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A Micro-Classification and CBIR System for Biomedical Images

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Abstract: In this paper we propose a content based image retrieval (CBIR) system for human brain CT images to identify the pathological regions of hemorrhage. This proposed study is the motivation for identification of abnormalities in brain that leads to several neurological diseases.The first step is to segment the region of hemorrhage from the brain CT image. Segmentation is implemented using Gabor filter which is a multi channel filtering technique. This Gabor filtering technique mimics the Human Visual System(HVS).The segmented images are then normalized to reduce the effects of differences in scales. Then for each segmented hemorrhage region, we calculate co-occurrence features at both global and pixel-level. Each pixel will be represented as a vector with ten elements, one for each feature, which are used for comparing the similarity between the query and the database candidate. The images will be retrieved based descending values of their similarity rank, displaying from the highest to the lowest in the descending order. Retrieval efficiency for a number of similarity techniques is analyzed.
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1. Introduction

Medical images have become a key investigation tool for medical diagnosis and pathology follow-ups. Digital imaging is becoming the standard for all image acquisition devices and with the generalization of digital acquisition, there is an increasing need for data storage and retrieval. Medical images represent an enormous amount of data: the annual production of a single average size radiology department represents tens of terabytes of data. Therefore, petabytes of medical images are produced in industrialized countries each year. For these data, there is a need for very long term archiving.

With the growth of medical databases, new applications devoted to statistical analysis of medical data have emerged such as breast cancer screening, lungs images analysis, or oncology in general. The datasets manipulated for these applications are not images of one patient or coming from on e radiology department but rather images showing a particular pathology or special features. This data set has to be dynamically assembled by automatically selected relevant images among available databases. Similarly, a physician is often interested by similar cases to the one he is studying and the similarity measurement usually involves a medical background. Archiving of tons of medical images is only relevant if adapted query tools exist that allow medical users to browse the data efficiently.

In the early years of image database assembling, image indexing used to be mostly text-based and manual: images were annotated with keywords and retrieved by using a text based database management system. In the medical world, acquired images are usually accompanied by metadata related to the patient, the image acquisition and the radiology department responsible for the acquisition. Nevertheless, textual information is limited for two main reasons: the large increase of the data volume, which makes manual annotation tiresome and the difficulty to express the image content with keywords which are often inconsistently assigned among different indexers: medical records are complex and difficult to analyze.

2. System Characterization

General CBIR systems use the global features like average value, standard deviation, and histograms for analysis and retrieval. In medical images, the image histograms are not very informative as the images are usually intensity images only and the histogram may be very variable for different resolutions. Hence we need to design a system which does the analysis based on the local features of the image which is very important because the medical images are rich in local content than global content.

The Human Visual System relies on texture perception for image interpretation and analysis. In addition we can see that texture dominates in medical images rather than intensity. So it would be ideal if we could design a model which would analyze and retrieve based images based on texture to match the human visual system. In our approach, we use both global and local-level co-occurrence texture features to retrieve pathological hemorrhagic anatomical regions produced by Computed Tomography as the imaging modality.

Since there is no similarity measure known to perform the best for the CT modality, we have made a comparative study of the eight metrics and show how the selection of a similarity metric affects the retrieval.

3. Review of recent systems

General CBIR systems that extract automatically low-level image features from pixel data have been intensively explored by several researchers.

Glatard et al. [1] introduced a CBIR system which uses Gabor filters extracted from segmented cardiac Magnetic Resonance Imaging (MRI)'s to perform clinically relevant queries on large image databases that do not require user supervision. Brodley et al. [2] introduced a CBIR system for the retrieval of CT lung images; their proposed system uses several features (such as co-occurrence texture features, Fourier descriptors and moments), and relies on expert interaction with the system in addition to various machine learning and computer vision techniques. Wei et al. [3] proposed a CBIR system for the mammography imaging modality using the co-occurrence texture signatures as global features.Shyu et al. [4] implemented a physician-in-the-loop approach to retrieving images of high resolution computed tomography (HRCT).

To overcome the difficulties and in- conveniences of the above discussed technique we propose a new system which is based on texture based image analysis and retrieval.

4. Proposed System

Our proposed micro classification system is represented in figure 1.At data entry time; pre-defined numerical features are computed from each image stored within the database. Using the Query by examples (QBE) approach, the same features are extracted from the query image and compared to the features stored within the database. The images that correspond to the most similar features are then retrieved from the database and presented to the user to answer his query. This system is designed in such a way to maximally utilize the texture features in the Brain CT image in order to mimic the human visual system for accurate results. Now we will see the detailed design of each block in the proposed model in figure 1.

The steps involved are

- Query Formation
- Segmentation
- Feature extraction
- Similarity Calculation
- Image retrieval

4.1 Query Formation

The proposed model uses the concept of query by reference. This is nothing but searching image databases for specific images that are similar to a given query image. Here, the search is based on the appearance of the images. A sample image is presented to the system, which answers this query by returning all similar matches. This concept is referred to as the query by example (QBE) paradigm. It was introduced by Niblack, when presenting the query by image content (QBIC) system in the early 1990s [5]. A physician is often interested by similar cases to the one he is studying and the similarity measurement usually involves a medical background, brain hemorrhage in our case.

4.2 Segmentation

Medical images are rich in texture content. So we go in for a texture based segmentation to mimic the human visual system for accurate results. Texture segmentation requires simultaneous measurements in both the spatial and the spatial-frequency domains. In fact, one well known class of functions that are known to achieve both spatial and spatial-frequency localization is the Gabor function. This wavelet has been used extensively in texture segmentation due to the ability to tune a Gabor filter to specific spatial frequency and orientation, and achieve both localization in the spatial and the spatial-frequency domains. The process of texture segmentation is shown in figure 2.

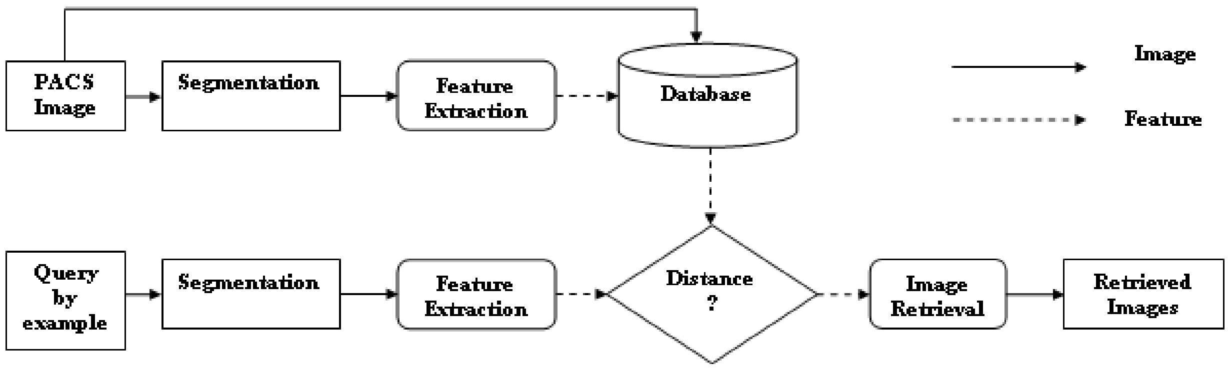


Figure 1. The proposed micro classification system

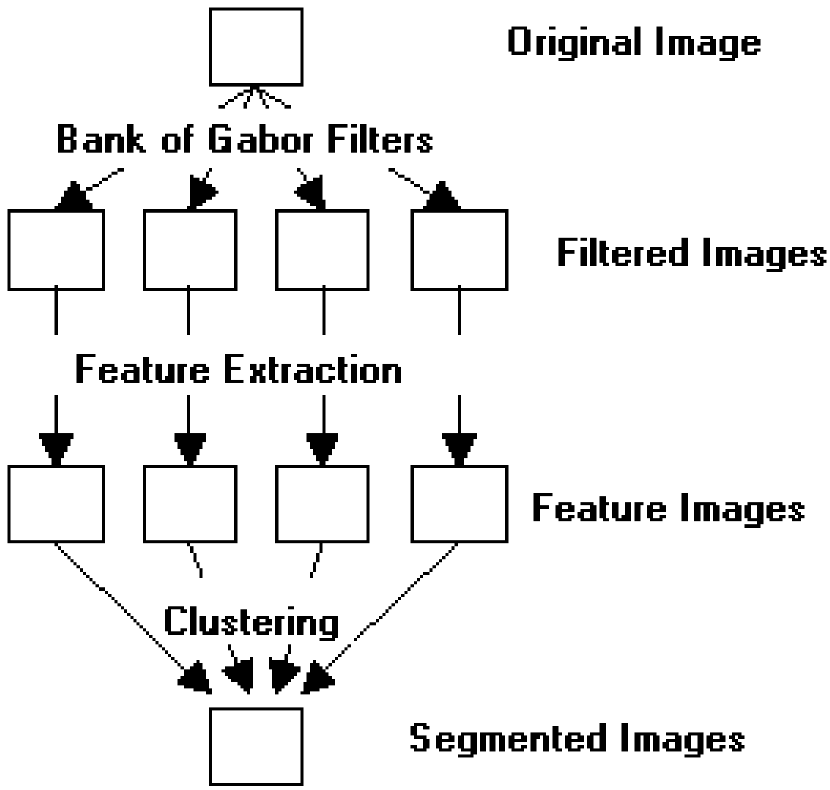


Figure 2. Texture segmentation process

The process of texture segmentation using multi-channel filtering involves the following steps:

- Filter bank design,
- Decomposition of the input image using the filter bank
- Feature extraction, and
- Clustering of pixels in the feature space.

4.2.1 Filter bank design.

We employ a scheme proposed by A. K. Jain and E Farrokhnia [6] for calculation of parameters and filter bank design. A Gabor function is a Gaussian function modulating a sinusoid. The expression for real-valued 2-D Gabor filter is given by:

$$h(x,y)=\exp\left\{-\frac{1}{2}\left[\frac{(x)^2}{\sigma_x^2}+\frac{(y)^2}{\sigma_y^2}\right]\right\}\cos[2\pi Fx] \quad (1)$$

Where F is the center frequency and σ_x and σ_y are the variance of the Gaussian envelope along the x and y axes respectively. The spatial-frequency domain representation is given by

$$H(u,v)=\exp\{-2\pi^2[\sigma_x^2(u-u_0)+\sigma_y^2v^2\} + \exp\{-2\pi^2[\sigma_x^2(u+u_0)+\sigma_y^2v^2\} \quad (2)$$

Where $2\pi\sigma_x\ \sigma_y$ and $\sigma_u = 1 / (2\pi\sigma_x)$, $\sigma_v = 1/ (2\pi\sigma_y)$ and different orientations of filters are obtained via a rotation of x-y coordinate system using

$$(x', y') = (x\cos\theta + y\sin\theta, -x\sin\theta + y\sin\theta) \quad (3)$$

4.2.2 Selection of Parameters.

By appropriate selection of parameters, a Gabor filter bank that uniformly covers the spatial-frequency domain and thus has a minimum amount of overlap between the filters can be obtained. The parameters in this scheme were calculated using:

$$\sigma_u=\left(\frac{2^{s+1}\sqrt{2}}{N\sqrt{2\ln 2}}\right)\frac{(2^{B_r}-1)}{(2^{B_r}+1)} \quad (4)$$

$$\sigma_v=\left(\frac{2^{s+1}\sqrt{2}}{N\sqrt{2\ln 2}}\right)\tan\left(\frac{B_t}{2}\right) \quad (5)$$

$$\sigma_x=\frac{1}{2\pi\sigma_u}, \quad \sigma_y=\frac{1}{2\pi\sigma_v} \quad (6), (7)$$

Where N is the width of the image (in this work only square images were used). $B_T = 0.7$ and $B_t = \pi/4$. s = 1, 2 . . . S, is the number of the scale being used, S being total number of scales used. The following center frequency (F) values were used: $1\sqrt{2}, 2\sqrt{2}, 4\sqrt{2}, 8\sqrt{2}..........(N/4)\sqrt{2}$ Cycles per width. The above center frequencies are 1 octave apart. This choice of center frequencies also guarantees that the pass band of the Gabor filter with the highest center frequency ((N/4) √2) lies in the size of the image array N. Thus for example an image of size 256 x 256, a filter bank can be created with a total of 7 center frequencies.

4.2.3 Feature Extraction. The filtering operation is carried out by calculating a circular convolution of the input image I (x, y) with the selected filter.

$$O_{mn}(x,y)=\iint I(x_1,y_1)h_{mn}(x-x_1,y-y_1)dx_1dy_1 \quad (8)$$

Where m and n represent the scale and orientation respectively and I is the original input image. The filtered images are divided into small non-overlapping blocks and for each block, the mean μ_{mn} and the standard deviation σ_{mn} of the pixel intensities are calculated. A feature vector $\underline{f}$ is constructed using μ_{mn} and σ_{mn} as feature components.

$$\underline{f}=[\mu_{00}\sigma_{00}\mu_{01}\sigma_{01}....\mu_{S-1K-1}\sigma_{S-1K-1}]^T \quad (9)$$

Where S and K represent the total number of scales and orientations that are used

4.2.4 Clustering. We now cluster the feature vectors thus generated using a k-means clustering algorithm for the segmentation of brain infarct.

4.2.5 Experimental Results. The above texture segmentation algorithm was applied to 10 images of size 512 x 512. The results were good. To improve the detection accuracy and computational speed we propose the improved detection method.

4.2.6 Improved detection method. Since Gabor filters are band-pass in nature, and clustered infarcts lie in a particular frequency range, we choose only a subset of Gabor filter bank in this method. The selected filters have a particular center frequency and different orientations. While developing a filter bank we made the following changes to the technique discussed in section 5: (i) the aspect ratio was made unity (ii) The filters were complex valued (iii) Only a subset of Gabor filter bank that has a particular scale (i. e. fixed center frequency) and different orientations is used. Each Gabor filtered image was subjected to a histogram based thresholding to obtain a binary image. The threshold T is computed from the histogram of the Gabor-filtered image using: T = mean + V, where V = variance + k_t (P -mode), where P is the value corresponding to the maximum pixel intensity in the filtered image. k_t is a constant. A feature vector was constructed using the binary image. Images were divided into non-overlapping blocks size 6 x 6. The features calculated include: (i) Number non-zero pixels in the window. (ii) Number of non-zero pixels in the neighboring eight blocks of size 6 x 6.Automatic classification of the feature vectors was carried out using the k- means clustering algorithm. The results of the proposed segmentation algorithm are given in section 5**.**

4.3 Feature Extraction

For each segmented image, we calculate a set of ten Haralick features at both global and pixel-level; therefore, each segmented region or pixel will be represented as a vector with ten elements that will be further used for comparing the similarity among the images. In our current implementation, we propose to use the Haralick co-occurrence texture model and its texture descriptors that capture the spatial dependence of gray-level values and texture structures within an image [7]. We are using the following ten descriptors: entropy, energy (angular second moment), contrast, homogeneity, sum mean, variance, correlation, maximum probability, inverse difference moment and cluster tendency [8]. These descriptors are calculated at both local (pixel) and global-level depending on the similarity measures to be used and the fundamental structures present in the images. To compute global-level features, the normalized co-occurrence matrices are calculated in four directions (0^0, 45^0, 90^0, and 135^0) and five displacements (d=1, 2, 3, 4, 5) generating twenty matrices per segmented image. The ten Haralick features are calculated for each of the twenty matrices and then, the twenty values are averaged and recorded as a mean-based feature vector for the corresponding segmented image.

To compute pixel-level features, a 5-by-5 neighborhood is considered for each pixel within the segmented region and a co-occurrence matrix is calculated for each neighborhood within the corresponding region. While co-occurrence matrices are normally defined for a fixed distance and direction when calculated at the global level, for the pixel-level approach, we do not calculate the co-occurrence along fixed directions and displacements. Instead we consider all pixel pairs within that neighborhood such that there will be enough samples (pairs) for calculating the co-occurrence matrix in order to produce statistically significant results. Thus, our implementation produces a single co-occurrence matrix for each pixel rather than for each choice of distance and direction. Then, for each co-occurrence matrix (each pixel), we calculate ten Haralick features, which can be related to specific characteristics in the image. Since the gray-levels for our images range from 0 to 4096, for reasons of computational efficiency, the number of gray levels can be reduced if one chooses to bin them, thus reducing the size of the co-occurrence matrix as well. In our approach, before calculating the matrices at both levels, we applied a linear binning such that the range [0, 4096] was mapped to [0,256].

4.4 Similarity measures

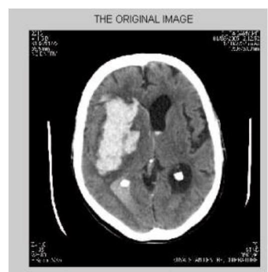
Similarity metrics are measures that describe how similar two images are (Brain CT showing hemorrhage in our case). We implement eight similarity measures as follows: 1. Euclidean distance, 2. Minkowski 1-distance (city block distance or L1 norm), 3. Chi-square (χ^2) statistics (used to distinguish whether distributions of the descriptors differ from each other), 4. weighted-mean variance (WMV – uses the means and standard deviations for each of the considered features), 5. Jeffrey-divergence (used to compute the distance between class distributions of two values of the same feature), 6. Cramer-von Mises (similar to the squared Euclidean distance but calculated between the distributions and as the maximal discrepancy between the cumulative distributions), 7. Kolmogorov-Smirnov distance, and 8.Hausdorff distance. For the mathematical definitions of these metrics, we refer the reader to [8].

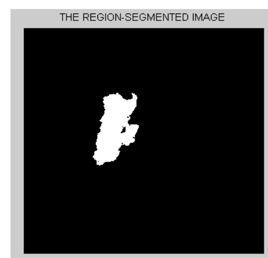
4.5 Image Retrieval

For all the above defined methods we calculate the similarity measure between the database candidate and the query image. A rank order is created. The database candidates are given as retrieval results in the descending order of their ranks.

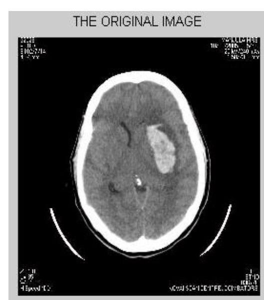
5. Results

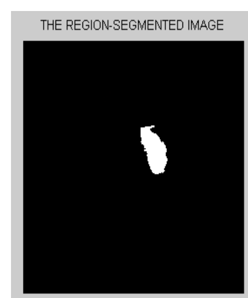
The results of the segmentation technique proposed in this paper for brain hemorrhage can be seen in the figure 3.





3.1(a) 3.1(b)





3.2(a) 3.2(b)

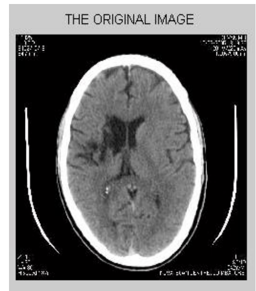
Figure 3. Results of segmentation using the proposed technique for brain hemorrhage

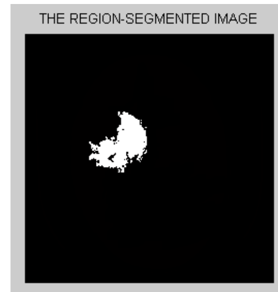
Fig 3.1(a) Original Brain CT of patient 1 having brain hemorrhage 3.1 (b) Segmented brain hemorrhage of patient 1using the proposed method Fig 3.2(a) Original Brain CT of patient 2 having brain hemorrhage 3.2 (b) Segmented brain hemorrhage of patient 2 using the proposed method.

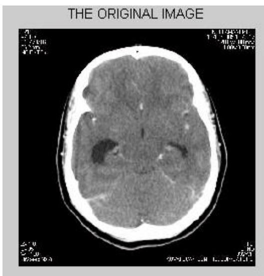
6. Extended Results

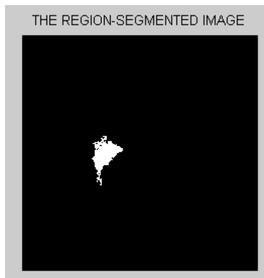
The proposed segmentation algorithm when applied to a different application (to detect early stage brain infarct) produced very good results. The results are shown in figure.

4.1(a) 4.1(b)

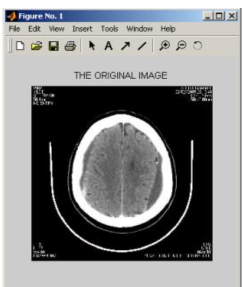


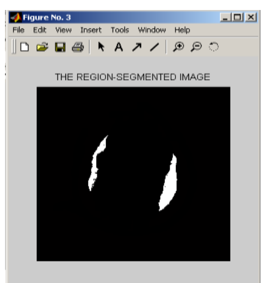




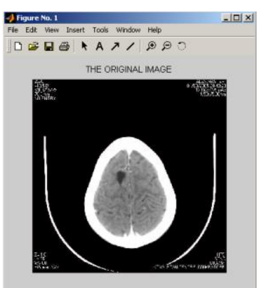


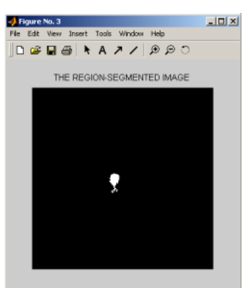
4.2(a) 4.2(b)





4.3(a) 4.3(b)





4.4(a) 4.4(b)

Figure 4. Results of segmentation using the proposed technique for early stage brain infarct

4.1(a) Original Brain CT of patient 1 having brain infarct 4.1(b) Segmented brain infarct of patient 1using the proposed method 4.2(a)Original Brain CT of patient 2 having brain infarct 4.2(b) Segmented brain infarct of patient 2 using the proposed method 4.3(a)Original Brain CT of patient 3 having brain infarct 4.3(b) Segmented brain infarct of patient 3 using the proposed method 4.4(a)Original Brain CT of patient 4 having brain infarct 4.4(b) Segmented brain infarct of patient 4 using the proposed method

7. Conclusion

The proposed method in this paper was tested on the human brain Hemorrhages images form CT brain images from Kaggle database. Highly accurate results were obtained for Gabor filter based segmentation technique. CBIR is in the implementation stage. Our preliminary study results show that the combination of the pixel-level texture data and the Jeffrey-divergence metric will allow building medical CBIR systems for accurate retrieval of pathological regions of brain hemorrhage in human brain CT images.

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