A PHASE CODED DISK APPROACH TO THICK CURVILINEAR LINE DETECTION

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ABSTRACT

This paper examines the well-known problem of line detection, but where the lines are wider than one pixel. The motivation behind the paper is the extraction of road information from high resolution photogrammetry and Light Detection and Ranging (LIDAR) data. Wide lines cause varying problems during detection. The HOUGH or RADON transform approaches do not find the road centrelines accurately; *diagonals* of the thick lines are found instead whilst other methods also tend to be error prone. Our approach convolves a raw, pixelated, binary road classification with a complex-valued disk. The technique provides three separate pieces of information about the road or thick line: the centreline, the direction and the width of the road at any point along the centreline. The road centreline can be detected from the position of the peak of the magnitude image resulting from the complex convolution. Road width can also be estimated from the magnitude peak whilst the direction of the road may be obtained from the phase image.

1. INTRODUCTION

The problem of extracting road parameter information is a well-studied one; see [1] for a brief summary. There are many difficulties associated with detecting roads from an aerial image. The detection of the road centreline, width and direction are all important and information that is required for parameterization of the detected road.

Common line detection methods such as the HOUGH or RADON transform detect the longest one pixel thin line within the thick line as opposed to the centre line. Morphological skeletonisation of the road tends to yield a noisy centreline with unwanted 'dendrite' artifacts. Other methods that involve varying scale space and using snake algorithms have other limitations. The use of lower resolution images degrades the accuracy of any detection methods used and thus generally requires another higher resolution image to be used simultaneously during the extraction process [2]. Other algorithms such as snakes, watershed and genetic algorithms have been used with varying success [2] [3].

The detection of the road parameters, width and direction, is extra information that can be extracted from a road image. Previous methods do not extract some or all of this information directly [2]. The accurate detection of the centreline, thickness and direction parameters will allow future determination of the roads design components in terms of straights, curves and spirals.

The ideas proposed in [4] combined with road extraction by operator fusion [5] have inspired the development of a phase coded disk (PCD). This is a complex kernel which uses phase to code for the angle of the line. By convolving the original image with a PCD not only is the centreline accurately detected but the direction and width can be obtained at any point along the detected centreline. Furthermore, our technique has several advantages over the HOUGH transform, for example, it is not iterative, it can accurately detect both thin (1 pixel) and thick lines as well as detecting curvilinear lines as opposed to just straight lines.

This paper presents results on the extraction of road data from Light Detection and Ranging (LIDAR) image data. Section 2 describes the background of road extraction including previous road detection methods and various other related feature detection methods using convolution. Section 3 describes our new method for constructing the PCD and the convolution with the pre-classified binary image. Results from a sample data set are discussed in Section 4 whilst conclusions and future work are examined in Section 5.

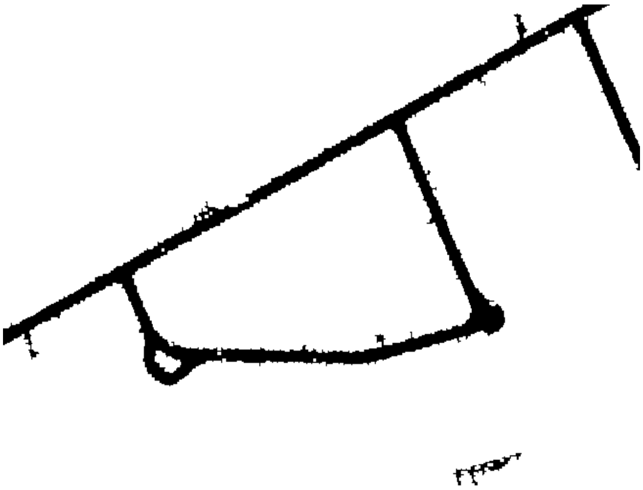

Figure 1: An example binary road image.

2. BACKGROUND

2.1 The Test Data

LIDAR data from Fairfield in Sydney, Australia, was initially collected with an approximate point density of 1 point per 1.3 m^2. The last pulse LIDAR data was initially sampled into a regular grid with minimal filtering to produce a last pulse digital surface model (DSM).

A digital terrain model (DTM) was created from the last pulse DSM by morphological grey scale opening using a square structural element. By progressively changing the size of the structural element and removing non-terrain type objects an accurate DTM was obtained [6]. LIDAR points were selected if their last pulse intensity values were between the acceptable range for the type of road being detected (in this case bitumen) and met a minimum candidate point density criterion. Points within a specified tolerance of the DTM were accepted as road candidate points [7] and sampled into a binary image of 1 metre pixel size. A morphological closing with a small structural element of 3 pixels was performed to remove

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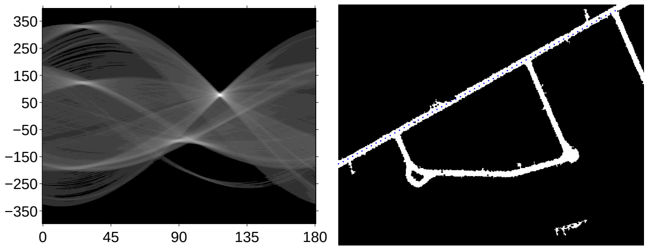
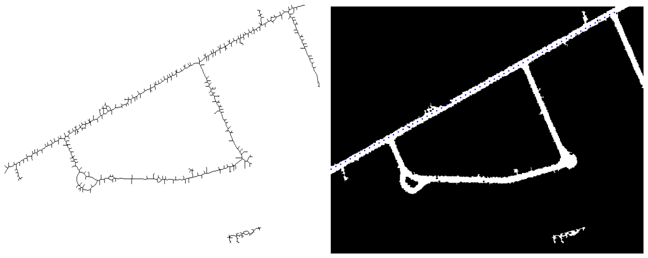
any small gaps produced from creating a 1 metre resolution image from laser points with a point density of approximately 1 point per 1.3 m^2. The resultant image is a binary classification of road pixels generated from the raw LIDAR data is seen in Figure 1.



(a) Radon Transform of Fig. 1 (b) Best line fit of peak in Fig. 2(a)

Figure 2: Radon transform



(a) Skeletonisation of Fig. 1 (b) Largest line fit from Fig. 3(a)

Figure 3: Skeletonisation

2.2 Hough and Radon Transforms

A common method for detecting lines in images is the Hough or Radon transform. Figure 2(a) shows the Radon transform [8] of Figure 1. The white peak at (116,75) is quite broad, so that the exact line of best fit is hard to distinguish. Even if this peak is sufficiently accurate, the other straight line segments in the image are not distinct in the transform.

Selecting the peak and overlaying the resulting line on Figure 1 is shown in Figure 2(b). This line does not run along the road's centreline, but across the "diagonal" (allowing for noise effects). This effect is present as the diagonal line is actually longer than the centreline thus the diagonal line yields a higher score in the accumulator space. The use of the Hough or Radon transform for road detection is usually used in conjunction with a change in scale space to improve results as in [2].

2.3 Skeletonisation

In an attempt to reduce this 'diagonal' effect morphological skeletonision was used on the image. Skeletonisation should force the detected line to be one pixel wide. Figure 3 shows the result of skeletonising Figure 1. Clearly there are unwanted 'dendrite' artifacts.

If the process of Radon transform followed by peak selection is performed on Figure 3(a) as in section 2.2, the detected line is still not the centreline. Figure 3(b) displays the resultant line overlaid on the original image (Figure 1).

2.4 Other line extraction Methods

Heipke et. al. [2] use two similar but different approaches to road detection. Both methods are based upon the extraction of lines in an image of reduced resolution using the approach of [9]. The first method combines extraction of edges in high resolution images to form hypothesis of road sides and consequently construct quadrilaterals. The second approach combines "ribbon-snakes" to verify roads by means of width. Automatic detection of roads using these methods in highly textured areas could not be achieved, thus restricting the extraction to open areas.

In [5] road extraction is performed using operator fusion based on road edge presence and centreline continuity. Huber [5] assumes a road is characterised by a central homogenous region adjacent to two homogenous regions on both sides of the road. A Hough transform or Active Contour Model (ACM) is then used to identify real road points.

2.5 Detection of other features using Convolution

Atherton and Kerbyson [4] detect size invariant circles from digital images. By introducing a complex phase coding along "spokes" in an annulus operator the size of the circle being detected is represented by the phase coding itself. Convolution using a kernel similar to that described will result in a peak position at the centre of the circle and the phase at the peak representing the detected circle size.

3. A PHASE CODED DISK APPROACH

The pre-classified binary image is assumed to be ideal is defined as follows

$$f(x,y) = \begin{cases} 1 & \text{if } (x,y) \text{ is road,} \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

For the purpose of discussion in this section, this image is assumed to be continuous valued in intensity and in spatial coordinates.

A convolution approach is used to calculate a Hough-like transform similar to that proposed by Atherton and Kerbyson [4] for circle parameter estimation and extended and analyzed by Zelniker and Clarkson [10]. This will take the form of

$$Q(x,y) = f(x,y) \otimes O_{PCD}(x,y), \tag{2}$$

where Q is the resultant, $\otimes$ is convolution and O_{PCD} is the phase-coded disk.

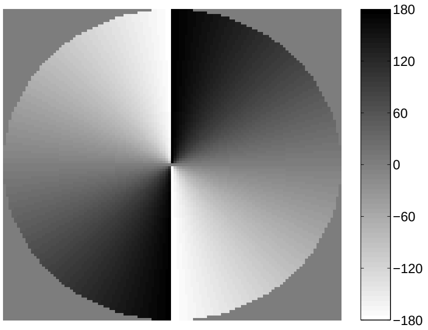


Figure 4: Phase coding of the kernel.

3.1 Defining the Disk

The PCD that we propose is

$$O_{PCD}(x,y) = e^{j\gamma(x,y)}, \tag{3}$$

where

$$\gamma(x,y) = 2\tan^{-1}(y,x) \tag{4}$$

and $\tan^{-1}(\cdot,\cdot)$ is the four-quadrant arctangent function. Figure 4 illustrates this phase coding which sets a constant amplitude across the disk. The radius of the disk, r, should be at least as long as the maximum road width to be detected. Figure 5 shows an example of a disk of radius r overlaid on a road of width w. The road is tilted at an angle ϕ to the horizontal.

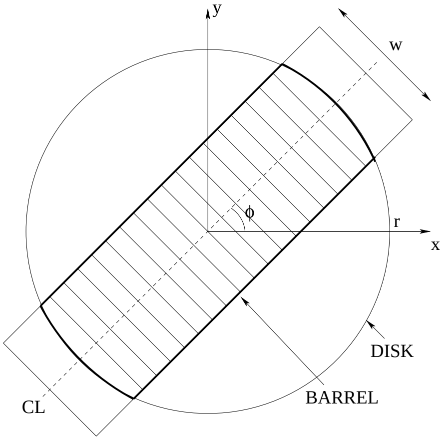


Figure 5: Disk and road segment sizes.

3.2 The Convolution of the Fairfield data with the PCD

To allow extraction for any road orientation, the convolution must satisfy

$$\left|\int_{-r}^{+r}\int_{\max(-\frac{w}{2},-\sqrt{r^2-y^2})}^{\min(+\frac{w}{2},\sqrt{r^2-y^2})} O_{PCD}(X,Y)\,dx\,dy\right| = \left|\int_{-r}^{+r}\int_{\max(-\frac{w}{2},-\sqrt{r^2-y^2})}^{\min(+\frac{w}{2},\sqrt{r^2-y^2})} O_{PCD}(x,y)\,dx\,dy\right|, \tag{5}$$

where

$$\begin{aligned} X &= x\cos\phi - y\sin\phi, \\ Y &= x\sin\phi + y\cos\phi, \end{aligned}$$

for all values of ϕ. This constraint says that the integral defined in (5) has to be invariant with respect to the orientation of the disk (or, equivalently, the road segment).

The result of the convolution defined in (2) yields two images, a magnitude image and a phase image. The magnitude image, M, is defined by

$$M = |f(x,y) \otimes O_{PCD}(x,y)|, \tag{6}$$

whilst the phase image is defined by

$$\phi = \frac{1}{2}\arg\left(f(x,y) \otimes O_{PCD}(x,y)\right). \tag{7}$$

3.3 Line Information

From the construction of the disk (3), it is straight forward to show that the magnitude will be at a maximum on the road centreline. Points off centre will have a magnitude value less than that at the centreline.

In order to show that the phase at the peak is twice the line orientation we split the complex integral

$$\iint_{\text{barrel}} k e^{j2\theta}\,dk\,d\theta \tag{8}$$

into two components on either side of the centreline. Each component will be at an orientation of $\phi-\theta$ and $\phi+\theta$. Substituting into (8) and simplifying using the trigonometric identity $-\sin(\theta) = \sin(-\theta)$ yields

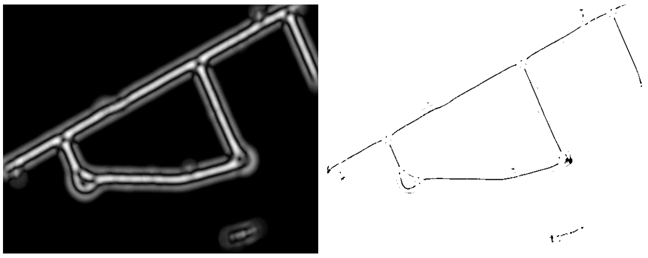
$$e^{j2\phi}\iint_{\text{barrel}} 2k\cos 2\theta\,dk\,d\theta \tag{9}$$

The argument (phase) of equation (9) does not depend on the result of the integral (except if it is zero), so the phase of $Q(x,y)$ at any position represents twice the angle of the underlying line.

What we have discussed in this section is the convolution of an ideal complex kernel and an ideal image. However, the kernel and images used in Section 4 are discretised as they are digital in nature. This discretisation will produce coarser estimates.

4. RESULTS

The magnitude of the convolution of Figure 1 with the phase coded disk (Figure 4) is shown in Figure 6(a). A close inspection of the image reveals that the peak of the magnitude corresponds to the centreline of the road. The magnitude peak has been extracted and displayed in Figure 6(b). Figure 7 shows the centreline of the road overlaid on the original image.



(a) The magnitude image.

(b) The centreline of the road.

Figure 6: Magnitude Results

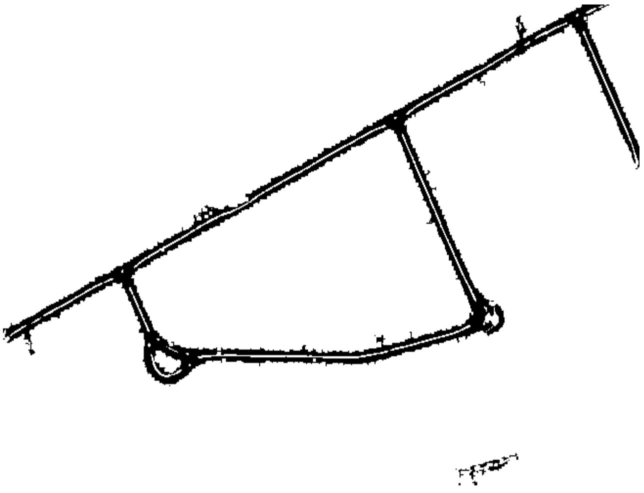


Figure 7: The centreline is overlaid on the original image.

Figure 8 shows the magnitude image overlaid with arrows indicating the direction of half the phase. It can be clearly seen that at the centreline the half phase value is along the line, whilst at the road edges the half phase is 90° out from the value at the line.

To demonstrate the flexibility of convolving images with our PCD, a second image portion is displayed in Figure 9(a). The image shows a windy suburban road from the Fairfield data set. Figure 9(b) displays the magnitude image for the convolution based

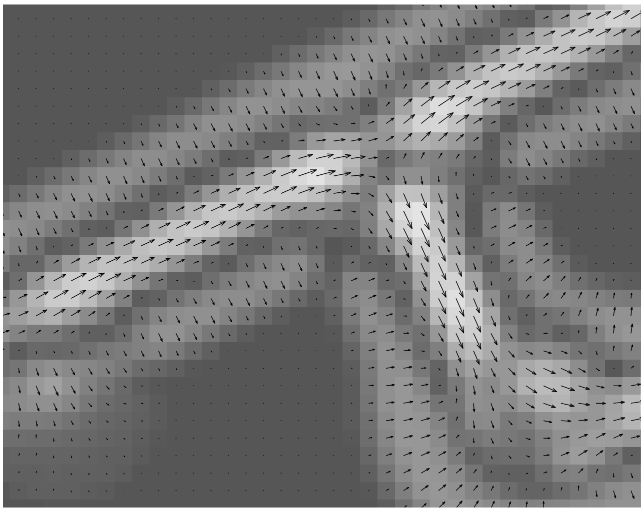
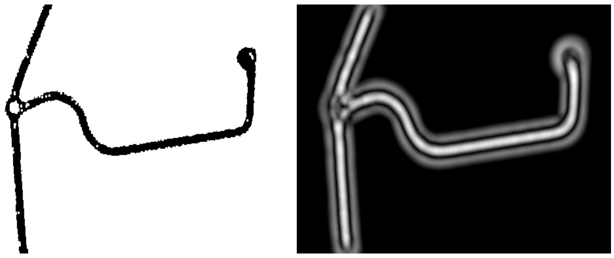


Figure 8: Quiver plot of directions overlaid on magnitude.



(a) A curvilinear road section. (b) Magnitude image of Fig. 9(a)

Figure 9: Curvilinear line extraction example

on the binary image displayed in Figure 9(a). A continuous thick peak is seen throughout the windy road segment demonstrating the accurate detection on the centreline in such scenarios.

5. CONCLUSION AND FUTURE WORK

5.1 Conclusion

We have presented a new method for detecting thick curvilinear lines from within images with specific application to road detection. We have shown its applicability with actual data from a test site. In our test, we put more emphasis on detecting thick lines from pre-classified road pixels than the pre-classification process itself.

The method is still work in progress. Preliminary results show that, using this method, it was possible to detect the centreline of continuous thick curvilinear lines accurately along with the direction of the curvilinear line at any point. At present, the width of the curvilinear line can be calculated from a look-up table or similar, generated from (10).

5.2 Future Work

The width of the line can be calculated from the relationship between the Magnitude (M), the width of the road (w) and the radius of the PCD. The relationship is defined by (6) and is simplified to

$$M = w^2 \cos^{-1}\left(\frac{w}{2r}\right) - 2w\sqrt{r^2 - \frac{w^2}{4}}. \tag{10}$$

We especially want to improve the calculation method of the width of the line. Ideally a direct closed solution is sought. At present a look up table derived from (10), (Figure 10), must be used to

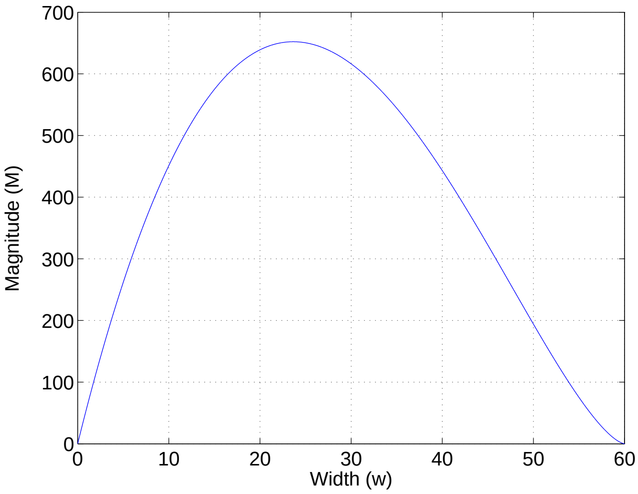


Figure 10: Look up table for a disk of radius 30.

calculate the width of the road. Though, clearly, some method of ambiguity resolution is required (e.g. a magnitude of 600 could imply a width of 17 or 32).

Improvements on the detection method to enhance the detection of road intersections and junctions is a high priority. The use of phase change information to approximate road straight, curve and spiral design primitives will also be investigated.

6. ACKNOWLEDGEMENTS

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