

MEDICAL IMAGE RETRIEVAL USING BANDELET

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ABSTRACT

Content based medical image retrieval systems are helpful to the radiologists in diagnosis of breast cancer. This paper presents a method for retrieving mammogram images as cancer or normal by using bandelet transform. Bandelet transform is appropriate for analysis of edges and textures of images based on which image features are extracted. The main contribution in this paper is of three directions. First, Pre-processing is very important to correct and adjust the mammogram image for further study and processing. Second, feature extraction is a key issue in content based medical image retrieval. Bandelet coefficients are calculated from the pre-processed images and statistical parameters are calculated for these coefficients which form feature vector for the image. Third, based on the similarity measurement images are retrieved through graphical user interface and classified by using KNN. Classification accuracy and precision of 93.737% and 0.945 are obtained.

KEYWORDS: content based medical image retrieval, feature extraction, bandelet, KNN, GUI.

1. INTRODUCTION

In CBMIR system, the term [CBIR] describes the process of retrieving desired images from a large collection

on the basis of features (such as colour, texture and shape) that can be automatically extracted from the images themselves. The features which are

extracted from an image can uniquely identify an image from others. The extraction of features from the image pixels is termed as feature extraction. Using the extracted features from the process of feature extraction, similarity between indexed image and query image is measured.

Breast cancer is the leading type of cancer in women and the second most fatal type of cancer in women. Breast cancer is a malignant tumor that starts in the cells of the breast. A malignant tumor is a collection of cancer cells that can produce into (overrun) neighboring tissues or spread to distant areas of the body. The disease occurs around wholly in women, but in some cases men also. In the medical imaging context the aim of CBIR is to provide radiologists with the diagnostic aid in the form of display of relevant past cases along with proven pathology and other suitable information. Medical image data have been expanded rapidly in quantity, content and dimension – due to an enormous increase in the number of diverse clinical exams performed in digital form and to the large range of image modalities available. It has, therefore, led to an increased demand for efficient medical image data

retrieval and management. In current medical image databases, images are mainly indexed and retrieved by alphanumeric keywords, classified by human experts. However, purely text-based retrieval methods are unable to sufficiently describe the rich visual properties or features inside the images content, and therefore pose significant limitations on medical image data retrieval. The ability to search by medical image content is becoming increasingly important, especially with the current trend toward evidence-based practice of medicine. In the clinical practice of reading and interpreting medical images, clinicians (i.e., radiologists) often refer to and compare the similar cases with verified diagnostic results in their decision making of detecting and diagnosing suspicious lesions or diseases. However, searching for and identifying the similar reference cases (or images) from the large and diverse clinical databases (either the conventional film/paper based libraries or advanced digital image storage systems) is a quite difficult task. The advance in digital technologies for computing, networking, and database storage has enabled the automated searching for clinically relevant and visually similar medical

examinations (cases) to the queried case from the large image databases. There are two types of general approaches in medical image retrieval namely, the text (or semantic) based image retrieval (TBIR) and the content-based image retrieval (CBIR). Currently, the most of available search systems (or tools) developed and implemented in medical informatics and picture archiving and communication systems (PACS) use TBIR schemes that are based on the annotated textual information to select similar or clinically relevant references (cases) [1-4]. This approach is typically limited to retrieve or select the same type of medical images (i.e., mammograms or CT brain images). However, the relevant clinical information depicted on medical images is locally presented (i.e., breast masses depicted on mammograms and emphysema lesions depicted on lung CT images). In the clinical practice of reading and interpreting medical images, the nature of the queried suspicious regions is often undetermined. Thus, the CBIR is the only available and reliable approach to retrieve the clinically relevant (reference) cases along with the proven pathology and other related clinical information. As a result, developing

CBIR schemes has been attracting extensive research interest in the areas of medical informatics and PACS for the last decade [5-10]. Despite the fact that CBIR approach is still in its early development stage facing many technical challenges (i.e., region segmentation, semantic gap, and computational efficiency), as the digital medical images are produced in ever increasing quantities and used for diagnosis and therapy, the researchers believe that the advance of CBIR development will play more and more important role in future medical image diagnosis and patient treatment (or management) [11].

Mammography is one of the effective tools in early detection of breast cancer. Mammography is a low dose x-ray procedure for the visualization of internal structure of breast. Mammography has been proven the most reliable method and it is the key screening tool for the early detection of breast cancer. Mammography is highly accurate, but like most medical tests, it is not perfect. On average, mammography will detect about 80–90% of the breast cancers in women without symptoms.

The common characteristics of the medical images like as unknown noise, poor image contrast, in homogeneity, weak boundaries and unrelated parts will affect the content of the medical images. This problem rectified by pre-processing techniques. The pre-processing are fundamental steps in the medical image processing to produce better image quality for segmentation and feature extractions.

2. PROPOSED METHOD

THE BANDELET TRANSFORM

Bandelet transform, introduced by Le Pennec and Mallat built a base adapted to the geometric content of an image. The bandelet are obtained from a local deformation of space to align the direction of regularity with a fixed direction (horizontal or vertical) and is reduced to a separable basis. In bandelet transform, a geometric flow of vectors is defined to represent the edges of image. These vectors give the local directions in which the image has regular variations. Orthogonal bandelet bases are constructed by dividing the image support in regions inside which the geometric flow is parallel. Image is portioned into small regions, each region includes almost one contour. If

the region does not include any contour, the image intensity is uniform and flow is not defined. In bandelet these regions are approximated in separable wavelet basis of $L^2(\Omega)$ in [12]

$$\left\{ \begin{array}{l} \phi_{j,m_1}(x_1) \psi_{j,m_2}(x_2) \\ \psi_{j,m_1}(x_1) \phi_{j,m_2}(x_2) \\ \psi_{j,m_1}(x_1) \psi_{j,m_2}(x_2) \end{array} \right\}_{(j,m_1,m_2) \in I_\Omega}$$

Where I_Ω is an index set that depends upon the geometry of the boundary of Ω , and x_1, x_2 denotes the location of pixel in the image, $\phi_{j,m_1}(x_1) \psi_{j,m_2}(x_2)$, $\psi_{j,m_1}(x_1) \phi_{j,m_2}(x_2)$, and $\psi_{j,m_1}(x_1) \psi_{j,m_2}(x_2)$ are the modified wavelets at the boundary. If a geometric flow is calculated in Ω , this wavelet basis is replaced by a bandelet orthonormal basis of $L^2(\Omega)$ in

$$\left\{ \begin{array}{l} \phi_{l,m_1}(x_1) \psi_{j,m_2}(x_2 - c(x_1)) \\ \psi_{j,m_1}(x_1) \phi_{j,m_2}(x_2 - c(x_1)) \\ \psi_{j,m_1}(x_1) \psi_{j,m_2}(x_2 - c(x_1)) \end{array} \right\}_{j,l > j, m_1, m_2}$$

Which is got by intersecting bandelet in the warped wavelet basis in

$$\left\{ \begin{array}{l} \phi_{l,m_1}(x_1) \psi_{j,m_2}(x_2 - c(x_1)) \\ \psi_{j,m_1}(x_1) \phi_{j,m_2}(x_2 - c(x_1)) \\ \psi_{j,m_1}(x_1) \psi_{j,m_2}(x_2 - c(x_1)) \end{array} \right\}_{(j,m_1,m_2) \in I_{\omega\Omega}}$$

In the above expressions, $c(x)$ denotes a flow line associated to a fixed translation parameter $x_2, (x_1, x_2 + c(x_1)) \in \Omega$ is a set of point for x_1 varying, and l is

the direction of geometric flow which is more elongated ($2^l > 2^j$) and $c(x)$ is defined as

$$c(x) = \int_{x_{\min}}^x e^i(u) du.$$

In the bandelet representation, the parameters include the bandelet coefficients used for computing and the parameters that specify the image partition and the geometric flow in square regions, which are subdivided into four smaller squares, corresponding to a node having four children in the quad tree, as shown fig 1. In order to achieve appropriate image geometry of image f , the best geometry is employed to an approximation error $\|f - f_M\|$.

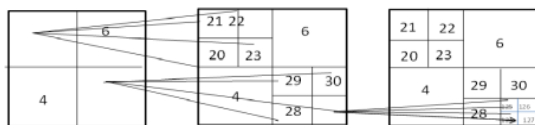


Figure 1: Quad tree of dyadic square image segmentation

In each region Ω_l of the segmentation, one must decide if there should be a geometric flow. If this flow is parallel, $c'(t)$ is calculated as an expansion over translated B-spline functions dilated by a scale factor 2^l over a square Ω of width, the flow at a scale 2^l is characterized by 2^{k-l} coefficients α_n ,

$$c'(t) = \sum_{n=1}^{2^{k-l}} \alpha_n b(2^{-l}t - n).$$

The scale parameter 2^l is adjusted through a global optimization of the geometry. When the image f has contours that are curves c^α which meet at corners or junctions, and that f is c^α away from these curves, this procedure leads to a bandelet approximation that has an optional asymptotic error decay rate R .

$$R = \|f - f_M\|^2 \leq CM^{-\alpha},$$

Standard wavelet bases are optimal to represent functions with point wise singularities. However they fail to capture the geometric regularity along the singularities of the surfaces, because of their isotropic support. For C^α geometrically regular functions, the distortion-rate of a wavelet image transform code with R bits satisfies

$$\|f - f_R\|^2 \leq CR^{-1} \log(R)$$

The following steps for the proposed method as shown in fig2. Firstly apply haar transform to the preprocessed mammogram image .secondlyto compute the best direction, first selects this set of directions and stores them in Theta, and then computes the Lagragian for each direction. It then chooses the

direction which gives rise to the smallest Lagrangian. Thirdly To construct a bandelet basis on the whole wavelet domain, a quadtree segmentation of each wavelet scale in dyadic squares is used.

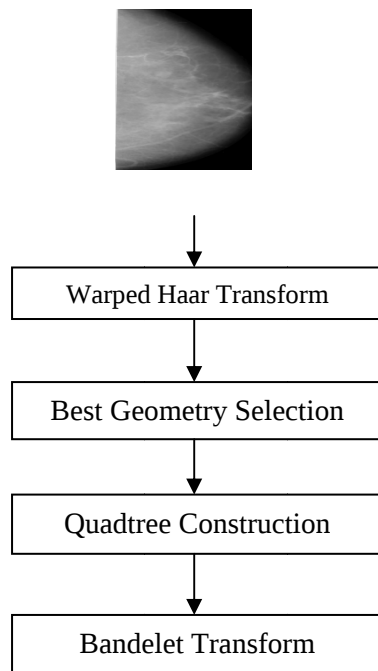


Figure 2: Block diagram of proposed method

3. METHODOLOGY

3.1 IMAGE DATA SET

The Digital for Screening Mammography (DDSM) [13] is the largest publicly available database of mammographic data. It contains approximately 2620 screening mammography cases. From the total number of images included in the DDSM database, a total of 478 images consisting of both cancer and normal images are chosen, were used in this work.

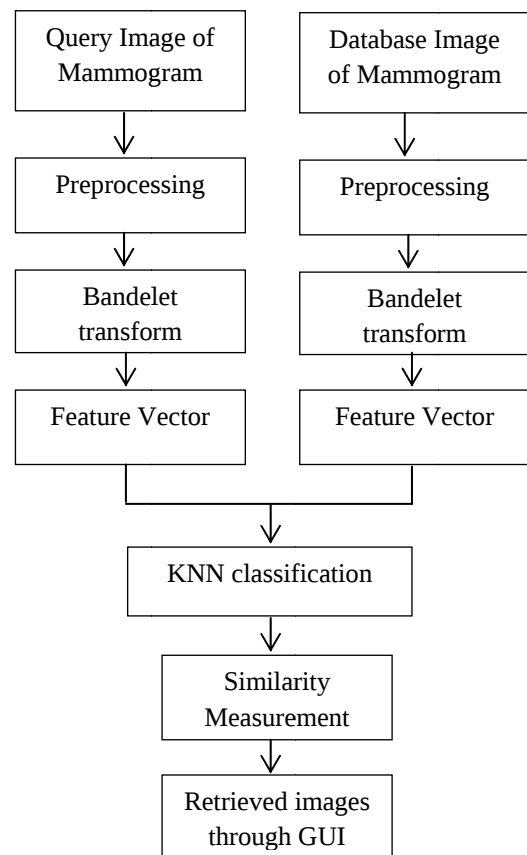


Figure 3: Basic block diagram of cbir system using proposed method

3.2 PREPROCESSING

Image pre-processing techniques are necessary, in order to find the orientation of the mammogram, to remove the noise and to enhance the quality of the image [14]. Before any image-processing algorithm can be applied on mammogram, preprocessing steps are very important in order to limit the search for abnormalities without undue influence from background of the mammogram.

Digital mammograms are medical images that are difficult to be interpreted, thus a preparation phase is

needed in order to improve the image quality and make the segmentation results more accurate. The main objective of this process is to improve the quality of the image to make it ready to further processing by removing or reducing the unrelated and surplus parts in the background of the mammogram images. Mammograms are medical images that complicated to interpret. Hence pre-processing is essential to improve the quality. The noise and high frequency components removed by filters. The following successive steps take place for breast region extraction.

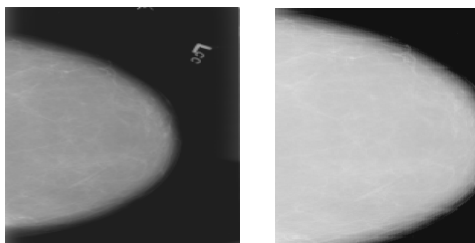


Figure 4: a. original image b. preprocessed image

Image enhancement improves the class (clarity) of images for human viewing. Eliminating blurring of images and noise, increasing contrast, and enlightening details are examples of augmentation operations. For example, an image might be in use of an endothelial cell and image might be of low contrast and blurred. Plummeting the noise and blurring and increasing

the contrast range could enhance the image. In second step, an automated thresholding method to obtain a binarization of the enhanced image using Otsu's method is used. The third step permits to identify the orientation of the breast region. For that, the image is divided into two equal parts and calculate the number of pixels of each part: if the number of white pixels is big in left part, the direction of breast region is from left to right (respectively, if the number of white pixels is big in the right part, the direction of breast region is from right to left). Separation of the breast region from the background the connected component labelling algorithm to divide the binary image into different labels is used. For breast region selection by looking at the image generated, note that breast region has the largest area. For this reason, the area criteria to select the label that represents the breast region is consider and to eliminate the unlikely labels as shown in fig 4.

3.3 k-NN CLASSIFICATION ALGORITHM

In pattern recognition field, KNN is one of the most important non-parameter algorithms and used for classification and regression. In both cases, the input

consists of the k closest training examples in the feature space. The output depends on whether k -NN is used for classification or regression:

- In k -NN classification, the output is a class membership. An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors (k is a positive integer, typically small). If $k = 1$, then the object is simply assigned to the class of that single nearest neighbor.
- In k -NN regression, the output is the property value for the object. This value is the average of the values of its k nearest neighbors.

k -NN is a type of instance-based learning, or lazy learning, where the function is only approximated locally and all computation is deferred until classification. The k -NN algorithm is among the simplest of all machine learning algorithms.

Both for classification and regression, it can be useful to weight the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant ones. For example, a common weighting scheme consists in giving each neighbor

a weight of $1/d$, where d is the distance to the neighbor.

The neighbors are taken from a set of objects for which the class (for k -NN classification) or the object property value (for k -NN regression) is known. This can be thought of as the training set for the algorithm, though no explicit training step is required. It is a supervised learning algorithm. The classification rules are generated by the training samples themselves without any additional data. The KNN classification algorithm predicts the test sample's category according to the K training samples which are the nearest neighbors to the test sample, and judge it to that category which has the largest category probability. The process of KNN algorithm to classify sample X is :

- Suppose there are j training categories $C_1, C_2, \dots, C_j$ and the sum of the training samples is N after feature reduction, they become m -dimension feature vector.
- Make sample X to be the same feature vector of the form $(X_1, X_2, \dots, X_m)$, as all training samples.
- Calculate the similarities between all training samples and X . Taking the i^{th} sample d_i ($d_{i1}, d_{i2}, \dots, d_{im}$) as

an example, the similarity $SIM(X, d_i)$ is as following:

$$SIM(X, d_i) = \frac{\sum_{j=1}^m X_j \cdot d_{ij}}{\sqrt{\left(\sum_{j=1}^m X_j\right)^2} \cdot \sqrt{\left(\sum_{j=1}^m d_{ij}\right)^2}}$$

- Choose k samples which are larger from N similarities of $SIM(X, d_i)$, ($i=1, 2, \dots, N$), and treat them as a KNN collection of X . Then, calculate the probability of X belong to each category respectively with the following formula.

$$P(X, C_j) = \sum_d SIM(X, d_i) \cdot y(d_i, C_j)$$

Where $y(d_i, C_j)$ is a category attribute function, which satisfied

$$y(d_i, C_j) = \begin{cases} 1, & d_i \in C_j \\ 0, & d_i \notin C_j \end{cases}$$

- Judge sample X to be the category which has the largest $P(X, C_j)$.

3.4 SIMILARITY MEASUREMENT

Manhattan distance

Manhattan distance is given by

$$\sum_{i=1}^n |x_i - y_i|$$

The minimum distance value signifies an exact match with the query. Manhattan distance is not always the best metric. The fact that the distances in each dimension are modulated before

summation, places great emphasis on those features for which the dissimilarity is large. Hence it is necessary to normalize the individual feature components before finding the distance between two images.

3.5 GUI - Graphical User Interface

In computing, a graphical user interface is a type of interface that allows users to interact with electronic devices through graphical icons and visual indicators such as secondary notation, as opposed to text-based interfaces, typed command labels or text navigation. The GUI is as simple and intuitive as possible so that user doesn't need to spend much time in learning how to use it. It allows a person to work easily with a computer by using a mouse to point to small pictures and other elements on the screen. The actions in a GUI are usually performed through direct manipulation of the graphical elements. As well as computers, GUIs can be found in hand-held devices such as MP3 players, portable media players, gaming devices and smaller household, office and industry equipment.

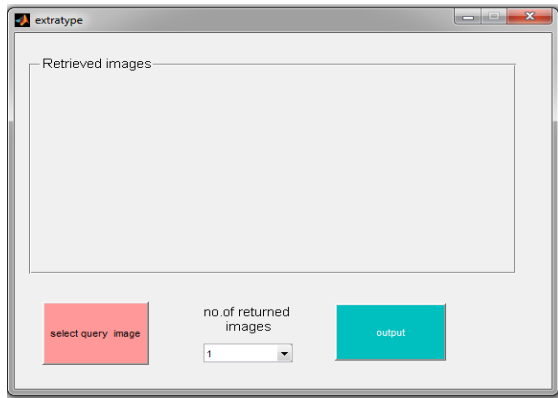


Figure 5: screenshots of the main window

Figure 5 shows screenshots of the main window. The main window composed of select query image (lower left), no of returned images (middle), output (lower right) and retrieved image (upper).

4. EVALUATION OF THE RETRIEVAL SYSTEM

Performance measures are based on precision and recall .They are defined as follows:

$$\text{Precision} = \frac{\text{No. of relevant items retrieved}}{\text{No. of all items retrieved}}$$

$$\text{Recall} = \frac{\text{No. of relevant items retrieved}}{\text{No. of all relevant retrieved}}$$

5. RESULTS

The images for the proposed research were collected from the online digital base for screening mammography. The images are preprocessed and segmented. Features are extracted from images using bandelet transform. To

obtain the retrieved images through GUI, firstly run gui application and then select the query image from folder. Secondly select no of returned images which returns no of retrieved images and thirdly click output to display the retrieved images as shown in fig 6 and mean while returns classification accuracy and precision using KNN classification, also display the predict to which class the image belongs in command window.

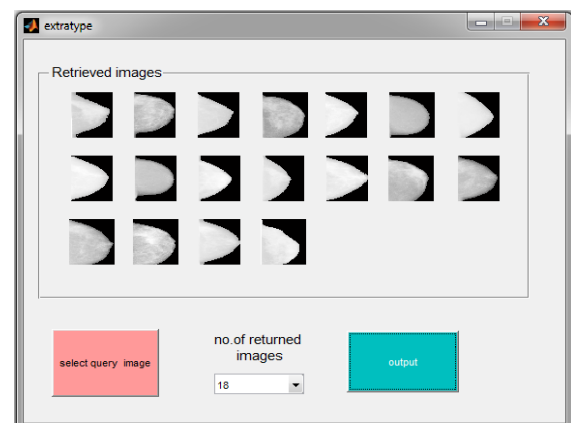


Figure 6: Retrieved images through GUI

6. CONCLUSION

In this paper, a new method is proposed for feature extraction which will be helpful to the radiologist to predict whether the image is cancer or normal at early stage. By using this proposed method the classification accuracy acquired is 93.709% and precision is 0.945 for ddsM database with KNN classification algorithm and image

retrieved through graphical user interface (GUI).

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