A Novel PDE Based Diffusion Technique for Image Denoising

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Abstract— Images are often corrupted with noise during acquisition, transmission, and retrieval from storage media. Many dots can be spotted in a Photograph taken with a digital camera under low lighting conditions. A crucial research is how to filter noise caused by the nature, system and processing of transfers and so on. The noise mixed with the useful images or signals and brings the researchers lots of troubles. In many research areas related, such as target detecting and tracking, edge detecting and image registration, image denoising is the first step of process and the effect of it is very important to the following processes. In this paper, we proposed an image denoising method using partial differential equation and bi-dimensional empirical mode decomposition. The bi-dimensional empirical mode decomposition transforms the image into intrinsic mode functions and residue. Different components of the intrinsic mode functions present different frequency of the image. The different with the classic method of partial differential equation denoising is that we use partial differential equation of the intrinsic mode functions to filter noise. Finally, we reconstruct the image with the filtered intrinsic mode functions and residue. The experiments show the reliability of our algorithm.

Keywords— Image Denoising, Bi-dimensional Empirical Mode Decomposition, Intrinsic Mode Function, Partial Differential Equation.

I. INTRODUCTION

Many related algorithms had been proposed recently, such as algorithms based on wavelet transform [1] [2] [3], algorithm based on spatial filters [4] and algorithm based on fuzzy theory [5]. In [6] and [7] the authors used the method of least squares support vector machines and image decomposition respectively. Later, some researchers proposed an algorithm using non-aliasing contour let transform [8] and partial differential equation [9]. Empirical mode decomposition (EMD) was firstly proposed by Huang [10]. EMD is mainly used to one dimension signals processing, such as sound signals. Later, bi-dimensional empirical mode decomposition (BEMD) was used to image signal processing [11] [12] [13]. In this paper, we proposed the algorithm using partial differential equation & bi-dimensional empirical mode decomposition. Firstly, we execute BEMD to original image and get the intrinsic mode functions (imfs) and residue. Secondly, we filter noise of the imfs with partial differential equation (PDE). Lastly, we reconstruct the image with the filtered imfs and residue.

II. BEMD REVIEW

BEMD is to decompose bi-dimensional image into intrinsic mode functions (imfs) and residue like one dimensional EMD. Someone used EMD to image denoising, which viewed the image as one dimensional row signals. But this ignores the relationship between adjacent pixels. Later, a BEMD was proposed.

A complicated data set can be adaptively decomposed into a finite number of components of different frequencies called IMFs using an iterative shifting process that continues until the number of extrema is < 2 (one maximum and one minimum). The method can be used to extract local high-frequency oscillations from the original data set. IMFs have the following features: (a) each IMF has the same number of zero crossings and extrema; (b) at any point, the mean value of the upper envelope defined by the local maxima and the lower envelope defined by the local minima tends to zero. The detailed process can be described as follows

1) Look for the local extremum and form the envelopments of the original image f(x, y).
2) Compute the average m_i(x, y) of the top envelopment and bottom envelopment and denote that
   \[ I_1(x, y) = f(x, y) - m_1(x, y) \]  \hspace{1cm} (1)
3) Replace f(x, y), with I_1(x, y), and execute the above three steps. Then we can get I_1(x, y), until the standard deviation \( SD \) is smaller than the threshold predefined. We used \( I_n(x, y) \) to replace \( I_1(x, y) \). If the local mean of \( I_1(x, y) \) is zero, we view it as IMF_1. Where
   \[ SD = \sum_{x=0}^{X} \sum_{y=0}^{Y} \left( \frac{I_{i+1}(x, y) - I_i(x, y)}{I_i(x, y)} \right)^2 \]  \hspace{1cm} (2)
4) Replace f(x,y) with f(x,y) - I_n(x, y) and execute the above four steps until the extremum number of residue is smaller than two. Then we complete the decomposition.
   \[ f(x, y) = \sum_{i=1}^{N} IMF_i(x, y) + r_n(x, y) \]  \hspace{1cm} (3)

III. OUR ALGORITHM

Image denoising is an emerging area of research. There are various techniques available in the literature for effective denoising of images but it still remain an open problem because every technique has one or more shortcomings as listed below.
1. Filtering operation often affects clean pixels as well. Resulting in overall blurring and reduction of overall quality of the image.

2. In the process of reducing the noise the edges also get blurred.

3. Denoising process creates unwanted blockings and ripple effect in the restored image.

4. The effectiveness of denoising process depends on the type of noise under consideration i.e. no single technique can remove all types of noise.

5. There is loss of signal information in restored image as compared to original image.

Ideally, we want Filtering (diffusion) within the object boundary and No filtering across the edge orientation. I will try to reduce the affect of these shortcomings on restored image by improving anisotropic diffusion technique based on PDE for image denoising. The capability of PDE-based methods in image denoising prompted many researchers to search for an improvement in the technique.

IV. EXPERIMENT RESULT

We used the Matlab2007 to run the experiment under the PC environment of Windows XP and CPU Pentium Dual-core which frequency is 2.62 GHz and memory with 3.50 GB.

In order to prove the performance of our algorithm, we used Lena image with different noises in the experiment and we used SNR to evaluate the algorithm. The figure 3 and table are the results of some algorithms. The noise added obeys normal distribution with mean 0 and standard deviation 1. In table the noise parameter is multiplied to the former noise. Then all was added to the original image.

TABLE I. SNR COMPARISON OF DIFFERENT DENOISING METHODS

<table>
<thead>
<tr>
<th>Noise Parameter</th>
<th>SNR Image Noise</th>
<th>SNR With Mean Filter</th>
<th>SNR PDE Denoising</th>
<th>SNR BEMD &amp; PDE</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>8.656</td>
<td>13.886</td>
<td>15.365</td>
<td>18.776</td>
</tr>
</tbody>
</table>

Figure 3. The effect comparison of different algorithms

Figure 2. Process of BEMD and PDE Denoising
V. CONCLUSION

In contrast to the other algorithms, we introduce both PDE and BEMD to image denoising. The BEMD transforms the image into imfs which have different frequencies. Then we use PDE to filter the imfs with different threshold parameters. The final image is composed with the filtered imfs and the residue.

The experiments show that the fused algorithm is more accurate and higher reliability. The capability of PDE-based methods in image denoising prompted many researchers to search for an improvement in the technique. Furthermore, more researches should be done on reducing the time of denoising while unaffected the accuracy.

VI. REFERENCES