K-Means Algorithm Using Texture Directionality for Natural Image Segmentation

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Abstract

The goal of this research is to describe relations between impressions and elements in an image (i.e. color, texture and contours). Adequate image segmentation technique to extract these elements is required. We think that a sketch and a realistic painting are examples of optimal segmented images for our purpose because brush strokes are seem to be segmented areas and realistic paintings should remain the same impression as the model. For the reason, in this paper the segmentation technique which can create realistic painting-like segmentation is exploited. It is shown that the realistic painting-like segmentation is suitable for analyzing images.

1. Introduction

The aim of our research is to construct a knowledge system which analyzes images (ex. photographs and paintings) and shows these impressions. To produce such a system, it is important to research the relations between impressions and combinations of color and texture on a image. There are some previous researches about extracting the image elements (for example, lines and colors) in relation to impressions [1] and about an image retrieving system by these relations [2]. The only image elements such as lines, colors and local arrangement of colors are not enough for our research. Specially, arrangement of colors and textures in the wide area of an image is important. For clearly grasping such features, an appropriate image segmentation is important. Then, extracting characteristics such as an average color and a texture at each segment in the segmented image are required.

There are many different segmentation techniques. Almost all of them, however, are used for image recognition and contour detection [3]. There are not many conventional image segmentation methods [4] which meet our requirements. As the information extracted from the segments is used for analyzing impressions of a picture, these segments should have a natural appearance. We propose a new natural image segmentation algorithm.

2. Image segmentation

2.1 Basic concept

It is difficult to describe the features of the segmented image with natural appearance. However, we think that the segmented image with natural appearance is what have the same feature as a realistic painting or a sketch because brush strokes are seem to be segmented areas and realistic paintings should remain the similar impression as the model.

In the past, we observed how painters sketch a model [5]. The results of these observations have much useful information for creating our segmentation algorithm. The results of these observations show the following rules about expression.

(1) Strokes on contours are very thin.

(2) Strokes on details are fine. On the contrary, strokes on coarse parts are large.

(3) At the fine texture parts like hair, strokes are also fine but usually do not express hair one by one. The shape of such a stroke is usually stretched along the direction of texture.

(4) If a non-texture area is surround by texture areas, shapes of strokes on the no-texture area are affected by shapes of strokes on texture areas.

These are not strict rules. To produce brush strokes as mentioned above, a 5-dimensional K-means clustering algorithm is adopted. The five dimensions consist of two position data and three color data, because a brush stroke must be a collection of pixels being near in position and in color space. Furthermore, to control brush strokes in accordance with above-mentioned rules, the 5-dimensional K-means clustering algorithm has to be revised for treating information of direction and strength about texture. In following section, we describe how to calculate direction and strength of texture, and how to use this information.

2.2 Notation

We select the CIELAB color space, which the Commission International de l'Eclairage or CIE decided, because this color space is fit for human vision and is easy to define the formula of a color difference calculation. Here, we define the symbols used in this paper.

- G : An original image.
- l : L*.
- a : a*.
- b : b*.
- db_n : Strength of the edge on the nth pixel.
- da_n : Direction of the edge on the nth pixel.
- $Da_{i,j}$: Direction of texture of the jth segment at the ith iteration.
- $Dd_{i,j}$: Strength of directionality of the jth segment at the ith iteration.
- $Dc_{i,j}$: Strength of texture of the jth segment at the ith iteration.

First, the strength and the direction of color discontinuity at each pixel need to be extracted from an original image. The convolutions between each of the two masks $M_{3\text{-}1}$ and $M_{3\text{-}2}$ shown in Figure 1 and the l component of the original image G are performed. Then, da_n and db_n are calculated by following equations:

$$da_n = \frac{16}{\pi}\left(\tan^{-1}\left(\frac{LL}{CC}\right)+\frac{\pi}{2}\right), \qquad (1)$$

$$db_n = \log(LL^2+CC^2+1), \qquad (2)$$

$$CC = G*M_{3\text{-}1}, \qquad (3)$$

$$LL = G*M_{3\text{-}2}, \qquad (4)$$

where * means convolution, and da_n and db_n are quantized and expressed by integers ranging from 0 to 15. The values of da_n express the directions shown in Fig. 2.

2.3 Three texture factors extracted from texture in a segment

A K-means algorithm is a method to iterate calculations of a distance between a pixel and a center of a segment successively until shapes of segments will not change. Accordingly, to give the segmenting algorithm the ability to treat texture, the distance function have to be modified to be able to treat texture information.

Generally speaking, to perceive some texture, a single pixel is not enough. A small area consisting of some pixels is required. We will show how to extract texture information from da_n and db_n of a segment in the following procedures. Let i be an index of iteration. First, $N_{0,i,j}$ is defined as the number of pixels which meet the conditions $da_n = 0$ and $db_n > 1$ in the jth segment at the ith iteration. In the same manner, $N_{k,i,j}$ (k = 1~15) are defined. Then, $N_{16,i,j}$ is defined as the number of pixels having no direction (i.e. the number of pixels meeting the condition $db_n \leq 1$ in the jth segment at the ith iteration). We have found that the threshold $db \leq 1$ works well. The maximum value is chosen from $N_{0,i,j}$ to $N_{15,i,j}$. If this value is larger than $N_{16,i,j}/10$, it is set to $Da_{i,j}$ as a representative direction of jth segment. On the other hand, if the maximum number is equal to or smaller than $N_{16,i,j}/10$, the number 16 is assigned to $Da_{i,j}$. This number mean that jth segment has no texture.

We introduce the measure $Dd_{i,j}$ which indicates how clearly $Da_{i,j}$ represents the direction of the segment. It is assumed that a human is able to discriminate at most two texture directions at a time and if there is a second direction, it must differ from the first direction by about $\pi/2$. Therefor, $Dd_{i,j}$ is expressed by the following equations:

$$Dd_{i,j} = k_2\left(N_{Da_{i,j}} - N^{\perp}_{Da_{i,j}}\right)/\left(N_{Da_{i,j}} + N^{\perp}_{Da_{i,j}}\right) \qquad (5)$$

$$N^{\perp}_{Da_{i,j}} = \left(N_{Da_{i,j}+7} + N_{Da_{i,j}+8} + N_{Da_{i,j}+9}\right)/3 \qquad (6)$$

$$\begin{array}{|c|c|c|}\hline -1 & -1 & -1 \\ \hline 0 & 0 & 0 \\ \hline 1 & 1 & 1 \\ \hline \end{array} \qquad \begin{array}{|c|c|c|}\hline -1 & 0 & 1 \\ \hline -1 & 0 & 1 \\ \hline -1 & 0 & 1 \\ \hline \end{array}$$

M $_{3\text{-}1}$ **M** $_{3\text{-}2}$

Figure 1: The masks $M_{3\text{-}1}$,$M_{3\text{-}2}$

where k_2 is a real constant which ranges from 0 to 1.
If the result of calculation of $Da_{i,j}$ is less than 0, $Da_{i,j}$ must be added by 16 . On the other hand, if the result of calculation of $Da_{i,j}$ is more than 15, $Da_{i,j}$ must be subtracted by 16. The threshold $N_{16,i,j}/10$ is chosen from previous trial experiments.
These two characteristics of texture $Da_{i,j}$ and $Dd_{i,j}$ are not enough to enable a segmentation algorithm to treat texture. As was mentioned before, when painters draw fine texture, they paint that part by fine strokes. However they are inclined to neglect too fine detail and boldly paint the fine texture with one stroke. To produce the algorithm which can simulate the features described above, strength of texture $Dc_{i,j}$ is necessary to control the condition of the segmentation. $Dc_{i,j}$ is calculated by the following equation:

$$Dc_{i,j} = k_1 \sum_{k=0}^{15} N_{k,i,j} / N_{i,j} \tag{7}$$

where k_1 is a positive constant.
These three texture factors ($Da_{i,j}, Dd_{i,j}, Dc_{i,j}$) are used for controlling the distance function in this algorithm.

2.4 K-Means algorithm with three factors of texture

As was mentioned in the previous section, this algorithm is one of methods to iterate the calculations of the distance function until the result converges. This segmentation algorithm is executed according to the following steps.

Step 1 Initial arrangement of segment centers

Let K be the initial number of segments. A total of K rectangles are put side by side on an original image G. These rectangles are regarded as initial segments on G, and all the above mentioned characteristics in segments are calculated. The characteristics of the jth segment at the ith iteration ($C_{i,j}$) consist of a center of gravity ($X_{i,j}, Y_{i,j}$), a number of pixels ($N_{i,j}$), an average color ($L_{i,j}, A_{i,j}, B_{i,j}$), a direction of texture ($Da_{i,j}$), strength of directionality ($Dd_{i,j}$) and strength of texture ($Dc_{i,j}$). In short, $C_{i,j}$ consist of ($X_{i,j}, Y_{i,j}, N_{i,j}, L_{i,j}, A_{i,j}, B_{i,j}, Da_{i,j}, Dd_{i,j}, Dc_{i,j}$). Initial segment characteristics (i.e. $i = 0$) $C_{0,j}$ are calculated and written to the characteristic table. Similar calculations are repeated at each iterations until a stopping condition is satisfied. Assuming that $C_{i,j}$ are being calculated at the ith iteration, we will illustrate following steps .

Step 2 Judging a Segment

Pixels are chosen one by one. Then, weighted Euclidean distance $H_{i,j,n}$ between $C_{i,j}$ and chosen nth pixel is calculated by the following equations (8)~(12). First, the distance between the center of gravity and the pixel position, and the color difference between $C_{i,j}$ and nth pixel are calculated.

$$\Delta x_{i,j,n} = (X_{i,j} - x_n) \tag{8}$$

$$\Delta y_{i,j,n} = (Y_{i,j} - y_n) \tag{9}$$

$$\Delta l_{i,j,n} = (L_{i,j} - l_n) \tag{10}$$

$$\Delta a_{i,j,n} = (A_{i,j} - a_n) \tag{11}$$

$$\Delta b_{i,j,n} = (B_{i,j} - b_n) \tag{12}$$

Second, the weighted distance between the center of gravity and the pixel's position is calculated, taking account of the texture.

$$\Delta x'_{i,j,n} = F(\Delta x_{i,j,n}, \Delta y_{i,j,n}, Da_{i,j}, Dd_{i,j}, Dc_{i,j}) \Delta x_{i,j,n} \tag{13}$$

$$\Delta y'_{i,j,n} = F(\Delta x_{i,j,n}, \Delta y_{i,j,n}, Da_{i,j}, Dd_{i,j}, Dc_{i,j}) \Delta y_{i,j,n} \tag{14}$$

where $F()$ is the function to control the shape and size of segments.

If $\left| Da_{i,j} - \left(\tan^{-1}\left(\frac{-\Delta y_{i,j,n}}{\Delta x_{i,j,n}}\right) + \frac{\pi}{2} \right) \frac{16}{\pi} \right| < 8$

then

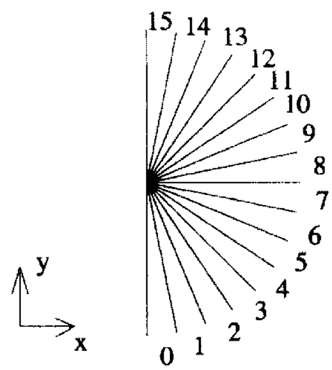

Figure 2: The directions from 0 to 15

$$F(\Delta x_{i,j,n}, \Delta y_{i,j,n}, Da_{i,j}, Dd_{i,j}, Dc_{i,j}) = 1 + Dc_{i,j}$$

$$\times \{1 + Dd_{i,j} \left| Da_{i,j} - (\tan^{-1}(\frac{-\Delta y_{i,j,n}}{\Delta x_{i,j,n}}) + \frac{\pi}{2}) \frac{16}{\pi} \right| /4 - 1\} \quad (15)$$

If $\left| Da_{i,j} - (\tan^{-1}(\frac{-\Delta y_{i,j,n}}{\Delta x_{i,j,n}}) + \frac{\pi}{2}) \frac{16}{\pi} \right| \geq 8$

then

$$F(\Delta x_{i,j,n}, \Delta y_{i,j,n}, Da_{i,j}, Dd_{i,j}, Dc_{i,j}) = 1 + Dc_{i,j}$$

$$\times \{1 + Dd_{i,j} (16 - \left| Da_{i,j} - (\tan^{-1}(\frac{-\Delta y_{i,j,n}}{\Delta x_{i,j,n}}) + \frac{\pi}{2}) \frac{16}{\pi} \right| /4 - 1)\} \quad (16)$$

These equations are combined and $H_{i,j,n}$ is defined as

$$H_{i,j,n} = k_x \Delta x'^{\,2}_{i,j,n} + k_x \Delta y'^{\,2}_{i,j,n} + k_l \Delta l^2_{i,j,n} + k_a \Delta a^2_{i,j,n} + k_b \Delta b^2_{i,j,n} \quad (17)$$

where k_x, k_l, k_a, k_b are constants.

The distance $H_{i,j,n}$ between all the segments and the nth pixel are calculated and the nth pixel is included in the jth segment with the smallest value of $H_{i,j,n}$. Fig. 3 shows the relation between the vector from the center of gravity $(X_{i,j}, Y_{i,j})$ to the nth pixel and the direction of texture in a segment $Da_{i,j}$. If the direction of this vector comes close to $Da_{i,j}$, the value of $H_{i,j,n}$ is decreased. On the other hand, if the direction differ from $Da_{i,j}$ by $\pi/2$, the value of $H_{i,j,n}$ is increased. As a result, the jth segment includes more pixels in the close directions to $Da_{i,j}$ or $Da_{i,j} + \pi$ than in the other directions. Furthermore, if almost all of pixels in the jth segment have similar values to da_n and satisfy the condition $db_n > 1$, then $Dd_{i,j} \approx k_2$. Finally, a shape of the segment is stretched to be a narrow ellipse. On the contrary, if many pixels in the jth segment satisfy only the condition: $db_n > 1$ regardless of the direction, then $Dc_{i,j} \approx k_1$. Finally, the size of the jth segment becomes small and the contour of a segment becomes simple, because if the value of $Dc_{i,j}$ is close to k_1, $F(\,)$ comes to be a large value. These calculations are successively executed for every segment.

Step 3 Recording to the characteristic table

$C_{i,j}$ in all newly calculated segments are written over $C_{i-1,j}$ in the characteristic table.

Step 4 Checking The Stopping Condition

Discrepancy $H'_{i,j}$ between $C_{i,j}$ and $C_{i-1,j}$ is calculated by following equations:

$$\Delta_{X,i+1,j} = (X_{i+1,j} - X_{i,j}) \quad (18)$$

$$\Delta_{Y,i+1,j} = (Y_{i+1,j} - Y_{i,j}) \quad (19)$$

$$\Delta_{L,i+1,j} = (L_{i+1,j} - L_{i,j}) \quad (20)$$

$$\Delta_{A,i+1,j} = (A_{i+1,j} - A_{i,j}) \quad (21)$$

$$\Delta_{B,i+1,j} = (B_{i+1,j} - B_{i,j}) \quad (22)$$

and

$$H'_{i+1,j} = k'_x (\Delta^2_{X,i+1,j} + \Delta^2_{Y,i+1,j}) + k'_l \Delta^2_{L,i+1,j} + k'_a \Delta^2_{A,i+1,j} + k'_b \Delta^2_{B,i+1,j} \quad (23)$$

The above steps are repeated until $H'_{i,j}$ has a smaller value than previously chosen a certain value (Cd_1). We have found

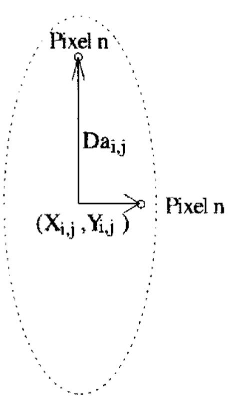

Figure 3: Positional relation between the pixel n and the center of gravity of the jth segment $(X_{i,j}, Y_{i,j})$

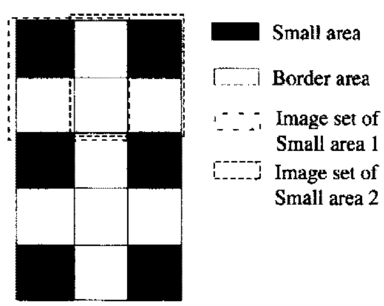

Fig. 4: A example of an image which is divided by many small areas.

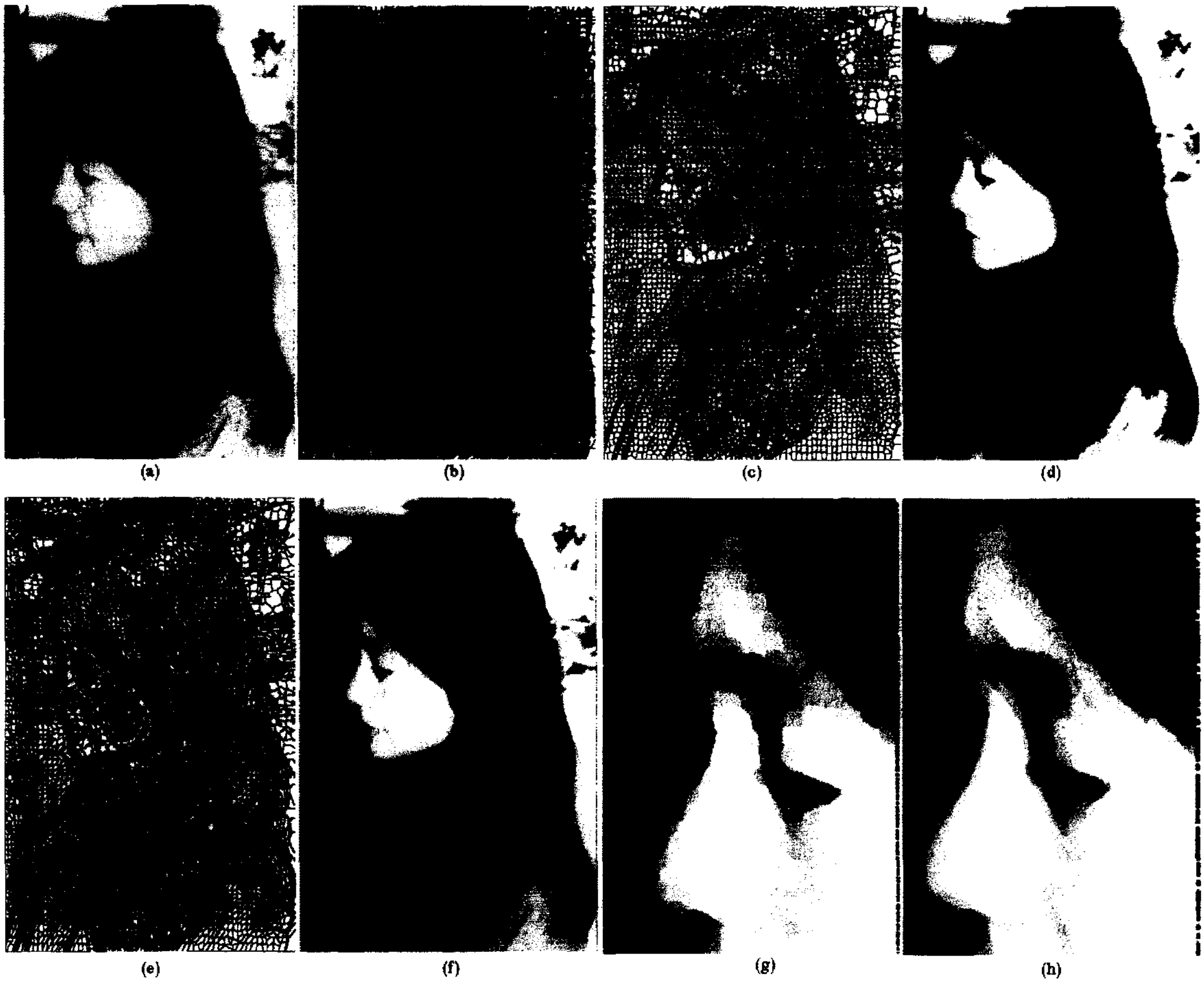

Fig. 5 An original image and processed images (a) An original image, (b) An segmented image at the condition of $k_1=0, k_2=0$, (c) An segmented image at the condition of k1=6, k2=0, (d) The image which has segmented areas of Fig. (d) painted by average color of the segmented area, (e) An segmented image at the condition of $k_1=6$, k2=0.9, (f) The image which has segmented areas of Fig. (e) painted by average color of the segmented area, (g) An enlarged image of (d), (h) An enlarged image of (f).

that a value of $Cd_1 = 1$ works well. When this repeated process stops, the segmentation is completed.

As this new 5-dimensional K-means clustering algorithm is a very time consuming process, we must apply this process to the small rectangular areas divided from a original image. Figure 3 shows the rectangular areas consisting of a core area and overlapping areas [6]. The overlapping areas surround the core area. The new clustering algorithm is applied to each rectangular area. Without overlapping areas, each small rectangular area would be clustered independently. That would cause a discontinuity of a segment on the border. However, if there are overlapping areas, these are clustered several times. This procedure decreases the defects of discontinuity caused by separately applying K-means clustering algorithm to small areas.

These are the outline of our new clustering algorithm. Regarding this algorithm, from the beginning deciding a suitable number of segments is difficult. However, this algorithm can segment each small area with different conditions. The conditions are changed while this algorithm is repeatedly apply to the same small rectangular area. Accordingly, the number of segments can be increased until the maximum color deviation of pixels in a segment is within a certain value (Cd_2). We have found that a value of $Cd_2 = 20$ works well. This additional segment increasing process efficiently produce enough segments for the realistic imaging. Finally, when whole process is finished, the group of characteristics C_{ij} is written to the corresponding cell (C_j)

in the characteristic table. In the following sections, we will call this algorithm the adaptive K-means method.

3. Results of segmentation

Fig. 5-(a) is an original photograph. Fig. 5-(b), 5-(c) and 5-(e) show the results which are segmented by the above process. Fig. 5-(b) is a result image segmented under the conditions: $k_1 = 0$ and $k_2 = 0$. These conditions mean that both area and shape of a segment are not changed by strengths and directions of texture. This is basically the same result as Izumi proposed [7] except for using divided K-means algorithm. This image has simple shaped segments on the facial part, but on the other parts segments are mixed with each other. In other words, on the part with the strong texture, pixels belonging to the same segment are distributed in the wide area. For the reason, the image in Fig. 5-(b) looks almost black except the facial part. We consider that the shapes of segments should be important information for image impression analysis. As the segments in Fig. 5-(b) is not classified by the shapes of segments, This segmentation is not adequate for our purpose.

Fig. 5-(c) shows the result of the segmented image under conditions $k_1=6, k_2=0$. This condition makes segments small and simple on the areas having strong texture. Fig 5-(d) is created to paint the segments of Fig. 5-(c) with average colors and Fig. 5-(g) is the enlarged image of Fig 5-(d). In this image, rectangle segments are standing out and it presents an unnatural appearance. Fig 5-(e) is a segmented image under conditions $k_1=6$, $k_2=0.9$. This image has simple and elliptic segments distorted along the direction of the texture. The segments at the hair part are stretched along the flow of the woman's hair. Fig. 5-(f) is created to paint the segments of the Fig 5-(e) with average color and Fig. 5-(h) is the enlarged image of Fig 5-(f). This image is more similar to original image than Fig. 5-(d). Compared with Fig. 5-(d), the number of segments in Fig. 5-(e) is 7003, while the one in Fig. 5-(c) is 8032. The number of segments in Fig. 5-(e) is fewer than the one in Fig. 5-(c) . This is another advantage of this algorithm for the analysis because too many characteristics are hard to be handled.

4. Conclusion

In this paper, we proposed a new image segmentation algorithm which generates segments adaptively changed according to strength and direction of texture. The segmented image and the reconstructed image of which segments are painted by average colors of segments were displayed. A reconstructed image by a proposed segmentation method was shown being more similar to the original image than the reconstructed image by a conventional method without texture. For the reason, the characteristics extracted from segments generated by this method is expected to be utilized for analyzing impression of a image. When the image segmentation is finished, the characteristic table is completed storing the average color, number of pixels and direction of texture in every segment. As a next step of this study, we would like to use the characteristics in a characteristic table to analyze the impression of image .

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