https://doi.org/10.2352/EI.2022.34.9.IQSP-341

Generation of Reference Images using Filtered Radon Transform and Truncated SVD for Structural Artifacts

Seungwan Jeon, Yukyung Lee, Kundong Kim, Daeil Yu, Sung-su Kim, and Joonseo Yim; S.LSI Division, Samsung Electronics; Hwaseong-si, Gyeonggi-do, Republic of Korea

Abstract

Image quality assessment (IQA) is an effective way to evaluate image/signal processes (ISPs). Here, we present a single value decomposition (SVD)-based IQA method to quantitatively evaluate morphological distortion of chessboard patterns. Incorrect ISP tuning parameters can create suboptimal images with artifacts on the edges of small text or high-frequency patterns. We reproduced those artifacts by using a small chessboard pattern and quantitatively evaluated the morphological distortion in the pattern. Then, we verified our method through qualitative evaluation survey and Pearson correlation. As a result, the score of the proposed method was in good agreement with the qualitative evaluation result and had a Pearson correlation coefficient (PCC) of 0.97.

Introduction

Modern digital color images are obtained by complementary metal oxide semiconductor (CMOS) image sensors (CIS) with color filter arrays (CFAs). Through CFAs, CMOS acquires several single-color images with sparse density. This incomplete color image is converted to a full color image via various image/signal processes (ISPs). Bayer pattern is the most common CFA pattern consisting of 2 green, 1 red, and blue pixels in successive 2×2 patches. Recently, several novel CFAs with non-Bayer patterns (e.g., Quad Bayer) have been introduced to improve image SNR under low-light conditions [1]. However, compared to the Bayer pattern, these patterns require more complex ISPs to recover the original high-frequency information (e.g., edge direction detection process before correcting bad pixels or making full-color image). As a result, it becomes difficult to optimize these ISPs to get the most out of CIS hardware/software performance. Accordingly, optimizing ISP is becoming more and more important in the CIS industry. Image quality assessment (IQA) is an effective way to evaluate the image optimization [2]. However, most IQA methods have focused on image resolution, color error, or SNR [3], despite the possibility of structural distortions such as broken lines and zipper edges.

In this paper, we present a single value decomposition (SVD)-based IQA method to quantitatively evaluate the morphological distortion of chessboard patterns. Incorrect tuning parameters can create artifacts on the edges of small text or high-frequency patterns, so we reproduced these distortions by using a chessboard chart and demonstrated IQA on this chart. Our method exploits the feature that the images with orthogonal patterns can be well compressed by the SVD image compression technique. We used the compressed image as a pseudo reference and quantified the difference between the original and reference images. In addition, we enhanced the robustness of our method by precisely aligning the chart before the SVD compression. After that, we compute Pearson correlations coefficient (PCC) to verify that the quantitative evaluation results are well matched with qualitative evaluations.

Method

Generally, our method has three-step processes: image alignment, SVD image compression, and difference calculation (Figure 1).

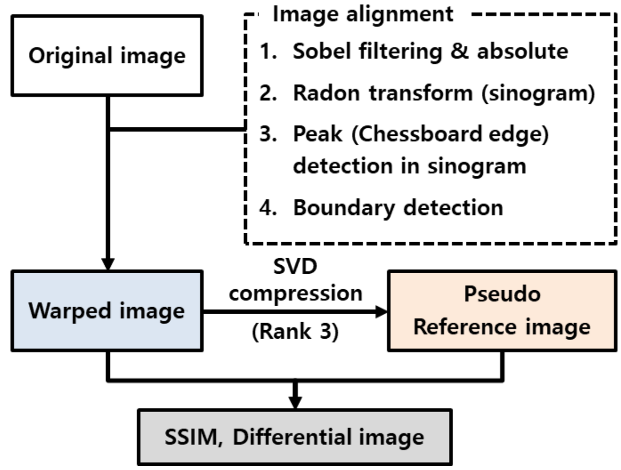

Figure 1. Flowchart of the SVD-based corner artifact metric. SVD, single value decomposition; and SSIM, structural similarity index.

Radon transform-based image alignment

In this step, we detect the four outer edges of the chessboard chart and extract the region of interest (ROI) so that all edges are aligned horizontally and vertically. This step is the most important part of our method because this pre-process can guarantee the robustness of this SVD-based method. SVD image compression converts the image into a low-rank matrix. Thus, the edges could be collapsed when the image has many diagonal edges. For this reason, the SVD-based IQA results may be more sensitive to viewing angles rather than image artifacts. Unfortunately, it is practically difficult to capture the chart in a perfectly normal angle. To deal with this problem, we should align the image prior to the SVD compression to exclude the unwanted factors. In this alignment process, we adopted Radon transform.

Hough-line detection [4] and Harris corner detection [5], which are the most common edge/corner detections, also might be used for the image alignment. Hough-line transform is similar to Radon transform in that they convert points in spatial domain into lines in the Hough or Radon domain. However, Hough-line transform requires a hyper parameter for image binarization (i.e., threshold), which adversely affects the detection robustness because the optimal threshold varies depending on the extrinsic conditions such as illuminance and target color. Further, the dichotomous detection contribution of pixels above the threshold could decrease the detection accuracy. This is because even edges in trivial places such as noise or bumpy sides can affect the edge detection equally with the other major edges if they just exceed the threshold. Meanwhile, Harris corner detection exploits the fact that the gradient is locally maximized on corners. However, this approach is not suitable for our applications because it has low accuracy in images with many distortions at the edges or corners, such as our image targets.

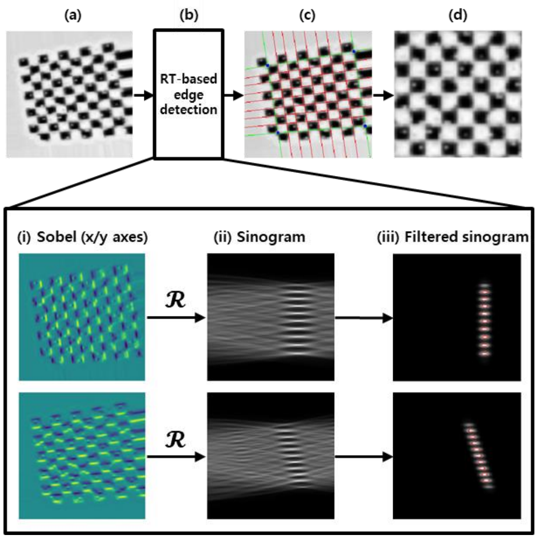

Figure 2. (a) Pre-aligned image. (b) Radon transform-based edge detection. (c) Detected outer edges. (d) Aligned image. RT, Radon transform.

To overcome these problems, we introduced Radon transform-based edge detection. The Radon transform is expressed as bellows:

$$\mathcal{R}f(t,\theta) = \int_{-\infty}^{\infty} f\big(x(z), y(z)\big)dz \tag{1}$$

$$= \int_{-\infty}^{\infty} f\big(x(z\sin\theta + t\cos\theta\ ), y(-z\cos\theta + t\sin\theta\ )\big)dz$$

As shown in the equation (1), Radon transform accumulates the pixel values along a straight line. Accordingly, a line in the spatial domain appears as a peak in the Radon domain. Note that Radon transformation do not need such a prior process unlike the Hough transform, which could make our method relatively robust. The proposed Radon transform-based edge detection consists of 4 steps: 1) Sobel filtering & absolute operation, 2) Radon transform, 3) peak detection, and 4) warping (Figure 2). Firstly, we applied the Sobel filter (Figure 2b(i)) and absolute operations on the x and y axes. Through this step, we could extract the major edges composing the chessboard as well as minor edges from artifacts or noise. In the next steps the minor edge components will be excluded. Secondly, we performed a Radon transformation to obtain sinogram (Radon-domain image). In the sinogram, we could observe several the peaks (bright points in Figure 2b(ii)) and they were lined up. Note that the peaks in Radon domain is standing for a straight line in the spatial domain. To accurately locate the peaks, we conducted two preprocesses: 1) filtering out the unwanted area using a Hanning window and 2) blurring the filtered sinogram. Then, we found peaks in the sinogram as many as the number of edges in the image (Figure 2b(iii)). In this study, we used the "peak_local_max" function in a python library, "skimage". Among the detected edges, we specified the 4 outermost edges (green lines in Figure 2c) and calculated their 4 intersections. Finally, we warped the corresponding ROI into a square shape to get an aligned chessboard image (Figure 2d).

SVD image compression

We compressed the aligned ROI by using truncated SVD. Through SVD, a matrix M can be decomposed as:

$$M = U\Sigma V^{*}, \text{where } \Sigma = diag(\sigma_1, \sigma_2, \dots \sigma_n) \tag{2}$$

where U and V is unitary matrix and Σ is a diagonal matrix including the singular values, σ. Typically, the singular values in Σ are biased to the first column/row. Thus, the original matrix M can be restored to some extent with the part of the singular values, ignoring the small σ. This is called truncated SVD and is used for SVD-based image compression. Using the truncated SVD, we compressed the original ROI image and use the compressed image as a pseudo reference image. Theoretically, we need only 2 singular values to make the pseudo reference image because an ideal chessboard pattern can be represented as a 2-rank matrix. With the 2 singular values, however, our IQA method would be too sensitive to extrinsic factors rather than the artifacts. Hence, we empirically determined the rank threshold to be 3 so that the pseudo reference image can be expressed as below:

$$\widetilde{M} = U_t\Sigma_t V_t^{*}, where\ \Sigma_t = diag(\sigma_1, \sigma_2, \sigma_3). \tag{3}$$

Difference calculation

We quantified the artifact by comparing the aligned original image and the pseudo reference image. In the propose method, we adopted the structural similarity index (SSIM) [6] between the two images. Practically, the calculated SSIM values had a small variation (approximately distributed from 0.9 to 1.0). Thus, we calibrated the SSIM value as below to highlight the effective range.

$$Score = 100 \times max\big(0, 1 - 5(1 - SSIM)\big). \tag{6}$$

Simulation experiment

The objective of our IQA is to evaluate the artifact on the image. To achieve this, the proposed method should exclusively assesse the structural distortion while being insensitive to the others (mostly the sharpness). To verify the exclusiveness, we tested our method in a simulation with the various images distorted as follows:

$$O_{x,y}(\rho_{SP}, \sigma_{GS}) = M\left(N\big(I_{x,y}, \rho_{SP}\big)\right) * G(\sigma_{GS}) \tag{4}$$

where

$$N\big(I_{x,y}, \rho_{SP}\big) = \begin{cases} 0, & if\ \varepsilon < \rho_{SP} \\ 255, & if\ \varepsilon > 1 - \rho_{SP}, \quad \varepsilon \sim U[0,1], \\ I_{x,y}, & else \end{cases} \tag{5}$$

$I_{x,y}$ is the ideal 250×250 chessboard image, $N\big(I_{x,y}, \rho_{SP}\big)$ is salt & pepper noise addition function, $M(\cdot)$ is a median filter function with a 5×5 kernel, $G(\sigma_{GS})$ is the 2D Gaussian kernel with the sigma of σ_{GS}, and $O_{x,y}(\rho_{SP}, \sigma_{GS})$ is the image distorted with the salt & pepper noise and Gaussian blur. By adjusting the 2 parameters (i.e., ρ_{SP} and σ_{GS}), we obtained the datasets with various image blurring and artifact levels and measured each score of the proposed IQA method (Figure 3).

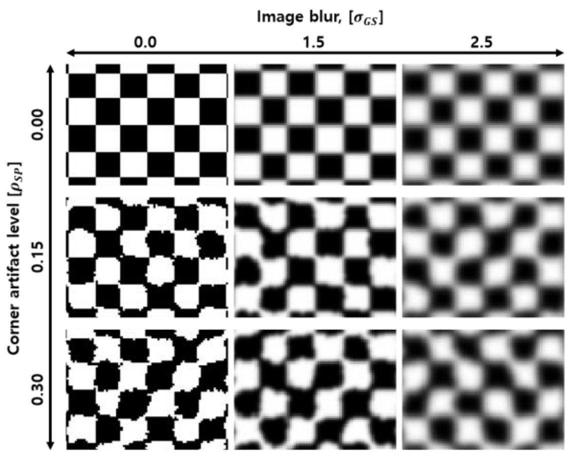

Figure 3. Representative chessboard image datasets distorted according to the various image blurring levels, σ_{GS}, and artifact levels, ρ_{SP}.

Result and Discussion

In order to verify the image alignment performance, we randomly distorted a single chessboard image 10 times and then calculated their IQA scores. As a result, the average score was 91.94 and the standard deviation was 0.11. In this experiment, as shown in Figure 4, we conducted this repetition test under an extreme condition in which the images were more severely distorted than a practical condition. Therefore, we expect that the proposed IQA could show better robustness in practical tests.

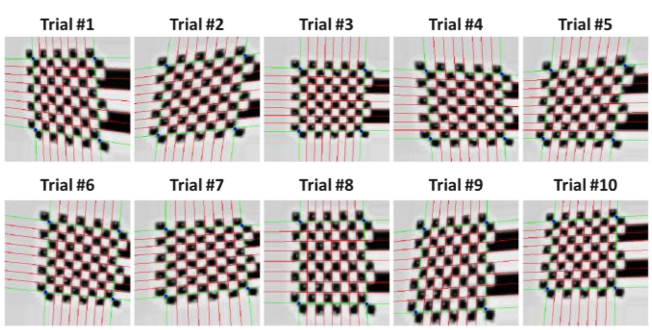

Figure 4. The results of the outermost edge detection repetition experiment. The green lines are the detected outermost edges.

Using the SVD image compression technique, we obtained pseudo reference images from the aligned original images. In the original image, there were several notable artifacts such as collapsed edge, dirty block, blur corner, and stain (Figure 5a(i-iv, respectively)). In the SVD compressed image, in contrast, the artifacts were well restored and the overall image sharpness was maintained (Figure 5b). Due to this feature, we could confirm the potential that the proposed IQA is mostly insensitive to the image sharpness.

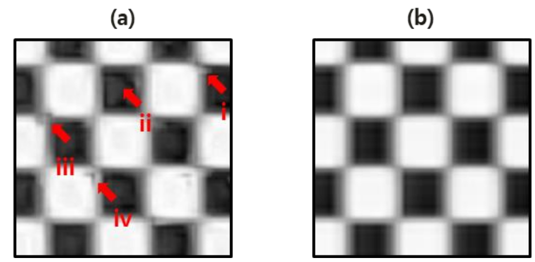

Figure 5. (a) Original image before SVD compression. (b) Corresponding image after SVD compression (pseudo reference image). SVD, single value decomposition.

In the simulation study, we measured the proposed IQA score of the virtual images distorted with the various blurring levels, σ_{GS}, and artifact levels, ρ_{SP}, to confirm how the two factors affect the IQA score (Figure 6). Overall, the score varied depending on the both artifact level and blurring level, and was more sensitive to the artifact level. The sensitivity to the artifact level was greater as the image was sharper (as the blurring level was low), and this numerical result was also seen in the actual images (please note that irregular artifacts in Figure 6c were more noticeable than those in Figure 6d even though they are distorted with the same artifact level). Without the artifact (at $\rho_{SP} = 0$), however, the score remained the same regardless of the blurring level (Figure 6a and Figure 6b). From this, we could infer that the SVD compression could generate pseudo reference images that maintain the sharpness of the original images, which makes our IQA invariant to the point spread function (PSF).

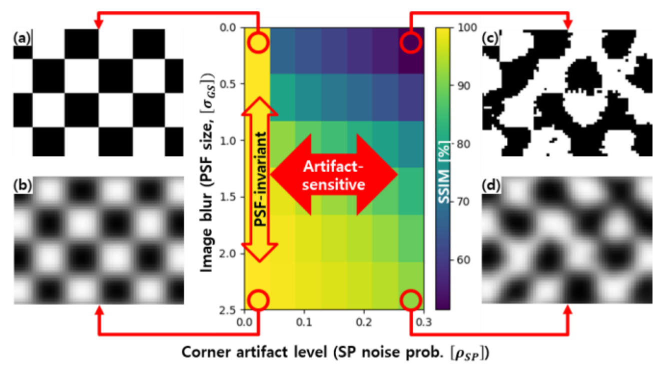

Figure 6. (a-e) Original image before SVD compression. (b) Corresponding SVD compressed image. SVD, single value decomposition; and PSF, point spread function.

We also verified the consistency between the qualitative score and qualitative evaluation. Figure 7 shows the representative test images and the corresponding IQA score. There were more artifacts in Figure 7a than Figure 7c and the resultant scores are well matched with the actual images. For objective verification, we conducted a survey with 10 images and 14 participants and calculated the PCC between the proposed quantitative assessment score and the mean opinion score (MOS; 1 (bad) - 5 (good); Figure 7). In the study, the PCC was calculated to be 0.97 (Figure 7d), which means that the quantitatively and qualitatively evaluated scores are highly correlated.

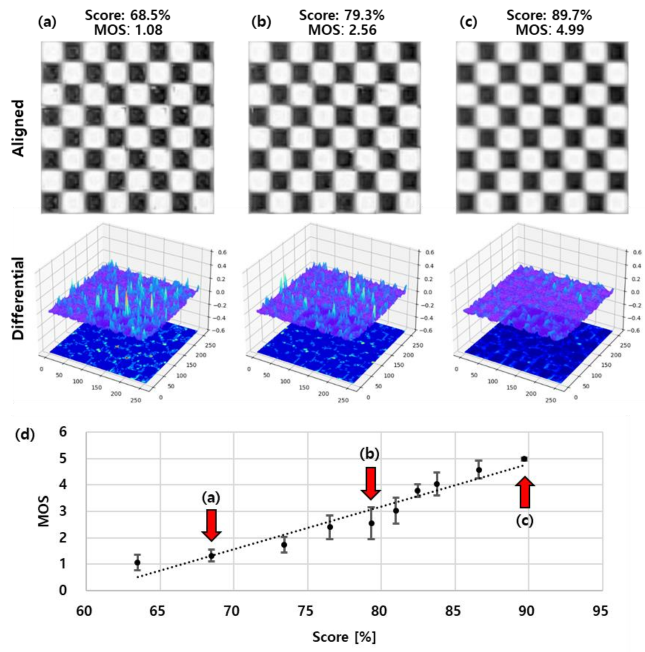

Figure 7. (a-c) Representative aligned (top) and differential (bottom) images and the corresponding IQA score and MOS. (d) Relation between IQA score vs. MOS, Calculated PCC = 0.97. MOS, Mean opinion score; and PCC, Pearson correlation coefficient.

Conclusion

We developed a robust method to assess morphological artifacts in a chessboard pattern. The proposed method compresses the test images and quantify the artifact by comparing the original image and the compressed images. We confirmed that the compressed images maintain the basic structure of the chessboard pattern and the sharpness of the original images. We successfully used this compressed image as a pseudo reference image to exclusively quantify the artifact of the image. Further, using Radon transform, we complemented the SVD image compression to improve the robustness of our IQA method and showed high correlation in the qualitative-quantitative consistency test. Therefore, we believe our method could be used as a helpful index for ISP evaluation or optimization.

References

[1] T. Okawa *et al.*, “A 1/2inch 48M all PDAF CMOS image sensor using 0.8 μm Quad Bayer coding 22OCL with 1.0 lux minimum AF illuminance level,” in *2019 IEEE International Electron Devices Meeting (IEDM)*, 2019, pp. 13–16.

[2] J. Preiss, F. Fernandes, and P. Urban, “Color-image quality assessment: From prediction to optimization,” *IEEE Trans. Image Process.*, vol. 23, no. 3, pp. 1366–1378, 2014.

[3] O. Shakar, J. S. J. Li, and S. Randhawa, “Quantification of color artifacts for the evaluation of color filter array demosaicking,” *J. Image Graph.*, vol. 6, no. 1, pp. 48–53, 2018.

[4] P. V. C. Hough, “Method and means for recognizing complex patterns.” Google Patents, 1962.

[5] K. G. Derpanis, “The harris corner detector,” *York Univ.*, vol. 2, 2004.

[6] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, “Image quality assessment: from error visibility to structural similarity,” *IEEE Trans. image Process.*, vol. 13, no. 4, pp. 600–612, 2004.

Author Biography

Seungwan Jeon was born in Republic of Korea in 1989. He received the B.S. degree in biomedical engineering from Yonsei University in 2014, and the Ph.D. degree in creative IT engineering from POSTECH in 2020. His Ph.D. research focused on photoacoustic/ultrasound imaging techniques using image/signal processing, beamforming, and deep learning. Since 2020, he is with Samsung Electronics, Republic of Korea, as a Staff engineer. His current research interests include camera sensor, computer vision, and image quality assessment.