Content Based Medical Image Retrieval with Radon Barcode Annotations

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Abstract- *Content Based Image Retrieval (CBIR) is a technique used for extracting similar images from an image database. Recently, the concept of 'barcode annotation' has been proposed as a method for fast image searching and content based barcode annotations. In this work, a content-based medical image retrieval method is proposed by combining Radon projections and the support vector machines (SVM).Query image is transformed into form of feature vector using LBP and RBC features. Then radon transform applied to LBP and RBC processed matrix .The LBP and RBC features are calculated using four angle projections and then, the barcode has been generated. Each image labels are classified using SVM classifier. Finally the similar images for given query images are retrieved. The IRMA database with training images and testing images is used to verify.*

Keywords- Content Based Image Retrieval (CBIR), Support Vector Machine (SVM), Radon Barcodes (RBCs), Local Binary Patterns (LBPs), Radon Transform (RT).

I. INTRODUCTION

In recent years, there has been an increasing number of works proposing different methods for barcode annotations, e.g., local binary patterns (LBPs) and Radon barcodes (RBCs). Binary features have distinct benefits compared to conventional features, when Content-based image retrieval (CBIR) has been a very active research discipline. CBIR is a technique for extracting similar image from an image database. Content means search and analysis based on the Content of image. "Content "refers to the colors, shapes, textures or any other information that can be derived from the image itself. In a generic CBIR system, given a user-

supplied query image, the system is supposed to search the database and return the images that have high similarity to the user's query image. For medical applications, such a system could assist clinicians in more reliable diagnosis or timely detection of malignancies by retrieving similar cases from the image archive or database.

II. LITERATURE SURVEY

H.R. Tizhoosh et al [1] proposed radon features and barcodes for medical image retrieval via SVM. H.R.Tizhoosh et al [2] proposed barcode annotation for medical image retrieval by using hamming distance. James Tung et al [3] proposed radon-Gabor barcode for medical image retrieval by using Radon and Gabor features.Mehrdad J.Gangeh et al [4] proposed tumors ROI estimation in ultrasound images via radon barcodes in patients with locally advanced breast cancer. H.R. Tizhoosh et al [5] proposed a binary code for tagging X-ray Images via deep de-noising auto encoders.

III. METHODOLOGY

Fig.1 gives the block diagram of the proposed system. It consists of the following steps. The images are taken from the IRMA database. For these images, LBP (Local Binary Pattern) and radon features are extracted. Radon features, LBP features are calculated using four angle radon projections. Then Radon transformation is applied to LBP and radon features processed matrix. Radon projection to works on radon features to generate the Radon barcode (RBC). By using SVM classifier, images are classified and CBIR method correctly identified the similar images for the given query image.

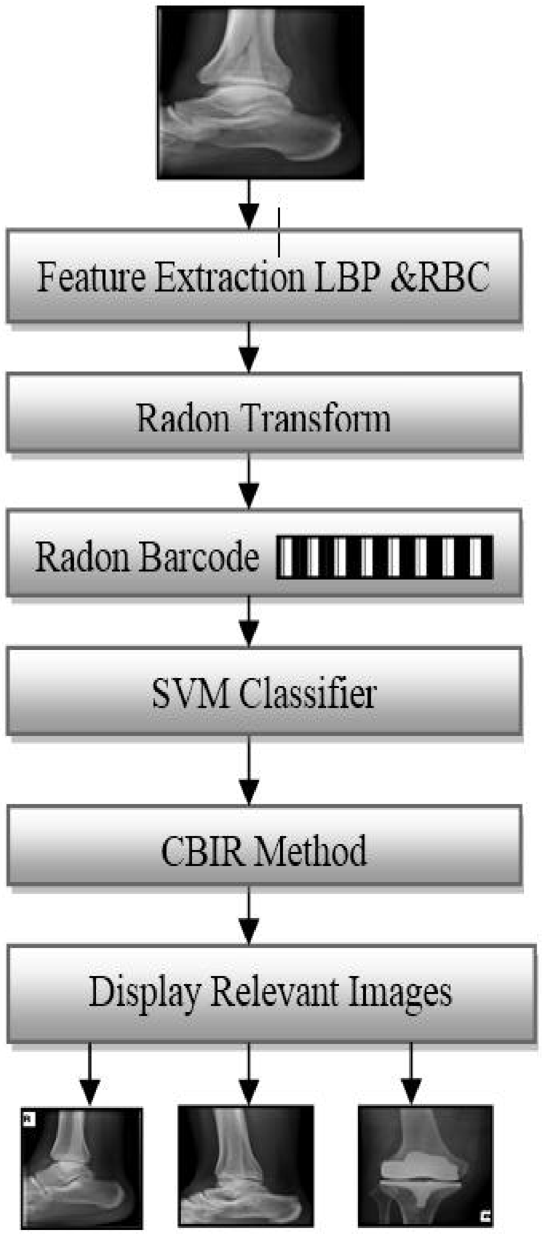


Figure 1. Block diagram of the proposed system

A. Local Binary Patterns(LBPs)

The local binary pattern operator is an image operator which transforms an image into an array or image of integer labels describing small-scale appearance of the image. These labels or their statistics, most commonly the histogram, are then used for further image analysis as follows

47	51	65
62	70	79
80	83	78

a) Sample

-23	-19	-5
-8	0	9
10	13	8

b) Differences

0	0	0
0	0	1
1	1	1

c) Threshold

Figure 2. LBP threshold value

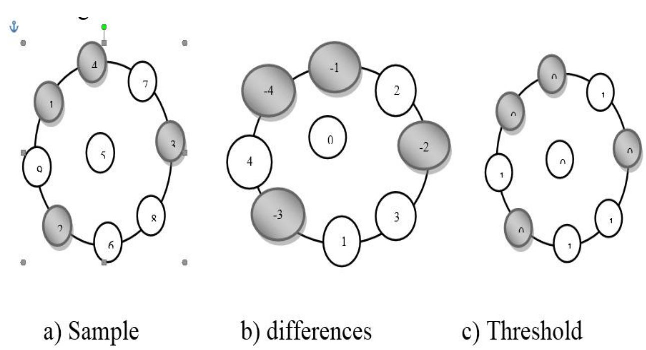
Fig.2 denotes the calculated LBP threshold value. The LBP feature vector divided the 3×3 pixels for each cell, where the central pixel's value is different from the neighbor's pixel values. If the current pixel value is negative and equal to the neighboring pixel values the corresponding bit in the binary array is set to 0 and if the current pixel value is positive, then the corresponding bit in the binary array is set to 1.We then continue to move to the next neighboring pixel until we reach the 8th neighboring pixel.

a) Rotational Invariance

The LBP patterns to translate into a different location and to rotate about their origin. Computing the histogram of LBP codes normalizes for translation and normalization for rotation is achieved by rotation invariant mapping. In this mapping, each LBP binary Code is circularly rotated into its minimum value.

$$LBP_{p,r}^{ri} = \min ROR(LBP_{p,R}, i) \qquad (1)$$

Where ROR(x, i) denotes the circular bitwise rotation of right bit sequences x by i step right bit sequence x by for instance 8 bit code is invariants only to rotation of input image by angle. In this rotation invariance features form a uniform LBP histogram.



a) Sample b) differences c) Threshold

Figure 3. LBP feature for neighbor 8 pixels

Fig.3 shows the LBP feature of neighbor 8 pixels classification. If the current pixel value is negative and equal to the center pixel values the corresponding bit in the binary circle is set to 0 and if the current pixel value is positive, then corresponding bit in the binary circle is set to 1.We then continue to move to the next neighboring pixel until we reach the 8th neighboring pixel.

B. Radon Transform

The radon transform is an integral transform which compute the projection along various directions. The Radon transform is a 2D image f (x, y) for a given set of angles can be defined as θ. The resulting projection is the sum of the intensities of the pixels in each direction (a line integral). The result is a new image R (ρ,θ).

This can be written mathematically by defining

$$R = x\cos\theta + y\sin\theta \qquad (2)$$

Radon transform can be written as

$$R(\rho,\theta) = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f(x,y)\,\delta(\rho - x\cos\theta - y\sin\theta)\,dx\,dy \qquad (3)$$

Where δ (·) is the Dirac delta generalized function. This is non-zero only on s axis and it's integral. The Radon transform has the capacity to accentuate straight line features from an image by integrating the image intensity over the straight line to a single point.

C. Radon Barcodes(RBCs)

Query image is transformed in the form of feature vector. The whole feature dataset of image transformed is in a matrix of radon feature and LBP feature using radon transform and Radon barcode is generated.

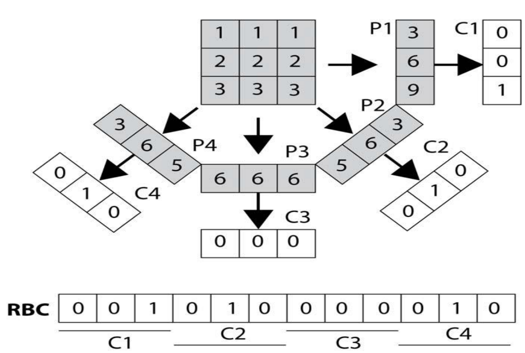


Figure 4. Radon Barcode (RBC) generation

Projections (P1, P2, P3, P4) are threshold to generate code fragments C1, C2, C3, and C4.

Figure 3.shows the radon barcode generation. The given image is Radon transformed. Radon barcode generation consists of a matrix form where each value consists of four projections (P1, P2, P3 and P4). As proposed, one can threshold all projection values for individual angles based on a "local" threshold for that angle. Subsequently, one can assemble a barcode of all thresholds. If the current pixel value is greater than the neighboring pixel value, then the value in the binary array is set to 1 and current pixel values less than and equal the neighboring pixel value, the corresponding bit in the binary array is set to 0. Then it continues to move to the next neighboring pixel until we reach the 4th projection. A simple way for thresholding the projections is to calculate a typical value via median operator applied on all non-zero values of each projection. The concatenation of all code fragments delivers the barcode RBC.

Algorithm 1 describes barcode generation

Algorithm 1 Radon Barcode (RBC) Generation

1. Initialize radon barcode $\boldsymbol{r} \leftarrow \emptyset$
2. Initialize angle $\theta \leftarrow 0$ and $RN = CN \leftarrow 256$
3. Normalize the input image $I = normalize(i, RN, CN)$
4. Set the number of projection angle np← 4
5. While $\theta < 180$ $\boldsymbol{do}$
6. Get all projection P for θ
7. Find typical value Typical ←meadian i|(pi)≠ pi0
8. Binarized projections' b← $\boldsymbol{P}$ ≥Ttypical
9. Append the new row r ←append (r, b)
10. $\theta \leftarrow + \frac{180}{np}$
11. End while
12. Return r

D. SVM Classifier

Support Vector Machines (SVM) gives a set of separable training samples which belongs to two different classes; a linear SVM constructs a hyper plane which contains the largest number of samples of the same class on the same side, while achieving the largest distance to the nearest training-data point of any class by the hyper plane. SVM classifier involves the following stages: Training stage and Retrieval stage.

a) Training Stage

Algorithm 2 describes Training stage

1. Initialize angle θ and image size R_N=C_N ← N
2. While I <training samples do
3. Normalize the imageI_i =Normalize (I,R_N, C_N,)

4. Radon transform R_i=Radon (I_i)
5. Binarized projection: $b_i \leftarrow = R_i$Threshold
6. Generate radon a barcode B_i=Barcode (b_i)
7. End while
8. Get the label L
9. Build SVM classifier M=TrainSVM (b_i,L)

Algorithm 2 shows the generic overview of the training stage with IRMA dataset. Combining with the label that defines the image class, the Radon features are used to train multi- SVM. The multi-class SVM used in this procedure implements the "one-against-one" approach. The SVM kernel is set to Radial Basis Function. The setting of other parameters is empirical. In the training stage, the Radon projections are binarized to generate Radon barcode.

b) Retrieval Stage

In the retrieval stage, the query image is processed to generate its corresponding Image and Radon barcode.

Algorithm 3 describes Retrieval stage

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1. Query initialization$Iq = Normalize(Iq, RN, CN)$
2. Generate Radon Projection: Rq=Radon (Iq)
3. Predict image class: label p=predictsSVM (Rq,**M**)
4. Generate query RBC: **B**q=Barcode (Rq)
5. Obtain Radon barcode: Bp$\leftarrow = Bi\backslash i = labelp$
6. Set the desired number k of retrieved images
7. Search the top k images: **I**k=SSIM (**B**p,Bq,k)
8...Return retrieved images **I**k

Algorithm 3 describes the retrieval stage. Radon projection is then used to assign a class to the image by the multi-class SVM classifier. According to the classified image label, the images within the same category are selected from the database, and the Radon barcode generated from the query image is compared with all images within that class by using CBIR method. Eventually, the most similar images in the same class can be indexed out.

IV. EXPERIMENTS AND DISCUSSION

a. IRMA Dataset

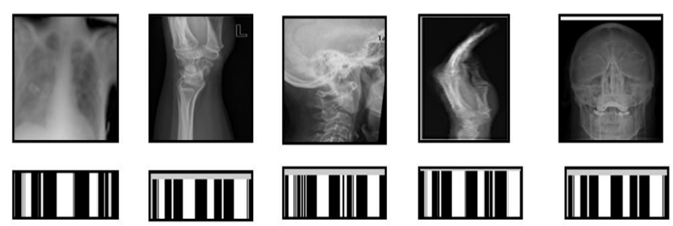
IRMA (Image Retrieval in Medical Applications) is a cooperative project of the Department of Diagnostic Radiology, the Department of Medical Informatics, Division of Medical Image Processing and the Chair of Computer Science VI at the Aachen University of Technology (RWTH Aachen). Aim of the project is the development and implementation of high-level methods for content-based image retrieval with prototypical application to medical diagnostic tasks on a radiologic image archive. This work has been used in IRMA database 2009 medical images. IRMA code comprises of four axes with three to four positions each,

- The technical code (T)-defines the image modality
- The directional code (D)-deals with the body orientations
- The anatomical code (A)-describes the body region
- The biological code (B)-explains the biological system examined

The IRMA code can be defines as, TTTT-DDD-AAA-BBB. The complete IRMA code consists of 13 string characters, such as {0…9, a…z}. Fig.4 shows sample images from database with IRMA code. Fig.5 Shows sample x-ray images and corresponding generate barcode

a)1121-120-200-700 b)1121-127-700-500

Figure 4. Shows sample images from IRMA database with code



a)3232.png b)11471.png c)11727.png d)11472.png e)11609.png

Figure 5. Shows sample x-ray images and corresponding generate barcode

b. Error measurement

In this work based on IRMA (Image Retrieval in Medical Applications) database images both training and testing describes the SVM based classification accuracy. the following equation is used to calculate to the total error of image retrieval in IRMA database.

$$E_{total} = \sum_{k=1}^{1733}\sum_{i=1}^{n_p}\sum_{j=1}^{l_i}\frac{1}{d_{l_{j,i}}}\frac{1}{j}\delta\left(I_{lj,i}^{k}, I_{lj,i}^{\sim k}\right) \quad (4)$$

Where, k - describes each image in database

- j-is the structure IRMA code-Ex 1121-120-200-700(l_1=4, l_2=3, l_3=3, l_4=3)
- n_p -Defined as number of projections
- l_i is defined as number of character in a particular structure in IRMA code(Ex. $l_{1,1}$=1, $l_{4,1}$=7)
- $I_{lj,i}^{k}$-Testing images,
- $I_{lj,i}^{\sim k}$-Top retrieved images.
- $d_{l_{j,i}}$-denotes the number of branches in IRMA code.

According to the following equation, {0, 1} denotes

$$\delta\left(I_{lj,i}^{k}, I_{lj,i}^{\sim k}\right) = \begin{cases} 0, I_{lj,i}^{k}, h = I_{lj,i}^{\sim k} & , h \ \forall \ h \le i \\ 1, I_{lj,i}^{k} \ h \ne I_{lj,i}^{\sim k} & , h \ \exists \ h \le i \end{cases} \quad (5)$$

C. Classification Accuracy

In this work, SVM classifier is used to classify the medical images. Training is the process to learn from training samples images by adaptively updating testing images. In this input query image ,the desired set of output images are retrieved. Training assumes that each input vector is paired with a target vector representing the desired output; together these are called a training pair.

True Positive (TP) : Test images correctly identified.
False Positive (FP) : Test images incorrectly identified.
True Negative (TN) : Test images correctly rejected.
False Negative (FN) : Test images incorrectly rejected.

In order to examine the classification techniques more closely the sensitivity, specificity and accuracy value have been calculated using the performance measures.

Precision is the ratio of the number of relevant records retrieved to the total number of irrelevant and relevant record retrieved

$$\text{Precision (P)} = 100 \times \frac{TP}{TP+FN} \quad (6)$$

Recall is the ratio of the number of relevant record retrieved to the total number of relevant record in the database.

Recall(R) = (TP/TP) +FN (7)

F-Measure is harmonics mean of precision and recall.

F-Measure (F) =2PR/ (P+R) (8)

Accuracy is defined as,

$$\text{Accuracy (ACC)} = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

A proposed RBC and LBP feature obtained an accuracy of 80.6% . We have used 107 images for training and 15 images for testing .we have obtained an error rate of 22.72.

Table 1. Performances measures

Image Name	Precision	Recall	F-measure	Accuracy
3232.png	0.8	0.8	0.8	72.7
11471.png	0.9	0.9	0.9	84.6
11472.png	1	0.9	0.9	91.6
11727.png	1	0.8	0.8	80
11609.png	1	0.5	0.5	50

In Table 1 show Precisions, Recall, F-measure and Accuracy value for the proposed work. The graphical representation of F-measure and Accuracy values are show in figure 6 and figure 7.Fig.8 shows x-ray image retrieved from the IRMA database.

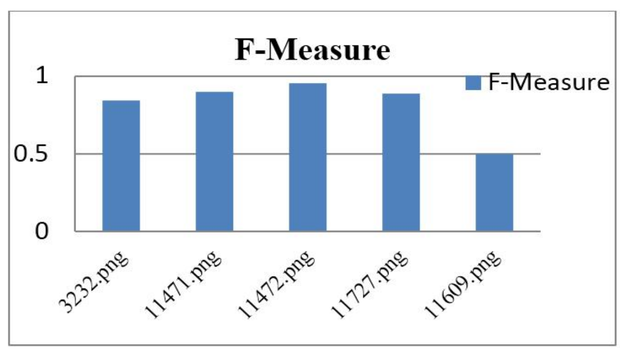


Figure 6. Bar chart for F-measure of the input x-ray images

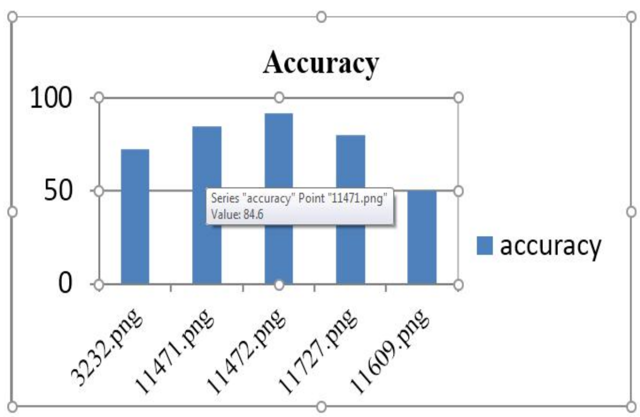


Figure 7. Bar chart for accuracy of the input x-ray images

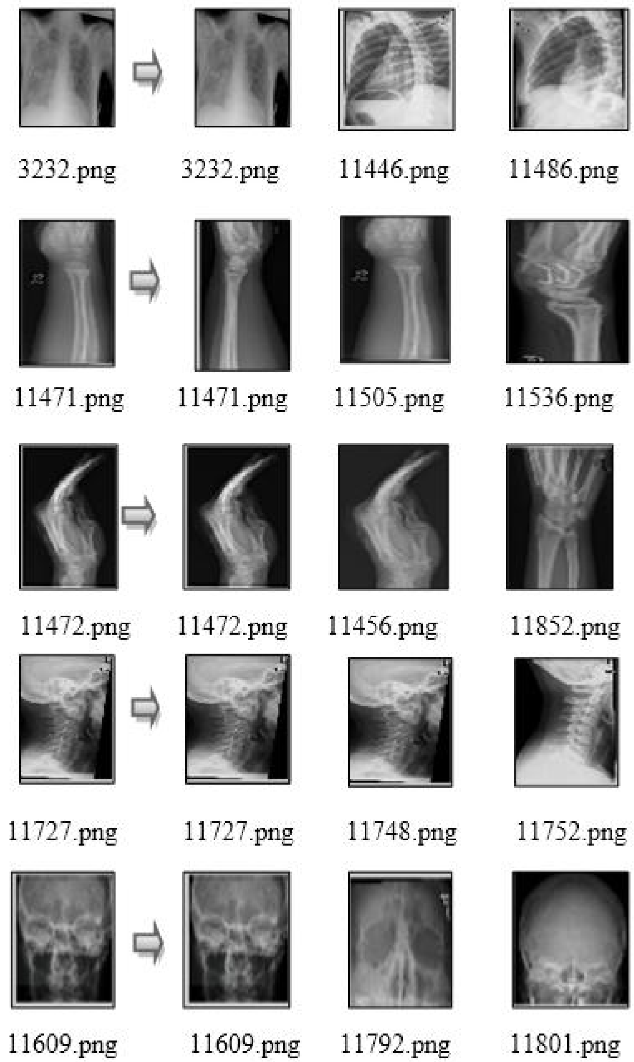


Figure 8. Retrieved medical x-ray images

V. CONCLUSION

In this work, based on SVM classification and Radon barcodes, a content-based image retrieval method is proposed. The extracted Radon features are used to train a SVM classifier in order to categorize query images. Radon barcodes which represent the image in a binary format makes it efficient CBIR method to search for similar images. Experimental results demonstrate that the proposed method is able to retrieve similar responses to the correctly identified query image. This project is successfully implemented. The idea of barcode annotations auxiliary information besides feature for medical image retrieval was proposed in this project. Radon projections are thresholded to assemble barcodes. IRMA database with training and testing was used to verify the performance of barcode based image retrieval. Radon barcode appears to provide short but expressive code useful for medical image retrieval. Gabor-barcode and other classification methods can be used in the future work.

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