Modified Jointly-Blue Noise Mask Approach Using S-CIELAB Color Difference

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Abstract

This paper proposes a modified jointly-blue noise mask (MJBNM) method using an S-CIELAB color measure. For color image halftoning, the jointly-blue noise mask (JBNM) method provides a visually pleasing pattern for single and multiple color planes. However, the halftone outputs of a JBNM mask show a higher chrominance error. The S-CIELAB metric, a modified color metric from CIELAB, includes the spatial-color sensitivity of the human eye in the metric to account for how spatial patterns influence color appearance and color discrimination. To reduce the chrominance error, the low-pass filtered error and S-CIELAB chrominance error are both considered during the mask generation procedure and calculated for single and combined patterns. Based on the calculated low-pass filtered error, the patterns are then updated by either adding or removing dots from the multiple binary patterns. Finally, the pattern that shows the lower S-CIELAB chrominance error is selected. The proposed algorithm can produce a visually pleasing halftoned image with a lower chrominance error than the JBNM method.

1. Introduction

For digital image rendering applications, the output devices need to be able to produce perceptually high quality images with a limited number of output states. Accordingly, digital halftoning techniques have been active research area over the last three decades in an effort to meet this challenge. Digital halftoning techniques include ordered dithering, error diffusion, blue noise masks (BNM), etc.

In conventional color halftoning, a clustered-dot screen is used to control color placing on the paper. The same screen is used to halftone the cyan, magenta, yellow, and black planes separately. One immediate problem of this scheme is a noticeable spatial artifact occurs in halftoned color images. This artifact is often called a Moiré. To reduce Moiré patterns, each screen is typically oriented at different angles. However, there is a limit to the number of the orientation angle selections. Therefore, it can be difficult to apply conventional color halftoning techniques to high-fidelity color printing.[1,2]

With the emergence of blue noise halftoning, the problems related to Moiré patterns in conventional screen designs were replaced by color image quality issues related to the overlaid blue noise patterns. A number of different schemes have been proposed for generating one or more blue noise masks for color halftoning. These schemes include the Dot-On-Dot scheme, Shifted Masks scheme, Inverted Masks scheme, and Four-Masks scheme.[3] However, none of these schemes involves an analysis of the properties of the overlaid blue noise binary patterns and the interaction between color channels is only partially considered.

In the following section 2, JBNM method is reviewed. Section 3 is devoted to color fidelity metric that has incorporated color difference measure. Section 4 describes a new color mask generation algorithm. Section 5 discusses the experiments and the results. Section 6 is a brief conclusion.

2. Conventional Jointly-Blue Noise Masks

Wang and Parker suggested an algorithm that generates a set of JBNM.[4] They inspected various combinations of binary patterns and explored the elementary properties of combinations of blue noise binary patterns. Then, based on this analysis, they proposed an algorithm that makes three individual masks jointly. The masks produce a high quality blue noise pattern whether they are used individually or jointly. When three individual single patterns are overlaid, one triple pattern and three double patterns are constructed. Wang and Parker attempted to make three independent masks that preserve good blue noise characteristics in each single pattern and also yield a high quality blue noise appearance in combined patterns. Accordingly, based on digital filtering techniques, the set of blue noise masks is designed jointly to provide high quality color halftone outputs with minimal visibility to the human eye by adding or removing dots from multiple binary patterns. JBNM provides a visually pleasing pattern for a single color plane, plus a visually pleasing joint pattern for multiple color planes. Because the JBNM algorithm is designed to focus on achieving minimally visible halftone outputs, the halftone outputs are visually pleasing and exhibit a lower luminance error than BNM schemes. However, the halftone outputs of JBNM show a higher chrominance error.

3. Color Image Fidelity Metric

The CIELAB metric[5] is a widely used color metric that works reasonably well in applications involving large uniform patches viewed under standard illuminants. The effects of visual adaptation are partially included in the original CIELAB metric. However, standard CIELAB calculations can not clarify the performance well (Wandell and Brainard),[6] therefore, Fairchild and Berns proposed a set of computations to improve on the original CIELAB definitions.[7]

Zhang and Wandell introduced a new color image fidelity metric, a spatial extension of CIELAB, called the S-CIELAB metric.[8] They included the spatial-color sensitivity of the human eye in the metric to account for how a spatial pattern influences color appearance and color discrimination. The S-CIELAB metric incorporates the different spatial sensitivities of the three opponent color channels by adding a spatial pre-processing step before the standard CIELAB $\Delta \boldsymbol{E}$ calculation. An input image is initially converted into an opponent color format. Each component image is then passed through a spatial filter that is selected according to the spatial sensitivity of the human eye for that color component. This spatial extension is designed to account for human spatial color sensitivity and thus improve the performance of the CIELAB ΔE metric for patterned targets. There were two goals in designing the S-CIELAB error measure. The first was to simulate the spatial blurring of the human visual system by applying a spatial filtering to a color image. The second was to create a consistent extension to the basic CIELAB calculation when an input image has large uniform areas. Therefore, the S-CIELAB measure not only produces a better error prediction than CIELAB for textured or patterned images like printed halftone patterns, but also provides a consistent extension to the basic CIELAB measure for images which have large uniform areas.[9].

4. Modified Jointly-Blue Noise Masks Method

This paper proposes MJBNM method based on the S-CIELAB color measure. The JBNM method produces visually pleasing halftoned outputs with a lower luminance error, yet creates higher chrominance error outputs. In the procedure of generating optimized JBNM, only the optimality of the multiple dot patterns themselves is taken into consideration. Although the use of a low-pass filtering technique is sufficient to achieve either single or combined patterns that exhibit blue noise characteristics, no consideration of the output chrominance error is present.

The proposed algorithm can consider the low pass filtered error and the S-CIELAB chrominance error during the mask generation procedure. The low-pass filtered error and S-CIELAB chrominance error are both calculated for single and combined patterns. Based on the calculated low-pass filtered error, the patterns are updated by either adding or removing dots from the multiple binary patterns. Then, the S-CIELAB chrominance error is calculated for the updated patterns and examined. The pattern that shows the lower S-CIELAB chrominance error is finally selected.

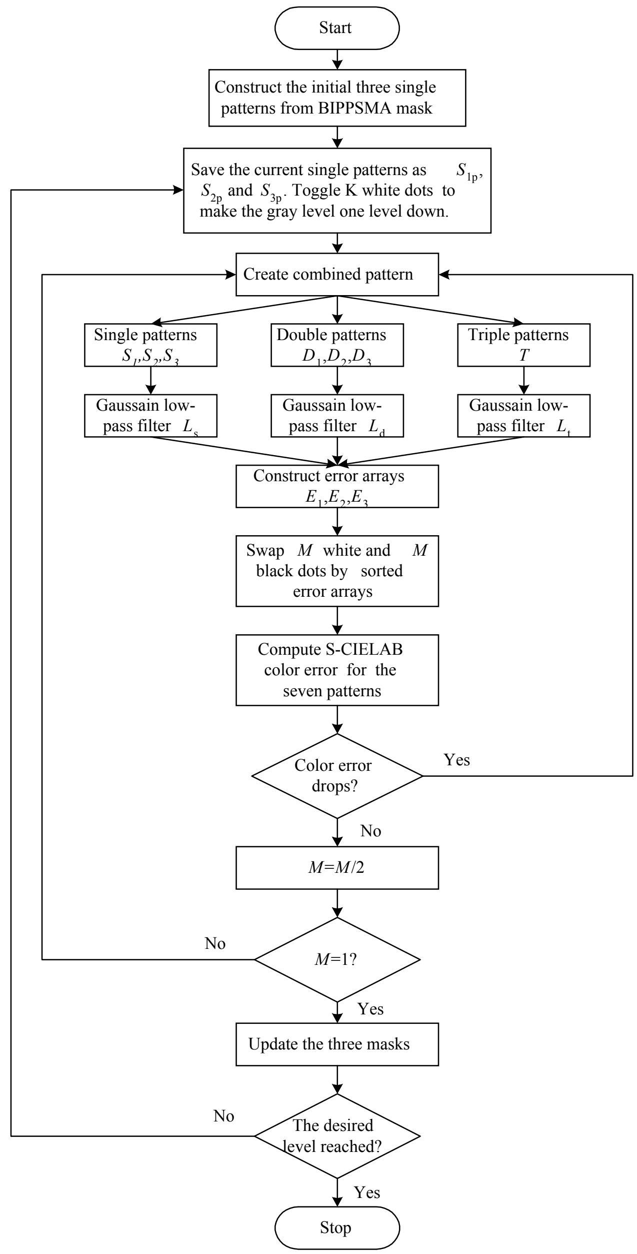


Figure 1. Flowchart for constructing MJBNM.

4.1. Construction of MJBNM

Figure 1 shows the flowchart of the construction of the proposed MJBNM. The input is a mask generated by a binary pattern power spectrum manipulating algorithm (BIPPSMA).[10] The output is three masks for three-color channels. The whole procedure is as follows:

4.1.1. Generation of Three Initial Pattern

From the input mask, three single patterns S_1, S_2, and S_3 are constructed. Set the gray level of S_1 to the initial gray level. In order to obtain three mutually exclusive single patterns, set the gray level of S_2 at a gray level where the number of black dots becomes exactly twice that of the S_1 pattern. Similarly, set S_3 at a gray level where the number of black dots becomes exactly three times that of the S_1 pattern.

Each single pattern is thresholded by the input mask. Then, for the S_2 pattern, change the black dots, where the S_1 pattern has black dots at the same location, into white dots. Similarly, for the S_3 pattern, change the black dots, where the S_1 or S_2 pattern has black dots at the same location, into white dots. Finally, the three initial single patterns S_1, S_2, and S_3 are constructed with the same gray level. In this way, mutual exclusivity can be guaranteed in the initial single patterns.

4.1.2. Making One Gray Level Down

Store the current three binary blue noise patterns as S_{1p}, S_{2p}, and S_{3p}. To make the gray level of a single pattern one level down, change randomly selected K white dots into black dots for each pattern. If the size of the mask is N-by-N and the total number of levels is L, then

$$K=N*N/L. \tag{1}$$

4.1.3. Creation of Combined Patterns

From the three single patterns S_1, S_2, and S_3, create four combined patterns. Three double patterns D_1, D_2, and D_3 are created by combining two single patterns, and one triple pattern T is created by combining all three single patterns. When combining patterns, a combined pattern's pixel can only be white when all the pixels of the single patterns are white at the same location. If any one of the pixels in the single patterns is black, the combined pattern's pixel will be black.

4.1.4. Generation of Three Low-Pass Filter

Construct three 2-D Gaussian low pass filters LF_s, LF_d, and LF_t respectively for the single, double, and triple patterns. The three different filters are needed, because the power spectrum of a blue noise pattern varies according to the given gray level. Gaussian low-pass filters are shaped by adjusting the sigma value according to the gray levels of the single, double, and triple patterns.

4.1.5. Error Array and Pattern Update

Three error array are constructed as follows:

$$\begin{aligned} E_1 &= LF_s(S_1) + LF_d(D_1 + D_3) + LF_t(T) \\ E_2 &= LF_s(S_2) + LF_d(D_1 + D_2) + LF_t(T)\,, \\ E_3 &= LF_s(S_3) + LF_d(D_2 + D_3) + LF_t(T) \end{aligned} \tag{2}$$

Where $LF_s(\ )$ denotes the low-pass filtered error of the single pattern, $LF_d(\ )$ associates with the double pattern, and $LF_t(\ )$ associates with the triple pattern. The E_1 error array reflects the effects on the single, double, and triple patterns when changing the single pattern S_1. Likewise, E_2 associates with the single pattern S_2 and E_3 associates with the single pattern S_3.

After constructing error arrays, error arrays are sorted. For the S_1 single pattern, M black dots, that have the largest error values in the sorted error array E_1 and white dots at the same locations in the saved S_{1p}, are found. Then, these M black dots are swapped with M white dots having the smallest error values. Similarly, update the single patterns S_2 and S_3 according to the sorted error arrays E_2 and E_3, respectively.

By selecting the black dots that have white dots at the same location in the stored pattern S_{1p}, S_{2p}, and S_{3p}, the stacking constraint is satisfied in the resulting masks. The stacking constraint provides a correlation between successive levels. For a level that is higher than the initial gray level, mutual exclusivity is automatically achieved if the stacking constraint is satisfied. This automation is also related to the mutual exclusivity of the initial single patterns.

4.1.6. Computing S-CIELAB Color Difference

The seven S-CIELAB color differences of the three single patterns, three double patterns, and one triple pattern are calculated. The three single patterns are considered as cyan, magenta, and yellow patterns, respectively. As such, the double patterns are considered as colored patterns that only have two color components, and the triple pattern is considered as a gray pattern.

The color transformation converts each pattern, specified in terms of the tristimulus values, into CIE 1931 XYZ values.[5] Then, each pattern having XYZ values is converted into three opponent-color planes that represent the luminance, red-green, and blue-yellow values. After obtaining opponent color planes, a spatial low pass filtering technique is used to account for human spatial color sensitivity. The data in each plane are filtered by two-dimensional separable spatial kernels.[8] The filtered patterns are then converted back into XYZ values and then back into Lab values. Thereafter, the procedure of calculating the color difference is exactly the same as the CIELAB ΔE method.

4.1.7. Decision of Iteration

Compute the summation of the S-CIELAB color difference of the seven patterns. If the color difference decreases, go back to the pattern generation step and repeat the same process. If the color difference does not decrease and $M\neq 1$, set $M=M/2$, and go back to the pattern generation step, otherwise, reset M to the initial value as specified previously, and update the three masks based on the three updated patterns S_1, S_2, and S_3, then decrease the gray level by 1 and repeat the steps after the initial mask generation step until the zero gray level is reached.

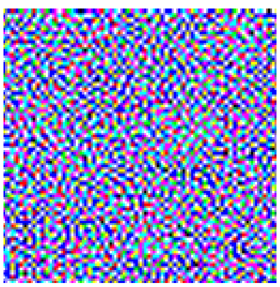
4.1.8. Upward Mask Generation

When the downward mask generation is completed, the upward mask generation is carried out, starting from the initial gray level. This procedure is basically same as the downward mask generation, except that the white dots are replaced with black dots. Finally, when the gray level reaches *L*, all mask components are completely built and the whole mask generation procedure stops.

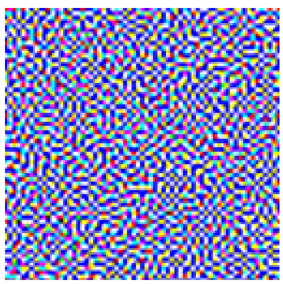
5. Experiments

For the experiments, the size of the output masks and the input BIPPSMA mask was 64 x 64. The swapping number *M* was 16, which was the same as the *K* value. The initial gray level was 191 out of 256. The MacBeth ColorChecker and bicycle image were used as the test images.

Figure 2 shows the halftoned patches created by the JBNM and MJBNM methods. The RGB values of the original image were 128, 128, and 197, respectively. The left patch showed structured patterns or low frequency patterns, whereas the right patch showed less structured patterns and a pleasing result.



(a)



(b)

Figure 2. Halftoned patched(R:128, G:128, B:197) created by (a)JBNM method (b)proposed MJBNM method

Table 1. S-CIELAB ΔE value for six patches

Method \ Patch	1	2	3	4	5	6	Ave.
JBNM	**12.01**	**19.40**	**11.01**	**22.93**	**20.23**	**13.45**	**16.50**
MJBNM	**11.09**	**18.05**	**10.81**	**21.15**	**19.01**	**12.51**	**15.44**

Several 256 x 256 patches were tested. Table 1 shows that the MJBNM method produced less color difference between the original patches and the halftoned patches than the JBNM method. All patches were made up of RGB values from the MacBeth ColorChecker. An S-CIELAB color difference value greater than 1 implies that the color difference is detectable by humans.[11] In this sense, MJBNM succeeded in producing less perceptual color difference than JBNM.

When the proposed method was applied to a natural image, see figure 3, the resulting halftoned image also exhibited a lower chrominance error and maximally distributed color dots in the highlight region.

6. Conclusion

This paper proposed the MJBNM method using an S-CIELAB color difference measure. In the mask generation process, the low-pass filtered error and S-CIELAB chrominance error are both considered. In experiments, the proposed method produced halftoned images with a lower chrominance error than the conventional JBNM method, while also achieving high quality and visually pleasing color halftoned patterns.

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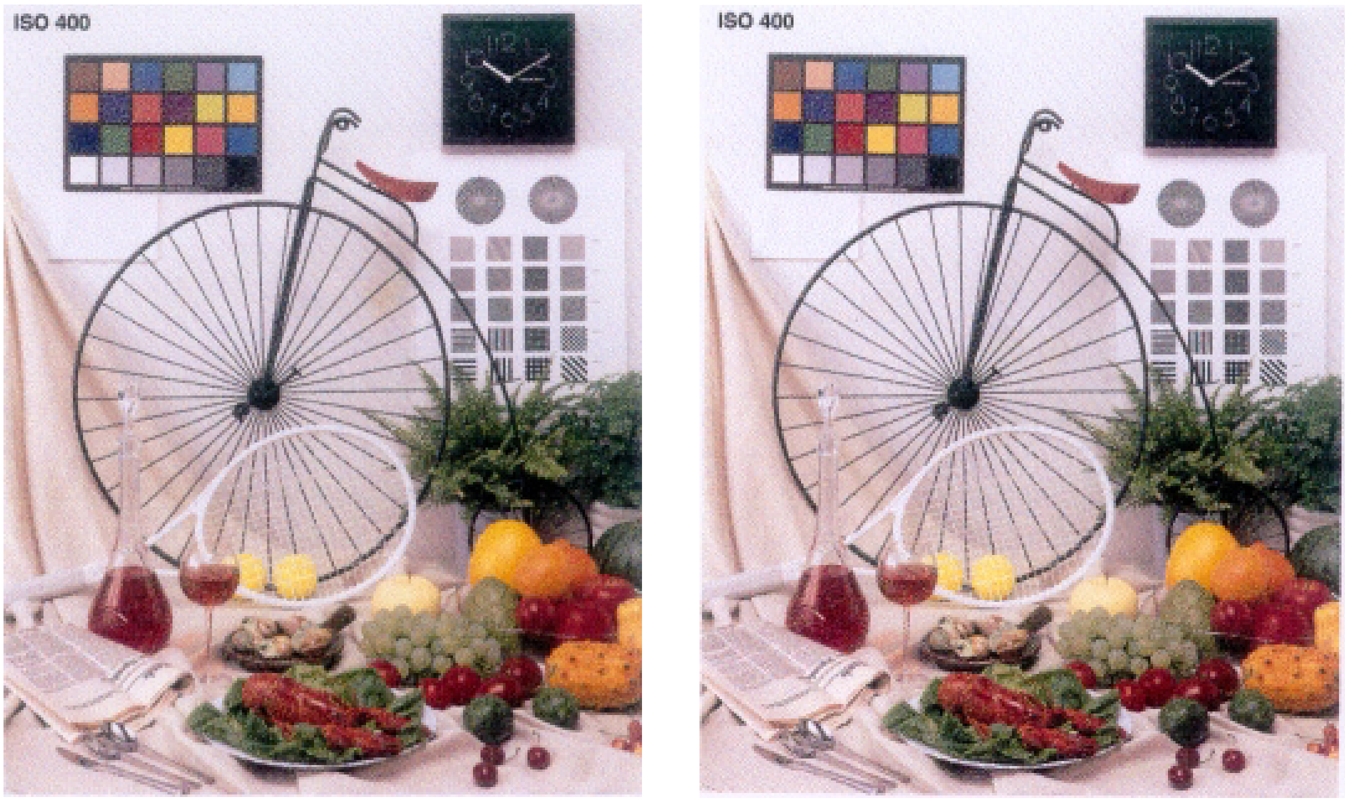

(a) *(b)*

Figure 3. Result for bicycle image (a) JBNM , (b) MJBNM

Biography

Yong-Sung Kwon received his B. S. in Electrical Engineering and Computer Science from Kyungpook National University, in 2000, where he is also currently pursuing his M. S. in the School of Electronic and Electrical Engineering. His main interest is digital halftoning.

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