SMART SIGN TECHNOLOGY FOR CONTINUOUS EASEMENT INTERFERENCE MONITORING

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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 solution is currently midway through the trial phase, after being 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.

Keywords: IoT, AI, remote monitoring, network integrity

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 preliminary results of the first stage of the trial.

Background

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 PCA 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 FY21. Gas is also supplied to industrial and commercial customers and for residential use.

Industry Need

Under AS 2285, 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 in isolation would provide sufficient management of external interference. One detection method is patrolling the ROW, both in the air and on the ground. This is to specifically monitor for third party or environmental events that have 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 detection of 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.

Proposed Solution

To enhance threat detection capabilities, a continuous and intelligent solution is required to improve on current detection methods. This will allow for earlier detection of external interference and hence, reduce the response time of an infrastructure operator to respond 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 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.

Outcomes Sought by Solution

The outcome of the new surveillance system trial will be determined by comparing the results to those obtained by conventional pipeline patrols in various areas. 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 the minimum 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 encroachments, reducing the overall risk profile to underground pipelines.

Enhanced operational efficiency:

- The system should provide the ability to redeploy labour currently dedicated to pipeline patrol activities to support long term cost savings. 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.

Proposed Solution – 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.

Network Architecture

The network architecture is summarised in Figure 1.

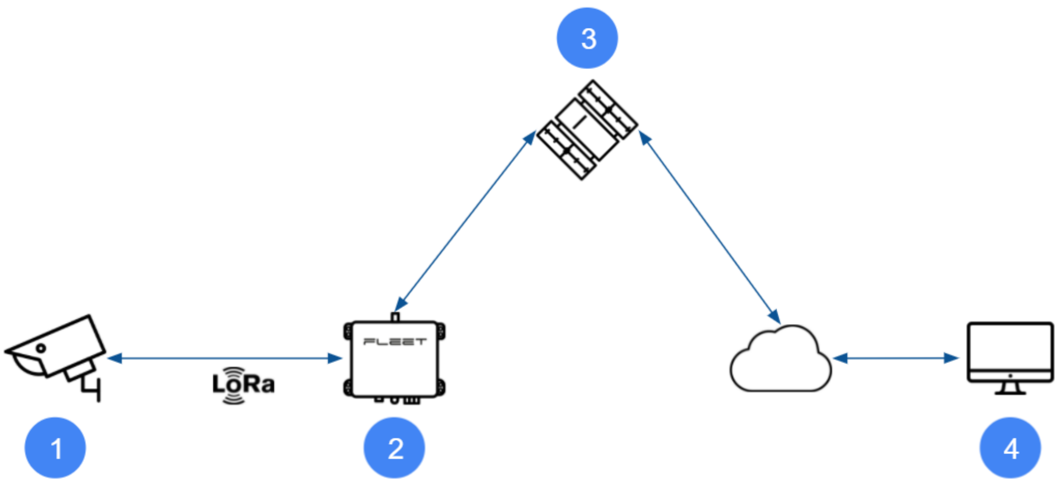

Figure 1: Network architecture summary diagram.

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.

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 additional 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.

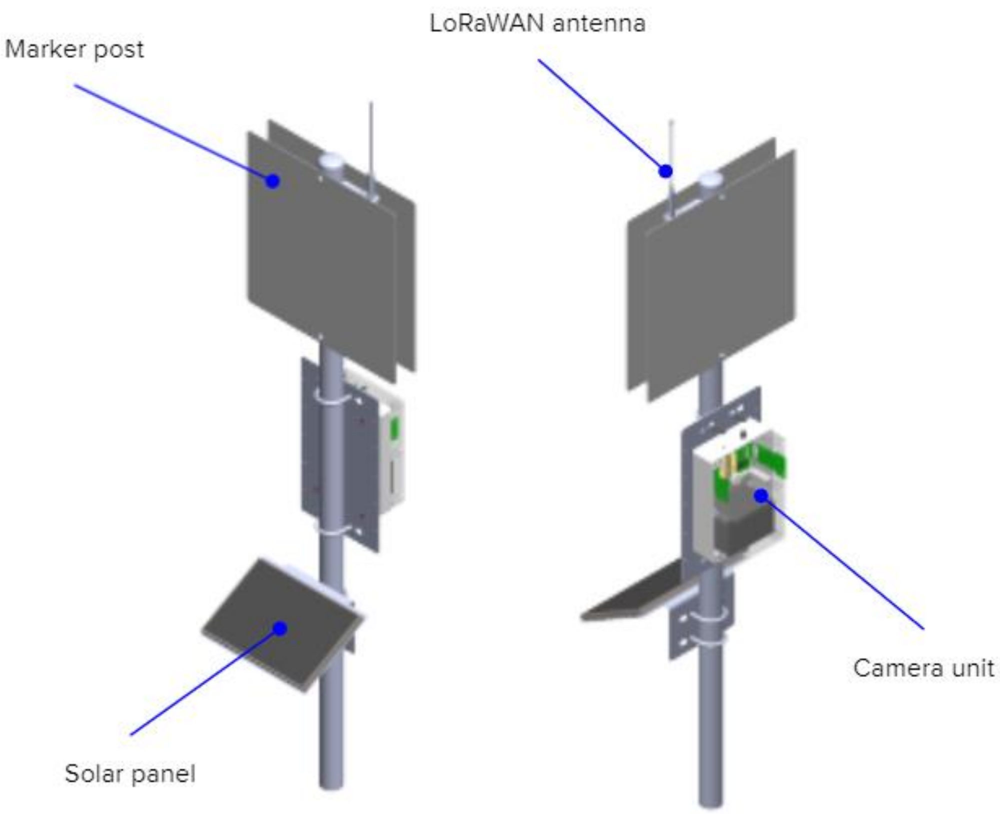

Figure 2: The camera assembly mounted to the pipeline marker signs.

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), while 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 pipeline marker signs (grey dots).

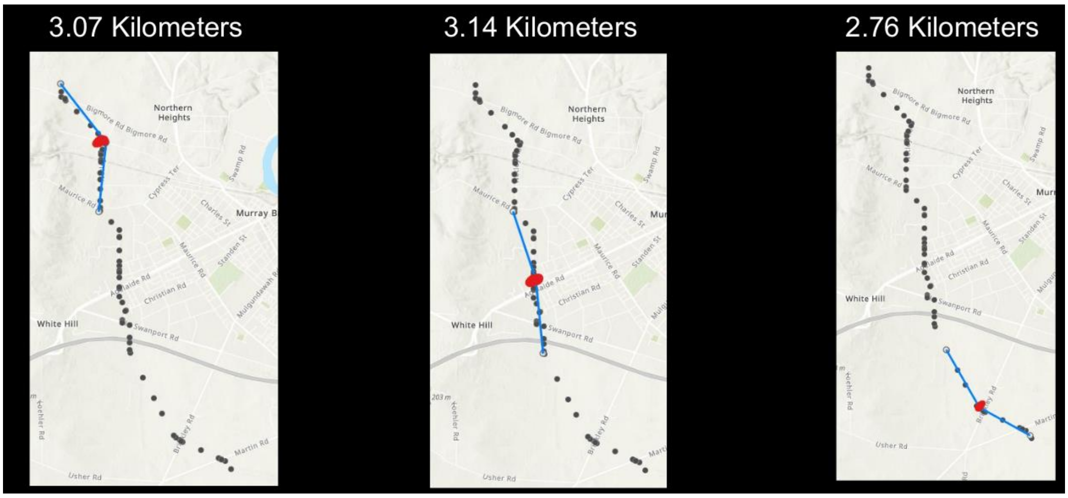

Figure 3: Network plan

Figure 4: Portal in situ

There are two types of camera units in use throughout the trial area. The first is a 10-degree camera, which is ideal for long distance detection where the signage is over the top of the pipeline. The detection length of this camera is up to approximately 140-metres. The second is a 136-degree camera, which is ideal for offset signage due to its maximum spread of coverage. The detection length of this camera is up to approximately 25-metres. Figure 5 shows the difference in ranges and camera angles.

Proposed Solution – Artificial Intelligence Architecture and Training

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 predict both the location of a threat in the image (in the form of a bounding box), and its type, as shown in Figure 5.

Figure 5: 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 6 and sample images with their target annotation are shown in Figure 7.

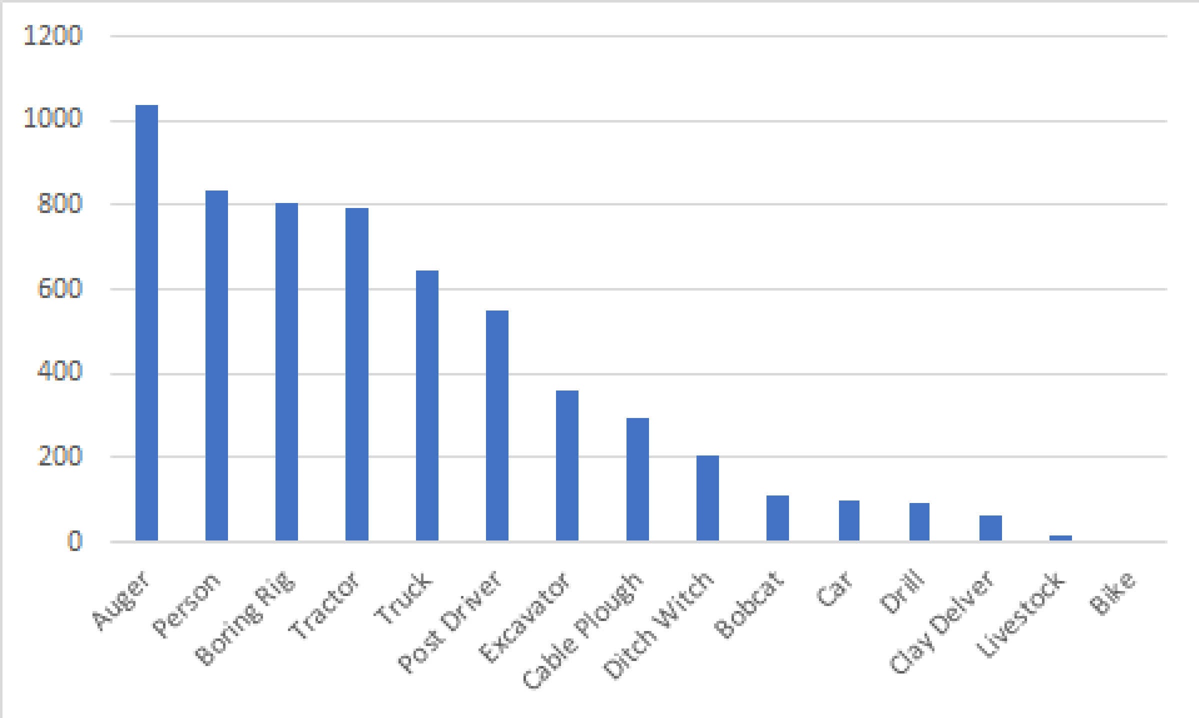

Figure 6: Distribution of the threats in the current database

Figure 7: Image containing a clay delver in database

Results from Implemented Solution

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 [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.

Conclusion and Future Work

The sensors and associated network are capable of continuously monitoring the easement for potential threats. The initial deployment of the solution indicates that it can successfully detect visual threats. The solution will 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 improvement in some areas.

A larger dataset is required to further improve the training and performance of the detection AI, which will require industry assistance. As the trial is ongoing, not all the intended outcomes have been demonstrated yet. Further testing and data from the field trial is required to better understand if the project can be scaled up. While the current application is on a pipeline ROW, security monitoring at other locations such as compressor, metering and scraper stations could be considered if the concept proves feasible. The benefits of this surveillance solution would not only be realised in the pipeline industry, both locally and globally, but could be broadened to other industries comprising linear infrastructure, such as electricity transmission networks.

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