Lung Nodule Classification Using Deep Features in Ct Images

A. Mangalakshmi, G. Saranya, I. Sobana Devi, V. Syamala Devi.
Assistant Professor, Christ College Engineering and Technology, Pondicherry, India
Student, Christ College Engineering and Technology, Pondicherry, India

Abstract-- This paper suggest a novel arrangement technique for the four varieties of lung nodules, i.e., well-circumscribed, vascularized, juxta-pleural, and pleural-tail, in minute dose computed tomography scans. The proposed technique is built on contextual analysis by merging the lung nodule and adjacent anatomical structures, and has three main stages: an adaptive patch-based division is used to build concentric multilevel partition; then, a new feature set is planned to incorporate intensity, texture, and gradient information for image patch feature description, and then a contextual latent semantic analysis-based classifier is designed to compute the probabilistic estimations for the related images. Our proposed method was estimated on a publicly existing dataset and obviously demonstrated promising classification performance.

Keywords: Computer Tomography, contextual analysis, patch-based division, probabilistic estimation.

I. INTRODUCTION

The word digital image denotes to processing of a two dimensional picture by a digital computer. In a broader context, it suggests digital processing of any two dimensional data. A digital image is an array of actual or intricate numbers denoted by a finite number of bits. An image given in the method of a transparency, slide, photograph or an X-ray is first digitized and deposited as a matrix of binary digits in computer memory. This digitized image can then be computed and/or presented on a high-resolution television monitor. For presentation, the image is kept in a rapid-access buffer memory, which restores the monitor at a rate of 25 frames per second to yield a visually constant display.

Digital image processing refers processing of the image in digital form. Modern cameras may directly take the image in digital form but generally images are originated in optical form. They are captured by video cameras and digitalized. The digitalization process includes sampling, quantization. Then these images are processed by the five fundamental processes, at least any one of them, not necessarily all of them.

II. SCOPE OF THE PROJECT

A administered classifier was planned through merging level-nodule probability and level context probability. The results from the research on the ELCAP dataset presented favorable performance of our technique. We also suggest that the proposed method can be usually relevant to other medical or general imaging fields.

III. RELATED WORKS

Grayscale Morphology: Watershed of the gradient of the cardiac image In grayscale morphology, images are functions mapping a Euclidean space or grid E into, where is the set of reals, is an element larger than any real number, and is an element smaller than any real number. Grayscale structuring elements are also functions from the set of real numbers, called "structuring functions". Denoting an image by f(x) and the structuring function by b(x), the grayscale dilation of f by b is given by where "sup" denotes the supremum. Similarly, the erosion of f by b is given by, where "inf" denotes the infimum. Just like in binary morphology; the opening and closing are given respectively.

Flat Structuring functions: It is common to use flat structuring elements in morphological applications. Flat structuring functions are functions b(x) in the form where. In this case, the dilation and erosion are greatly simplified, and given respectively by in the bounded, discrete case (E is a grid and B is bounded), the supremum and infimum operators can be replaced by the maximum and minimum. Thus, dilation and erosion are particular cases of order statistics filters, with dilation returning the maximum value within a moving window (the symmetric of the structuring function support B), and the erosion returning the minimum value within the moving window B.

Image Segmentation by clustering pixels: Clustering is a process whereby a data set is replaced by clusters, which are collections of data points that “belong together”. It is natural to think of image segmentation as clustering; we would like to represent an image in terms of clusters of pixels that “belong together”. The specific criterion to be used depends on the application. Pixels may belong together because they have the same colour and/or they have the same texture and/or they are nearby, etc.

K-means Clustering method: Simple clustering methods use greedy interactions with existing clusters to come up with a good overall representation. For example, in agglomerative clustering we repeatedly make the best available merge. However, the methods are not explicit about the objective function that the methods are attempting to optimize. An
alternative approach is to write down an objective function that expresses how good a representation is, and then build an algorithm for obtaining the best representation. A natural objective function can be obtained by assuming that we know there are k clusters, where k is known. Each cluster is assumed to have a center; we write the center of the i’th cluster as ci. The j’th element to be clustered is described by a feature vector xj. For example, if we were segmenting scattered points, then x would be the coordinates of the points; if we were segmenting an intensity image, x might be the intensity at a pixel. We now assume that elements are close to the center of their cluster, yielding the objective function.

\[ \Phi(\text{clusters}, \text{data}) = \sum_{i \in \text{clusters}} \left\{ \sum_{c_i \in i'} (x_j - c_i)^T (x_j - c_i) \right\} \]

Quick Shift Clustering method: Quick shift is a kernelized version of a mode seeking algorithm similar to mean shift or medoid shift. Given N data points x1, : : : , xN, it computes a Parzen density estimate around each point using, for example, an isotropic Gaussian window:

\[ P(x) = \frac{1}{2\pi \sigma^2 N} \sum_{i=1}^{N} e^{-\frac{(x-x_i)^2}{2\sigma^2}} \]

Once the density estimate P(x) has been computed, quick shift connects each point to the nearest point in the feature space which has a higher density estimate. Each connection has a distance dx associated with it, and the set of connections for all pixels forms a tree, where the root of the tree is the point with the highest density estimate.

IV. SYSTEM ANALYSIS

A. Existing Work

In the existing system, we present our primary study on the improvement of an advanced multiple thresholding method for the computerized recognition of minor lung nodules. The technique uses a three-step approach. The first step is to automatically excerpt the lungs from MSCT images by evaluating the volumetric density histogram, thresholding the unique images, and consequently applying a morphological operation to the subsequent images. The second step is to detect higher density arrangements e.g., nodules, vessels extent throughout the mined lungs using a local density maximum LDM algorithm. The last step is to reduce false-positive results from the sensed nodule candidates using an earlier knowledge of the lung nodules. The detection method has been validated with computer replicated minor lung nodules.

B. Drawbacks in Existing System

- Direct classification from these would still be problematic.
- Contextual information surrounding the lung nodules could be incorporated to improve nodule classification is complicated segmentation process.
- Image segmentation is quite hard because of noise interference.
- Overlapped or over placed lung nodules are difficult to find

C. Proposed System

This paper presents a novel image classification method for the four common types of lung nodules. We suggest that the major contributions of our work are as follows: i) a patch-based image representation with multilevel concentric partition, ii) a feature set design for image patch description, and iii) a contextual latent semantic analysis-based classifier to calculate the probabilistic estimations for each lung nodule image. More specifically, a concentric level partition of the image is designed in an adaptive manner with: (1) an improved super pixel clustering method based on quick shift is designed to generate the patch division; (2) multilevel partition of the derived patches is used to construct level-nodule (i.e., patches containing the nodules), and level-context (i.e., patches containing the contextual structures). A concentric level partition is thus constructed to tackle the rigid partitioning problem.

Second, a feature set of three components is extracted for each patch of the image that are as follows: (1) a SIFT descriptor, depicting the overall intensity, texture, and gradient information; (2) a MR8+LBP descriptor, representing a richer texture feature incorporating MR8 filters before calculating LBP histograms; (3) a multi orientation HOG descriptor, describing the gradients and accommodating rotation variance in a multi coordinate system.

Third, the category of the lung nodule image is finally determined with a probabilistic estimation based on the combination of the nodule structure and surrounding anatomical context: (1) SVM is used to compute the classification probability based on level-nodule; (2) pLSA with contextual voting is employed to calculate the classification probability based on level-context. The designed classifier can obtain better classification accuracy, with SVM capturing the differences from various nodules, and pLSA further revising the decision by analyzing the context.

D. Proposed System Advantages

- Super pixel formulation dividing an image into multiple segments, and reduce spurious labeling due to noise
- To overcome the problem of the lung nodule overlapping adjacent structures.
- Direct classification from complicated locations also very easy.
- Contextual information surrounding the lung nodules will be more useful to improve nodule classification in segmentation process.
V. SYSTEM ARCHITECTURE

VI. MODULE DESCRIPTION

MODULE 1: CONCENTRIC LEVEL PARTITION:
Our technique is built upon a patch-based image representation. The present methods are usually based on patches with static shape and size, such as separating the image into the square patches or into circular sectors based on radial partitions with a predefined number of pixels in these areas. However, such rigid partition methods would necessarily cluster distinct pixels together; ideally, pixels in the same patch should share matching information, such as intensities. Therefore, we designed an adaptive patch partitioning technique framing super pixels using an enhanced quick shift clustering process. Then, a concentric level partition model is made based on the spaces from patches to the centroid of the lung nodule. The shape and size of our patches are derived adaptively according to the local intensity difference, instead of being predefined by rigid partitioning.

MODULE 2: FEATURE EXTRACTION
The efficiency of image feature description depends on difference and invariance, which means that the descriptor requests to capture the typical features and be robust to adapt to the various imaging conditions. Based on our pictorial analysis the lung nodules, we propose that concentration, grain, and slope can illustrate the many nodules and the diverse on textual structures. We thus planned the feature set of the mixture of SIFT for overall description, MR8+LBP for texture, and multi-orientation HOG for slope. For suitability, we mention to this feature set as the FS3 feature.

MODULE 3: CONTEXT ANALYSIS CLASSIFICATION:
With the concentric level partition and feature set, the next stage is to label each image with one of the four nodule types. Considering that the morphology of lung nodules forms a continuum, which means the arrangements of lung nodules among different types are similar, even with the complete feature design, it remains difficult to categorize the images exactly. So to aid arrangement, we combined the related information. The suggested technique involves SVM analysis for lung nodule patches, and pLSA analysis for context patches. In a directed manner, besides the obvious label evidence (with SVM), we also extracted the inherent dormant semantic evidence hidden in the relationship between the images and their types (with pLSA). In this way, the training data are used double, which attains much more evidence.

VII. CONCLUSION
Directed arrangement techniques for lung nodule LDCT images are presented in this paper. The four main categories of lung nodules well-circumscribed, vascularized, juxta-pleural, and pleural-tail were the objects to be differentiated. We designed a novel method to overcome the problem of the lung nodule overlapping adjacent structures. Our method had three components: concentric level partition, feature extraction, and context analysis classification. A concentric level partition was constructed by an improved quick shift super pixel formulation. Then, a FS3 feature set including SIFT, MR8+LBP, and multi-orientation HOG was generated to describe the image patch from various perspectives. Finally, a supervised classifier was designed through combining level-nodule probability and level context probability. The results from the experiments on the ELCAP dataset showed promising performance of our method. We also suggest that the proposed method can be generally applicable to other medical or general imaging domains.

REFERENCES


