Using Color Difference with Shape Context for Logo Recognition

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***Abstract*—Logos belonging to the same brand can be diverse in shape and color, so logo recognition is a challenging research topic. Because of the diversity of logos, if we consider only the shapes of logos in the recognition process, we will suffer from the high cost in terms of the overall execution time. In this paper, we propose to use shapes as well as colors of logos in the recognition process. Before using shapes of logos to recognize the brand of an interested logo image, we calculate the color difference between it and the brand logo images in the database. Then, we select from the database the images to which the interested logo image is similar according to their color difference, and we measure the similarity between the shape of the interested logo image and the shape of each of the selected images. We recognize the interested logo image as the brand logo that is most similar to it. The experimental results show the following: Compared to that we use only shapes in the recognition process, if we use color difference before using shape, then we can save a significant amount of time, and the proposed approach has the potential to improve the overall recognition rate.**

***Index Terms*—Color difference, logo recognition, shape context**

I. Introduction

A brand logo may be composed of text, graph, or the combination of text and graph. No matter of what type a brand logo is, the most important thing is that it can exhibit the characteristics of a brand. The main goal of this paper is to recognize brand logos so that a person who is not familiar with a brand can know what brand it is after seeing an interested logo image.

Logo recognition can be applied to a wide range of applications. For example, it can be used as part of a solution that addresses the recently increasingly rampant piracy issues. Some brands use logos that look very similar to well-known brand logos to attract attentions. Logo recognition can be used to detect logos that have similar appearances and those that may be imitated trademarks. It can also be applied to non-trademark patterns. For example, some organized criminals use special symbols and change them periodically for some purposes, and logo recognition can be used to track these symbols.

Because a brand logo itself has no particular style, we adopt the shape of the logo to recognize the brand. We use shape context, which is a popular method proposed by researchers in 2000. When we use shape context, we need to obtain a subset of the contour points of a logo, and hence the execution time for recognition depends on the sample size. However, a small sample size will probably result in poor recognition rate, while a large sample size will increase the recognition time. In order to address this issue, we intend to use a preprocessing step before using shape context. Because a brand logo usually has vivid colors, we can first analyze color difference between images and then remove the images that have large values of color difference. After that, we only use the images that have small values of color difference with shape context and thereby reduce the overall recognition time.

Our database is “Best Global Brands 2012”, published on the Interbrand website[1], and we have done two sets of experiments on the database. One uses only shape context for recognition and the other uses color difference before using shape context for recognition. The flow charts of our experiments are showed in Figure 1.

When we use color difference to select 50% of the images in the database as candidate images, the results show that using color difference can reduce the overall execution time. When the sample size is 100, we can save about 44.5% of the overall execution time, and when the sample size is increased to 200, using color difference can reduce 59% of the overall execution time. Furthermore, the recognition rate of using color difference and shape context is slightly higher than using

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[1] http://www.interbrand.com/en/best-global-brands/2012/Best-Global-Brands-2012-Brand-View.aspx

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only shape context in both situations. Hence, the use of color difference can help reduce a significant amount of time while maintaining comparable quality when doing logo recognition.

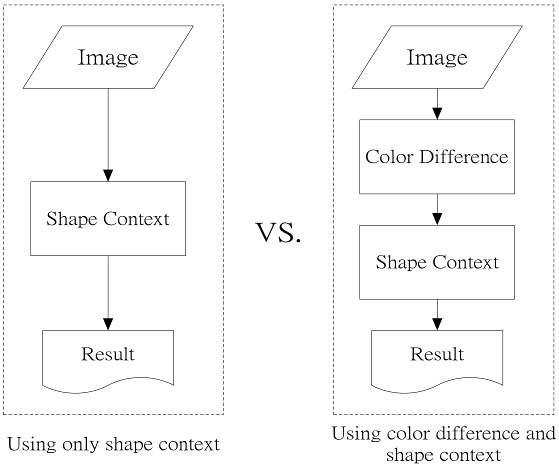

Figure 1. The flow charts of the experiments.

The remainder of this paper is structured as follows: We discuss related studies in Section II. In Section III, we describe the details of shape context and color difference. The experiments and the results are presented in Section VI, and we conclude this paper in Section V.

II. Related Studies

Logo recognition has been a popular research topic for a long time. It can be traced back to 1996. Doermann et al. presented an application of algebraic and differential invariants to the problem, and their method can handle cases whether the whole shape of the logo is known or not [1]. In 1997, Cesarini et al. used artificial neural networks to deal with spot-noisy logos [2]. Hausdorff distance was proposed by Chenet al. in 2003, and it was used to compute dissimilarity between two sets of line segments [3]. In addition to logo recognition, logo detection is also a research topic of a great interest. Zhu and Doermann proposed an approach to logo detection and extraction in document images with an evaluation metric to measure the quality of the approach [4]. Some other approaches were proposed for logo detection [5], [6]. As an example, Wang and Chen proposed a method based on the boundary extension of feature rectangles [5]. Additionally, some systems were developed to deal with both logo detection and logo recognition [7], [8].

In addition, there is a growing number of applications of logo recognition, such as vehicle logo recognition [9], [10], which can be used to determine if the car is stolen or not. Furthermore, there is an application of logo recognition on the mobile phone [11]. In summary, it can be seen that the applications of logo recognition will become increasingly widespread in our daily lives.

III. The Proposed Approach

Shape context, a descriptor of a shape, was first proposed by Belongie and Malik in 2000 [12]. In the proposed approach, first, we use canny edge detector [13] to obtain n points of the outline of a shape, and then we consider the set of vectors originating from a point to all other sample points on the shape. These vectors express the configuration of the entire shape corresponding to the reference point. It is clear that, as n gets larger, the shape becomes more accurate. For a point p_i on a shape, we compute a coarse histogram of the relative coordinates of the remaining n-1 points by the method given in [14]. The histogram is defined to be the shape context of p_i. We use the log-polar coordinates to compute the histogram. Figure 2 shows an example (which can be found in [14][2]).

As we can see from Figure 2, the more points we take, the more detailed the shape will be. However, the execution time will also be longer as the sample size increases. Since we are given a legacy system by which the execution of shape context cannot be accelerated, we intend to use a filter in the preprocessing step before we use shape context to do recognition so that we can reduce the number of images inputted to the shape context module for recognition. Because colors of a logo are usually vivid, we can classify our logos according to the extent of their color difference. We exclude images that have larger values of difference and only use the images that have smaller values of differences in the recognition process.

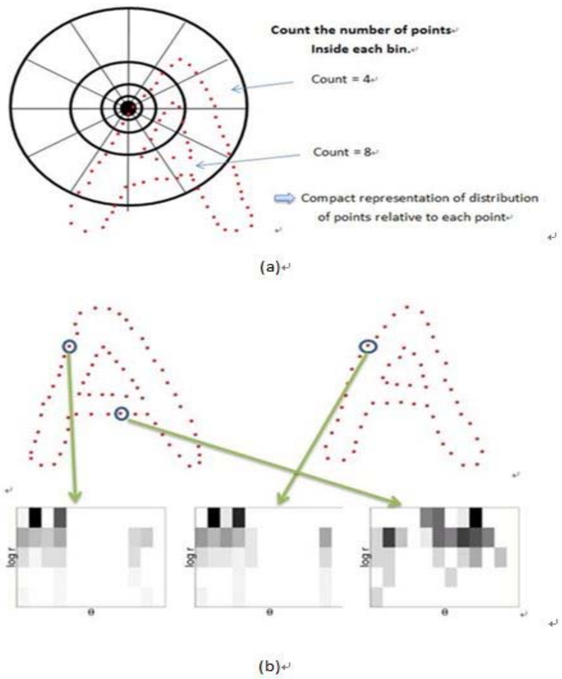

Figure 2. (a)The diagram of the log-polar bins used to compute the shape context (reproduced from [14]). (b)The sampled contour of the shapes and their shape context (reproduced from [14]).

The formula we use to compute the color difference is called CIEDE2000, which was proposed by Sharma et al. in 2005 [15]. It is designed to address the perceptual uniformity problem. This formula uses Lab color space, and it is an informal abbreviation for the CIE1976 (***L****, ***a****,

[2]http://www.eecs.berkeley.edu/Research/Projects/CS/vision/shape/sc_digits.html

b*) color space. Lab color space is a color-opponent space: The ***L*** component represents lightness, while the ***a*** and ***b*** components represent the color-opponent dimensions. The advantage of using Lab color space is that it is designed to approximate human vision. Its ***L*** component closely matches human brightness perception. Thus, it can be used to make accurate color balance corrections by modifying the ***a*** and ***b*** components, and the ***L*** component can be used to adjust the lightness contrast. The definitions of the three coordinates of LAB are as follows[3]:

1. ***L*** = 0 yields black and ***L*** = 100 indicates diffuse white.
2. ***a***: negative values indicate green while positive values indicate magenta.
3. ***b***: negative values indicate blue and positive values indicate yellow.

Below we show a picture in RGB color space and Lab color space separately. We use Google as the test image. Figure 3 is the RGB image of the logo. Then, we transform the test image into Lab images, as shown in Figure 4. We can see that because ***L*** image displays the brightness of an image and the brightest letter is yellow in the test image, the letter is in white in ***L*** image. Moreover, ***a*** image indicates the distance between red and green colors, and the letters in red and green are in respectively white and black in ***a*** image; ***b*** image shows the distance between yellow and blue, and the letters in yellow and blue are in respectively white and black in ***b*** image.

Figure 3. Example: The logo of Google in RGB color space

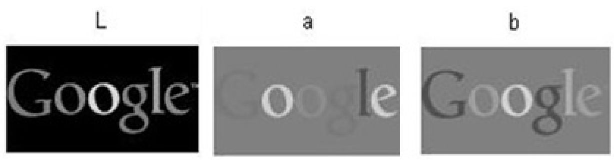

Figure 4. Example: The logo of Google in Lab color space.

Because the background of a logo is mostly in white (or a single color), we remove the background before calculating the color difference. By making the background of the logo black, we can reduce the number of pixels we need in the analysis. Furthermore, a logo typically has a moderate (or small) number of distinct colors (while it is their arrangement that makes them vivid). The color of a pixel and the colors of its neighboring pixels often have similar or even the same RGB values. After removing the background, we delete the duplicate RGB values. Then, we arrange the remaining values in accordance with the RGB values in ascending order and take only 10% of the original RGB values as our input RGB values.

In summary, the proposed approach is illustrated in Figure 5 and each step is described below:

1. Remove the background in the input image.
2. Find all the distinct RGB values in the image.
3. Take 10% of the distinct RGB values (found in the last step) as representative RGB values for the input image.
4. Transform these RGB values into Lab values.
5. Calculate the values of color difference between the input image and the images in the database.
6. Use the images in the database that have small values of color difference as candidate images for shape context (and here we use 50% of the images as candidate images).

After using the proposed approach, we use shape context for recognition. Finally, we obtain the results in which the most similar logo (determined by the proposed approach and shape context) is ranked first.

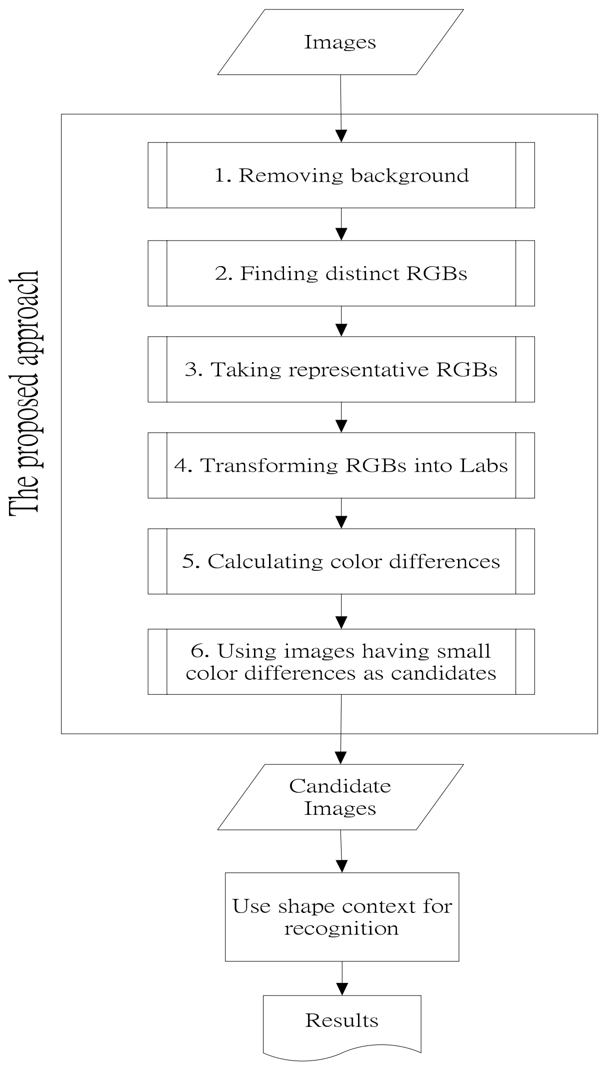

Figure 5. The proposed approach.

IV. Experiments and Results

[3] https://en.wikipedia.org/wiki/Lab_color_space

We run our experiments on a computer with an Intel Core i7-2600 (running at 3.4 GHz) and 8GB memory. Our code runs on Matlab R2012b and our data source is as described earlier. The 100 images in our database are shown in Figure 6.

Figure 6. Best Global Brands 2012.

After removing the background of an input image, we intend to reduce the number of pixels for color difference analysis in order to reduce the execution time. We have done an experiment to validate the idea of using only 10% of the colors. In the experiment, one trial uses the original image for color difference analysis (with all the colors), while the other trial uses only 10% of the colors of the original image. We use Google as our test image. There are minor differences between the results given by the two trials. Therefore, in the following experiments, we use 10% of the colors of the original image.

In what follows, we use logo images of 10 brands to evaluate the proposed approach: Google, Coca-Cola, Toyota, Pepsi, Ford, Sprite, Shell, Pizza hut, Starbucks and Yahoo. These brands are chosen because each of them can be associated with logos diverse in shape and in color. For each of the above brands we use five different logo images and hence there are fifty test images in total.

As mentioned above, we have done two sets of experiments: In one set, we use only shape context for recognition; in the other set, we use color difference before using shape context. In addition, each set can be further divided into two parts: Small sample and large sample. We introduce them in the following subsections.

A. *Small Samples*

Here, we take 100 sample points of the contour of each image and then use shape context. The output is shown in Table I, whose format is as follows: 1) The first column is the images in the database; 2) the second column is the ranks of the recognition results when only shape context is used; 3) the third column is the test images; 4) the fourth column is the ranks given by color difference; 5) the fifth column is the ranks of the recognition results when shape context is used after color difference is used. If the rank of Lab is greater than 50, then the image will not be considered as a candidate and the rank will not be recorded. Such cases exist because we consider only 50% of the images in the database as candidate images. We marked such a case with an asterisk.

TABLE I.
RANKS OF IMAGES WITH SAMPLE POINTS = 100.

The images in the database	Shape Context only	Test images	Rank of Lab	Lab and Shape Context
Coca-cola	21		59	*
	20		58	*
	4		61	*
	61		58	*
	4		58	*
Google	24		47	6
	5		45	7
	1		32	1
	51		46	19
	2		47	1
Toyota	1		17	1
	22		21	18
	77		18	1
	25		21	15
	52		20	6
Pepsi	80		12	41
	78		17	42
	87		14	36
	73		16	43
	89		13	33
Ford	6		9	17
	35		3	12
	17		7	2
	16		7	1
	1		4	1
Sprite	45		1	28
	68		1	38
	76		1	35
	38		1	39
	26		1	33
Shell	8		3	1
	10		2	18
	24		4	16
	1		4	16
	6		1	7
Pizzahut	59		14	5
	38		13	30
	51		13	25
	25		5	11
	31		11	34
Starbucks	21		4	3
	2		7	2
	38		4	18
	1		16	7
	23		9	8
Yahoo	9		69	*
	26		76	*
	26		74	*
	37		75	*
	6		73	*
Total Time	19111 sec = 5.3 hr		10587 sec = 2.94hr	

The values of the total execution time are given at the bottom of the table. As we can see, it takes about 5.3 hours when only shape context is used. On the other hand, if we analyze color difference before using shape context, the execution time can be reduced to 2.94 hours. That is, we can save about 44.5% of the time. This is related to the fact that we filter out 50% of the images in the database by using color difference.

Please note that if a logo is correctly recognized then its rank value will be 1. We define the recognition rate as follows:

$$Rec.\ rate = \frac{\#\,correct\ images}{\#\,images} \tag{1}$$

In (1), ***Rec. rate*** is short for recognition rate; the numerator (***# correct images***) is the number of images that are correctly recognized; the denominator (***# images***) is the total number of images in the database.

We can see from Table I that if we use only shape context for recognition, the recognition rate is 5/50 = 0.1 (since there are 5 rows whose values in the 2^{nd} column are 1); if we use color difference before shape context, the recognition rate is 7/50 = 0.14 (since there are 7 rows whose values in the 4^{th} column are 1). That is, the proposed approach can save a significant amount of time and simultaneously achieve a higher value of recognition rate.

If we want to further improve the overall recognition rate, we can do some post-processing after shape context. For a test image, the smaller its rank is, the greater the potential it will be correctly recognized. For example, we consider the fourth image of Google in Table I, the rank is 51 when we use only shape context for recognition, while the rank is 19 when we use color difference before shape context. There will be a greater potential that the image will be correctly recognized in post-processing.

Here we consider the improvement in ranking. That is, we want to know that, through the use of color difference, how much we can enhance the rank of an image. In Table II, there are 31 images whose ranks have been improved (including the pictures that have the same ranks before and after the use of color difference), so the percentage of improvement in ranking is 31/50 = 62%. That is, the proposed approach can not only save time but also improve ranking.

B. Large Samples

Because shape context uses sample points of the contour of an image for recognition, the larger the sample size is, the more accurate the results will be. In this subsection, we increase our sample points to 200. The output is shown in Table II, whose format is the same as that of Table I.

As we can see from Table II that if we use only shape context with 200 sample points, the total execution time will be substantially increased to 36.31 hours (compared to 5.3 hours when the sample size is set to 100). However, if we use color difference with shape context, the total execution time will be 14.9 hours (compared to 2.94 hours when the sample size is set to 100), which is 41% of the total execution time required by using only shape context.

As for the recognition rate, when the sample size is 200, the recognition rate is 6/50 = 12% if we use only shape context, and it is 7/50 = 14% if we use color difference before shape context. Besides, there are 35 images whose ranks have been improved by the proposed approach, so the percentage of improvement in ranking is 35/50 = 70%.

TABLE II.
RANKS OF IMAGES WITH SAMPLE POINTS = 200.

The images in the database	Shape Context only	Test images	Rank of Lab	Lab and Shape
	24		59	*
	7		58	*
Coca-cola	1		61	*
	63		58	*
	3		58	*
	15		47	9
	3		45	7
Google	1		32	1
	14		46	15
	2		47	1
	1		17	1
	36		21	14
Toyota	37		18	28
	53		21	24
	50		20	14
	92		12	46
	94		17	43
Pepsi	83		14	41
	90		16	45
	81		13	40
	5		9	10
	17		3	13
Ford	6		7	6
	31		7	1
	1		4	1
	79		1	32
	40		1	28
Sprite	49		1	35
	59		1	23
	38		1	9
	2		3	4
	1		2	1
Shell	14		4	9
	3		4	2
	25		1	14
	33		14	18
	49		13	25
Pizzahut	58		13	21
	49		5	21
	39		11	17
	4		4	2
	1		7	3
Starbucks	3		4	2
	5		16	1
	7		9	2
	6		69	*
	12		76	*
Yahoo	5		74	*
	38		75	*
	2		73	*
Total Time	130718 sec = 36.31 hr		53643 sec = 14.9 hr	

In addition, we can also observe that doubling the number sample points will not increase the recognition rate much. Because 100 sample points can already present most of the appearance of a logo, we may not be able to improve the recognition rate even though we increase the sample points.

V. CONCLUSIONS AND FUTURE WORK

Because logos usually have a great diversity from one to another, logo recognition can be challenging. We intend to minimize the execution time required for recognition. In this paper, we propose to use color difference before using shape context for recognition. The goal is to make the time required for the entire process reduced significantly. We use color difference to select the images in the database that have similar colors. From this point of view, the proposed approach is similar to *k*-nearest neighbors algorithm in some sense (with *k*=1).

If we want to further improve the overall recognition rate, we can use thin plate spline (TPS) [16] after shape context. TPS is a transformation model in image alignment and shape matching[4]. In this paper, we focus on the improvement given by a method used in the preprocessing step. TPS can be used as a post-processing method to improve the overall recognition rate, but it will increase the overall execution time and thus is out of the scope of this paper. Of course, one can use the proposed approach with TPS (or any other post-processing method) to gain better results.

The main goal of this paper is to discuss the impact of preprocessing the images before using shape context in the recognition process. As for the future work, we plan to explore different preprocessing methods. For example, we can cluster the images in the database into different groups according to their colors, and by doing so we can reduce the execution time. Of course, as part of the future work, we would like to add more brand logo images to the database, especially different versions of images.

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