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Wearable Sensors for Improving Occupational Health and Safety of Workers in the Forestry Industry: A Pilot Prototype for Harvesting and Processing Operations

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Wearable Sensors for Improving Occupational Health and Safety of Workers in the Forestry Industry: A Pilot Prototype for Harvesting and Processing Operations

Prepared for

National Institute for Forest Products Innovation

Mount Gambier

by

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Executive Summary

This report describes the results of a vision-based collision prevention system trialled at timber mills in Mount Gambier, South Australia to investigate its applicability in real world surroundings. The results of this study provide a novel approach for automating remote monitoring of forestry workers safety behaviour by fusing data on their location and proximity to hazards. The proposed solution can potentially contribute to accident prevention (avoidance) and reduction and ensure worker welfare through the supply chain, from plantation harvesting to sawmill. This study also aims to bring development and implementation costs of the solution to a minimum by carefully selecting low cost and easy to maintain components with a shared cost arrangement, as part of the existing personal protective devices.

This project had a primary goal of understanding the needs, challenges, and opportunities of using sensor-based remote hazard monitoring, and developing a workwear embedded with such technology for harvesting and sawmilling operations to ensure the wellbeing of workers. This project aimed to:

(a) Identify business requirements of the safety device covering multiple perspectives including health and safety, welfare of workers, etc.,
(b) Evaluate a technology feasibility and adoption framework, and
(c) Develop a proof-of-concept demonstration system with the understanding of worker perceptions of the technology.

This project has successfully identified and assessed health and safety hazards of forestry operations based on literature, past accident data, interviews and observation/work-studies carried out in the field. It identified parameter requirements for hazard monitoring in forestry operations against readily available sensors. Several successor measures (e.g. accuracy, adaptability, etc) and coverage scenarios were emerged as the testing base for the proof-of-concept system.

The project has also evaluated the suitability of readily available sensors and short-range communication technologies that could help monitor health and safety hazards in harvesting and sawmilling operations of the forestry supply chain. These include the integration of real-time location sensing (RTLS), physiological status monitoring (PSM), and proximity sensing (PS) using fusion of data technology. However, it was determined that existing solutions fail short in the context of this project. Problems include high individual unit cost, limited scenario coverage, lack of required network infrastructure, etc.

Based on the literature and interview findings, this project has successfully designed and delivered an image-based detection system which can accurately detect vehicles and humans to alert potential collision. The system was designed as an Android mobile application based on the standard on-device cameras. Videos taken from the field were used in the testing. The project participants were satisfied with the proof-of-concept system with its highly accurate detection rate. It is expected that the mobile devices can be mounted on the vest, helmet and other personal wear. In addition, the application can also be easily modified for other embedded devices in the market.

Table of Contents

Introduction

The forestry is considered as a hazardous industry based on its health and safety record (Gejdos et al., 2019). Forestry operations rank highly in terms of fatality rates, especially harvesting operations (Melemez, 2015). Forestry operations pose a high risk of accidents due to factors such as, a work environment involving difficult terrain and weather conditions; use of heavy machinery and power tools; work conditions such as exposure to noise, dust, vibration, exhaust fume, body posture; and worker fatigue (Gejdos et al., 2019). Personal and work characteristics combined with the work environment are believed to influence the creation of a hazardous environment that could be triggered by different mechanisms that could cause an accident. To prevent accidents in forestry, a number of initiatives have been taken including: stricter workplace health and safety regulations; mechanisation of forestry operations; safety awareness and training among workers; enhanced commitment of the higher management; improved safety behaviour of workers; to name a few (Tremblay & Badri, 2018). In recent years, researchers have attempted to develop early warning systems to alert workers on the impending hazards (Newman et al., 2018) with real-time alerts using sensor-based technology becoming very popular (Bowen et al., 2019).

The Internet of Things (IoT) is bringing the internet into every aspect of work environments – from engineering to health, infrastructure, agriculture, providing a revolution of connected sensing technologies and communication platforms. Despite significant progress within the monitoring device industry, the widespread integration of this technology into workplace health and safety portfolios remains limited. Although technology has undoubtedly played a major role in the improvement of forest management and processing activities, its application for personalised safety monitoring has not been fully explored. The forestry sector lags some other industries such as manufacturing, mining and construction in the trialling and introduction of these technologies. Due to the hazardous working environments in the forestry sector, workers frequently face safety and health risks throughout the supply chain. The IoT trend is well underway in Machine-to-Machine (M2M) communications and is poised to radically change the world’s business environment. Automated hazard monitoring systems based on sensor and short-range communication technologies are considered one of the most promising methods to help manage these risks. Automated monitoring systems can acquire data, convert it into structured information, and immediately deliver these to the worker as an early warning for corrective action.

The availability of powerful yet inexpensive small sensing devices coupled with communication network allow applications which previously not being possible, such as wearable sensor system for worker safety with real-time monitoring and warning. The adoption of wearable technology has the potential for a result-oriented data collection and analysis approach to providing real-time information and early warning of potential hazards to forestry workers. A review of the literature indicates that the existing wearable technologies applied in other industrial sectors can be used to monitor and measure a wide variety of ergonomic and safety performance metrics within the forest industry.

The most popular development in the construction and mining sectors is proximity sensors used to monitor and alert the worker amidst a plethora of large moving equipment on sites (Teizer and Cheng, 2015). These technologies are capable of monitoring and providing real-time geo-referenced steaming of the site environment to safety managers (Mayton et al. 2012). They monitor gases, dust, noise, light quality, altitude, etc., and help safety managers to continuously assess risks to workers and localise their prevalence. The resultant knowledge accumulated on the frequent crossovers between workers and heavy equipment could lead to better site layout designs (Teizer and Cheng, 2015). The ability for early warning of workers on potential collision is another benefit of these proximity sensors which uses a personal tag on the worker and a reader on the equipment with an antenna and other communication technology to trigger alerts when there is an overlap of the radio frequency fields that defines each units' proximity warning space (Teizer et at., 2010; Marks & Teizer, 2013). The other application is to create a virtual fencing of danger zones, locate 3D coordinates of workers using ultra-wide band (Carbonari et al., 2011; Giretti et al., 2009) or mobile infrared/ultrasonic sensors (Lee et al., 2009) to alert when they are within or close to such zones. Park et al (2016) found Bluetooth technology is better than magnetic and radio-frequency identification (RFID) based technologies for proximity sensors in avoiding worker and heavy machinery collision on construction sites (Chae et al., 2010).

Benefits of individual wearable sensors or systems can be integrated based on their attributes for multi-parameter monitoring of ergonomic and safety performance. While the existing sensor technology is being trialled in many industries, their application in forestry is limited due to both systemic issues and environmental conditions. The sensor-based techniques suffer from software instability, interruptions with very high electrical voltage in timber mills, the need for multiple tags and receivers limit practical deployment, and some technologies (such as GPS) won't be suitable for internal environments. From an environmental perspective, traditional sensor-based technologies cannot deal with the dynamic nature of forestry operations, particularly RFID-based technologies need direct line of sight, and environmental heat can cause errors in sensors (such as pressure sensors). Compared to the above, vision-based systems have the advantage of not requiring the installation of multiple tags, they incur lower costs and are easier to maintain (Zhang et al., 2020).

This project developed a prototype of a personal protection equipment (PPE) embeddable vision-based system that monitors the health and safety hazards in sawmill operations and provide early warning to the individual worker. The prototype relies on a method that uses 'fusion of data' from continuous remote monitoring of workers' location and proximity to hazardous conditions. The proposed solution is expected to prevent work-related injuries in forestry operations to help maintain the health and wellbeing of workers. It could reduce work-related injury expenses such as insurance claims, lost days, and lost productivity. As an indirect impact, it could improve the productivity of a worker as they are alerted on potential hazards cross referenced to the work environment to provide real-time safety situation-awareness, so that workers feel safer. In addition, to active workers, it could also help workers recovering from accidents and have returned to work, and help new workers to become proficient and safe in their jobs with confidence.

Methodology

Experimental Design

The research had the primary goal of understanding the needs, challenges, and opportunities of using sensor-based remote hazard monitoring and developing a workwear embedded with such technology for harvesting and sawmilling operations to ensure the wellbeing of workers. This project aimed to:

(a) Identify business requirements of the safety device covering multiple perspectives including health and safety, welfare of workers, etc.,
(b) Evaluate a technology feasibility and adoption framework, and
(c) Develop a roof-of-concept demonstration system with the understanding of worker perceptions of the technology.

The research was undertaken in three phases. Phase 1 covered two site/plant visits, N.F. McDonnell & Sons and OneFortyOne Jubilee Sawmill, Mount Gambier, South Australia. A comprehensive Phase 1 assessment to understand the potential value of the application for the worker safety by using the latest available wearable sensor technology was one of the key outcomes. Phase 2 included a literature review to support technology selection and a laboratory pilot trial. Phase 3 included a case study with extensive field trials to test the proof-of-concept in a real work environment. Details of these three phases and trial procedures are given below.

Phase 1: Inception Meeting, Interviews and Survey – Requirement Analysis

The research started with an inception and planning meeting with the project steering committee to define the evaluation and screening criteria of both industry needs and available technologies. A detailed and a refined work plan was provided after the inception meeting to outline the requirements for implementation of the project and ensure quality objectives were achieved. Health and safety hazards of harvesting/sawmilling operations were identified based on literature, accident data obtained from the SafeWork SA, and observation/work-studies carried out in the field. This was followed by an interview/survey approach from the tentative list of participants obtained during the inception meeting. The report was intended to include an analysis of the responses received as a validation that the needs and opportunities described by the representatives interviewed were considered. For details of Phase 1 outcome, refer Appendix 1.

Phase 2: Technology Selection and Laboratory Trial – Development

Phase 2 of the project was based on the outcomes obtained in Phase 1 and mainly focused on mitigation measures. The various stages involved in Phase 2 are as follows.

(a) Establish parameter requirements for hazard monitoring in critical operations identified in Phase 1 against available sensors.
(b) Contextualise sensor technologies to those critical operations and integrate with information sharing and early warning through smart phone.
(c) Development of a prototype of the sensor-embedded PPE and calibration in laboratory environment.

(d) Investigation of privacy concerns regarding person metrics data (further consultation with stakeholders needed).

The communication component and stakeholder engagement were also key components of this project. Sharing knowledge amongst industry partners was an important objective of this project, particularly sharing the experience of building successful business cases for the implementation of this new development. The project has also considered the importance of implementation (research outcome transfer to operational tools). Industry partners have guided the research team regarding industry requirements.

Phase 3: Case Study Selection / Field Trial

Prior to the case study/field trial, the research team tested the proof-of-concept detection algorithm on the roadside of suburban streets to detect people and vehicle interactions – the initial experiment trial. Based on the results, the detection algorithm was adjusted for the field trial. Case studies were consequently selected as these provide the most relevant and realistic industry requirements. In particular, they also serve as testing grounds for the proposed detection method, especially for the accuracy measures. As a consequence, two large sawmills in Mount Gambier, South Australia, participated in this study. Initial consultations identified mobile plant and pedestrian interactions would be the key focus. Forklifts in confined spaces having to manoeuvre between production lines and aisles with ground workers involved in manual operations (such as stacking, strapping, wrapping, packing, quality inspections, segregation etc.) in proximity poses severe hazards of potential collision. The 15-ton loaders operating outside the mill could come in contact with forklifts and ground workers in this confined space. The visibility of loaders is poor due to stacks of finished timber piled on the ground. In addition, the mobile plant operator (both forklift and loader) could lose visibility due to blind spots and the large loads carried. When the loader-forklift and ground workers are both present in these confined spaces, with a large and heavy timber load, risk of contact collision is high. This situation is exacerbated by the temporary blindness experienced by the plant operator when suddenly moving from poorly lit indoor spaces to outdoor.

Therefore, mobile plant-worker and plant-plant interactions were identified as the most critical, hence, selected as the case studies for this technology development. Among them, four scenarios were selected for detailed analysis.

i. Human to Vehicle (Forklift and Truck) – indoor
ii. Human to Vehicle (Forklift and Truck) – outdoor
iii. Vehicle to Vehicle – indoor (less common)
iv. Vehicle to Vehicle – outdoor, especially when a forklift and a loader are closer to each other.

With respect to the embeddable requirements, an Android mobile application based on the standard on-device cameras was selected for the proof-of-concept. The mobile devices could be mounted on the vest, helmet and other personal wear. In addition, the application can also be easily modified to other embedded devices in the market. The core of this solution is a machine learning model which is built based on Artificial Intelligence (AI), AI-based image processing algorithms, detecting both vehicles and human movements. The proposed solution does not rely on any communication network or require additional cloud hardware. Due to these unique characteristics, it can be deployed rapidly in any environment. Hence, this technology is deemed suitable for forestry operations and field trials were conducted as described below.

Field Trial Procedures

Videos were captured in two occasions (pilot and testing). In total, approximately 8 videos were taken to represent different scenarios. Therefore, the testing was able to cover all scenarios including both indoor and outdoor, ideal vs sub-optimal lighting conditions, human to vehicle and vehicle to vehicle. The system was developed as an Android application which captured the video feeds directly from the camera on the mobile device. It was later modified to take video feeds from pre-captured mp4 files. Since the underlying algorithm stayed the same, the result was applicable in real world scenarios.

Due to COVID restrictions, all site visits were suspended. For field trials, a purpose made helmet mount of a plant supervisor was used during routine work to capture video footage for system development and testing purposes.

Figure 1: DIY helmet mounted system (Smart Phone in use) –
camera focusing set to 1 to 50 meters

Evaluation Criteria

Several measures were employed to evaluate the success of this development:

i. *Accuracy:* Can the technology detect potential risks in the above scenarios real-time?
ii. *Reliability:* Can the technology be stable in hash environments (e.g. rain, dust, low light) with minimum human intervention for a sustained period?
iii. *Cost:* Does the adoption of technology (individual or vehicle based) result in excessive cost?
iv. *Adaptability:* Can the technology be used in less ideal environments (e.g. indoor, no network connectivity, etc.).

Results

This section reports the results obtained in the desktop assessment, laboratory evaluation, and field trial assessment.

Desktop Assessment of Technologies

The literature and technology market scan suggested that the current sensor technologies cannot address the issues found in forestry operations satisfactory. Current commercial state of the art solutions has been developed based on proximity sensors which uses radio signals such as Bluetooth and WiFi network to detect approaching vehicles and humans. However, each device costs about A$5000-A$8000, which is too costly for day-to-day scalable adoption. These solutions also rely on an expensive underlying network coverage which may not be available at all sites.

Some deployment and support capabilities and challenges identified include:

- Ultrasound/IR/laser: Directional, multiple sensors are required to cover 360 degrees resulting in data processing issues and increasing hardware cost and time to fit into equipment.
- *Radio-based systems such as Bluetooth:* Easily interfered by the plant and equipment setup.
- *Location awareness such as GPS:* Existing technologies may fit well in one set of scenarios (e.g. GPS location tracking for outdoor), they do not fit well for others such as inside the mill where signals can be distorted or not available.
- *Commercial solutions:* Require whole site data and a very expensive solution yet limited in accuracy.
- *Administrative controls:* This solution involves the separation of workers and vehicles, but this is not always feasible.

The study further examined the emerging technologies and determined that a risk identification approach through AI-based image processing (object detection) could be viable, as such an approach has proven to be effective in other applications (e.g. public monitoring) as shown in the example below.

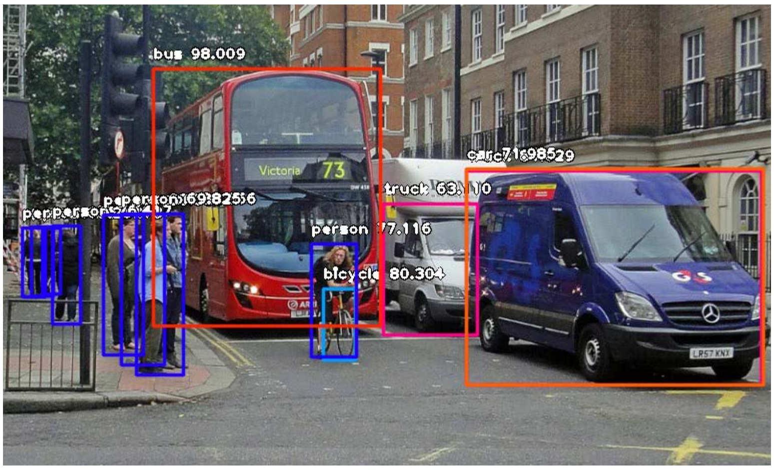

Figure 2: Example of vehicle and human detection

Image Recognition Trial

Image recognitions trials were conducted in two stages. First an experimental trial followed by field trials. The results obtained from the experimental trial was fed into the field trial and used for planning of the field trial.

a. Initial Experimental Trial

An experimental trial was conducted on the roadside of Adelaide's suburban streets to verify the applicability of the image detection algorithm against full size and moving objects. This was used as a demonstration in the discussion with the industry partners to facilitate the planning of the field trial. Special attention was given to obstructed views where people or vehicles were only partially captured.

Note that the raw detection algorithm threshold values cannot be used as an accuracy measure. These thresholds are calculated based on two factors:

1. Whether or not there are recognisable objects within the identified area, and
2. Whether or not the correct object type is assigned.

Therefore, this experimental trial also formed part of the initial setup to decide the optimum weighted detection threshold for the field trial. A higher threshold cut-off value is likely to result in fewer detected objects. However, once the object is detected, the assigned type (e.g. car, truck, people) is likely to be accurate. In contrast, a lower threshold cut-off value is likely to result more detected objects. However, the assigned type is likely to be inaccurate.

After the experimental trial, the research team was confident of the merit of the proposed image detection approach as demonstrated in Figure 3. More importantly, the team identified a balanced value for the field trial. Based on a number of experimental trials, an internal cut-off value of 40% was set. In other words, the Proof-of-Concept algorithm treats any detection with an internal threshold value above 40% as a correct object-detection event relating to safety monitoring (human and vehicle).

Figure 3: Initial experimental trial to demonstrate the object detection ability with % accuracy in the display

b. Case Study / Field Trial

With the on-site supervisors' assistance, several video clips were recorded to cover both indoor and outdoor scenarios. Given that the indoor lighting is constant, special attention was given to the outdoor lighting conditions to cover both bright mid-day light and later afternoon low light (cloudy late afternoon) conditions.

To provide an accurate measurement of the real-world application, human manual assessment is essential. Thus, in total, 58 indoor, 61 outdoor bright light and 53 outdoor lowlight images were randomly extracted from the recorded video clips for verification. The human tagger was given the raw images and the result spreadsheet (for example, see below). After checking the original image, the tagger manually assigned the value 1 for correct detection and 0 for incorrect detection.

Table 1: Human tagging example

Image	**Time**	**Type**	**Area**	**Detection Success**
22	00:25.6	Vehicle	RectF(-15.923696, 658.1464, 812.1965, 1560.0878)	1
57	01:06.5	Person	RectF(812.2905, 1268.6532, 958.5147, 1741.5225)	1

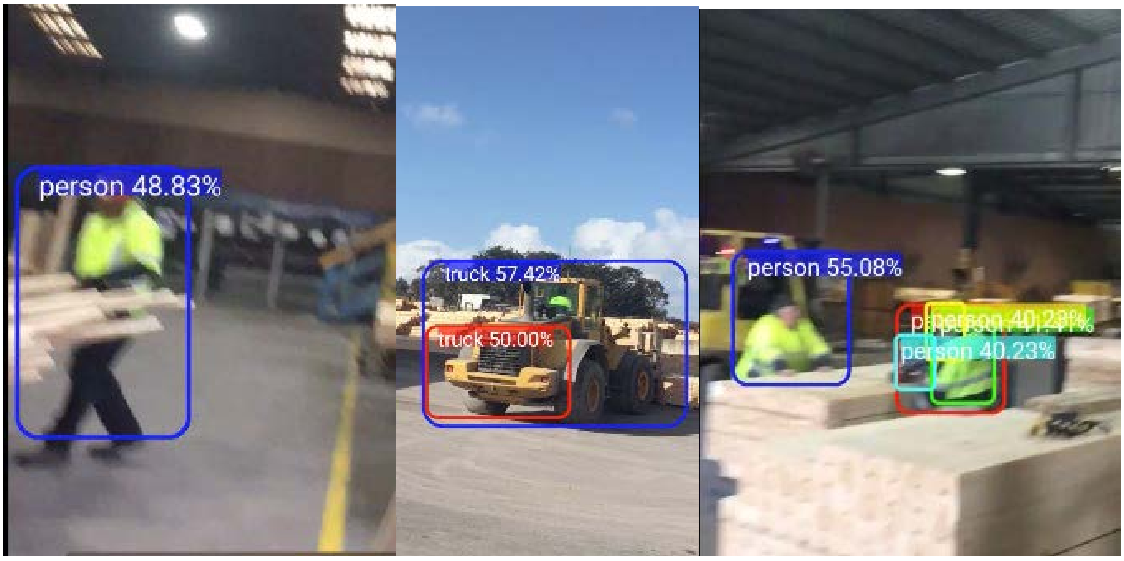

Figure 4: Field trial with indoor and outdoor detection examples with the object identified with % accuracy displayed.

Based on the human tagging results, the overall detection accuracy is shown below.

Table 2: Accuracy measure

	Success-People	Success - Vehicle	Errors-People	Errors-Vehicle	Accuracy
Outdoor lowlight	10	23	5	15	62.26%
Outdoor daylight	26	29	1	5	**90.16%**
Indoor constant light	27	27	2	2	**93.10%**
Total	63	79	8	22	82.56%

Overall, the image processing algorithm is found highly accurate, especially, under good lighting conditions. The false alarms and misses were also identified, and reasons were also found. For example, some of the mobile trays were detected as vehicles as they shared similar characteristics to vehicles due to the presence of wheels.

Figure 5: Error – A mobile trolley is recognised as a vehicle

Discussion

The discussion is presented in three parts: the first part discusses outcomes that are literature based (worker safety / accident data analysis); the second part on wearable sensing technologies and their suitability (technology scan); and the third, outcomes that were experimental based.

Worker Safety / Accident Data Analysis

The data for this study was obtained from SafeWork SA which collates compensation claims data obtained from WorkCover SA into a database for policy analysis. WorkCover SA is a government agency, responsible for the prevention and compensation of occupational accidents and diseases in South Australia. It is entrusted with the administration and regulation of the Workers Rehabilitation and Compensation Act 1986 and the South Australian Workers Rehabilitation and Compensation scheme. It maintains a large and most comprehensive database representative of all reported workplace accident compensation claims in South Australia. The data contained a total of 330,000 workers compensation claims reported during 1st July 2002-31st June 2013 in South Australia, out of which 860 under the industry category 'forestry' based on the Australian and New Zealand Standard industrial

Classification (ANZSIC) coding. Australia uses the Type of Occurrence Classification System (TOOCS2) as a coding guideline for recording of compensation claims and that enabled the researchers to extract ‘forestry’ accidents and segregate them into standardised categories of injury type, mechanism of accident, agency, body location of injury, and whether the victim was hospitalised for treatment. In addition, the database contained the day and time of accidents, location (postcode), occupation, gender, and a detailed description of the event. All 860 reported accidents were analysed to obtain the profile of accidents and the average cost of it in ‘logging’ and ‘processing’ operations (these represented only the cost of lost days and treatment). The ‘severity’ of an accident was used as a means of estimating the cost of lost days and cost of treatment.

The classification of the severity of an accident is determined by the severity of injuries suffered by the victim. Different methods and classifications of injury severity were used in WHS research. The National Patient Safety Agency (NPSA) of the United States categorises injuries into five groups based on the treatment necessitated for the victim. A ‘negligible’ injury is one which the victim does not need treatment, whereas a ‘minor’ injury will only necessitate minor treatment. A ‘moderate injury’ requires the victim to undergo professional treatment and care. A ‘major injury’ is one which the victim suffered a long-term incapacitation. The highest in the scale, ‘catastrophic’ refers to injuries leading to death, multiple permanent incapacities or irreversible health effects. Using a similar methodology, Aneziris et al. (2012) classified injuries into three groups: recoverable, non-lethal permanent, and lethal. Between NPSA and Aneziris et al., (2012), the former is more practical and contains many intermediate levels of non-fatal injuries. Nevertheless, both classifications suffer from potential data collection issues as the treatment records would only be available through hospital or health sources. Therefore, accidents which did not use treatment outcomes will not be captured through these classifications. In this context, proxy measures of injury severity would become very useful. Dumrak et al. (2013) used a combination of hospitalisation and number of lost days from work as a means of classifying accident severity into six groups. Using a similar philosophy, the research team employed two measures to obtain the severity of the reported accidents which enabled the quantification of the cost of an injury: injury classified as ‘minor’ and ‘major’ based on number of lost days from work; and the cost of treatment ($).

A ‘minor’ injury is defined as one with zero lost days while ‘major’ injury necessitates the victim to be absent from work for recovery. As the cost of recovery is directly proportional to the amount claimed as cost of treatment, the dollar value is used as an alternative measure of accident severity. These two proxy severity measures are useful in three ways. First, they do not depend on treatment to physical injuries and need not be from hospital or health sources. Therefore, it eliminates all potential biases of non-capture of minor injuries that never sought treatment or hospitalisation. Second, it captures non-physical injuries such as socio-psychological, which are neglected in WHS research. However, due to an increasing number of such injuries in workplaces, researchers are now paying close attention to socio-psychological health at workplaces. As they cannot be ignored, proxy severity classifications become very useful in capturing those injuries. Third, proxy measures are not biased towards either end of the severity continuum as most of the treatment-based methods do and provide a balanced representation of the accident severity.

A total of 18,778 lost days were reported by the 860 forest industry accident victims which translates into an average of 22 lost days per accident. Similarly, victims claimed $12.1 million as compensation for medical treatment with an average of $14,033 per accident. Forestry operations are typically characterised as physically demanding tasks that are often performed in harsh environments. Because of the continuous and repetitive exposure to physically demanding work, strains and sprains are the most common type of work-related, nonfatal injuries, which constitute 18% and 26% of harvesting and sawmilling injuries reported in South Australia. Furthermore, the continuous exposure to an excessive level of physical strain can lead to physical fatigue, which may result in decreased productivity and motivation, inattentiveness, poor judgment, poor quality work, job dissatisfaction, and increase in the risk of developing worker-related musculoskeletal injuries (MSIs) or cardiovascular disorders.

The data analysis found that MSIs are the largest injury types that accounted for 35% of total injuries followed by incidence of struck by or trap between moving objects (26%). It revealed that lower back injuries are among the most common MSIs among those reported (43%). These occur when the demand of work exceeds the capacity of a worker's body or the worker repetitively performs heavy activities. Musculoskeletal injuries can also be found in other parts of the body, such as the shoulders (21%), Chests (11%), and wrists (7%). They are usually caused by overexertion, which is a leading cause of time-loss injury for the reported accidents. The analysis showed that half of the injuries, more than 100 lost days are attributable to overexertion. Overexertion is not only the most common event category, but also the most expensive, resulting in $6.2 million in direct medical expenses to the industry during the review period. Because of this harsh and dynamic environment with added overexertion, there is very high potential for vehicle-human collision in the workplace. This was shown by the incidence of struck by or trap between moving objects contributing to 26% of accidents reported in the database. This was further evidenced in the interviews conducted during the site visits where 'mobile equipment and pedestrian interactions' were cited as the most concerning WHS issue for timber mills (refer Appendix 1). Hence, the next stages of this research mainly focused on solving this issue by enhancing the situational awareness of the worker (pedestrian) and the plant operator using early warnings with the help of wearable sensing technology.

Wearable Sensing Technology

According to Pantelopoulos and Bourbakis (2010), wearable technologies are based on different systems ranging from bio-signal sensors for body sensor networks such as body temperature probes, pulse oximeters, skin electrodes, phonocardiographs, galvanic skin response (GSR), accelerometers, gyroscopes, and magnetometers electrocardiogram (ECG/EKG), and electromyography (EMG); multimedia sensors such as video and static cameras, magnetic and ultrasonic devices; communication and localisation devices such as Bluetooth and Global Positing System (GPS). Processing of data collected from these devices using data fusion algorithms facilitates continuous monitoring for various applications including occupational health and safety (Valero et al., 2016; Gravina et al., 2017). The evolution of digital and mobile technology has transformed many aspects of the workplace with many examples for worker health and safety. Innovations in sensor technology have been essential to the implementation of body sensor networks and have been combined with progress in short-range communication technologies such as Bluetooth which have enabled the implementation of wearable computing devices.

Wearable sensors can be utilised in conjunction with ambient sensors, such as proximity sensors mounted at hazardous locations or mobile heavy machinery. Proximity sensing will apply similar techniques from autonomous vehicles, using LIDAR and stereoscopic cameras for depth map acquisition, and panoramic camera for 360 video captures (including near infrared sensors for scenarios with low luminance conditions) (Dou et al., 2017; Kukkala et al., 2018). Depth map and visual information captured by these devices is processed with computer vision and machine intelligence algorithms (specifically, using deep learning) to detect field staff and identify the distance to hazardous locations (Patel et al., 2012).

Different categories of wearable technology have been applied across industries such as health care, sports and fitness, manufacturing, mining, construction, defence etc. Some of these technologies and their applications are summarised in Table 3. Previous studies suggest that ergonomic and physiology-related attributes, such as posture, body acceleration, and heart rate can be measured using remote sensing technology. One example is Physiological Status Monitoring (PSM) technology. Commercially available PSM devices have shown to provide reliable information during similar activities in industries such as construction and mining. The problem with PSM is, however, that it does not record nor relate the location of the worker and whether there any other hazards that are in proximity. This shortcoming can be solved by fusing PSM data with data from Real-Time Location Sensing (RTLS) devices, such as Global Positioning System (GPS) sand Proximity Sensors (PS).

Table 3: Application of wearable technology in other industries

Sector	Application	Features
Healthcare	• Record of physiological data from patients • Remote patient monitoring	People keep track of their health while avoiding unnecessary visits to the doctor
Manufacturing	Tracking heart rate, activity, respiration, body temperature, and posture	Lower healthcare costs and increase productivity and safety of workers
Sports and fitness	• GPS watches, heart rate monitors and pedometers • Sensors in helmets of National Football League (NFL) players in USA to detect concussion • Smart compression shirts to determine a pitcher's effectiveness in USA’s Major League Baseball (MLB) • Wristband wearable in golf practice sessions to improve swing mechanics	Obtain real-time information about performance and safety of players
Mining and transport	Proximity warning system (PWS) based on GPS and peer-to-peer communication	Prevent collisions between mining equipment, small vehicles, and stationary structures
Construction	Proximity detection and alert systems	Promote safety on construction sites

Case study / Field Trial

Two workshops were arranged during the development stage. The first one demonstrated the mobile app function against road traffic for accurate object detection. The second demonstrated the results from the video images captured during the field trial. The development team has captured all the detection points (time elapsed in the video) in a separate spreadsheet and checked against the real footage. The image processing is found highly accurate (90%+) under good lighting. Where false alarms and misses were identified, explanations were given.

The use of sound data was found problematic due to high ambient noise (indoor machinery) and wind (outdoor). The accuracy of combining sound and visual data in a noisy factory setting has posed a number of issues. Unlike image captures (taken from either front or real cameras), microphones on mobile devices are often front-facing only. When taking images from rear cameras, the body of the device itself often prevents the front-facing microphones from capturing clear sound. Due to poor quality sound data and ambient noise the combination of sound and image was proven difficult to achieve.

Conclusions

Due to hazardous work environments in the forestry sector, workers frequently face safety and health risks throughout the supply chain. Automated hazard monitoring systems based on sensor and short-range communication technologies are considered one of the most promising methods to help manage these risks. Automated monitoring systems can acquire data, convert it into structured information, and immediately deliver these to the worker as an early warning for corrective action. While industries such as healthcare, sports and fitness, manufacturing, mining, construction etc. have started using above technologies, the forestry sector has been slow in trialling and using personalised safety monitoring systems in its workplaces.

These technologies have a great potential to reduce health and safety incidents and injuries. The estimated direct cost of accidents to the South Australian forest industry is $1,050,000 per annum (accounting only for lost days and medical cost). This study has successfully identified and assessed health and safety hazards of forestry operations based on literature, past accident data, interviews and observation/work-studies carried out in the field. It identified parameter requirements for hazard monitoring in forestry operations against readily available sensors. Success measures and coverage scenarios emerged as the testing base for the proof-of-concept system.

Overall, the end user participants of the study were highly satisfied with the proof-of-concept system and the highly accurate detection rate (90%+) under good lighting conditions that the system produced. However, the researchers still believe that the underlying AI object algorithm can be further enhanced to improve overall accuracy. For example, by combining detection results from multiple images within a short period (e.g. +2 -2 seconds), the detection accuracy could be improved significantly. Also, a new detection model can be developed (trained) for unfavourable conditions such as low ambient light.

In addition to the development and testing, it was found that existing off-of-the-shelf algorithms to identify the proximity and direction of movement of a vehicle based on image processing techniques could be used in the future commercial developments. When the camera is mounted in a relatively fixed position (e.g. on top of a forklift or factory wall), it is possible to derive distances between two tracked objects through triangulation by calculating the angle of the ground surface. However, this can be complex as both objects may be moving and this information needs to be calculated rapidly, multiple times per second, and then linked to the potential collision algorithm to identify and alert of possible impacts.

Recommendations

The AI-based image processing system developed in this project is expected to prevent work-related injuries in forestry operations and help maintain the health and wellbeing of workers. It could reduce work-related injury expenses such as insurance claims, lost days and lost productivity. As an indirect impact, it could improve the productivity of a worker as they are provided with real-time safety situation-awareness information to help workers feel safe. In addition to those who are healthy, it could also help workers who recovering from accidents and who have returned to work, and new workers to become proficient and safe in their jobs with confidence.

The potential system deployment and ongoing operational cost must be considered in the future commercial adoption. For example, many proximity sensors use WiFi networks to transmit data real-time, so where there is insufficient WiFi coverage on site, the technology cannot function normally.

The project team is keen to undertake the development of this proof-of-concept to an implementation project. A factsheet has been developed to highlight the features of this potential development (see Appendix 2). In addition, a brief implementation project plan with indicative funding requirements have been prepared (see Appendix 3).

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Researcher’s Disclaimer (if required)

The research application software (“app”) is provided by University of South Australia (UniSA) as a demonstrator. You may use, copy and distribute copies of the app in any medium, provided that you keep intact this entire notice. You may improve, modify and create derivative works of the app or any portion of the app, and you may copy and distribute such modifications or works. Modified works should carry a notice stating that you changed the app and should note the date and nature of any such change. Please explicitly acknowledge the University of South Australia as the source of the app.

Appendix 1

Phase 1: Inception Meeting and Interview Outcomes

N.F. McDonnell & Sons, Mount Gambier, South Australia

1. The site has 150 workers. Hard hats are not mandatory in all areas, hence sensors need to be embedded on safety vests (safety vests preferred) or maybe boots could be an option too. In most cases, safety glasses are required.
2. When asked about the Wi-Fi coverage within the site, we were assured that generally the coverage is OK. Wi-Fi is strong in Mill 3, however there are a few blackspots in the Log Yard and Mill 2. The main server is in the Site Office and a fiber optic cable runs from there to Mill 2. A Wi-Fi extender could be added to extend the coverage range.
3. When asked about the willingness to pay for sensor embedded safety vests, $200 p.a. per vest would be affordable if it could reduce risks considerably. The investment could be more justifiable per item of mobile plant than per worker due to the numbers involved (few items of mobile plant compared to workers). It is noted that at this stage, they are not looking into devices that require heavy modifications to the existing infrastructure (e.g. systems that would auto stop the forklifts).
4. When asked about the main WHS concerns that the sensors could deal with, McDonnells agreed on the following three priorities:
    - Mobile equipment and pedestrian interactions,
    - Health and wellbeing of workers, and
    - Tracking workers in remote locations and working alone.

<u>Mobile plant- pedestrian interactions</u>

5. There are some manual operations (such as stacking, strapping, wrapping, quality inspections, segregation etc.) occurring in Mill 3 where workers can come in close contact with forklifts. Forklifts were observed in confined spaces having to maneuver between production lines and aisles with ground workers involved in packaging etc. Most critically ground workers are often in the vicinity of working forklifts. Though the visibility is reasonable (compared to loaders), there are no demarcated exclusion zones. Fortunately, there were no incidents in the past, however, it is a high-risk area from a WHS perspective. Generally, around 20 people work in Mill 3 with 2 forklifts operating most of the time.

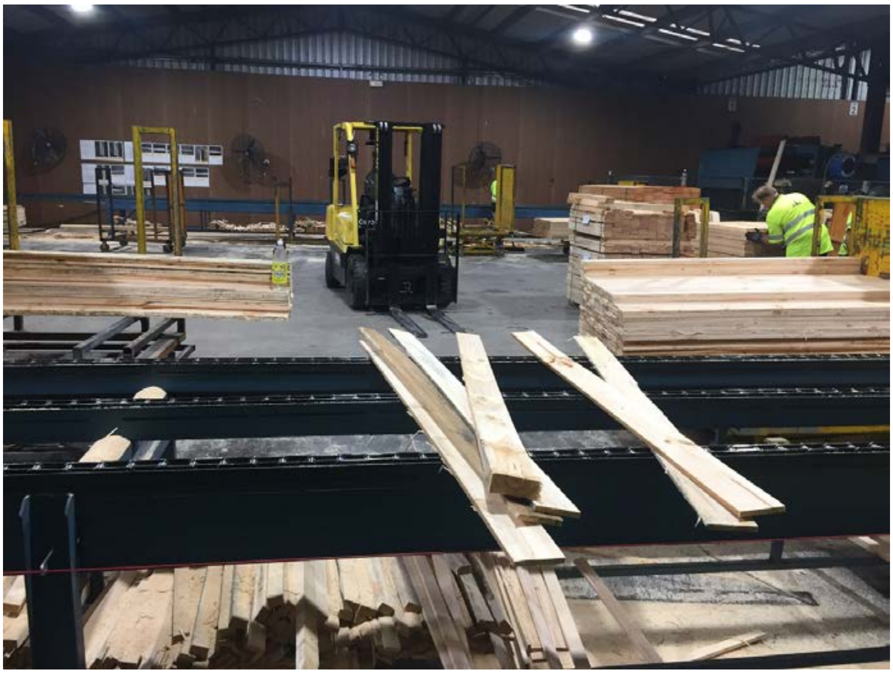

Figure 1: Areas with Mobile Plant - Pedestrian Interaction.

6. The 15 Ton loaders operating outside the mill (Mill 3 exit and Pack Docker zone) could come in contact with forklifts and ground workers in this confined space. The visibility of loaders is poor due to stacks of finished timber piled on the ground. In addition, the mobile plant operator (both forklift and loader) has lack of visibility due to blind spots caused by the size of the load carried (very long timber). When the loader-forklift and ground worker are present in these confined spaces, with a large and heavy timber load in front of the plant, there is a risk of contact collision. It must be noted that the stacks of products can block both people and drivers' views entirely.

Figure 2: Potential Blind Spots in the Yard.

7. The common hazardous situations observed on this site can be categorized into:
    - Moving plant and static worker,
    - Moving plant and moving worker,
    - Two-pieces of moving equipment, especially when a forklift and a loader are closer to each other.
8. At present most of these risks are handled through administrative controls. When administrative controls fail, a reliable real-time proximity detection and alert system is needed on this site to provide ground workers with another layer of safety protection. All agreed that proximity sensors are the highest priority for this site.

<u>Health and wellbeing of workers</u>

9. Heat is a problem within the mill. It is important to monitor the health of workers, especially the possibility of de-hydration and it would be an easy sell among workers. Worker health fed into an App could help monitor workers, rotate them according to their health condition, and allow enough breaks in between work. The type of an alarm could be visual, auditory, vibrating or a combination of them. McDonnells staff felt visual cues are more important than alerts to a worker's mobile phone in the form of auditory or vibration signal (due to the noisy environment within the mill).

   The current site has mist fans to operate in hot days. However, there is no measurement taken on the effectiveness of these mist fans.

<u>Tracking workers in remote locations and working alone</u>

10. It is important to monitor workers in remote locations such as the de-barking area, especially when they are alone. This applies to contractors as well. It becomes critical to know people's exact location in emergency situations when there is a need for evacuation.

OneFortyOne Jubilee Sawmill, Mount Gambier, South Australia

1. The research team introduced the aim and objectives of the project and the main items discussed where the best situation to use and place to locate the sensors. Embedding them inside a safety vest was not favorable to OFO employees as the temperature of some of the enclosed workspaces such as dry mills could go up to 40-45C during summer (despite having large fans to disperse the heat) when the outside ambient temperature is around 34-35C. Other options discussed were the safety helmet, goggles or boots. Similarly, a hard hat is not required for the current staff (required for visitors). However, protection glasses are compulsory.
2. OFO employees interviewed identified and prioritized the following as their main WHS concerns within the site.
    - Mobile plant-pedestrian interactions
    - Manning pedestrian crossings in heavy mobile-plant movement areas
    - Contractor management
    - Work in isolation or remote areas

<u>Mobile plant-pedestrian interactions</u>

3. The major WHS concern in OFO is the mobile plant-pedestrian interaction which could lead to accidents or near misses particularly in confined areas. This was confirmed by OFO employees as well as our observations.

Figure 3: Areas with Mobile Plant-Pedestrian Interaction.

4. Forklifts are the main mobile plant used inside Dry Mill A and B. There is a 3m exclusion zone between the forklift and ground worker within enclosed spaces demarcated by a blue static colour arc light from the forklift. The blue light is intended to alert workers of their proximity to the forklift. However, there are confined spaces which do not provide a 3m safe zone, particularly when the plant is turning around with timber on it. Packaging and Tally desk in Dry Mill B could be identified as one of the confined areas with constant movement of a forklift. It is noted that the blue lights mark points and do not cover 360 degree zones. The blue light may be missed if it is not directed at the workers.
5. Workers would normally step outside the production area as soon as they see a forklift. However, when they are heavily concentrating on a job or get used to the constant movement of forklifts, complacency can creep in which poses a hazard to the worker. In addition, when someone steps inside the production area, they could hit by stationary or moving objects or caught in between objects (machine). The stacks of products and the physical layout of the factory floor may not give the workers safe zones to move to in an emergency.
6. During summer, the temperature inside dry mills could exceed 35C and the fans could increase the noise levels which combined with worker fatigue during a 10hr shift could very easily distract the concentration of a worker. The repetitive nature of tasks can cause workers to experience a decrease in awareness as well as limited visibility for forklift operator.
7. The other factor that could lead to accidents would be ‘domestic blindness’ and the fact that workers getting used to the movement of forklifts and the demarcation blue lights. Change of color, when tested, did not work. A flashlight, something that is dynamic, with an irregular pattern could help get the attention of workers.
8. The other issue we discussed was the change of light vision of the forklift operator between open areas and enclosed areas of the timber mill. The constant movement between open areas with sunshine to shed lighting could affect the operator’s reflexes and impact the ability to negotiate the plant’s movement when a pedestrian is in the transition zone.

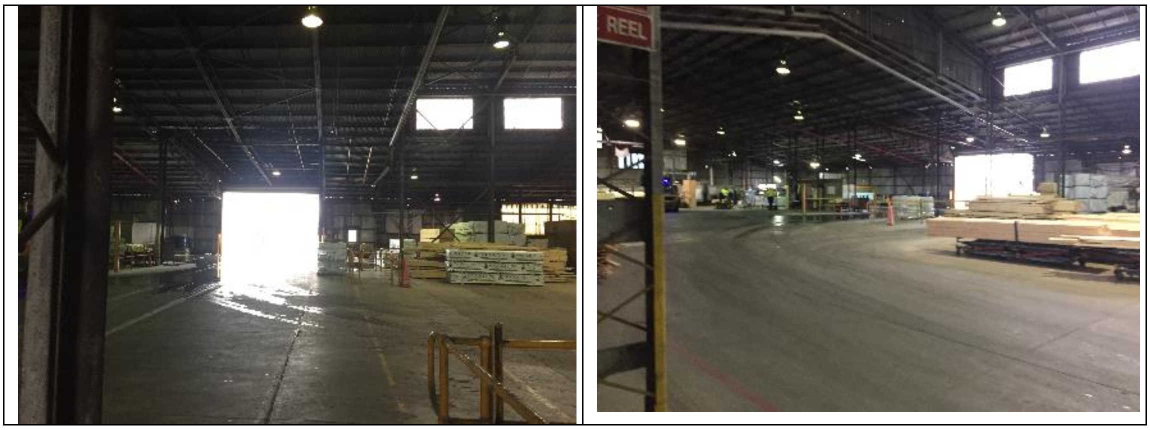

Figure 4: Change of Light Vision of the Forklift Operator Between Open Areas and Enclosed Areas.

9. There is a 5m exclusion zone in the log yard.

Figure 5: Exclusion Zone in the Log Yard.

10. The speed limit for mobile plant inside enclosed areas is 10km/h whereas in open areas it is 15-20km/h.
11. The current smart tracking system employed for forklifts is not robust enough. Forklifts have GPS installed and can track outside but not inside locations where the GPS signal fails. Accuracy of speed tracking speed is poor.
12. The timber stacks obstruct the view of mobile plant in open areas posing collision hazards.
13. One of the other concerns is prevention of collision between two forklifts or between a forklift and a contractor’s vehicle (for example maintenance) inside dry mill areas.
14. In summary, the risk of contact collision between ground worker and forklifts was found to be very high. Therefore, all agreed that providing alerts in real-time when hazardous proximity conditions were present between forklifts and ground workers is a priority for OFO.

Manning pedestrian crossings

15. There are 4 cross-over points which are accessed using manual gates. Can they be automated based on mobile plant movements? Mentioned in the conversation about putting sensors in work boot or other wearable sensors to detect worker at the gate.

Figure 6: Manual Gate to Separate Pedestrian and Mobile Plant.

Contractor management

16. OFO receives a number of contractors and other short-term visitors to the site regularly. Though they are being instructed to be within certain designated zones (such as driver rest area) and inside their vehicles etc., it is difficult to monitor their movements. Tracking their location would be very useful to the security and WHS personnel, particularly during an emergency. At the entry and exit they sign a visitor's book. However, there are plans to introduce a swipe card in the future for regular contractors. A clip-on e-tag with GPS could be a solution for tracking their movements.

Work in isolation

17. There are situations where workers must be in remote and isolated areas working alone. Currently there is a 'call in man-down system'. However, a better automated system would be very useful from a WHS perspective.
18. Contactors may move to different sites (getting new jobs on the run), making it difficult to track the last location.

Based on the Phase 1 result, four safety concerns / scenarios were identified as the priority of this project.

1. Human to Vehicle (Forklift and Truck) – indoor
2. Human to Vehicle (Forklift and Truck) – outdoor
3. Vehicle to Vehicle – indoor (less common)
4. Vehicle to Vehicle - outdoor

Appendix 2 – Factsheet

NIF083-1819
Wearable Sensors for Improving Occupational Health and Safety of Workers in the Forestry Industry

Executive Summary

This project has a primary goal of understanding the needs, challenges, and opportunities of using sensor-based remote hazard monitoring and developing a workwear embedded with such technology for harvesting and sawmilling operations in order to ensure the wellbeing of the workers.

The feasibility study suggests that the current proximate sensor based wearable devices are not suitable for the identified scenarios for reasons such as lack of required network infrastructure, extra hardware cost and potential accuracy due to signal interference. Therefore, the project team focused on developing an adaptable image-based object detection algorithm which can be easily implemented on a wide-range of devices (e.g. wearable smart devices on vest and helmet, centrally mounted cameras) to meet the project objectives.

Why we need to develop a sensing system for forestry workers?

Due to the hazardous working environments in the forestry sector, workers frequently face safety and health risks throughout the supply chain. Automated hazard monitoring systems based on sensor and short-range communication technologies, can acquire data, convert it to structured information, and immediately deliver these to the worker as an early warning for corrective action; considered one of the most promising methods to help manage these risks.

Approach

The Internet of Things (IoT) trend is well underway in Machine-to-Machine (M2M) communications and is poised to radically change the world's business environment. However, the availability of powerful inexpensive small sensing devices coupled with a communication network allow previously impractical applications to become possible, such as wearable sensor system for worker safety with real-time monitoring and warning.

UniSA, with industry partners N.F. McDonnell & Sons and OneFortyOne and funded by NIFPI, developed a solution adopted from currently available machine vision / object detection technology, the core of which is a machine learning model based on image data.

With respect to the future embeddable requirements, the project team decided to develop a mobile application using the standard on-device cameras with a proof of concept AI algorithm to test its suitability.

A DIY helmet mounted system (smart phone) was used to capture a video footage during the field trial in a work environment and the video was analysed frame by frame.

Four safety concerns / scenarios were identified as the priority of this project. 1. Human to Vehicle (Forklift and Truck) – indoor, 2. Human to Vehicle (Forklift and Truck) – outdoor, 3. Vehicle to Vehicle – indoor (less common) and 4. Vehicle to Vehicle – outdoor.

In the first stage, if object is detected then the box is drawn in the picture. The % is the threshold of the object boundary in relationship to the object type – for example, the software produces an initial estimate of 49% confident that within this area there could be a person. In the second stage the detection. In the trial this resulted in a better than 90% accuracy. It could be expected that this could be improved with further testing.

The testing was able to cover all scenarios including both in-house and outdoor, ideal vs sub-optimal lighting condition, people to vehicle and vehicle to vehicle. This algorithm is capable of detecting three objects: trucks, forklifts and human in an accurate and efficient manner.

Project Highlights

- This project has successfully identified and assessed health and safety hazards of forestry operations based on literature, past accident data, interviews and observation/work-studies carried out in the field / identify the parameter requirements for hazard monitoring in forestry operations against readily available sensors.
- This development also aims to minimise development and implementation costs by carefully selecting low cost and easy to maintain components, and with a shared cost arrangement as part of the existing personal protection devices.
- Several successful measures (e.g. accuracy, adaptability, etc) and coverage scenarios emerged as the testing base for the proof-of-concept system with image processing accuracy of >90%.
- This project has successfully designed and delivered an image-based detection algorithm which can accurately detect vehicles and humans to alert for potential collisions.

Potential Benefits

- The proposed sensing system is expected to help prevent work-related injuries in forestry operations, in addition to help maintain the health and wellbeing of workers.
- It could reduce work-related injury expenses such as insurance claims, lost days and lost productivity.
- As an indirect impact, it could improve the productivity of a worker as they are alerted on the work environment to provide real-time safety situation-awareness that workers feel safer.
- It is expected that the mobile devices can be mounted on the vest, helmet and other personal wear. In addition, the application can also be easily modified for other embedded devices in the market.

What's Next?

Explore implementation and commercialisation options and the development of an implementation project to further confirm the applicability.

Future options

It was found that existing off-of-the-shelf algorithms to identify the proximity and direction of movement of a vehicle based on image processing techniques could be used in the future commercial development. If the camera is mounted in a relatively fixed position (e.g. on top of a forklift or helmet), it is possible to derive distances between two tracked objects through triangulation by calculating the angle of the ground surface. However, this can be complex as both objects may be moving and this information needs to be calculated rapidly, multiple times per second, and then linked to the potential impact algorithm to identify and alert of possible impacts.

Additional resources and efforts are required to move the project from POC to a minimum viable product for implementation including alters. Some required works include:

- Selection of hardware devices (e.g. centrally mounted devices vs wearable devices) will impact on the image detection algorithm training and tuning as well as alerting methods.

- Organisation-specific solution vs generic solution will impact on the development cycle and overall resource requirement.

What have we discovered and achieved?

- Image-based object detection can improve safety in the identified scenarios with high accuracy;

- An app can be installed on Android phones and tablet for organisations to trial the algorithm;

- Flexible options (decentralized vs centralized monitoring) are required to move the POC to the next stage.

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Appendix 3 – Implementation Project Plan

Intelligent Image-based Hazard Identification System for Worker Safety in Forestry Operations (HISWSFO)

Driver of need

The estimated direct cost of human-vehicle accidents to the South Australian forestry industry is $1,050,000 per annum (as a minimum accounting only for lost days and medical costs)*. This does not address the full cost of injuries nor reflect the human cost to staff. Legal obligations of duty of care require the continuous improvement of safety in a workplace.

Description

Forestry operations are typically characterised as physically demanding tasks that are often performed in harsh environments, therefore frequently exposing staff to safety risks. An automated hazard monitoring system based on sensor and short-range communication technologies; can acquire data, convert it to structured information, and immediately deliver a 'notification' to a worker as an early warning to trigger a corrective action. This is considered one of the most promising methods to help manage these risks.

A proof-of-concept National Institute for Forest Products Innovations (NIFPI) project "*NIF083-1819 Wearable Sensors for Improving Occupational Health and Safety of Workers in the Forestry Industry (2019-2020)*" has identified and assessed safety hazards in forestry operations based on literature, past accident data, interviews and observation/work-studies carried out in the field. It also identified the parameters required for hazard monitoring in forestry operations against readily available sensor systems via a technology scan. The project has successfully delivered an image-based detection algorithm which can accurately detect heavy equipment and staff (>90% accuracy) to alert for potential collisions.

Application

UniSA, with industry partners N.F. McDonnell & Sons and OneFortyOne and co-funded by NIFPI, developed a prototype solution adopted from currently available machine vision / object detection technology; the core of which is a machine learning model based on image data. With respect to the future embeddable requirements, the project team selected a mobile application (for use with mobile phones and tablets) using the standard on-device cameras with an artificial intelligence (AI) algorithm. This camera system is intended to be worn / mounted on the worker's personal protective equipment (PPE) or a forklift to capture video image in the field / work environment with real-time image processing to provide a safety warning.

Stage of Development

Based on the developed prototype, a do-it-yourself (DIY) helmet mounted system (for a smart phone) was trialled to capture video footages in a real work environment and the video analysed frame by frame. Four safety concerns / scenarios were identified as priority: 1. Human to vehicle (forklift and truck) – indoor, 2. Human to vehicle (forklift and truck) – outdoor, 3. Vehicle to Vehicle – indoor (less common) and 4. Vehicle to vehicle – outdoor.

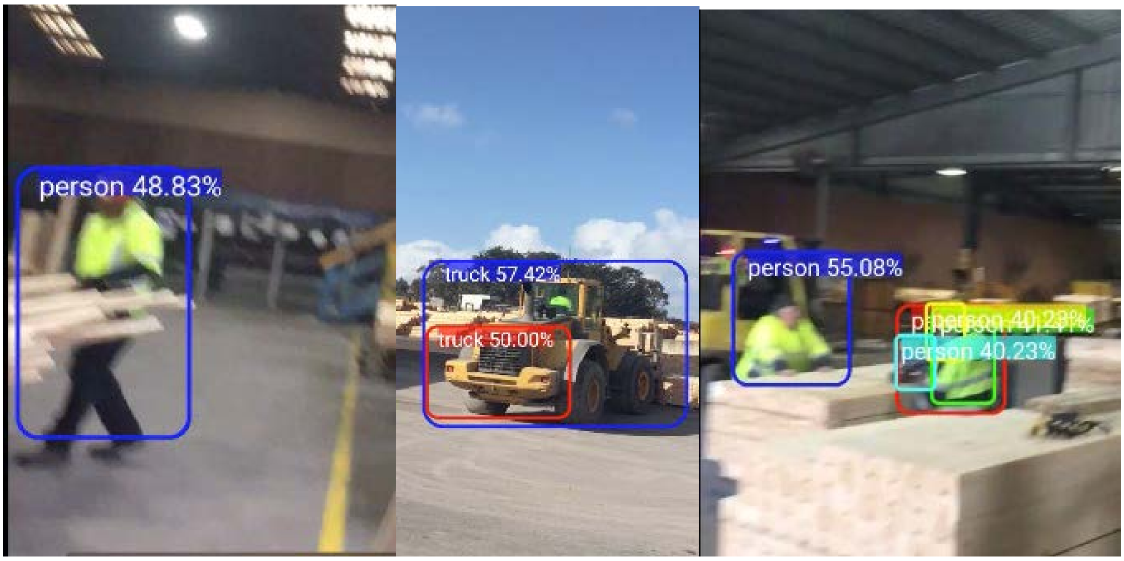

Figure 1: An illustration of object detection system for a single image indicating the % detection threshold.

In the first stage of development, if an object is detected in single image a box is drawn around the object in the image.

As shown in Figure 1, the percentage is the threshold of the object boundary in relationship to the object type in a single image – for example, the software produces an initial estimate with 49% confidence that within this area there could be a person. In the second stage the software used our trained algorithm to confirm the detection. In the trial this resulted in a better than 90% accuracy in the real work environment. It is expected that this could be improved with further testing. An important point is that the system makes use of video streams, hence multiple video frames (images) are used for the image analysis process; this is a fundamental step for improving the accuracy of detection.

The testing was able to cover all scenarios including indoor and outdoor, ideal compared to sub-optimal lighting conditions, people to heavy-equipment and heavy-equipment to heavy-equipment. This algorithm can detect multiple objects at the same time: trucks, forklifts, and humans in an accurate and efficient manner.

Unique Selling Point

The project aims to minimise development and implementation costs by carefully selecting low cost and easy to maintain components, and with a shared cost arrangement as part of existing PPE devices. It was found that existing off-of-the-shelf algorithms to identify the proximity and direction of movement of a vehicle based on image processing techniques could be used in future commercial developments with an upgradable pathway. If a camera is mounted in a fixed position (e.g. on top of a forklift or helmet), it is possible to derive distances between two ‘tracked objects’ through triangulation by calculating the angle of the ground surface. However, this can be complex as both objects may be moving, and this information needs to be calculated rapidly, multiple times per second, and then linked to the potential impact algorithm to identify and alert of possible impacts. In short, the system can be considered as a simple, flexible, and low-cost universal solution.

Business Case

The adoption of the proposed early warning sensor system to remotely detect safety hazards and trigger timely warnings could reduce occurrence of some of injuries happening through the proposed direct mechanisms (assuming a 50% adoption rate of the technology resulting in a 60% reduction in accidents for our impact calculations).

The proposed project

The project team proposes to run a 9-month development and implementation project (a 6-month trial / field test + 3-month fine tuning and report preparation). The following variables are proposed to provide 6 scenarios:

- Test situation:

1. Human to vehicle (forklift and truck) – indoor
2. Human to vehicle (forklift and truck) – outdoor
3. Vehicle to vehicle – indoor (less common)
4. Vehicle to vehicle – outdoor.

- The following camera mounting locations are proposed:

1. PPE - helmet
2. Forklifts

Funding (cash) requirements: $60K ($45K Research Assistant, $10K hardware and $5K travel / site visit). The project plan is shown below:

	Month								
	1	2	3	4	5	6	7	8	9
Kick-off meeting / plan field trail									
Initial design and lab testing									
Field Trial									
Initial report to industry partners									
System fine tuning & report preparation									
Final report and project completion									

Risk Assessment

COVID impacts on delay in field trial and data collection.

A risk to be managed is the potential for trust issues, that such technology allows managers to track individual staff onsite.

Expected Outcomes

The resulting sensor system is expected to help reduce work-related injuries in forestry and processing operations and to help maintain the wellbeing of staff. It could reduce work-related injury expenses such as insurance claims, lost days, and lost productivity and most importantly the human impact of injury. In addition, a real-time continuous safety monitoring system can give staff the confidence that their work environment is safe providing a feeling of being protected at work. In such safe work environment, it could improve staff productivity as an indirect impact.

*Annual figure is the total average cost of accidents to the industry based on SafeWork SA's compensation claims database. It is used to determine the estimated impacts of this project for next five years based on an assumed 50% adoption rate for this technology. The estimated cost of accidents to the South Australian forestry industry is $1,050,000 per annum (accounting only for lost days and medical costs). The estimated economic benefit to the industry from the project for next 5 years is based on 67% of injury mechanisms that are directly relevant (wearable sensor-based applications could mediate direct mechanisms) and an assumed 60% reduction of those accidents due to the adoption of this technology by 2026.

Cost of accidents	$1,050,000
Contributions from direct mechanism	0.67
Proportion of reduction	0.6
Adoption rate	0.5

This will have an incremental $ impact for the next five years with a steady state by 2026 as follows.

2022	$42,210.00
2023	$84,420.00
2024	$84,420.20
2025	$126,630.20
2026	$211,050.20