Novel Post-processing Algorithm to Reduce Still Image Compression Artifacts*

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Abstract: A post-processing algorithm of still image compression was proposed. Iterative contourlet-based image interpolation was implemented to revive the highpass information, which was then fused with the highpass information of the decompressed image to further preserve the significant wavelet coefficients. The algorithm helped to reduce compression artifacts and improve regularity along edges of the decompressed image at low bitrates especially. The ability of the proposed method was demonstrated under JPEG2 000 and SPIHT compression systems. Only for once iteration, the PSNR (peak signal-to-noise ratio) of the post-processed image may improve 0.05～0.2 dB than that of the decompressed image. Ringing artifacts decrease with the increase of the number iteration.

Key words: Still image compression; Wavelet transform; Contourlet transform; Image interpolation

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0 Introduction

It is well known that several image compression method based on wavelet transform[1-2] such as SPIHT[3], SPECK[4], JPEG2000[5-6] successfully reduced the block artifacts found in the conventional JPEG. Even then, the quantization for wavelet coefficients causes ringing artifacts around the sharp edges in the decompressed image. Simultaneously, image compression system, which can be equivalent to band-pass filter, also brings blur artifacts to decompressed image. These artifacts inevitably bring bad effect on posterior image processing such as image segmentation, target detection and decision. So some modifications should be made for the compression algorithm in order to reduce the artifacts, but for a given compression system, post-processing is usually adopted to improve image quality such as edges.

In year 2000, FAN[7] proposed a post-processing algorithm based on the edge model to rebuild the destruct edges, however, by reasons of the distortion artifacts, the edges of the decompressed image do not accord with those of the original image, so the post-processed edges are not always expected. Yang[8] proposed the maximum-likelihood parameter estimate method to decrease the ringing artifacts, and Nostratinia[9] applied compression to the shifted versions of the pending decompressed image and averaged the results for the removal of coding artifacts. Whereas, the post-processed image is not satisfying at low bitrates and with heavy edge degeneration.

A post-processing algorithm based on the Contourlet transform[10-13] is presented in this paper. It employs the interpolation algorithm on the wavelet lowpass subband of the decompressed image to revive highpass information and improve regularity along edges in the post-processed image.

1 Iterative Contourlet-based image interpolation

In image compression, wavelet coefficients whose absolute value are smaller than quantization step size always locate in the high-frequency subbands and are set zero. Said[3] pointed out that for binary tree-structured wavelet transform, the parent-child coefficients always have strong correlation, which is also the foundation of SPIHT[3] coding. So it is possible to predict the corresponding high-frequency subband coefficients using low-frequency ones. Based on this idea, Mueller proposed the Contourlet-based interpolation algorithm[12].

In order to realize 2×2 zoom, the paper [12] assumes the low resolution image is the low-pass subband L of the first level wavelet transform of

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the original image I, while all the coefficients in the highpass subbands are set 0 in the first iteration. Then the high-resolution image $\hat{I}_k$ is achieved by performing 2D inverse wavelet transform. But $\hat{I}_k$ is usually considered as a noisy version of the original image I. In order to denoise the $\hat{I}_k$ as well as retain the important coefficients near edges, the paper [12] proposed hard-thresholding denosing algorithm based on Contourlet transform[11], and the algorithm can be wrote as

$$\tilde{I}_k = C^{-1} D_{T_k} C \hat{I}_k \tag{1}$$

Where, C and C^{-1} denote forward and inverse Contourlet transform respectively. D_{T_k} is denoising operator by which insignificant coefficients whose absolute values are smaller than thresholding T_k are set zero. $\tilde{I}_k$ is denoised high-resolution image. A new version of the Contourlet transform (Contourlet-2. 3), recently proposed by Lu and Do[11], is employed. The basis images from the new transform has better frequency locatization and directionality, and can restrain the frequency aliasing caused by down-sampling effectively.

2　Proposed post-processing algorithm of compression image

Note that to perform iterative Contourlet-based image interpolation algorithm only on lowpass subband L can rebuild image edges and contours effectively. In this paper we develop this idea and present a new post-processing structure for decompressed image by reusing the three discarded high-pass subbands of the first level. The block diagram of the proposed structure is shown in Fig. 1.

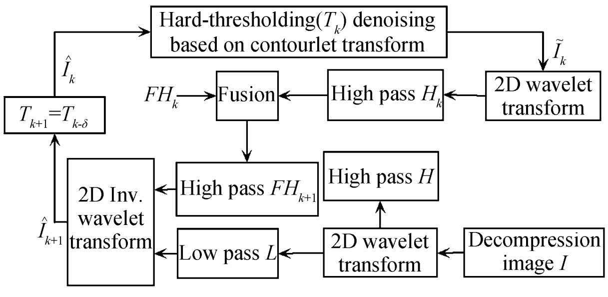

Fig. 1　Block diagram of the proposed post-processing of compression image

Seen from Fig. 1, the contourlet-based interpolation algorithm presented by Mueller[12] is included in our structure. Besides that, in order to acquire further high-frequency information, we employ fusion technology based on maximum selection to update the highpass subband FH_{k+1} as follows

$$FH_{k+1} = \mathrm{sign}(FH_k + H_k)\mathrm{Max}(|FH_k|, |H_k|) \tag{2}$$

Where, H_k denotes the highpass subband of the first level wavelet transform of $\tilde{I}_k$. In the first iteration ($k=0$), $FH_0 = 0$ and $H_0 = 0$, and in the second iteration ($k=1$), $FH_1 = H$. In wavelet transform, the large wavelet coefficients usually have small probability. Through the viewpoint of information theory, large wavelet coefficients contain more important information than small wavelet coefficients do. So the fusion method preserves the significant wavelet coefficients at the high-frequency subbands, which helps to protect the important information such as image contours and edges.

According to Fig. 1, the proposed algorithm can be summarized as follows:

Step 1 We start the algorithm by taking decompressed image I, then perform 2D wavelet decomposition on I and regard the lowpass subband coefficients L as low-resolution image. The initial high resolution image $\hat{I}_k$ ($k=0$) is achieved by one level wavelet interpolation, and the initial threshold is chosen to be $T_0 = T$.

Step 2 Implement hard-thresholding denosing based on Contourlet transform for $\hat{I}_k$ using equation (1), then we can obtain the highpass coefficients H_k by performing 2D wavelet transform on $\tilde{I}_k$, finally, FH_{k+1} is updated by fusing FH_k and H_k using equation(2).

Step 3 Perform 2D inverse wavelet transform on lowpass L and highpass FH_{k+1}, then obtain the post-processed image $\hat{I}_{k+1}$.

Step 4 We gradually decrease the threshold value T_k by a small amount δ in each iteration, i. e., $T_{k+1} = T_k - \delta$. And, iteration number is increased as $k = k+1$.

Step 5 Return to step 2 and keep iterating, until the generated images are pleasing or a predetermined maximum iteration number has been reached.

3　Computational complexity analysis

In the proposed algorithm, Contourlet transform and wavelet transform play the main roles, and the computational complexity of the front is much higher than the latter, so we only give the computational complexity of Contourlet-2. 3 transform[11] and omit that of wavelet transform. Thus, for an N-pixels image and after

J-levels decomposition, the complexity of the LP [10-11] stage in the contourlet-2.3 is

$$C_{\mathrm{LP}}=C_{\mathrm{FFT}}(N(1+\sum_{j=2}^{J}(1/4)^{j-2})) \tag{3}$$

$C_{\mathrm{FFT}}(N)$ is the complexity of 2D FFT for N-pixels image. For the DFB [10-11], its filter banks require L_d operations per input sample, and the complexity is

$$C_{\mathrm{DFB}}=NL_d\left[l_1+\sum_{j=2}^{J}l_j\left[\frac{1}{4}\right]^{j-2}\right] \tag{4}$$

Where, the j-th level subband of LP decomposition is preformed l_j levels tree-structured directional decomposition. So the total complexity of Contourlet-2.3 transform is $C_{\mathrm{LP}}+C_{\mathrm{DFB}}$.

4 Experimental results and analysis

At high bitrate, the decompressed image usually has a good quality, so the initial threshold T cannot be chosen too high for avoiding removing the useful information and degrading post-processed image quality. But at low bitrate, the decompressed image has already lost much information of the original image, consequently, only few high-frequency coefficients can be restored exactly. In order to discard the incorrect reconstruction coefficients, higher threshold should be adopted. Having done lots of experiments, we choose the initial threshold as follows

$$T=\begin{cases}1, R>0.3\\ 10-30R, R<0.3\end{cases} \tag{5}$$

Where, R denotes bitrate. And threshold T is decreased by $\delta=0.2$ in each iteration. Equation (5) indicates that the initial threshold is large at low bitrate, but the initial threshold is small at high bitrate, which helps to retain the useful coefficients and remove the inessential ones.

Fig. 2 gives the PSNR of the post-processed image varied with iteration number via JPEG 2 000[5] compression at different bitrates. The number of iterations being zero denotes that none post-processing is implemented. At low bitrates, the highest PSNR is commonly achieved after only once iteration, and PSNR is decreasing along with increase of iteration number owing to denoising.

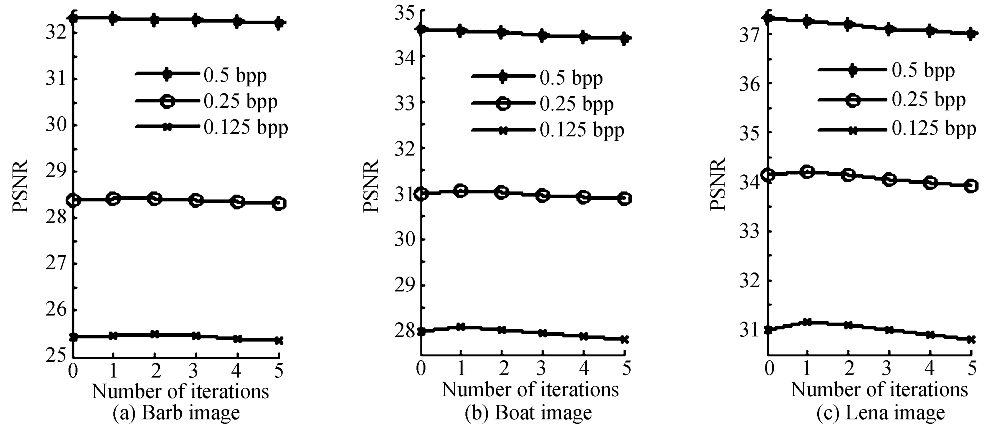

Fig. 2 PSNR vs. number of iterations of the Barb, Boat and Lena images

Fig. 3 shows the experiment results of Lena image at bitrate of 0.15 bpp using the proposed method and the algorithm[9] individually. Evidently, with the increase of the iteration number, the ringing artifacts around edges decrease much and the visual quality will be more pleasing, but the PSNR value is decreasing gradually and even below the decompressed image. So there should be a trade-off between number of iterations and the evaluations (including the objective and subjective evaluation) of post-processed image. Therefore, when a higher PSNR is requested, once iteration is enough, and the PSNR may improve 0.05~0.2 dB than the

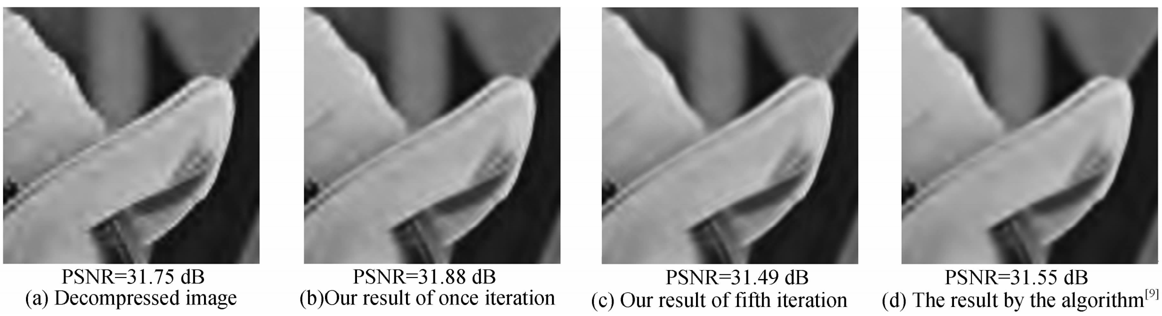

Fig. 3 Experiment results of the Lena image at bitrate of 0.15 bpp

decompressed image. And when requesting less ringing artifacts, the number of iterations should be increased to a proper value (e. g. not beyond 5), or else, the PSNR will decrease a lot.

Fig. 4 illustrates the post-processed results of Boat image by SPIHT compression[3] at bitrate of 0. 15 bpp. It is obviously that the proposed algorithm is still applicable for SPIHT compression .

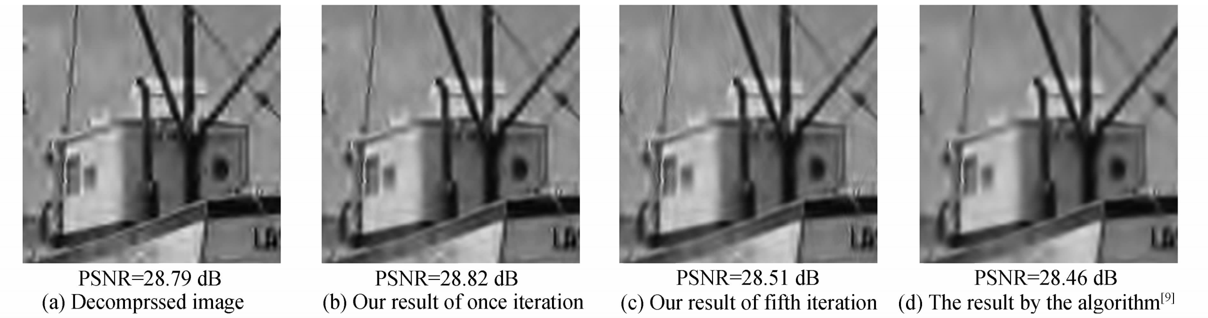

Fig. 4 Experiment results of the Boat image at bitrate of 0. 15 bpp

It is obviously that our algorithm can effectively protect image edge as well as restrain ringing artifacts, whereas Nosratinia's algorithm[9] appears slightly low-passed effect due to the average of the shifted decompressed image.

5 Conclusion

We have proposed a novel post-processing algorithm of still image compression. In this paper, denosing based on Contourlet transform and fusion method have been used for post-processing. This approach has reduced the compression artifacts. But in order to obtain satisfying performance, we should decide the number of iterations carefully.

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一种减小静止图像压缩效应的后处理算法

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摘 要:提出了一种静止图像压缩的后处理算法.执行了基于Contourlet变换的图像插值迭代方法来恢复图像的高频通带信息,然后该信息和解压图像的高频信息相融合以进一步保护重要的小波系数.在低码率情况下,该算法有助于减小压缩效应并且提高解压图像沿边缘的正则性.在JPEG2 000和SPIHT压缩系统中证实了该方法的性能.仅仅通过一次迭代,后处理图像的峰值信噪比相比于解压图像可提高0.05~0.2 dB.当迭代次数增加时,振铃效应将进一步降低.

关键词:静止图像压缩;小波变换;Contourlet变换;图像插值

SUN Wen-fang was born in 1979. He is currently pursuing the Ph. D. degree, and his research interests focus on areas of image compression and transform, nonuniformity correction of infrared image, etc.