

# Lesion Detection and Characterization with Context Driven Approximation in Thoracic FDG PET-CT Images of NSCLC Studies



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## Abstract:

We present a lesion detection and characterization method for Fluorodeoxyglucose positron emission tomography—computed tomography (FDG PET-CT) images of the thorax in the evaluation of patients with primary non small cell lung cancer (NSCLC) with regional nodal disease. Lesion detection can be difficult due to low contrast between lesions and lymph nodes by using Region based fusion classification. Lesion characterization is difficult due to spatial relation between two organs by using multi stage discriminative model. So to over this problems this problems we are moving into sparse representation and multi atlas technique.

## Keywords:

Approximation, characterization, detection, multi-atlas model, sparse representation.

## Introduction:

Positron emission tomography—computed tomography (better known as PET-CT or PET/CT) is a medical imaging technique using a device which combines in a single gantry system both a positron emission tomography (PET) scanner and an x-ray computed tomography (CT) scanner, so that images acquired from both devices can be taken sequentially, in the same session, and combined into a single superposed (co-registered) image.

Thus, functional imaging obtained by PET, which depicts the spatial distribution of metabolic or biochemical activity in the body can be more precisely aligned or correlated with anatomic imaging obtained by CT scanning. Two- and three-dimensional image reconstruction may be rendered as a function of a common software and control system. PET-CT has revolutionized medical diagnosis in many fields, by adding precision of anatomic localization to functional imaging, which was previously lacking from pure PET imaging. For example, many diagnostic imaging procedures in oncology, planning, radiation and cancer staging have been changing rapidly under the influence of PET-CT availability, and centers have been gradually abandoning conventional PET devices and substituting them by PET-CTs. Although the combined/hybrid device is considerably more expensive, it has the advantage of providing both functions as stand-alone examinations, being, in fact, two devices in one.

The only other obstacle to the wider use of PET-CT is the difficulty and cost of producing and transporting the radiopharmaceuticals used for PET imaging, which are usually extremely short-lived (for instance, the half life of radioactive fluorine<sup>18</sup> used to trace glucose metabolism (using fluorodeoxyglucose, FDG) is two hours only. Its production requires a very expensive cyclotron as well as a production line for the radiopharmaceuticals. NSCLC staging takes into account the location and extent of the primary tumor, spread to regional lymph nodes and to sites beyond the thorax.

FDG PET-CT is the most accurate imaging modality for lung cancer staging. While FDG PET was a valuable non-invasive imaging technique to detect functional rather than anatomical data, its main limitation was the lack of spatial resolution. The combination of PET and CT in one device helps overcome this limitation. Manual interpretation of a PET-CT study is time-consuming due to the large volume of data and requires extensive experience and so can suffer from inter-observer differences.

In thoracic PET-CT studies, the main challenges to automated lesion detection are low contrast between normal anatomical structures and lesions, and inter-subject variations in temporal FDG uptake. On CT, lesions usually appear similar to the soft tissues, which is problematic when lesions are located adjacent to the chest wall or mediastinal structures. For PET, although lesions are typically more FDG-avid than surrounding structures, some lesions have only mild FDG uptake; and there can be elevated FDG uptake in normal structures.

Such low contrast implies that detecting lesions based on the within-subject information can be complicated. Lung tumors can invade the mediastinum and lymph nodes can be adjacent to the lung parenchyma. In both examples, the two lesion types have similar spatial characteristics and it is difficult to differentiate between them.

## Existing system:

In the existing system region based fusion classification and multi stage discriminative model techniques are used. In region based fusion classification characteristics of each region are calculated and region based approach is used to fuse the images region-by-region, in the wavelet domain. The multi stage discriminative model is used for automatically detect both tumors and abnormal lymph nodes simultaneously from PET-CT images. But in the existing system noise can't be eliminated. So the proposed system can overcome the above drawback.

## Methods to find FDG PET-CT:

Lesion detection methods on PET-CT images are based on thresholding.

The standard uptake value (SUV), which is a semi-quantitative measure of FDG uptake, is widely used to determine the threshold. Adaptive threshold values have been proposed to better accommodate the subject or region-level characteristics, such as the contrast based threshold and the iterative threshold. Some studies have reported on the detection of only one lesion type—the primary lung tumor or lymph nodes—with the assumption that there is only single lesion type in the image. Without such an assumption, the lung fields can be firstly segmented, and then lung tumors are detected within the segmented lung fields. However, in cases where the lung tumors invade the mediastinum, the segmentation of the lung fields is often unreliable.

With the multi-atlas method, reference data are referred to as atlases. Majority voting or weighted combination of multiple atlases transfers to the labeling of a testing image. Most commonly the weights are determined based on predefined formulas, such as local similarity between atlases and the test image. Sparse representation has been successfully applied to solve classification problems with applications in face recognition, and recently in the medical imaging domain. Briefly, a reference set is constructed to represent each class, and a reconstruction difference is computed for the test data based on each reference set. The class corresponding to the lowest difference is then the class label of the test data.

In multi-atlas and sparse representation approaches, improvement over the basic sparse regularization has mainly focused on spatial constraints, such as group sparsity. Another technique is to incorporate dictionary learning in place of the raw reference data. However, in these methods, the optimization is usually to improve the reconstruction, which might not correspond to better classification.

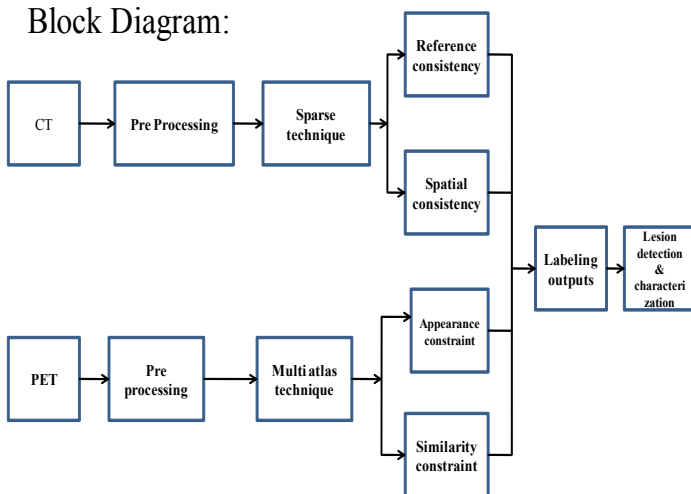
## Benefaction of FDG PET-CT:

We propose a lesion detection and characterization method for thoracic FDG PET-CT images in patients with NSCLC. For lesion detection, image patches that clearly represent the lung fields, mediastinum or the lung lesion are first detected with thresholding operations. The remaining patches are then labeled as lesion or mediastinum based on their approximation of the detected lesion and mediastinum patches.

In context driven approximation (CDA). For lesion detection, an approximation method based on sparse representation was designed to label image patches as a lesion or mediastinum. Region-level contexts extracted from the test image were used as reference data in the approximation. Compared to the existing sparse representation techniques, we designed reference and spatial consistency constraints for a more effective discrimination of low - contrast data. For lesion characterization, an approximation method based on multi-atlas was designed to estimate the original lung fields and mediastinum. Image -level contexts obtained from the reference images were used as atlases in the approximation. We improved the multi-atlas model with appearance and similarity constraints, to handle the inter-subject variations caused by lesions and normal anatomical differences.

The approximation method adapts the reference data to the test image with constraint modeling and reconstruction-based optimization, and does not rely on feature space separation by classifiers. This suggests that simple image features could lead to good labeling.

**Block Diagram:**



**Fig: Block Diagram for Proposed System**

**Lesion detection with Region level constraint:**

Lesions typically exhibit high CT densities similar to the mediastinum and higher FDG uptake than the normal anatomical structures. To locate such areas, contrast information between a region of interest (ROI) and the other regions in the 3-D test image is important.

Regions that are obviously representative of lung fields (LF), mediastinum (MS), or lesion (LS) are labeled first. The remaining regions (UN) are further labeled as MS or LS based on their approximation of the detected MS and LS regions. Our design motivation can be explained by the following. 1) While most areas on a FDG PET-CT image can be easily identified as LF, MS, or LS, there are some regions that show in-distinct features and can be easily misidentified. For example, a non lesion mediastinal region can have elevated FDG uptake, and a lesion can have relatively low FDG uptake. We hypothesize that these UN regions can be labeled based on their degree of approximation of the identified MS and LS regions. 2) The degree of approximation is computed only based on the MS/LS regions within the same image as the UN region. Approximation of lesion detection with region level contexts: Let  $f \in \mathbb{R}^{H \times 1}$  represent the H -dimensional feature vector of an image patch  $p_i$ . Suppose a set of image patches  $\{p_i\}$  is given with known labels  $L(p_i) = l \in \{1, \dots, L\}$ , where L denotes the number of distinct labels.

$$v_l = \operatorname{argmin}_{v_l} \|f_x - D_l v_l\|_2^2 \quad s.t. \|v_l\|_0 \leq C$$

$$f_x^l = D_l v_l$$

Where  $c = \text{constant}$   
 $D_l = \text{reference dictionary}$

$$\mathcal{L}(p_x) = \operatorname{argmin}_l \|f_x - f_x^l\|_2$$

Where  $f_x - f_x^l = \text{difference between labels}$

**1) Reference consistency constraint:**

To reduce the possibility that a good approximation could be obtained from a mismatched reference dictionary. 1) reference patches that are visually similar should contribute similarly to the approximation; and 2) reference patches that are more visually similar to the test patch should contribute more to the approximation. Formally, the following construct is defined:

$$v_l = \operatorname{argmin}_{v_l} \|f_x - D_l v_l\|_2^2 + \Theta(v_l) + \Phi(v_l)$$

$$s.t. \|v_l\|_0 \leq C$$

$$\Theta(v_l) = \sum_{i=1}^{N_i-1} \sum_{j=i+1}^{N_i} \exp\{-d(f_i, f_j)\} |v_l(i) - v_l(j)|$$

$$\Phi(v_l) = \sum_{i=1}^{N_i} d(f_x, f_i) v_l(i)$$

$$U_l((i, j), k) = \begin{cases} \exp\{-d(f_i, f_j)\}, & \text{if } k = i \\ -\exp\{-d(f_i, f_j)\}, & \text{if } k = j \\ 0, & \text{otherwise} \end{cases}$$

$$V_l(i) = d(f_x, f_i)$$

$$v_l = \operatorname{argmin}_{v_l} \|f_x - D_l v_l\|_2^2 + \|U_l v_l\|_2^2 + \|V_l v_l\|_2^2$$

$$= \operatorname{argmin}_{v_l} \left\| \begin{pmatrix} f_x \\ 0^{0.5N_l(N_l-1) \times 1} \\ 0 \end{pmatrix} - \begin{pmatrix} D_l \\ U_l \\ V_l \end{pmatrix} v_l \right\|_2^2$$

$$= \operatorname{argmin}_{v_l} \|F_x - \Omega_l v_l\|_2^2 \quad \text{s.t.} \quad \|v_l\|_0 \leq C$$

$$F_x^l = \Omega_l v_l.$$

## 2) Spatial consistency constraint:

To encourage spatially consistent labels in a local region, our idea is to encode the spatial consistency preference into the labeling phase. In particular, rather than determining the label of a test patch  $p_x$  based on the approximation difference only as in (2), we propose that the label of  $p_x$  should also be affected by the surrounding patches, which could contain other test patches or patches with known labels. If  $p_x$  is visually similar to the surrounding patches, similar labels should be assigned among them. A local region is defined as a connected component comprising A number of image patches  $\{p_x\}$  with unknown Labels and R is surrounding by images patches  $\{p_i\}$  with known labels.

$$E(\mathcal{L}|\mathcal{G}) = \sum_m \varphi_m(l_m) + \alpha \sum_{m, m'} \psi_{m, m'}(l_m, l_{m'})$$

$$\varphi_m(l_m) = \beta^{-1} \|F_m - F_m^{l_m}\|_2$$

$$\psi_{m, m'}(l_m, l_{m'}) = \exp\left(-\frac{\|f_m - f_{m'}\|^2}{2\gamma}\right) \mathbb{1}(l_m \neq l_{m'})$$

## Lesion characterization:

The detected lesions in thoracic FDG PET- CT images comprise two types: primary lung tumor (LT) and abnormal lymph nodes (LN). There can also be false positive detection that is actually high FDG uptake in the myocardium (MC), which is normal and nonpathological. LT lies inside the lung fields, LNs are in the hilar or mediastinal regions, and MC is a large area in the mediastinum near the left lung field.

Therefore, our underlying algorithm identifies the lung fields and mediastinum to extract the spatial characteristics. The LF/MS regions labeled during lesion detection exclude the lesions. These considerations suggest that we need to estimate the actual lung fields and the mediastinum from the image.

## Approximation of lesion characterization with image level contexts:

This is based on the observation that there is great similarity in the normal anatomical appearances between images, even though patient-specific conditions introduce variation. Therefore, given a test image, the approach is to estimate the lung fields and mediastinum based on reference images. The estimation is equivalent to relabeling the patches in I as LF or MS. For each axial I<sub>s</sub> the test image I, a feature vector  $g_x \in \mathbb{R}^{Q \times 1}$  is computed by concatenating the patch-wise labels derived during lesion detection. In  $g_x$ , each element  $g_x(p_i)$  represents the labels (LF, MS, or LS) of patch  $P_i \in I_s$ , with numeric values 1, 2, or 1.5. The value 1.5 means that the LS patches can be relabeled as LF or MS with equal probabilities. A multi-atlas model with sparse regularization is then formulated to derive the LF/MS labels for  $s$ .

$$w = \operatorname{argmin}_w \|g_x - Tw\|_2^2 \quad \text{s.t.} \quad \|w\|_0 \leq C$$

$$g_x^* = Tw$$

where  $w$  is a weight vector with nonzero elements, and  $C$  is a constant. The vector  $w$  contains real numbers that are approximations of LF/MS labels. To further enhance the labeling performance, we designed two additional constraints—appearance and similarity constraints.

## 1) Appearance Constraint:

One limitation with the multi-atlas model in (12) is that, the feature vector contains the label information only. It also restricts the approximation target in accommodating the appearance variations between subjects. We thus include the patch-wise average CT density as a second feature vector. PET data are not used given the low spatial resolution and relatively large inter-subject variations compared to the CT data.

$$\begin{aligned}
 w &= \underset{w}{\operatorname{argmin}} \|g_x - Tw\|_2^2 + \|h_x - Aw\|_2^2 \\
 &\text{s.t. } \|w\|_0 \leq C \\
 &= \underset{w}{\operatorname{argmin}} \left\| \begin{pmatrix} g_x \\ h_x \end{pmatrix} - \begin{pmatrix} T \\ A \end{pmatrix} w \right\|_2^2 \\
 &\text{s.t. } \|w\|_0 \leq C \\
 g_x^* &= Tw.
 \end{aligned}$$

$$h_x(p_i) = \lambda c_1 + (1 - \lambda)c_2$$

## 2) Similarity constraint:

Image  $J_{k,s}$  corresponds to a single weight element  $w_k$  in  $w$ . This means that all patches in  $J_{k,s}$  would contribute equally to the approximation. However, due to the nonrigid structure of the thorax and presence of abnormalities, it is normal that only a portion of  $J_{k,s}$  is similar to  $J_{r,s}$ , patch-wise similarity information between the test image and the reference images to allocate different weights to different patches.

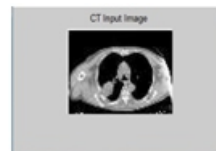
## Patch based detection:

The patch - based labeling method for the lesion detection. The objective is to label the patches into LF, MS or LS categories:  $J_{k,s}$ , the LS patches would be lesions detected. we perform a four-class labeling:  $J_{k,s}$ ,  $J_{k,s}$ ,  $J_{k,s}$ ,  $J_{k,s}$ , where UN represents the patches of un-sure (i.e., MS or LS) category. Specifically, Otsu thresholding is used to separate the LF patches from the rest based on the average CT densities of patches, since the lung fields exhibit much lower CT densities compared to the other three categories.

The PET image is then used to differentiate MS, LS, and UN.  $J_{k,s}$ , the UN patches  $\{p_x\}$   $\{p_i\}$  are further labeled as MS or LS [Fig. 2(b)]. To do this, each image patch  $J_{k,s}$  is represented by a four-dimensional feature vector  $f_{k,s}$ : its mean and standard deviation of CT densities, and mean and standard deviation of SUV. Next, for a UN patch  $J_{k,s}$ , two reference dictionaries are constructed based on the labeled MS and LS patches in an image I: DMS and DLS. Two features approximations  $F_{xMS}$  are thus derived using.

## Results and Discussion:

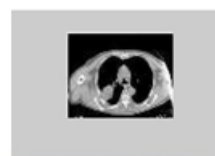
CT input image:



CT input image with lung cancer  
PET input image:



PET input image with lung cancer  
Preprocessing image:



The PET-CT image doesn't consists of noise, reflections and masking.

Sparse image:



CT image with high Contrast data  
Spatial output image:



CT image with improved detection

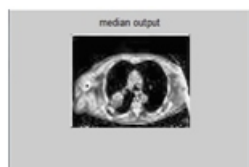
Performance

Noisy image:

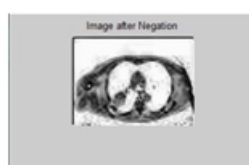


CT image which represents noise  
Median output:

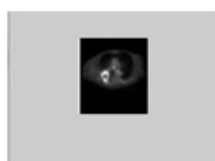
CT image represents the elimination of noise  
Image after negation:



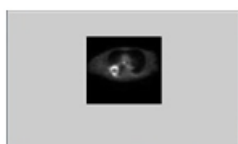
CT image shows elimination of background noise  
Multi-atlas image:



The PET image shows abnormal part  
Similarity image:



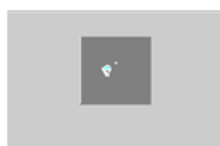
The PET image shows lesion output  
Fused Image:



The image shows the lesion detection of PET-CT  
Lesion image:



The image shows the lesion detection of PET-CT.

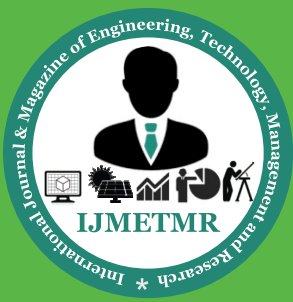


## Conclusion and Future Scope :

We present the sparse representation and multi-atlas technique to detect and characterize the primary lung tumor and disease in regional lymph nodes for NSCLC studies using FDG PET-CT images. The output images of this paper are used for clinical dataset for doctors to analyze the tumor and diseases in regional lymph nodes. The future scope is to distinguish between lesions and soft tissues, and between lung tumors and abnormal lymph nodes. New sparse representation and multi-atlas models were designed with additional constraints to improve the labeling performance.

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