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Identify Curvilinear Structure Based on Oriented Phase Congruency in Live Cell Images

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Abstract

To allow high-throughput measurements semiautomatic segmentation finding of curvilinear structures in images many biomedical applications require identifying curvilinear structures based on oriented phase congruency, i.e., the Phase Congruency Tensor (PCT). A contrast independent approach to identify curvilinear structure based on oriented phase congruency, i.e., the Phase Congruency Tensor (PCT) is proposed and the proposed method is largely insensitive to intensity variations along. The curve and provides successful detection within the noisy regions.

Key terms: Curvilinear, biological images, blood vessels, Vesselness, Neuriteness, Live-Wire Tracing, Synthetic Images, Fungal Network.

1. Introduction

Tracing of curvilinear structures is one of the fundamental tools in the quantitative analysis of biological images, for extracting information about structures such as blood vessels, neurons, microtubules, and similar entities. A number of potential applications exist in the analysis of biological structures from images, such as blood vessels, neurons, and microtubules. Live cell studies rely on fluorescence imaging, which presents atypical challenges for the analysis of these images.

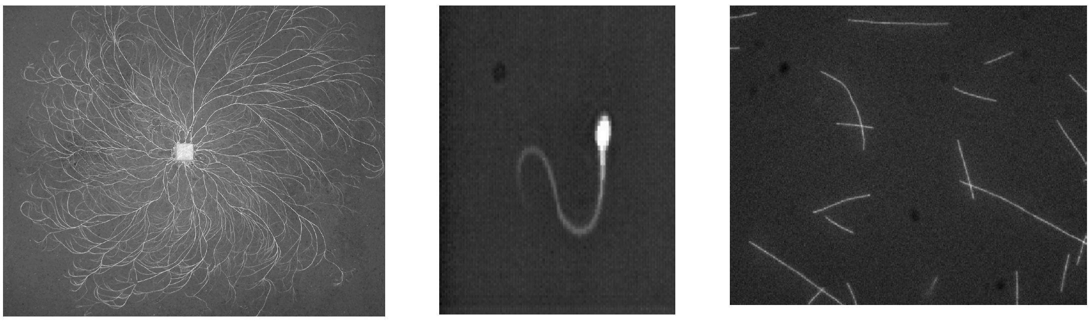
The discussion of the most common image processing methods for the detection and the tracking of curvilinear objects. The phase congruency tensor (PCT), which is a novel contrast independent concept for curvilinear feature detection. The basic idea behind these filters is to locate the positions of objects represented by the ridges and the ravines in the image intensity function. Therefore, the shape of the matched filter is based on the spatial properties of the object to be recognized. In order to preserve rotation invariance, the filter is often rotated to a reasonable set of possible object orientations, and the maximum response from the filter bank is calculated. A common approach to represent local image structure through a tensor is to consider the first terms of the Taylor series expansion.

2. Sections

A number of tracing algorithms were proposed for extracting curvilinear structures from images, such as the anisotropic Gauss filtering, differential geometric properties of images and using active contour approaches. In, the authors propose a curvature-guided technique for tracing curves. improves upon by constraining the linking procedure of curve segments.

2.1 Curvilinear structures in biology Live Cell Images

The study of living cells using time-lapse microscopy. It is used by scientists to obtain a better understanding of biological function through the study of cellular dynamics. Live cell imaging was pioneered in first decade of the 20th century. One of the first time-lapse micro cinematographic films of cells ever made was made by Julius Ries, showing the fertilization and development of the sea urchin egg. Since then, several microscopy methods has been developed which allow researchers to study living cells in greater detail with less effort.



(a) **(b)** **(c)**

Figure 1: Curvilinear structures observed in bio images: (a) fungal network, (b) human sperm cell - phase contrast microscopy, (c) microtubules - epiuorescence video microscopy.

2.2 Phase Congruency Tensor

The detection of curvilinear structures is particularly affected by variations of intensity contrast within the image. Intensity differences between curvilinear structures and with the background, common to many biomedical imaging applications, because traditional intensity-based methods to produce widely varying outputs, which, in turn, make it difficult for post processing methods to delineate the structures. Additionally, the boundaries of low-contrast structures may not be detected by methods based on the image gradient.

Phase congruency is a measure of feature significance in computer images, a method of edge detection that is particularly robust against changes in illumination and contrast. The square-wave example is naive in that most edge detection methods deal with it equally well. For example, the first derivative has a maximal magnitude at the edges.

2.3 Selecting the best path

2.3.1 Comparison of proposed approach with Jiang's method

1. The trace distance error E_d [10] was estimated for trypanosome cell, microtubules and sperm cell.
2. E_d is defined as the average distance from all the points on the ground truth trace to all the points on the automatic trace.

Table 1: Trace distance error (for twenty randomly selected images).

	Trace distance error Ed [pixel]	
	Proposed method	Jiang's method
Trypanosome	1.43	1.59
Microtubules	1.23	1.28
Sperm	0.80	0.84

2.3.2 Live-wire tracing algorithm

In order to apply the live-wire tracing method, the eight-connected graph representation of the image is constructed. Then, the cost map combining the image intensity cost C_i and the vector-field cost C_v (2) is calculated. We study the use of different cost functions based on previously available intensity-based techniques and our proposed PCT.

The shortest path from pixel p to an eight-connected neighboring pixel r is computed using following steps:

Calculate the cost map:

$$C(p,r) = \gamma C_i(r) + (1-\gamma)C_V(p,r) \quad (1)$$

Where

$$C_V(p,r) = \frac{1}{2}\{\sqrt{1-||\phi(p,r)||} + \sqrt{1-||\phi(r,p)||}\} \quad (2)$$

$$\phi(p,r) = |V(p).d(p,r)| \quad (3)$$

$$d(p,r) = (r-p)/||r-p|| \quad (4)$$

C_i and C_v are intensity and vector field based cost maps.

2.3.3 Cost maps

2.3.3.1 Image intensity and vector field based cost maps:

A. Hessian

For a given image and a given scale , the neighborhood of point can be approximated by its Taylor expansion, i.e.

$$I_\sigma(p + \Delta p) \approx I_\sigma(p) + \Delta p^T \nabla I_\sigma(p) + \Delta p^T H_\sigma(p)\Delta p \qquad (5)$$

where I_σ is the image representation at the given scale, defined by the convolution with a Gaussian kernel with variance σ. The Hessian matrix (5) is the tensor of second partial derivatives of image I at scale σ and point p. By performing an eigen analysis of the tensor representing the local structure, we can calculate the principal orientations and the output of the feature detector.

B. Neuriteness

For a given scale , an alternative measurement of piecewise linear segments that is also based on the Hessian matrix was proposed (7) , i.e.,

$$N_\sigma = \begin{cases} \frac{\lambda_\sigma}{\lambda_{\sigma,min}} \; if \; \lambda_\sigma < 0 \\ 0, if \; \lambda_\sigma \geq 0 \end{cases} \qquad (6)$$

Where

$$\lambda^1{}_{\sigma,1} = \lambda_{\sigma,1} + \alpha\lambda_{\sigma,2} \qquad (7)$$

$$\lambda^1{}_{\sigma,2} = \lambda_{\sigma,2} + \alpha\lambda_{\sigma,1} \qquad (8)$$

$$\lambda_\sigma = \max\left(\left|\lambda^1{}_{\sigma,1}\right|, \left|\lambda^1{}_{\sigma,2}\right|\right) \qquad (9)$$

$$\lambda_{\sigma.min} = \min_{p \in I}(\lambda_\sigma) \qquad (10)$$

Where $\lambda_{\sigma,1}$ and $\lambda_{\sigma,2}$ are the eigen values of the Hessian matrix H_σ (p) for a given scale parameter σ . Parameter α is chosen such that the equivalent steerable filter used in the calculation of the Hessian matrix is maximally.

2.3.3.2 Image intensity based cost maps:

A. Vesselness

For a given scale σ, the Hessian matrix of the image is computed, and the following measure is calculated (this corresponds to the 2-D case, but it can be easily extended to n dimensions), i.e.,

$$V_S = \exp\left(\frac{R_B}{2\beta^2}\right)(1 - \exp(-\frac{S^2}{2C^2}) \qquad (11)$$

Where

$$S = \sqrt{\lambda_1{}^2 + \lambda_2{}^2}\ ;\ R_B = \frac{\lambda_1}{\lambda_2}\ and\ V_{max} = \max(\{V_S\})$$

A neighborhood of a point X can be described as a Taylor expansion as follows

$$I(x + \delta x, s) \approx I(x, s) + \delta x^T \nabla_s + \delta x^T \mathcal{H}_s\, \delta x \tag{12}$$

Where δ is the gradient Vector and $\mathcal{H}$ is Hessian matrix

The following equation can be explained the differential operator for Hassian matrix

$$\frac{\partial}{\partial x} I(x, s) = I(x) * \frac{\partial}{\partial x} G(x, s) \tag{13}$$

Where

$$G(x, s) = \frac{1}{\sqrt{2\pi s^2}} exp^{-\frac{||x||^2}{2s^2}} ans\ s - the\ scale$$

B. Gaussian

For comparison, we calculated the outputs of relevant previously available methods including a Gaussian (14) matched filter. The parameters used in these tests were manually optimized to provide the best visual detection, with the PCT-based parameters kept exactly the same as those for their respective intensity-based measures.

$$G(x, y)_\theta = -exp^{-\frac{u^2}{2\sigma^2}}\ \forall [u\ v] \epsilon N \tag{14}$$

Where

$$[u\ v] = R_\theta [x\ y], N = \{|u| \le 3\sigma, |v| \le \frac{L}{2}\}$$

3. Conclusion

To evaluate the performance of the new approach, we applied a PCT-based live-wire tracing method to detect fungal networks, and the results are obtained. The PCT-based measure evens out the output from low and high-contrast structures, making the detection of the correct branch much more likely. The definition of PCT is easily extendable to 3-D or higher dimensionality images.

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