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FARKLI BOYUTLARDA GÖRÜNTÜLERDE UYARLAMALI YEREL PENCERE İLE BENZERLİK ÖLÇÜMÜ

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Anahtar Kelimeler
Histogram karşılaştırma,
İçerik Tabanlı Görüntü Erişimi,
Yerel pencere.

Özet
İçerik tabanlı görüntü erişim yöntemleri, renk, desen ve şekil bilgileri gibi farklı özelliklere ihtiyaç duymaktadır. Araştırmacılar, görüntü histogramından elde edilen verileri de bu bağlamda kullanmaktadır. Histogram bilgileri, yerel veya global olarak hesaplanır. Ancak, aynı içeriğe sahip olsalar da, farklı en / boy oranlarına sahip görüntülerde yerel yaklaşımlar kullanılamamakta ve tüm pikselleri işleyen yöntemler ile de her zaman istenilen sonuca varılamamaktadır. Bu çalışmada, farklı boyutlarda iki görüntüden, eşit sayıda pencere alınarak, görüntülerin benzerlik ölçümünde kullanılan ve yerel histograma dayanan yeni bir yöntem geliştirilmiştir. Geliştirilen yöntem, Weizmann tekli nesne görüntü bölütleme veritabanındaki 100 görüntü üzerinde test edilmiş ve yöntemin başarısı global histogram yaklaşımlarıyla karşılaştırılmıştır.

SIMILARITY MEASURE WITH ADAPTIVE LOCAL WINDOW IN DIFFERENT SIZE IMAGES

Keywords
Histogram comparison,
Content based image retrieval,
Local window.

Abstract
Content based image retrieval methods require different features such as color, pattern and shape information. The researchers also use the data obtained from the image histogram in this context. The histogram information is calculated locally or globally. However, even though they have the same content, local approaches cannot be used in images with different aspect ratios, and methods that process over the entire pixels cannot always give the desired results. In this study, a new method based on the local histogram, which is used for the similarity measurement of images, has been developed by providing equal number of windows from two images of different sizes. The developed method is tested on 100 images on Weizmann single object image segmentation database and the success of the method is compared with global histogram approaches.

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1. Introduction

Nowadays, image indexing and retrieval is rapidly becoming widespread due to the increase in the amount of memory used in the electronic environment and therefore the growth of picture collections. On the other hand, along with this increase, various image processing applications have been developed which serve various purposes and search for similarity. In the examination of forensic cases, there is database, which is indexed by 16.9 trillion images, especially in the web environment like TinEye, in order to detect fake images (“TinEye”, 2016). In addition, Google is currently offering such database for searching images online (“What is the,”, 2016). A search for missing relatives through the image is also a striking example (“Who were they,”, 2016). In such applications, algorithms such as content based image retrieval and face similarity detection are used.

Content based image retrieval is done by extracting properties from pixels. Current methods focus on three basic elements. These are feature extraction, multidimensional indexing and the design of retrieval systems. The feature extraction is used to obtain better quality images and is based on a series of numeric parameters. It represents characteristics such as color, texture or shape of the image. Indexing is used for speed searching. These features indicate vector quantity. Thus, calculating distance between a designated metric and corresponding vector, images are compared (Vassilieva, 2009).

The extraction of color related information from features is an important step as it also appeals to people's visual perception mechanism. Researchers have developed methods that use histogram (Chitkara, 2001; Stricker & Orengo, 1995; Swain & Ballard, 1991; Niblack et al., 1993; Ioka, 1989; Vassilieva & Novikov, 2005) and various statistical methods (Stricker & Orengo, 1995; Stricker & Dimai, 1997) to achieve the relevant situation. From the current recommendations, the simplest and most commonly used method is the histogram (Vassilieva, 2009). The contribution to be provided in the field is important, in order to extract color-related characteristics. Vassilieva (2009) showed that methods using histograms are superior to approaches using statistical methods, with 285 Corel Photo images. However, taking local histogram information at two images with different sizes is a major problem. Because, in order to be able to compare two images, the number of local windows received from the queried image must be equal to the number of windows received from the compared one. For images of different sizes, when the same number, for example 3x3, 5x5, etc. local windows are used, incomparable region will remain in large image just like Figure 1.

Figure 1 shows an example of a comparison process using local windows of the same size in images of different sizes with the same content. The blue marked region is incomparable field. Obviously, the algorithm that makes a similarity search with the same number of local windows will not work when the width and height values of the images are different.

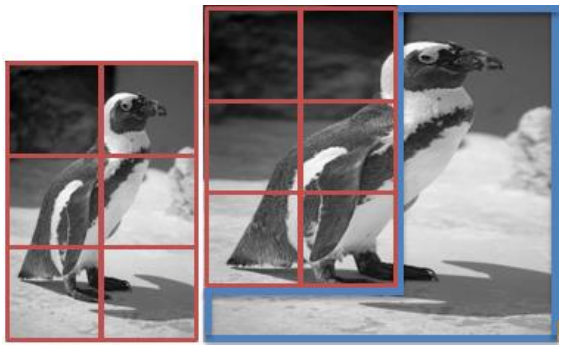

Figure 1. Using of equal size local windows on different size images.

According to literature surveys up to date, there are many approaches to be used for image retrieval or similarity, using global and local histograms, or simply choosing one of them. However, the use of local histograms is not found in comparing images of different dimensions (Cha, 2007; Suhasini et al., 2017).

In this work, an adaptive local window approach is proposed for algorithms based on histogram similarity. Thus, for images with different sizes, color-related features can be extracted with the help of local windows. The study was organized into three sections. First, the approaches used in histogram similarity are discussed. Then the proposed method is expressed and finally the results obtained are given.

2. Histogram

A numerical image is represented by color values, called pixels, on the spatial coordinate axis. The histogram shows the relative frequency value, or distribution, of each pixel in the color space of the corresponding image. The histogram of the view in Figure 2. (a) is given in Figure 2. (b). With the help of histogram, it is possible to obtain information about the brightness and darkness of the scene.

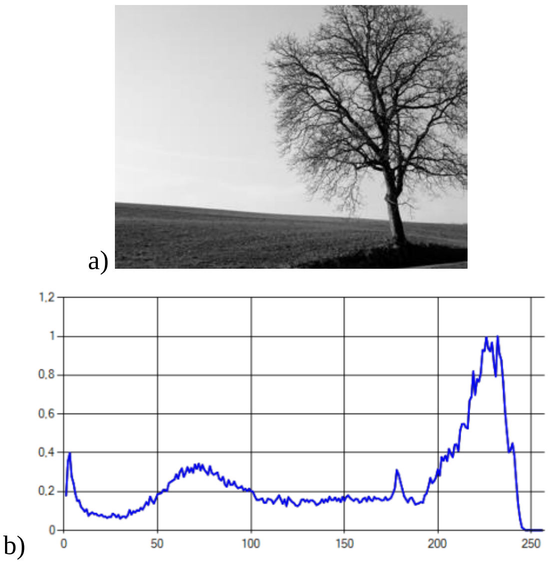

Figure 2. Image and histogram; a) Sample image, b) Histogram of (a)

It is mentioned in section 1 that similarity search approaches such as content-based image retrieval use histograms to extract color related features are more successful than statistical methods. However, in obtaining histogram information of two pictures of different sizes, global methods can be used easily, but local methods cannot be used. This is because local methods require that windows be equally sized (3x3, 5x5, etc.) on both images. In other words, if the process is completed, when the local window filled in the small picture is over, there will remain unexplored regions. Therefore, in the images to be compared, both pictures must be of equal size so that the local histogram information can be retrieved. In addition, the Structural Similarity Index Measurement (SSIM) algorithm, which looks for similarity by comparing the brightness, contrast, and structure properties of two images, also requires images of the same size as the structure (Wang et al., 2004).

The similarity approach will not work because the query and comparison database will not always be the same size image. In this case, the images must be equal in size. However, since the change in height and width is done by interpolation, information loss will occur in the image (Tanyeri et al., 2017).

Similarity methods using histograms measure the distance between two histograms. The commonly used methods in this sense are Bhattacharyya (B), Intersection (I) (Xu et al., 2012) and Cosine (C) (Zhang et al., 2016). If H1, H2 are assumed to be the histograms of the first and second pictures respectively, the distance measurements are calculated as follows in Equations (1-3):

$$B(H1,H2)=\sqrt{1-\sqrt{\sum_{i=0}^{L-1} H1_i H2_i}} \tag{1}$$

$$I(H1,H2)=\sum_{i=0}^{L-1}\min(H1_i,H2_i) \tag{2}$$

$$C(H1,H2)=\sum_{i=0}^{L-1} H1_i H2_i \Big/ \sqrt{\sum_{i=0}^{L-1} H1_i^2}\sqrt{\sum_{i=0}^{L-1} H2_i^2} \tag{3}$$

Here L represents the number of gray levels and is taken as 256 throughout the study.

3. Adaptive Local Window Design

With the developed approach, the adaptive local window is calculated on the image at different sizes. For this, the appropriate window size (CDSPN-Common Divisor Smallest Prime Number) is determined by taking the smallest prime, which divides both width and height values in the query image (m1xn1) and compared the image (m2xn2) (Figure 3).

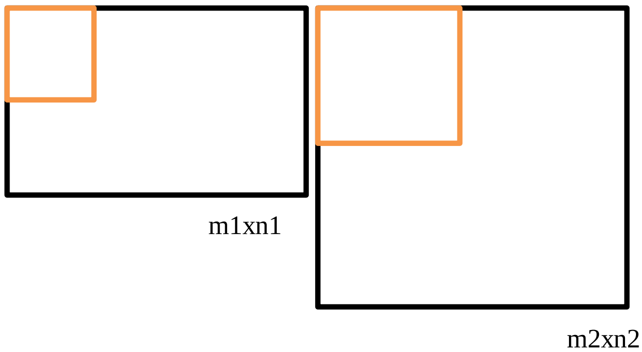

Figure 3. Identification of adaptive local windows.

Figure 3 shows how the modified local window is calculated. This makes it possible to navigate both pictures with an equal number of local windows. Figure 4 shows how the proposed method is used for similarity search.

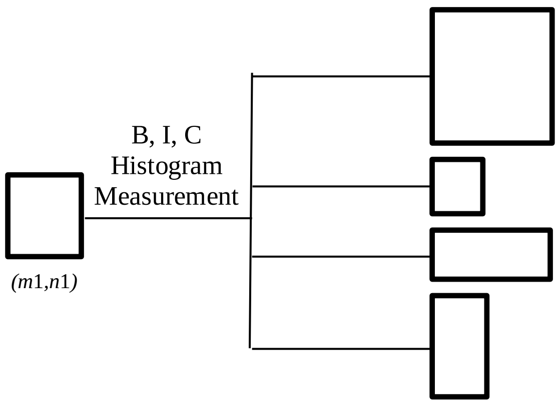

Figure 4. Searching for similarities with adaptive local windows.

4. Findings

Our current method has two different test groups. First, images of different sizes belonging to the same image obtained by interpolation are used. Secondly, it is processed between images with different sizes and different contents. The results are compared with the information from the global histogram in order to show the success of the proposed technique in all operations performed. In these tests, Weizmann uses 100 images in the single object image segmentation database (Alpert et al., 2012). In the first group study, 2 reduced images and 2 enlarged images are generated from related images, using randomly selected values (A and B). Random values are calculated with values ranging from 10% to 90%. Thus, each image comes out of 4 different images with the same content but with a changed size.

Equation (4) shows the calculation used to obtain images of different sizes. In the images generated, similarity was observed with 4 images derived from each image by both the proposed local and global method, using histogram techniques using B, I and C distance measurements. Thus, similarity values were calculated in a total of 400 different sized images. Then, there is averages of similarity results obtained with each technique.

$$\begin{aligned}(m2,n2) &= (m1+A, n1+B)\\ (m2,n2) &= (m1-A, n1+B)\\ (m2,n2) &= (m1+A, n1-B)\\ (m2,n2) &= (m1-A, n1-B)\end{aligned} \tag{4}$$

In Table 1, similarity value averages between 400 images and their original images are shown through the global and developed local method.

Table 1. Mean Values of Similarity Comparisons in Images Obtained by Interpolation.

Techniques	Developed Method (Local)	Global
Bhattacharyya (B)	0,9929	0,9979
Cosine (C)	0,9908	0,9965
Intersection (I)	0,9391	0,9649

When Table 1 is examined, it is noticed that the similarity value is preserved in the images whose size has been changed. In other words, the change in very small increments is due to the interpolation. For images with the same content, the proposed method has the same effect as the global one, indicating that our method maintains consistency.

The second set of experiments, comparing images with different contents and different sizes, is based on 100x100 = 10000 image processing. In the relevant test, it is expected that the similarity comparison of images with different contents will be low. Table 2 gives the similarity comparison averages in the Weizmann database with each other, except for the picture itself.

Table 2. Mean Values of Similarity Comparisons in Images with Different Content.

Techniques	Developed Method (Local)	Global
Bhattacharyya (B)	0,5572	0,7094
Cosine (C)	0,3075	0,4117
Intersection (I)	0,3183	0,4337

When Table 2 is examined, it can be seen that the proposed method shows that the images have different contents according to the similarity comparison averages, about 21% with distance B, 25% with C and 26% with I technique. In addition, in order to show that the proposed method is better, the tests made under this group were carried out on the four random images shown in Figure 5.

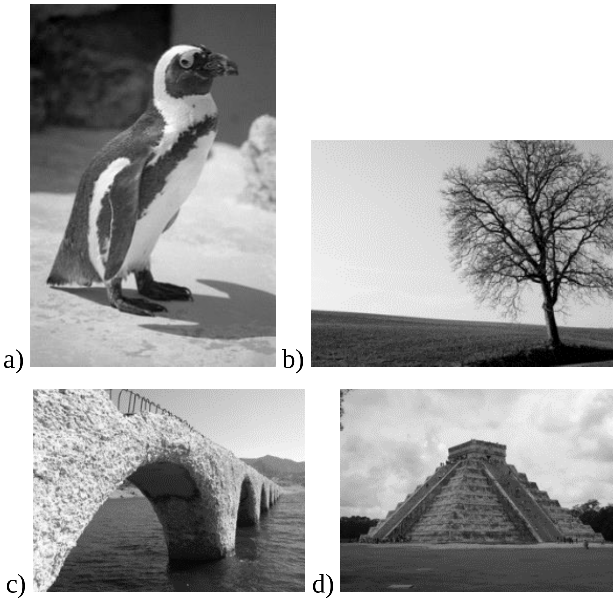

Figure 5. Random selected images; a) Penguin (300x444) b) Tree (300x225) c) Bridge (300x225) d) Pyramid (300x225).

Each picture given in Fig. 5 is compared with other pictures except for itself and the similarity values are measured as given in Table 3.

Table 3. The Result of Similarity Comparison Obtained on Four Randomly Selected Images.

Global	Bhattacharyya (B)	Cosine (C)	Intersection (I)
Penguin-Tree	0,9068	0,7308	0,6617
Penguin-Bridge	0,9486	0,8693	0,7584
Penguin-Pyramid	0,9223	0,8058	0,6769
Developed Method (Local)	Bhattacharyya (B)	Cosine (C)	Intersection (I)
Penguin-Tree	0,5048	0,2658	0,2876
Penguin-Bridge	0,5388	0,2534	0,2771
Penguin-Pyramid	0,5000	0,2982	0,2900

When Table 3 is examined, the difference in content between images can be approximated by different distance measurement techniques as Penguin and Tree, 44% at B, 63% at C, 56% at I; Penguin and Bridge, 43% at B, 70% at C, 63% at I, and Penguin and Pyramid, 45% at B, 62% at C, 57% at I. The results show that the proposed method expresses the difference between the pictures in a much better way.

5. Conclusion

In the proposed study, a new method has been developed which allows equal number of windows to be taken from the images so that they can be compared locally on different sized images. Our method is used to compare images obtained with different sizes of the same image, and the localized similarity values have been found to be very close to global values. However, the results obtained with the global histogram in the tests in which different images are compared with each other in content are found to be much higher than the developed method, incorrectly.

It is thought that the approach will be further improved by using the content-based image retrieval and color-related feature extraction. It was planned to develop a content based image retrieval system design based on the approach proposed in the future studies.

Information

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Conflict of Interest

No conflict of interest was declared by the authors.

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