Node quality control using drones and object detection

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SUMMARY

Wireless nodal surveys are now commonplace in Australian land seismic. It is essential that rigorous QC of the condition of the nodes is performed during these surveys. Acquiring footage using off-the-shelf drones can assist with this.

Analysis of drone footage using open-source machine-learning algorithms can reduce the amount of human analysis hours required. The best results were obtained by using a combination of OpenCV blob detection, and the Tensor Flow Convolutional Neural Networks.

Key words: UAV, seismic, machine-learning, computer vision.

INTRODUCTION

Small Unmanned Aerial Vehicles (UAVs or Drones) have become commonplace in both the private and commercial sectors.

Likewise, the seismic exploration industry has started making use of drones. This has included using them to QC the deployment of nodes (e.g. Stevenson and Strong, 2019; Dean *et al*, 2020). This has generally required manual intervention to determine the state of the node on the acquired video footage.

In this investigation we are focusing on using a standard off-the-shelf quadcopter (DJI Mavic 2 Zoom) to QC the infield condition of a nodal seismic system. Of particular interest are using computer vision and machine-learning algorithms to automatically optimise the process.

Computer vision is one of the leading fields of computer science and has undergone remarkable growth in the last 5-10 years, but it remains a difficult problem (Ratan, 2020). However, for our purposes of identifying what is essentially a small white square in an image the difficulty level is relatively low.

We have tested three node detection methods. These are based on a mixture of computer vision and machine/deep learning techniques and include:

- OpenCV blob detector
- In-house node detection methods
- Convolutional Neural Network using Keras with Python (part of Tensor flow)

SIMPLE DETECTION METHODS

Smart solo nodes were used in this investigation. These have a white top and a blue base. Generally speaking we observed that our nodes tend to be the whitest object in the drone images.

OpenCV

Our first approach was to identifying any white objects in the image. We used the OpenCV (Open Source Computer Vision) image processing library which contains over 2500 optimised algorithms.

The image was converted to grey scale (pixel value of 255 for whitest to 0 for darkest) and a threshold applied where any pixels with a grey-scale value of 240 to 255 will appear as full 255 white. This is shown in Figure 1.

Often due to lighting effects or dirt covering the node, the threshold grey-scale value of 240 did not capture any node pixels. In this case the algorithm steadily reduced the threshold range until it did capture the node.

OpenCV has an algorithm for blob detection. Where a blob is a group of connected pixels in an image that share some common property (in our case a grey-scale value of 255). The algorithm will return the x and y coordinates of the blob, allowing us to pinpoint the location of the node in the image (Figure 1c).

Applying this simple approach to 150 test set images we were able to detect the node in 131 cases. However there were 140 false positives (e.g. Figure 2).

One of the options for the OpenCV blob detector is to test for shape by counting the number of edges. Applying this to identify square shapes helped reduce the number of false positives to 64. However, the number of correct detections fell to 91 due to many of the nodes being partly covered in dirt, grass or shade.

Modified OpenCV Algorithm

To improve the results of OpenCV we have added a QC step in an attempt to determine if the blob represented a node or not. We cropped the image 40 x 40 pixels from the centre of the blob and created an inner and outer boundary. We then summed the number of white pixels in and out of this boundary.

After extensive trial and error, the best results we could obtain were 135 detections, 15 misses, 18 false positives. For this we set the boundary divider to be 4 pixels from the edge. We required the white pixels count in the outer boundary to be zero and the inner count to be between 22 and 250. This relies on fine tuning 3 parameters which would likely need adjusting for different terrain and certainly for different image resolution or drone flight heights. Therefore, we need to look at more advanced methods.

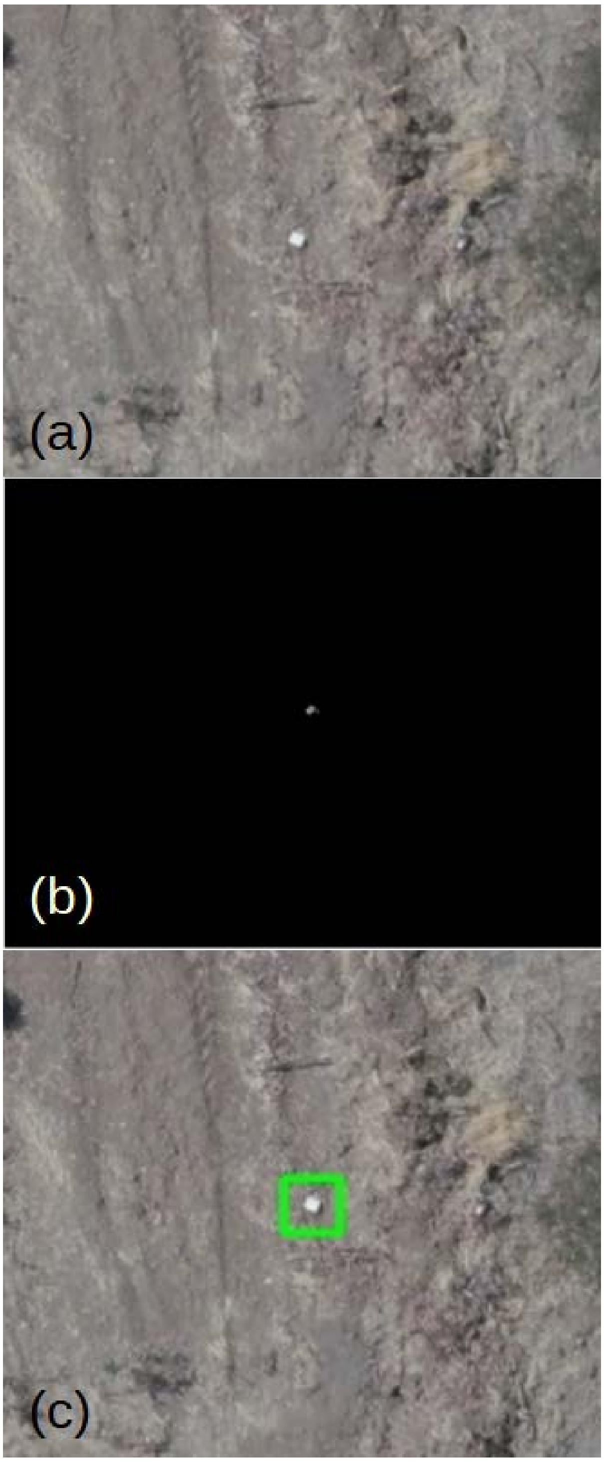

Figure 1. Implementation of OpenCV. (a) cropped image with a planted node at the middle. (b) black/white threshold converted image after grey-scale. (c) node location identified using OpenCV blob detection.

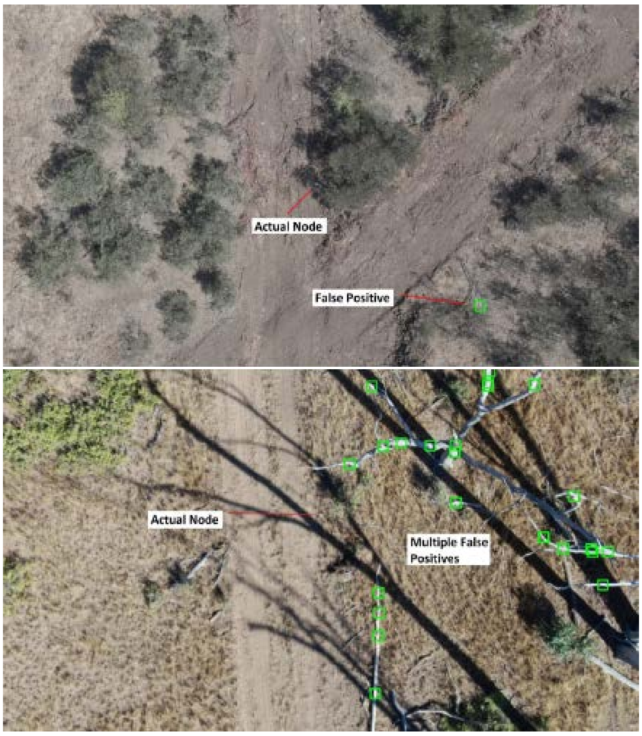

Figure 2. Examples of false node identification by OpenCV simple blob detection.

CNN MACHINE LEARNING

Machine Learning is the set of tools that allow computers to "learn" to recognise patterns within data without specific coding. These algorithms have been shown to be quite useful for the geophysical industry (e.g. Naeini and Prindle, 2018, Maniar et al, 2018)

Machine Learning techniques that utilise neural networks are arguably some of the most powerful (Ratan, 2020). These can be grouped in four different categories: Supervised Learning, Unsupervised Learning, Self-supervised Learning, and Reinforcement Learning. In this paper we are concentrating on a Supervised Learning approach.

For this investigation we have used the Convolutional Neural Network (CNN) which is commonly used in computer vision applications. The theory behind neural networks can quickly become quite complex. In this paper we have mainly focused on their application. Figure 3 provides simplified work flow of the concept.

When training the CNN model the labelled data consisted of 700 images of nodes correctly in the ground, 300 non-node images and 100 images of a node out of the ground. All images were 40x40 pixels in size. There were actually only 8 occasions where a node was out of the ground during the drone flights, so to make 100 images we had to take multiple shots of the same node at slightly different angles from the video footage.

Since we only have a limited dataset we needed to guide the CNN to focus on only the parts of the image where nodes are likely to be. To achieve this we have used the OpenCV blob detection algorithm to select possible node locations. Then CNN is used to identify these as "not a node", "node in the ground" or "node out of the ground"

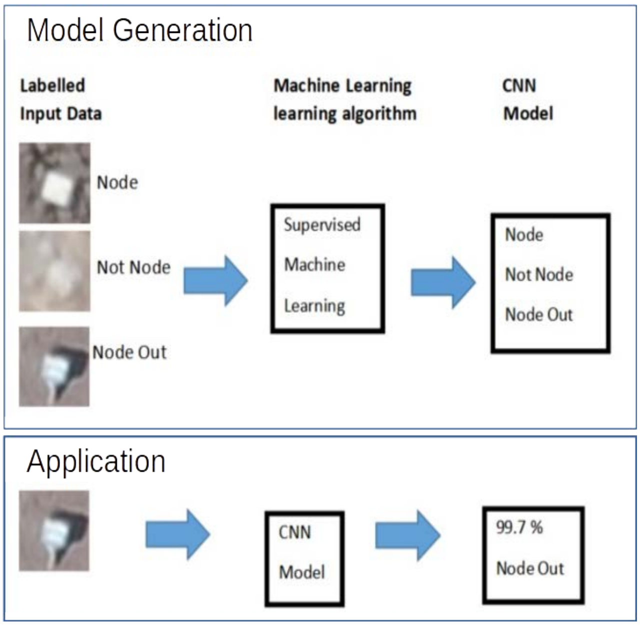

Figure 3. Basic CNN work flow as applied to our application. (top) A training dataset is created including images in various states. These are labelled. The machine learning algorithm is applied to generate a model. (bottom) This is applied to new data.

Applying the CNN method on the same 150 images used in the previous section (grey-scale threshold range 210 to 240) did a great job of eliminating all the false positives.

Of course, the nodes that were not detected by the blob detector were not analysed. Widening the grey-scale threshold range has increase the number of detections but also increased the number of false positives (Table 1). It is likely that more training data may improve this further.

Table 1. Node detections and false positives for various threshold ranges.

Grey scale Range	Correct detection	False Positives
220-240	133/150	0
210-240	141/150	0
200-240	141/150	1
190-240	141/150	3
180-240	143/150	13

We next tested the CNN Model on a set of 420 images from a second drone flight. The results are quite good with 410 correctly detected nodes, 1 false positive, 5 of 7 node-out correctly identified.

The CNN model did a good job of distinguishing the difference between a node-in and a not-node image. However it was less effective at distinguishing between a node-in and a node-out. We were able to detect all nodes-out correctly by running two separate CNN models, one for (node-in and not-node) and one for (node-in and node-out).

Figure 4 shows a screen shot of the program we built to view the results.

CONCLUSIONS

The use of drones as a support tool for seismic operations will only grow with time.

We have shown that open-source computer-vision and machine-learning algorithms can provide useful tools for the identification of the state of nodes. In this case the best results were derived by using the OpenCV blob detection algorithm in conjunction with multiple Convolutional Neural Networks (Tensor Flow).

These results will reduce the human hours required to QC nodal surveys which will improve cost effectiveness and quality.

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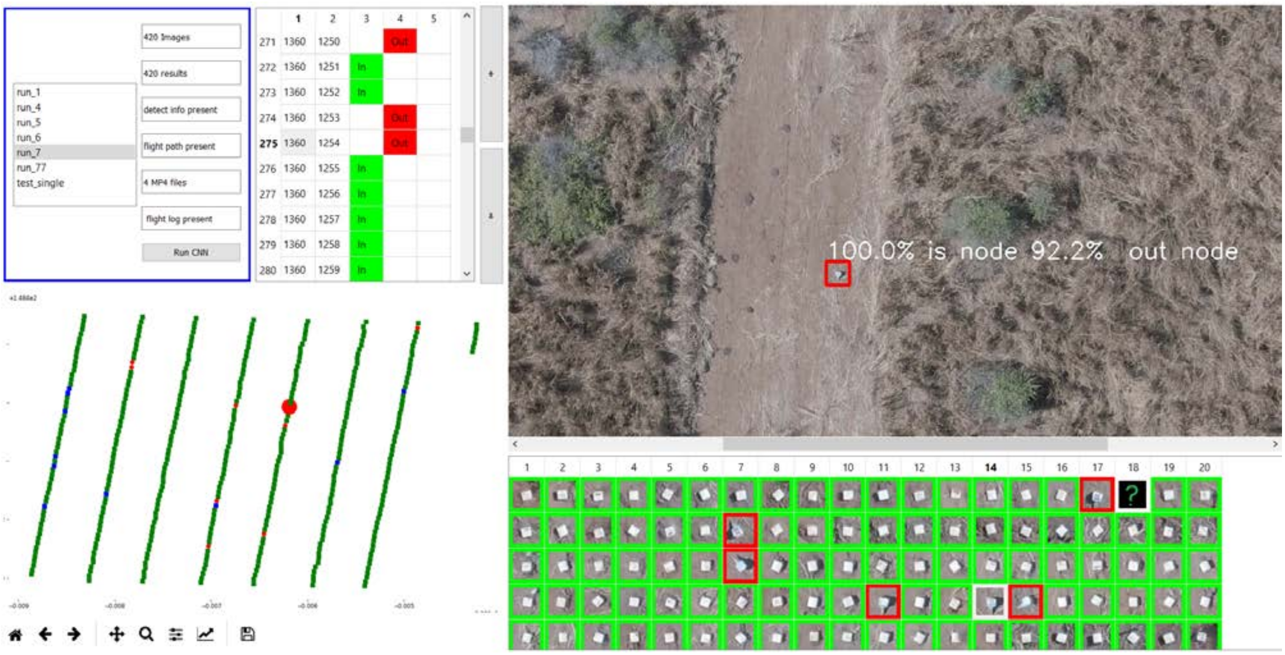

Figure 4. Display software used to view the results of the CNN analysis. (top left) table of image status. (bottom left) colour coded map of flight. (top right) selected analysis location. (bottom right) surrounding node images.