Multi-scale Shape Feature Extraction of Erythrocyte SEMed Image Through Curvelet Transform

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Abstract. The shape of red blood cell plays an important role to its deformability and filterability. In real clinic blood-related disease diagnosing case, the irregularity and deformation give rise to huge challenges. Thus the shape feature extraction of red blood cell will make sense for medical image compute aided diagnosing. In this paper, the different shape representation was introduced firstly. And then some background knowledge about Curvelet transform was reviewed. We conduct wrapping-based curvelet transform on red blood cell image and obtained its reconstruction with transformed multi-scale coefficients to extract the shape feature and draw some conclusion, as well as some future works are proposed.

Introduction

There is considerable evidence showing that the red blood cell (erythrocyte) deformability plays an important role in the filterability of blood. Meanwhile the shape of red blood cell is also a critical factor to determine its deformability and filterability. Therefore for clinic treatment, the shape feature extracting of erythrocyte will make sense for physician to diagnose what kind of illness the patient suffered by means of blood analyzing.

In our experiment, the input original images we are aiming to deal with are captured by Scanned Electronic Microscope (SEM). As shown in Figure 1, different cells probably take on various kinds of shapes. This kind of shape diversity and deformation with different directions bring more challenges to our problems.

Figure 1. Different shapes of Red Blood Cells.

Under normal circumstance, the shape of red blood cell should look like a binconcave disc, whereas in real clinic blood related diagnosing case, the shape of irregularity and its deformation along with different direction give rise huge difficulties to medical image computer aided diagnosing. Fortunately, in recent years, a kind of new multi resolution geometrical analysis approach has been proposed, called curvelet transform, which provides a possible method to solve this kind of problems.

The rest of the paper is organized as follows. In Section 2, we review the curvelet transform. Experiments with some discussions are presented in Section 3, and the conclusion addressed in Section 4.

Curvelet Transform

During the past three decades, wavelet analysis has been widely used as it provides an effective tool for multi resolution analysis of image. Wavelet shows good performance at catching zero-dimensional or point singularities, whereas such is not the case in two dimensions. In fact, wavelet transform extracts horizontal, vertical and diagonal activities in an image, which is not
enough to capture more directional information in images in real case such as the shape feature extraction of deformable red blood cell [1].

In order to overcome the failure of conventional wavelet multi-scale representation, a new multi resolution analysis tool has been proposed in 2000 [2], namely curvelet transform. The fundamental idea of curvelet transform is to regard a curve as a superposition of different functions with various lengths and widths which conform to the specific scaling law.

\[ \text{width} \approx \text{length}^2 \]

E.J. Candes and D.L. Donoho constructed a tight frame of curvelets which provides stable, efficient, and near-optimal representation of otherwise smooth objects having discontinuities along smooth curves [3]. They draw a conclusion that wavelet performs very well for objects with point singularities in dimensions 1 and 2. Neither wavelets nor sinusoids really sparsify two-dimensional objects with edges (although wavelets are better than sinusoids).

As shown in Figure 2, the wavelet approximation is limited to using square-shaped brush strokes along the contour. Different sizes square are used corresponding to the multi resolution structure of wavelets. On the other hand, the new style as shown in (b) of Figure 2, exploits effectively the smoothness of the contour by making brush strokes with different elongated shapes and in a variety of directions following the contour [4, 5, 6].

Some researchers have made great achievements with curvelet transform. Jun Liu, Jiyan Huang, et.al, proposed a novel face recognition approach to eliminate the “Halo” phenomenon and obtain high recognition rate based on separate processing on the approximate and detailed components of curvelet transform [7]. In [8], the authors confirmed that anisotropic Curvelet transform make the weld defect edges were more clearly. And the curvelet coefficients were processed by the threshold and the method of semi-soft threshold function. Afterwards the edge details of defect in image can be preserved and the noise of the weld defect image is eliminated by inverse curvelet transform.

Curvelet transform is capable of multiscale analyzing in two dimensional signal processing, and it produce better performance for obtaining singularities along curves than traditional wavelet transform.

Similar to wavelet transform, curvelet transform has its own corresponding formula. The curvelet coefficient can be obtained by the following equation:

\[
C(j,l,k) = < f, \varphi_{j,l,k} > = \int_{\mathbb{R}} f(x) \varphi_{j,l,k}(x) dx
\]

where \( j \) is the scale, \( l \) is the direction, and \( k \) is the position (ie, the Curvelet coefficient).

Let \( f[t_1,t_2]|0 \leq t_1, t_2 < n \) is taken to be a Cartesian array, and \( \hat{f}[n_1,n_2] \) denotes its 2D Discrete Fourier Transform,

1. Apply the 2D FFT to the image \( f[t_1,t_2]|0 \leq t_1, t_2 < n \) to obtain the Fourier samples

\[
\hat{f}[n_1,n_2] = \frac{1}{n} e^{-j2\pi\frac{n}{2}}
\]

2. For each scale \( j \) and angle \( l \), compute

\[
\hat{U}_{j,l}[n_1,n_2] \hat{f}[n_1,n_2]
\]

where \( \hat{U}_{j,l}[n_1,n_2] \) is the discrete localizing window.
3. Wrapping the product around the origin to obtain

$$\tilde{f}_{j,l}(n_1, n_2) = W\left(\tilde{U}_{j,l}\tilde{f}\right)[n_1, n_2]$$

4. Apply the inverse 2D FFT to each $\tilde{f}_{j,l}$ and collect the discrete coefficient $C^0(j,k,l)$

**Experiment**

There are two implementations of curvelet transform. One is based on unequally spaced first Fourier transforms (USFFT) many times. The other is based on the wrapping of specially selected Fourier samples. Curvelet transform with wrapping has been conducted in our work regarding it is the fastest curvelet transform currently available.

**Processing Flowchart**

Our input original image is clipped from a size 1024*768 whole cell image, whose size is 256*256 regarding the input image size should be $2^n*2^n$ when using CurveLab [9]. Firstly the customized image with three channels should be converted to a single channel one with size customized with 256*256 rather than 256*256*3 using rgb2gray function in Matlab.

![Figure 3. Implementation flow chart.](image)

![Figure 4. CurveLab Implementation procedure.](image)

**Curvelet Coefficients**

As shown in Table 1, it depicts the Curvelet Transform Coefficients at different scale from coarse, detail to fine and the construction of different coefficients.

<table>
<thead>
<tr>
<th>Scale</th>
<th>Coefficients</th>
<th>Number of Direction Parameters</th>
<th>Matrix Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coarse</td>
<td>C{1}</td>
<td>1</td>
<td>21*21</td>
</tr>
<tr>
<td>Detail</td>
<td>C{2}</td>
<td>16</td>
<td>18<em>22 16</em>22 22<em>18 22</em>16</td>
</tr>
<tr>
<td></td>
<td>C{3}</td>
<td>32</td>
<td>34<em>22 32</em>22 22<em>32 22</em>34</td>
</tr>
<tr>
<td></td>
<td>C{4}</td>
<td>32</td>
<td>67<em>44 64</em>43 64<em>44 44</em>64 44*67</td>
</tr>
<tr>
<td></td>
<td>C{5}</td>
<td>64</td>
<td>131<em>44 128</em>43 128<em>44 44</em>128 43<em>128 44</em>131</td>
</tr>
<tr>
<td>Fine</td>
<td>C{6}</td>
<td>1</td>
<td>512*512</td>
</tr>
</tbody>
</table>

Table 1. Curvelet Transform Coefficients Description.
We implement curvelet transform with wrapping algorithm to decompose the input original customized image. We can obtain coarse, detail and fine coefficients with curvelet transform as shown in Figure 5.

![Image of original image and curvelet transform coefficients](image)

Figure 5. The original image (a) and its coefficients of curvelet transform (b).

**Different Scale Reconstruction of Curvelet Transform**

We apply inverse curvelet transform to the cell image with different scale from 1 to 6, and get the different level reconstructed image varies from coarse (scale=1), detail (scale =2~5) to fine (scale=6), as illustrated in Figure 6.

![Reconstructed images with different scales](image)

Figure 6. Reconstructed Image with different scale respectively.

**Conclusion and Future Work**

Lots of improvements have been achieved by using curvelet transform for medical image processing. In the future, we will conduct the curvelet transform onto the extracted individual cell image as shown in Figure 7, which is segmented with guided contour algorithm [10] and 4- neighborhood region growing algorithm [11].

![Extracted cell image](image)

Figure 7. Extracted individual cell image with guided contour and region growing.
The obtained coefficients with different scales and various angles could not be used to train the classifier directly. Some coefficients will be processed further with dimensional reduce method, which will be treated as feature vector to train and recognize for SVM classifier.

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References


