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Identification of Transformed Image Using the Composition of Features

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ABSTRACT

Image identification is the process of checking whether the query image is the transformed version of the specific original image or not. In this paper, image identification method based on feature composition is proposed. Used features include color distance, texture information and average pixel intensity. We extract color characteristics using color distance and texture information by Modified Generalized Symmetry Transform as well as average intensity of each pixel as features. Individual feature is quantized adaptively to be used as bins of histogram. The histogram is normalized according to data type and it is used as the signature in comparing the query image with database images. In matching part, Manhattan distance is used for measuring distance between two signatures. To evaluate the performance of the proposed method, independent test and accuracy test are achieved. In independent test, 60,433 images are used to evaluate the ability of discrimination between different images. And 4,002 original images and its 29 transformed versions are used in accuracy test, which evaluate the ability that the proposed algorithm can find the original image correctly when some transforms was applied in original image. Experiment results show that the proposed identification method has good performance in accuracy test. And the proposed method is very useful in real environment because of its high accuracy and fast matching capacity.

Key words: Identification, Color Distance, MGST, Image Signature

1. INTRODUCTION

In recent year, digital contents are produced exponentially as the supply of digital camera increases and User Create Contents (UCC) is popularizing. Also, copyright problems for digital contents are raised as the controversial social issue. As a specific case, digital image content needs small storage and is very easy to copy so that the reproduced contents is increasing rapidly with ignoring copyright.

The major method to protect copyright is digital watermarking. Watermarking is the technique that embeds the copyright information into the original contents [1]. In general, digital watermarking technology decides whether contents are legal or illegal by confirming the embedded watermark. But it still has some problems in various situations. After watermark is inserted to original contents, copyright protection for contents is available at last. In other words, if a copy of the original contents before embedding watermark is stolen, the copyright

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of those contents cannot be protected any more. And, the embedded watermark is broken easily by various attacks. Although original data is sometimes copied in itself, usually the data is copied after user modifies its original data. Because watermark is inserted in original data, it can be broken easily if original data is transformed.

In order to complement these inherent watermarking deficiencies, another research has been investigated for copyright protection is started. This research comes under many different name, i.e. multimedia fingerprinting [2-4], robust or perceptual hashing [5-7], and replica recognition/detection [8-10]. It extracts feature vector, called perceptual hash, fingerprint or signature, in digital contents and measures similarity using it. This technology can be used in Digital Rights Management (DRM) system. At first, the system collects commercial contents that want to be protected for illegal copyright infringement into database. And, for the query data, this system measures similarity between database and query data. Then it decides whether the query data is illegal copy (replica) or not.

Watermarking has advantage that it can classify right contents that user pay money fairly. Because the contents that user pay money fairly only have right watermark. If some contents have no watermark or cracked watermark, it is illegal contents. On the other hands, the advantage of this technology, unlike watermarking, is the needlessness to embed information within the digital contents. So, it can keep original data to be protected by perfect quality. Furthermore, it can also be used for contents which have been already distributed in public domain.

The identification method must satisfy some requirements to be utilized in actual industry. One of them is uniqueness of signature extracted from each image. One content must have unique signature and survive strongly for various transformations imposed on digital contents. Also, the similarity should be very small between different contents, but it should have big similarities between contents that transformed from original contents. Another requirement is the complexity and it must minimize the computational complexity in extracting the similarity measure to be used in real application. Because huge amount of contents are produced in short time, the extraction and matching time should be very short.

The descriptors in MPEG-7 standard [11] which is published by ISO/IEC MPEG standard group satisfy some parts of requirements and shows good performance under limited condition. And methods such as SIFT [12] or Harris-Laplacian [13] based on feature points show good performance to image identification. However MPEG-7 tools show satisfied performance for only specific conditions individually. And feature points-based methods cannot be applied in real application because of high computational complexity in the extraction and the matching. Therefore, a new technology which satisfies all requirements is needed.

In this paper, we propose new image identification method using the composition of features. The rest of this paper is organized as follows: In Section 2, we describe new image identification model. We explain the proposed method for extracting image signature and matching in Section 3. Section 4 presents the experiment results of our image identification method. And we offer discussion in Section 5 and concluding remarks in Section 6.

2. NEW IMAGE IDENTIFICATION MODEL

The traditional image identification model is constructed based on retrieval system structure. Retrieval is the process of finding similar contents. For example, if we use a mountain image as a query, retrieval system extracts various characteristics such as green color and many trees. And it finds some images which have similar characteristics inside database. The identification also goes through the similar process. The creator requests to find the replica of image which is created by him exists inside database or not. If replica image exists in database, image identification system shows result images that are decided as replicas. But this type of model is very inefficiency because image identification system must have big database to reply to the request of creator. It can cause storage problems. Because the images are produced exponentially, it is impossible that image identification system stores all produced images in database. Furthermore, the requested query image is compared with all database images. As the database is so big, processing time to find replica is very long.

To overcome inefficiency of traditional image identification model, we propose a new image identification model. It requires low storage capability and shorter matching time than that of the traditional model. The image identification system just stores original images in the database. It means that the creator should register original image into the database to protect the copyright. And, if someone find image which is doubted as the replica, he requests to the image identification system to find out whether the doubted image is the replica or not. Then the image identification system compares the query image with original images which are stored in database. Although the original image should be registered to find its replica, this new image identification model is stronger in real application. Fig. 1. is the flow chart of the proposed new image identification model.

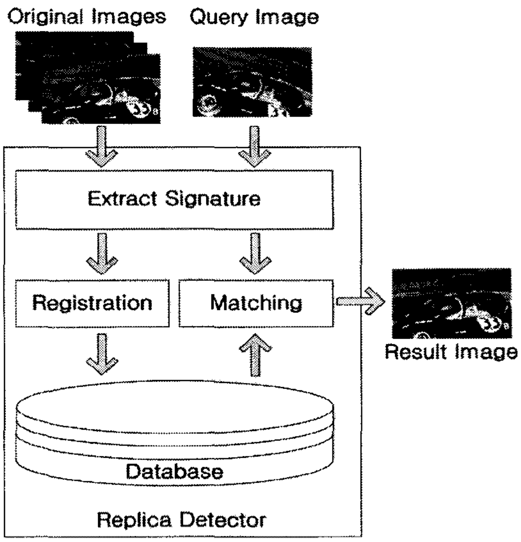

Fig. 1. The flow chart of the proposed image identification model.

3. THE PROPOSED METHOD

3.1 Image Signature Extraction

To detect the replica image, the comparison between the query and database is performed. The proposed image identification method compares two images using only their signatures. The signature is the unique characteristics which are extracted from image. Different images have different signatures each other, but perceptually similar images such as replicas have similar signatures. Furthermore, the signature must be simple and compact for fast comparison.

The proposed method extracts three different features from the image as the signature. They are color distance value, texture information and average intensity value. At first, if an image is inserted into image identification system, preprocessing is implemented. Image is down-sampled for each red, green and blue channel individually. Down-sampling can remove noise and reduce the processing time by decreasing image resolution. The noise which is occurred by image processing is gaussian noise, color noise produced by color reduction, etc. It looks like salt-and-pepper noise. So we use average value of 2x2 block as one pixel value. It is named down-sampling method.

After preprocessing, the color characteristics of each pixel is extracted using color distance method. And color image is converted into gray image to extract texture feature and average intensity value.

The method which is used in gray conversion is NTSC method. Because it also used in transformation condition. Modified Generalized Symmetry Transform (MGST) is used to extract the texture information. Finally image identification system makes three dimensional histogram using three features as image signature. Overall extraction process is described in Fig. 2.

The first feature extracted for image signature is related to color. Color information is one of most important low-level features which are used to index image database [14]. Color features used in many researches are almost useless information in comparing the color image with gray image. But the proposed color distance can be applied not only in comparing between color images but also in comparing color image with gray image.

To extract color distance feature, we have to select the dominant color of image. Firstly, we convert color space from RGB to HSV to select the dominant color. HSV color space is consisted of hue, saturation and value. And it can be converted from RGB color space by using Eq. 1.

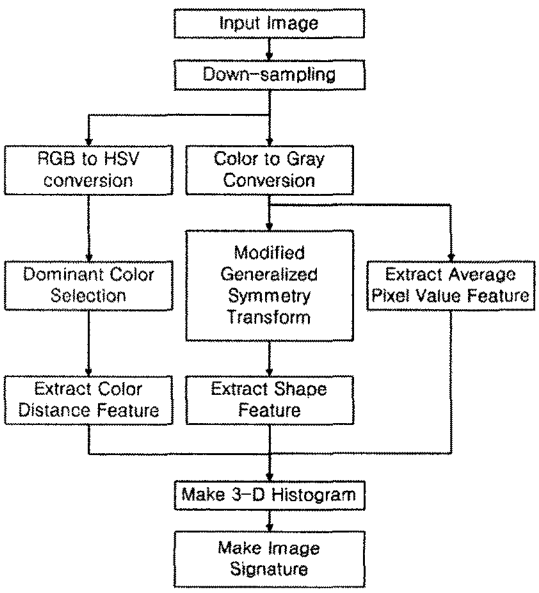

Fig. 2. Overall block diagram for extracting image signature.

$$H=\begin{cases} \text{undefined}, & \text{if } MAX(R,G,B) = MIN(R,G,B) \\ 60^\circ \times \dfrac{G-B}{MAX(R,G,B)-MIN(R,G,B)}+0^\circ, & \text{if } MAX(R,G,B)=R \text{ and } G \geq B \\ 60^\circ \times \dfrac{G-B}{MAX(R,G,B)-MIN(R,G,B)}+360^\circ, & \text{if } MAX(R,G,B)=R \text{ and } G < B \\ 60^\circ \times \dfrac{B-R}{MAX(R,G,B)-MIN(R,G,B)}+120^\circ, & \text{if } MAX(R,G,B)=G \\ 60^\circ \times \dfrac{R-G}{MAX(R,G,B)-MIN(R,G,B)}+240^\circ, & \text{if } MAX(R,G,B)=B \end{cases}$$

$$S=\begin{cases} 0, & \text{if } MAX(R,G,B)=0 \\ 1-\dfrac{MIN(R,G,B)}{MAX(R,G,B)}, & \text{otherwise} \end{cases}$$

$$V=MAX(R,G,B) \tag{1}$$

Then we make histogram of each channel independently. And we select the value that has maximum moving average. The maximum moving average is calculated by Eq. 2.

$$MA[n]=H[n]*M$$
$$MMA=\arg\max_{n} MA[n] \tag{2}$$

In Eq 2, MA means moving average and M is moving average mask. Moving average mask is composed as {1/4, 1/2, 1/4}. MMA means index of maximum moving average. At first, we perform convolution between histogram of each channel and moving average mask. Then we select maximum index of convolution result in each channel. The combination of selected values is dominant color of image. To measure color distance, dominant color which is represented in HSV color space is re-converted to RGB color space. Color distance is calculated using Euclidean distance between dominant color and each pixel in RGB space. If input is gray image, it just has value channel which represents intensity. So dominant color is also represented gray intensity and Euclidean distance between dominant intensity and intensity of each pixel is used as color distance in this case. Because we use Euclidean distance as color feature, this method can be applied comparing between color image and gray image. Color distance feature is quantized into 10 levels so that we use it as the axis of histogram.

The second feature used in the proposed signature is the texture information. To extract texture information, we apply MGST to gray converted image. MGST is the combined method which uses the phase weight function proposed by Park [15] over the original generalized symmetry transform introduced by Daniel Reisfeld [16]. It is the transform that calculates how symmetric the pixel peripheral is. In MGST, to obtain symmetry value, we calculate gradient magnitude γ_i, γ_j and its direction θ_i, θ_j at pixel q_i, q_j. Gradient magnitude and its direction is calculated by Eq. 3 [16].

$$\nabla q_k = \left(\frac{\partial}{\partial x} q_k, \frac{\partial}{\partial y} q_k\right)$$
$$\gamma_k = \log_2(1 + \|\nabla q_k\|)$$
$$\theta_k = \arctan\left(\frac{\partial}{\partial x} q_k \Big/ \frac{\partial}{\partial y} q_k\right) \tag{3}$$

We calculate x-gradient and y-gradient separately. And magnitude of gradient and its phase is calculated by gradient of two direction. Phase weight function is defined as Eq. 4 [15].

$$P(i,j) = \sin\left(\frac{\theta_j + \theta_i}{2} - \alpha_{ij}\right) \times \sin\left(\frac{\theta_j - \theta_i}{2}\right) \tag{4}$$

Index i and j mean two different pixels. α_{ij} is the angle value between a line which is composed by two pixels and horizontal line. The first term of phase weight function means that the weight has maximum value when the gradient at q_i and q_j are oriented in the same direction towards each other. And second term means that the weight has maximum value when each gradient direction at q_i and q_j are oriented in direction of 90 degree from the straight line between q_i and q_j.

Distance weight function D is defined as Eq. 5 [16]. If two pixels are closed, distance weight function returns large value.

$$D(i,j) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{\|i-j\|}{2\sigma}} \tag{5}$$

σ is the standard deviation of Gaussian function. It is calculated by the area that the symmetry transform is applied around some pixel. Result of distance weight function is represented by floating number of range from 0 to 1.

Symmetry contribution value between two pixels is defined as Eq. 6 [16]. Symmetry value is the sum of symmetry contribution value in symmetry pixel pair set.

$$C(i,j) = D(i,j)P(i,j)\gamma_i\gamma_j \tag{6}$$

Finally, symmetry magnitude value of some pixel is calculated by Eq. 7 [16].

$$M(p) = \sum C(i,j) \tag{7}$$

In general, symmetry magnitude value of each pixel has range from -700 to 700 in natural images. The value of range could be derived from statistical experiment with 10 million natural images. The frequency of each value is decreased exponentially via zero. It means that lower absolute values appear more frequently rather than higher absolute values. Because the proposed image signature is composed by three dimensional histogram, symmetry magnitude value has to be expressed in certain levels. So, we apply non-uniform quantization function to the symmetry magnitude to make each bin have similar frequency. Fig. 3. represents non-uniform quantization function used in the proposed method.

The third feature is intensity of pixel. Intensity value is most basic information of pixel. But pixel intensity itself is affected easily by some modification. So, we use average value of 3x3 areas around the basis pixel as third information. Intensity value of pixel can have value from 0 to 255 in normal 8 bits depth image. To use pixel intensity value as an axis of three dimension histogram, it is also quantized adaptively. We divide the whole range into 10 levels by using quantization method.

The histogram is used by signature when

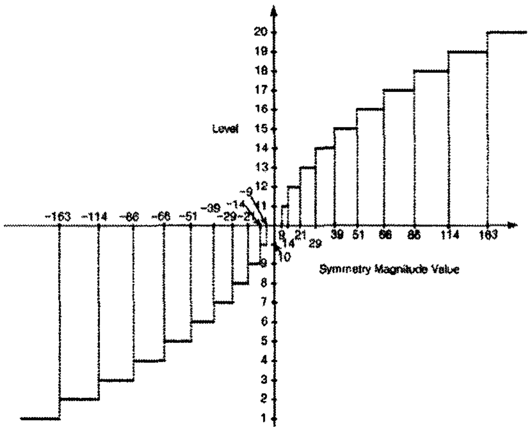

Fig. 3. Non-uniform quantization function that is used in proposed method

distance between two images is calculated. And total number of accumulated pixels is corresponding to image size. So, if we compare two images which have difference image size, it has some distance even if two images are very similar. This phenomenon is opposed in characteristic that image signature must have. In other words, signature must have characteristic that the distance between similar images is small and the distance between different image is large, but the phenomenon which occurred by difference image size is opposed this characteristic of signature. In general, to compare two histograms, histogram normalization is applied. Histogram normalization is the method that changing the value of each bin from absolute to relative value. It is calculated by Eq. 8.

$$H_i = \alpha \times \frac{h_i}{\sum_{k=0}^{M} h_k} \tag{8}$$

h is original histogram, and H is normalized histogram. α is weight factor to make H_i as integer value. We apply 100,000 as α value in proposed method.

The image signature must be made more simply for fast matching. So we use unsigned short type variable for histogram. Therefore, we apply Eq. 9. into the each value of normalized histogram.

$$H_i = \begin{cases} 65535, & \text{if } H_i > 65535 \\ H_i, & \text{otherwise} \end{cases} \tag{9}$$

Finally, if we perform all method that described until now, we can get one separated bin and three dimension histogram which has 2000 bins that consist of unsigned short type variable as image signature of inputted image.

3.2 Matching Process for Image Identification

Image identification is performed through matching process by deciding if query image is replica of one of images in database. Matching is carried out by calculating distance between two image signatures. To calculate distance between image signatures, we use Manhattan Distance. Manhattan Distance is the method to calculate distance between two vectors. Eq. 10. shows the method for calculating Manhattan Distance.

$$d(S_i, S_j) = |S_i(0) - S_j(0)| + \sum_l \sum_m \sum_n |S_i(l,m,n) - S_j(l,m,n)| \tag{10}$$

S_i and S_j are image signatures which are extracted from image i and j. Image signature which is extracted by extraction process has one separate bin and three-dimension histogram that has 2000 bins. First term of Eq. 10. means absolute difference of separated bin and second term is to calculate the distance of three dimensional histogram where. l,m,n mean quantization level of three features. So l has 20 and m,n has 10.

4. EXPERIMENTAL RESULTS

As we propose a new image identification model, our experiment is suitably composed for the proposed image identification model. To evaluate the performance of proposed image identification method, two kinds of experiments are carried out. Firstly, we calculate distance threshold value under 10 ppm (parts per million) false positive rate. This threshold value is applied to the second experiment. 10 ppm false positive rate means that it permits only one mismatch out of 100,000 matching times. We call this experiment independent test. Then, we measure the accuracy of the proposed image identification method. Accuracy is evaluated by how well the proposed image identification method finds replica image for each transformation and it uses correct retrieval ratio (CRR). Correct retrieval ratio is calculated by following process. At first, prepare M original images as database and M "transformed" version (e.g. blurred images) of original image. When the transformed version of original image is inputted as a query, the image that has minimum distance from inputted query image is selected. If the selected image is the original version of the query image, the numbers of true pair that are classified as containing copies (K) are counted. Then the correct retrieval ratio of specific transformation is calculated by Eq. 11.

$$CRR = \frac{K}{M} \tag{11}$$

We use 60,433 different images for calculating distance threshold. It includes various image size and contents. And 4,002 images are used as original image in accuracy test. Then we make transformed version of original image using 29 kinds of transformation in 15 categories. Fig. 4. shows a sample image of original and transformed images. And detailed condition of transformations is described in Table 1.

4.1 Independent Test

When we process independent test, we use 60,433 different images. The number of pairs which can be generated by 60,433 images is 1,826,043,528. So, 10 ppm threshold value is 18,260th value of all pairs when sorted the distance of all pairs in ascending order. Fig. 5. shows cross distance histogram which is made by independent test. 10 ppm threshold value is 20,348 and its normalized distance threshold is 0.104.

4.2 Accuracy Test

The accuracy is evaluated by correct retrieval ratio. The method for calculating CRR is de-

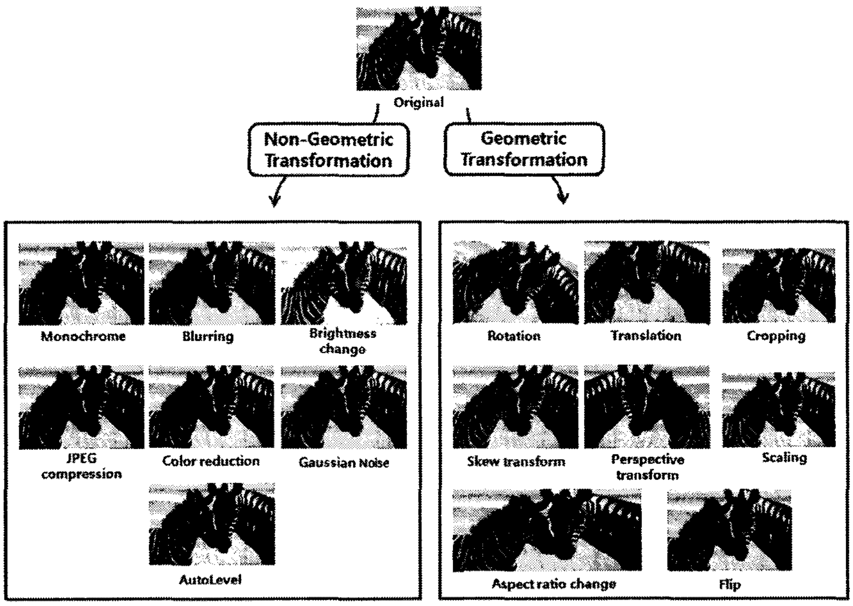

Fig. 4. A sample of original image and its transformed versions

Table 1. Specification of each transformation that is used for experiment

Transformation \ Level		Heavy	Light
Non-geometric Transformation	Brightness change	+10	+5
	Color to monochrome conversion	I = 0.299R + 0.587G + 0.114B	
	JPEG compression with varying quality factors	QF 60	QF 80
	Color reduction	GIF 8bit version	16bit: RGB(565)
	Gaussian noise	8.0	4.0
	Image enhancement via auto-level	YES	
	Blur	mask size: 5×5	mask size: 3×3
Geometric Transformation	Simple rotation	180°	90°
	Rotation	25°	10°
	Scaling (width-height ratio)	70%	90%
	Translation	15%	10%
	Flip	left-right	
	Aspect ratio change	4:3 → 6:3	4:3 → 16:9
	Crop	80%	90%
	Skew	+6°	+4°
	Perspective (Focal length=500)	+6°	+4°

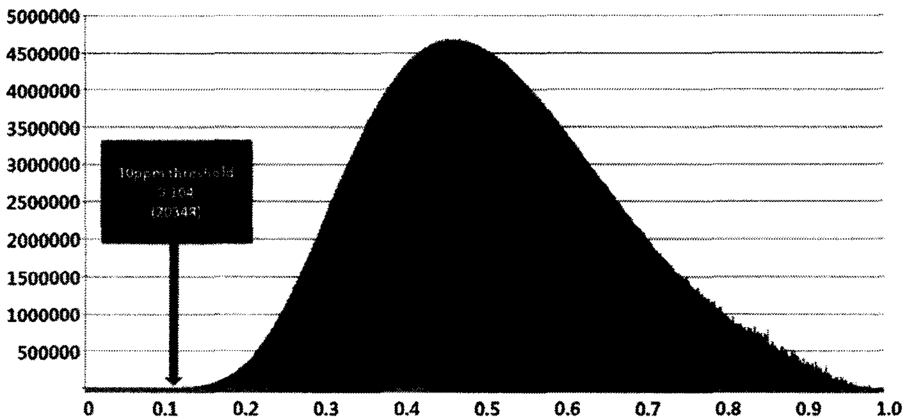

Fig. 5. The cross distance histogram that is made by independent test

scribed in Eq. 11. And distance threshold value which is calculated in independent test is applied in this process. In other words, we do not count K if distance between matched two images is far more than distance threshold that decided by independent test even if query image and database image are matched correctly. The correct retrieval ratio of each transformation is described in Table 2.

4.3 Signature Size and Complexity

The image signature that is used in the proposed image identification method is quite simple. The image signature is composed of one integer type bin and 2,000 unsigned short type bins. So signature size is totally 4,004 bytes. And the matching time for 4,002 by 4,002 pairs is about 356,672 milliseconds in personal computer. So the computing

Table 2. Correct retrieval ratio for each transformation

Transformation \ Level		Heavy	Light
Non-geometric Transformation	Brightness change	0.9663	0.9913
	Color to monochrome conversion	0.9878	
	JPEG compression with varying quality factors	0.9980	0.9995
	Color reduction	0.9000	0.9620
	Gaussian noise	0.9253	0.9678
	Image enhancement via auto-level	0.4425	
	Blur	0.9863	0.9993
Geometric Transformation	Simple rotation	1.0000	1.0000
	Rotation	0.9900	0.9993
	Scaling (width-height ratio)	0.7964	0.9705
	Translation	0.5007	0.8276
	Flip	1.0000	
	Aspect ratio change	0.9880	0.9958
	Crop	0.6599	0.9958
	Skew	1.0000	1.0000
	Perspective (Focal length=500)	0.9900	0.9943

power of proposed image identification method is 44,904 pairs per second. And the time for extracting the signature from an image is about 600 milliseconds.

4.4 Comparison

For performance evaluation, the proposed method is compared with several descriptors of MPEG-7 standard [11]. We select three descriptors and experiment under same conditions. The selected descriptors are Edge Histogram, Homogeneous Texture and Color Layout. The reason for selecting these three descriptors is that the proposed method has similar characteristics with shape/texture descriptor and it also uses color characteristics. Table 3 represents accuracy comparison between the proposed method and selected descriptors.

In Table 3, edge histogram descriptor is the most comparable with the proposed method because it shows better performance than other MPEG-7 descriptors. Edge histogram descriptor shows good performance in most of non-geometric modifications. But it shows bad performance in geometric modification like rotation. On the other hand, the proposed method shows good performance in all modifications.

5. DISCUSSION

In this paper, we propose identification of transformed image using the combination of features. We perform down-sampling as a preprocess. And we extract new characteristics which are invariant for various transformations by calculating color distance and applying MGST to image. The feature using color distance can be used for comparing the color image with gray image. Symmetry value has characteristic like a texture of peripheral area. And average pixel intensity is the strong characteristic of a pixel even if it is one of the simplest features. Additionally, we can increase the robustness of signature for heavy transformations by combining three characteristics. We use the histogram as the image signature. We decide whether the input query image is the replica of stored image in data-

Table 3. Accuracy comparison between the proposed method and MPEG-7 descriptors

	Proposed Method	Edge Histogram	Homogeneous Texture	Color Layout
bright5	0.9913	1.000	0.9614	0.9896
bright10	0.9663	0.9989	0.9137	0.9231
monochrome	0.9878	0.9984	0.9005	0.2536
QF95	0.9995	1.000	1.000	1.000
QF80	0.9980	1.000	0.9992	1.000
color_reduction8	0.9620	0.9992	0.6249	0.9934
color_reduction16	0.9000	1.000	0.9680	0.9997
addGaussian(2.5)	0.9678	1.000	0.9703	1.000
addGaussian(4.5)	0.9253	1.000	0.8414	1.000
autolevel	0.4425	0.9411	0.6994	0.698
blur3x3	0.9993	0.9994	0.4506	1.000
blur5x5	0.9863	0.9946	0.3078	1.000
simple_rot90	1.000	0.0334	0.0101	0.0816
simple_rot180	1.000	0.0824	0.0284	0.0694
rot10	0.9993	0.9142	0.2787	0.9802
rot25	0.9900	0.1846	0.0421	0.7108
scale10	0.9705	0.9855	0.8962	1.000
scale30	0.7964	0.9873	0.3507	1.000
trans10	0.8276	0.7707	0.3279	0.7509
trans15	0.5009	0.1326	0.0984	0.2607
flip	1.000	0.2759	0.0816	0.3735
4:3 → 16:9	0.9958	0.9272	0.6332	1.000
4:3 → 6:3	0.9880	0.8407	0.3865	1.000
crop10	0.9958	0.9677	0.6870	0.9863
crop20	0.6599	0.5675	0.1552	0.6543
skew4	1.000	0.9946	0.9715	0.9997
skew6	1.000	0.9954	0.9330	0.9992
perspective4	0.9943	0.9842	0.9274	0.9997
perspective6	0.9900	0.9868	0.8650	0.9989

base or not by comparing image signatures. By using histogram as the image signature, we can get not only good performance in various transformation but also fast matching time. Therefore the proposed image identification method shows high performance in various transformations and the matching time is very short.

The normalized distance of 10 ppm distance threshold is 0.076 in independent test. In this test, high threshold value means that the method can discriminate different images efficiently. 10 ppm distance threshold for the Edge Histogram is about 0.057, Color Layout is about 0.012 and Homogeneous Texture is almost zero. We use various transformations including non-geometric and geometric transformations for accuracy test and the degree of distortion for each transformation is separated into two levels. The kind and degree of transformation conditions is taken into account to check if the proposed method is invariant and robust for various distortions. We confirm that the proposed method shows good performance in all transformations and levels except some minor cases. And we showed the comparison between the proposed method and descriptors of MPEG-7 in Table 3. For Edge Histogram, it shows very good CRR in non-geometric transformations. But it has low CRR in geometric transformations. Edge Histogram divides the whole image by 16 sub regions. So, it is weak in geometric transformations because the information change is occurred in sub region by geometric transformations. Other descriptors show similar results. On the other hand, the proposed method shows good performance over all transformations since information obtained from color distance and MGST is invariant against geometrical transformation of image as well as the extracted global histograms have high robustness for stationary image distortion.

We use the vector of unsigned short type number as the signature. To get high matching speed and compact signature size, it is best way to use signature which is represented by bits since bitwise operation needs the minimum computation power in all basic computational operations. Because bit can just represent 0 or 1, however, it is not enough to represent various images. On the other hands, although signature based on stream of number spends longer time for matching, it can represent various contents by its scale of each element and it can get satisfactory matching speed if we adjust elements adaptively.

However, because of the limitation of dominant color and MGST, it shows disappointing results in some cases. MGST is calculated based on gradient of pixel. Although we apply logarithm function in gradient, it is still very sensitive in gradient change. So, the proposed method shows low CRR in the transformations that change pixel value independently such as gaussian noise, color reduction and auto level. And the dominant color selection process is incorrect in geometric transformation. So, it also shows low CRR in some heavy geometric transformations.

6. CONCLUSION

In this paper, we propose identification of transformed image using the composition of features. The proposed method extracts characteristics of pixel and area as the signature and it determines whether the input image is the replica or not by comparing the signatures. Experimental results show that the proposed image identification method has good performance for various transformations and short matching time which is the major advantage of the proposed method.

Because of incorrectness of the dominant color selection process and sensitiveness of the MGST in gradient change of pixel, the performance of the proposed method decreases for some transformations. And performance of the proposed method decreases rapidly when geometric transformation is applied heavily because we use global feature i.e. histogram as the image signature. If we improve the dominant color selection process and correct MGST so that it is invariant to pixel gradient change and add characteristics of local feature, the better results can be obtained. Future work includes the improvement of color feature of image and the development of more robust invariant transform method relative to MGST to cover both non-geometrical and geometrical transformations.

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