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Color image arrangement by elastic transform based on histogram matching

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Abstract: Aiming at automated affective color image arrangement, this paper proposes a new method using histogram based Elastic Transform (ET) on some kinds of axis including Lightness axis. If we represent a pixel of input image as a vector in the three-dimensional RGB color space, the input image corresponds to a set of the three-dimensional pixel vectors. As for axis other than the Lightness axis, there are PC axes that can be obtained by Principal Component Analysis (PCA) from the set of three-dimensional vectors. In this paper, we present a principle of the ET on the Lightness axis and PC one. We also illustrate that HMGD (Histogram Matching based on Gaussian distribution) is regarded as one of the ET method. In addition, for the investigation of the performance, we show the experimental results by applying the transform (especially HMGD) to some images.

Keywords: Color arrangement, elastic transform, histogram equalization, histogram matching.

1 INTRODUCTION

Recently, automated image processing for enhancement and/or arrangement is becoming more familiar to us according to the spreading of Digital Camera, Smart Phone, DVD, etc. ([1]-[3]). However, we consider that the research on the automated image arrangement method with sensibility effect is still on the way to practical use.

In this paper, we propose a method for image arrangement by elastic transform utilizing histogram (e.g. Histogram Equalization (HE), Histogram Matching (HM)) on some kinds of axis ([4]-[6]). As for the axis, there are Lightness axis and principal component axis that can be obtained by Principal Component Analysis (PCA). Also in this paper, we show the principle of the method and some application results.

2 ELASTIC TRANSFORM (ET)

2.1 Principle

We describe the principle of histogram based elastic transform in the following. Let $f(x)$ and $g(y)$ be two probabilistic density functions on real variables x and y, respectively. The probabilistic density function (pdf) is corresponding to histogram of gray level image. However, the histogram is defined on discrete variable. In addition, let $y = \phi(x)$ be a continuous and monotonous increase function between variables x and y as shown in Fig. 1. In addition, let value of x be the range from 0 to L. Accordingly, variable y ranges from 0 to $\phi(L)$. Let P mean the probability. From the above definitions and Fig.1, we have Eq.(1)-Eq.(3). From Eq.(3), we obtain Eq.(4)and Eq.(5).

Thus, if we know the $y = \phi(x)$ and $g(y)$, then we have the $f(x)$.

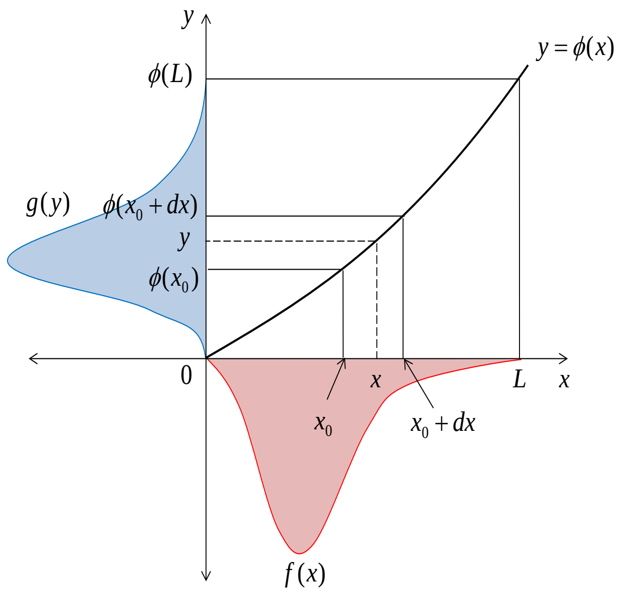


Fig.1. Continuous and monotonous increase function $y = \phi(x)$ and probabilistic density functions $f(x)$ and $g(y)$.

$$P(0 \le x \le L) = \int_{x=0}^{x=L} f(x)dx = 1 \tag{1}$$

$$P(0 \le y \le \phi(L)) = \int_{y=0}^{y=\phi(L)} g(y)dy = 1 \tag{2}$$

$$\begin{aligned} f(x)dx &= P(x_0 \le x \le x_0 + dx) \\ &= P(\phi(x_0) \le y \le \phi(x_0 + dx)) \\ &= P(y_0 \le y \le y_0 + dy) \\ &= g(y)dy \end{aligned} \tag{3}$$

where $y_0 = \phi(x_0)$, $y_0 + dx = \phi(x_0 + dx)$.

$$f(x)dx = g(y)dy = g(y)\phi'(x)dx \tag{4}$$

$$f(x) = g(y)\phi'(x) \tag{5}$$

Using the above equations, we derive the principle of Histogram Equalization (HE). Let $\phi(x)$ be defined by the following Eq.(6).

$$\phi(x) = L\int_0^x f(x)dx \tag{6}$$

Since $\phi'(x) = Lf(x)$, according to Eq.(5),

$$f(x) = g(y)Lf(x) \tag{7}$$

Then we have

$$g(y)L = 1 \text{ and } g(y) = 1/L. \tag{8}$$

Using the above equations, we derive the principle of Histogram Equalization (HE). Let $\phi(x)$ be defined by the following Eq.(6).

Therefore, we understand that, if we take the transform function as Eq.(6), $g(y)$ becomes uniform distribution as shown in Fig.2. It corresponds to the Histogram Equalization (HE) processing, which means that function defined by cumulative histogram transforms the original histogram into the uniform one.

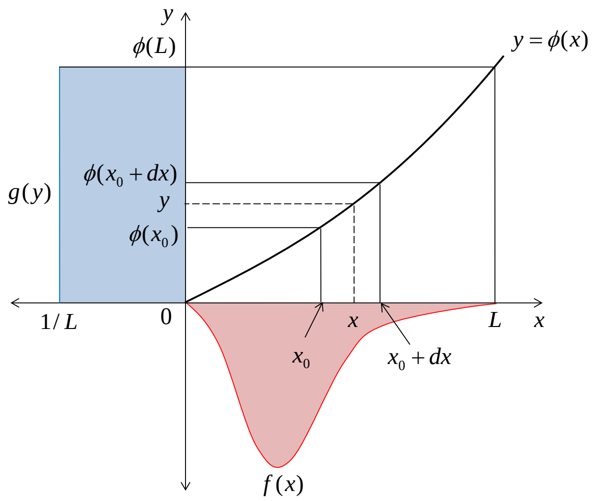


Fig.2. Conceptual image of the relation between uniform distribution and original distribution.

Inversely, if we define the transform function $\phi(x)$ as an integral of desired pdf $f(x)$ for example, Gaussian distribution, we can obtain the desired pdf using the $\phi(x)$ and the uniform distribution such as Eq.(8) (Fig.3).

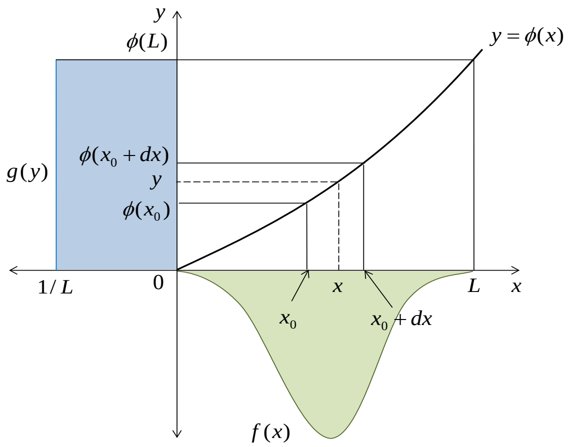


Fig.3. Conceptual image of the transform from uniform distribution (pdf) to the desired one (pdf).

The abovementioned theory means that, if we combine the both transform, we can obtain the transformation from an original distribution (pdf) to a desired one. This means that an image with original histogram can be transformed into another image with desired histogram. We consider that it is the principle of the Histogram Matching (HM) [4] (Fig.4).

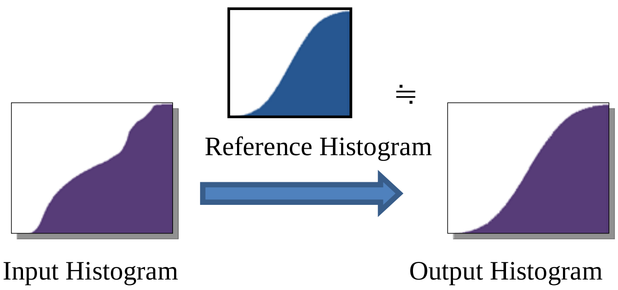


Fig.4. Histogram Matching (HM) [4].

2.2 Transform on axis

We can choose the abovementioned transform such as HE and HM on arbitrary axis (for example, principal component axis) in the color attribute space (RGB space) as shown in Fig.5.

For example, if we choose HE processing on the light axis, it can bring about image enhancement by contrast stretching. In addition, if we choose the HE on a principal component axis in RGB space, we guess that the contrast stretching will be done along to a certain tone of color. Fig.6 shows examples of the HE on Lightness axis and PC (Principal Component) axis.

For example, if we choose HE (Histogram Equalization) processing on the light axis, it can bring about image enhancement by contrast stretching. And if we choose the HE on a principal component axis in RGB space, we guess that the contrast stretching will be done along to a certain tone of color as shown in Fig.6 that shows examples of the HE on Lightness axis and PC (Principal Component) axis.

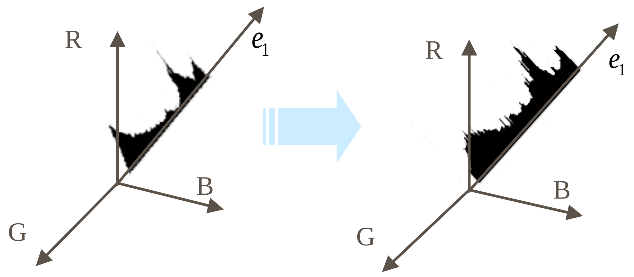
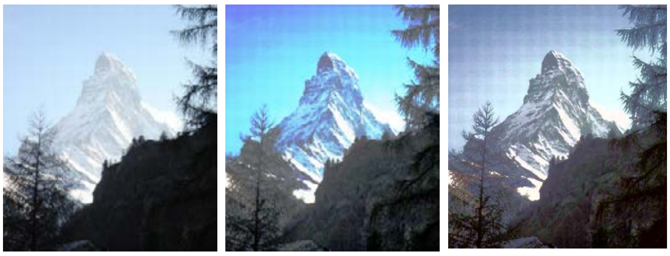


Fig.5. Conceptual image of histogram based elastic transform on arbitrary axis in the RGB space.



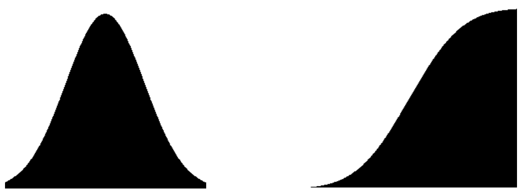
(a)Original image. (b)Lightness axis. (c)PC axis.
Fig.6. Examples of the HE on Lightness and PC axis.

3 HISTOGRAM MATCHING BASED ET

The abovementioned Histogram Matching (HM) can be regarded as one of the Elastic Transform (ET) method. Since there are many kinds of reference histogram and axis, we will find various ET methods as much.

As one of those ETs, we focus on a histogram based ET method in which the reference histogram is Gaussian distribution (Fig.6) on Lightness axis. We call it "Histogram Matching based on Gaussian Distribution (HMGD)".

Fig.7 shows the results by two histogram based ET methods such as HE and HMGD on Lightness axis. From this, we find that HMGD results in moderate transformation from the original image, comparing with HE.



(a) Gaussian distribution (b)Cumulative histogram
Fig.6. Gaussian distribution histogram.

4 INVESTIGATION OF HMGD

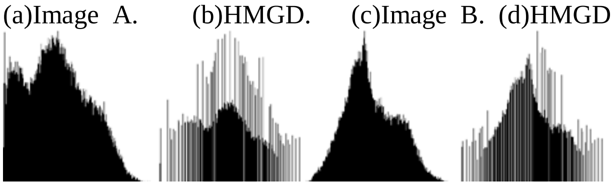
In this paper, we investigate the effects by the HMGD. Fig.8 shows examples that HMGD works well from feeling impression. From Fig.9, we can find out that the cumulative histogram of the resultant image clearly approaches to the cumulative Gaussian distribution.

(a)Original image. (b)HE. (c)HMGD.
Fig.7. Example of the results by HE and HMGD.

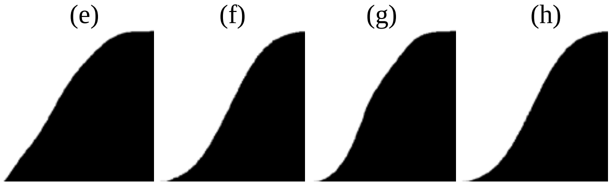
(a)Input image A (b) Output image A

(c)Input image B (d) Output image B
Fig.8. Examples of the resultant HMGD.

(a)Image A. (b)HMGD. (c)Image B. (d)HMGD



(e) (f) (g) (h)



(i) (j) (k) (l)
Fig.9. Results of HMGD and the corresponding histogram ((e)-(h): histogram of the above image, (i)-(l):cumulative histogram of the above histogram).

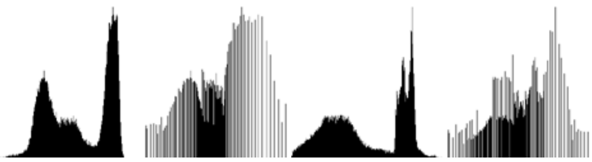
On the contrary, Fig.10 shows examples that it does not so work well, judging from our feeling impression. From, Fig.11 shows that the corresponding histograms. If we compare with Fig.9, we can find out that there are double peaks in the histogram of Image C and D (Fig.12), while there is single peak in that of the Image A and B.

(a)Input image C (b) Output image C

(c)Input image D (d) Output image D

Fig.10. Examples of the resultant HMGD in the case where it does not work well.

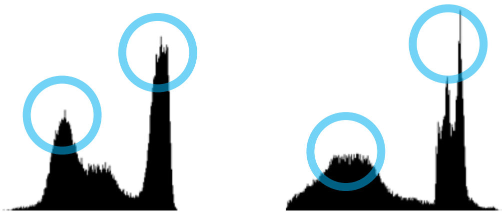
(a) Image C. (b)HMGD. (c)Image D. (d)HMGD.



(e) (f) (g) (h)

(i) (j) (k) (l)

Fig.11. Results of HMGD and the corresponding histogram ((e)-(h): histogram of the above image, (i)-(l):cumulative histogram of the above histogram).



(a)Histogram of Image C. (b)Histogram of Image D.

Fig.12. Bimodality histogram on Lightness of Image C and D. ((a) and (b): the same as (e)and (g) in Fig.11,respectively. There are double peaks in each histogram.)

5 CONCLUSION

Aiming at automated affective color image arrangement, we have proposed a concept of Elastic Transformation (ET) method based on histogram, that varies on some kinds of axis such as Lightness axis and Principal Component one in RGB space. We also have described the principle in the details. And we have explained that HMGD (Histogram Matching based on Gaussian Distribution) is regarded as one of the ET method. Moreover, for the investigation of the performance, we have shown the experimental results. From the experimentation, we have found that HMGD works well for images if the histogram has single peak. Then we consider that automated detection of the single peak is promising for our aim.

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