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Image Distortion Inference based on Correlation between Line Pattern and Character

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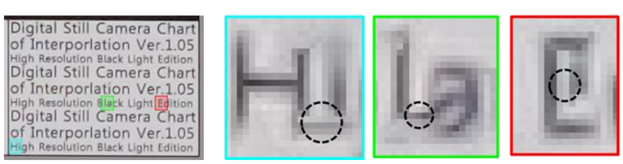
Abstract

Samsung introduced pixel-merging technologies such as Tetrapixel, and these enabled the mobile image sensors to reproduce colors properly depend on light conditions. High resolution image can be acquired when in well-lit area, by reorganize colors on the color filter array to RGB Bayer pattern. The aforementioned process is called remosaic algorithm, based on estimating direction information. It causes some artifacts on edges with various or unclear direction, for example in text-image, especially at high spatial frequencies. We focused on such artifacts caused by remosaicing, and proposed suitable image quality metric that can measure a degree of the artifacts.

Introduction

As market demands for mobile image sensor with high resolution increase in recent years, Samsung introduced pixel-merging technologies such as Tetrapixel and Nonapixel. These require Remosaic algorithm to reorganize colors on the color filter array (CFA) to RGB Bayer pattern for common image signal processor (ISP) input format. Because the remosaicing is based on detecting directions of edges, it managed to interpolate to Bayer pattern at middle/low spatial frequencies. However, it is difficult to estimate the direction of edges at high frequencies due to various artifacts such as loss of detail, moire, false colors and so on. There are a few existing metrics for measuring image quality based on well-known charts but most of them deal with artifacts globally, e.g. acutance, color distance.

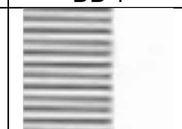
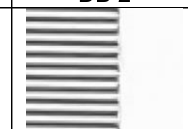
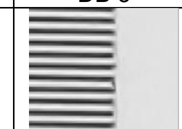
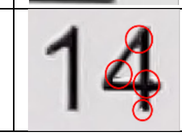


(a) **(b)**

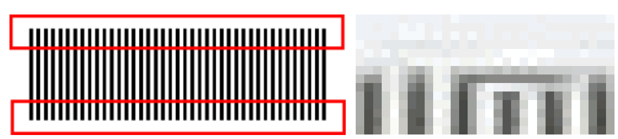
Figure 1*. Edge artifacts within text region of an image: (a) Fuziki chart. (b) Examples of degraded regions.*

Most people can easily notice edge artifacts within text region of images, as they already know the original shapes of characters. Fig. 1 shows an example of a text-image and the artifacts on some letters. It can be seen that alphabet ‘H’ and ‘i’ are abnormally connected. On the other hand, ‘E’ has an ill-defined horizontal line. To the best of our knowledge, these artifacts are due to the above remosaicing and can be made worse by other post processing (e.g. sharpening). In our another experiment (Table 1), we found out that those shrunk or connected edges occurred in not only the text patch but also simple line patterns with same image sensor. In this case DB 1 is the best and DB 3 is the worst in terms of a degree of the edge artifacts.

Table 1. Co-occurrence of edge artifacts on ISO12233 chart image

	DB 1	DB 2	DB 3
Region 1			
Region 2			

Since edges contain useful information about an image, there have been many studies to analyze them from various perspectives. In the field of image quality, edges are utilized for assessing image sharpness (e.g., spatial frequency response (SFR) and modulation transfer function (MTF)) [3]. These metrics are inappropriate for the edge artifacts that need to be locally analyzed. So we focused on measuring local edge artifacts caused by the remosaicing. To simplify the problem, an ideal line pattern that the artifacts can be easily identified is used instead of a text patch. In several test, most edge artifacts usually appeared near the upper and lower edges of the line patterns. This is because estimating direction of edges accurately during the remosaicing is difficult in those areas.



(a) **(b)**

Figure 2. *Line pattern for measuring the edge artifacts: (a) Ideal pattern, (b) Degraded pattern in an actual image.*

Given the nature of the artifacts, a region of interest (ROI) is set as shown in Fig. 2 (a). We only focused on the shapes of the edges not about false colors introduced by remosacing, so the input images are converted to grayscale. In all of our experiments, the width of the line patterns is about 100~200 pixels according to the image sensors (108 or 200 megapixels). Although we set the line patterns for four directions (horizontal, vertical, forward slash and backslash), all of the patterns are currently horizontal-aligned (Fig. 2 (a)). Typically, there are two types of the artifacts on line patterns that shrunk or connected lines (Fig. 2 (b)). Some artifacts in other real images are hard to be categorized, so we do not use modeling approaches for various types of the edge artifacts.

In this paper, we propose a method for quantifying a degree of edge artifacts caused by the inaccurate remosaicing. The basic idea of our method is analyzing the line pattern in spatial and frequency domain independently (Fig. 3). Finally, the method scores a degree of the edge artifacts of the pattern on a fifty-fifty basis. This approach can utilize complementary domain-specific information.

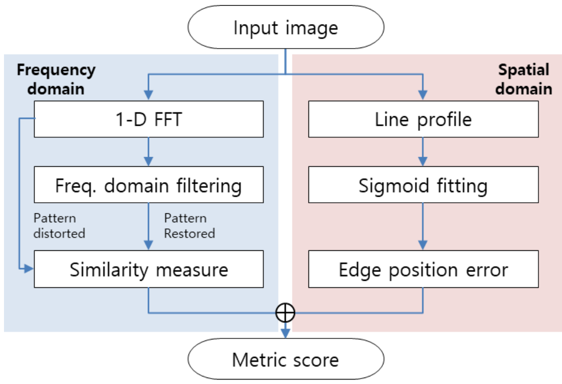
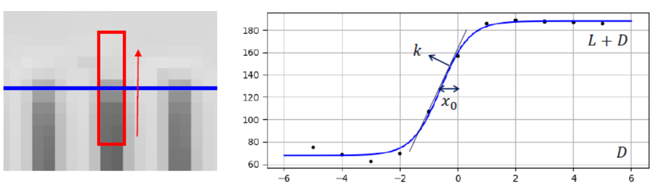


Figure 3. *Flowchart of proposed method.*

Proposed Methods

Spatial domain analysis

Edge spread function (ESF) is commonly used for evaluating an imaging system performances such as MTF. Based on the idea, we use a sigmoid curve fitting for analyzing the line pattern along the column-wise direction. The positions of horizontal edges for each line can be precisely estimated in this way.



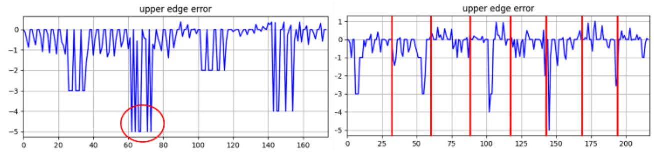
(a) **(b)**

Figure 4*. Modeling edges with sigmoid curve: (a) Example of a line profile. (b) Curve fitting result of (a).*

Fig. 4 shows the above mentioned method in details. First, a blue baseline refers to the reference edge position and is set by marker of charts. Each line profile, red box, is sampled according to the baseline. Profiles that have contrast over a certain level and monotonically increasing intensities (direction of red arrow in Fig. 4 (a)) are considered lines. We construct a sigmoid curve that has the best fit to those lines as shown in Eq. (1).

$$f(x) = \frac{L}{1 + e^{-k(x-x_0)}} + D \qquad (1)$$

where, x_0 denotes the x-coordinates of the sigmoid center, k the steepness of the curve and $L+D$, D the upper, lower asymptote, respectively [4]. We use x_0 as estimated position of line edges, directly. Some initial guess for the parameters (x_0, k, L, D) and bounds on them can help avoid abnormal fitting (Fig. 4 (b)).



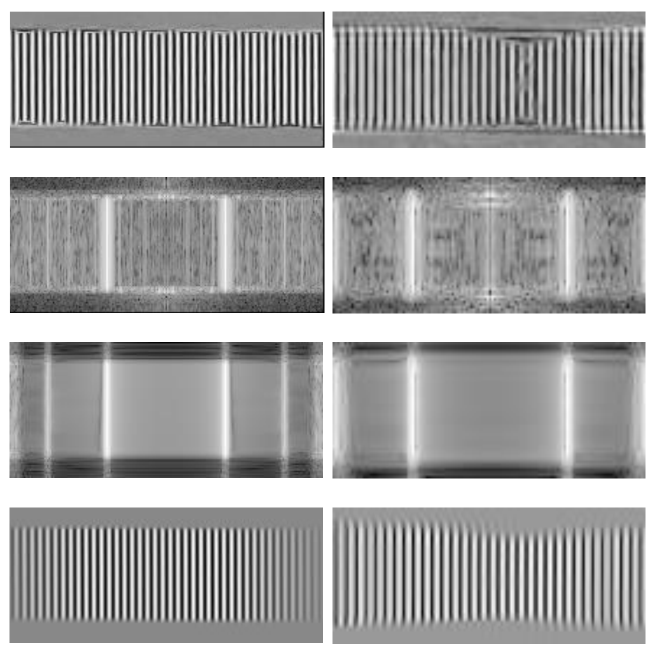
(a) **(b)**

Figure 5*. Examples of estimating edge position errors: (a) Maximum error with red circle, (b) Partitioning for top-N errors (N=8).*

Total error can be defined from the statistics of x_0 values. To prevent severe artifacts being cancelled out by other small errors, we used partitioning and picking top-N error strategy (Fig. 5). The patterns are partitioned into some sections and the sum of top-N absolute deviation is used instead of mean absolute deviation (MAD) for all lines. We use N values of 5~8. Fitting would result in large error value or fail when conducted on the spaces between lines or lines with severe artifacts. Blank space can easily be denied by identifying line profile with overall low contrast. We regard in case that a sign of gradients of a line profile changes more than two times as a distorted line profile. Sigmoid fitting is effective but has limitations that estimating edge positions errors of lines with severe artifacts. Hence we use frequency domain method together for those cases.

Frequency domain analysis

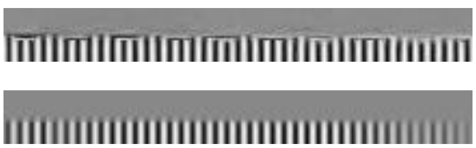
Line patterns can be usefully analyzed in frequency domain given that lines placed at regular intervals have certain frequency components. We focused on the horizontal direction which have the dominant frequency of the line patterns. In this method, an ideal line pattern is restored from distorted pattern in an image and then used as a reference to measure a degree of artifacts.



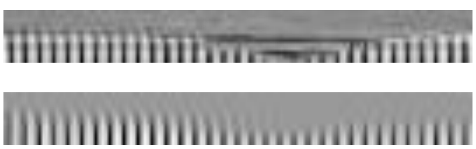
(a) **(b)**

Figure 6. *Process of restoring line patterns: Input image with DC removed (first row), Magnitude spectrum (second row), Magnitude spectrum after band-pass filtering (third row), Pattern restored (fourth row): (a) Moderate quality line pattern, (b) Bad quality line pattern*

First, a ROI is set in an input image and the DC component of regions is removed by subtracting the mean value in the row direction, as shown in Fig. 6 first row. To prevent spectral leakage due to end-point discontinuity on both lateral sides, we use a windowing function such as Tukey window [1]. Then Fourier transform is performed in row direction (Fig. 6 second row). It has peak frequency components that have a magnitude that is more than twice as high as the surrounding frequency of magnitude. And extract frequencies from -2 to 2 relative to peak frequency by band-pass filtering (Fig. 6 third row). The line pattern can be restored by inverse Fourier transform of the filtered spectrum, as shown in Fig. 6 fourth row. Fig. 6 (b) shows that our method can restore worse quality of line pattern as much as possible. Finally, the degree of the artifact is defined by the difference between the input pattern and the restored pattern from above process. We use structural similarity index (SSIM) [2] as a similarity measure and both edges (upper and lower) are evenly measured. Fig. 7 shows the examples of resulting SSIM values for image used in Fig. 6. As the quality of line patterns get worse, the corresponding metric score from frequency domain lowers.



(a)



(b)

Figure 7. *Examples of SSIM between original and restored patterns: (a) 0.80, (b) 0.59.*

Experimental results

Mean opinion score

In this section, we present the evaluation examples of the proposed methods. First, we compared our metric scores and subjective mean opinion scores (MOS) for a dataset. The dataset consists of 15 images and MOS results are acquired by 15 people who have experience in the image quality assessment. We chose the images from multiple different sensors to cover various degree of artifacts.

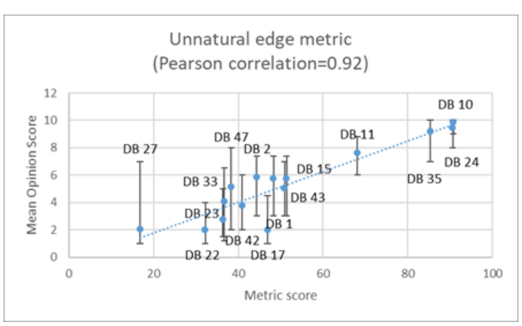
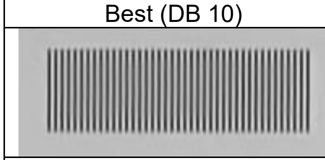
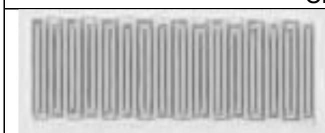
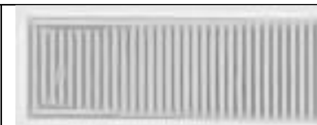
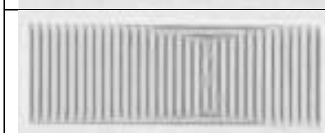
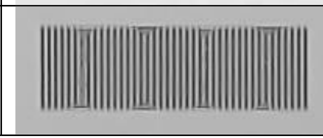


Figure 8. *Human MOS against metric score*

Fig. 8 shows a plot of the metric scores versus MOS for the dataset. Due to the nature of the artifacts, there were wide variations in opinion scores for each image. Some people put a greater importance on blurred edges, whereas others on a length of the connected lines, a zigzag borders and so on. Table 2 shows some example images in the dataset. DB 10 is the best and DB 27 is the worst case. The clusters are patterns scored between 30 and 50. We used the Pearson linear correlation coefficient (PLCC) as evaluation criteria and the result value is 0.92.

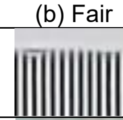
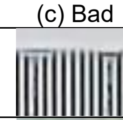
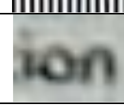
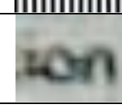
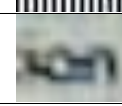
Table 2. Sample images of MOS dataset

Best (DB 10)	Worst (DB 27)
	
Cluster	
	
	

Correlation between Line pattern and Characters

In this experiment, we verified the correlation between the metric scores and the text qualities in same images. For this test, we composed a single chart that contains line patterns and some text patches. Each column refers to certain settings of remosaicing parameters. We chose three images with noticeable differences in the line patterns. In result, as the metric score lowers, the abnormal connections between alphabets increased (Table 3). Thus, our metric score effectively reflects the degree of artifacts in text patch.

Table 3. Metric score of lines and corresponding text-patch

	(a) Good	(b) Fair	(c) Bad
Line pattern			
Text patch			
Metric score	84.88	69.07	45.65

CONCLUSION

In this paper, we proposed the method for quantifying a degree of the edge artifacts on text-images. The artifacts are caused by the inaccuracy in the remosaicing algorithm. First, by using line patterns we simplified the problem that characters in images are hard to be modeled. And we used two complementary methods to utilize each domain specific information. The experiments show that our method represents a degree of the artifacts not only for simplified line patterns but also for challenging text-images. We demonstrate that our method can be used as partial solution to assess the quality of mobile cameras. For future works we plan to modify the line patterns to have various spatial frequencies and improve the methods.

References

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