Image Identification Based on Color and Luminance Information by Using an Optical Correlator

H. Kuboyama*, K. Moriyama¹, S. Arai¹, M. Fukuda¹, M. Kato², T. Kawaguchi², S. Yamamoto³ and M. Inoue¹

¹Department of Electrical and Electronic Information Engineering, Toyohashi University of Technology, 1-1 Hibarigaoka, Tempaku-cho, Toyohashi, Aichi 441-8580, Japan
²PaPaLaB Ltd., 3-1-7 Wachiyama, Naka-ku Hamamatsu, Shizuoka 433-8123, Japan
³Hamamatsu University School of Medicine, 1-20-1 Handayama, Hamamatsu, Shizuoka 431-3192, Japan

E-mail: fukuda@ee.tut.ac.jp

Abstract. A technique for distinguishing real-world images has been developed using a joint transform correlator. The real-world images, taken with a digital camera, are converted into luminance-intensity histograms and x-y chromaticity diagrams in the correlator system. These two-dimensional patterns are displayed on a spatial light modulator and are distinguished using the correlator system. The proposed identification techniques could distinguish an object image similar to the reference image of an apple among various fruits and vegetables, and could also distinguish tumor cell images from other cell images using the correlator system. These experimental results demonstrate the feasibility of using an optical correlator for the identification of complex real-world images containing large volumes of information.

1. Introduction

The optical correlator is generally used for pattern recognition, and involves the use of an optical Fourier transform technique. For facial recognition and fingerprint recognition systems, several techniques for distinguishing the pattern information have been reported [1-2]. However, image identification using pattern information is only applicable to images having shape information, like faces and fingerprints. Also, if the image pattern is expanded or rotated, pattern recognition is markedly degraded in the optical correlator. In other words, image identification based on pattern information lacks flexibility, and has difficulty in distinguishing real-world images containing large volumes of information. Accordingly, we have investigated the influence of statistical color and luminance information on image recognition to address the weaknesses of the optical correlator.

The purpose of this study is to distinguish real-world images with techniques based on the statistical color and luminance information of the images on the optical correlator. In this paper, the details of these techniques and the experimental results for image identification using the developed techniques are described. The characteristics and architecture of the optical correlator are described in section 2. In section 3, the techniques for using the statistical color and luminance information of the image are described. In section 4, the experimental results are described and discussed. The results obtained in this study are summarized in section 5.
2. Joint transform correlator

Two main configurations are used to perform spatial correlation using optical systems: the VanderLugt correlator (VLC) [3] and the joint transform correlator (JTC) [4]. Compared to the VLC, the JTC has a disadvantage in that the processing speed is low. However, the JTC has the important advantage that images can be updated in real time. The JTC has two further advantages with regard to the hardware: compact size and a simple optical system without the requirement for complicated adjustments to the optical axis, and it is therefore smaller than the VLC. Consequently, a compact “slot-in type” optical correlator was developed previously [5].

2.1. Experimental set-up

The optical system of a JTC is shown in Fig. 1. A laser diode operating at a wavelength of 658 nm is used as a coherent source. A spatial light modulator (SLM) and a CMOS sensor are used as the system input plane and output plane, respectively. The light emitted from the laser diode is collimated with a lens having a focal length, \( f \), of 100 mm. The collimated light is transformed from elliptically polarized light to linearly polarized light by the polarizer, with a polarization angle of 45° toward the horizontal direction, and the transformed light illuminates the SLM displaying the reference pattern (the letter “C”) and the retrieved pattern (the letter “C”) at a distance of ±d in the x-direction from the central part of the SLM (Fig. 1a). The reflected light from the SLM is phase-modulated according to the grey-scale of the input image and converted to an intensity-modulated signal with the polarizer set at a polarization angle of 135° from the horizontal axis. The intensity-modulated light is guided to the CMOS sensor by a lens with \( f \) of 120 mm. A Fourier-transformed pattern of the input image therefore appears on the CMOS sensor. The Fourier-transformed pattern is recorded as a power spectrum on the CMOS sensor. The recorded power-spectrum pattern is fed back to the SLM, and a similar process to that described above is repeated. The Fourier-transformed pattern of the power spectrum pattern is finally formed on the CMOS sensor. The cross-correlation spots, from which the optical intensity is expressed with the cross-correlation function of the retrieved and reference patterns, appear at a distance of ±2d in the x-axis from the central part of the CMOS sensor (Fig. 1b).

Figure 1. Block diagram of joint-transform correlator. Images (a) and (b) are the input and output images.
3. Color and luminance identification techniques

The optical correlator is generally applied to pattern recognition. Electrically addressed liquid crystal (LC) modulators are ordinarily used in optical correlators as the spatial modulators to input reference and retrieved data to the optical system. The input data are displayed with on-off (or black and white) pixel data on the modulator. The input data are therefore two-dimensional (2D) data, and displaying multi-dimensional data such as color information is difficult. Therefore, to distinguish images with the color and luminance information of the images on the optical correlator, this color and luminance information must be transformed into 2D patterns. Also, the "statistical" color and luminance information of the images is transformed into 2D patterns because the “statistical” information of the images scarcely depends on structural variation of the images, like an image expansion or rotation. The x-y chromaticity diagrams and luminance histograms were used to transform the statistical color and luminance information of the images into 2D patterns. The details of these techniques are described in sections 3.1 and 3.2.

3.1. Color identification technique

To transform the statistical color information into 2D patterns, a color specification system was used. The main color specification systems are the Munsell color system based on a color appearance system and the CIE (Commission Internationale de l’Eclairage) standard colorimetric system based on a color mixing system. Because the CIE standard colorimetric system has high precision in displaying optional colors when compared with the Munsell color system, the CIE system was used in this study. In the CIE standard colorimetric system, the techniques for transforming the color information of images into a chromaticity diagram have been reported in detail [6]. In these techniques, an x-y chromaticity diagram was used to transform the grey values of red, green, and blue included in each pixel of the images to a value given with X-Y-Z values and maps the value on to the color chart. In other words, the color information of the images can be transformed into a 2D pattern on the x-y chromaticity diagram. Accordingly, we have previously distinguished the color information of the images by pattern matching the color pattern on the x-y chromaticity diagram [7]. The procedure that is used to transform the color information of all of the image pixels into the x-y chromaticity diagram is shown in the flowchart (Fig. 2).

![Flowchart for making x-y chromaticity diagrams.](image)

3.2. Luminance identification technique

The luminance information of the images has been used for image texture analysis. In previous studies of texture analysis, some techniques that have been used to transform the statistical luminance information of images into 2D patterns have been reported [8]. From these techniques, we selected the luminance histogram. When a person sees the surfaces of an object, he or she can distinguish textures, such as glossiness and transparency, as well as color. In these textures, the glossiness and lightness that the person perceives has a high correlation with the skewness of the
A luminance histogram is a 2D pattern where the x-axis and y-axis represent the luminance and the number of pixels, respectively. Accordingly, we have previously distinguished the texture information (luminance information) of the images by pattern matching the shape of the luminance histogram [10]. The procedure for deducing the luminance information of all of the image pixels for the luminance histograms is shown in the flowchart below (Fig. 3).

![Flowchart for making luminance histograms](image)

**Figure 3. Flowchart for making luminance histograms.**

### 4. Identification experiments

#### 4.1. Images for identification experiments

The images of fruits and vegetables and the normal cell and tumor cell images taken by a digital camera were used as the real-world images. These images were distinguished with the identification techniques mentioned above on the JTC system. The details of these images are described in sections 4.1.1 and 4.1.2.

#### 4.1.1. Object images

The object images of fruits and vegetables are shown in Fig. 4. In the experiment, the images of the fruits and vegetables, which generally contain many different kinds of object information, were used (Fig. 4). Nine kinds of fruit and vegetables were photographed using the digital camera, the object patterns were extracted from the images taken, and the extracted object patterns were pasted into an image composed of 512×512 pixels (Fig. 4). In the experiment, 10 images of 9 kinds of fruit and vegetables were used.

![Images of fruit and vegetables](image)

**Figure 4. Images of fruit and vegetables (size of images: 512x512 pixels).**
4.1.2. Cell images.

A whole image of a brain tumor cell of a rat taken using a digital camera in a microscope is shown in Fig. 5. The central part of Fig. 5 is the tumor cell, and the surrounding part is a normal cell. Figure 6 shows the images taken of the cell of Fig. 5 by the digital camera under a microscope at 400 times magnification (Figures 6(a) and (b) are the normal and tumor cell images.). These images are composed of 2048×1536 pixels. The tumor cells have a high affinity to dye and show hyperplasia when compared to normal cells [11]. In the experiment, 30 images of normal and tumor cells, taken from the cell of Fig. 5 using the microscope with 400 times magnification, were used. In these 30 images, 15 images are the normal cell images and the other images are the tumor cell images.

![Figure 5. Whole image of a brain tumor cell of a rat (size of image: 2048×1536 pixels).](image)

![Figure 6. (a) Normal cell image; (b) Tumor cell image (size of images: 2048×1536 pixels).](image)

4.2. Identification experiment on object image

4.2.1. Identification experiment with color identification technique.

The color information from the object images of Fig. 4 was transformed into 2D color patterns on the color chart (Fig. 7). In Fig. 7, the color patterns of each object are distributed on each color region of the color chart (for example, the color patterns of an apple and a tomato are distributed on the red region of the color chart.). To calculate the correlation between the 2D color patterns on the JTC system, the image that placed the 2D color patterns in the same plane was given as the input image (Fig. 8), and was displayed on the SLM of the JTC system. In the experiment, the color pattern of the apple shown in Fig. 7 was used as the reference, and various object images were distinguished. Figure 9 shows examples of patterns from similar images, and shows that the intensity of the cross-correlation spot was high when the retrieval pattern coincided with the reference. The cross-correlation spot is expressed as the cross-correlation function of the retrieval and reference patterns, and the
intensity of the cross-correlation spot depends on the similarity of the 2D patterns. For this reason, we assume that the intensity of the cross-correlation spot is equivalent to the similarity of the patterns.

Figure 7. XY chromaticity diagrams of object images (size of images: 128×128 pixels).

Figure 8. Input image to the JTC system (size of images: 800×600 pixels).

Figure 9. (a) is the output image from the JTC system when the retrieval pattern coincided with the reference, and (b) is the three-dimensional image of (a).
4.2.2. Identification experiment with luminance identification technique.

The luminance information from the object images of Fig. 4 was transformed into 2D histograms corresponding to the luminance intensity (Fig. 10). In Fig. 10, the luminance histograms for a potato, onion, and carrot (which had matte surfaces) do not have a tail towards the high luminance direction. In contrast, the luminance histograms for the other objects (which had glossy surfaces) have a tail towards the high luminance direction.

The difference in luminance histogram among the samples depends on the glossiness of the sample surface. If surface is smooth (or rough), specular (or diffuse) reflection is generated at the surface in corresponding to the smoothness (or roughness). Here, diffuse reflection occurs over the surface of sample, while specular reflection is partially generated at the surface. Consequently, the luminance histograms of samples with glossy surface have high luminance components of low frequency and low/medium luminance components of high frequency. This results in the tail in the histogram of luminance intensity for glossy samples except for onion, carrot, and potato in Fig. 10.

In the experiment, the luminance histogram of the apple shown in Fig. 10 was used as the reference, and various object images were distinguished.

![Luminance histograms of object images (size of images: 128×128 pixels).](image)

4.2.3. The results of the identification experiment with the color identification technique.

The 2D color patterns of Fig. 7 were distinguished on the JTC system, and the results are shown in Fig. 11. The vertical axis in Fig. 11 was standardized using the intensity of the cross-correlation spot, obtained by using the same pattern as the retrieval and reference patterns. The object images were arranged according to the intensity of their cross-correlation spots along the horizontal axis of Fig. 11. In Fig. 11, the intensity of the cross-correlation spot for the tomato (i.e., a red object like the apple), the two apples and the carrot (i.e., a reddish object) was high, and that for the other objects was low. However, although the color pattern of the apple was used as the reference, the intensity of the cross-correlation spot for the tomato was higher than the intensity of the cross-correlation spot for the two apples. Therefore, this technique could not distinguish the color information of the images perfectly.
4.2.4. The results of the identification experiment with the luminance identification technique.

The 2D histograms of Fig. 10 were also distinguished on the JTC system, and the results are shown in Fig. 12. In Fig. 12, the intensity of the cross-correlation spot for the two apples, the tomato, the lemon and the grapefruit (i.e., objects with a glossy surface like the apple) was high, and that for the potato, the onion, and the carrot (i.e., objects with matte surfaces) was low. However, although the green pepper and the cucumber have a glossy surface, the intensity of the cross-correlation spot for these objects was low. Therefore, this technique also could not perfectly distinguish the luminance (texture) information of the images.
4.2.5. Comparison of proposed and previous identification techniques.

The results of object image identification with color and luminance information, and that with pattern information were compared. The identification results found with the color and luminance information are shown in Fig. 13 as the black-filled bar. The vertical axis of Fig. 13 shows the mean value of the normalized cross-correlation spot intensity for each object of Fig. 11 and Fig. 12. Meanwhile, the identification results found with pattern information are described below. In facial recognition and fingerprint recognition systems, several techniques for distinguishing the pattern information have already been reported. One of these techniques, facial recognition with edge detection (which emphasizes the outline of the shape), has been developed, and has achieved recognition results with high accuracy [1]. Edge detection was therefore used for the identification technique with pattern information, and the object images were distinguished on the JTC system by using patterns that emphasized the outline of the object pattern (Fig. 14). The identification results with pattern information are shown in Fig. 13 as the white-filled bar.

According to the identification results with pattern information in Fig. 13, the intensities of the cross-correlation spots for the tomato, the onion, and the grapefruit (i.e., circular shapes like the apple) were high; while that for the cucumber and the carrot (i.e., slender shapes) was low. However, the intensity of the cross-correlation spot for the two apples (i.e., circular shapes) was low, because the object size of the two apples was not equal to the object size of the single apple. This technique for distinguishing shapes was therefore ineffective for images with different object sizes. According to the identification results with color and luminance information in Fig. 13, the intensity of the cross-correlation spot for the two apples and the tomato were high; and that for the other objects was low. Accordingly, although the object size of the two apples was not equal to the object size of the apple, the identification technique with the color and luminance information could distinguish the object image as being similar to the reference image of an apple.
4.3. Identification experiment for cell images

4.3.1. Identification experiment with color identification technique.

Image processing was applied to the color patterns converted from the cell images to enhance the accuracy of the cell image identification. These image-processing steps are described below. The color patterns converted from Figs. 6(a) and (b) are shown in Figs. 15(a) and (b) (size of images: 128×128 pixels). As shown in Fig. 15, the color patterns converted from the tumor cell images were larger than those from normal cell images, and the color patterns converted from all cell images were distributed only on the blue region of the color chart. The reason for this is that the tumor cells have a higher affinity to dye when compared to the normal cells [11]. These color patterns were thus enlarged to emphasize the differences in the shapes of each color pattern between normal and tumor cells. Also, the enlarged color patterns were given edge detection image processing to enhance the sensitivity of the pattern matching. Figs. 16(a) and (b) (size of images: 128×128 pixels) are the color patterns that resulted from this image processing of the color patterns of Figs. 15(a) and (b). In the experiment, the color pattern of the arbitrarily selected tumor cell image was used as the reference, and the cell images were distinguished using the JTC system.

(a) 
(b)

Figure 15. Color patterns of (a) normal and (b) tumor cells.

(a) 
(b)

Figure 16. Color patterns following image processing of (a) normal and (b) tumor cells.
4.3.2. Identification experiment with luminance identification technique.

Some image processing was also provided for the luminance histograms converted from the cell images to enhance the accuracy of the cell image identification. These image-processing steps are described below. The luminance histograms converted from Figs. 6(a) and (b) are shown in Fig. 17(a) and (b) (size of images: 128×128 pixels). As shown in Fig. 17, the luminance histogram converted from the tumor cell image increased in the low luminance range, as compared to the normal cell image. The reason for this is that the tumor cells show hyperplasia when compared to normal cells [11]. Accordingly, the vertical axis of the luminance histograms was expressed logarithmically to emphasize the differences between the shapes of the histograms for the normal and tumor cells. Also, the luminance histograms for the high luminance range were removed to distinguish using only the low luminance range histograms. Figs. 18(a) and (b) (size of images: 128×128 pixels) are the luminance histograms that resulted from the above image processing of the luminance histograms of Figs. 17(a) and (b). In the experiment, the luminance histogram of the arbitrarily selected tumor cell image was again used as the reference, and the cell images were distinguished using the JTC system.

![Luminance histograms of normal and tumor cells](image1.png)

**Figure 17.** Luminance histograms of (a) normal and (b) tumor cells.

![Luminance histograms after image processing of normal and tumor cells](image2.png)

**Figure 18.** Luminance histograms after image processing of (a) normal and (b) tumor cells.

4.3.3. The results of identification experiments with color identification technique.

The 2D color patterns converted from the cell images were distinguished using the JTC system, and the results are shown in Fig. 19. The vertical axis in Fig. 19 was standardized by the intensity of the cross-correlation spot, obtained by using the same pattern as the retrieval and reference patterns. The horizontal axis of Fig. 19 denotes the numbers of the cell images; numbers 1–15 are the normal cell images, and numbers 16–30 are the tumor cell images. Tumor cell image no. 19 was used as the reference image. In Fig. 19, the intensities of the cross-correlation spots for the normal cells...
were low, while the intensities for the tumor cells were high. The dispersion of the intensity of Fig. 19 is described as a normal distribution in Fig. 20. The vertical axis in Fig. 20 was standardized using the maximum of the probability density. In Fig. 20, the two distributions had similar standard deviations, and these distributions were well separated. However, a little part of the two distributions overlapped. The spot intensity at the crossover point of the two distributions was used as the threshold between the normal cells and the tumor cells. When the threshold was 0.49, the false acceptance rate (FAR) and the false rejection rate (FRR) were approximately 2.0% and 2.0%, respectively.

Figure 19. Results of cell image identification with the color identification technique.

Figure 20. Normal distribution of the intensity of the cross-correlation spot.
4.3.4. The results of identification experiments with luminance identification technique.

The two-dimensional histograms converted from the cell images were distinguished using the JTC system, and the results are shown in Fig. 21. In Fig. 21, the intensities of the cross-correlation spots for the normal cells were low, and the intensities for the tumor cells were also comparatively low. The histogram for tumor cell image nos. 19, 28, and 29 are shown in Fig. 22. In Fig. 22, the histogram of no. 29 decreased in the low luminance range when compared with the other histograms, because the cell density of cell image no. 29 was low compared with the other cell images (Fig. 23). This means that a histogram in the low luminance range depends on the cell density of the cell image. Accordingly, the tumor cell images where the cell density was small compared to the reference image had low cross-correlation spot intensity. The dispersion of the intensity of Fig. 21 is described as a normal distribution in Fig. 24. In Fig. 24, the standard deviation of the normal distribution for the tumor cells was larger than that for the normal cells, and large parts of these distributions overlapped. When the threshold between the normal cells and the tumor cells was 0.22, FAR and FRR were approximately 33.1% and 22.3%, respectively.

Figure 21. Results of cell image identification with the luminance identification technique.
Figure 22. Luminance histograms converted from tumor cell images.

Figure 23. (a) Tumor cell image no. 28. (b) Tumor cell image no. 29 (size of images: 2048×1536 pixels).
4.3.5. The results of identification experiments with color and luminance identification techniques.

The results of cell image identification with both the color and the luminance information are shown in Fig. 25. The vertical axis of Fig. 25 shows the mean value of the normalized cross-correlation spot intensity for each cell image of Fig. 19 and Fig. 21. In Fig. 25, the intensities of the cross-correlation spots for the tumor cells were high as compared with the intensities for the normal cells. The dispersion of the intensity of Fig. 25 is described as a normal distribution in Fig. 26. In Fig. 26, the standard deviation of the normal distribution of the tumor cells was large compared with that of the normal cells, and part of these distributions overlapped. When the threshold between the normal cells and the tumor cells was 0.315, FAR and FRR were approximately 9.3% and 9.2%, respectively.
5. Summary

A technique for distinguishing real-world images has been developed using a joint transform correlator. The statistical color and luminance information in the various real-world images was converted from digital images into 2D patterns and then distinguished using the optical correlator. The identification technique using the statistical color and luminance information could distinguish an object image similar to the reference image of an apple, unlike the identification technique using shape information, and could also distinguish tumor cell images from other cell images with high accuracy (FAR of 9.3% and FRR of 9.2% were achieved). These experimental results demonstrate the feasibility of using an optical correlator for the identification of complex real-world images containing large volumes of information.

Acknowledgment

This work was partially supported by the Hamamatsu Cluster of the Knowledge Cluster Project of the Ministry of Education, Culture, Sports, Science and Technology, Japan.

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