A Novel Smart Bilateral Filter for Ringing Artifacts Removal in JPEG2000 Images

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Abstract

Ringing artifacts arise near edges in highly compressed JPEG2000 images. This paper proposes original image ringing detection and suppression techniques. On the first stage edge detection and ringing estimation algorithms are applied to calculate the ringing map of a compressed input image. On the second stage this ringing map is utilized to adjust the smart bilateral filter for effectively protecting the image detail from blur effect. Experimental results show that the proposed smart bilateral filter allows to remove ringing artifacts while introducing no additional blurring and thus to increase visual quality of compressed JPEG2000 images.

Keywords: *image compression artifacts, JPEG2000, ringing, blurring, bilateral filter, ringing map*

1. INTRODUCTION

The work presented in this paper is motivated by the ringing distortion concealment for highly compressed JPEG2000 images. JPEG2000 is the latest international still image compression standard. It offers a strong compression performance with many practical features [1]. Considerable fidelity loss, namely compression ratio of about 40:1 or even 100:1, generally is acceptable in JPEG2000 compression. In this paper we propose a post-processing technique that can efficiently improve visual quality for highly compressed JPEG2000 images.

Unlike the DCT-based compression methods, JPEG2000 doesn't produce blocking artifacts, but it introduces ringing and blurring artifacts into an image. Ringing effect (Gibbs phenomenon) is caused by the quantization or truncation of the high frequency coefficients. Moreover, it appears as distortion along sharp edges in an image. Ringing artifacts are, in general, more difficult to characterize and remove than block-transform compression artifacts. Blurring is another artifact resulting from the absence of high frequencies in highly compressed images. It appears around the sharp edges, and all image details become blurred. This effect is very similar to ringing artifact, and sometimes it is hard to distinguish between them. The difference between these two effects is that they appear on different sides: horizontal or vertical (Fig. 1).

One of the main problems of ringing artifacts removal is to detect the presence of ringing effect and to estimate the necessary ringing suppression level. A few algorithms which estimate ringing and blurring level in compressed images have been proposed recently [2-6]. In [2], ringing effect is modeled by ideal low-pass filter which truncates high frequency data. Image ringing level is estimated using the analysis of ringing level of 1D normal cross-sections of image edges obtained by an edge detection algorithm. A full- and no-reference blur metric and a full-reference ringing metric are proposed in [3].

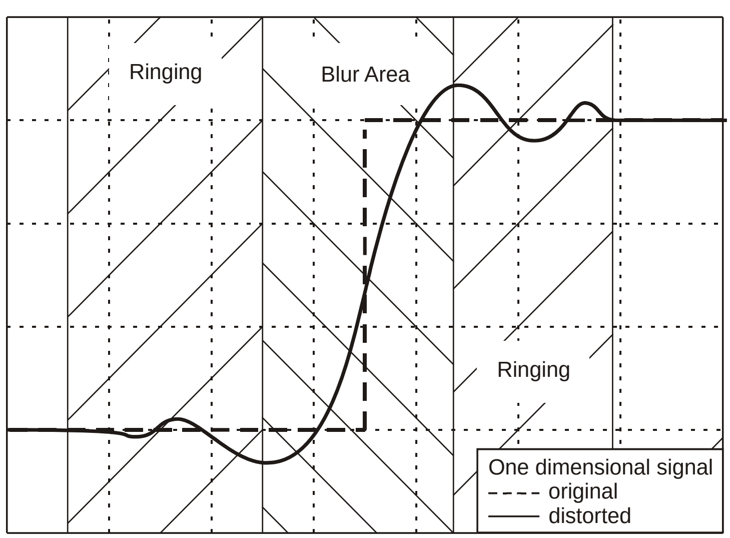

Fig. 1. Ringing and edge blur in one dimensional signal

The proposed metrics are defined in the spatial domain and are based on the analysis of the edges in an image. The ringing metric is defined as maximum of the differences between pixel values of the reference image and the processed image in the edge neighborhood. In [4], wavelet decomposition is used and ringing effect is measured for JPEG2000 compression as a difference between correlations of neighbor coefficients of different wavelet subbands. The work [5] does not introduce a ringing estimation method, but it presents an algorithm to find regions where the ringing effect is the most visible. It is based on luminance masking and texture masking as typical for the human visual system. In [6], a no-reference ringing detection method using Gabor filtering was suggested. It shows good results but it fails if image contains periodic structures like fence, geometrical textures, etc.

Several wavelet-based de-ringing algorithms have been proposed in [7-10]. Fan and Cham [7] perform edge reconstruction on wavelet-based compression images using a model-based method. However it cannot achieve image enhancement when the image carries less edge distortion or deadly distorted edges. In [8], a new edge directed filter for wavelet-based images is proposed. It adopts a Partial Difference Equations based (or PDE-based) iterative algorithm. The method can get image quality enhancement, although the computation cost is high. Nosratinia [9] employs further compression to the shifted versions of the received image and selectively cuts off the high frequency signal of them. In [10], adaptive nonlinear filtering method to reduce ringing artifacts in the received image is proposed. The coefficients around edge areas are selectively processed in spatial domain and each decomposition level. The shift variance character of decimated wavelet transform in JPEG2000 is utilized. Several shift versions of the received images are used to estimate the variance of the compression noise.

The problem of image de-ringing after JPEG2000 compression is also considered in [11-15]. The de-ringing algorithm proposed in [11] utilizes a quad-tree partitioning scheme for post-processing the reconstructed image in a spatially varying manner. Voting strategy is used to determine a set of morphological filters for reducing the ringing artifacts. In [12], each pixel value is replaced with a function of the values of neighboring pixels that are within a specified window. To avoid conflict with the above goal, that is smooth shade regions and sharp edges, the de-ringing algorithm uses a number of adaptive noise reduction algorithms. In [13], binary morphological operators are used to isolate the regions of an image where the ringing artifact is most prominent to the human visual system. Then a gray-level morphological nonlinear smoothing filter is applied to the unmasked regions of the image under the filtering mask to eliminate ringing within the constraint region. An adaptive nonlinear diffusion method to reduce ringing artifacts is proposed in [14]. The diffusion coefficient is defined as the linear combination of three membership functions that correspond to the different gradient scales. The parameters are tuned using a stochastic optimization technique so that the diffusion coefficient can adapt to the given image data to achieve better restoration performance. In [15], a maximum likelihood approach to the ringing artifact removal problem is presented. It employs a parameter estimation method based on the k-means algorithm with the number of clusters determined by a cluster separation measure.

Despite the fact that essential progress has been reached, the problem of ringing artifact removal still remains actual. None of the proposed no-reference ringing estimation metrics can effectively detect ringing artifacts and measure their level in general case. Most of the proposed ringing reduction schemes introduce additional blurring into processed images. Others have too high computational cost. That's why we propose ringing detection and ringing removal algorithms which are deprived of the described above lacks. Our scheme achieves ringing reduction while preserving the same level of blurring artifacts.

The rest of the paper is organized as follows. In section 2, we introduce a blurring estimation metric. In section 3, we introduce a method of ringing level estimation in compressed JPEG2000 images. In section 4, we propose the smart bilateral filter for ringing artifacts removal. In section 5, we present experimental results of applying of the proposed filter. Section 6 concludes the paper.

2. BLURRING METRIC CALCULATION

JPEG2000 encoder uses separable wavelet transform with biorthogonal Daubechies 9/7 wavelet-basis [1] for image compression. This transform is applied consistently first to rows and then to columns of an image. That's why it is quite enough to consider the influence of JPEG2000 compression algorithm only on image rows.

Let's consider an image row $\{x_1, x_2, ..., x_N\}$, where x_i – image pixel luminance value. To detect edges on this row we apply Sobel filter. The result of this operation is a set of values $\{p_1, p_2, ..., p_K\}$, where $K < N$, which indicates the position of edges in the row.

For each point p_k we find the location of the local luminance extrema closest to the left – l_k, and the local luminance extrema closest to the right – r_k. The local blur metric for one edge we define as $w_k = r_k - l_k$. Edge width on an image is numerically equal to w_k.

The Blurring Metric (BM) of an image we then define as the average value of local blur metrics calculated for each of M rows:

$$BM = \frac{\sum_{j=1}^{M}\sum_{k=1}^{K} w_{k,j}}{\sum_{j=1}^{M} K_j}. \tag{1}$$

On the basis of experimental results the top threshold value of the blurring metric, which is not exceeded for natural compressed images, has been calculated. Taking this threshold value into account, normalized blurring measure has the following form:

$$0 \le \frac{BM}{20} \le 1. \tag{2}$$

The proposed algorithm lends itself to both a full-reference and a no-reference implementation. The difference between them is that a set of values $\{p_1, p_2, ..., p_K\}$, indicating the position of edges, is calculated for original images in the case of full-reference metric, and for decoded images in the case of no-reference metric.

3. RINGING METRIC CALCULATION

The results acquired on the stage of blurring level estimation are used to construct the ringing metric. Let's define the local ringing metric for the edge with position p_k as:

$$(w_{ring})_k = \left|\max(x_i - \tilde{x}_i) - \min(x_i - \tilde{x}_i)\right| \times \left|w_f - l_k\right| + \\ + \left|\max(x_j - \tilde{x}_j) - \min(x_j - \tilde{x}_j)\right| \times \left|w_f - \mathrm{r}_k\right|, \quad (3) \\ i \in \left[p_k - w_f, l_k\right], \\ j \in \left[r_k, p_k + w_f\right],$$

where x_i – original image pixel luminance value, $\tilde{x}_i$ – decoded image pixel luminance value, w_f – the fixed ringing width which was acquired during the analysis of distortion factors influence on the ideal signal. On the contrary to the blurring metric's calculation, the point p_k must be located strictly in the middle of the edge, i.e. $|l_k - p_k| = |r_k - p_k|$.

To estimate the total ringing level we calculate the average value of received local ringing metrics. The sum is taken only over those p_k for which local ringing exists. In this case, the resulting Ringing Metric (RM) will show the amplitude of ringing artifacts, taking into account the size of a region where they appear, and will not depend on other types of distortions:

$$RM = \frac{\sum_{j=1}^{M}\sum_{k=1}^{K}(w_{ring})_{k,j}}{\sum_{p_k} 1}. \quad (4)$$

On the basis of experimental results the top threshold value of the ringing metric, which is not exceeded for JPEG2000 compressed images, has been calculated:

$$0 \le \frac{RM}{512} \le 1. \quad (5)$$

As the ringing estimation algorithm uses the original image, it supposes only full-reference implementation. It is necessary to note that the ringing metric includes all operations for the blurring metric's calculation.

4. SMART BILATERAL FILTER FOR RINGING REDUCTION

Let's consider the influence of bilateral, median and linear low-pass filters on ringing artifacts. We define the level of ringing artifacts reduction as the percentage difference between the ringing metric value before filtration and the ringing metric value after filtration. By averaging the level of ringing artifacts reduction on the whole test set (10 images); we acquire the average level of ringing artifacts reduction. Results of this test for each filter are presented in Table 1. Here CR stands for Compression Ratio of test images.

Results of filter comparison show that the best reduction of ringing artifacts can be acquired by the use of bilateral filter. However, the visual and numerical analysis of the processed images shows that bilateral filter introduces the greatest amount of blurring into an image. For elimination of this lack we will try to modify the scheme of bilateral filter, and to process not the whole image and even not all edges but only those fragments of an image where ringing is really visible. Actually it is necessary to construct a ringing map for an image and then to filter only those pixels which belong to this map.

On the first stage we detect all edges on the decoded image and find segments $\left[p_k - w_f/2, l_k\right) \cup \left(r_k, p_k + w_f/2\right]$ for each location of p_k. Each segment should be plotted on a map – an empty image with the same size as the input image.

As the ringing metric considers only vertical edges, we apply the same operations to horizontal edges. For this purpose we apply horizontal Sobel filter and find p_k for each column of input image. Then we consider the transposed column of the image, find segments for each p_k and plot them on the corresponding columns of the ringing map. It is necessary to note that acquired ringing map will contain vicinities of edges which are subject to blurring. Filtration of these areas will inevitably cause blurring increase. Hence we should delete vicinities of edges from the ringing map to preserve the level of blurring in the input image. To carry it out we unite all areas on which the blurring metric is calculated and subtract the received set of points from the ringing map.

Table 1. Ringing level reduction using low-pass filters

Filter	The average level of ringing artifact reduction **(%)**				
	CR=25	CR=35	CR=50	CR=75	CR=100
Bilateral	**6.83**	**11.49**	**13.76**	**14.01**	**15.69**
Median	5.37	8.52	9.88	9.84	10.70
Linear	3.29	6.17	7.90	8.15	8.76

Thus, the ringing map will contain pixels subject to ringing and will not contain pixels subject to blurring. The ringing map, containing areas of horizontally and vertically directed ringing, is imposed on an image. Examples of the ringing map calculated for several test images are presented in Fig. 2.

On the next stage of the proposed ringing reduction scheme we perform image filtration by bilateral filter. Filter mask is applied only to those pixels which belong to the ringing map. Let's define this algorithm as smart bilateral filter. The described scheme of image processing is presented in Fig. 3.

Fig. 2. Ringing maps for compressed test images (CR=17) "Barbara" (left), Scarlett (center), Peppers (right)

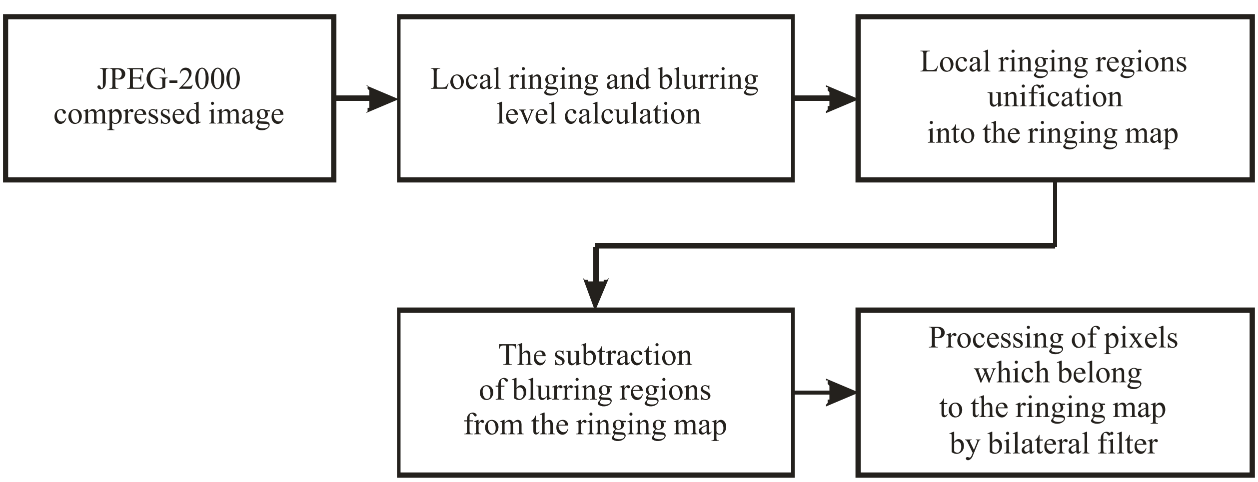

Fig. 3. Ringing detection and reduction algorithm

Smart bilateral filter has same parameters as classic bilateral filter [16, 17]: the mask size w, spatial mean square displacement σ_s, and luminance mean square displacement σ_i. For the purpose of testing, these parameters have been fixed to the following values: w=5, σ_s=3, σ_i=0.5. Pixel luminance values have been preliminary normalized to be distributed inside a segment [0, 1].

5. EXPERIMENRAL RESULTS

Comparative results of bilateral and smart bilateral filtering for test images "Lenna" and "Baboon", concerning the proposed ringing and blurring metrics, are presented in Fig. 4. The received diagrams show that in the case of low compression (CR<20), the ringing reduction procedure leads to the opposite effect – natural fluctuations of luminance are blurred by bilateral filter. The growth of the ringing metric indicates that the algorithm's application is incorrect in the case of low compression. Filtration of highly compressed images by smart bilateral filter gives high level of ringing suppression with preservation of the same level of blurring. Smart bilateral filter efficiency increases for highly detailed images (such as "Baboon"). At the same time filtration by classic bilateral filter leads to the substantial growth of blurring in images and a slightly higher level of ringing suppression.

Evaluation of the proposed algorithm by standard quality metrics such as peak signal-to-noise ratio (PSNR) shows that classic bilateral filter reduces image quality compared to smart bilateral filter (Fig. 5). This is explained by the fact that classic bilateral filter removes ringing artifacts not by smoothing fluctuations of luminance but by blurring image edges.

Experimental results show that computing complexity of smart bilateral filter compared to that of bilateral filter decreases with the increase of image size (Fig. 6). For an image with 768 rows smart bilateral filter works 1.5 times faster compared to classic bilateral filter and for an image with 1024 rows – 2 times faster.

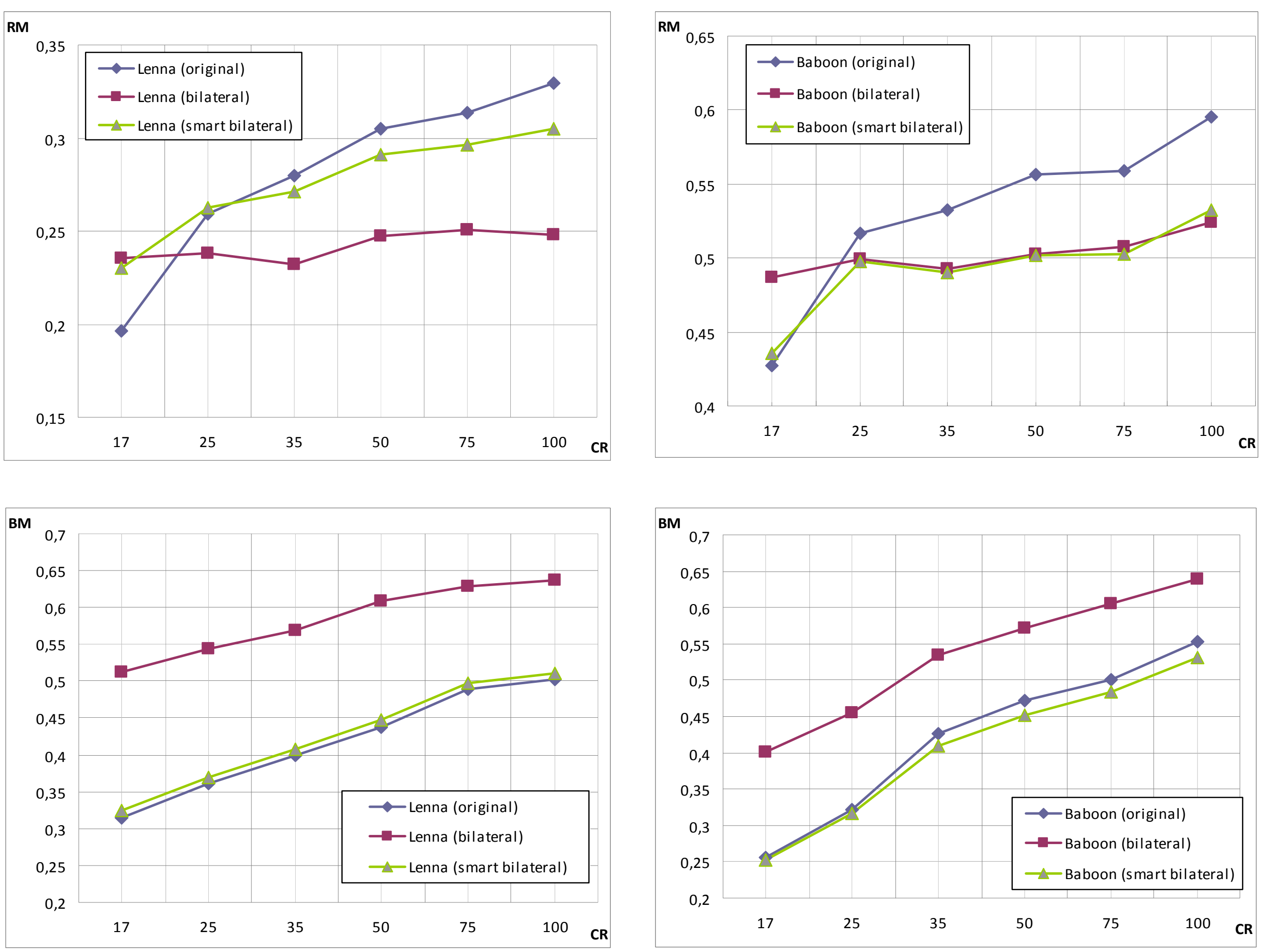

Fig. 4. Bilateral and smart bilateral filtration comparative results for "Lenna" and "Baboon" compressed images

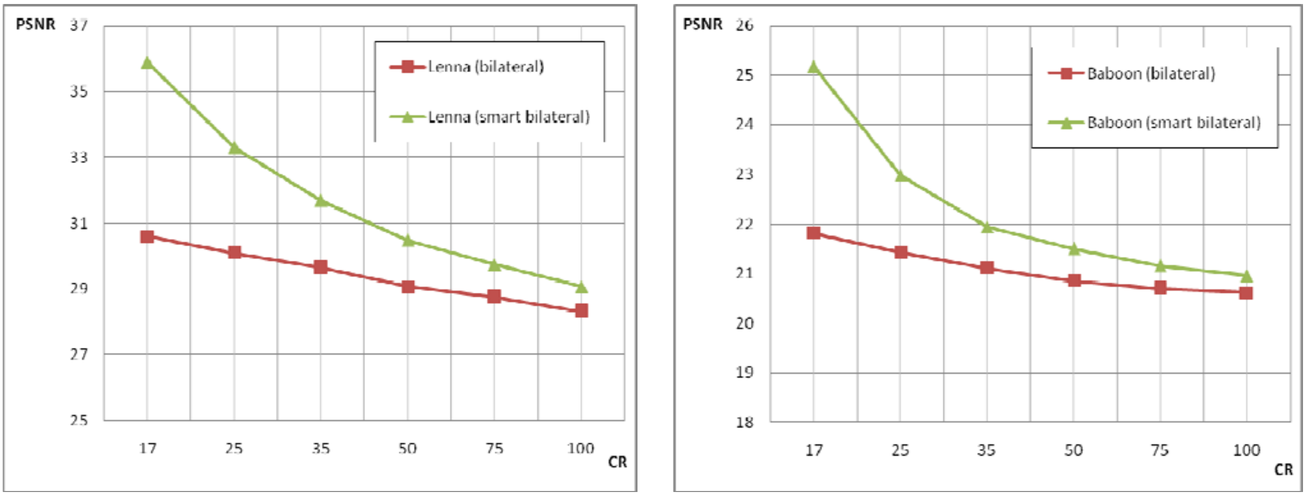

Fig. 5. Peak signal-to-noise ratio for “Lenna” and “Baboon” images processed by bilateral and smart bilateral filters

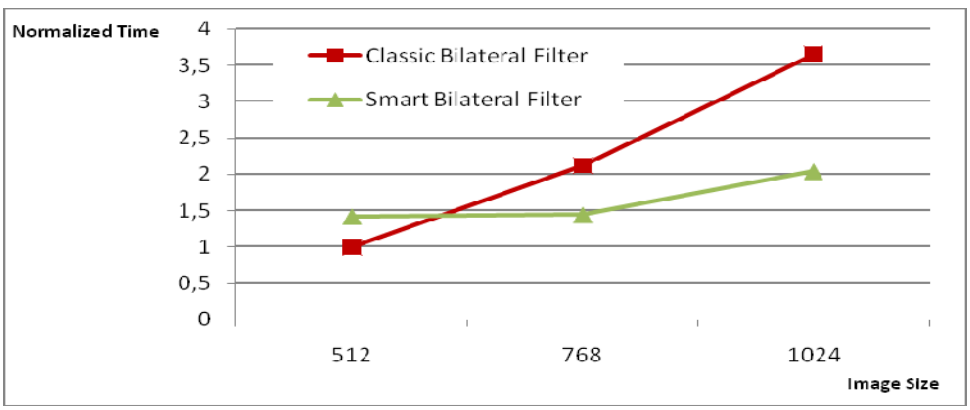

Fig. 6. Computing complexity comparison of bilateral and smart bilateral filtration

6. CONCLUSIONS

Blurring and ringing distortions have strong nonlinear dependence from each other. Suppression of one of these types of distortions by standard filters can lead to the growth of another type. Therefore there is an important problem of ringing artifacts reduction with the preservation of the level of compressed image blurring.

The proposed smart bilateral filter gives the solution of this problem in application to JPEG2000 images. The application of classic bilateral filter to the whole image requires much more time than the application of smart bilateral filter to image fragment belonging to the ringing map. Therefore computing complexity of smart bilateral filter is lower even taking into account calculations we perform to acquire the ringing map.

7. ACKNOWLEDGMENT

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