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Adaptive Content-Based Medical Image Retrieval Based On Local Features Extraction In Shearlet Domain

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Abstract

Image retrieval system is an urgent issue for in medicine. In the past, traditional image retrieval system based solely on the label of images and gave limited results. To reduce this disadvantage, the content-based medical image retrieval has been developed. However, this system still has many challenges. In this paper, we proposed a new method for content-based medical image retrieval. The proposed method includes two stages: the offline task and online task in medical image database. In the first stage, we extracted local object features of medical images in shearlet domain. Then, we detect the contour of object in images by active contour model. In the second stage, we make online task for content-based image retrieval in database. Our system receipts a query image and shows the similar in images by similarity comparison with the information collected from the first stage. Experimental results have shown that the proposed method is better than the other methods.

Keywords: medical image, content-based medical retrieval, segmentation, active contour model, shearlet

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1. Introduction

The image storage plays a big role in the cutting-edge life. In the medical field, the information of patients must be saved by medical images such as: CT, MRI, X-ray, etc. The number of images is stored more and more over time. This is a large resource for research or diagnosis in many cases. Therefore, finding or collecting needs an image retrieval system.

The approach which uses information of labeled images has many drawbacks: low compatibility for many different applications or description on the label which decides image semantics. Because of these reasons, modern systems must give the searching results which depend on image's features. This is a complex demand for the concern of people around the world due to the fact that the accurate results are very vital. In medicine, this demand is always a pressing issue, and this is also in computer vision. As a result, content-based image retrieval (CBIR) was developed to adapt with demand which creates a query based on the content of input images.

Creating a query from the content of images is the process which depends on their characteristics. The details which include color, texture and shape are the base of this system [1, 2, 16]. In simple terms, the authors of these algorithms do not depend on text or name of query image. Suharjito [1] applied the multiclass support vector machine and visual words for creating query. The same idea with visual words had proposed in [3, 4]. However, Avni [3] had based on the organ and pathology level in X-ray images while the authors of [4] had proceed with relationship between pixels together. Besides, a wide range of methods were found as: the binary codes in frequency domain [2], deep convolutional neural network [5], deep learning [6]. Nowadays, with the positive results have been bringing from wavelet, the space domain starts a powerful tool for image processing [8, 9, 10, 11, 13]. And [7] is one of the opening shoots for content-based medical retrieval in wavelet domain at a new stage. Notwithstanding, the tasks for content-based image retrieval have still a host of challenges for researchers.

In this paper, we proposed a method for content based medical image retrieval in the database image. The proposed method for medical image retrieval includes two periods: Firstly, we make offline task in medical image database. In this period, we extracted local object features in medical image in domain and collected the result of segmentation by active contour model. Secondly, we make online task for content-based image retrieval in database. We undervested the proposed method by calculating Canberra distance values. Experimental results of the proposed method performed well compared to the other methods.

Main contributions of this paper are: (i) advantages of shearlet transform for local features extraction are shown and (ii) the proposal of a method for medical image retrieval based on texture feature extraction in shearlet domain. The rest of this paper is organized as follows: in section 2, we described the shearlet transform and its advantages for medical image retrieval, the section 3 present the proposed method for medical image retrieval. The results of our way are given in the section 4 and conclusions are made in section 5.

2. Shearlet transform

Shearlet is similar to curvelet in that both perform a multi-scale and multi-directional analysis. There are two different types of shearlet systems: band-limited shearlet systems and compactly supported shearlet systems [19]. The band-limited shearlet transform have higher computational complexity in frequency domain.

The digitization of discrete shearlet transform performed in the frequency domain. The discrete shearlet transform is the form [20]:

$$f \mapsto \langle f, \psi_n \rangle = \langle \hat{f}, \hat{\psi}_n \rangle = \langle \hat{f}, 2^{-j\frac{3}{2}} \hat{\psi}(s_k^T A_{4^{-j.}}) e^{2\Pi i < A_{4^{-j}S_k m, .}>} \rangle \qquad (1)$$

where n = (j, k, m, i) indexes scale j, orientation k, position m, and cone i.

Shearlets perform a multiscale and multidirectional analysis. For images f(x) are C^2 everywhere, where f(x) is piecewise C^2, the approximation error of a reconstruction with the N-largest coefficients ($f_N(x)$) in the shearlet expansion is given by [21]:

$$\|f - f_N\|_2^2 \le B.N^{-2}(\log N)^3, \qquad N \to \infty \qquad (2)$$

The author has chosen shearlet transform because it not only has high directionality but also represents salient features (edges, curves and contours) of image in a better way compared with wavelet transform. Shearlet transform is useful for medical image retrieval due to its following properties [22]:

(i) Frame property: It is helpful to a stable reconstruction of an image.
(ii) Localization: Each of shearlet frame elements needs to be localized in both the space and the frequency domain.
(iii) Efficient implementation.
(iv)Sparse approximation: to provide sparse approximation comparable to the band-limited shearlets.

The shearlet transform will produce a highly redundant decomposition when implemented in an undecimated form [23]. Like the curvelet transform, the most essential information in the image is compressed into a few relatively large coefficients, which coincides with the area of major spatial activity in shearlet domain. Thus, setting the small coefficients to zero will not affect the major spatial activity of the image.

3. Medical image retrieval based on local features extraction in shearlet domain

The object in medical images have the characteristics such as: shape, position, texture, etc. These characteristics are important basis for our idea. In addition, the digitization of discrete shearlet transform performed in the frequency domain, the multi-scale and multi-directional analysis are one of the optimal choices for extracted features of the query image. In this section, the method for medical image retrieval based on local features extraction in shearlet domain is proposed as figure 1.

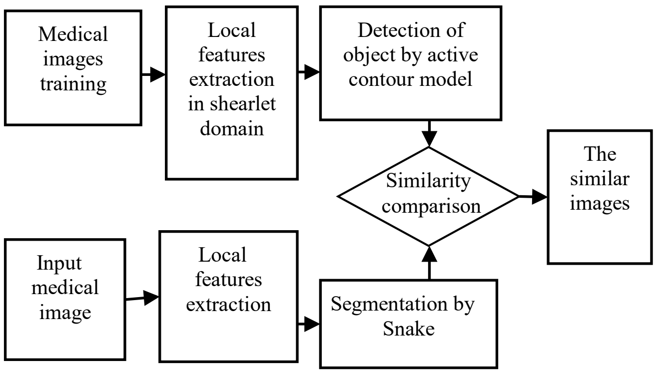


Figure 1. The proposed method for medical image retrieval system

The proposed method is divided into two periods. Firstly, the offline task in medical image database is built. In this period, we extracted local object features in medical images from the scenes depending on shape, texture and intensity in shearlet domain. Then, we detect the shape and contour of each image by segmentation with active contour model - snake.

Secondly, we make online task for content-based image retrieval in database. From the query image which the user gives in graphic user interface, the features extraction and segmentation are applied. After that, we compare with the information of the first period and show the results.

3.1 Local Feature Extraction

The single feature could not present the complete information of an image. We need the combine of local and global features such as shape and position to define object in medical images. The local features help in local variations. The global features capture holistic ideas of an image. The processing for feature extraction is as follows:

(i) Divide the image I into n sub-images with the non-overlapping A_i such as I = {A_1, A_2, A_3, …, An}
(ii) We split each of these A_i sub-images into other B blocks, where A_i = {B_1, B_2, B_3, ... B_m}, in shearlet domain.
(iii) For each block B_i (i = 1, 2, 3, …., m), construct a block representing set of texture feature vectors depend on its location.
(iv) Use the EM (Expectation Maximization) algorithm to cluster the feature vectors into several classes for each sub-image A independently.
(v) For each cluster in A_i (i = 1, 2, ... , n), construct a subimage representing set of texture feature vectors V = {v_1 ,v_2, ... , v_n} where n is the number of classes each of which contains X texture features.
(vi) Build the final set of texture features representing the overall image in the form of a single transaction of the final dataset (set of images), D = {d_1, d_2, d_3,…d_n} where n is the number of images, d_i is a vector of the size (A x N x X).
(vii) For each d_i, (i = 1, 2, ..., n) add the class label of its image.

3.2 Detection the shape of object by active contour model

As define in [13], we can define the context as any information like: pixel, noise, strong edge, and weak edge in a medical image that is considered relevant to the interaction between pixels and pixels including noise, weak and strong edge themselves [13]. To find the boundary of object in an image, we segment the medical image by snakes.

The result of segmentation is the areas which show the number of objects in an image. The energy minimizing is the profound contribution of active contour model - Snakes [17]. The function of energy is calculated by:

$$E^*_{snake} = \int_0^1 E_{snake}(v(s))ds = \int_0^1 E_{\text{int}}(v(s)) + E_{image}(v(s)) + E_{con}(v(s))ds \quad (3)$$

with:

$$E_{\text{int}} = (\alpha(s)|v_s(s)|^2 + \beta(s)|v_s(s)|^2)/2 \quad (4)$$

$$E_{con} = \frac{1}{2}(\alpha(s)|v_s(s)|^2) \quad (5)$$

$$E_{image} = w_{line}E_{line} + w_{edge}E_{edge} + w_{term}E_{term} \quad (6)$$

where E_{int} represents the internal energy of spline due to bending, E_{image} gives rise to the image forces, and E_{con} gives rise to the external constraint forces, $\alpha(s)$ and $\beta(s)$ are user-defined weights, $\alpha(s)$ is a large weight for the continuity term penalizes. The distance between points in the contour is changed by $\alpha(s)$. And $\beta(s)$ is for the smoothing term of the contour; w_{line}, w_{edge}, w_{term} are weights of these salient features. On other hands, v(s) = (x(s), y(s)) is the position of a snake parametrically.

The target of active contour model is E_{snake}, the boundaries values. E_{snake} is also the intensity values which can be decreased or increased by self-affine forces. This approach includes five steps:

(i) Starting from a wide range of areas in domain, the block matching algorithm is applied in self-affine maps. Therefore, the parameters of maps are given.
(ii) A matching cose is evaluated by the intensity values in form domain. The final aim of evaluating is minimum cost which is created by computing forces in each scale.
(iii) Forces are connected by wavelet scales. These values are the indicate Gaussian potential forces of decomposition. And they also improve the results in previous steps.
(iv) All forces create boundary of objects. This contour can be moved by the sum of E_{int} and E_{con}. The case is true that the intensity values can be gone up or gone down.
(v) Increasing of capture range, coefficient scales have access to in reconstruction steps of transform, shearlet transform. If n is the number of scales and L is the distance which is calculated by 8-connected neighborhood, we will have the number of scales as: 2^n x R > L and n > $\log_2$(L/R).

3.3 Similarity comparison

To similarity comparison, we used Canberra distance [18] to comprise similarity. This Canberra metric is similar to the Manhattan distance. The distinction between the variables of the two objects is divided by the sum of the absolute variable values before summing. The form in vector space is:

$$d(p,q) = \sum_{i=1}^{n} \frac{|p_i - q_i|}{|p_i| + |q_i|} \quad (7)$$

where d is Canberra distance of vector p and q in an n-dimensional vector space, vector p (p_1, p_2, …, p_n) and q (q_1, q_2, …, q_n).

4. Experiments and results of the proposed method

4.1 Material

Our dataset includes 750 medical images which collected from many hospitals with different sizes: 256 x 256, 512 x 512. We tested on many medical images from this dataset. Some representative medical images in this dataset are shown in figure 2.

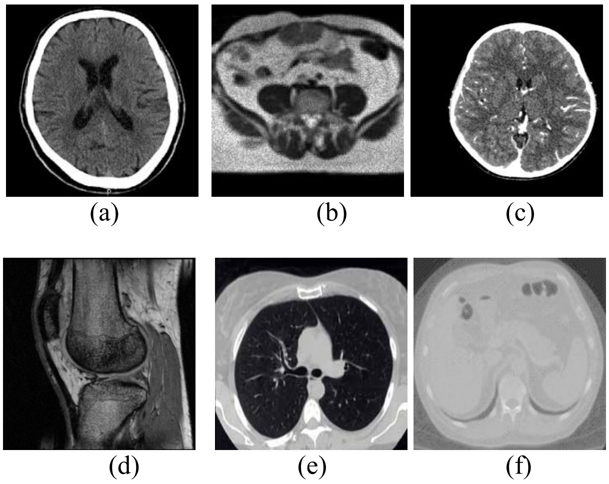


Figure 2. Sample images from dataset

Experimental programs were developed in Matlab 2013a with configure of computer of Intel core i7, 3.2 GHz CPU and 8 GB DDR3 memory.

4.2 Evaluation criteria

We have used precision P and recall R criteria to evaluate of performance of the above proposed method. The precision P is the ratio of total number of relevant images retrieved (TI_R) to the total number of images retrieved (T_R), defined as:

$$P = \frac{TI_R}{T_R} \tag{8}$$

Recall R is the ratio of total number of relevant images retrieved (TI_R) to the total number of relevant images in the above dataset (TN_R), defined as:

$$R = \frac{TI_R}{TN_R} \tag{9}$$

The higher the value of P, R is, the better it is.

4.3 Implementation the proposed method

Now, we have implemented our proposed method for the above dataset. With TI_R = 2 and TN_R = 20, we test all images in the above dataset.

Each image of this database will be taken as a query image. We input the medical image, the system should return the same input medical image or images which belong to the same category from the above image dataset. We tested many cases with the above dataset.

Table 1. Precision and recall for each image in figure 2

Medical input as figure 2	R (%)	P (%)
Image a	64.23	24.49
Image b	47.52	25.38
Image c	54.38	23.71
Image d	54.23	32.14
Image e	88.91	93.27
Image f	87.47	82.34

In here, we present some cases as figure 2. The results of experiments are presented in table 1, table 2 and table 3. Table 1 shows the result of the performance of medical images for each image in figure 2 of precision and recall. Table 2 shows the result of the performance for random medical images in above dataset.

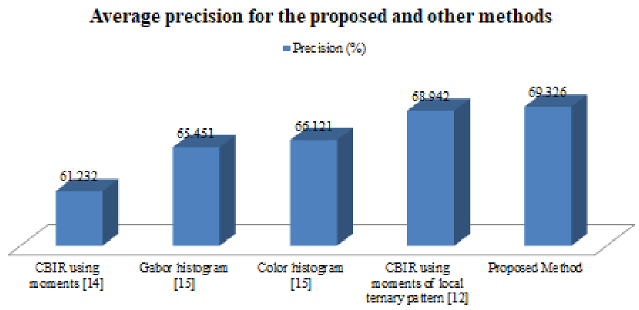
Table 2. Precision and recall for random images in above dataset.

Medical input number random	R (%)	P (%)
Image Number 43	74.83	64.91
Image Number 200	58.54	43.15
Image Number 289	61.85	47.78
Image Number 389	72.27	47.74
Image Number 428	81.95	91.34
Image Number 589	85.34	81.27
Image Number 634	51.47	45.24
Image Number 720	76.45	71.42

Table 3 and figure 3 also shows the average performance of medical images retrieval in the above dataset in terms of precision and recall.

Table 3. Average precision and recall values for the proposed and other methods.

Methods	Precision (%)	Recall (%)
CBIR using moments [14]	61.232	78.753
Gabor histogram [15]	65.451	78.863
Color histogram [15]	66.121	79.539
CBIR using moments of local ternary pattern [12]	68.942	81.193
Proposed Method	69.326	81.233



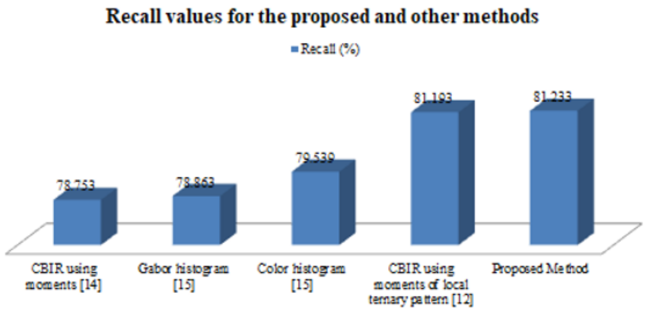


Figure 3. The grap present the average precision and recall values for the proposed and other methods

As the results presented in table 1, table 2, table 3 and other experiments, the results of the proposed method are better than the other methods as shown in the table 3.

As mentioned in section 2 and section 3, the shearlet is similar to curvelet in that both perform a multi-scale and multi-directional analysis. Medical images which are saved in database always have the fixed shape and position. These characteristics are important basis for our idea. In addition, the digitization of discrete shearlet transform performed in the frequency domain, the multi-scale and multi-directional analysis are one of the optimal choices for extracted features of a query image. Therefore, the proposed method implements better than the other methods.

5. Conclusions

In the past, traditional image retrieval system based solely on the label of images and gave limited results. This system is hard to find similar images in medical image database. To reduce this disadvantage, the content-based medical retrieval has been developed. However, this system still has many challenges. The efficiency of content-based image retrieval must improve. In this paper, we proposed a method for content-based medical image retrieval in the medical database images. Our remedy includes two periods: offline task and online task. In the offline task, we extracted local object features in shearlet domain and detected shape of object by segmentation with active contour model in each image. This information which is collected from this step is main values for finding results. In the online task, user points a query image from graphic user interface for local features extraction and segmentation by snake. Then, we compare information which collects in online period with the first period. As a result, all of similar images will be shown in the interface. We also compare our outcomes with other recent algorithms, and conclude the way which is proposed in this paper is better than others. In future work, we should concern about the depth and shape of objects in the query image.

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