IMAGE DEBLOCKING BY SINGULARITY DETECTION

Tai-Chiu Hsung and Daniel Pak-Kong Lun

Department of Electronic Engineering The Hong Kong Polytechnic University, Hung Hom, Hong Kong email:enpklun@polyu.edu.hk Fax:(852)23628439

ABSTRACT

Blocking effect is considered as the most disturbing artifact of JPEG decoded images. Many researchers have suggested various methods to tackle this problem. Recently, the wavelet transform modulus maxima (WTMM) approach was proposed and gives a significant improvement over the previous methods in terms of signal-to-noise ratio and visual quality. However, the WTMM deblocking algorithm is an iterative algorithm that requires a long computation time to reconstruct the processed WTMM to obtain the deblocked image. In this paper, a new wavelet based algorithm for JPEG image deblocking is proposed. The new algorithm is based on the idea that, besides using the WTMM, the singularity of an image can also be detected by computing the sums of the wavelet coefficients inside the so-called "directional cone of influence" in different scales of the image. The new algorithm has the advantage as the WTMM approach that it can effectively identify the edge and the smooth regions of an image irrespective the discontinuities introduced by the blocking effect. It improves over the WTMM approach in that only a simple inverse wavelet transform is required to reconstruct the processed wavelet coefficients to obtain the deblocked image. As the WTMM approach, the new algorithm gives consistent and significant improvement over the previous methods for JPEG image deblocking.

1. INTRODUCTION

For most of the current block-based image coding techniques, blocking effect is often resulted due to the quantization errors introduced in the encoding process of different blocks of the transformed images. Since these coding techniques are generally applied in the prevalent JPEG and MPEG standards, it has been a general interest to study the method to alleviate the blocking effect problem. Traditional approaches, such as, the low-pass filtering method [1], the constrained optimization methods [2, 3], the projection onto convex set technique [4] and the neural network method [5], use different optimization cost functions and constraints, such as, to limit the variation of block boundaries, etc., to smooth out the discontinuity incurred. These methods reduce the blocking effect in the sense of improving the signal to noise ratio. However, the visual quality of the processed image sometimes does not appear to be very much improved. One of the reasons for this is that the visual importance is not included in the cost function of these optimization methods for deblocking.

Recently, we proposed the wavelet transform modulus maxima (WTMM) approach [6] for JPEG image deblocking. By using the WTMM representation, the blocking effect is characterized as the following three sub-problems: 1) small modulus maxima at block boundaries over smooth regions; 2) noises or irregular structures near strong edges and 3) corrupted edges across block boundaries. Simple and local operations are then applied to the WTMM of the blocky image to solve the problems one by one. Finally, the deblocked image is reconstructed from the processed WTMM using an iterative projection onto convex set (POCS) technique [7]. Although the WTMM approach has many advantages as compared with the traditional approaches, the time consuming reconstruction process allows the approach to be useful only in some non-realtime applications.

The basic idea of the WTMM approach is to detect the discontinuities of the blocky image, since the blocking effect generally appears as discontinuity. However, we recently found that [8] we can also detect the discontinuity of an image by a much simpler approach, i.e., by simply computing the sums of the wavelet coefficients inside the so-called "directional cone of influence" in different scales of the image [8]. This approach has an obvious advantage over the WTMM approach in that only a simple inverse wavelet transform is required for reconstruction as compared to the complicated POCS technique used in the WTMM approach. Based on this idea, we propose in this paper a new deblocking algorithm. In the following sections, we first briefly introduce the singularity detection denoising technique and then we describe how it is applied to image deblocking.

2. SINGULARITY DETECTION DENOISING ALGORITHM

The local regularity of certain types of non-isolated singularities in an image can be characterized by their Lipschitz exponents [7]. By evaluating these Lipschitz exponents, we can identify noise from original contents of an image. It has been shown that [8] the Lipschitz exponents of an image can be evaluated by computing the sums of the wavelet coefficients inside the so-called "directional cone of influence" in different scales of the image. We refer this algorithm as the Singularity Detection denoising algorithm. Define the discrete dyadic wavelet transform [7] of a discrete im- $\text{age } f \text{ to be } \left\{S_{2^J}f, \left(W_{2^j}^1f\right)_{1 \le j \le J}, \left(W_{2^j}^2f\right)_{1 \le j \le J}\right\} \text{ where } f \in$ $L^{2}(R^{2})$. The components are obtained by the convolutions of f(x, y) with the scaling function and the dilated wavelets: $S_{2^J}f =$ $f \ast \phi_{2^J}(x,y), W^1_{2^j}f(x,y) = f \ast \psi^1_{2^j}(x,y), W^2_{2^j}f(x,y) = f \ast$ $\psi_{2i}^2(x,y)$. The wavelets are designed to be the partial derivatives of a smoothing function along x-direction and y-direction respectively. That's, $\psi^1(x,y) = \partial \Phi(x,y)/\partial x$ and $\psi^2(x,y) =$ $\partial \Phi(x,y)/\partial y$. Denote also the modulus of the wavelet transform $M_{2^{j}}f(x,y)$ as $\sqrt{|W_{2^{j}}^{1}f(x,y)|^{2}+|W_{2^{j}}^{2}f(x,y)|^{2}}$ and the phase $A_{2^j}f(x,y)$ as $\arctan\left(W_{2^j}^2f(x,y)/W_{2^j}^1f(x,y)\right)$. They indicate the magnitude and orientation of the gradient vector of the wavelet

This work is supported by PolyU research grant 357/021.

coefficient at a particular point (x, y). Since the orientation of the gradient vector of the wavelet coefficients indicates the direction where the maximum local variation of a signal is found, we only need to measure the Lipschitz exponent in that direction in order to identify the singularity of f(x, y).

The Lipschitz exponent α at a point (x_0, y_0) of a 2-d function f in a particular direction is related to the modulus of the wavelet coefficients of this function in scales s by the following equation, $|M_s f(x, y)| \leq Bs^{\alpha}$, where B is a constant. Instead of directly fitting the Lipschitz exponent from a set of neighboring coefficients in scale-space or tracing the maxima curves across scales as indicated in [7], we compute the integral of the wavelet transform modulus inside the so-called directional cone of influence. The directional cone of influence is defined as the support of the wavelet function in different scales and in the direction where the maximum local variation of a signal is found. We define an operator N which is dubbed as the "directional sum" of the wavelet transform modulus inside the directional cone of influence of a function, such that.

$$N_s f(x_0, y_0) = \int_{(x,y) \in \mathcal{D}_s} M_s f(x, y) dx dy \tag{1}$$

where $D_s = \{(x, y) : (x - x_0)^2 + (y - y_0)^2 \le Ks^2, (y - y_0)/(x - x_0) = tan(A_{2j}f(x_0, y_0))\}$ is the directional cone of influence. We implement the line integral of eqn.1 with a linear interpolation since not all wavelet coefficients lie exactly in the direction indicated by $A_s f$. From eqn.1, it can be proved that [8], $N_s f(x_0, y_0) \le B' s^{\alpha+1}$, where B' is a constant. Therefore, the Lipschitz exponent α can be estimated from the upper bound of the slope of $log(N_s f)$. It is known that [7] the Lipschitz exponent α of Gaussian noise usually possesses negative value. In the case that $\alpha \le -1$,

$$N_{2j+1}f(x_o, y_o) \le N_{2j}f(x_o, y_o) \quad for \quad 1 \le j < J$$

where J is the total number of scales. By making use of this relationship, we can identify Gaussian noise from the original contents of an image. First, we compute the wavelet transform of the noisy image and derive the directional sum $N_s f$. We select the wavelet coefficients that give positive Lipschitz exponents. They are indicated by those $N_s f$'s that decrease or remain the same as the scale increases. More specifically, if the point (x_o, y_o) corresponds to the edge or the regular part of the function f, the Lipschitz exponent α at this point is greater than or equal to 0 such that

$$N_{2^{j+1}}f(x_0, y_0)/N_{2^j}f(x_0, y_0) > 2.$$
⁽²⁾

By selecting the wavelet coefficients that fulfill this "interscale ratio" condition, as stated in eqn.2, we can effectively remove noise while the edges and the regular parts of the signal can be preserved.

The use of the interscale ratio method provides a simple means to select the wavelet coefficients that correspond to the regular parts of the signal. Nevertheless, due to the error generated during the estimation of $N_s f$ as well as the alias that may introduce from the cone of influence of nearby singularities, it is observed that some small irregular signal will have its wavelet coefficients fulfill the criterion defined in eqn.2. This effect is more obvious for those irregular signals which have $-1 < \alpha < 0$. Therefore, we also need the interscale difference condition to reject small irregular signal,

$$N_{2^{j+1}}f(x_0, y_0) - N_{2^j}f(x_0, y_0) > \gamma$$
(3)

where γ is a threshold. For the case that the value of γ is not comparable to the amplitude of the signal at any location, i.e. $\gamma \simeq$

1

0, the condition as stated in eqn.3 becomes the original interscale ratio condition as stated in eqn.2. It is because all data that satisfy eqn.2 will satisfy eqn.3. In actual practice, certain tolerance is allowed in using eqn.2 and eqn.3 to select the required wavelet coefficients. It is particular important for some classes of signals with known regularity range.

3. SINGULARITY DETECTION FOR DEBLOCKING

The blocking effect, which is incurred by the quantization errors of the image blocks, affects the decoded image in several ways. The most significant ones are, first, it may introduce small discontinuities at block boundaries; second, if there are edges inside or across several blocks, it will also introduce "ringing" artifacts. In the sequel, we propose a new deblocking algorithm based on the singularity detection technique to solve these two problems.

Although the discontinuities introduced by the blocking effect occurred only in the block boundaries, the wavelet coefficients that the discontinuities incurred spread over the whole image. They mix with the wavelet coefficients of the original image such that explicit removal of them may accidentally remove the wanted wavelet coefficients and lead to the "over-smooth" situation. Fortunately, the blocking effect is most observable in smooth regions of the image, where there should only be a few wavelet coefficients that have significant values (even for the case that we are using a wavelet function with only one vanishing moment). Consequently, most of the wavelet coefficients, if found, in the smooth regions are contributed by the blocking effect. To remove these wavelet coefficients, we first perform a segmentation to identify the smooth region, or more exactly, to identify the non-smooth regions of the image. Then we perform a hard thresholding to the wavelet coefficients in the smooth regions to reduce the blocking effect.

To identify the non-smooth regions of the image, we again make use of the local Lipschitz exponents. By non-smooth regions, we refer to the regions that have low (but not no) local variation of regularity among the neighboring coefficients. Two examples are the hair of "Lena" and "Baboon". Since the Lipschitz exponents show the local regularity of the image, it is a good indicator to identify these regions. Direct evaluation of the Lipschitz exponents may incur a long computation time and, in fact, what we need is only a classifier that tells a particular pixel belongs to the smooth region or the non-smooth region. From eqn.2, we know that if the interscale ratio of $N_{2^{j+1}}f(x_0, y_0)$ and $N_{2^j}f(x_0, y_0)$ at point $f(x_0, y_0)$ is greater than 2, it implies that the Lipschitz exponent at that point most probably is greater than 0, i.e., it either belongs to an edge or the smooth region. This formulation shows that we can make use of the interscale ratio to approximate the Lipschitz exponents. More specifically, we make use of the local variance of the interscale ratio as follows:

$$V_{2^{j}}(x,y) = \frac{1}{3} \sum_{u=-1}^{1} \left(l_{2^{j}}(x_{u},y_{u}) - \bar{l}_{2^{j}}(x,y) \right)^{2}$$
(4)

where we denote the interscale ratio at pixel (x, y) at level 2^{j} to be $l_{2j}(x, y)$. We define also $l_{2j}(x_u, y_u)$ to be the interscale ratio evaluated at pixel (x_u, y_u) that is adjacent to (x, y) and is in the direction parallel to that of $l_{2j}(x, y)$. The local mean of $l_{2j}(x, y)$ is defined to be $\bar{l}_{2j}(x, y)$. By evaluating the variance of interscale ratio, we can determine the variation of regularity of adjacent pixels of an image. Those pixels that have low variation will be classified as those belong to the non-smooth region. In practice, we use the following segmentation algorithm to generate the so-called "non-smooth region" map:

- 1. Compute $V_{2^{j}}(x, y)$ of the blocky image for scale 2^{1} to 2^{J} ;
- 2. classify the irregular coefficient to be inside the "non-smooth" region if $V_{2^{j}}^{low} < V_{2^{j}}(x, y) < V_{2^{j}}^{up}$;

where the parameters V_{2j}^{low} , V_{2j}^{up} can be obtained empirically and they work for all images. For those areas that are not non-smooth regions, we perform a hard thresholding, i.e. to remove those wavelet coefficients that have values smaller than a threshold. Figure 1 shows the result of segmentation for "lena". The gray pixels indicate the corresponding locations where the wavelet coefficients are selected after the hard thresholding. The black pixels indicate those small wavelet coefficients that originally should have removed by hard thresholding but are retained since they belong to the "non-smooth region" of the image. We can see that most of the wavelet coefficients introduced due to the blocking effect in smooth regions, such as the shoulder and face in "lena", are removed.

Besides the discontinuities that are generated in block boundaries, the ringing artifacts that occur near strong edges are also an annoying distortion introduced by the blocking effect. Human beings are sensitive to edges so that distortion near edges will be very much observable. Traditional techniques which aim at smoothing the irregular ringing artifacts may also smooth out the edges of the image. To better remove these irregular ringing artifacts, we can apply the singularity detection denoising algorithm. By using this algorithm, the ringing artifacts are considered as irregular patterns and the corresponding wavelet coefficients are removed as they do not fulfill the interscale ratio and interscale difference conditions. Since the singularity detection algorithm can easily identify edges from irregular pattern, the edges of the image can be preserved. The proposed deblocking algorithm can be summarized as follows:

Singularity Detection Deblocking algorithm:

- *I.* Compute $W_{2^j}^1 f$, $W_{2^j}^2 f$ and $N_{2^j} f$ for $1 \le j \le J$.
- 2. For a particular scale 2^{j} , compute $N_{2j+1}f/N_{2j}f$ (the interscale ratio) and its variance at all points (x, y).
- 3. In that scale, generate the non-smooth region map and perform hard thresholding in the smooth regions, i.e. select $W_{2i}^1 f$, $W_{2i}^2 f$ if they are greater than a threshold value in these regions.
- 4. Reject those $W_{2j}^1 f$, $W_{2j}^2 f$ at (x_0, y_0) if they do not fulfill the interscale ratio and interscale difference conditions, i.e., $N_{2j+1}f/N_{2j}f \ge 2$ and $N_{2j+1}f - N_{2j}f \ge \gamma$, where γ is a threshold value.
- 5. Repeat step 2 for the next scale.
- Reconstruct image from the selected wavelet coefficients using the inverse wavelet transform.

We show the results of applying the proposed singularity detection deblocking algorithm to "lena" and "baboon". Figure 2.a show the JPEG decoded "lena". Figure 2.b show the CLS deblocked. Figure 2.c show the singularity detection deblocked. We can see that the proposed deblocking method improves the JPEG decoded image in both visual appearance as well as signal-to-noise ratio. In the experiments, we use the same set of parameters for deblocking the test images since the quantization tables used in generating the test images are the same. Table 1 shows a comparison of the performance of the singularity detection deblocking with other conventional methods, such as, the Nonlinear Interpolative Decoding (Nid_o)[9], Constraint Least Square (Cls)[2], Projection Onto Convex Set method: $Pocs_{ygk}$ from [2]. We denote SD to be the proposed singularity detection deblocking method. We also denote bpp to be the number of bit per pixel, ΔSNR to be the difference of the deblocked image in SNR from the original JPEG decoded image. It is seen in the table that the singularity detection deblocking algorithm gives a consistent improvement in SNR for all test images. Furthermore, the improvement is the largest for the proposed algorithm as compared with other approaches.

4. CONCLUSION

In this paper, we proposed a new algorithm for JPEG decoded image deblocking using the singularity detection denoising technique. As similar to the WTMM deblocking approach, the new algorithm detects the singularity of an image to identify the unwanted wavelet coefficients which are introduced by the blocking effect. However, the new approach achieves this by a much simpler approach, that is, by computing the sums of the wavelet coefficients inside the "directional cone of influence" in different scales of the image. The new algorithm has the advantage as the WTMM approach that it can effectively identify the edges and the smooth regions of an image irrespective the discontinuities introduced by the blocking effect. It improves over the WTMM approach in that only a simple inverse wavelet transform is required to reconstruct the processed wavelet coefficients to obtain the deblocked image. The new deblocking algorithm follows the approach of WTMM deblocking which enhances the image in the senses of visual quality as well as signal-to-noise ratio. It gives a performance consistently and substantially better than the traditional approaches. As compared with the WTMM deblocking algorithm, it requires much less computation effort that the computation time can be reduced up to a few orders of magnitude.

			~	5	<i>A</i>D
Image	bpp	Nid_o	Cls	$Pocs_{ygk}$	SD
		ΔSNR	ΔSNR	$\Delta S N R$	ΔSNR
Airplane	0.29	-0.33dB	0.25dB	0.32dB	0.51dB
Baboon	0.45	-0.08dB	0.11dB	0.08dB	0.15dB
Couple	0.20	0.07dB	0.21dB	0.46dB	0.51dB
Face	0.23	0.15dB	0.26dB	0.65dB	0.67dB
Germany	0.20	0.41dB	0.20dB	0.34dB	0.58dB
Girl	0.20	0.56dB	0.20dB	0.47dB	0.65dB
House	0.28	-0.40dB	0.27dB	0.43dB	0.77dB
Lena	0.26	0.95dB	0.21dB	0.36dB	0.61dB
Peppers	0.27	0.89dB	0.21dB	0.35dB	0.61dB
Sailboat	0.29	-0.02dB	0.21dB	0.28dB	0.43dB
Tiffany	0.19	-0.07dB	0.26dB	0.38dB	0.72dB

Table 1: Comparison of the performance of SD deblocking with other conventional methods for JPEG-encoded images.

5. REFERENCES

- H. C. Reeve and J. S. Lim. "Reduction of blocking effect in image coding". *Optical Engineering*, 23(1):34–37, January 1984.
- [2] Y. Yang, N. P. Galatsanos, and A. K. Katsaggelos. "Regularized reconstruction to reduce blocking artifacts of block discrete cosine transform compressed images". *IEEE Transactions on Circuits and Systems for Video Technology*, 3(6):421– 432, December 1993.

- [3] Shigenobu Minami and Avideh Zakhor. "An optimization approach for removing blocking effects in transform coding". *IEEE Transactions on Circuits and Systems for Video Technology*, 5(2):pp.74–82, April 1995.
- [4] Yongyi Yang, Nikolas P. Galatsanos, and Aggelos K. Katsaggelos. "Projection-based spatially adaptive reconstruction of block-transform compressed images". *IEEE Transactions* on *Image Processing*, 4(7):896–908, July 1995.
- [5] Sung-Wai Hong, Yuk-Hee Chan, and Wan-Chi Siu. "The Neural Network Modelled POCS Method for Removing Blocking Effect". *IEEE International Conference on Neural Networks (ICNN'95)*, volume III, pages pp.1422–1425, November 1995.
- [6] Tai-Chiu Hsung, Daniel Pak-Kong Lun, and Wan-Chi Siu. "A Deblocking Technique for Block-Transform Compressed Image using Wavelet Transform Modulus Maxima". *IEEE Transactions on Image Processing*, (To appear).



Figure 1: Wavelet coefficients selection map (see text).

- [7] Stephane Mallat and W. L. Hwang. "Singularity detection and processing with wavelets". *IEEE Transactions on Information Theory*, 38:617–643, 1992.
- [8] Tai-Chiu Hsung and Daniel Pak-Kong LUN. "Denoising by Singularity Rejection". Proceeding of the 1997 IEEE International Symposium on Circuits and Systems, volume 1, pages 205–208, 1997.
- [9] S.W. Wu and A. Gersho. "NonLinear Interpolative Decoding of Standard Transform Coded Images and Vido". SPIE Conference on Image Processing Algorithms and Techniques III, 1657:88–99, 1992.



(a) JPEG coded lena.(20.70dB)



(b) CLS deblocked.(20.91dB)



(c) SD deblocked.(21.31dB)

Figure 2: Deblocking results for lena.