Generalized Rotation-gray Element Co-occurrence Matrix Based Optimization for CBIR in Web-based Mini-PACS

Xiaocao Cao, Xubo Yang, Lixu Gu*, Ying Yuan, Mingting Yu

***Abstract*—Since the algorithm based on gray level co-occurrence matrix does not have scale invariance and rotation invariance, a new concept called generalized grayscale pixel rotation element is proposed in this paper. This concept involves both resizing factor and rotation factor of the image. On that basis, a new algorithm called GRECM (Generalized Rotation-gray Element Co-occurrence Matrix)-based algorithm is proposed for optimizing GLCM-based algorithm. By applying this algorithm as one of the CBIR(Content-Based Image Retrieval) algorithms to the mini-PACS(Picture Archiving and Communication System) platform, ideal experimental results have been obtained. Compared with the traditional algorithm based on GLCM(Gray Level Co-occurrence Matrix) or GGLCM (Generalized Gray Level Co-occurrence Matrix), the new algorithm largely reduces its sensitivity to the scale of the image or the direction of the object in the image. So this algorithm has very good performance in improving the retrieval precision when there are a lot of images resized or rotated by the same image in the image library.**

I. INTRODUCTION

Nowadays, with the rapid development of information technology, doctors simply need sit before the computer to view all the images obtained from the hospital information center. In this case, PACS comes with the tide of fashion[1].

As to PACS platform, the image retrieval function is one of its most core functions. With the retrieval demand rising, traditional TBIR (Text-Based Image Retrieval) can no longer meet the needs of doctors. In order to enrich the retrieval methods in PACS platform, some researchers and scholars have suggested applying CBIR to PACS[2]. With CBIR technology becoming more and more mature, it plays an increasingly important role in PACS platform. CBIR is a relatively mature technology. One of classical CBIR algorithms called GLCM-based algorithm[3] has been frequently applied in some PACS platforms. But GLCM is high sensitive to the scale of the image or the direction of the object in the image. So it does not have rotation invariance and scale invariance. In order to fix these defects of GLCM, some researchers propose another algorithm called GGLCM-based algorithm[4]. But this algorithm plays a role only in maintaining scale invariance but takes little effect on maintaining rotation invariance. The main reason is that the algorithm emphasizes taking advantage of spatial information of the image to restrain the impact of the image scale over the image feature, but considers little for how to restrain the impact arising from direction factor of the object in the image [5]. So we propose a new concept called generalized grayscale pixel rotation element to compensate the disadvantages of GGLCM. As can be seen from the results which are obtained by a lot of experiments on our mini-PACS platform, we find that GRECM-based algorithm is obviously better than GLCM-based and GGLCM-based algorithms from the retrieving precision perspective.

This paper is organized as follows: in section Ⅱ, there will be the introduction of the main frame of our system and related work; in section Ⅲ, we will recall the traditional algorithms; In section Ⅳ, the new algorithm will be proposed. In section Ⅴ, the experimental results and conclusions will be given. In the last section, we will make discussions and give proposals for future work.

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II. ARCHITECTURE OF THE WHOLE MINI-PACS SYSTEM AND RELATED WORK

A. Architecture

Our system is different from most of PACS platform, because it is a web-based system. We build the system on MVC pattern. The main framework of this system is shown in Fig. 1. We use "servlet" to replace the gateway used by traditional PACS systems based on C/S architecture. "servlet" features include the distribution of orders, dealing with the page logic, and so on. Our system has the basic functions which a traditional PACS system should have, such as medical images communication and archiving, image display and image retrieval and so on. As to the image retrieval module, it is based on two approaches. First one is TBIR that is text based image retrieval. This approach executes retrieving by taking advantage of the text information obtained by parsing the image. However, this approach is relatively simple. The other one is CBIR. CBIR uses a variety of content features for image retrieval.

B. Related work

Our system focuses both on the retrieval precision and timeliness of the prospective algorithms. So every algorithm applied in the mini-PACS system should have fast retrieval speed in order to meet the needs of users. But the general CBIR algorithms are very complicated and time consuming.

The retrieving procedure is shown in Fig. 2. So, the contradiction arises. How to coordinate the real-time interaction and retrieval accuracy is our main objective. Because the computing of GLCM-based algorithm is relatively simple, so it's suitable for mini-PACS platform. Actually, three kinds of classical content-based image retrieval algorithm are applied in our system. They are based on mutual information, gray level co-occurrence matrix and edge direction histogram respectively. They belong to three major categories. The three categories are gray level histogram-based algorithm, texture-based algorithm and shape-based algorithm respectively[6]. From the results of some experiments, we find that the GLCM-based algorithm is the best one among the above three from precision and timeliness perspective simultaneously[7]. So we do some improvements based on this algorithm.

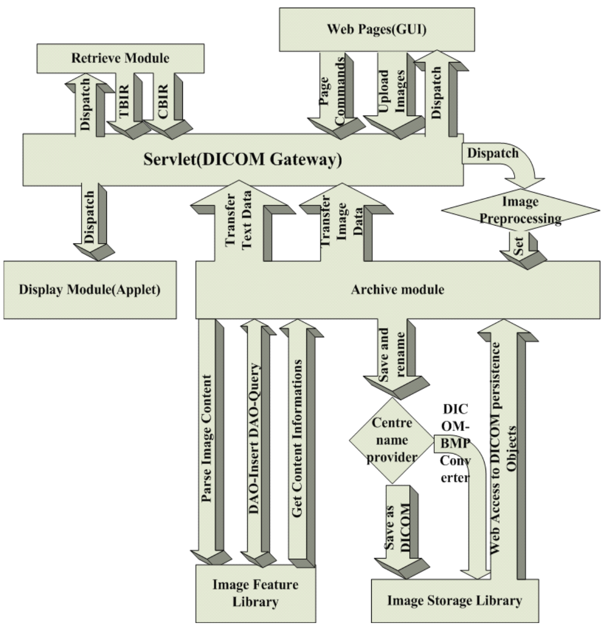

Fig. 1. Framework of the whole system

III. Traditional Algorithms Recall

A. GLCM-based algorithm

Because the traditional GLCM-based algorithm is the foundation stone of the new algorithm and our optimizations are based on it, so we introduce it briefly[8].

GLCM-based algorithm is one of the texture-based CBIR algorithms which can get the features by the joint distributions of the gray-level of the two given images.

Gray-level image G can be expressed as formula (1).

$$p(i,j) = \{(x,y)|f(x,y)=i \text{ and } f(x+dx, y+dy)=j;\ x,y=0,1,2\ldots N-1,\ i,j=0,1,2,\ldots L-1\} \quad (1)$$

For gray image G, we can use formula (2) to represent its gray co-occurrence matrix:

$$P(\delta, L) = \begin{bmatrix} p_{00} \ldots\ldots\ldots p_{0(L-1)} \\ \ldots\ldots\ldots\ldots\ldots\ldots \\ p_{(L-1)0} \ldots p_{(L-1)(L-1)} \end{bmatrix} \quad (2)$$

In this matrix, x and y are both the coordinates of pixels in the image and f(x, y) is the gray-level of pixel(x, y). More over, L is the count of the different gray-levels. The two differentiation operators dx and dy are the offset on x axis and y axis respectively. And if we add the direction element to the fixed relation δ, then we can get different co-occurrence matrix with different rotate angles.

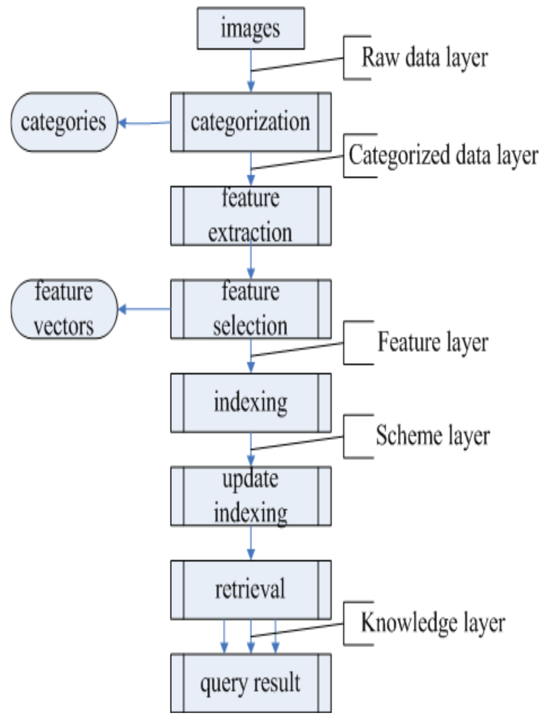

Fig. 2. Preview of retrieving procedures

B. GGLCM-based algorithm

This algorithm takes advantage of the generalized image obtained by the gray level joint distribution of the original image and transformed image[9]. After the generalized image being obtained, we can compute the co-occurrence matrix of the generalized image. The computation procedure is the same as GLCM. The unique difference between the computed matrix and the original grayscale pixel matrix is that the elements in the new matrix are all with the compound gray level other than with the gray level. As mentioned before, this algorithm takes little effect on maintaining rotation invariance because it considers little for how to restrain the impact arising from direction factor. We can see the new algorithm how to resolve this problem in next section..

IV. Optimization Based on The New Algorithm

A. *Grayscale Pixel Rotation Element*

Since GLCM is sensitive to direction of the target object in the image, so if there are lots of images which are obtained by rotating or resizing the same image, the retrieving precision will be greatly decreased. For these reasons, we propose the GRECM-based algorithm. The core of the algorithm is generalized grayscale pixel rotation element. This is a new concept. As implied by the name, the grayscale of the rotation element combines the grayscale of the original image with any rotated images. Then we give the detail description of it.

The first step, we should determine the rotation step length. From Fig. 3, we can see a square image is rotated by 90, 180 and 270 degrees respectively. Now we give the definition of compound-rotation-grayscale with this figure.

As the images shown in Fig. 3, image Ⅱ, Ⅲ and Ⅳ are obtained by anticlockwise rotating original image by 90, 180 and 270 degrees respectively. Obviously, the rotation step length for this case is 90 degrees because every rotation-degrees in image Ⅱ, Ⅲ and Ⅳ is an integer multiple of 90. Combination of the four images, we can get the compound-rotation-grayscale of pixel (x, y) in original image. It is the sum of the grayscale of pixel (x, y) in every image. For example, if the grayscale of pixel (x, y) in original image is 80, and the grayscales of pixel (x, y) in the other three images are 90, 60 and 70 respectively, we can say the compound-rotation-grayscale of pixel (x, y) is 300(300=80 +90+60+70). The compound grayscale of pixel (x, y) reflects the sum of the grayscales which probably appear in pixel (x, y) while the original image is being rotated. Obviously, if an image is obtained by rotating original image by an integer multiple of given rotation step length, the compound-rotation-grayscale of every pixel in the image is the same as the compound-rotation-grayscale of every corresponding pixel in the original image. Based on this point, the shorter the rotation step length is, the greater the probability of the rotated image has the same compound-rotation-grayscale as its original image on every pixel. So the rotation step length is a very important variable because it's directly related to the algorithm's rotation invariance.

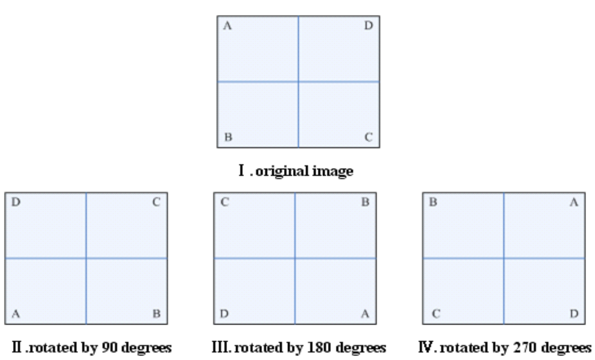

Fig. 3. A square image rotated by 90 degrees, 180 degrees and 270 degrees respectively

The second step, the grayscale pixel rotation element can be got. After the rotation step length is determined, we can get the compound-rotation-grayscale of every pixel in the image. Then we replace the grayscale of every pixel in the original image with the compound-rotation-grayscale of every pixel. Now we've obtained a matrix which is constituted by the compound-rotation-grayscale of every pixel. In order to take the condition that the rotation-degrees is less than the rotation step length into account as far as possible, we should calculate the average value of every element and its four neighbor's elements in the new matrix. This new value is called grayscale pixel rotation element. Of course, we can also use the value of eight neighbor's elements to execute calculation. As can be seen from above, every pixel has its corresponding grayscale pixel rotation element. This property is the same as GGLCM. In the procedure of computing GGLCM, every pixel of original image has its corresponding generalized grayscale.

B. *The new algorithm*

From the above the description, we can summarize a new algorithm based on generalized grayscale pixel rotation element co-occurrence matrix. Of course, this algorithm cannot eliminate its sensitivity to rotation entirely, but it can decrease this sensitivity largely. We will get this point from the experimental results listed in section Ⅴ.

First of all, we should get the grayscale pixel rotation element matrix of the given image. Since there is the one to one relationship between the grayscale pixel and its corresponding rotation element, we can replace every element in the matrix composed of the grayscale of every pixel in the given image. So we get the grayscale pixel rotation element matrix.

Next, the generalized rotation-gray element matrix can be obtained. As can be seen from the former section, generalized gray level co-occurrence matrix is obtained by the gray level joint distribution of the original image and transformed image. According to this description, we can do as the two steps. First, we should get the grayscale pixel rotation element matrix of the image which is smoothed from the original image. Second, combination of the grayscale pixel rotation element matrix of the original image and of the smoothed image, we can get the generalized grayscale pixel rotation element matrix.

In the last, we can get the generalized grayscale pixel rotation element co-occurrence matrix. This step is similar to the procedure of calculating the gray-level co-occurrence in the algorithm based on GLCM. The unique difference between them is that this step calculates the co-occurrence matrix based on grayscale pixel rotation elements while the GLCM-based algorithm calculates the co-occurrence matrix based on gray-level pixels. So we won't go into details.

V. Experimental results and conclusions

A. *Test case I*

Test by 50 images which are rotated by random degrees from the same image. The results are shown in TABLE I.

TABLE I
THE COMPARISON TABLE OF THE NUMBER OF RETRIEVED IMAGES BY DIFFERENT WAYS

retrieving algorithm	GLCM	GGLCM	GRECM with 90-degrees as its rotation step length	GRECM with 45-degrees as its rotation step length	GRECM with 30-degrees as its rotation step length	GRECM with 22.5-degrees as its rotation step length	GRECM with 18-degrees as its rotation step length
the number of retrieved images	3	7	13	21	32	36	42

TABLE Ⅱ
THE COMPARISON TABLE OF THE RECALL AND PRECISION RATIO BY DIFFERENT WAYS

retrieving algorithm	GLCM	GGLCM	GRECM with 18-degrees as its rotation step length
recall ratio	55.96%	76.72%	96.98%
precision ratio	51.75%	71.47%	88.93%

TABLE Ⅲ
THE RATIO OF RETRIEV AL ACCURACY AND RETRIEVAL TIME V ARYIN G WITH THE ROTATION STEP LENGTH

rotation step length(degree)	90	45	30	22.5	18	14.4	12
ratio	7.36	8.98	9.27	9.42	9.51	8.47	7.26

B. Test case Ⅱ

Test by the testing set with 328 medical images which include 86 images rotated from and 72 images resized from the example image for retrieval. The results is shown in TABLE Ⅱ.

C. Conclusions

As the results shown in TABLE I, we can conclude that the new algorithm maintains more rotation invariance. And with the rotation step length becoming shorter and shorter, the rotation invariance present more and more obvious. As the results shown in TABLE Ⅱ, we can see that the recall ratio and precision ratio of the new algorithm is much higher than the other two when there are a lot of rotated or resized images in the testing set. At the same time, the result can also verify that the new algorithm has low sensitivity to the scale of the given image because there are many resized images form one example image.

As TABLE Ⅲ shown, although the recall and precision ratio is increasing with the rotation step length, but there is more and more time consuming at the same time. We use the ratio of the retrieval accuracy and the retrieval time as the measurements. The ratio can be expressed by formula (3).

$$E = (R + P)*100/T \quad (3)$$

(In this expression, E, R, P and T represent the ratio of the retrieval accuracy and the retrieval time, the recall ratio, the precision ratio and the retrieval time respectively. The unit of T is second.) We can select the rotation step length with the best ratio of the retrieval accuracy and the retrieval time. So, from the description above, we can reach a conclusion that the GRECM-based algorithm has better performance in image retrieval than the other two algorithms both from the scale invariance perspective and the rotation invariance perspective.

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