EPRG-PRCI-APGA
23rd Joint Technical Meeting
Edinburgh, Scotland
6–10 June 2022

PAPER TITLE: SMART SIGN TECHNOLOGY FOR CONTINUOUS EASEMENT INTERFERENCE MONITORING
PAPER NUMBER: 34

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ABSTRACT

This paper presents the Smart Signs project, which describes the development of an autonomous, continuous, remote monitoring solution able to detect third party encroachment on pipeline easements using state-of-the-art computer vision methods. External interference threats, arising from third party activity, pose a significant risk to high pressure transmission pipelines.

The prototype solution has been deployed along a 10-kilometre stretch of easement through a rural township, approximately 100-kilometres south-east of Adelaide. The design of the device, the artificial intelligence used to detect the threats and the early results of deployment and field tests are detailed in this paper, showcasing the potential of the solution.

DISCLAIMER

1. INTRODUCTION

External interference threats, arising from third party activity, pose a significant risk to high pressure transmission pipelines. Proactive management of these threats is paramount in ensuring that underground assets are not interfered with. Australian Standard AS 2885 (Pipelines – Gas and Liquid Petroleum) outlines the approach for prevention, detection and control of external interference threats to a pipeline. Even with many preventative measures in place, best practice pipeline operators still record instances of encroachment. The need for high quality detection strategies is vital for the few occasions where preventative controls fail to avoid potentially catastrophic consequences. This paper details an alternative surveillance method for protecting pipeline easements against external interference. The specifics of the system are detailed, along with the outcomes sought for project success and the results of the first stage of the trial.

2. BACKGROUND

2.1. SEA Gas

SEA Gas was established in 2002 to own and operate the 700km long underground high-pressure natural gas transmission pipeline system that delivers gas from Port Campbell in Victoria to Adelaide in South Australia. Since 2002, SEA Gas' assets have expanded to include the Mortlake Pipeline in Victoria and lateral pipeline extensions. The Port Campbell to Adelaide pipeline currently delivers approximately 40% of South Australia's gas demand. South Australia relies heavily upon natural gas for power generation, with gas fired generation supplying nearly 50% of power generation in the state during 2021. Gas is also supplied to industrial and commercial customers and for residential use.

2.2. Industry need

Under the Australian pipeline Standard, AS 2885, pipeline licensees are required to complete a safety management study (SMS) to demonstrate adequate physical and procedural measures are in place to protect the pipeline. The SMS identifies and assesses threats to a pipeline and records controls in place to prevent and mitigate identified threats; and where pipeline failure is not prevented assesses the risk of a pipeline failure. Pipeline operators are required to monitor the effectiveness of controls put in place and identify new threats as they arise.

AS 2885 requires procedural controls that are capable of both preventing and detecting unauthorised works on a pipeline Right Of Way (ROW), as neither prevention nor detection in isolation would provide sufficient management of external interference. One detection method is patrolling the ROW, both from the air and on the ground. This is to specifically monitor for third party or environmental events that have threatened or will prove threatening to the pipeline. As threats can only be detected shortly before or as they are unfolding, traditional patrolling methods providing periodic detection are limited. This, in combination with increasing easement activity near pipelines due to population growth and urban expansion, suggests that current patrolling methods have limited effectiveness as a method of detecting third party activity. The limitations around pipeline patrolling are not unique to Australia; this is likely to be an issue throughout the global pipeline and linear infrastructure industry.

Other industries, like the mining industry, have been able to implement sophisticated drone technology to complete more frequent, less invasive, value adding surveillance techniques to monitor sites and detect threats. SEA Gas' investigation into the use of drone and satellite technology for the purpose of detecting external interference has identified that there are practical issues with these technologies, such as physical limitations (commercially available drones are not all weather) and climate limitations (satellite photogrammetry is limited by cloud). Even if technically feasible, they are not economically feasible for linear assets at scale. It is for this reason that SEA Gas, with the support of the Future Fuels CRC, has partnered with Fleet Space Technologies and the University of Wollongong in search of a more reliable pipeline surveillance alternative.

3. PROPOSED SOLUTION

To improve on current threat detection capabilities, a continuous and intelligent solution is required. This will allow earlier detection of external interference and hence, reduce the response time of an infrastructure operator to encroachments. The proposed solution includes attaching sensors onto existing pipeline easement marker signs. These sensors, connected to an IoT infrastructure solution, are capable of analysing and identifying threats using artificial intelligence, as trained by the Future Fuels CRC researchers at the University of Wollongong in combination with Fleet Space, to recognise threats common to pipeline operators. Additional details on the solution are given in subsequent sections. A 10-kilometre trial area was selected through a rural township approximately 100-kilometres south-east of Adelaide.

3.1. Outcomes sought by Solution

The effectiveness of the new surveillance system will be determined by comparing the outcomes of the trial to those obtained by conventional pipeline patrols. Specific criteria that will be considered in demonstrating proof of concept are as follows:

Feasibility of deployment along a ROW:

- The technology must demonstrate that it meets specific requirements, such as communication range, area of coverage per sensor, data transmission network reliability and latency between detection and notification to the SEA Gas System Control Centre.

Enhanced detection and categorisation of threats:

- The system should distinguish between the type of activity (ie. differentiate between a human, machinery and vehicles) for accurate detection of impending threats in real-time.

Enhanced quality of data & provision of records of historic third-party activity for threat analysis:

- The data collected from the sensors must be meaningful and representative of actual activities surrounding the ROW over time.
- The data should be able to be stored to provide better knowledge of past events to support threat analysis.

Enhanced prevention and decrease in incidents:

- The solution should provide earlier detection of threats, and ultimately, result in fewer interference incidents, reducing the overall risk profile to underground pipelines.

Enhanced operational efficiency:

- An effective system should allow the pipeline operator to redeploy labour currently dedicated to pipeline patrol activities. The cost and time of a technician, with tools and vehicle, currently dedicated to pipeline patrol would be significantly reduced. The frequency of encroachment can be low. With this system in place, higher value adding activity may be undertaken by the technician, only requiring a response when there is an actual threat to be mitigated.

4. SMART SIGN TECHNOLOGY – NETWORK SUMMARY

The connectivity element of the solution was enabled using Fleet Space Technologies IoT communications solution, which is comprised of Portal Gateways (which provide the terrestrial connectivity and the backhaul via satellite/cellular capability) and the networked sensor devices (the smart camera devices). The network is designed to provide a resilient and highly available network, right sized for the IoT device data, which can operate in areas of limited or patchy connectivity and can also deliver data over traditional cellular networks.

4.1 Network Architecture

The network architecture is summarised in Figure 1.

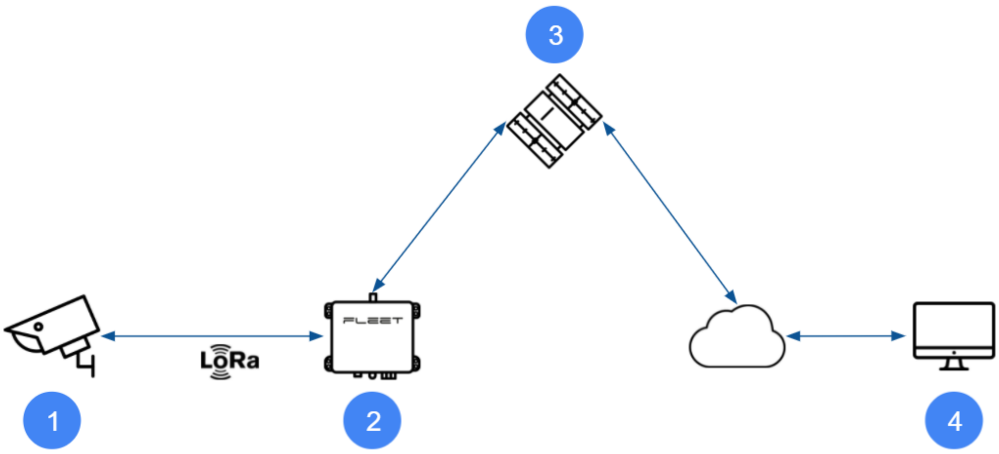

Figure 1: Network architecture summary diagram.

1. Camera sensors provide the detection capability in the network. The devices have Edge computing capabilities onboard enabling the artificial intelligence (AI) to run at the Edge of the network such that only alerts need to be sent across the network rather than sending unprocessed images. During the image capture phase of the project, the cameras are also equipped with 4G connectivity to enable images captured to be sent back to an online database for training purposes. This feature will be removed when training is complete.

2. The Fleet Portal Gateways in the solution augment and process the sensor data and can further refine alert transmission with additional Edge computing capability. Required information is routed through the satellite/cellular backhaul.

3. The satellite network enables connectivity between cloud and terrestrial network elements and enables coverage in areas with no other connectivity options.

4. Nebula is the control surface where data is aggregated and enables all network management operations to be performed. It also provides connectivity for other platforms via API or webhook. In this case the GAP (Global Alerting Platform) is integrated with the solution to surface alerts.

4.2 Deployment Scheme

The pre-existing pipeline marker signs along the pipeline easement served as a good attachment point for the smart camera sensor units as they provide good ground clearance for optimal line-of-sight and they are regularly distributed along the pipeline length which affords good coverage. Another benefit is that the marker signs have a common post width, so only one attachment method is required, which minimised deployment cost, safety management and time effort. The assembly is depicted in Figure 2.

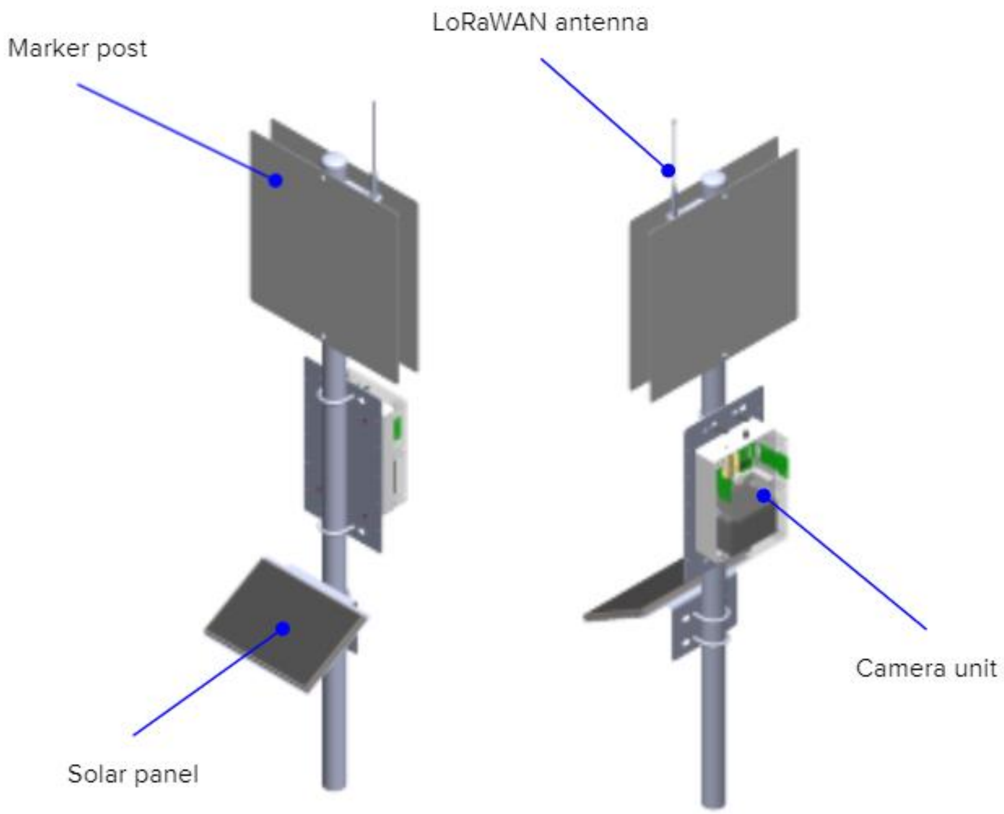

Figure 2: The camera assembly mounted to the pipeline marker signs.

60 such marker signs were identified along the Murray Bridge section of the PCA easement (approximately a 10 km stretch). This area was selected as it provides sufficient variety in land use (pipeline travels through farm land, crown land, roadways including major highways and adjacent to houses and businesses), and is also an area of increasing land development. This section was divided into 3 coverage areas each of which is supported by a network gateway (Portal, see Figure 4). The Portal locations were selected to provide roughly equidistant separation between the Portals and to provide the best possible line of sight to all marker signs. Figure 3 indicates the Portals locations (red dots), the distance they are servicing along the pipeline and the locations of marker signs (grey dots).

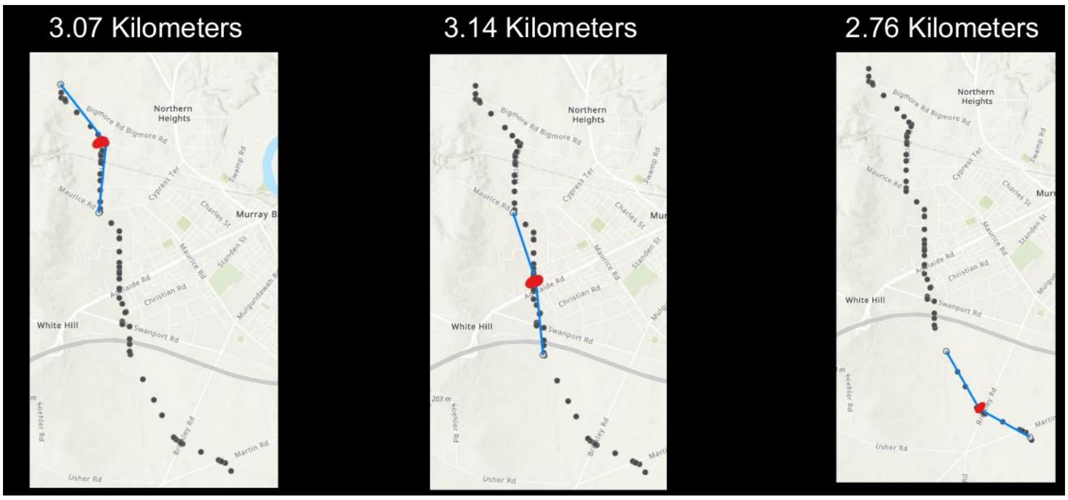

Figure 3: Network plan

Figure 4: Portal in situ

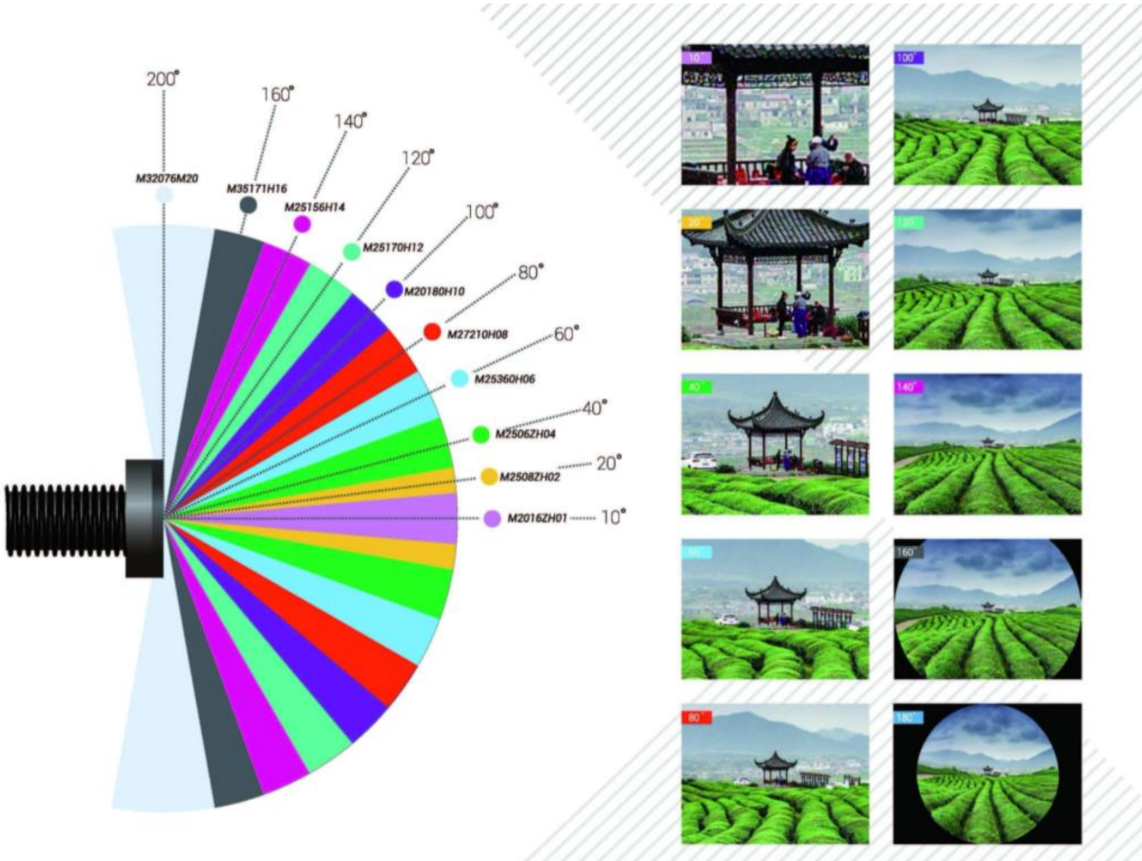

Figure 5: Difference in ranges and camera angles

5 SMART SIGN TECHNOLOGY – ARTIFICIAL INTELLENGE

The threat detection algorithm at the core of the solution is an AI solution belonging to the family of computer vision methods. It is based on the YOLO v4 object detector which is a deep learning model made of nearly 50 million parameters [1].

The AI processes images predicting both the location of a threat in the image (in the form of a bounding box), and its type, as shown in Figure 6.

Figure 6: Output of the YOLO v4 object detector: objects location in the form of bounding boxes and classification.

Like all models, the parameters of YOLO v4 need to be optimized and tuned so that it can accurately perform threat detection. This process is known as training the AI. Being a deep learning approach, this is done by repeatedly presenting sample images with desired target outputs until the model learns by itself which features to look for in the images to make an accurate detection. As there was no database publicly available for training the AI, a new one had to be created for this work. The current image dataset comprises approximately 6,000 raw images coming from Internet and research groups covering the following type of threats as described in Table 1.

Livestock	**Persons**	**Bike**	**Auger**
Car	**Ute**	**Truck**	**Post driver**
Boring rig	**Tractor**	**Excavator**	**Cable plough**
Bobcat	**Ditch witch**	**Horizontal drill**	**Clay delver**

Table 1: Categories of threats detectable by the Artificial Intelligence.

The distribution of those categories in the database is illustrated in Figure 7 and sample images with their target annotation are shown in Figure 8.

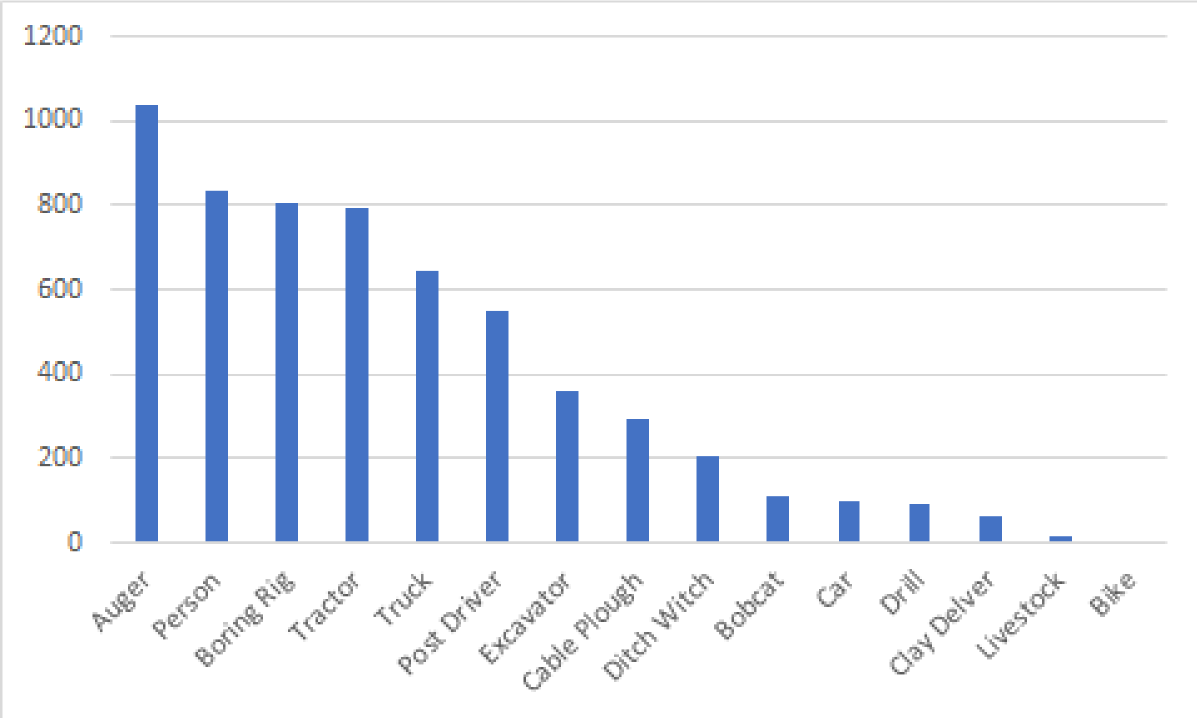

Figure 7: Distribution of the threats in the current database

Figure 8: Image containing a clay delver in database

6 RESULTS FROM IMPLEMENTED SOLUTON

To assess the performance of the AI, the AI is exposed to images that are not in the training database and compute the mean average precision (mAP) for the classes. This metric is based on the Intersection over Union (IoU), a measure of the overlap between the predicted bounding box and the ground truth. A prediction is correct if the IoU between the predicted bounding box and the ground truth is above a given threshold t. The mAP is a metric in between 0-1, summarising the performance of the AI for different overlapping thresholds t. This corresponds to finding the area under the precision-recall curve of the model. A value close to 1 indicates an accurate model.

Our current model is achieving a mAP score of 0.70. While this is the first time an AI is trained on such a dataset, and is the de facto current benchmark, it should be noted that this mAP is on par with other AI's applied in similar object detection context on databases such as COCO, Google OpenImages and ImageNet [2,3,4].

While the mAP gives a general overview of the AI's performance, we also need to investigate its performance for each type of object that can be detected. The average precision for every class is thus shown in Table Z, highlighting the need to improve the AI for some classes. This will be achieved by collecting more images for the problematic classes.

Category	Test AP	Category	Test AP	Category	Test AP
Bobcat	0.90736	Cable plough	0.77156	Person	0.46308
Excavator	0.88291	Boring rig	0.73971	Truck	0.37691
Tractor	0.83866	Ditch witch drill	0.73633	Car	0.31734
Ditch witch	0.82808	Auger	0.72512	Livestock	0.00000
Post driver	0.78829	Clay delver	0.51754		

Table 2: Average Precision for different classes on images not used during the training process.

7 SMART SIGN TECHNOLOGY – FIELD TEST

One smart monitoring device has been set up with an excavator in its field of view, as shown in Figure 9, to test the following:

- Detection of a stationary excavator at different distance and location in the field of view, and different time of day.
- Detection of an excavator passing by the monitoring device at different distance and location in the field of view, and different time of day.
- Testing the time-based and manual trigger for the device.
- The data transmission
- The hibernation, power saving and wake up mechanisms of the device
- The resistance to water
- The true positive, false positive and false negative rates of the AI

Figure 9. The unit installed in the field and the excavator used for the tests.

7.1. Hardware tests

7.1.1. Data transmission

The smart sign monitoring devices uses LoRaWAN as the protocol to transmit the detections. The alerts generated by the unit during the tests went through a Portal, forwarding the data and alerts to the user interface. The LoRaWAN data transmission has been reliable for the tests and the devices already deployed in the field.

7.1.2 Power management

In order for the smart sign monitoring device to remain operational when powered using batteries (12V, 12Ah) and solar panel (10W), the devices are configured to be in hibernation mode and wake up every 15 minutes to monitor the area in its field of view.

7.1.3 Water resistance

The smart sign monitoring device is designed to be waterproof. By monitoring the devices in the field, minor condensation appeared on around 15% to 20% of the units. The occurrences were rare and were only noticed on days with large variations in temperature.

7.1.4 Device health monitoring

The temperature, humidity and battery life sensors of the device are regularly transmitted via LoRaWAN messages. If needed, this information can also be available on demand. The message contains the temperature in Celsius, relative humidty in percentage and battery voltage.

7.2 Performance of the AI

As illustrated in Figures10 and 11, the AI was able to detect the excavator. Nonetheless, the field tests also showed that the AI also produced a number of incorrect detections as illustrated in Figure 12. This indicates that the AI needs more data coming from the sensors to recalibrate it as the images captured by the device present some optical and chromatic distortions. This explains the errors.

Figure 10. Excavator detected by the device.

Figure 11. Excavator detected by the device.

Figure 12. Incorrect detections made by the AI.

The tests related to the performance of the AI can be divided into 2 parts: functional tests, and 24 hours uninterrupted test.

7.2.1 Functional test

The functional tests involve detecting stationary and moving objects at different locations (distance and angle from direct line of sight). Firstly, the result of distance and angle tests imply that the camera in some instances had difficulty with objects at long distances and distortions near the edge of the frames. This is likely due to the wide field of view of the camera lens, generating optical distortion and chromatic aberrations. Finally, the movement tests aim to simulate the scenario of an excavator moving and with its arm ready to dig. The unit can successfully detect an excavator with its arm automated and moving up and down.

7.2.1 24 hours test

The unit was set up for running continuously for 24 hours to collect data for false/true positive/negative analysis and luminescence tests.

The luminescence tests were conducted to assess the daily operational time window when the unit can perform object recognition. Since the camera in the unit does not have night vision capability, the performance of the AI dropped during night-time (between 21:00 and 06:00). The devices were still capable of detecting objects in dusk, dawn, and direct sunlight scenarios.

It should be noted that the unit will only forward the highest confidence level for the same object detected over the 3 consecutive images taken every 15 minutes by the device. For example, if the unit detects an excavator in the sequence of images with confidence level 90%, 91% and 95% in image 1, 2 and 3, the unit will only forward the alert with confidence level 95%. Note that 95% is not a threshold.

When considering all the categories that can be recognised by the AI, the unit achieved a true positive rate (detecting the right object) of 67.30%, and a false positive rate (detecting the wrong object or missing a detection) 32.70%.

When only focusing the tests on the excavator category, the test results in the 24 hours test has false negative rate 14.74% (not detecting an object when there is one) and true negative rate 85.26% (not detecting an object when there is none). There is no true/false positive rate for this category due to missing data during the test.

This performance indicators illustrate that the AI needs to be further improved to cope with the lens being used by the camera.

8 CONCLUSION AND FUTURE WORK

This paper detailed the current development status of the Smart Signs remote monitoring solution for detecting potential threats for underground pipelines. The monitoring devices have been designed following the Edge-computing paradigm. They rely on long-range wireless data transmission networks and solar power or batteries. This allows the sensors to be autonomous and deployed in remote environments. A batch of 48 devices and the network infrastructure to carry the alerts to the operator were deployed in the field in August 2021.

Further dedicated field tests were conducted in February 2022 to assess the durability and longevity of the smart device, as well as the performance of AI for detecting excavators.

The features not related to the AI and computer vision of the unit, such as the LoRaWAN and power management, were reliable in the field test. While the AI showed its potential to detect threats, it was observed that, before the device can be reliably deployed, its training requires images taken by the actual device to cope with the optical and chromatic distortions created by the lens of the camera. This additional data will improve the real-world performance of the AI.

The solution will also need to be tested in urban locations to determine its suitability in more populated areas. Even with the AI showing promising results on par with similar object detectors used in other contexts, it requires further development in different environments.

While the current application is on a pipeline ROW, security monitoring at other locations such as compressor, metering and scraper stations could be considered. The benefits of this surveillance solution could be realised in the pipeline industry, both locally and globally, and could be broadened to other industries comprising linear infrastructure, such as electricity transmission networks.

9 ACKNOWLEDGEMENT

This is work is funded by the Future Fuels CRC, supported through the Australian Government's Cooperative Research Centres Program. We gratefully acknowledge the cash and in-kind support from all our research, government, and industry participants.

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