A Robust Approach for Detecting the Edges of Outdoor Wire Fences

Guntur Tanjung, Tien-Fu Lu, Peter Lozo* and Tommie Liddy
School of Mechanical Engineering, University of Adelaide
Engineering South Building, North Terrace Campus, Adelaide, 5005
***Weapons Systems Division, Defence Science and Technology Organisation**
PO Box 1500, Edinburgh, SA, 5111
guntur.tanjung@student.adelaide.edu.au, tien-fu.lu@adelaide.edu.au, peter.lozo@dsto.defence.gov.au and tommie.liddy@student.adelaide.edu.au

Abstract

Detection of outdoor wire fences in images is an important and preliminary step in an automated image analysis algorithm for the detection of wire-fence integrity. The challenge is that not only are the wires of the fences in general very thin, a daytime variation in illumination makes the task even more difficult as this may cause non-uniform illumination across the fences. We address the problem of wire-fence detection by an image processing algorithm that combines the Sobel edge operator with an adaptive thresholding technique to generate a binary image. Simulation results demonstrate that the edges of wire fences can be detected accurately under different illumination conditions.

1 Introduction

In Australia, large protected areas such as airfields and the perimeters of defence bases are commonly marked by wire fences. These protected areas are regularly patrolled by human guards whose task is to check whether there are any intruders, whether there are any suspicious objects left by the intruders and/or whether there are any breaches in the integrity of the wire fences (e.g. holes). In addition to the human patrols, it would also be useful to have an automated system (e.g. a patrolling robot equipped with various sensors and an automated sensor data processing system) whose role would be to assist the human guards. Thus a robust sensor data processing (e.g. an image processing system for visual and/or infrared (IR) images) will be needed for such robotic applications. Normally, intruders breach wire fences by making sizeable holes. Location and the recognition of these types of breaches can be determined in an image by detecting the discontinuities in fence wires. However, this will require an image processing system that can detect the edges of the wire fences in the first place so that a higher level automated analysis system can search for and detect such breaches.

Automated extraction of the edges of outdoor wire fences from an image is in general a very difficult problem. Not only the wires very thin, the problem is that there could be considerable background clutter, as well as a significant daytime variation in illumination across the fences.

Many edge detectors such as the Sobel, Prewitt, Roberts operators [Wang, *et al.*, 2003], the Laplacian of Gaussian (LoG) operator [Basu, 2002] and the Canny operator [Peihua, 2007] were discussed in the literature [Kang and Wang, 2007]. The edge detectors are generally divided into two categories: derivative-based and gradient-based. Derivative-based methods take first or second derivatives on each pixel in the image. In the case of the first derivative, if there is a rapid change of intensity at a pixel, then the pixel is categorized as an edge in the image. While in the case of the second derivatives, if there is a zero pixel value at a pixel, referred to as zero-crossing, the pixel is classified as an edge in the image. As a consequence of taking the derivative of each pixel of the image, derivative-based methods require considerable computer memories and computational times; hence, they are not practical in real-time applications. To overcome this issue, an operation, known as kernel operation, is performed in such derivative-based methods.

The Sobel, Roberts and Prewitt operators are included in the first derivative-based method [Wang, *et al.*, 2003]. The Sobel, Roberts and Prewitt operators find edges in an intesity image using approximations to the derivative. They return edges at those points where the gradient of the intensity image is maximum. A second derivative-based method is the Laplacian of Gaussian (LoG) method [Basu, 2002]. The Laplacian of Gaussian (LoG) method finds edges by looking for zero crosing after filtering an intensity image with a Laplacian of Gaussian filter.

The Canny edge detection method is a gradient-based approach [Peihua, 2007]. It is probably the most used edge detector in machine vision because it is generally superior to other edge detection methods in terms of detection, localization and a single response to a true edge. To extract edges in an image, the Canny detector firstly applies a Gaussian kernel in order to reduce false alarms (the number of no-change pixels incorrectly detected as change). For each pixel, it takes gradient components and computes gradient magnitudes and directions. Secondly, it performs non-maximal suppression in finding of true edge locations. The Canny detector uses two thresholds, to detect strong and weak edges, and includes the weak edges in the output only if they are connected to strong edges.

The available edge detectors are able to detect the edges of wire fences in gray-level images, referred to as edge images, but their robustness is susceptible to noise, background clutter and the variation in illumination. This poses a problem if its is desired to binarise the edge processed images (e.g. for further automated high level analysis in detection of any breaches in the wire-fence integrity) because of a need to find an appropiate global threshold level.

In this paper, we describe an edge based image processing algorithm that overcomes the above mentioned problem of varying illumination of the wire fences, and eliminates the search for a global threshold. Our approach consists of two main steps: (1) the extraction of regions of interest (ROIs) from the original images; and (2) the enhancement (and the subsequent binarization) of the edges in ROI images (in order to detect the fence wires) by an edge detector that combines the Sobel edge detector with an adaptive thresholding technique.

This paper is structured as follows: Section 2 describes the edge based algorithm; Section 3 describes the computer simulation results on several examples of outdoor images; Section 4 discusses the advantage of the proposed edge based algorithm. Finally, conclusions are presented in Section 5.

2 The Edge Detection Approach

The proposed edge detection approach consists of two main steps. The first step is used to extract ROIs from current colour input images. The second step is used to detect the edges of wire fences by using the combination of the Sobel edge detector and an adaptive thresholding technique. Figure 1, below, depicts an overview of the edge detection approach.

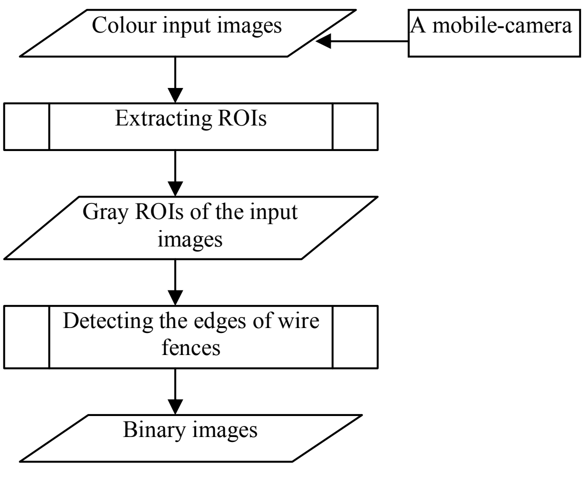


Figure 1. The overview of the edge detection approach

2.1 Extracting Regions of Interest

Outdoor scenes provide complex backgrounds such as trees, grasses and the sky. As focus of this study is only to detect the edges of wire fences, hence such complex backgrounds were automatically removed from the colour input images.

The step used for extracting ROIs from current colour input images is outlined below.

1. Crop the colour input image to a specified rectangle. The rectangle is a four-element vector with the form [xmin ymin width height]; these values are specified in spatial coordinates and obtained by using the following equations.

$$x\min = 1 \tag{1}$$

$$y\min = h/2 \tag{2}$$

$$width = w \tag{3}$$

$$height = h/2 \tag{4}$$

   in which h and w are the height and width of the input image in pixels. In order to provide enough information of wires of the fences, a 4Mb file was used for each input image. The size of a 4Mb file is 2304 by 1728 pixels. Hence, in this study h is 1728 pixels and w is 2304 pixels.

2. Supress the grass from the rectangular image by using colour-based segmentation using K-Means clustering [Su *et al.*, 2007] in order to generate a colour ROI of the input image (colourROI).

3. Convert the colourROI into a grayROI image (I(i,j)).

2.2 The Combined Sobel Edge Detector and an Adaptive Thresholding Technique

The grayROI image (I(i,j)) was then used as input into the combined Sobel edge detector and the adaptive thresholding in detection of the edges of wire fences. The step is as follows.

1. Perform the Sobel edge operator on I(i,j) without performing any global thresholding by using the following formula [Baldock and Graham, 2000].

$$A_1 = \begin{bmatrix} 0 & 1 & 2 \\ -1 & 0 & 1 \\ -2 & -1 & 0 \end{bmatrix} \tag{5}$$

$$A_2 = \begin{bmatrix} 2 & 1 & 0 \\ 1 & 0 & -1 \\ 0 & -1 & -2 \end{bmatrix} \tag{6}$$

$$I_1(i,j) = I(i,j) * A_1 = \sum_{k=\frac{m}{2}}^{\frac{m}{2}} \sum_{k=\frac{m}{2}}^{\frac{m}{2}} A_1(h,k)\, I(i-h, j-k) \tag{7}$$

$$I_2(i,j) = I(i,j) * A_2 = \sum_{k=\frac{m}{2}}^{\frac{m}{2}} \sum_{k=\frac{m}{2}}^{\frac{m}{2}} A_2(h,k)\, I(i-h, j-k) \tag{8}$$

   where * indicates a discrete convolution, A_1 and A_2 are the Sobel masks, in which A_1 is a m x m image and I(i,j) is a h x w image.

Compute the gradient magnitude approximation at each pixel (i,j) as

$$|G(i,j)| = |I_1(i,j)| + |I_2(i,j)| \tag{9}$$

To generate an edge image (E(i,j)), for every pixel in the G(i,j),

$$G(i,j) > 255 \rightarrow G(i,j) = 255 \tag{10}$$

$$E(i,j) = 255 - G(i,j) \tag{11}$$

2. Apply adaptive thresholding to the edge image (E(i,j)).

$$C(i,j) = E(i,j) * MF(m,m) \tag{12}$$

$$S(i,j) = C(i,j) - E(i,j) \tag{13}$$

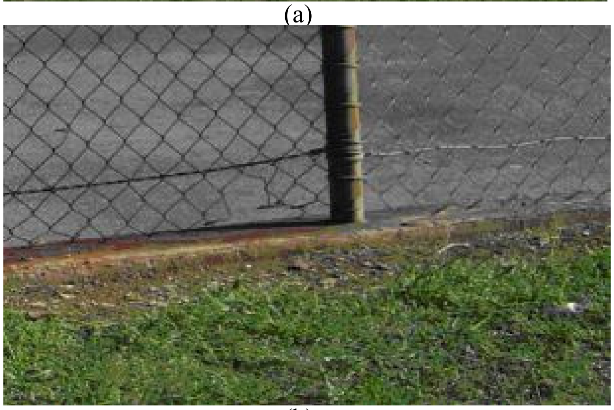
$$B(i,j) = S(i,j) > 0 \tag{14}$$

where * indicates a convolution process, $MF(m,m)$ is an image with a 50 by 50 filter containing equal weights, referred as the averaging filter, $S(i,j)$ is a subtracted image of the edge image (E(i,j)) from the convolved image ($C(i,j)$) and $B(i,j)$ is a binary image after thresholding in which the thresh value is 0.

3 Experimental Results

To test robustness of the edge detection approach, colour input images depicted in Figures 2 (a) and (c), below, are used.

(a)



(b)

(c)

Figure 2. The first input image (a), enlarging of the cut region (b) and the second input image (c)

As can be seen in Figure 2 (a), the image shows that there are: (1) a large breach on the fence, (2) a small cut indicated by a T (see enlarging of the cut region in Figure 2 (b)), (3) green grass in front of the wire fence, (4) trees in the backgrond and (5) other objects behind the wire fence. The first input image (figure 2 (a)) was captured on a sunny day.

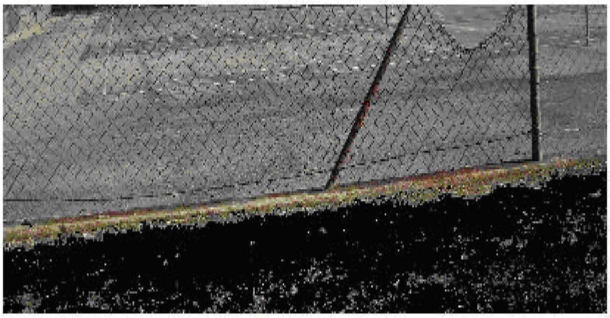
The second input image in Figure 2 (c), above, was captured on a cloudy day. There are also three additional objects in the second input image.

Figure 3, below, depicts a colour ROI cropped automatically from the first colour input image based on equations 1, 2, 3 and 4.

Figure 3. The colour ROI of the input image

To remove the green grass, a colour-based segmentation using K-Mean clustering was applied to the region of interest in Figure 3. The K-Mean clustering was used to cluster same colour objects in the ROI using the Euclidean distance metric. Figures 4 (a) and (b), below, depict the results of colour-based segmentation towards the green grass, most of the grass has been removed from the colour ROI.

(a)



(b)

Figure 4. The colour-based segmentation of the grass (a) and removing the grass from the colour ROI (b)

Next the colour ROI image in Figure 4(b) was converted into a grayROI image (I(i,j)). Figure 5, below, depicts the grayROI image and it was then used as input into the combined Sobel edge detector and the adaptive thresholding technique.

Figure 5. The grayROI image (I(i,j)) of the first input image

Based on equations 5, 6, 7, 8, 9, 10 and 11, an edge image (E(i,j)) was generated. Figure 6, below, depicts the edge image.

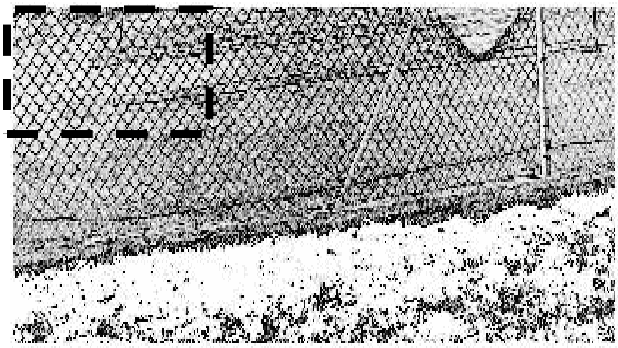


Figure 6. The edge image (E(i,j))

Figure 7, below, depicts the result of enlarging a small section at the top left of the edge image marked by a dash line (see Figure 6).

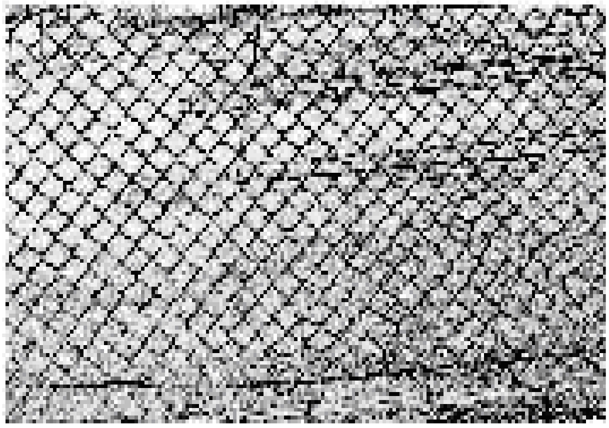


Figure 7. Enlarging the small left top part of the edge image

As seen in Figure 7, edges of the wire fence are not uniform in darker areas. The edges often change from darker areas into lighter areas. These conditions are caused of the non-uniform illumination that occurs along the wire fence.

Based on equations 12, 13 and 14, a binary image (B(i,j)) was generated. Figure 8, below, depicts the binary image after performing the adaptive thresholding towards the edge image in Figure 6, above.

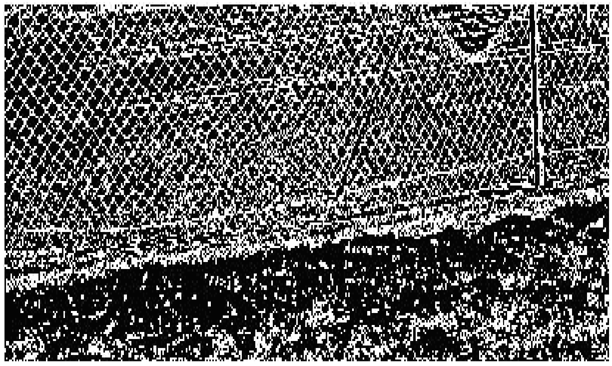
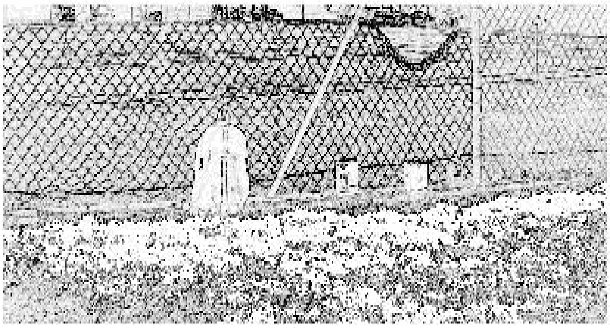


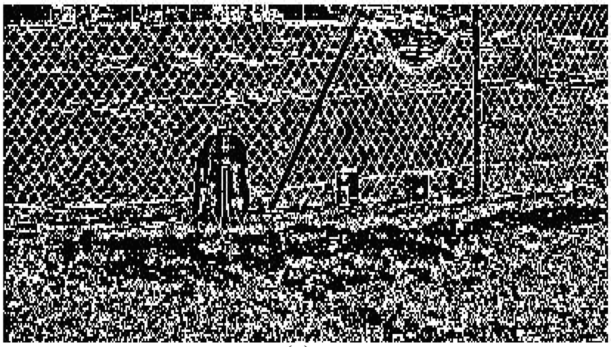
Figure 8. The binary image (B(i,j)) after performing the adaptive thresholding towards the edge image

Figures 9 (a), (b) and (c), below, depict the result of detecting the edge of the wire fence from the second input image.

(a)



(b)



(c)

Figure 9. Detecting the edge of the wire fence from the second input image. The grayROI image (I(i,j)) extracted from the second input image (a), the edge image after performing the Sobel edge detection (b) and the binary image after performing the adaptive thresholding (c)

As seen in Figure 9 (a), the grayROI image extracted from the second input image is darker because it was captured on a cloudy day. The edge of the wire fence visually appears in the binary image in Figure 9 (c) above.

4 Discussion

Available edge detectors such as the Prewitt, Roberts, Laplacian of Gaussian and Canny operators can be used to generate edge images. For further processing like boundary tracing, the edge images often have to be converted into binary images.

The available edge detectors commonly use one or two global threshold values, the Canny operator uses two threshold values, to generate binary images from edge images. In the case of detecting the edges of wire fences during the day, the use of global threshold values is hard to be the best solution.

In fact, illumination varies during the day and wire fences are composed from metal material. As a consequence, specular reflections observably appear on the wire fences during a sunny day and the wire fences appear darker during an overcast day. As a result, non-uniform illumination occurs along the wire fences. In such a situation, the process of fine tuning one or two appropriate global threshold values can become a complex and time-consuming task.

To overcome this complexity, the use of the adaptive thresholding can be the best solution. By using the adaptive thresholding, we do not need to search any threshold value.

Results in Figures 8 and 9 (c) above show that the edges of wire fences are accurately detected in both binary images. The study demonstrates that the combination of the Sobel operator and the adaptive thresholding is quite robust towards illumination variations as well as no manual parameter setting (i.e. global threshold values) is required for being connected into binary images.

5 Conclusions

In the case of detecting the edges of outdoor wire fences during the day, edge detection approaches, which use one or two global threshold values in order to produce binary images from edge images, may be not the best solution because of the non-uniform illumination that occurs on the wire fences. To overcome the non-uniform illumination on the wire fences, a robust edge detection approach was presented. The approach consists of two main steps: (1) extracting ROIs from current input images and (2) detecting the edges of wire fences by performing the combination of the Sobel operator and an adaptive thresholding technique.

Results in the binary images (see Figures 8 and 9 (c)) produced by the combination of the Sobel detector and the adaptive thresholding show that the edges of wire fences is robustly detected. In addition, the presented edge detection approach is quite robust towards varying illumination conditions.

The edges of wire fences in the binary images generated by the combined Sobel edge detector and the adaptive thresholding can also be enhanced by performing morphological operations such as removing small objects and dilation by using a diagonal line direction structure element [Gonzalez and Woods, 2008]. When the edges of wire fences can be detected without confusion from input images, detecting breaches on outdoor wire fences during the day can be achieved.

Acknowledgments

The authors would like to thank DSTO for supporting this work and Ms. Dorothy Missingham for vetting the paper.

References

[Arques *et al.*, 2006] P. Arques, F. Aznar , M. Pujol and R. Rizo, *Real Time Image Segmentation Using an Adaptive Thresholding Approach,* Book Chapter, Lecture Notes in Computer Science, pp. 389-398, Springer Berlin / Heidelberg, 2006.

[Baldock and Graham, 2000] R. Baldock and J. Graham, *Image Processing and Analysis: A Practical Approach*, Oxford University Press, New York, 2000.

[Basu, 2002] M. Basu, Gaussian-based edge-detection methods-a survey, *IEEE Trans. On Systems, Man and Cybernetics*, Volume: 32, Issue: 3, pp. 252-260, August 2002.

[Gonzalez and Woods, 2008], Rafael C. Gonzalez and Richard E. Woods, *Digital Image Processing, 3rd edition*, Prentice Hall, Upper Saddle River, New Jersey, 2008.

[Kang and Wang, 2007] Chung-Chia Kang and Wen-June Wang, A novel edge detection method based on the maximizing objective function, *Pattern Recognition,* Volume 40, Issue 2, , pp. 609-618, February 2007.

[Peihua, 2007] Qiu Peihua, Jump surface estimation, edge detection, and image restoration, *Journal of the American Statistical Association*, Volume 102, Number 478, pp. 745-756, June 2007.

[Su *et al.*, 2007] Chunhua Su; Feng Bao; Jianying Zhou; Tsuyoshi Takagi and Kouichi Sakurai, Privacy-preserving two-party k-means clustering via secure approximation, *International Conference on Advanced Information Networking and Applications Workshops,* Volume 1, Issue , 21-23, pp. 385-391, May 2007.

[Wang *et al.*, 2003] W. Wang, F. Bergholm and B. Yang, Froth delineation based on image classification, *Mineral Engineering*, Volume 16, Issue 11, pp. 1183-1192, November 2003.