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CANDIDATE TREE-IN-BUD PATTERN SELECTION AND CLASSIFICATION USING BALL SCALE ENCODING ALGORITHM

T. Akilandeswari[1], N. Balaganesh[2] and S. RadhaKrishnan[3]

[1, 2]*Department of Computer Science and Engineering, Mepco Schlenk Engineering College, India*
E-mail: [1]akila2read@gmail.com, [2]balaganesh@mepcoeng.ac.in
[3]*Department of Information Technology, Kamaraj College of Engineering and Technology, India*
E-mail: radhakrishs.2009@gmail.com

Abstract

Asthma, Chronic obstructive pulmonary disease, influenza, pneumonia, tuberculosis, lung cancer and many other breathing problems are the leading causes of death and disability all over the world. These diseases affect the lung. Radiology is a primary assessing method with low specificity of the prediction of the presence of these diseases. Computer Assisted Detection (CAD) will help the specialists in detecting one of these diseases in an early stage. A method has been proposed by Ulas Bagci to detect lung abnormalities using Fuzzy connected object estimation, Ball scale encoding and comparing various features extracted from local patches of the lung images (CT scan). In this paper, the Tree-in-Bud patterns are selected after segmentation by using ball scale encoding algorithm.

Keywords:

Computer Assisted Detection, Tree in Bud Opacities, Fuzzy Connectedness, Ball Scale encoding, Wilmore Energy Features, Support Vector Machine

1. INTRODUCTION

Lungs are crucial part of the human respiratory system. The human body consists of two lungs the left lung and the right lung. Figure 1 shows the various parts of the human lungs. Many diseases related to lung such as asthma, chronic obstructive pulmonary disease, influenza, pneumonia, tuberculosis, lung cancer cause death and disability. For many diseases the tree in bud (TIB) is the symptom.

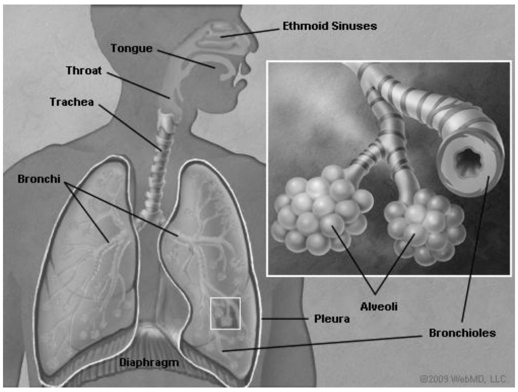
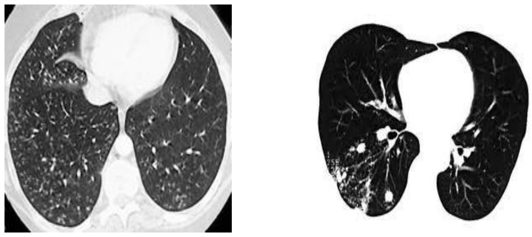


Fig.1. Human Lung [17]



(a) (b)

Fig.2 Represents H influenza pneumonia in a 49-year-old woman with breast cancer, fever and a productive cough. High-resolution CT scan shows diffuse centrilobular nodules and branching linear opacities, resulting in the tree-in-bud pattern [15]. (b) TB infiltration with tree in bud pattern [16]

1.1 TREE IN BUD OPACITIES

TIB is a sign of abnormality of a lung. The TIB has the following characteristics,

i) It has small size (2-4mm in diameter)
ii) It is Centrilobular
iii) It is well defined nodules of soft tissue attenuation are connected to linear, branching opacities that have more than one contiguous branching site, thus termed as tree in bud opacities.
iv) TIB pattern has a complex shape with
    - Varying intensities over discontinuing branches
    - High curvature
    - Strong textural similarity of micro nodules and
    - Thickened airways

TIB patterns are caused by disease in the small airways in the respiratory system. They results in inflammatory bronchiolitis and bronchiolar luminal impaction with mucus, pus, and cell. These TIB patterns are invisible in respiratory system. But they are visible in a CT scan images, represent the diseases. So detection of TIB patterns detects disease. Figure 2 shows a CT scan image with TIB patterns.

1.2 COMPUTED TOMOGRAPHY (CT)

CT scan plays a major role in detecting and diagnosing lung diseases. It provides better i) identification ii) localization iii) quantification of small lung nodules. It has some restrictions. Specificity measures the proportion of negatives which are correctly identified i.e. the percentage of healthy people who are correctly identified as not having the condition. Sensitivity measures the proportion of positives which are correctly identified i.e. the percentage of sick people who have the symptoms. CT scan images are restricted to low specificity for causal infectious organisms. It has low capacity to find the severity of the disease. To enhance the sensitivity and specificity metrics the experts use Computer Assisted Detection (CAD). It also helps them in the decision making process of disease detection.

1.3 COMPUTER ASSISTED DETECTION (CAD)

CAD improves the sensitivity and specificity of the diagnostic decision making of the experts. CAD systems are widely used to detect and diagnose numerous abnormalities in routine clinical work. They are usually specialized for anatomical regions such as the chest, breast and for certain imaging technologies such as radiography, CT, or MRI. Applications of CAD systems include the detection of clustered micro-calcifications in mammograms, intracranial aneurysms in magnetic resonance angiography (MRA) and interval changes in successive whole body bone scan.

The development of new CAD system typically begins with the identification of a clinically important problem. The problem is then analyzed using imaging and clinical findings, based on human recognition of normal and abnormal features. Radiologists' visual interpretations, combined with physicians' clinical data analysis, contribute significantly to understanding clinical needs at this step. Third, the imaging and clinical findings are incorporated into the computational environment by means of automated or semi automated algorithms. This step includes texture, shape and spatial analysis of observed patterns and their classifications.

The three major steps in computerized detection and analysis of diseases are:

- Understanding the use of imaging to identify, understand and diagnose infectious pulmonary disease.
- Preprocessing algorithms for segmentation and registration of pulmonary anatomical structure.
- Detection and Classification discusses the application of texture and shape analysis to image processing to develop accurate, reliable and robust detection and classification system.

This paper is organized as follows. Section 2 discusses the overview of CAD methods. Section 3 presents Lung Segmentation and Candidate TIB pattern selection and classification techniques. Section 4 gives results and conclusion.

2. OVERVIEW OF CAD METHODOLOGY

CAD methodology includes two processing steps. 1) Lung segmentation for the CT data using Fuzzy connected object estimation method. In this approach, strength of connectedness is determined between every pair of image elements. This is done by considering all possible connecting paths between the two elements in each pair. The strength assigned to a particular path is defined as the weakest affinity between successive pairs of elements along the path. Affinity specifies the degree to which elements hang together locally in the image. This leads to more effective object segmentation. 2) Candidate TIB pattern selection from the fuzzy connectivity scene using ball scale encoding algorithm. This process removes large homogeneous regions from consideration which results in a fast localization candidate TIB patterns.

3. LUNG SEGMENTATION AND CANDIDATE TIB PATTERN SELECTION AND CLASSIFICATION

3.1 LUNG SEGMENTATION

Segmentation is an essential step prior to the description, recognition or classification of an image or its constituents. Its purpose is to divide an image into regions which are meaningful for a particular task. Fuzzy connected object estimation is used to achieve successful delineations. In FC framework left and right lungs are recognized by user-defined or automatically assigned seeds, which initiate FC segmentation. One seed per lung volume (i.e., left or right) is set by only considering the locations of small intensity valued pixel inside the object region.

In this framework, a local fuzzy relation called affinity is defined on the image domain which assigns to every pair of nearby image elements a strength of local hanging togetherness which has a value in [0,1]. A global fuzzy relation called fuzzy connectedness is defined on the image domain which assigns to every pair (c, d) of image elements a strength of global hanging togetherness that has value in [0,1]. To determine this value, every possible path from c to d (a sequence of nearby elements starting from c and ending at d) is considered and the minimum affinity of pair wise elements along the path is determined. This affinity represents the strength of hanging togetherness (connectedness) between c and d is the largest of the strengths of all paths between c and d.

Fuzzy spel affinity i.e. affinity between spels c and d is depends on i) how near they are spatially, ii) how near they are based on their intensity features iii) their actual locations in the scene domain. In [2], it is represented by using the formula,

$$\mu_k(c, d) = w_1 g_1[f(c), f(d)] + w_2 g_2[f(c), f(d)] \tag{1}$$

where, g_1 and g_2 are Gaussian functions and w_1 and w_2 non negative weights. Here g_1 represents a homogeneity based component and g_2 represents an object feature based component. The homogeneity based component g_2 is a Zero mean Gaussian and the idea is to capture the degree of local hanging togetherness of c and d based on intensity homogeneity. The more homogeneous the region to which c and d belong, the greater is the component of affinity. The object feature based component g_1 is a Gaussian with mean and variance that are related to the mean and variance of the intensity of the object. These components are expressed in the affinity relation of μ_k as,

$$\mu_k(c, d) = \mu_\alpha(c, d) g[\mu_\psi(c, d), \mu_\Phi(c, d)] \tag{2}$$

where, μ_ψ and μ_Φ represent the homogeneity based and object feature based components of affinity respectively. Next is to select the functional forms for g, μ_ψ, μ_Φ.

First is to define functional form of Homogeneity based component between any two spels c and d can be characterized by $|f(c) - f(d)|$ and express $\mu_\psi(c, d)$ as,

$$\mu_\psi(c, d) = W_\psi(|f(c) - f(d)|) \tag{3}$$

where the function W_ψ should satisfy the following properties:

- The range of W_ψ should be [0, 1] and $W_\psi(0) = 1$
- W_ψ should be monotonically non increasing with $|f(c) - f(d)|$

To satisfy these requirements a membership function corresponding to the fuzzy proposition "x is small" is an appropriate candidate for W_ψ. And here the value of x is defined as $x = |f(c) - f(d)|$. Then the functional form of W_ψ is expressed as follows,

$$W_\Psi = e^{-\frac{x^2}{2k_\Psi^2}}, \quad k_{\Psi>0} \tag{4}$$

where, $k_\psi = M_h + t\sigma_h$, M_h, σ_h are mean and standard deviations of intensity differences $|f(c) - f(d)|$ for all possible pairs (c, d) such that $c \neq d$ and $\mu_\alpha(c, d) > 0$. Fig.3 represents the functional form of W_ψ.

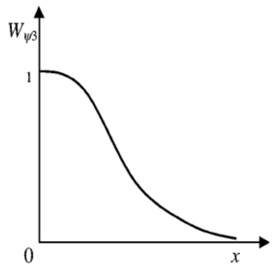


Fig.3. Functional form of W_ψ

Second, Object feature based component of affinity, the only feature considered here is the spel intensity itself. To formulate μ_Φ it needs object feature W_o as well as background feature W_b such that any membership function corresponding to the fuzzy proposition "x is close to an expected value" is an appropriate candidate for W_o and W_b. The spel c and d to have a high object feature based affinity should have low background belongingness. The functional form reflect this is,

$$\mu_\Phi(c,d) = \begin{cases} 1 & \text{if } c = d \\ \dfrac{W_o(c,d)}{W_o(c,d) + W_b(c,d)} & \text{if } W_o(c,d) \neq 0 \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where,

$$W_o(c, d) = \min[W_o(f(c)), W_o(f(d))] \tag{6}$$

and

$$W_b(c, d) = \max[W_b(f(c)), W_b(f(d))] \tag{7}$$

Then the functional form of W_o and W_b is expressed as follows,

$$W_o(x) = e^{-\frac{(x-m_o)^2}{2k_\Phi^2}}, \qquad k_{\Phi>0} \tag{8}$$

and

$$W_b = e^{-\frac{(x-m_b)^2}{2k_b^2}}, \qquad k_{b>0}\,. \tag{9}$$

Here, $k_o = t\sigma_o$ and $k_b = t\sigma_b$ further m_o, m_b, σ_o, σ_b are mean and variance of intensities of object and background. In both the cases the value of t varies between 2 to 3. (The rationale for this is that in a normal distribution, 2 to 3 standard deviation on the two sides of the mean cover 95.4 %– 99.7 % of the population). Fig.4 represents the functional form of W_o.

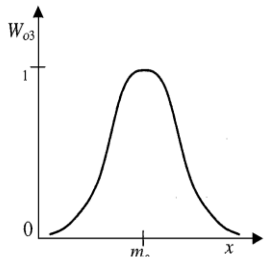


Fig.4. Functional form of W_o

After defining $\mu_\psi(c, d)$, $\mu_\Phi(c, d)$ the function g is now defined as follows,

$$g[\mu_\Psi(c,d), \mu_\Phi(c,d)] = \sqrt{\mu_\Psi \mu_\Phi} \tag{10}$$

And this function should satisfy the following conditions:

- The range of g should be [0, 1]
- Affinity should increase with each component (Homogeneity and object feature based component)

At last by substituting these all we will get $\mu_\alpha \sqrt{\mu_\Psi \mu_\Phi}$ as a value of $\mu_k(c, d)$. In this equation μ_α is the fuzzy spel adjacency. This is defined as, for any spel c, $\mu_\alpha(c, c) = 1$ and for any spels c and d $\mu_\alpha(c, d) = 1$, if c and d differ in exactly one co-ordinate by 1. Otherwise it is zero. For 2-Dimensional image fuzzy spel adjacency for any pixel is 4 adjacent one.

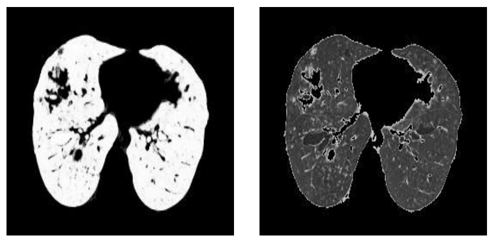
Next to that membership values of k-affinity scene of c is defined as,

$$f_k(c) = \frac{1}{N(c)} \sum_{d \varepsilon N(c)} \mu_k(c,d) \tag{11}$$

where,

$$N(c) = \{d \varepsilon C \mid \text{for } 1 \leq i \leq n,\ d_i - c_i \geq 0,\ c \neq d \ \&\ \mu_\alpha(c, d) > 0\} \tag{12}$$

$f_k(c)$ represents the average of the affinities of c with its immediate neighbors below and to the right (assuming the positive co-ordinate directions to be from the top to bottom and from left to right). Refer Fig.5 for segmentation results.



(a) (b)

Fig.5.(a). Segmented Lung without intensity mapping
(b). Segmented Lung with intensity mapping

3.2 CANDIDATE TIB PATTERN SELECTION

Candidate TIB patterns are extracted from the segmented lung region, using Ball scale encoding algorithm. This algorithm helps in locating all possible abnormal patterns in the images.

TIB pattern has a complex shape with varying intensities over discontinues branches (i.e. buds) TIB patterns have intensity characteristics with high variation toward nearby pixels. Fig.2 represents TIB patterns with various diseases. In other words, TIB patterns do not constitute sufficiently large homogeneous regions.

Ball scale algorithm [2] [6] [7] assigns every internal pixel of a lung a membership value reflecting the size (i.e. scale) of the homogeneous region that the pixel belongs to. According to this concept an object with the largest homogeneous region is assigned with the highest scale value and the pixels nearby the boundary of objects have small scale values. From this observation it clearly depicts that TIB pattern s constitute only small scale values; thus it is reasonable to consider pixels with small b-scale values as Candidate TIB patterns. So at last after assigning scale values to all pixels, it discards pixels with high b-scale values form candidate selection procedure. See Figure 5 for results of ball scale algorithm. Figure 6 depicts the results of Ball scale algorithm for candidate TIB pattern selection.

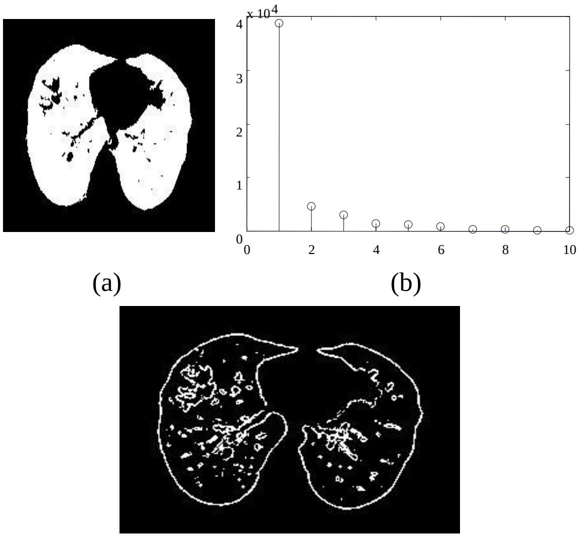


Fig.6.(a). Ball scale value assignment in segmented Lung (b). Stem of scale values assigned to segmented Lung (c). Thresholded B- Scale scene, of a Candidate TIB patterns

3.3 BALL SCALE COMPUTATION PROCESS

The B-scale model is extremely useful in object recognition [7], image segmentation [2][12], filtering [6], in homogeneity correction [10] and image registration [10][11]. Based on continuity of homogenous regions, geometric properties of objects (i.e., size information) can be identified, and this new representation is called scale images, i.e., b-scale. B-scale encoding method is well established for *n*D images.

In the 2D digital space a scene is represented by a rectangular array of pixels C. A Ball $B_k(c)$ of radius $k > 0$ and with center at a pixel $c \,\varepsilon\, C$ is defined by,

$$B_k(c) = \left\{ e \in C \mid \sqrt{\sum_{i=1}^{n} (c_i - e_i)^2 \le k} \right\} \tag{13}$$

The fraction of object is denoted by $FO_k(c)$ and indicates the fraction of the ball boundary occupied by a region which is sufficiently homogeneous with c. $FO_k(c)$ is defined as,

$$FO_k(c) = \frac{\sum_{e \in B_k(c) - B_{k-1}(c)} W_\Psi\left(\left| f(c) - f(d) \right|\right)}{\left| B_k(c) - B_{k-1}(c) \right|} \tag{14}$$

where,

W_ψ is the homogeneity component, refer Eq.(4).

$B_k(c) - B_{k\text{-}1}(c)$ is the number of pixels in $B_k(c)$ and $B_{k\text{-}1}(c)$.

The b-scale algorithm is explained as follows: the ball radius k is iteratively increased starting from one, and the algorithm checks for $FO_k(c)$, the fraction of object containing C that is contained that the ball . When this fraction falls below a predefined threshold, it is considered that the ball contains an object region different from that to which c belongs [6]. This process is repeated for each pixel within a scene [18].

3.4 FEATURE EXTRACTION

Feature extraction requires acquisition of representative features characterizing shape and texture of TIB patterns efficiently. Since TIB is a complex shape pattern consisting of curvilinear structures with nodular structures nearby, to extract these curvilinear shape features Willmore energy [14] shape features are used. And for texture feature extraction the famous Haralick's [13] Gray level Co-occurrence Matrix is used.

Willmore energy of surface plays an important role in digital geometry, elastic membranes, and image processing [14]. Hessian Matrix is used to extract geometric meaning of the shape of interest. So first of all to define Willmore energy function Hessian matrix should be defined. Its elements approximate second order derivatives, and therefore encode the shape information – both a qualitative and quantitative description of how the normal to an iso-surface changes. It is defined as follows,

$$H = \begin{bmatrix} \dfrac{\partial^2 G}{\partial x^2} & \dfrac{\partial^2 G}{\partial x \partial y} \\ \dfrac{\partial^2 G}{\partial x \partial y} & \dfrac{\partial^2 G}{\partial y^2} \end{bmatrix} \tag{15}$$

From the Eigen values of Hessian matrix Willmore energy function is calculated using the formulae,

$$W = \frac{1}{4} \int_s (k_1 - k_2)^2 \, dA \tag{16}$$

Willmore energy is always non negative. As TIB patterns are high curved and small in size, the total curvature / energy are High in TIB region and can be used as a discriminative feature. Willmore energy helps in extracting various shape features such as shape index, Gaussian curvature, mean curvature, elongation, distortion, shear and compactness.

Texture is one of the important characteristics used in identifying objects or regions of interest in an image. This is calculated based on gray tone spatial dependencies. Spatial statistics based on Gray Level Co-occurrence Matrix are very useful in discriminating and quantifying patterns pertaining to lung diseases. Here 18 features are extracted from each local patch including auto correlation, contrast, entropy, variance, dissimilarity, homogeneity, cluster shade, energy, maximum probability, sum of squares of variance, sum of averages, sum of variance, sum of entropy, difference of entropy, difference of variance, normalize inverse difference moment, cluster prominence, and mutual information.

GLCM calculates how often a pixel with gray-level (grayscale intensity) value *i* occurs horizontally adjacent to a pixel with the value *j*. Each element (*i, j*) in GLCM specifies the number of times that the pixel with value *i* occurred horizontally adjacent to a pixel with value *j*. And at last the extracted GLCM feature vector combined with Willmore energy shape features to form complete feature vector to identify the lung abnormalities from CT scans.

3.5 CLASSIFICATION

A classification task usually involves separating data into training and testing sets. Each instance in the training set contains one "target value" (i.e. the class labels) and several "attributes" (i.e. the features or observed variables). Here the goal is to produce a model (based on the training data) which predicts the TIB values of the test data given only the test data attributes.

4. RESULTS AND CONCLUSION

4.1 RESULTS

Radiologist suggested TIB lung scan images were used for training and testing process. Here the feature extraction methodology extracts texture features and shape features for efficient detection of TIB. For feature extraction all the training and testing images were divided into 9 × 9 patches. So it extracts features from all patches and forms a feature vector. Total number of patches trained was 4134. Testing image will have different number of patches based on their image size. The results of each feature vector are given below.

Table.1. Classification Results of TIB Patterns

Feature	Patch Size	Specificity	Sensitivity	Accuracy
GLCM + Shape	9 × 9	23	720	701/744 94.22%
Shape	9 × 9	162	581	581/744 78.06%

From the practical observation the shape features which use willmore energy function for extracting the features has produced 78% accuracy (as stated in the above table). But to get the accurate results, the shape features are combined with Haralick's texture features which produce 95% accuracy.

4.2 CONCLUSION

The Segmentation using Fuzzy connected object estimation gives accurate results for lung region extraction. Usage of Ball scale encoding algorithm perfectly detects the Candidate TIB patterns presents in a Lung CT scan image. Also various features extracted from the Segmented Lung and Ball scale scene gives accurate results for classification. This system helps in Clinical work to correctly detect and quantify the severity of TIB patterns.

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