Image Enhancement Based on a Nonlinear Multiscale Method Using Dual-Tree Complex Wavelet Transform

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Abstract—This paper proposes a new nonlinear multiscale reconstruction method for image enhancement using dual-tree complex wavelet transform. The enhanced image is obtained by successively combining each coarser scale image with the corresponding nonlinearly modified interscale (detail) images. This image enhancement method reduces additive noise while preserving the sharpness of the image. Simulation results show the improved performance of our image enhancement method in comparison with that of the existing methods.

Index Terms—Image Enhancement, Dual-Tree Complex Wavelet Transform, Nonlinear Multiscale Reconstruction

I. INTRODUCTION

Image enhancement can be thought of as two-dimensional digital filters. There are mainly two classes of filters: linear filters and nonlinear filters. They can be used both in the spatial domain and in the transform domain [4]. To suppress noise in images, we can use conventional linear or nonlinear filtering. They have different advantages and disadvantages. Linear techniques are simple, but they blur the edges and have a poor performance in the presence of noise. Usually, nonlinear methods are more complex than linear ones. But they have some good properties such as preserving the sharpness of the edges. One such nonlinear method is incorporated with the Nagao filter. To preserve the edges while smoothing, it uses masks of different shapes in order to find the neighborhood of least variance, after which a local mean is computed using the selected masks [6].

Generally speaking, the structures in an image may have very different sizes, so it is often attractive to perform a multiscale decomposition when dealing with the image processing problems. In the multiscale decomposition process, an approximate image and a detail image (or more than one detail images) are obtained at each successively coarser decomposition resolution. The detail images are defined as the difference of information between the approximate images at two consecutive resolutions. Such a scheme is mathematically described by the dyadic wavelet transform (WT) [1], in which the signal can be completely represented by a series of details and the approximate image at the coarsest resolution. All the decomposition resolutions are powers of two. The reversal of the multiresolution decomposition, i.e., reconstruction, is the synthesis form of the scheme, where a finer representation is constructed via coarse-to-fine scale recursion. On the other hand, the edges as features of an image, contain useful information that belongs to the high frequency component. Human visual system (HVS) is more sensitive to the edges than the homogeneous regions. Thus, the sharpness of the edges should be preserved when we suppress noise using multiscale decomposition and reconstruction scheme.

In our reconstruction scheme, the nonlinear processings are performed by the edge detector, which is applied to each low-pass image at different levels. The lowpass image is processed by the edge detector to obtain a binary edge image. This binary edge image is then used for selecting which pixels of the detail images to be retained. We use an efficient edge detector based on variance-weighted mean estimator (VWME) as proposed in [5]. A standard image degraded by additive noise is used in order to illustrate the performance. Quantitative measures are presented for comparison between different enhancement methods. In this context, the performances of the average filter, median filter and Nagao filter are presented.

Section II presents the theory and properties of the dual-tree complex wavelet transform (CWT). The nonlinear multiscale method is presented in Section III. In Section IV, the simulation results is given. Section V concludes the paper.

II. DUAL-TREE COMPLEX WAVELET TRANSFORM

In the dual-tree complex wavelet transform [2], two parallel fully decimated trees (a and b, both of them are real discrete WT) are used to achieve the approximate shift invariance property (See Fig. 1). To get the uniform intervals between samples from the two trees below level 1, odd-length filters are required to be used in one tree and even-length in the other tree. Furthermore, odd and even filters are applied alternately in each tree from level to level so that greater symmetry between the two trees occurs.

For the dual trees, linear-phase perfect reconstruction (PR) biorthogonal filter sets are selected. The odd-length highpass filters have even symmetry about their mid points, and the even-length highpass filters have odd symmetry. We can treat the impulse responses of these as the real and imaginary parts of a complex wavelet. Furthermore, the filters selected
are nearly orthogonal and have good smoothness and rational coefficients. The (13,19)/(7,9)-tap filters are used for the odd-length set, while the (12,16)/(14,14)-tap filters are used for the even-length set, so that the impulse responses to \( z^{-1} \) and \( z \) are as similar as possible in the sense of minimum mean squared error.

For the 2-D applications, separable filtering along columns and rows is implemented. To fully represent the real 2-D signal, two adjacent quadrants of the spectrum are needed. But we have suppressed the negative frequencies both along the columns and along the rows, so only the first quadrant of the 2-D signal spectrum is obtained. To get the enough information of the signal, the complex conjugates of the row filters are applied. Thus, in 2-D transformations, a 4:1 redundancy occurs.

The dual-tree complex WT produces six bandpass subimages, three in each of the spectral quadrants 1 and 2 at each level. These six complex coefficients are strongly oriented at angles \( \pm 15^\circ, \pm 45^\circ, \pm 75^\circ \) as shown in Fig. 2. The reason of the good directional selectivity property of the dual-tree complex WT is that the complex filters can separate positive from negative frequencies vertically and horizontally. While it is obvious in Fig. 2 that the traditional real WT is short of directional selectivity at \( f_{45^\circ} \).

**III. THE NONLINEAR MULTISCALE METHOD**

**A. Proposed Algorithm**

Generally, noises are mainly high frequency components in signals. Thus the detail images contain both the noise and the edges. It is difficult to differentiate them in the detail images. While in the lowpass images, the noise variance is lower. Furthermore, if an object covers a large number of pixels, it has a frequency content that is essentially lowpass. Thus, most of its edge information is preserved when we decimate the image. Therefore, it is easier and more precise to detect the edges in the lowpass images of lower resolutions. So, we can enhance the image through modifying the reconstruction process.

The edge detector is applied to each lowpass image at each level. The binary edge image at the \( m \)th stage, \( w_m \), is then used for selecting which pixels of the detail images to be retained. We use an efficient edge detector based on variance-weighted mean estimator (VWME) [5]. In each scale, an edge detector is applied to the interpolated lowpass images \( d_m \), \( i = 1, \ldots, 6 \) and the mask, \( w_m \), only the useful highpass information of the edges is preserved while the noise is removed. Then we reconstruct the image from the modified detail images at every stage.

**B. Edge Detection**

The edge detector uses variance-weighted mean estimation (VWME) that is carried out in a square window centered at pixel \((n_1, n_2)\). As indicated in Fig. 3, the pixels within the window are arranged into eight groups, \( \{x(n_1-i, n_2-j)\}_{i,j} \), \( p = 1, 2, \ldots, 8 \), where \( s_p \) are the subsets of the window. The mean of the image intensity in subset number \( p \) is denoted by \( b_p(n_1, n_2) \), while the corresponding sample variance is denoted by \( \sigma_p^2(n_1, n_2) \).

The variance-weighted mean estimate is now given by

\[
\mu_{VWME}(n_1, n_2) = \frac{\sum_{p=1}^{8} b_p(n_1, n_2) \cdot \mu_p(n_1, n_2)}{\sum_{p=1}^{8} b_p(n_1, n_2)},
\]

where \( b_p(n_1, n_2) = \frac{1}{\sigma_p^2(n_1, n_2)} \).

In the degenerate case where \( \sigma_p^2(n_1, n_2) \) approaches zero for some \( p \), Eq. (1) should be interpreted in the limit sense. For edge detection, \( \mu_{VWME}(n_1, n_2) \) is compared with the arithmetic mean, \( \mu_{AM}(n_1, n_2) \) computed over the entire window.

The VWME performs similar to an arithmetic mean operator when the window covers a homogeneous region, but the weights of the window vary due to the abrupt change of
where $\Delta s(i,j)$ is a highpass filtered version of $s(i,j)$, obtained with a 3 x 3-pixel standard approximation of the Laplacian operator. The correlation measures of (3) and (5) should be high, i.e., close to unity when the estimated image is similar to the reference image.

**C. Results**

As shown in Fig. 4, the blurred and noisy *lena* image (see Fig. 4(b)) is enhanced by using the presented multiscale method with the described approach of edge detection at each reconstruction stage.
Table I

<table>
<thead>
<tr>
<th>Method</th>
<th>$\rho$</th>
<th>$\alpha$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiscale method</td>
<td>95.8</td>
<td>48.4</td>
</tr>
<tr>
<td>Nagao filtering</td>
<td>95.4</td>
<td>21.3</td>
</tr>
<tr>
<td>Average filtering (3 x 3)</td>
<td>95.2</td>
<td>23.3</td>
</tr>
<tr>
<td>Median filtering  (3 x 3)</td>
<td>95.0</td>
<td>27.6</td>
</tr>
</tbody>
</table>

in Figs. 4(e) and 4(f), respectively. Visual examinations of the images in Figs. 4 (c)-(f), for the blurred noisy lena image, the present multiscale method performs edge preserving smoothing more efficiently than the other filters.

In our simulation, the nonlinear VWME edge detection is performed using a window of size $5 \times 5$. For every reconstruction stage, we set the threshold to $TVWME = 0.1$, which is high enough to reject most of the detail information in homogeneous regions. The choice of the threshold, however, does not seem to be crucial for the quality of the enhanced image.

The performance measures of (3) and (5) are evaluated for images enhanced by the described multiscale method. The highest performance is achieved by the proposed method. Comparison of the present method with some other techniques in terms of $\rho$, $\alpha$ is given in Table I. Our multiscale results concern two-stage processing. The motive for limiting the number of stages is due to scale limitations. The resolution imposes a lower limit to the object size that can be represented. Also, the finite support of the images makes boundary effects more compromising at a coarse resolution. At scales larger than that of the inner most stage, no highpass information—desired or undesired—is suppressed. If too many stages are used, an edge may be missed at a coarse scale and thereby at each finer scale.

V. Conclusion

We have introduced a new image enhancement method for still images that have been blurred and corrupted by additive white Gaussian noise. The method is able to reduce the noise, while retaining the sharpness of the images. However, comparing with the results of other methods, the sharpness preservation seems to be more prominent than the noise reduction effect. In our simulation example, we have used a two-level multiresolution scheme because with this scheme noise reduction is found to be satisfactory without excessive loss of image details. The dual-tree complex WT is used to reduce the computational complexity and to obtain good performance due to its directional feature.

VI. Acknowledgment

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REFERENCES