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Lung Nodule Classification Using Lsvm Classifier for Low Dose Computed Tomography Images

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Abstract: The Four type of lung nodules are classified that are well-circumscribed, vascularized, juxta-pleural and pleural-tail based on low dose computed tomography (LDCT) scanned images. Analysis done by combining both lung nodule and surrounding anatomical structures. With an adaptive patch-based division level-nodule and level-context are constructed. Then, a new feature set is designed to integrate intensity, texture and gradient information for image patch feature description. The feature description contains MR8+LBP descriptor, multi-orientation HOG descriptor and SIFTS descriptor. Finally, the class of the lung nodule LDCT image is finally determined by probabilistic estimation based on the combination of the nodule structure and surrounding anatomical context. Linear SVM is used to compute the classification probability based on level-nodule. The classifier finally show the result whether lung nodule found or not and produce accurate position of the lung nodule.

Key words: LDCT · Lung nodule · Linear

INTRODUCTION

Medical imaging is a process of creating visual representations of interior of a body for clinical analysis and medical intervention. It helps to disclose the skin and bones hidden internal structure and it is also used to diagnose and treat disease. Different types of medical images are their like Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Ultrasound images etc. Computed Tomography (CT) images are also called as "CAT scanning" (Computed Axial Tomography). It provides different forms of imaging known as cross-sectional imaging. A CT imaging system produces the cross sectional images or slices of anatomy, like the slices in a loaf of bread. The cross sectional images are used for a variety of diagnostic and therapeutic process. A CT scan takes data from several X-ray images of structures inside the body and then converts them into pictures. The Low Dose Computed Tomography (LDCT) images are used. In lung cancer screening, individuals who have a high risk of developing lung cancer but no signs or symptoms of the disease undergo low-dose computed tomography (LDCT) scanning of the chest. LDCT produces images of sufficient quality to detect many lung diseases and abnormalities using up to 90 percent less ionizing radiation than a conventional chest CT scan.

Lung cancer is the most common to the cancer related death, whose survival is highly dependent on the early and accurate diagnosis. In early years, various efforts have been conducted to study the indications of lung cancer from various symptoms of lung related diseases. Among them, although most of lung nodules have benign causes, many of them represent lung cancers, with nearly 20%-30% of patients with lung cancer initially diagnosed with lung nodule. The initial evaluation of the suspected lung nodules, which is to differentiate benign to malignant ones, is important to detection of lung cancer in early stage.

Lung nodule is the lung tissue abnormally that is roughly opacity. Normally the intra parenchyma nodules that solitarily locate in the central of lung tend to be more malignant than those connected to the surrounding anatomical structures, such as vessels and pleurae. Thus, according to its relative positions regarding to

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these structure, lung nodule is usually categorized into four different types and Detailed information of four type of lung nodule shown in Fig. 1.1. Four types of lung nodule named as Well-circumscribed (W), vascularized(V), Juxta pleural(J) and Pleural-tail(P).

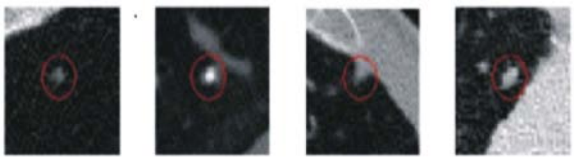

Fig. 1.1: Sample LDCT images for four types of lung nodule. A) Well-circumscribed nodule is located solitarily in the lung without any connection to other structures B) vascularized with the nodule present centrally in the lung but closely connected to neighboring vessels. C) juxta-pleural with a large portion of the nodule connected to the pleural surface and D)pleural-tail with the nodule near the pleural surface connected by a thin tail.

Related Work: Many studies have reported about the detection and segmentation of lung nodules [1, 2, 3, 4], there are only limited data in lung nodule classification. Farag et al. reported on some of the required basic studies in the classification problem [5]. Feature design and an advanced classifier improve the performance. In [5], contextual analysis was made by combining the lung nodule and surrounding anatomical structures, including its three main stages such as an adaptive patch-based division constructs the concentric multi-level partition; then, a new feature set incorporates the intensity, gradient information and texture for image patch feature description. A contextual latent semantic analysis-based classifier calculates the probabilistic estimations for the relevant images. An overlapping nodule identification procedure helps the classification, but its work mainly focused on identifying the nodules located in the intersections among different types [6].

The contextual information surrounding the lung nodules could be incorporated to improve nodule classification [7]; however, this method required a complicated segmentation process. Contextual information refers to the complicated anatomical structures around the nodules, within which some structures are only present in certain type of nodules and some are common across more than one type. For example, W and V nodules are similar in location and shape, which makes it difficult to distinguish them, merely based on the nodule information. V nodules are closely connected to the neighboring vessels and W nodules are isolated from other structures, so identifying connected vessels from V nodules provides an important clue to separate these from each other. Contextual patterns are similarly important for the other nodule types and patch-based approaches can be effective in tackling such a problem. A patch-based approach, which is based on partitioning the original image into an order less collection of smaller patches, is usually used to construct the bag-of-feature (BOF) model [8]. Compared to an overall description of the image, patch based methods can capture local details to better represent the heterogeneous structures. Thus, such methods can be suitable for images of lung nodules that usually contain different anatomical structures. Up to date, patch-based approaches have been mainly designed for some medical and general imaging problems [8, 9, 10, 11, 12] other than lung nodule classification. Patch division methods either divide the image into square or as a circular sector patches where the partitioning is performed in a rigid manner, i.e., the shape and size of each patch are pre-defined, which unavoidably groups unrelated objects together. In particular, a rigid partition on lung nodule images would mix different contextual structures in one patch and cause difficulty in context description.

Superpixel formulation [13, 14, 15] provides an efficient tool for this aim, within each patch the pixels are closely related (e.g., similar intensities). Among the various approaches, quick shift [15] has been successfully employed in medical imaging analysis [7, 16, 17]. In particular, it is more suitable for the lung nodule image analysis due to its ability to better capture the irregular contextual structures than other methods, e.g., simple linear iterative clustering(SLIC) [13], which tends to generate more regular superpixels with similar size and shape.

Quick shift is a faster algorithm than some other methods, e:g:, mean shift [14], so that it could provide increased efficiency for lung nodule image classification that normally involves a large number of cases. Although quick shift shows its advantages on handling lung nodule image by incorporating the local spatial information and reducing spurious labeling due to noise, direct use of quick shift on such small images would group heterogeneous contents together. Therefore, the original quick shift process needs improvement to obtain better patches. Then, to describe the patches numerically, a patch could be translated into a feature vector [4].

In feature extraction stage, a classifier is needed to label the feature descriptors for image classification. Usually, feature-based image classification is based on supervised learning approaches [3, 6, 18, 19, 20] and the most commonly used classifiers include support vector machine (SVM), k-nearest neighbor (k-NN), etc. Among those, SVM has proven to be a highly effective classifier. However, for lung nodule image classification, SVM could be error prone due to the overlapping feature spaces of the nodules [6].

There are also topic based models [9] to incorporate the context information, building the relationship between the context and its label by extracting indirect knowledge. Specifically, probabilistic latent semantic analysis (pLSA) [10], which was originally used in the linguistic scenario, could extract the latent semantic topics and further classify the image based on these hidden topics. The reason that pLSA is suitable for contextual analysis is that it tries to find the common topics shared by various contexts and then determine the category upon these topics, instead of using the raw feature descriptors directly.

Proposed Work: A Linear SVM image classification method for the four common types of lung nodules have the some sequence of steps before applying classification method. The sequence of steps are as follows: i) a patch-based image representation with multi-level concentric partition using quick shift method, ii) a feature set design for image patch description using MR8+LBP, SIFT and MHOG iii) a Linear SVM classifier to calculate the probabilistic estimations for each lung nodule image.

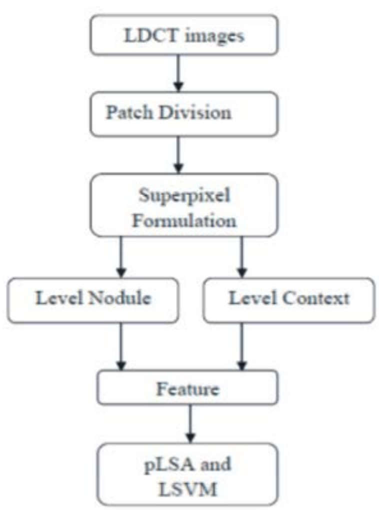

Fig. 3.1: System Architecture

Patch Division: The proposed method is built upon a patch-based image representation. The current approaches are usually based on patches with fixed shape and size, such as dividing 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 unavoidably group unrelated pixels together. Ideally, pixels in the same patch should share similar information, such as intensities. To overcome, designed an adaptive patch partitioning method formulating superpixels using an improved quick shift clustering method.

Then, a concentric level partition model is constructed based on the distances from patches to the centroids of the lung nodule. The shape and size of our patches are derived adaptively according to the local intensity variation, instead of being predefined by rigid partitioning.

Superpixel Formulation: The process of dividing an image into multiple segments is called superpixel formulation, which can incorporate local spatial information and reduce spurious labeling due to noise. Quick shift in an iterative way with image amplification and downsampling used for superpixel formulation. The quick shift method applied to the following input image which is Low Dose Computer Tomography scanned image shown in Fig. 3.2.

Fig. 3.2: LDCT input image

The quick shift method is applied to the amplified image in an iterative way. Two parameters are introduced in quick shift -kernel size, the size of the kernel used to estimate the density and maxdist, the maximum distance between points in the feature space that may be linked if the density is increased. Fixing them at particular values to perform best parameter settings that obtain the highest classification rate with the standard quick shift, generates too many patches, as shown in Fig. 3.3. Both kernel size and maxdist were initialized at 2, increased by 0.3 and 1 respectively in each of the three iterations in this experiments and the downsampling stage is employed to restore the superpixel image to the original size.

Fig. 3.3: Superpixel formulation using quick shift

Feature Extraction: Feature extraction is based on difference and invariance of images. Here use three different types of descriptors that are SIFT for overall description, MR8+LBP for texture description and finally multi orientation HOG for gradient description.

For overall convenience feature set described as *FE*, image as *I* comprising of *O* patches $P=\{pa_o|o=1, ...O\}$. The feature set FE is extracted as,

$$FE = \{SIFT(pa_o), MR8 + LBP(pa_o), MHOG(pa_o)\}$$

First, The SIFT process generates a 128-length vector for each key point. Since SIFT is invariant to image translation, scaling, rotation and illumination changes and robust to local geometric distortion, it is provides valuable lung nodule data Fig. 3.4.

SIFT is robust and is able to carry out semantic classification due to its ability to capture the texture and gradient information. Besides, it identifies the key points by computing extremum pixels in the image local area to incorporate the intensity information.

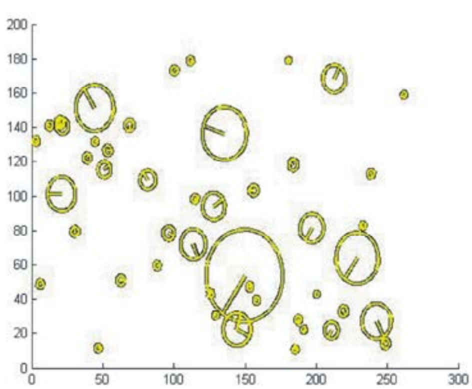

Fig. 3.4: SIFT descriptor for LDCT images

The combination of MR8 filters and LBP feature is designed to provide richer texture description of patches by incorporating multi-scale and rotation-invariant properties. LBP is a powerful feature for texture based image classification [21]. Although LBP can be easily configured to describe the local texture structure with multi-resolution and rotation-invariance, it captures too many trivial image variations. Therefore, we incorporate the MR filter set before computing LBP histogram. The MR set contains both isotropic and anisotropic filters at multiple orientations and multiple scales and records the angle of maximum response, which makes it possible to discriminate textures that appear to be very similar.

HOG is being widely used and can also improve performance considerably when coupled with LBP. However, unlike SIFT and MR8+LBP descriptors, the raw HOG descriptor cannot handle rotation-invariant problems. Therefore, here designed a multi-orientation HOG descriptor used to provide further an advanced gradient description in addition to that from SIFT. The designed descriptor is adaptive to the locations of patches relative to the centroids of the nodule, rather than having the same initial orientation for all patches.

Linear SVM: The support vector machine usually deals with pattern classification that means this algorithm is used mostly for classifying the different types of patterns. Now, there is different type of patterns i.e. Linear and non-linear. Fig. 3.5. shows that the processing of SVM classifier.

Linear SVM is the newest extremely fast machine learning algorithm for solving multiclass classification problems from ultra large data sets that implements an original proprietary version of a cutting plane algorithm for designing a linear support vector machine. Linear SVM is a linearly scalable routine meaning that it creates an SVM model in a CPU time which scales linearly with the size of the training data set.

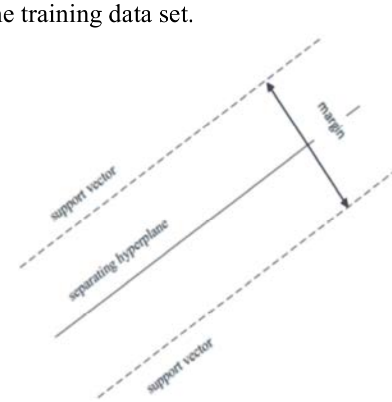

Fig. 3.5. Processing of SVM classifier

Mathematical Formulation: Data for training is set of points (vectors) x_j along with their category y_j For same dimensional,

$$x_j \,\square\, R^d \text{ and } y_j = \pm 1. \qquad (1)$$

The equation of hyperplane is, define as

$$f(x) = x'\beta + b = 0 \qquad (2)$$

where $\beta \,\square\, R^d$, b is real number. β and b minimize $||\beta||$ for all data points(x_j, y_j). $yi\ f(xj) \geq 1$ separating hyperplane based on the decision boundary.

Hyperplane found by minimizing following cost function.

$$J(x)=1/2\ x'\ z=1/2\ ||x||^2 \qquad (3)$$

Separability constraints,

$x'z_i+b \geq +1, for\ yi= 1$
or
$x'z_i+b \leq +1, for\ yi= -1$

Here $i=1, 2, 3, ...n$. Also these constraints can be written more compactly as like following,

$$yi(x'z_i+b) \geq 1; for\ i=1, 2, 3, ...n \qquad (4)$$

Training data may not be separable because of hyperplane have same slack(loose) variables. Here introduced constraints to relax the separability.

$$yi(x'z_i+b) \geq 1-\varepsilon_i\ \varepsilon_i=0,\ i=, 2, 3, ...n$$

Finally the cost function can be modified

$$J(z, \varepsilon_i)=1/2\ ||x||^2+c \sum_{i=1}^{n} \varepsilon_i \qquad (5)$$

where c is user defined positive parameter, ε_i is vector containing all the loose or slack variable. Finally the modified cost function balance the empirical risk that mean training error reflected by second term.

CONCLUSIONS

A supervised classification techniques used to four type of lung nodule classification like well-circumscribed, vascularized, juxta-pleural and pleural-tail with Linear Support Vector Machine using LDCT scanned images. The main components of lung nodule classification are patch division, Feature extraction and finally classification done by linear SVM classifier. Here, overcome the problem of low accuracy and adjacent structure overlapping in lung nodule. The final classification result obtained by both probability of level nodule and probability of level context.

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