Isoluminant Color Halftoning for Generating Pointillistic Tile Images and Photomosaics

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Abstract: We propose a non-photorealistic rendering (NPR) technique for generating mosaic images of which color composition is analogous to the pointillistic paintings. Input images are firstly downsampled. Next, the downsampled image is halftoned in the way where the luminance is preserved while the hue of colors is different between adjacent pixels. Finally, the halftoned image is upsampling to the original size of the input image by pasting patch images to each pixel in the halftoned image with preserving the average color of patches. When patches are geometrical tiles, results are colorful tile images while if the patches are small photographs then the enlarged image yields photomosaics.

Keywords: Non-photorealistic rendering, Isoluminant color halftoning, Pointillistic tile image, Photomosaics

1. Introduction

Images composed of many blocks or cells are called mosaics. In tile mosaic images, geometrical tiles are pasted at each cell as is shown in Fig.1[1][2]. Tiles are usually singly colored but sometimes textured such as shown in Fig.2. Figure 3 shows another example of tile images called Truchet tiles, which are monochromatic geometrical tiles[3]. Mosaics of which every block is pasted with small photographs as is shown in Fig.4 are called photomosaics[4]~[6].

The pointillism is a one style of mosaic painting composed of tiny cells, i.e. points. Impressionistic pointillism paints each point with isoluminant colors of which hue is different between neighboring points as is shown in Fig.5(a) and (b) of which luminance is shown in Fig.(c) and (d). This juxtaposition of isoluminant colors of different hue induces a perceptual tension and produces a visual effect for us to perceive colorful impression when viewing such images[7]~[11]. This impressive perception is due to the separate physiological pathway for luminance and color in our visual system in the brain.

In this paper, we propose a non-photorealistic rendering (NPR) technique for generating vivid mosaic images of which color composition is analogous to the pointillistic paintings.

2. Overview of Our Method

The method proposed in this paper proceeds as:

downsampling $\rightarrow$ halftoning $\rightarrow$ upsampling.

The procedure starts from the downsampling of an input image of width $km$ and height $kn$ to width $m$ and height $nD$

Next, colors in the downsampled image is halftoned, i.e. quantized. This color halftoning is the main process in our method. The halftoning modulates the color of each pixel by exploiting the color mixing throughout our visual blur similarly to pointillistic paintings. Especially in the impressionistic pointillistic drawings, colorful points are distributed with preserving the luminance of every pixel while changing the color hue between neighboring points. In our present method, the luminance is maintained to its original value in the downsampled image while the color saturation is maximized as large as possible to produce colorful mo-

![Figure 1: Tile images.](image1.png)

(a) irregular placement[1]
(b) irregular form[2]

![Figure 2: Textured tiles.](image2.png)
Finally the halftoned \( m \times n \) image is upscaled, i.e. enlarged back to the original size \( kn \times kn \) by pasting \( k \times k \) patch-images to each pixel in the halftoned \( m \times n \) image. Every patch is assumed to be a square for simplicity.

3. Isoluminant Halftoning of Downsampled Image

Let the color of a pixel in a downsampled image be \( c = [r, g, b] \) and its halftoned color be \( C = [R, G, B] \) (we omit the coordinate of pixels). In the pointillistic halftoning, \( C \) is required to satisfy the following conditions:

1) Blurred \( C \) is close to \( c \) (this smoothing corresponds to the visual blur).

2) The luminance of \( C \) is strictly equal to that of \( c \).

3) The saturation of \( C \), which is the distance between \( C \) and its grayscale \([l, l, l]\) where \( l \) is the luminance of \( C \), is maximal in the permissible range of \( C \), i.e. the RGB cube \([0, 255]^3\).

4) The color difference between \( C \) and the color of neighboring pixels is sufficiently large.

We formulate this multiobjective programming problem as

\[
\begin{align*}
\min_C & \quad \|\tilde{C} - c\|^2 - \lambda \sum_{n \in W} ||C - C_n||^2 \\
\text{subj. to} & \quad C \in \Omega, \quad q \cdot C = q \cdot c
\end{align*}
\]

where \( \tilde{C} = [\tilde{R}, \tilde{G}, \tilde{B}] \) is blurred \( C \), \( \Omega \) is the surface of the RGB cube, \( W \) is neighborhood of \( C \) (four neighborhood in the experiments below), \( C_n \) is the color of neighboring pixels and \( q = [1, 1, 1]/3C \), i.e. the inner product between \( q \) and \( c \), \( q \cdot c = (r + g + b)/3 \) is the luminance of \( c \). In eq.(1), the color difference \( \sum ||C - C_n||^2 \) in the neighborhood becomes large if the value of \( \lambda \) increases because the sign attached to \( \lambda \) is negative.

3.1 Extraction of Palette Colors

In the ordinary halftoning, a set of some palette colors is prepared in advance and then every pixel is quantized to one of them. The luminance at each pixel, however, cannot be maintained if a common palette is used throughout all pixels in the entire image. In our pointillistic halftoning in this paper, the color \( c \) of each pixel in the downsampled image is quantized to the color on the surface of the RGB cube nearest to \( c \). This yields palette colors different at each pixel.

Colors of which luminance is equal to that of \( c \) lies on the plane passing through \( c \) and perpendicular to the luminance line, i.e. the diagonal of the RGB cube. The color on this isoluminant plane maximizes its saturation at the intersection lines between this plane and the surface of the RGB cube. For instance, the color on the intersection line in the RGB surface plane with \( R = 255 \) nearest to \( c \) is \( C = [R = 255], G, B \) of which \( G \) and \( B \) is the solution of the following problem:

\[
\begin{align*}
\min_{G,B} & \quad (G - g)^2 + (B - b)^2 \\
\text{subj. to} & \quad 255 + G + B = 3l
\end{align*}
\]
where \( l = q \cdot c \) is the luminance of \( c \). The Lagrange multiplier method for this optimization problem leads to

\[
G = g + \frac{3l - 255 - g - b}{2} \tag{3}
\]

\[
B = b + \frac{3l - 255 - g - b}{2} \tag{4}
\]

Similarly, by fixing \( R = 0 \) or \( G = 0 \) or \( G = 255 \) or \( B = 0 \) or \( B = 255 \), we obtain the peripheral colors of the total number six, except for the cases \( l < 255/3 \) or \( l > 510/3 \), at such luminance values pixels of only three among six colors stay on the surface of the RGB cube as is illustrated with the white triangle in Fig.6. We adopt the set of these six or three colors as the palette at concerning pixels.

### 3.2 Color Quantization

When we quantize the color \( c \) of each pixel in a downsampled image to one color in the above palette, we select a color among the palette at that pixel such that the smoothed \( \tilde{C} \) of the quantized output \( C \) is close to \( c \) in accordance with eq.(1). We progress this quantization by scanning pixels sequentially in the image. We scanned images in a random order for protecting artificial patterns produced by a regular order such as a raster scanning. When quantizing a pixel, we set its color tentatively to one of palette colors and we smooth the quantized image \( C \) by fixing \( C \) of unprocessed pixels to \( c \). By executing this smoothing for each palette color, we get the smoothed output at that pixel of the number equal to the palette colors, i.e., three or six as mentioned above. Among these three or six colors, we select the one of which smoothed color \( \tilde{C} \) is nearest to \( c \). Thus selected color \( C \) is the quantized output at that pixel.

The quantized output for a downsampled image in Fig.7 is shown in Fig.8. Figure 8(a) shows a result of quantization of each pixel individually, which is not like to pointillistic images. The results of quantization by eq.(1) is shown from Fig.8(b) to (d). Figure 8(b) is the result with \( \lambda = 0 \) in eq.(1). The Gaussian filter (GF) with the standard deviation 2.5 and the window width 7 is used for smoothing \( C \). The image in Fig.8(b) resembles pointillistic images more than Fig.8(a), however similar color points are connected into lines which degrades the visual impression of the image. If we set \( \lambda = 1 \), the result becomes to Fig.8(c) where the color arrangement is more random than Fig.8(b), hence it becomes closer to pointillistic images than Fig.8(b), however tendency of alignment of similar color points along edges is still remaining. Figure 8(d) shows the result of changing the GF filter to the cross bilateral filter (CBF) with...
the weight of downsampled image \( c \) as

\[
\hat{C}_{ij} = \sum_{x=p}^{p} \sum_{y=p}^{p} w_{ijx} C_{x+y} / \sum_{x=p}^{p} \sum_{y=p}^{p} w_{ijx}
\]

(5)

with

\[
w_{ijx} = e^{-((x^2+y^2)/\sigma_x^2 - (x+y)^2)/\sigma_y^2}
\]

(6)

where we set \( \sigma_x = \sigma_y = 2.5 \) and \( p = 3 \). If we set \( \sigma_x = \infty \), eq.(5) is reduced to the above GF. In Fig.8(d), artificial line patterns are suppressed and approaches to a pointillistic halftoned image. This efficacy is the superiority of CBF over GF in weakening the influence of edges. The luminance of the images Fig.8(a)–(d) is shown in Fig.9, where all of them is identical to Fig.7(b).

4. Upsampling by Pasting Patch Images

We next paste small patch images to each pixel in the obtained halftone downsampled image \( C \) to enlarge the image to the original size. We select patch images of which luminance gradient is similar to the corresponding block in the original input image before downsampling as is explained below. When pasting patch images, its color is adjusted for its average color matching to \( C \). This color change ensures that the average luminance of resulted mosaic images is equal to that of input images. The color change rule is also explained below.

4.1 Set of Patch Images

The mosaic images are approximates of input ones with replacement of every block in the input image with patch images. Therefore, a set of patch images is desirable to be prepared as any luminance gradient in the block can be approximated by one of patch image in the set. The size of patches is \( 20 \times 20 \) in the experiments below.
4.1.1 Tile Patches A simple set of patch images is that of nine geometrical tile images shown in Fig.10 where top one is homogeneous without any gradient, the second row includes horizontal or vertical gradients and diagonal gradients are arrayed in the bottom row.

4.1.2 Photo Patches Small size photographs are needed for generating photomosaics. As such photo patches, we select among randomly collected 100 photographs of 20 × 20 size best matching to the above nine tile images in Fig.10. Their matching score is evaluated by their correlation coefficients. The correlation coefficient between two patch images is

\[ \rho = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2} \sqrt{\sum_i (y_i - \bar{y})^2}} \]  

(7)

where \( x_i \) and \( y_i \) are the luminance of \( i \)th pixel in each patch image and \( \bar{x} \) and \( \bar{y} \) are their averages.

Firstly, the image of which luminance variance is minimal is selected as a photo patch matching to the top image in Fig.10. For the remaining eight patterns in Fig.10, we select their corresponding photo patches with maximal correlation coefficients to each image in Fig.10 respectively. Selected photo patches are shown in Fig.11 where the order in images corresponds to that in Fig.10.

4.2 Selection of Patch Image The patch best matching to each pixel in the quantized downsampled image is selected from Fig.10 or Fig.11 and pasted to that pixel. By pasting images in Fig.10, we get tile images while Fig.11 yields photomosaics. This selection also utilizes the correlation coefficients. Firstly, we compute the standard deviation of the luminance of pixels in the block in the original input image corresponding to the pixel in the quantized downsampled image. If the standard deviation is smaller than a threshold (we set it to 5 in the following experiments), we select the top image in Fig.10 or Fig.11. If the standard deviation is larger than the threshold, we compute the correlation coefficients between the input block and eight patch images in Fig.10 or Fig.11, and we select the patch image of which correlation coefficient is largest.

4.3 Color Conversion of Patch Image Before pasting the selected patch image to each pixel of color \( C \) in the quantized downsampled image, we convert the color of every pixel in the selected patch image for the average of them becoming identical to \( C \) as below. This color conversion ensures that the average luminance of the patch image is equal to the luminance of \( C \).

This color conversion is required to be monotonically increasing function for each \( R, G, B \) and the converted value must lie in the range [0, 255]. The following conversion rule meets this requirement.

Let the color of a patch image in Fig.10 or Fig.11 be \( r_s, g_s, b_s \) (the coordinate of pixels is also omitted here). For instance, let the color \( C \) of a pixel in the quantized downsampled image be \( R = 255, G, B \). For the red component, we convert \( r_s \) to \( r'_s = 255 \). For the green component, we compute the average \( \bar{g'} \) of \( g_i \) in the patch image. If \( \bar{g'} < G \), the patch is darker, hence we brighten it by converting \( g_i \) to \( g'_i = g_i + (G - \bar{g'})/(255 - \bar{g'}) \) as is shown in Fig.12(a). Conversely, if \( \bar{g'} \geq G \), we then darken it by converting \( g_i \) to \( g'_i = Gg_i/\bar{g'} \) as in Fig.12(b).

The average of the resulted \( g'_i \) is coincident with \( G \) because the average of \( g'_i = g_i + (G - \bar{g'})(255 - g_i)/(255 - \bar{g'}) \) becomes \( G + (G - \bar{g'})(255 - g_i)/(255 - \bar{g'}) = G \) and also the average of \( g_i \), \( Gg_i/\bar{g'} \) is \( G \). For the blue component, we similarly convert it from \( b_s \) to \( b'_s \) of which average is equal to \( B \).

After this color conversion, we paste the patch image of thus changed color \( r'_s, g'_s, b'_s \) to the corresponding pixel in the quantized downsampled image.
5. Summary of Procedure
The above procedure for generating pointillistic mosaic images is summarized as:

1) Shrink an input image.
2) Quantize isoluminantly the shrunk image.
3) For each pixel in the quantized shrunk image, select a patch image best matching to the block in the input image corresponding to the pixel.
4) Convert the color of selected patches for their average to be coincident with the color of pixel in the quantized shrunk image.
5) Paste the patch of converted color to the pixel in the quantized shrunk image.

6. Experiments
A result of pasting patches in Fig.10 to the image in Fig.8(d) is shown in Fig.13(a) for which bump processing yields Fig.13(b) which resembles a tile image. A result of pasting patches in Fig.11 to the image in Fig.8(d) is shown in Fig.14(a) for which bump processing yields Fig.14(b) which resembles textured tile images in Fig.2. For other input images shown in Fig.15, their downsampled halftoning images are shown in Fig.16 and their tile images and photomosaics are shown from Fig.17 to Fig.19. As is seen in these output images, our method can produce colorful mosaic images.

7. Conclusion
A non-photorealistic rendering technique has been presented for pointillistic halftoning of color images by modulating colors with large difference in the hue while preserving the luminance. This pointillistic halftoning has been applied to generation of tile images and photomosaics. In the present method, the luminance is strictly preserved, while its slight variation is sometimes observed in hand-drawn pointillistic paintings. The restriction on the luminance preservation, hence, can be relaxed for output images more resembling the color configuration in practical paintings. An improvement for our method is also under study for higher reproducibility of color patterns in input images by increasing the variety in patch images.

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References
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