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An Optimized Algorithm For Ringing Region Detection In Compressed Images

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ABSTRACT

In current visual communication systems, the most essential task is to fit a large amount of visual information into the narrow bandwidth of transmission channels or into a limited storage space, while maintaining the best possible perceived quality for the viewer this is called compression, compression is useful because it helps reduce the consumption of expensive resources, such as hard disk space or transmission bandwidth. The occurrence of the compression induced artifacts depends on the data source, target bit rate, and underlying compression scheme, and their visibility can range from imperceptible to very annoying, thus affecting perceived quality In the last decades, a considerable amount of research has been devoted to the development of a blockiness metric, which has been already implemented for the optimization of image quality. Another common distortion type, namely ringing, intrinsically results from loss in the high-frequency component of the video signal due to coarse quantization. In the video chain of a current television set, e.g., various video enhancement algorithms, such as deblocking, deringing, and deblur, are typically employed to reduce compression artifacts prior to display An efficient approach toward a no-reference ringing metric intrinsically exists of two steps: first detecting regions in an image where ringing might occur, and second quantifying the ringing annoyance in these regions. In this direction an efficient algorithm for automatic detection of regions visually impaired by ringing artifacts in compressed images is presented. The proposed system will be implemented in MATLAB for its realization.

Keywords —**Luminance masking, perceptual edge, ringing metrics, texture masking .**

1. INTRODUCTION

Until recently, only a limited amount of research was devoted to perceived ringing. The methods in and both simply assume that ringing occurs unconditionally in regions surrounding strong edges in an image. This, however, does not always reflect human visual perception of ringing, because of the absence of spatial masking as typically present in the HVS. This issue is taken into account by incorporating properties of the HVS into the detection method. The approach in is based on the global edge map of an image, where binary morphological operators are used to generate a mask to expose regions that are likely to be contaminated with visible ringing artifacts. This procedure involves the identification of regions around all detected edges, and a further evaluation of these regions based on visual masking. A different way of including HVS masking properties is employed. This method classifies the potential smooth regions (i.e., regions in an image other than edges and their surroundings) into different objects based on their color similarity and texture features. The resulting objects are assigned as background around potential ringing regions. Texture masking is implemented by evaluating the contrast in activity between the potential ringing region and its assigned background (e.g., the higher the contrast in activity, the more visible ringing is assumed to be). Additionally, also luminance masking is implemented to further determine ringing visibility. There are two main concerns with the methods existing in literature. First of all, the edge detection methods employed to capture strong edges using an ordinary edge detector, such as a Sobel operator, where a certain threshold is applied to the gradient magnitudes to remove noise and insignificant edges. Depending on the choice of the threshold, these methods run the risk of omitting obvious ringing regions near nondetected edges (in case of a high threshold) or of increasing the computational power by modeling the HVS near irrelevant edges (in case of a low threshold). Fig. 3 illustrates the effect of the threshold value of a Sobel operator. The edge map in Fig. 3(c), resulting from a high threshold value, largely removes noisy edges while eliminating a number of important edges, at which ringing obviously exists [see Fig. 3(b)]. This may heavily degrade the accuracy of the prediction of perceived ringing. By lowering the threshold [as in Fig. 3(d)], all strong edges are maintained in the edge map, but it also contains more texture edges, which are nonrelevant to ringing detection, and consequently, result in a large number of unnecessary computations for ringing visibility. The second concern with the existing methods is related to the models of the HVS used, which are computationally very expensive. The HVS model involves a parameter estimation mechanism, which requires a number of calculations to achieve an optimal selection. The major cost of the HVS model is introduced by its clustering scheme embedded, which contains color clustering and texture clustering. Obviously, the optimal performance in terms of reducing the number of required computations, while maintaining the reliable detection of perceived ringing, can be achieved by optimizing two aspects: 1) the detection accuracy of relevant edges; and 2) the reduction in complexity of the HVS model itself. Hence, what is needed is an edge detector that only extracts edges most closely related to the occurrence of ringing, and a HVS model that is simpler (and thus more applicable for realtime implementation) than the approaches existing in literature. In this work, both aspects needed to efficiently detect regions with visible ringing are discussed. Our method mainly consists of two parts: 1) extraction of edges relevant for ringing, and 2) detection of visibility of ringing in the edge regions.

2. BACKGROUND

2.1. Perceived Ringing Artifacts

2.1.1 *Physical Structure*

Current image and video coding techniques are based on lossy data compression, which contains an inherent irreversible information loss. This loss is due to coarse quantization of the image's representation in the frequency domain. The loss within a certain spectral band of the signal in the transform domain reveals itself most prominently at those spatial locations where the contribution from this spectral band to the overall signal power is significant . Since the high-frequency components play a significant role in the representation of an edge, coarse quantization in this frequency range (i.e., truncation of the high-frequency transform coefficients) consequently results in apparent irregularities around edges in the spatial domain, which are usually referred to as ringing artifacts. More specifically, ringing artifacts manifest themselves in the form of ripples or oscillations around high-contrast edges in compressed images. They can range from imperceptible to very annoying, depending on the data source, target bit rate, or underlying compression scheme .As an example, Fig. 1 illustrates ringing artifacts induced by JPEG compression on a natural image.

The occurrence of ringing spreads out to a finite region surrounding the edges, depending on the specific implementation of the coding technique. For example, in discrete cosine transform (DCT) coding ringing appears outwards from the edge up to the encompassing block's boundary . An

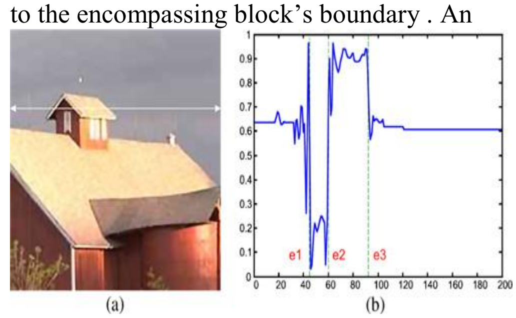


Fig. 1. Illustration of ringing artifacts.

(a) Natural image compressed with JPEG (MATLAB's imwrite function with "quality" of 30). (b) Gray-scale intensity profile along one row of the compressed image [indicated by the solid double arrowhead line in (a)]. Dashed lines "e1," "e2," and "e3" indicate the position of the sharp intensity transitions (i.e., edges) along that arrow. Ringing can be perceived as fluctuations in the gray-scale values around the edges at "e1," "e2," and "e3," while the image content here should be uniform.

example of how to calculate the extent of the ringing region in a particular codecs is given in . In addition to the edge location dependency, the behavior of ringing also depends on the strength of the edges. It is found in and that, over a wide range of compression ratios, the variance of the ringing artifacts is proportional to the contrast of the associated edge. These important findings have great potential in the design of a reliable ringing metric, and therefore, are explicitly adopted in our algorithm.

2.1.2 Masking of the HVS

Taking into account the way the HVS perceives artifacts, while removing perceptual redundancies, can be greatly beneficial for matching objective artifact measurement to the human perception of artifacts. Masking designates the reduction in the visibility of one stimulus due to the simultaneous presence of another, and it is strongest when both stimuli have the same or similar frequency, orientation, and location . It is basically due to the limitations in sensitivity of a certain cell or neuron at the retina in relation to the activity of its surrounding cells and neurons. There are two fundamental visual masking effects highly relevant to the perception of ringing artifacts . The first one is luminance masking, which refers to the effect that the visibility of a distortion (such as ringing) is maximum for medium background intensity, and it is reduced when the distortion occurs against a very low or very high intensity background . This masking phenomenon happens because of the brightness sensitivity of the HVS, where the average brightness of the surrounding background alters the visibility threshold of a distortion . The second masking effect is texture masking, which refers to the observation that a distortion (such as ringing) is more visible in homogenous areas than in textured or detailed areas . In textured image regions, small variations in the texture are masked by the macro properties of genuine high-frequency details, and therefore, are not perceived by the HVS. The effect of luminance and texture masking on ringing artifacts is illustrated in Figs. 2 and 3, respectively.

2.2. Existing Ringing Metrics

Until recently, only a limited amount of research effort was devoted to the development of a ringing metric. Some of these

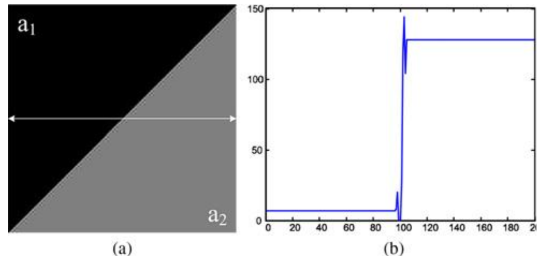


Fig. 2. Example of luminance masking on ringing artifacts.

(a) Image patch compressed with JPEG (MATLAB’s imwrite function with “quality” of 30). (b) Pixel intensity profile along one row of the compressed image patch [indicated by the solid double arrowhead line in (a)]. Original image includes two adjacent parts with different gray-scale levels (i.e., 5 for “a1” and 127 for “a2”). Note that although both sides of a step edge exhibit ringing artifacts, the visibility of ringing differs.

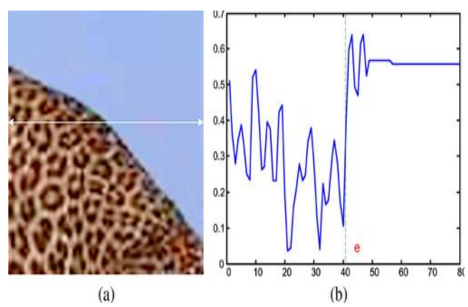


Fig. 3. Example of texture masking on ringing artifacts. (a) Image patch extracted from a JPEG compressed image of bit rate 0.59 bits per pixel (b/p). (b) Pixel intensity profile along one row of the compressed image patch [indicated by the solid double arrowhead line in (a)]. Dashed line “e” indicates the object boundary edge. Note that although both sides of the edge at “e” exhibit ringing artifacts, the visibility of ringing differs.

metrics are FR, others NR. A FR approach presented in starts from finding important edges in the original image (noise and insignificant edges are removed by applying a threshold to the Sobel gradient image), and then measures ringing around each edge by calculating the difference between the processed image and the reference. Since this metric needs the original image, it has its limitations, e.g., for the application in a TV chain. The NR ringing metric, proposed in , performs a anisotropic diffusion on the image and measures the noise spectrum filtered out by the anisotropic diffusion process. The basic idea behind this metric is that due to the effectiveness of anisotropic diffusion on deringing, the artifacts would be mostly assimilated into the spectrum of the filtered noise. The NR ringing metric described in indentifies the ringing regions around strong edges in the compressed image, and defines ringing as the ratio of the activity in middle low over middle high frequencies in these ringing regions. An obvious shortcoming of the metrics defined in and is the absence of masking, typically occurring in the HVS, with the consequence that these metrics do not always reflect perceived ringing. Typical masking characteristics, such as luminance and texture masking, are explicitly considered in the metrics defined in [and, in which ringing regions are no longer simply assumed to surround all strong edges in an image, but are determined by a model of the HVS. Including a HVS model in an objective metric might improve its accuracy, but often is computationally intensive for real-time applications. For example, the HVS model used in the metric presented in largely depends on a parameter estimation procedure, which requires a number of calculations to achieve an optimal selection. The model described in is based on a computationally heavy clustering scheme, including both color clustering and texture clustering. From a practical point of view, it is highly desirable to reduce the complexity of the HVS-based metric without compromising its overall performance.

The essential idea behind most of the existing metrics mentioned so far is that they consist of a two-step approach. The first step identifies the spatial location, where perceived ringing occurs, and the second step quantifies the visibility or annoyance of ringing in the detected regions. This approach intrinsically avoids the estimation of ringing in irrelevant regions in an image, thus making the quantification of ringing annoyance more reliable, and the calculation more efficient. Additionally, a local determination of the artifact metric provides a spatially varying quality degradation profile within an image, which is useful in, e.g., video chain optimization as mentioned in Section I. Since ringing occurs near sharp edges, where it is not visually masked by local texture or luminance, the detection of ringing regions largely relies on an edge detection method followed by a HVS model. Existing methods usually employ an ordinary edge detector, where a threshold is applied to the gradient image to capture strong edges. Depending on the choice of the threshold, this runs the risk of omitting obvious ringing regions near nondetected edges (e.g., in case of a high threshold) or of increasing the computational cost by modeling the rather complex HVS near irrelevant edges (e.g., in case of a low threshold). This implies that to ensure a reliable detection of perceived ringing while maintaining low complexity for real-time applications, an efficient approach for both detecting relevant edges and modeling the HVS is needed. Quantification of the annoyance of ringing in the detected areas can be easily achieved by calculating the signal difference between the ringing regions and their corresponding reference, as used in the FR approach described in. However, for a NR ringing metric, the quantification of ringing becomes more challenging mainly due to the lack of a reference. Metrics in literature estimate the visibility of ringing artifacts from the local variance in intensity around each pixel with in the detected ringing regions, and average these local variances over all ringing regions to obtain an overall annoyance score. This approach, however, has limited reliability, since it does not include background texture in the ringing regions, which might affect ringing visibility. To validate the performance of a ringing metric, its predicted quality degradation should be evaluated against subjectively perceived image quality. To prove whether a ringing metric is robust against different compression levels and different image content, the correlation between its objective predictions and subjective ringing ratings must be calculated. Unfortunately,

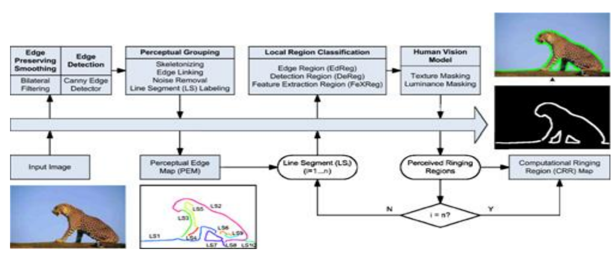
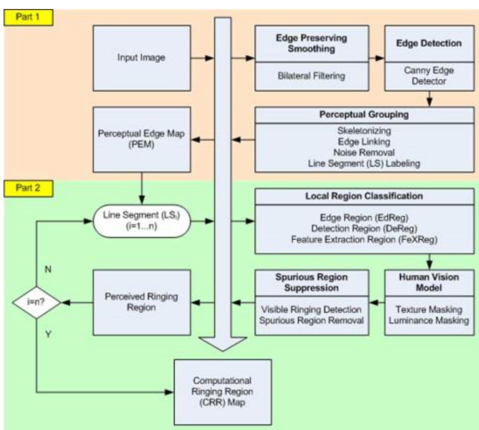


Fig. 4. Schematic overview of the proposed ringing region detection method.

In PEM, each perceptually relevant LS is labeled in a different color. In the CRR map, the white areas indicate the detected perceived ringing regions, and the spatial location of these regions is illustrated in a separate image by green areas. only the performance of the metric reported in is evaluated against subjective data of perceived ringing. For all other metrics nothing can be concluded with respect to their performance in predicting perceived ringing. Since we had no access to the data used in for our metric evaluation, we performed our own subjective experiment.1

In this paper, we propose a NR ringing metric based on the same two- step approach mentioned above. For the first step, we rely on our ringing region detection method , the performance of which in terms of extracting regions with perceived ringing has been shown to be promising . Therefore, we consider this part of the metric readily applicable for the second step, in which the ringing annoyance is quantified. To quantify ringing annoyance, we consider each detected ringing region as a perceptual element, in which the local visibility of ringing artifacts is estimated. The contrast in activity between each ringing region and its corresponding background is calculated as the local annoyance score, which is then averaged over all ringing regions to yield an overall ringing annoyance score. It should be noted that the proposed metric is built upon the luminance component of images only in order to reduce the computational load. The performance of the NR metric is evaluated against subjective ringing annoyance in JPEG compression.

3. PROPOSED ALGORITHM



Our method mainly consists of two parts: 1) extraction of edges relevant for ringing, and 2) detection of visibility of ringing in the edge regions.

3.1 PERCEPTUAL EDGE EXTRACTION

3.1.1 Edge Preserving Smoothing and Canny Edge Detection

When interpreting the surrounding world, humans tend to respond to differences between homogeneous regions rather than to structure within these homogeneous regions. Hence, finding perceptually strong edges mainly implies that texture existing in homogenous regions can be neglected as if viewed from a long distance. This can be implemented by smoothing the image progressively until textual details are significantly reduced, and then applying an edge detector. Traditional low-pass linear filtering (e.g., Gaussian filtering) smoothens out noise and texture, but also blurs edges, and consequently, changes their spatial location. Since ringing detection intrinsically requires accurate spatial localization of the edges, edge-preserving smoothing is needed. Bilateral filtering was introduced in as a simple and fast scheme for edge-preserving smoothing. . The advantage of using bilateral filtering instead of Gaussian filtering for the localization specific detection of perceptually strong edges. Canny edge detector is applied to the bilaterally filtered image to obtain the perceptually more meaningful edges. Since the input image is already filtered, the subsequent Canny algorithm is implemented without its inherent smoothing step, while keeping the other processing steps unchanged. The Canny edge detector uses two thresholds to detect strong and weak edges, and includes the weak edges in the output only if they are connected to strong edges. Their values is automatically set, depending on the image content .

3.1.2 Perceptual Edge Map Formation

Since the HVS does not perceive luminance variations at pixel level, the detected edge pixels are necessarily combined into perceptually salient elements, facilitating further analysis and processing. These perceptual elements, which we refer to as line segments (LS), are constructed over the Canny edge map and will be used as the basis for ringing region detection. The four steps are implemented to define the LS in the PEM.

Skeletonizing, Edge Linking , Noise Removal and Line Segment Labeling.

3.2. Ringing Region Detection

Each LS of the PEM is examined individually on the occurrence of visible ringing artifacts in their direct neighborhood, taking into account luminance and texture masking.

3.2.1 Local Region Classification

In order to characterize the visibility of ringing around a LS, its surrounding is classified into three different zones. Edge Region , Detection Region and Feature Extraction Region. These regions are defined by thickening the LS with a different size for the structuring element of a dilation operation.

3.2.1.1 Human vision model

Whether ringing is actually visible in the DeReg strongly depends (because of masking in the HVS) on the content of the original background, here represented by the FeXReg. Hence, the visibility of ringing is evaluated for each LS by applying a model for texture and luminance masking, using the texture and luminance characteristics of the FeXReg. As a result, DeReg regions, in which ringing is visually masked are eliminated, and only the perceptually prominent DeReg ringing regions remain.

3.2.1.2 Texture Masking

The visibility of ringing is significantly affected by the spatial activity in the local background, i.e. ringing is masked when located in a textured region, while it is most visible against a smooth background . Texture masking is modeled classifying the FeXReg of each detected edge segment into "smooth" and "textured" parts. The DeReg is segmented accordingly, and only the regions of which the corresponding FeXReg is clustered as "smooth" are retained. removing the corresponding texture regions in DeReg. Hence, the remaining regions of DeReg are only smooth regions around the detected strong edges.

3.2.1.3 Luminance Masking

The visibility of variations in luminance depends on the local mean luminance. As a result, the visibility of ringing is largely reduced in extremely dark or bright surroundings. The implementation of luminance masking is the same as for texture masking, but to guarantee efficiency, it is only applied to those regions of the DeReg remaining after the application of texture masking. Classifying the "smooth objects" of FeXReg further into "visible objects" and "invisible objects" depending on the invisible components. Removing the DeReg that correspond to "invisible objects," i.e., where ringing is not supposed to be visible against a very low or very high intensity background. Ultimately, only the regions of DeReg that yield visible ringing remain.

3.2.1.4 Spurious Ringing Region Suppression

The ringing region detection method described so far only exposes regions in an image which are likely to be impaired corresponding to (b) a JPEG compressed image.

by visible ringing artifacts. The resulting CRR map, however, still includes obvious spurious ringing regions, containing either "unimpaired" or "noisy" pixels misinterpreted as ringing pixels.

The occurrence of "unimpaired" pixels is in an uncompressed image. The ringing region detection algorithm described so far will find the regions that might be impaired with visible ringing, independent of the compression level. But in an uncompressed image, these regions do not contain visible ringing, and hence, should be removed from the CRR map. Note that without removal of these regions the overall objective ringing metric including the step of quantification of ringing annoyance would not be less accurate, but less efficient.

"Noisy pixels" are pixels in the detected regions of the CRR map, that actually belong to an edge or texture. They are accidentally misclassified to a ringing region as a consequence of the dilation operation used in the human vision model. To remove the spurious ringing regions, each detected ringing region (RR) is further examined by calculating its amount of visible ringing pixels. Those RRs with their number of visible ringing pixels below a certain threshold are considered as spurious, and consequently removed from the CRR map

4. RESULTS AND OBSERVATIONS

Original Image

Bilateral Filtered Image

Bilateral - Canny Edge

Noise Removal

Skeletonizing

Edge Linking

5. CONCLUSION

A novel approach toward the detection of perceived ringing regions in compressed images is presented. The algorithm relies on the compressed image only, which is promising for its applicability in a real-time video chain, e.g., to enhance the quality of artifact impaired video. It adopts a perceptually more meaningful edge detection method for the purpose of ringing region location. This intrinsically avoids the drawback of applying an ordinary edge detector, which has the risk of omitting obvious ringing artifacts near non detected edges or of increasing the computational cost by measuring ringing visibility near irrelevant edges. The objective detection in agreement with human visual perception of ringing artifacts is ensured by taking into account typical properties of the human visual system, such as texture masking and luminance masking. The human vision model is implemented, based on the local image characteristics around detected edges, to expose only the perceptually prominent ringing regions in an image. The proposed detection method is validated with respect to ringing regions resulting from a psychovisual experiment, and shows to be highly consistent with subjective data. The proposed ringing region detection method is meanwhile extended with a ringing annoyance metric that can quantify perceived ringing annoyance of compressed images.

6. FUTURESCOPE

In most visual surveillance systems, stationary cameras are typically used. However, because of inherent changes in the background itself, such as fluctuations in monitors and fluorescent lights, waving flags and trees, water surfaces, etc. the background of the video may not be completely stationary. In these types of backgrounds, referred to as quasi-stationary, a single background frame is not useful to detect moving regions.

Detecting regions of interest in video sequences is one of the most important tasks in many high level video-processing applications. In the future scope of this work we have to design a system, which detects foreground regions in videos with quasi-stationary backgrounds. The main contribution should be the novelty detection approach, which automatically segments video frames into background/foreground regions. By using support vector data description for each pixel, the decision boundary for the background class is modeled without the need to statistically model its probability density function. The proposed method is able to achieve very accurate foreground region detection rates even in very low contrast video sequences, and in the presence of quasi-stationary backgrounds.

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