Fast Linear Feature Detection Using Multiple Directional Non-Maximum Suppression

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Abstract

Linear feature detection is a very important issue in the areas of image analysis, computer vision, and pattern recognition. It has found applications in many diverse areas such as neurite outgrowth detection, compartment assay analysis, retinal vessel extraction, skin hair removal for malonoma detection, plant root analysis, and roads detection. We have developed a new algorithm for linear feature detection using multiple directional non-maximum suppression. The algorithm is very fast compared with methods in the literature. We also show a large number of application examples using our linear feature detection algorithm, and very good results have been obtained.

1. Introduction

Linear or elongated feature detection is a very important issue in the areas of image analysis, computer vision, and pattern recognition. It has a very wide range of applications such as in the medical or biometrics areas for retinal vessel extraction, skin hair removal for malonoma detection, and fingerprint analysis; in the biotechnology area for neurite outgrowth detection, compartment assay analysis; in areas related to biology samples such as tree bark, tree branches, plant roots, and leaf vein/skeleton detection; and in the infrastructure areas for road crack detection, roads and valleys detection in satellite images.

There are a number of techniques in the literature on linear feature detection. One type of techniques requires a series of directional filters to be applied to the image, including steerable filters [5], 2D matched filters [2], maximum gradient profiles [3], and directional morphological filtering [8]. This type of techniques can also be called template or model based; and they tend to be slow. Another approach uses the classical gradient/curvature or Hessian-based detectors. This includes thin nets or crest lines [6], and ridges [4].

Another type of techniques is based on tracking [1], including stick growing [7]. Tracking based approach requires initial locations of linear features which often need user intervention. Methods using edge operators to detect pairs of edges and graph searching techniques to find the centerlines of vessel segments are presented in [9]. These methods require the user to identify the areas of interest. There are also other related techniques which are edge or “roof” based [12]. Other algorithms include pixel classification using neural network scheme through supervised training [10], S-Gabor filter and deformable splines, and mathematical morphology [11].

In this paper, we propose a new algorithm for linear feature detection using multiple directional non-maximum suppression (NMS). This mainly involves the non-maximum suppression at multiple directions along linear windows. Because there is no computationally intensive filtering involved, our linear feature detection algorithm is very fast. The quality of linear feature detection is also better.

2. Multiple Directional Non-Maximum Suppression

Linear features are defined as a sequence of points where image has a maximum in the direction of the largest variance, gradient, or surface curvature. A directional local maximum is a pixel not surrounded by pixels of higher gray values in a linear window. We will take bright linear features as our example when we describe our algorithms. Dark features can be detected similarly by inverting the intensity of the input image, or using non-minimum suppression rather than non-maximum suppression.

The direction of a linear feature which produces largest variance or gradient may be obtained by the use of the computational expensive Hessian-based detectors or matched filters. Direct use of image gradient on linear features is not very reliable. Rather than finding the local direction of the linear features, we choose to use the responses of mul-

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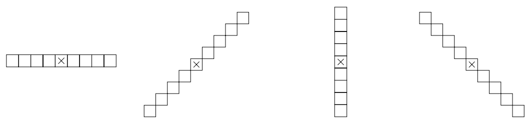
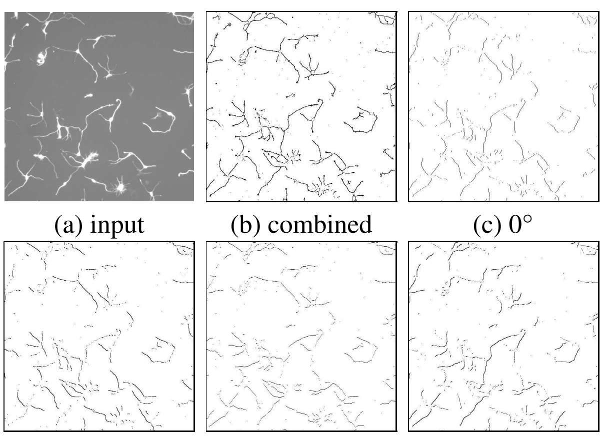
tiple directional non-maximum suppression (MDNMS) for linear feature detection.

Non-maximum suppression is a process for marking all pixels whose intensity is not maximal as zero within a certain local neighborhood. This local neighborhood can be a linear window at different directions. Figure 1 shows four examples of linear windows at angles of 0°, 45°, 90°, and 135°. Additional directions, such as those at 22.5°, 67.5°, 112.5°, and 157.5°, could also be used for obtaining the multiple directional non-maximum suppression.



(a) 0° (b) 45° (c) 90° (d) 135°

Figure 1. Illustration of several linear windows at different directions. "×" indicates the center of the linear windows. The length of the linear window shown is 9.



(a) input (b) combined (c) 0°

(d) 45° (e) 90° (f) 135°

Figure 2. Non-maximum suppression responses of four linear windows at different directions and the combined response. The length of the linear window used is 11.

3. Fast Linear Feature Detection

3.1. Combining Multiple Directional Non-Maximum Suppression

We propose to use the union of the outputs of multiple directional non-maximum suppression for linear feature detection. Here is a formula for combining the outputs of non-maximum suppression at different angles:

$$\mathtt{L} = \bigcup_{i=1}^{N_D} \mathtt{L}_{D_i} \tag{1}$$

where $\mathtt{L}_{D_i}$ is the result for non-maximum suppression at direction D_i, N_D is the number of directions used, and $\mathtt{L}$ is the combined result. The number of directions used N_D can be either 4 or 8 or more. Figure 2 shows example results of using directional non-maximum suppression. Figure 2(a) is the input image with linear features of neurite outgrowth. Figure 2(c-f) are the directional non-maximum suppression responses at angles 0°, 45°, 90°, and 135°. Figure 2(b) shows the union result of the multiple non-maximum suppression responses given in Figure 2(c-f). Due to the union effect, the linear features detected may be a few pixels wide.

3.2. Symmetry Check

One can expect that the cross feature intensity profile of the linear feature at a particular position is roughly symmetrical around the maximum point. Figure 3(left) illustrates the parameters that we use for checking whether a local maximum is along a linear feature in the image for a particular direction. I_{max} is the value of a local directional maximum. I_{average1} and I_{average2} are the average values of half windows on the two sides of the local maximum; and I_{diff1} and I_{diff2} are the differences between the maximum value and the two average values. For a linear feature in the image, both of the I_{diff1} and I_{diff2} values should be larger than a threshold. If only one of the difference values are large, the position of the local maximum resembles more like a step edge rather than a linear feature.

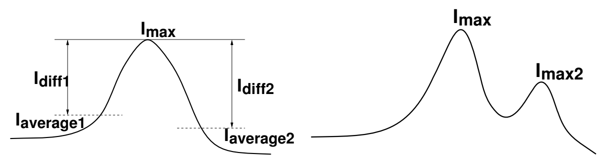


Figure 3. (left) Symmetry profile of a cross section of a linear feature. (right) Multiple local maxima within a linear window.

3.3. Extending to Multiple Local Maxima

In some images, certain linear features may be very close to each other. The NMS process described above may detect only one of the two or several linear features that are next to each other. Figure 3(right) shows an example that has two local maxima along this linear window. We can extend the NMS process so that multiple local maxima can be detected for any particular linear window. Once a local maximum has been found at the center of a linear window, a second or more local maxima within the same window can be searched so that for a particular linear window direction, multiple local maxima, hence multiple linear features, can be detected. Figure 3(right) shows that a second local maximum with intensity I_{max2} can be found. One may also check that the intensity I_{max2} should not be very different from I_{max}.

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3.4. Linking Broken Linear Features

The union of the multiple non-maximum suppression for linear features detection sometimes have gaps present. We can apply a linking process to connect the end points of neighboring linear features with a short line segment if the distance between end points is small.

For a pair of linear feature segments where each segment may have several end points detected and we would like to choose a best connection for the two segments using some of the end points that are close to each other. There may be several possible pairs of end points from the two segments to choose from. We can choose the connection where the average image intensity on the connecting line segment is the maximum. Other information that can be used when selecting the best connection include the intensity values on the end points, the distance between the two connecting end points, the orientation information of each segment at each of the end points. We can also use shortest path techniques to link features. This will ensure the links are going through the ridges of the linear features.

3.5. Extending to 3D Images

The 2D algorithms described above can be easily extended for 3D images. For 3D images, the linear windows used need to be oriented in 3D space. Figure 4 shows examples of the union of 3 and the union of 9 linear windows. Additional directions could also be used for obtaining the multiple directional non-maximum suppression for 3D images.

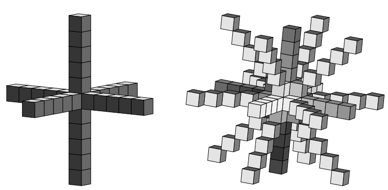


Figure 4. Illustration of 3D linear windows at different directions. (left) 3 linear windows together; (right) 9 linear windows together.

3.6. Algorithm Steps

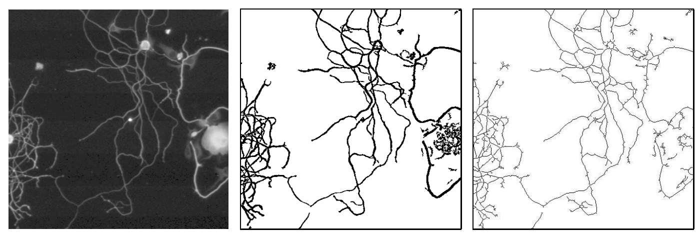
The steps of our linear feature detection algorithm are the following:

1. Carry out 4 or 8 (3 or 9 for 3D case) directional non-maximum suppression on the images, and combine the multiple NMS outputs into one image. The symmetry check is performed during the process of non-maximum suppression. Multiple local maxima can also be found within a linear window.
2. Remove small objects.
3. Obtain and link the end points of different linear objects when the end points are close to each other.
4. Thin the obtained image if necessary.

4. Experimental Results

This section shows some of the linear feature detection results obtained using our MDNMS algorithm. We also show some comparison results with the ranked filter approach.

Neurite outgrowth is a very important topic in neuronal research. Automating the process of neurite outgrowth analysis enables the high-throughput high content analysis. We have run our algorithm on a set of 93 neurite outgrowth images with a single set of parameters. Figure 5 shows an example result of neurite detection. Figure 5(a) is the input image; Figure 5(b) is the result using the ranked filter approach [8]; and Figure 5(c) shows the result using our algorithm. Our algorithm give better connection for linear features and is generally thinner. As will be shown later our algorithm is about five time faster than the ranked filter approach.



(a) (b) (c)

Figure 5. Example of neurite outgrowth detection. (a) input image; (b) result of the ranked filter approach; (c) result of our algorithm.

Figure 6 shows more application examples which include images with face wrinkles, fingerprints, retinal vessels, and cracking in paintings. Figure 7 shows one of our linear feature detection results for 3D images.

Table 1 shows the running times of the ranked filter approach and our method on different size of images. The computer used is a 2.40GHz CPU Intel Pentium 4 running Linux. Our new algorithm is about 5 time faster than the ranked filter approach. The main step of our algorithm is applying the non-maximum suppression at different directions along linear windows. The sensitivity of the algorithm can be controlled by the I_{diff1} and I_{diff2} values. There is no computational intensive operation such as matched filters or curvature calculation.

Table 1. Running times of the ranked filter algorithm and our MDNMS algorithm.

	Running Times (s)	
Image size	Rank filter	Our algorithm
512×512	1.72	0.30
1336×1206	10.72	1.90

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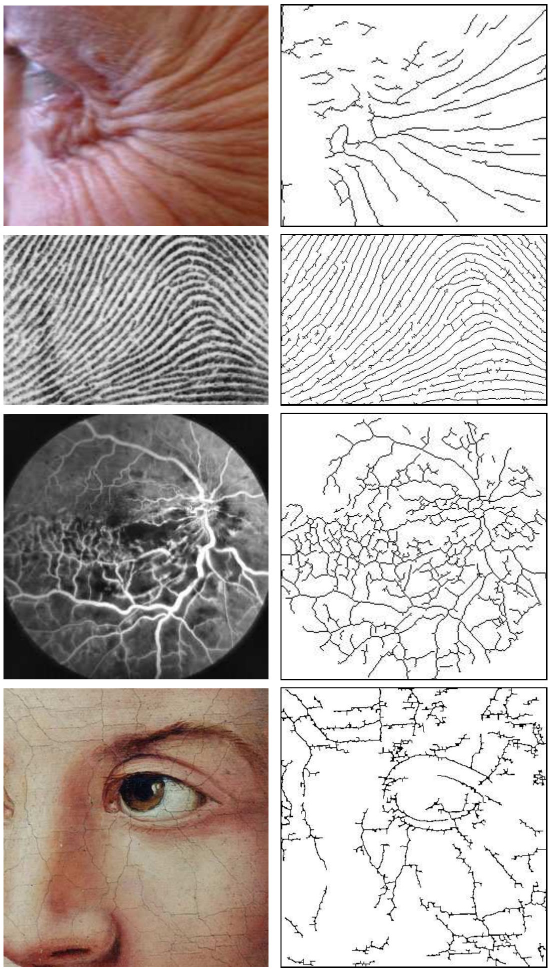

Figure 6. More example results.

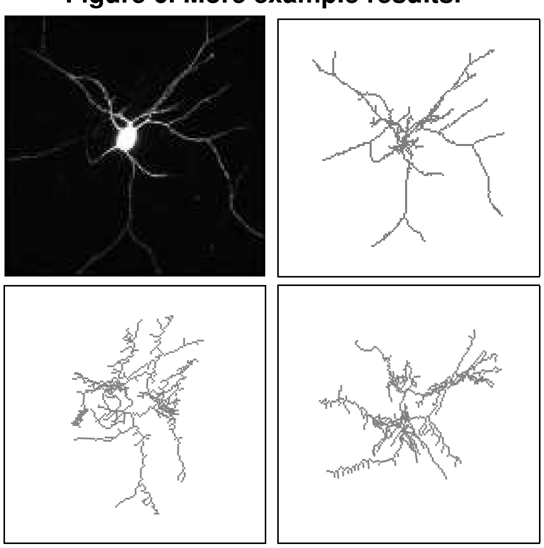

Figure 7. Transparent view of the input 3D image and three different views of the detected 3D neurite features.

5. Conclusions

We have developed a new algorithm for fast linear feature detection. The algorithm uses multiple directional non-maximum suppression for locating the linear features with symmetry checking. Multiple peaks within a linear window can also be used. Comparison is also carried out with the ranked filter approach, and favorable results are obtained with our algorithm in terms of both quality and speed. The new algorithm can be used in many areas of applications and a wide range example results have been shown.

References

[1] A. Can, H. Shen, J. N. Turner, H. L. Tanenbaum, and B. Roysam. Rapid automated tracing and feature extraction from retinal fundus images using direct exploratory algorithms. *IEEE Transactions on Information Technology in Biomedicine*, 3(2):125–138, June 1999.

[2] S. Chaudhuri, S. Chatterjee, N. Katz, M. Nelson, and M. Goldbaum. Detection of blood vessels in retinal images using two-dimensional matched filters. *IEEE Transactions on Medical Imaging*, 8(3):263–269, September 1989.

[3] A. C. F. Colchester, R. Ritchings, and N. D. Kodikara. Image segmentation using maximum gradient profiles orthogonal to edges. *Image and Vision Computing*, 8(3):211–217, August 1990.

[4] D. Eberly. *Ridges in Image and Data Analysis*. Kluwer Academic Publishers, 1996.

[5] M. Jacob and M. Unser. Design of steerable filters for feature detection using Canny-like criteria. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 26(8):1007–1019, August 2004.

[6] O. Monga, N. Armande, and P. Montesinos. Thin nets and crest lines: Application to satellite data and medical images. *Computer Vision and Image Understanding*, 67(3):285–295, September 1997.

[7] R. C. Nelson. Finding line segments by stick growing. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 16(5):519–523, May 1994.

[8] P. Soille and H. Talbot. Directional morphological filtering. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 23(11):1313–1329, November 2001.

[9] M. Sonka, M. D. Winniford, and S. M. Collins. Robust simultaneous detection of coronary borders in complex images. *IEEE Transactions on Medical Imaging*, 14(1):151–161, March 1995.

[10] J. Staal, M. D. Abramoff, M. Niemeijer, M. A. Viergever, and B. van Ginneken. Ridge-based vessel segmentation in color images of the retina. *IEEE Transactions on Medical Imaging*, 23(4):501–509, April 2004.

[11] F. Zana and J.-C. Klein. Segmentation of vessel-like patterns using mathematical morphologyand curvature evaluation. *IEEE Transactions on Image Processing*, 10(7):1010–1019, July 2001.

[12] Y. T. Zhou, V. Venkateswar, and R. Chellappa. Edge detection and linear feature extraction using a 2-D random field model. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 11(1):84–95, January 1989.

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