Road extraction from satellite images using Dominant Singular and Arc-Length Measures

T.T.Mirnalinee, Sukhendu Das
VP Lab, Dept. of Computer Science & Engineering,
IIT Madras, Chennai-600 036, India.
mirna@cse.iitm.ernet.in; sdas@iitm.ac.in

and Koshy Varghese
Dept. of Civil engineering
IIT Madras, Chennai-600036, India.
koshy@iitm.ac.in

***Abstract*—The problem of robust automatic road detection in remotely sensed images is complicated due to various factors such as, sensor, spatial resolution, acquisition conditions, road width, road orientation and road material composition. The estimation of image feature orientation is important in many areas of image and pattern analysis. A novel technique for detecting road pixels in remotely sensed images based on orientation or directional information is described. This paper addresses the extraction of roads from 1m-resolution satellite images. Describing the road features from high resolution satellite images becomes difficult in presence of building shadows and high trees. In this paper, we present dominant Singular Measure (DSM) computed using Principal Component Analysis (PCA) to extract the road segments and length discrimination criteria as a post processing technique to improve the quality of detected road segments.**

***Index Terms* - Road Extraction, High-Resolution Satellite Image, PCA, Orientation, Dominant Singular Measure (DSM).**

I. INTRODUCTION

Image local orientation estimation plays an important role in many computer vision and image processing tasks such as edge detection, image segmentation, and texture analysis. Several techniques for local orientation estimation have been proposed in the past [1][2]. Most established local orientation estimation techniques are based on the analysis of the local gradient field of the image. But the local gradients are very sensitive to noise, thus making the estimate of local orientation from these images unreliable. How to deal with the effect of noise is a major problem that all the gradient based methods have to face. It is quite clear that over most of the area the important information is contained in the orientation of the lines, rather than in the brightness values. Knutsson and Granlund [3] devised an elegant method for combining the outputs of quadrature pairs to extract a measure of orientation. Perona [4] extended the idea of anisotropic diffusion to orientation maps. Bigun et.al., [5] posed the problem as the least-squares fitting of a plane in the Fourier transform domain. Another set of techniques is based on steerable filters, but they are often limited in precision and generalization. In [6], Lyvers et.al examined the accuracy of various local differential operators for noiseless as well as in the presence of additive Gaussian noise. Zhou et al. [7] estimated the orientation by a Gaussian gradient filter. Wilson et al. [8] developed a multiscale orientation estimation approach. In [9] Jiang proposed an image integration operator which leads to unbiased orientation estimation. But our method of combining 1D canny [10] for gradient map and PCA for orientation estimation to extract road segments is novel, more efficient and produces more robust results. Almost all the established local orientation estimation techniques are based on the analysis of the local gradient field of the image. Road extraction was interrupted by occluded structures over roads, shadows, and vegetation such as trees. This may lead to unwanted areas that are parking lots and some large buildings wrongly identified as roads. Large size of parking lots has sufficient size of area and similarity of spectral characteristics. Such kind of unwanted areas pose an problem in road extraction because of similarities in spectral characteristics. This paper is organized as follows: Section II discusses about general PCA. In section II A we speak about computing Gradient map using 1D canny. In section II B we discusses about PCA for computing Orientation from gradient map and computing Dominant Singular Measure. In section IIC we discuss the post processing technique of length discrimination. We present experimental results in section III and conclude the paper in section IV.

II. PROPOSED METHOD

Natural images are full of discontinuities and local changes. This anisotropy can be used to associate directions with regions of the image. Much of the preceding research on orientation has been concerned with either purely gradient-based methods, or purely second derivative methods. Oriented features were extracted by sampling image patches. We propose a method for 2-D orientation estimation, as a process of 1D canny for computing gradient map and Principal Component analysis (PCA) for computing Orientation. We propose an operator that gives orientation estimates that are uniform and isotropic. In high resolution satellite images, we observe various types of road segments: highways, interchanges, main streets with vehicles, small roads between houses at various orientations. All these road appears more likely as regions than lines. This observation may imply that extraction of roads at this resolution is a region related problem. For each pixel in the image, we first calculate the gradients in its neighboring area, then perform SVD of the gradient matrix. This decomposition (PCA) is used for orientation estimation. Figure 1 shows the flowchart for the

proposed method. The entire framework for extraction of road segments can be logically divided into three phases:
1) Computing Gradient Map using 1D Canny.
2) Detection of dominant orientation using PCA.
3) Road segment refinement using length measure.

The image is first divided into small blocks, and then the algorithm is employed to identify the orientation for each block.

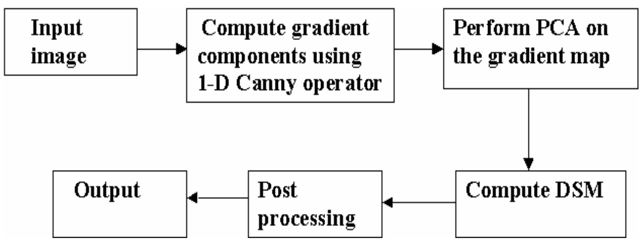

Figure 1. Framework of the proposed method

A. Gradient Map using 1D canny

Gradient operators are based on local derivatives of the image function. Since the speckles appearing in the aerial images can degrade the performance, we first need to reduce them. For this procedure we use one-dimensional processing for extracting gradient map from the input image [10]. 1-D Gaussian function is used for smoothing the image along horizontal (or vertical) scan lines to reduce noise. First derivative of 1-D Gaussian function is then applied along the orthogonal scan lines to find grey level transitions. So, 1-D smoothing provides a significant advantage to reduce noise. Gradient of image f(x, y) at point (x_x, y_k) is denoted by :

$$\nabla f(K) = \nabla f(x_k, y_k) = \left[\frac{\partial f(x_k, y_k)}{\partial(x)}, \frac{\partial f(x_k, y_k)}{\partial(y)}\right]^T \qquad (1)$$

The 1-D canny operator for computing derivative is given by:

$$\nabla \mathrm{G} = \frac{-\mathrm{y}}{\sqrt{2\pi\sigma^3}} \mathrm{e}^{\frac{-\mathrm{y}^2}{2\sigma^2}} \qquad (2)$$

where, σ is the spatial spread of the Gaussian. The method of 1-D processing differs from the traditional approaches based on 2-D operators, in the sense that smoothing is done along one direction, and the differential operator is applied along the orthogonal direction. The traditional 2-D operators smooth the image in all directions, thus resulting in loss of some edge information. Advantages of using 1-D processing for computing gradient map are:
This method (i) gives better results in images with complex structures, (ii) provides better continuity and (iii) requires lesser computational time.

B. PCA Analysis for image orientation

Analysis of local orientation is performed using Principal Components Analysis by computing the dominant vectors representing a given data set, which provides an optimal basis for minimum mean-squared reconstruction of the given data. It is also sometimes referred to as the Karhunen-Loeve Transform [11]. The computational basis of PCA is the calculation of the Singular Value Decomposition (SVD) [15] of the data matrix, or equivalently the eigen decomposition of the data covariance matrix. Gradient vectors are orthogonal to the dominant orientation of the image pattern. Let us assume that in the image of interest f(x,y), the orientation field is piecewise constant. Under this assumption, the gradient vectors in an image block should on average be orthogonal to the dominant orientation of the image pattern. So orientation estimation can be formulated as the task of finding a unit vector $\vec{\mathrm{a}}$,, to maximize the average of angles θ_i between $\vec{\mathrm{a}}$ and gradient vectors [12] $\overrightarrow{g_i} = \partial f(x_i, y_i), i = 1,2,..., n.$

PCA is a well-known metric method that produces the base axes of a distribution of data. Given an ideal straight line in two-dimension, it will produce principal components derived from the eigenvectors and eigenvalues of the scatter matrix. The dominant direction of scatter of the pixels from gradient map depends on the eigenvector corresponding to the largest eigenvalue. More than one non-zero eigenvalue means the derivatives are scattered in more than one direction. In the case of ideal straight line, the second eigenvalue should be zero. However, a digital line is represented stepwise, so that the second eigenvalue of the line is non-zero. In order to get the local orientation estimate, we rearrange the gradient vectors into a 2 *X N* matrix with a window size of 3 for each pixel as shown below:

$$G = \begin{bmatrix} \delta f(1)^T \\ \delta \mathbf{f}(\mathbf{2})^T \\ \delta \mathbf{f}(\mathbf{3})^T \\ . \\ . \\ . \\ \delta \mathbf{f}(\mathbf{N})^T \end{bmatrix}^T \qquad (3)$$

where, $\partial \mathrm{f}(\mathrm{i})^\mathrm{T}, \mathrm{i} = 1,2,..., \mathrm{N}$ is given by eqn 1. We then compute the SVD of the gradient matrix for each pixel (using a window of size '3*3'). SVD of gradient map is computed as.

$$A = USV^T \qquad (4)$$

where, U is a orthogonal 2*X* 2 matrix, in which the first column represents the dominant orientation of the gradient field. By rotating it by 90 degrees, we have the dominant orientation in the image block. S is a 2 *X N* matrix, representing the energy in the dominant direction and V is orthogonal matrix of size *N X N*. If both the eigenvalues are zero, the local neighborhood has constant values. If one eigenvalue is non-zero, the local neighborhood is a simple neighborhood with ideal orientation. If both eigenvalues are not equal to zero the gray values change in all directions. The eigenvector corresponding to the maximum eigenvalue gives the orientation of the local neighborhood. When we fail to observe an oriented structure in a neighborhood, then either gray value vary randomly or distributed orientations are encountered. The two singular values (s1 and s2) can be used as a measure of accuracy or dominance of the estimate.

1) Dominant Singular Measure: Dominant singular Measure (DSM) is computed as the ratio between the singular value of the major axis and the sum of the singular values. This measure approaches one for an elongated shape.

$$\mathrm{DSM} = \frac{s1}{s1 + s2} \quad , s1 \geq s2 \tag{5}$$

where, s1 is the largest singular value. When all the gradient components have the same direction, only one singular value is non-zero, which in turn makes the DSM value 1. If both the singular values are equal and non-zero, the DSM value gives 0.5. Range of the values of DSM is in the range [0.5- 1]. We can use this DSM to distinguish between scattered or disoriented image patterns and an image region with an orientation pattern. For any given image block, we can perform the PCA-based orientation estimation and compute DSM. If the DSM is less than a threshold T_D, it is very likely that the corresponding image block is noisy and contains no dominant orientation and is hence considered as background. The result of this orientation detection process is robust, and performs well on both synthetic and natural image. The results of DSM has therefore included the orientation information about streets/roads, rivers and other linear structures. However, if additional information and knowledge are available, non-road structures may be masked [13].

C. Road segment refinement

From the output of DSM based processing, the arc-length of each segment is used for further evaluation. In the case of satellite images, undesired or noisy structures will be wrongly clustered as road segments. To further eliminate those segments, we use connected component labeling algorithm [14] to extract the disjoint segments from the output of the previous stage of DSM-based processing. Then we compute the length (perimeter) of each extracted segment. Segments which are less than particular threshold T_L are deleted.

We applied additive Gaussian white noise on the test images in Fig. 2(a) and observed the performance of our algorithm on the noisy simulated images. Fig. 3 illustrates the algorithm applied to synthetic images with noise. As seen from Fig. 3(b), some noisy structures are also identified as dominant structures. From Fig. 3(c) it can be seen that almost all the short and isolated segments have been eliminated by the post-processing technique.

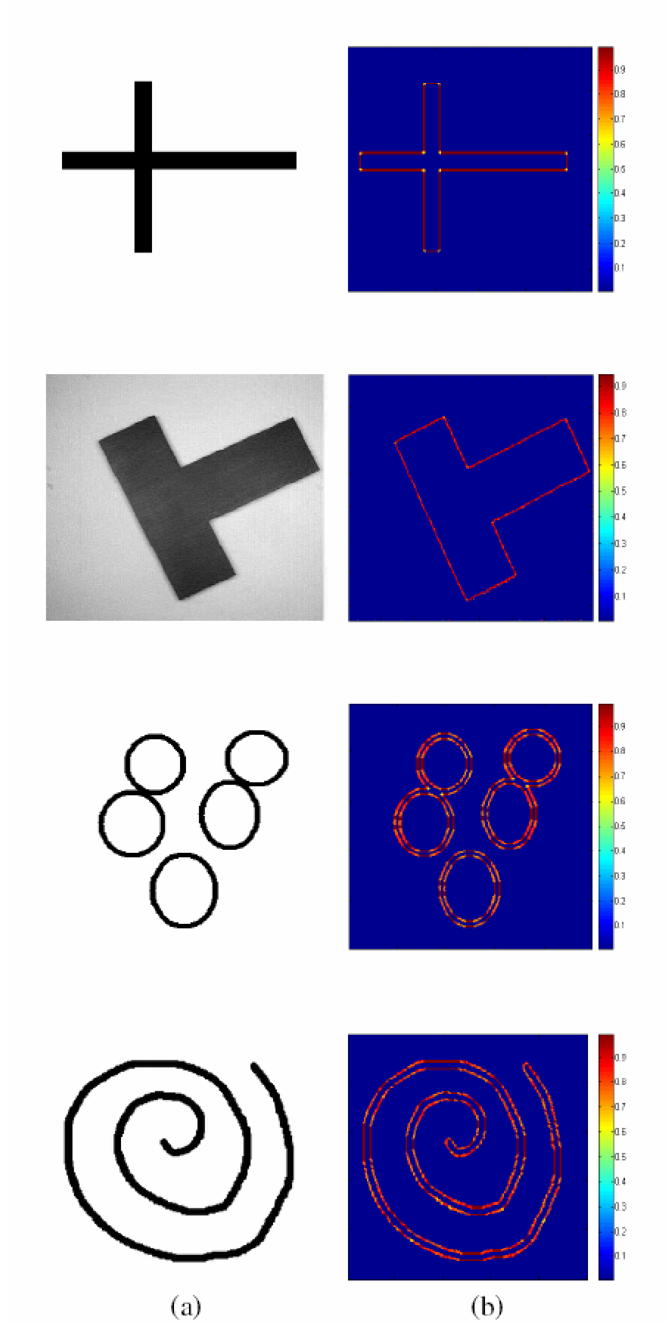

Figure 2. The results of our approach on synthetic images. (a) First column shows the input images. (b) second column shows corresponding DSM.

III. EXPERIMENTAL RESULTS & DISCUSSION

We now describe the experiments performed on synthetic and real world images using the algorithm as described above. As an application of image orientation, we use it to extract road segments from satellite images. The orientation homogeneity of roads is more dominant in local area. This characteristic can be used to find a start point or region for road tracing. Roads generally show some properties of same directions. The road networks can be recovered using this information. It is demonstrated that in high resolution images, regions provide a natural and computationally effective framework for extracting road network from satellite images. Looking at a main road, the boundaries of road, vehicles, markings, and pavements compose a set of parallel line segments in a local area. Edge pixels of these segments have approximately identical gradient orientations. So, in an appropriately sized patch including main roads, there must be a major part of edge pixels with identical gradient orientation. A real image is noisy and corrupted by occlusions, camera distortions, surface markings, varying surface reflectance, quantization, etc. The net result is that many of the lines extracted do not correspond to object boundaries, and those that correspond to object boundaries can be fragmented.

The accuracy of the orientation angle strongly depends on the implementation of derivative filter. The error can be significantly suppressed if better derivative filters are used. Consider the images in Fig. 2 and Fig. 4. It is quite clear that over most of the area of this picture the important information is contained in the orientation of the lines, rather than in the brightness values. We use both synthetic images with and without noise and real images to validate our algorithm. Fig. 2 shows the orientation filter applied to some synthetic images without noise. First column of Fig. 2 shows synthetic images with various oriented structures used to test our approach. The second column of Fig. 2 shows the DSM. When both the gradient components are varying constantly, only one singular value has non-zero value, which in turn dictates the value of DSM to 1 as shown in Fig. 2. If both the singular values are equal and non-zero, the DSM value gives 0.5. If both the singular values are zero, then there is no gradient change in that particular image block. In such cases, DSM value is set to 0. We show the performance of the proposed method on real images in Fig. 4. First column of Fig. 4 shows the real-world satellite images. Second column of Fig. 4 shows the corresponding DSM values computed by our approach. Third column of Fig. 4 shows the results of road segment extraction from high-resolution satellite images after applying the post-processing techniques to the intermediate results in the second column of Fig. 4.

When the change in curvature is less, only one dominant direction exists, causing the first singular value to dominate and the second one is close to zero. When the curvature starts to increase both the singular values contribute to the DSM measure and corresponding DSM value decreases.

IV. CONCLUSION

A novel and efficient method for automatically generating low-level representations of roads directly from satellite images based on Dominant Singular Measure has been introduced and demonstrated. The proposed algorithm is simple, and recognizes the most likely predominant orientation for any linear patterns. Although the proposed algorithm was developed for road orientation recognition in remotely sensed imagery, the algorithm itself has potential applications in other areas. We tested our methods on both real and synthetic images. The measured orientations and strengths accurately reflect the oriented structures of the input image. Our method will fail in case of junctions, certain textures, and transparent or overlapping objects, which may contain more than one local orientation. Future work will address techniques for connecting disconnected curve segments so that road map clutter can be further reduced. Work is currently in progress to establish the optimal framework to overcome this problem and to achieve better noise robustness.

V. REFERENCES

[1] F. Michelet, C. Germain, P. Baylou, and J. costa, “Local multiple orientation estimation: Isotropic and recursive oriented network,” in *”Proceedings of the 17th International Conference on Pattern Recognition (ICPR04)”*, vol. 1, pp. 712-715, 2004.

[2] M. Hanmandlu, “Fuzzy edge detector using entropy optimization,” in *”International Conference on Information Technology: Coding and Computing (ITCC’04)”*, vol. 1, pp. 665-670, 2004,.

[3] G. Granlund and H. Knutsson, *Signal processing for computer vision*. Kluwer Academic Publishers, Boston/Dordrecht/London, 1995.

[4] P. Perona, “Orientation diffusions,” *IEEE Transactions on Image processing*, vol. 7, no. 3, pp. 457–467, 1998.

[5] J. Bigun, G. H. Granlund, and J. Wiklund, “Multidimensional orientation estimation with applications to texture analysis and optical flow,” *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 13, no. 8, pp. 775–790, 1991.

[6] E. P. Lyvers and O. R. Mitchell, “Precision edge contrast and orientation estimation,” *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 10, no. 6, pp. 927–937, 1988.

[7] X. Zhou, J. P. Baird, and J. F. Arnold, “Fringe-orientation estimation by use of a gaussian gradient filter and neighboring-direction averaging,” *Applied Optics*, no. 38, pp. 795–804, 1999.

[8] R. Wilson, S. Clippingdale, and A. H. Bhalerao, “Robust estimation of local orientations in images using a multiresolution approach,” *SPIE Visual Communications and Image Processing, vol. 1360, pp. 1393-1403, 1990*.

[9] X. Jiang, “Extracting image orientation feature by using integration operator,” *Pattern Recognition*, No. 40, pp. 705–717, 2007.

[10] P.Kumar, S. Das, and B. Yegnanarayana, “One-dimensional processing of images,” in *International Conference on Multimedia Processing and Systems*, IIT Madras, pp. 451–454, Dec. 2000,.

[11] E. F. Deprettere, *SVD and signal processing: Algorithms, applications and architectures,*. North Holland, 1988.

[12] X. G. Feng and P. Milanfar, “Multiscale principal components analysis for image local orientation estimation,” in *”The 36th Asilomar Conference on Signals, Systems and Computers”*, vol. 1, pp. 478-482, 2002.

[13] l. H. Gruen, A., “Road extraction from aerial and satellite images by dynamic programming,” *ISPRS*, vol. 50, no. 4, pp. 11–20, 1995.

[14] Haralick, Robert M., and Linda G. Shapiro, Computer and Robot Vision, Volume I, Addison-Wesley, pp. 28-48, , 1992,.

[15] Gilbert Strang, “Linear Algebra and its applications”, Thomson, 2005.

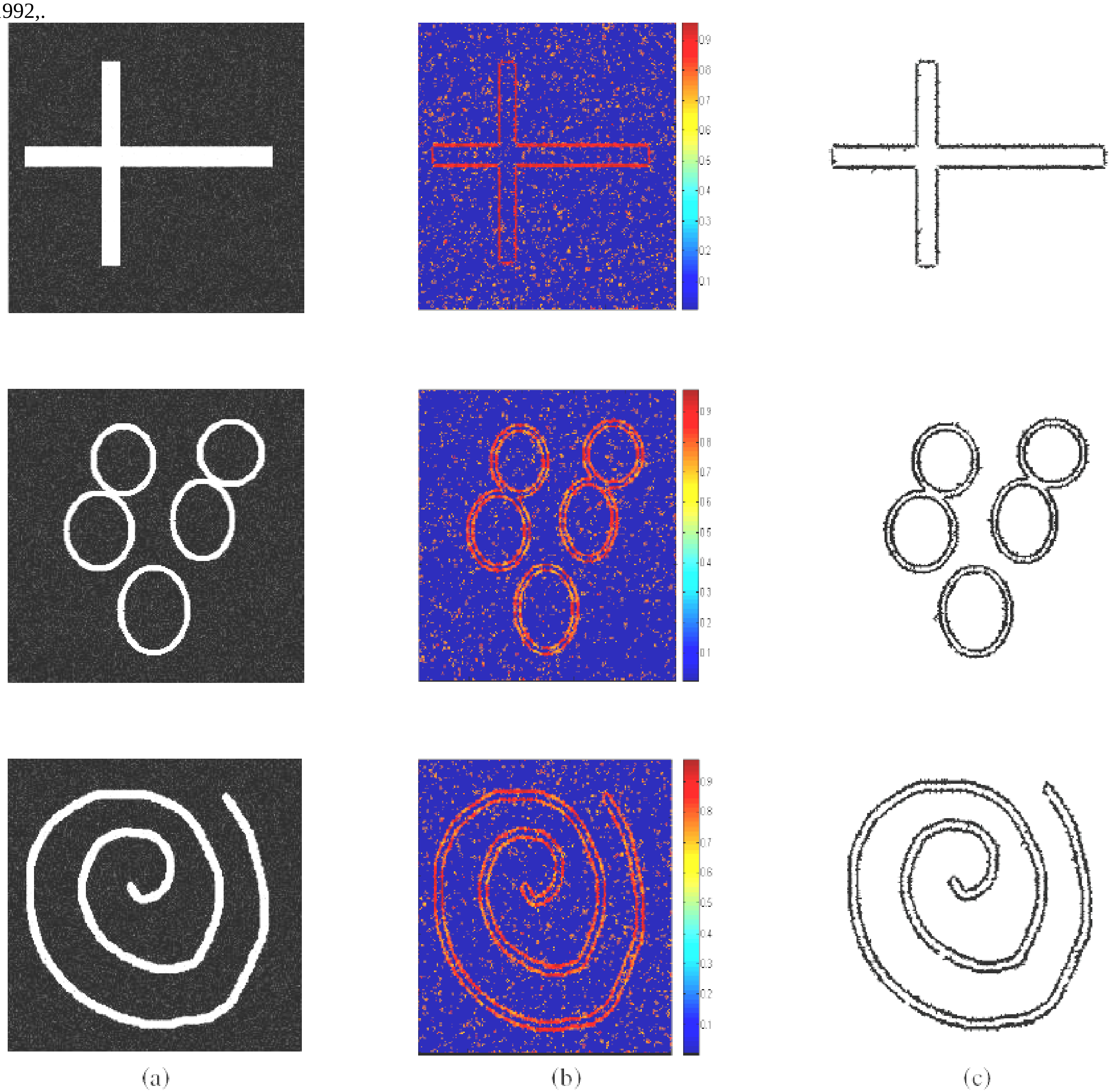

Figure 3. The results of our approach on synthetic image with noise. (a). First column shows the input images with Gaussian noise. (b). Second column shows corresponding DSM. (c). Third column shows the results after post processing.

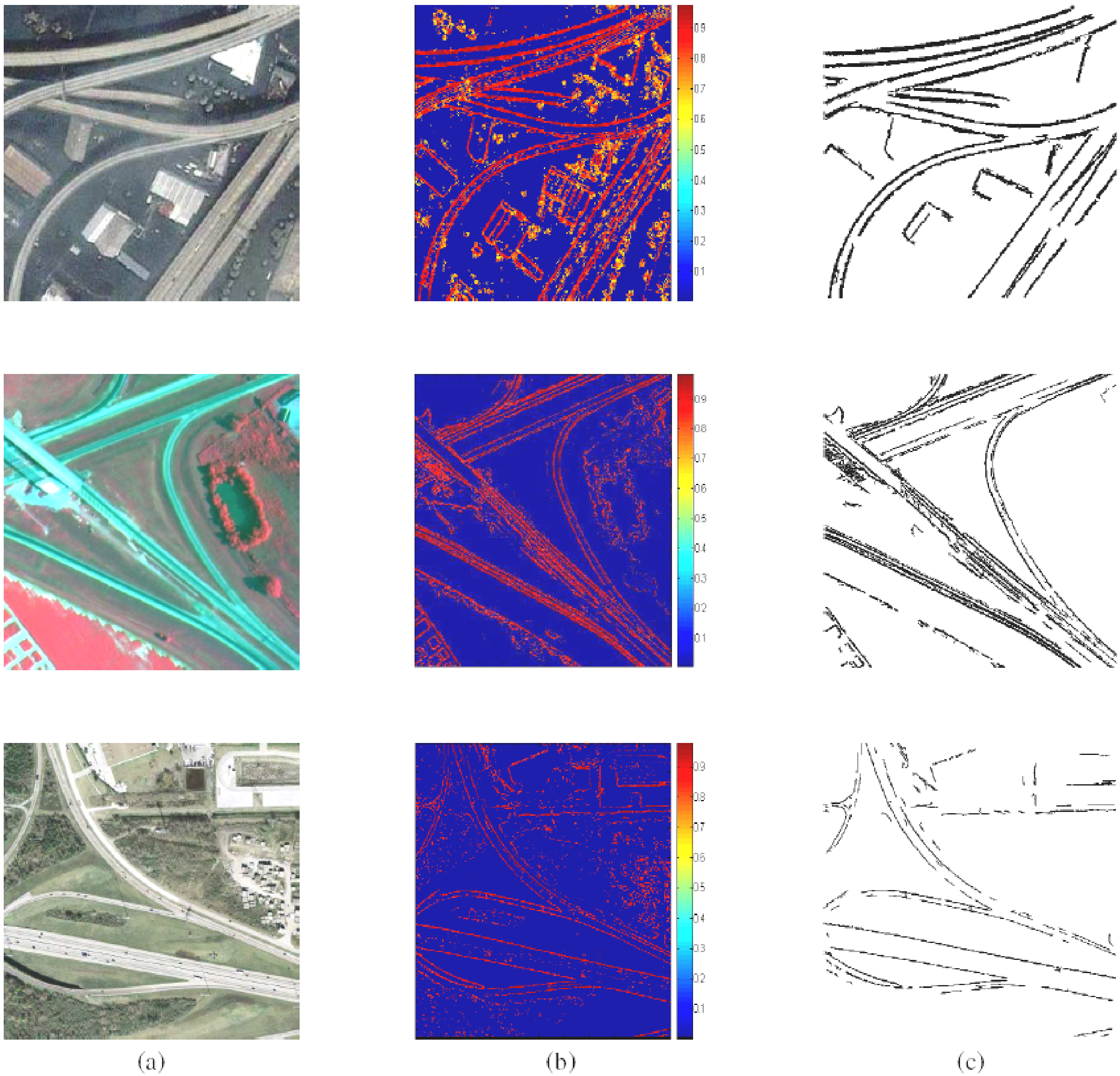

Figure 4. The results of our approach on real-world images. (a). First column shows the input images. (b). Second column shows corresponding DSM. (c). Third column shows the results after post processing.