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Artificial intelligence-based image processing for hazard identification in forestry operations – a sawmill case study

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Abstract

Monitoring forestry workers' safety through early warning and detection systems has potential to improve conditions and reduce costs incurred from preventable accidents and injuries (savings up to 0.5 million USD per annum) during timber harvesting and processing operations. This project has a primary goal of understanding the needs, challenges, and opportunities of using artificial intelligence image processing for hazard monitoring and developing a workwear embedded with such technology for sawmilling operations in order to ensure the wellbeing of the workers. The underlying algorithm can be further developed to be implemented with forklift mounted cameras and other wearable safety devices. The positive research findings can also be applied in other forestry environments such as harvesting where safety management for human and vehicle interactions are required.

Key words: hazard identification, image processing, safety management, vehicle human interaction, wearable device.

Introduction

Forestry industry is considered as one of the dangerous based on its health and safety record (Gejdoš et al. 2019). Some of these incidents are fatal. Forestry operations are considered to be among the top in terms of fatality rates, especially harvesting (Melemez 2015). They pose high risk of accidents due to factors such as: work environment involving difficult terrain and weather conditions; use of heavy machinery and power tools; harmful work conditions such as exposure to noise, dust, vibration, exhaust fume, and body posture; worker fatigue (Gejdoš 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 cause an accident. To prevent accidents in forestry, a number of initiatives have been taken over the years, which include: stricter workplace health and safety regulations; mechanization 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 and Badri 2018). In recent years, researchers have attempted to develop early warning systems to alert workers on the impending hazards (Newman et al. 2018). Among them, real-time alerts using sensor-based technology is becoming very popular (Bowen et al. 2019).

Despite significant progress within the monitoring device industry, the widespread integration of this technology into workplace health and safety portfolios remains limited. Although it 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. 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 the above technologies, the forestry sector lags in trialling and using personalised safety monitoring systems in its workplaces. For examples, there is an increase use of wearable sensor system for worker safety with real-time monitoring and warning in many industries. 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 within the forestry 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 could monitor gases, dust, noise, light quality, altitude, etc., and help safety managers to continuously assess risks to workers and localize their prevalence. The resultant knowledge accumulated on the frequent cross-overs 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 collusion is another benefit of these proximity sensors which uses a personal tag on the worker and a reader on the equipment with antenna and other communication technology to trigger alerts when the there is an overlap of the radio frequency fields that defines each units' proximity warning space (Teizer et at. 2010, Marks and Teizer 2013). The other application is to create a virtual fencing of danger zones, locate 3D coordinates of workers using ultra-wide band (Giretti et al. 2009, Carbonari et al. 2011) or mobile infrared/ultrasonic sensors (Lee et al. 2009) to alert when they are within or closer to such zones. Park et al. (2016) found Bluetooth technology is better than magnetic and RFID based technologies for proximity sensors in avoiding worker and heavy machinery collusion in construction sites.

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 will not be suitable for internal environments (such as GPS). From an environmental perspective, traditional sensor-based technologies cannot deal with the dynamic nature of forestry operations, particularly radio frequency-based technologies need direct line of sight, and environmental heat can cause errors in sensors (such as pressure ones). Compared to above, vision-based systems have the advantage of not requiring the installation of multiple tags, they incur lower costs and are easier to maintain.

This paper reports a vision-based collusion prevention development trialled at timber mills in Mount Gambier South Australia to investigate their applicability in forestry industry surroundings. This study aims to bring development and implementation costs to a minimum by carefully selecting low cost and easy to maintain components, and with shared cost arrangement as part of the existing personal protective devices. Results of this study are expected to provide a new approach for automating remote monitoring of forestry workers' safety behaviour by fusing data on their location, physical strain, and proximity to hazardous conditions. This proposed workwear can potentially contribute to accident prevention (avoidance) and reduction and ensure worker welfare from plantation harvesting to sawmill.

Research Design and Methodology

The approach used in this study includes:

– Identifying and assessing safety hazards of harvesting/sawmilling operations based on literature, accident data obtained from SafeWork South Australia, interviews with field staff, and observation/work-studies carried out in the field;

– Identifying parameter requirements for hazard monitoring in above operations against available sensors;

– Development of a prototype of the or a vision-based wearable device, calibration, and validation trials in actual forestry settings.

Case study selection

Case studies are 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. In result, two large sawmills in Mount Gambier, Limestone Coast, South Australia, participated in this study. Initial consultation identified mobile plant and pedestrian interactions would be the key focus. Forklifts 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 pose severe hazards of potential collusion. The 15-ton loaders operating outside the mill could come in contact with forklifts and ground workers there. 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 be in lack of visibility situation due to blind spots caused by the size of the load carried (very long timber). When the loader-forklift and ground worker presented in these confined spaces, with a large and heavy timber load in front of the plant, risk of contact collision would be or is high. It must be noted that the stacks of products can block both people and drivers' views entirely.

Therefore, mobile plant – worker interaction was the most critical area and selected as the case study for this development. Four scenarios were selected:

i. Human to vehicle (forklift and truck) – indoor;

ii. Human to vehicle (forklift and truck) – outdoor;

iii. Vehicle to vehicle (less common) – indoor;

iv. Vehicle to vehicle (forklifts and loaders) – outdoor.

With respect to the future embeddable requirements, an Android mobile application based on the standard on-device cameras was selected to develop this proof-of-concept system. The mobile devices could 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.

The core of this solution is a machine learning model which is built based on AI-based image processing algorithms, detecting both vehicles and human movement. This proposed solution does not rely on any network, nor additional cloud hardware to run so it can be rapidly deployed in any environment. The project team has designed and implemented a proof-of-concept (POC) AI algorithm to test the suitability of this approach in a multivehicle factory setting. This algorithm is expected to detect several objects: cars, trucks, forklifts and human in an accurate and efficient manner.

Trial procedures and Data Collection

Videos were captured in two occasions - pilot and testing. In total, approximately 8 video footage were taken to represent different scenarios. Therefore, 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.

The system was developed as an Android application which took the video feeds directly from the front and rear cameras on the mobile devices. It was later modified to take video feeds from pre-captured mp4 files. Since the underlying algorithm stayed same, the result was applicable in real world scenarios.

Due to Covid restrictions, all researcher site visits have been prohibited. Therefore, for the trail in the plant, a purpose made helmet mount (Fig. 1) was used on the helmet of the plant supervisor during his daily routine work to capture real video footage for the system development and testing purposes.

Evaluation criteria

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

– Accuracy: Can the technology detect the potential risks in the above scenarios real-time?

– Reliability: Can the technology run stably in all environment (e.g. rain, dust, low light) with minimum human intervention for a sustained period?

– Cost: Does the adoption of technology (individual or vehicle based) result in

Fig. 1. DIY helmet mounted system (smart phone in use) – camera focusing set to 1 to 50 m.

huge cost?

– Adaptability: Can the technology be used in less ideal environment (e.g. no network)?

AI image classifier/Object detection

In addition to the traditional proximity sensor-based technologies, researchers such as Torbaghan et al. (2022) find that the computer vision technology and AI algorithms has long focused on the manufacturing production (e.g. fault detection); however, the recent emerging area is the safety management. Especially, by using the standard mobile devices such as smartphones and harvesting the machine learning capability built-into the modern phone processors, Zhang (2021) suggests that this approach does not only reduce the overall implementation cost but also improve the overall accuracy as that the phone sensors are often more advanced than the ones found inside the surveillance cameras.

The primary AI algorithm in safety management is object detection. Unlike traditional AI-base image classification algorithms, the proposed approach requires a model to detect objects real-time. This can be achieved in developing an AI Convolutional Neural Network (CNN) image classifier model. Jawale et al. (2020) suggests that the CNN algorithm can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image to differentiate one from the other (Fig. 2).

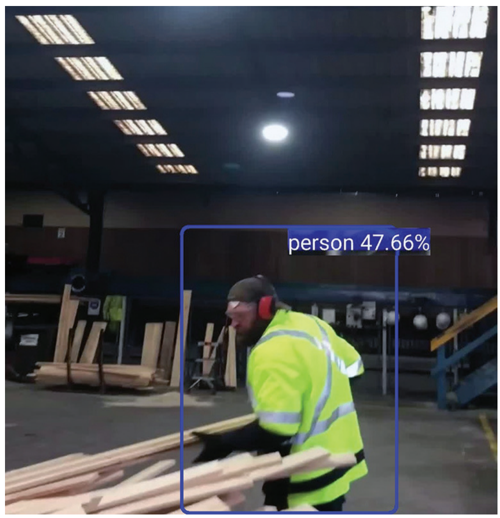

Fig. 2. Example of human detection.

CNN Image/object classification models usually have lots of parameters. Building an accurate model requires lots of labelled training data and computing power. In this project, the researcher team has decided to retrain an existing image classifier – Google TensorFlow image classifier, to fit with the proposed scenarios. This approach is often referred as ‘transfer learning’. It takes a piece of a model that has already been trained on a related task and reusing it in a new model. The existing image classifiers recognises a wide range of objects. However, there are only a few types that are of primary interest in the proposed scenarios such as people and vehicles (forklifts and trucks). Thus, during the retraining process, labelled vehicles’ images have been fed onto the base model in order to deliver a more suitable scenario-fit CNN classifier model for this project.

It is noted that the retraining CNN image classification model is only considered as one component in the proposed application. Figure 3 shows the overall process.

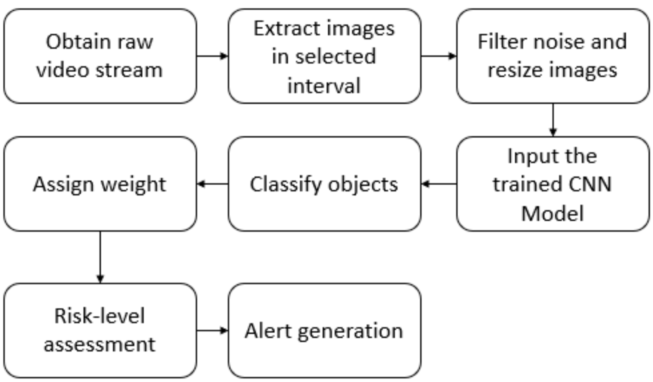

Fig. 3. Safety application flowchart.

Video stream to image: CNN classifier works at the image-level, thus, there is a need to take snapshots from the camera video stream periodically (1 image per second in this project).

Filter noise and resize images: Image denoising has a significant impact on CNN model accuracy. As reviewed by Ilesanmi and Ilesanmi (2021), there are several well-known methods such as linear and non-linear filters that can be applied to the input images. These methods are used in this project. In addition, by reducing the size of raw input images, the overall processing time can be reduced as well as extending device battery life. Thus, the raw image has been resized to 1024×768 before processing.

Assign weight to the classified results: it must be noted that the CNN classification does not give a binary result. Instead, it provides a threshold value. The higher values suggest that the detected objects are more likely to be a suggested type. While the retrained CNN model in this project does increase the threshold value of the detection of vehicles, it still presents mis-classified objects with lower threshold values. Especially, affected by real-time captures (e.g. blurred images due to movement), the overall threshold values are often lower than expected. Therefore, it requires a fine-tuning process to assign weight (cut-off threshold value) to the classified results. Once the classifier result is above this weighted value, then it is considered as a trustable detection.

Risk-level assessment and alert generation: in this project, the researcher team has primary focused on the object detection. In practice, the distance measure and vehicle speed are critical in the overall risk assessment. The actual risk assessment also needs to take other variables such as plant layout and organisation policy. More importantly, alert generation needs to consider human fatigue and other factors. Therefore, these two stages are considered as future research only.

Results and Discussion

Identify industry requirements: workplace health and safety concerns of the South Australian forestry industry

SafeWork SA collates worker compensation claims data obtained into a database for policy analysis. During 1st July 2002 – 31st June 2013, a total of 18,778 lost days were reported by the 860 forestry industry accident victims noted in the SafeWork SA database which translates into an average of 22 lost days per accident. Victims claimed AUD 12.1 million as compensation for medical treatment (an average of AUD 14,033 per accident). Given the number of accidents occurring in the forestry industry, harvesters, transporters and processors constantly seek novel strategies that promote safety. Innovation in implementing safer work methods and the use of technology has eliminated some of the traditional hazards, as indicated in the gradual reduction of accidents in South Australia. Forestry operations are typically characterised as physically demanding tasks that are often performed in harsh environment. Because of the continuous and repetitive exposure to physically demanding work, strains and sprains are the most common type of work-related, non-fatal 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 performing 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 AUD 6.2 million in direct medical expenses to the industry during the review period.

Hazard identification and current mitigation measures

Most of these risks are handled through administrative control. When it fails, a reliable real-time proximity detection and alert system is needed on this site to provide ground workers with another layer of safety protection. There is a 3 m 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 3 m safe zone, particularly when the forklift is turning around with timber on it. Workers would normally step inside 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.

During summer, the temperature inside dry mills could exceed 35°C and the fans could increase the noise levels which combined with worker fatigue during long shifts 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. The other factor that could lead to accidents is 'domestic blindness' and the fact that workers getting used to the movement of forklifts and the demarcation blue lights. Change of colour, when tested, did not work. A flashlight, something that is dynamic, with an irregular pattern could help get the attention of workers. The other major issue unearthed during the observations was the change of 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 the transition zone. This sudden blindness in the transit zone between in and outside of the timber mill poses serious hazards the pedestrians.

Initial desktop assessment of technologies

The literature and technology market scan suggest that the current sensor technology cannot address the above issues satisfactory. The current commercial state of art solutions has been developed based on proximity sensors which use radio signals such as Bluetooth and Wi-Fi network to detect approaching vehicles and human operators. However, each device costs about USD 5000–8000, which is too costly for day-to-day scalable adoption. These solutions also rely on expensive underlying network coverage which may not be available in all operation sites.

Some of the deployment and support 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 to equipment;

– Radio-based systems such as Bluetooth, etc.: easily interfered by the plant setup;

– Location awareness, e.g. GPS: existing technologies may fit well in one set of scenarios (e.g. GPS location tracking for outdoor), they do not fit well indoors where signals can be distorted or not available;

– Commercial solutions: require whole site data and high cost, limited accuracy;

– Administrative control: this solution involves separation of workers and machines, but this is not always feasible.

Therefore, with respects to the above-mentioned success measures, the study further examined the emerging technologies and determined that a risk Identification approach through AI-based image processing (object detection) could be a viable and justifiable approach.

Image recognition trial

With the on-site supervisors' assistance, a number of video clips were recorded to cover both indoor and outdoor scenarios. Given that the indoor lighting is constant, special attentions were made to the outdoor lighting conditions to cover both day light and low light (cloudy late afternoon) conditions. It must be noted that the raw detection algorithm threshold values cannot be used as an accuracy measure. These thresholds are calculated results based on two factors:

1. Whether or not there is a potential recognisable object within the identified area;

2. Whether or not the correct object type is assigned.

Therefore, in this project, based on a number of trials, we have set an internal cut-off point value of 40 % (assign weight). In other words, POC algorithm believes that any detection with an internal threshold value above 40 % is a correct object-detection event relating to safety monitoring (human and vehicle).

In order to provide an accurate measurement of the real-world application, human manual assessment is essential. Thus, in total, 58 indoor, 61 outdoor daylight and 53 outdoor lowlight images were randomly extracted from the 5 recorded video clips (total duration 1 h) for human verification. The tagging person has been given the raw images and the result spreadsheet (exampled in Table 1). After checking the original image, the tagging person manually assigns value 1 for each correct detection, 0 for each incorrect detection in the 'detection success' column.

Based on the human tagging results, the overall detection accuracy is shown in Table 2.

Table 1. Human tagging.

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

Table 2. Accuracy measure.

Lighting condition	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

Note: Above 90 % accuracy (in bold) is considered as desirable target outcomes.

In the case that false alarms and misses were identified, reasons were also found. For example, some of the mobile trays (e.g. Fig. 4) were detected as vehicles as they shared similar characteristics as real vehicles by having 4 wheels as well.

Overall, the image processing algorithm is found highly accurate, especially under good lighting conditions. For example, Figure 5 has shown examples of successful detection of human and vehicles in both indoor and outdoor settings. Figure 5 also shows that the recognition process works in obstructed views successfully.

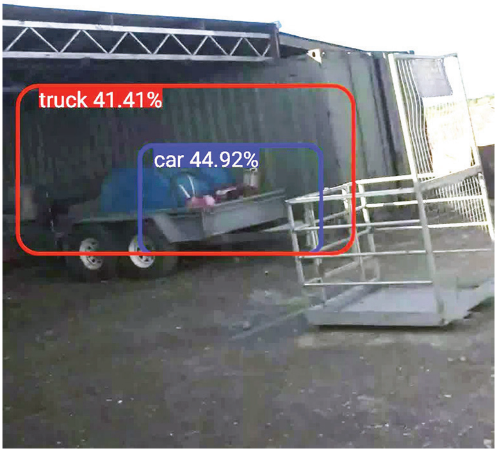

Fig. 4. Error – a mobile trailer is recognised as vehicles.

within a short period (e.g. ±2 s), the detection accuracy could be improved significantly. Also, a new detection model can be developed (trained) for lowlight conditions specifically.

In addition, from the development and testing, it was found that existing off-of-the-shelf algorithms to identify the proximity and direction of movement of the vehicle based on image processing techniques could be used in the future commercial development. When the camera has been mounted in a relatively fixed position (e.g. on top of the forklifts or factory walls), 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

Fig. 5. Success – indoor and outdoor detection examples.

Future work

In summary, 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

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.

This study has focused on safety management in the processing environment (sawmills). However, the research findings are also applicable in other forestry environments. For example, in the harvesting environment, heavy machines such as forestry skidders and log loaders are often used. Consequently, the safety management requirements for human and vehicle interactions are also significant. Therefore, it is expected to conduct research in the relevant settings in near future.

Conclusions

The estimated direct cost of accidents to the South Australian forestry industry is USD 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/ identify the parameter requirements for hazard monitoring in forestry operations against readily available sensors. Success measures and coverage scenarios were emerged as the testing base for the proof-of-concept system.

The developed AI-based image processing system is expected to prevent work-related injuries in forest 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 workers as they are provided with real-time safety situation-awareness that help them feel safer. In addition to those who are active, it could also help workers recovering from accidents and who have returned to work and new workers to become proficient and safe in their jobs with confidence.

There are many existing studies of the underlying AI technologies such as CNN for image processing in the field of computer science. However, turning these technologies into practical solutions indeed requires domain knowledge and practical experience. This applied research tried to explore the feasibilities of applying AI technologies in the forestry environment. Such a process is considered valuable in the forestry AI adoption projects.

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