a time.

7.1. Throughput results

We used the base station as the server and the body-worn unit as the client, testing throughput with iPerf3. Packet frequency targetting the maximum bandwidth of the base station (50 MBits/sec). The test was run for the duration of one hour, and repeated three times. Based on these three runs, we calculated an average network bandwidth, see Table 1.

Table 1: Throughput bandwidth results

Test Number	Total Amount of Data Sent	Average Speed
1	16.1 GB	38.3 Mbit/s
2	16.8 GB	40.0 Mbit/s
3	16.7 GB	39.8Mbit/s
Averages	16.53 GB	39.37 Mbit/s

The results of this test indicate that the network and the transfer protocol that is currently implemented in the system is sufficient for our application. Under normal circumstances, the body-worn unit will be sending small batches of data through to the base station, usually a few kilobytes at a time. These tests were sending many magnitudes more data at once and did not reach the maximum bandwidth of the base station.

[16] Flask is a web framework that aids in developing web applications in Python (https://palletsprojects.com/p/flask/).
[17] https://iperf.fr/

7.2. Packet Loss results

iPerf3 determines the packet loss per hour if transmitting at full speed. The test was run for one hour, and repeated three times. Table 2 shows the results for TCP packets. This indicated 0 packets were lost, and was running well under the full load for the network.

Table 2: TCP packet loss results

Test Number	Total Amount of Data Sent	Average Speed	Dropped Packets
1	8.87 GB	21.2 Mbit/s	0
2	7.54 GB	18.0 Mbit/s	0
3	8.84 GB	21.1 Mbit/s	0

UDP packet loss was also tested as a way to fully stress the network. Table 3 shows the results for UDP packets. This test identifies any lost datagrams. Again, the test was run for one hour, and repeated three times to ensure both the transfer speed and lost datagrams are consistent. As shown in the table, there were 0 packets lost.

Table 3: UDP packet loss results

Test Number	Total Amount of Data Sent	Average Speed	Network Jitter	Lost/Total Datagrams
1	16.9 GB	40.4 Mbit/s	0.366 ms	0/12564183
2	17.2 GB	40.9 Mbit/s	0.461 ms	0/12717799
3	16.9 GB	40.3 Mbit/s	0.304 ms	0/12537381
Average	17 GB	40.53 Mbit/s	0.377 ms	0 Lost

7.3. Redundancy results

Redundancy has been programmed into the system to ensure data safety. To test redundancy, we conducted a bulk transfer of data from the body-worn unit to the base station. Usually the body-worn unit would transfer packets to the base station multiple times a second. Using a bulk transfer imitates the behaviour of the body-worn unit when it has been out of range of the base station. Once the bulk transfer is complete, we then check the two databases against one another to ensure that the data has been copied correctly. We have also tested the redundancy by manually removing some of the database entries on the base station and ensuring these get re-filled when the connection is made again.

Table 4: Redundancy results

Test Number	Number of Entries to Copy	Number of Entries Copied	Number of Entries Lost	Lost/Total Datagrams
1	166602	166602	0	0/12564183
2	197124	197124	0	0/12717799
3	225753	225753	0	0/12537381
Averages	196493	196493	0	0 Lost

These tests were carried out with approximately three-days-worth of data each time (approximately one reading every 500 milliseconds, 8 hours per day, for 3 days). As shown in Table 4, no entries were lost during redundancy testing. This test showed that all entries were transferred from the body-worn unit to the base station successfully.

In conclusion, based on the the bandwidth and network speeds that are provided by the hardware, and the base station's ability to check for missing results, the base station has been shown to be able to handle more than the expected traffic and not miss any readings that are sent from the body-worn unit. Finally, we would like to note that this section tests the theoretical best performance of throughput and redundancy. Contingencies have been built into both the body-worn unit and the base station, both to ensure all packets are sent and received, and to ensure no packets are missing (see Section 6). However, there is a risk that this performance might degrade when the devices are deployed in a real forestry environment. This work is ongoing and additional field tests for further throughput and redundancy tests are planned in the future.

7.4. Battery Consumption Results

The body-worn unit must record physiological data for the full duration of a work day. This means that the body-worn unit must stay active for at least 8 hours at a time. Any issues with battery consumption could cause the device to power down and stop recording. As such, we have conducted a battery consumption test to evaluate a series of different battery types. The battery types that were evaluated are as follows.

1. A flat single cell battery
2. A cylindrical single cell battery
3. A flat double cell battery

Fig. 11: Double cell flat battery

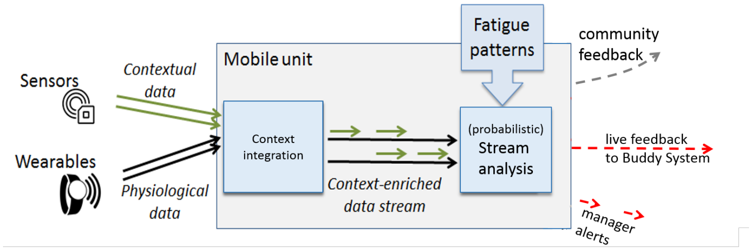


Fig. 12: Elements of the stream pattern matching process

Both the flat and cylindrical single cell batteries have a capacity of 2200mAh with a voltage of 3.7V. The flat double cell battery was created by soldering two of the flat single cell batteries together, as shown in Figure 11. By soldering in parallel, we were able to achieve the same voltage (3.7V) with double the capacity (4400mAh). This was checked before connecting any hardware and the voltage across the battery remained at 3.7V.

Table 5: Battery consumption results

	Single cell (flat)	Single cell (cylinder)	Double cell (flat)
Start	20:00:03	20:00:16	7:51:09
Stop	2:55:21	1:43:40	19:23:28
Duration	6 hours 55 minutes	5 hours 43 minutes	11 hours and 32 minutes

Table 5 shows the results of the battery consumption test. We connected each battery to the body-worn unit in turn, and let the device run until the point where it powered down due to insufficient battery. For each battery, the time that the unit was powered on, and the time when the unit powered down were both recorded. As shown in the table, the flat single cell battery ran for just under 6 hours, while the cylindrical single cell battery ran for just under 7 hours. Neither of these are sufficient for a full work day. In contrast, the double cell battery ran for approximately 11 and a half hours. As a result of this evaluation, the flat double cell battery has been chosen to be used for future studies on-site in the forestry industry.

8. Data Processing and Distribution

The captured data from the wearable devices and additional context information will be used to provide live feedback to the workers via a buddy system. We briefly sketch here both our pattern matching approach as well as the data delivery mechanism for the workers, and other parties.

8.1. Pattern Matching in Stream Processing

Once the personal (physiological) data from the workers and the contextual data from the environment and work context is captured, complex event processing (CEP) analysis is performed on the data streams, see Figure 12. As an outcome, the likelihoods of hazardous situations is calculated based on a probabilistic model, informing health and safety decisions.

Our approach aims to extend a CEP concept called Event Proximity (EProx) (Kristiansen et al., 2016). While CEP detects events of interest (EoI) that match a given pattern, the EProx function assesses the probability of the occurrence for such an event in the near future, based on the current event stream. In the case of forestry, instead of detecting accident events, we are interested in detecting hazardous situations that may lead to such accidents. In our context, EProx thus needs to assess the probability for the occurrence of a hazardous situation, based on current streaming data from wearable devices and contextual sensor data. Kristiansen et al. (2016) use the EProx approach within a home-care environment, allowing their system to calculate the closeness of, and react to, EoIs before they occur.

The approach relies on three elements: (1) a pattern describing events of interest, (2) the current streaming events within a sliding window, and (3) the closeness, or probability, of such an event occurring in the event stream. In our case, this relates to:

1. Identifying patterns for the forestry industry

2. The context-enriched data stream
3. Probabilistic stream analysis

First, patterns describing events of interest typically involve composite events, which are made up of more trivial low-level events. Low-level events could include physiological readings such as heart rate, heart rate variability, galvanic skin response, and activity level (i.e. acceleration data), and contextual readings such as time of day and environmental temperature. These low-level events can be combined to form patterns describing events of interest. For example, we could define a pattern to identify unusual occurrences of sinus tachycardia. Sinus tachycardia is when your heart beats faster than normal (**?**), which is expected when exercising, but could be unusual if your activity level is low. By combining heart rate with activity level, we can identify increases in heart rate while activity levels are low, which could signal anxiety, stress, or Inappropriate Sinus Tachycardia (IST) (**?**). In addition to this, research has shown that people with heat stroke can also experience sinus tachycardia (**?**). As such, by incorporating environmental temperature into our pattern, we can identify, not just anxiety or stress, but also the potential risks of heat stroke in forestry workers. Unfortunately, patterns describing events of interest in forestry are not currently available. The independent review by the Forestry Industry Contractors Association (Adams et al., 2014) relied on interviews and self-reporting, and as such, no formal data is available on the contextual situations of accidents. Our ongoing research is aiming to address this gap by collecting physiological and contextual data from the forestry industry in order to define suitable patterns. This work is ongoing. While there are numerous patterns that could be developed for the forestry industry, we are currently investigating three: physical fatigue, cognitive fatigue, and stress.

The second element in Event Proximity involves the context-enriched data stream. The Smart Shirt described in Section 5 uses ECG to record heart rate and heart rate variability, and GSR to record galvanic skin response. Both ECG and GSR data are read in at 700Hz (1 reading approximately every 1.4 milliseconds). This data stream is processed as a sliding window, with a window size of 60 seconds and a slide of 0.25 seconds, as recommended by (**?**). Heart rate, heart rate variability, and galvanic skin response values are extracted from this window with each slide. In addition to this, time of day is recorded for each window, and environmental temperature is included any time the Smart Shirt comes within range of an environmental beacon.

The third element involves combining the event patterns with the context-enriched data stream to perform probabilistic stream analysis. Each time the window shifts and the physiological data is extracted from the sensor readings, these values can be used as low-level events. These low-level events can be compared against the event patterns to identify whether a hazardous situation may occur. For example, we can collect the low-level events such as heart rate from the data stream and compare them against the pattern that has been defined for a sinus tachycardia event. The closer the heart rate value is to the heart rate pattern, the more likely that a sinus tachycardia event may occur. If the resulting probability reaches a predetermined threshold, then a notification can be sent.

Finally, Kristiansen et al. suggest to incorporate a fourth component describing what they term ‘normal’ behaviour, which could refer to healthy or compliant worker behaviour. For Hakituri, this could include a comparison with baseline health data. The context-enriched data stream can be used to update a workers baseline readings each day. The aspect of compliance is more challenging (as discussed in the context of Safety++ (Bernal et al., 2017) in Section 2.3). Extending this concept beyond the focus on each single worker to healthy crews requires further investigation as to how best to capture such data in an ethical and meaningful manner.

8.2. Buddy system

One of the important considerations we face for the Hakituri project is determining what should happen when the data stream processing and pattern matching identifies (a high probability of) a hazardous situation. Commercial monitoring technology that has been proposed for industry environments works on the assumption that either there is an immediate emergency (such as ‘man down’ technology for solo workers, like the Fujitsu VitalBand[18]) or that a report with a future fatigue predication, such as those produced by sleep tracking technology Readiband,[19] will mean that workers can be scheduled appropriately to work based around these predictions. The reality of the forestry environment is that neither of these situations are likely to be true. A ‘man down’ incident, where a solo worker has an accident is a small subset of the types of injuries that occur in forestry environments. While there have been accidents, and even fatalities, involving solo workers, these are unusual. It is more typical for pairs or small crews of workers to be operating together in roles such as harvesting and quality control, while silviculture typically involves larger crews of workers. In addition, relying on predictions of future fatigue levels raises the question of how this information should be addressed, and by whom. Many forestry contracting companies are small owner-operated businesses working to tight margins with a small number of workers. They are not in a position necessarily to stand someone down for an afternoon or give them lighter duties due to the potential for them to be fatigued. The worst case scenario is that they may send a worker home (unpaid) as unfit for work. This has ethical and legal implications. Whilst it is true that we can identify or predict fatigue, and fatigue is a known risk factor for accidents, there is not a direct correlation that states a fatigued person *will* have, or cause, an accident. This is part of our motivation in developing a solution that only reports immediate danger or accidents to management, but in general uses the data to provide information to workers and their families as a way to inform and encourage behaviour change.

This then raises the question as to how we provide information to workers in-situ, when data indicates a dangerous level of fatigue or dehydration has been reached. Forestry workers are predominantly male, working in a hard physical environment, and as such may be prone to the types of masculinity cultures identified in the literature as leading to ‘hyper-masculine behaviour’ (Brake; Fitzpatrick, 1980). In such environments it may be hard to self-identify as being fatigued or needing a rest, even if the wearable technology is indicating that this is the case. In addition, where workers are being paid for specific levels of outputs (e.g. silviculture workers who are paid per box planted) there is a temptation to ‘push past’ a fatigue point in order to complete ‘just one more box’. To try and obviate this potential for warnings to be ignored by workers we decided to focus on in-situ reporting via a peer support, or ‘buddy system’.

[18]https://www.fujitsu.com/global/about/resources/featurestories/2017060201.html

[19]https://www.fatiguescience.com/?creative=192861589659&keyword=readiband&matchtype=p

Peer support systems, such as the diving ‘buddy system’ rely on pairs of workers (or larger groups) looking after each other. In this way the personal responsibility of workers to look after themselves is shifted to a role where they are responsible for looking after their workmate, or ‘buddy’. In participatory design workshops we held with forestry workers, workers indicated that if they knew a workmate was tired or impaired they would step in to ensure they took a break, or had some hydration and/or food. This type of peer support has been shown to be effective in mobile health application domains such as diabetes management (Rotheram-Borus et al., 2012; Ojo et al., 2015), PTSD and suicide prevention (Greden et al., 2010), and smoking cessation (Ford et al., 2013). Bernal et al. (2017) reported that peer support was found to speed up the rescuing in case of man down incidents, and as a consequence increased worker perception of safety and protection at workplace. We hypothesise that a similar approach may be beneficial in providing fatigue warnings in our forestry setting.

As described in Section 5.1, output sensors (such as lights or lighting strips) can be attached to external clothing items such as safety vests or hard hats. When two workers, *A* and *B*, are paired via the buddy system, if a warning is issued for worker *A* who has been identified as fatigued, then the warning goes to *A* and the alert light on his clothing will become illuminated so that his buddy, *B*, has a visual cue that he needs to intervene. Initial design discussions around this solution have proved positive with the forestry workers, but we will need to undertake further investigations and usability studies to identify the most appropriate forms of notification between buddy pairs. We also need to consider the issue of escalation when warnings go unheeded. Our use of community feedback, where longer term aggregated data is provided back to the families and communities of the workers can be seen as an extension to this buddy system. It again relies on peer-support rather than individual decision-making alone.

8.3. Storage and Aggregated Data Visualisation

At the end of each work day the crew’s base station will be transported back to the company office where it will become accessible to an external network connection. Once it has a connection, any personal (physiological) and contextual data that was captured and sent to the base station for temporary storage throughout that work day will then be transferred to the secure server (shown at the bottom part in Figure 3). This data can then be analysed across the whole set to identify patterns and trends. Any situations that are detected as potentially hazardous can then be sent back to the base station and integrated into the more localised CEP. Data analysis could identify a recurrence of potentially hazardous situations, and identify strategies such as earlier or later starts, more hydration needed etc. This data storage also provides the source for visualisations to managers and worker communities.

9. Conclusion

This article introduced the architecture and details of our wearable IoT solution for workplace health and safety in rugged outdoor environments with specific focus on the requirements of New Zealand forestry. None of the existing commercial or research technology wearables were found to be suitable for this real-world setting. We outlined how our project integrates wearable devices, networking, data analytics, and a buddy system into a novel monitoring solution for worker health and safety. For the wearable solution, we reported on design decisions, interactions with the processing unit and communication with the RIoT network to achieve best quality outcomes for health and safety in the forestry domain. In developing this IoT wearable health application, we had to address challenges in a variety of areas, such as: a wearable device that is suitable for the forestry domain (in terms of usability, worker support, and data quality); an IoT networking solution to analyse streaming data in a changing rugged environment; monitoring of worker behaviour and environments; and social interactions and questions of data ownership to name just a few. In typical research, one would need to address one of these areas, but in the Hakituri project all these aspects need to be considered for an outcome that is suitable for deployment in the New Zealand forestry industry. We acknowledge there are a number of areas we did not discuss in detail in this paper as they are out of focus here: context and pattern recognition, interface design and usability for buddy system alerts, indigenous data sovereignty, and data visualisation for the community. We are currently testing the smart shirt in conjunction with the RIoT network with New Zealand forestry workers, and are analysing accident data we were provided by the forestry industry to identify contributing factors for fatigue patterns.

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