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Knowledge-based Power Line Detection for UAV Surveillance and Inspection Systems

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Abstract

Spatial information captured from optical remote sensors on board unmanned aerial vehicles (UAVs) has great potential in the automatic surveillance of electrical power infrastructure. For an automatic vision based power line inspection system, detecting power lines from cluttered background an important and challenging task. In this paper, we propose a knowledge-based power line detection method for a vision based UAV surveillance and inspection system. A PCNN filter is developed to remove background noise from the images prior to the Hough transform being employed to detect straight lines. Finally knowledge based line clustering is applied to refine the detection results. The experiment on real image data captured from a UAV platform demonstrates that the proposed approach is effective.

Keywords: Power line detection, UAV, Hough transform, PCNN, k-means clustering

1 Introduction

Surveillance and maintenance of electrical infrastructure is a significant cost component for energy companies. For example, Ergon Energy, one of the top electricity companies in Australia, currently spends approximately $80 million a year inspecting and managing vegetation that encroaches on power line assets. Most current vegetation management programs used by energy companies use calendar-based ground patrols [1]. However, calendar-based inspection by linesman is labour-intensive, time consuming and expensive. Satellites and aerial vehicles can pass over more regularly and automatically than the ground patrols. Therefore, spatial data captured from these platforms has a great potential in assisting surveillance and maintenance of electrical infrastructure [2].

One specific technology that has the potential to automate the entire surveillance process is Unmanned Aerial Vehicles (UAVs). Overhead power line inspection in remote and rural areas is an ideal application for UAVs due to low population density and widespread power distribution. UAVs can fly relatively close to the power line, providing a cheap and flexible way to gather spatial data from the power line corridor. In order to achieve automatic power line surveillance and inspection using UAVs, power line identification in captured images is required as: (1) it is useful for navigation, ensuring the UAV is accurately flying along the line and automatically collecting data in power line corridor; and (2) any risk assessment of power lines and the adjacent trees is meaningful only when power lines can be recognized.

There has been very limited investigation involved in developing algorithms for the automatic extraction of power lines from aerial images as power lines in traditional aerial images are too small to be detected due to the flight height and resolution of the camera. Although straight line detection is a common and well studied research area in computer vision, most of the existing algorithms take bottom-up approaches which just use the intensity of single pixels. However, the qualitative performance of these algorithms varies widely across application domains as our notion of what constitutes a line can vary from one application area to another. Due to the wide variation of line types encountered in the UAV images that are not of interest, we require a more top-down approach that takes advantage of our understanding of line in this application area.

In this paper, we combine the bottom-up and top-down approaches and propose a knowledge-based technique specifically for power line detection in aerial images. The proposed method is tested on real image data captured from a UAV platform in Queensland rural areas. Since the background of power lines is cluttered with a wide range of objects that are not of interest (e.g. grass, trees, roads and buildings), a filter based on Pulse Coupled Neural Network (PCNN) is used to remove the background of power lines. Then the Hough transform is

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employed to detect any straight lines remaining in the images. Finally the summarized characteristics of power lines are used to discriminate power lines from other linear objects.

The remainder of the paper is structured as follows. Section 2 briefly introduces related work in power line extraction. In Section 3, our proposed approaches for power line detection are described in detail. Section 4 presents and discusses experimental results, and Section 5 concludes our work.

2 Related work

Most energy companies use Geographic Information Systems (GIS) to record locations of their assets (e.g. power poles), from which power line information can be inferred. However, in general the accuracy of such information is only suitable as a general guide. For an automatic power line inspection system using computer vision, the major problem focuses on how to effectively extract power lines from complicated image backgrounds.

Automatic power line detection from aerial imagery is a rather challenging task, especially when the background is cluttered. There has been little investigation involved in developing algorithms for the automatic power line extraction due to the low resolution of traditional aerial images. Some work on the visual control of an Unmanned Aerial Vehicle (UAV) for power line inspection has been simulated using a laboratory test rig [3]. This work included an automatic power line detection method based on the Hough transform, but the approach was not evaluated in real image data from UAV. More recently, the Radon transform was used to extract line segments of the power lines, followed by a grouping method to link each segment, and a Kalman filter was finally applied to connect the segments into an entire line [4]. Although some properties of power lines in the aerial image are discussed, the algorithms in [4] just focus on straight line detection; image edges and other linear features which look similar to power lines were not considered.

3 Proposed approach

The Hough transform is an effective tool for detecting straight lines in images, thus it is a natural choice for the task of automatic power line detection. In real applications of straight line detection, an edge detector is often used before the Hough transform to remove irrelevant data that increase the computational cost of the Hough transform. However, the application of classic edge detectors to the aerial images has demonstrated that they are sensitive to image noise, due to complex and irregular ground coverage. In this paper, we take advantage of the characteristics of power lines in aerial image, and propose a filter based on Pulse-Coupled Neural Network (PCNN) to remove the background of power lines, and then use Hough transform to detect straight lines. Finally, k-means clustering is employed to discriminate power lines form other straight lines in the edge image.

3.1 Characteristics of Power Lines

Based on our observation, power lines in aerial images have the following characteristics:

(1) A power line has uniform brightness and is usually brighter than the background from downward view simply because it is made of specific metal and has larger light reflection.

(2) A power line approximates a straight line, and it is usually the longest line as it crosses the entire image. Often the lengths of each power line in images are similar.

(3) Power lines are approximately parallel to each other. Due to the forward angle of imaging sensor and deviation from centre, power lines in the image are not completely parallel. However, the intersection of two power lines usually occurs far out of range of the image due to the limited size of images, and the intersecting angle of two lines is usually very small. An example is shown in Figure 1.

Figure 1 Power lines from the forward view and offset centre

These characteristics can be used as knowledge to guild power line detection algorithms. For example, since power lines often have uniform brightness, a filter can be applied to remove much of the image background and reduce the computational cost of line detection algorithms.

3.2 PCNN Filter

Pulse-Coupled Neural Network (PCNN) is a relatively new biologically inspired approach based on the understanding of visual cortical models of small mammals. It is feasible to implement PCNN in hardware thus it has great potential for real-time processing.

3.2.1 Standard PCNN Model

Most PCNNs are based on the Eckhorn model [5]. When applied to image processing, PCNN is a single layered, two-dimensional, laterally connected neural network of pulse coupled neurons. Each neuron corresponds to one pixel in an input image, receiving its corresponding pixel's colour information (e.g. intensity) as an external stimulus. The neuron also connects with its neighbouring neurons, receiving local stimuli from them. Thus, every neuron can be represented as a specific structure as shown in Figure 2. The input part imports external and local inputs to the neuron by the feeding and linking part respectively. In the linking part, external and local stimulus are combined in an internal activation system, which accumulates the stimuli until it exceeds a dynamic threshold, then the pulse generator produce a pulse output. Through iterative computation, PCNN neurons produce temporal series of pulse outputs. Similarities in the input pixels cause the associated neurons to pulse synchronously, thus indicating similar structures or textures. These temporal series of pulse outputs contain information of input images and can be utilized for various image processing applications, such as image segmentation, edge detection, feature generation, noise reduction, etc. [6].

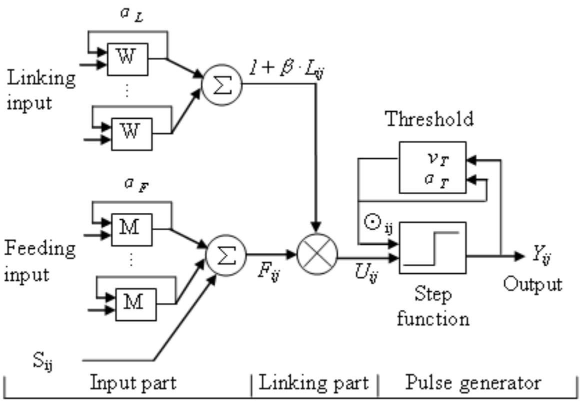


Figure 2 The structure of PCNN neuron [7]

3.2.2 A Filter using Modified PCNN Model

Classic PCNN model involves high computation cost because temporal dependence between iterations is explicitly used in the feeding, linking and threshold updating components. In this paper, a simplified model is proposed by cutting the feeding and linking inputs from the previous iteration (as described by equation 1-5). This simplified model still keeps the characteristics of classic PCNN in that temporal dependence is implicitly included as the neuron outputs in the linking part comes from the previous iteration.

$$F_{ij}(n) = quantified\_I \tag{1}$$

$$L_{ij}(n) = \alpha_L \times \sum_{k,l \in K} W_{Lkl} \times Y_{kl}(n-1) \tag{2}$$

$$U_{ij}(n) = F_{ij}(n) \times (1 + \beta \times L_{ij}(n)) \tag{3}$$

$$Y_{ij}(n) = \begin{cases} 1 & U_{ij}(n) > \Theta_{ij}(n) \\ 0 & other \end{cases} \tag{4}$$

$$\Theta_{ij}(n) = \begin{cases} \Theta_{ij}(n-1) - step & \\ V_T \times \Theta_{ij}(n) & if\ Ya_{ij}(n-1) \neq 0 \end{cases} \tag{5}$$

Where, n is the n^{th} iteration; $quantized\_I$ is the quantified component of a colour image; F and L are the feeding and linking compartment respectively; U is the internal activity of neurons; Y is the pulsed output of PCNN; W_L is the linking weight matrix; K is the neighbour range of neuron (i,j); α_L is the linking scales; V_T is the threshold magnitude scale which is larger than 1; β is the linking strength; Θ is the dynamic threshold which controls whether the neuron can impulse or not; $step$ is the decay coefficient and Y_a is the accumulation of previous output Y.

This modified model is used as a filter to reduce noises which hamper line detection. Power lines are usually brighter than the background because they are made of special metal and have higher light reflectance. So we transform the images from RGB to HIS colour space and use the intensity component I as the input of PCNN. Moreover, the intensity component is uniformly quantified to 64 levels in order to reduce the intensity variation in image regions. This is helpful for filtering regions with similar intensities.

This model also simplifies the feeding and linking parts. The feeding input only accepts the intensity while stimuli from neighbourhoods are not considered.

Moreover, 80 neighbours (i.e. 9×9 window) are adopted to calculate the linking weight matrix W_L. Each element in W_L is the reciprocal of Euclidean distance between this element and the centre of the window. In this case, neighbour neurons with the closer distance have greater impact on the central neuron. Here, we take a 3×3 window as illustration.

$1/\sqrt{2}$	1	$1/\sqrt{2}$
1	1	1
$1/\sqrt{2}$	1	$1/\sqrt{2}$

Figure 3 Linking weight matrix W_L of 3×3 window

The dynamic threshold is updated by a large magnitude scale. During the iteration, all pulsed neurons are recorded, and if a neuron impulses, a large threshold will be given to make sure this neuron can not impulse in the next iteration.

3.3 Straight Line Detection using the Hough Transform

The Hough transform is used to detect parameterized shapes by mapping each point to a new parameter space in which the location and orientation of certain shapes could be identified. When applied to detect straight lines in an image, the Hough Transform usually parameterizes a line in the Cartesian coordinate to a point in the Polar coordinate (Figure 4) based on the point-line duality using the equation.

$$x\cos(\theta) + y\sin(\theta) = \rho \qquad (6)$$

Alternatively, this parameterization maps collinear points into a set of intersecting sinusoidal curves in the parameter space. The lines in the Cartesian coordinate can be estimated by detecting points of intersections of these curves (i.e., peaks). These peaks in the parameter space can be obtained using a voting mechanism.

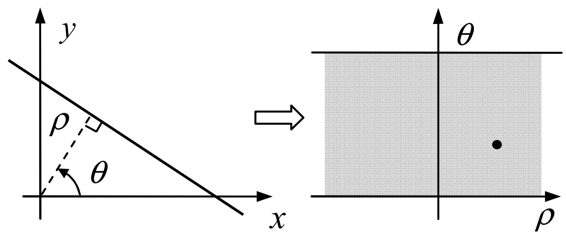


Figure 4 Mapping of a line to parameter space

The Hough Transform is an effective method for automatic line detection. However, it does have some limitations such as high computational cost and mistakable detection of spurious lines. In order to solve the problems, Leandro A.F. Fernandes proposed an improvement to the Hough transform with the introduction of a new voting scheme to avoid the brute-force approach of one pixel voting for all potential lines. Alternatively, the approach operates on clusters of approximately collinear pixels [8]. This improved approach significantly improves robustness of the Hough transform and allows a software implementation to achieve real-time performance even on relatively large images. In our research, this improved Hough transform is employed to detect straight lines in the PCNN filtered images.

3.4 Knowledge-based Line clustering

The Hough transform is an effective tool to detect straight lines, but does not intelligently identify power lines. Any linear objects will be detected, such as edge of roads and rivers, fences, etc. In order to discriminate power lines from other linear objects, we use a one dimensional k-means algorithm to cluster all detected lines to identify the lines of interest.

The objective of data acquisition in our project is to achieve a low flying altitude where a typical 12mm transmission lines will be represented by at lease two pixels. Therefore, each power line is detected at least two Hough lines in the edge image. Power lines are almost parallel, and thus have very similar angles, while other detected lines do not have this regular property. Based on this idea, a cluster schema is employed to group the detected Hough lines and remove the unparallel lines (as shown in Algorithm 1).

Algorithm 1 Remove the unparallel lines

Input: detected Hough line set Ls

Output: refined Hough line set RLs

1: calculate the line groups C_i ($i=1,\ldots,n$) using K-means on θ values of all detected lines (n is the number of line clusters)

2: find the cluster C_k with the largest lines as the candidates of power lines

3: $$C_k = \max(|C_i|)$$

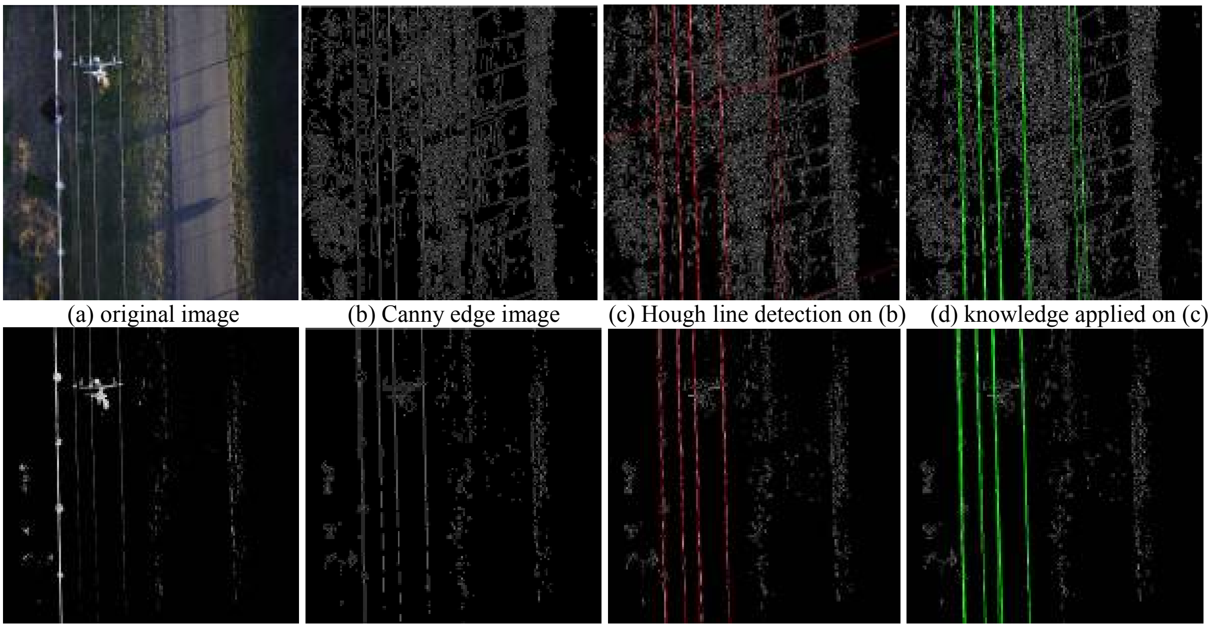
where $i = 1,\ldots,n$; $|C_i|$ is the size of cluster C_i

4: $RLs = C_k$

4 Experiment and Discussion

An experiment is performed on real image data captured form Unmanned Aerial Vehicle (UAV) platform (V-TOL Aerospace BAT-3).

Figure 5 show the straight line detection results on edge image with and without using a PCNN filter. As is shown in Figure 5 (a), there are many linear features in the original image: power lines, edges of road, shadows, etc. These linear features will be detected by Hough transform (see Figure 5 (c), shown in red lines). Although some of these lines can be eliminated by applying knowledge based line clustering, lines such as road edges are hard to remove because they are parallel to power lines (see Figure 5(d), shown in green lines). A better choice is trying to avoid the misleading information before detecting power lines. In this paper, we use the proposed PCNN filter to remove the background of power lines. It can be seen from Figure 5 (d) that most irrelevant points are filtered, though some noise still exists. This is because PCNN has the characteristic of grouping pixels according to the space or gray similarity. It reduces the local gray differences of images and makes up local tiny discontinuous points in image regions. Power lines are made of special metal and have uniform brightness on images while the background is different on textures and intensities. Neurons stimulated by power lines generate different spectral stimuli from that of the background, and then they pulse non-synchronously. Thus, power lines are discriminated from the background. From Figure 5 (f) and (g), we can see that after using PCNN filter, power lines are correctly detected no matter using knowledge based line clustering or not. However, it should be mentioned that the approach is not perfect. Metallic fence line is also detected (see the left line in Figure 5), because it has very similar characteristics



(a) original image (b) Canny edge image (c) Hough line detection on (b) (d) knowledge applied on (c)

(d) PCNN filtered image (e) Canny edge detection on (d) (f) Hough line detection on (e) (g) knowledge applied on (f)

Figure 5 power line detection results using PCNN filter and knowledge based post-processing

with power lines. In Australia, it is not uncommon that the fence lines are existed in power line corridor and in many cases they are parallel to power lines. Future work is to discriminate these very mistakable linear features (e.g. paralleled fence lines) from power lines. Prospective improvement is to combine more knowledge about the differences of power lines and other mistakable linear features.

Figure 6 shows more results of the experiment. The first row is the original images. Row 2 shows the results after using PCNN filter. Row 3 and Row 4 are the Hough line detection results on Canny edge image and PCNN filtered edge image without using knowledge-base line clustering. Row 5 and row 6 are the results after using knowledge based line clustering. From the experiment, it is clear that the proposed PCNN filter is useful as a pre-processing tool. Most of the noise is filtered and power lines are prominent in the images. After using PCNN filter, fewer irrelevant lines exist (see row 4 in Figure 6). Applying knowledge based line clustering also increase the accuracy of power line detection (see row 6 in Figure 6). Combination of these techniques can significantly increase the accuracy of power line detection in complex environment.

5 Conclusion

In this paper, a knowledge based approach is proposed to automatically detect power lines. First, a PCNN filter is used as a pre-processor to remove the irrelevant information in the image. Then Hough transform is employed to detect straight lines in the PCNN filtered images. Finally K-means clustering is employed to discriminate power lines from other mistakable linear objects. The experiment on real image data captured from UAV demonstrated that the proposed approach is effective for automatic power line detection. In the future, more knowledge will be applied to make the algorithm more robust.

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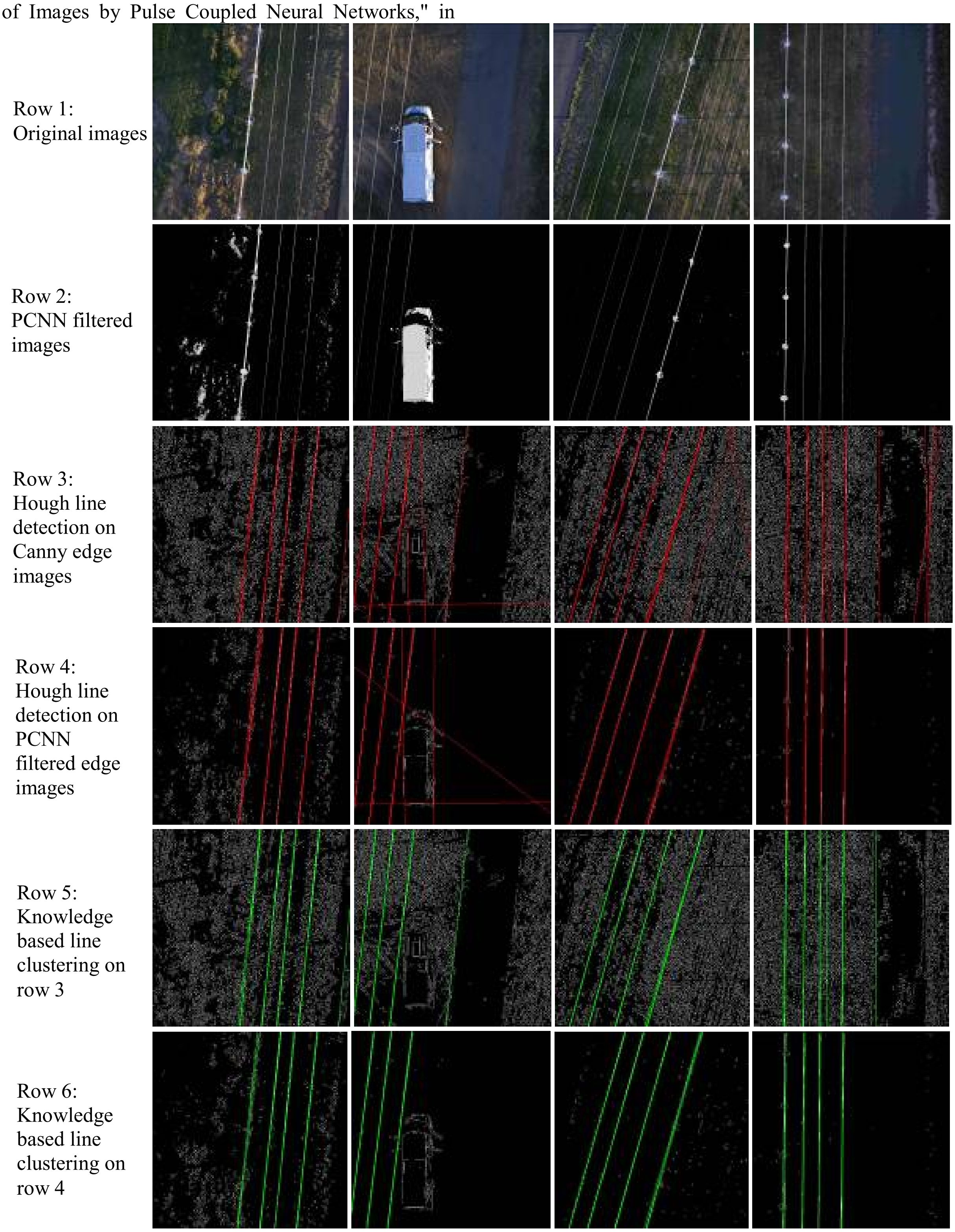

Figure 6 Experimental results on real image data captured from UAV platform