Automatic Descending Aorta Segmentation in Whole-Body PET-CT Studies for PERCIST-based Thresholding

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Abstract—Medical imaging is a fundamental component of modern healthcare where majority of medical conditions can benefit from some kinds of imaging. A dual-modal positron emission tomography – computed tomography (PET-CT) has increasingly become the preferred imaging method to stage the common cancers and to assess treatment response. For example, PET image can quantitatively assess the treatment before morphological changes that can be detected on anatomical CT image. PET response criterion (PERCIST) is a widely recognised thresholding method for detecting malignant lesions (high metabolic value) in treatment response. It is based on the calculation of standardised uptake value with lean body mass (SUV_LBM), together with a volume of interest (VOI) reference placed on the right lobe of the liver or the descending aorta (when the liver is abnormal e.g., liver cancer). These two structures are considered to have stable metabolism among the PET patient population and therefore can be used to normalise the SUV. The current practice of PERCIST thresholding depends on the manual delineation of the VOI reference which is a time consuming and operator-dependent process. Furthermore, such VOI selection is more difficult on the smaller descending aorta structure when compared to the liver. In this study, we propose a fully automatic approach to the segmentation of the descending aorta for use in the calculation of the PERCIST thresholding. A multi-atlas registration coupled with weighted decision function was used in the whole-body CT for the segmentation of the descending aorta, with the resulting VOI reference mapped to the co-aligned PET counterpart. We evaluated our method with 30 clinical PET-CT studies with preliminary results demonstrating reliability and robustness.

Image Segmentation; Multi-atlas Image Registration; Multi-modal PET-CT; Aorta Segmentation; PERCIST

I. INTRODUCTION

Medical imaging is becoming ever more important in modern medicine due to its ability to non-invasively visualise internal anatomical structure or functional information for diagnosis, treatment planning and assessment [1]. Computerised imaging techniques have been applied in medical imaging to provide digitalised images for visualisation [2]. Functional imaging modality of Positron Emission Tomography (PET) is capable of visualising early functional change; for example, varied metabolic activity of malignant lesions, prior to significant morphological abnormalities that can be seen by using anatomical imaging such as computed tomography (CT) [3]. Multi-modal PET-CT scanner, which combines PET and CT in one imaging device, provides detailed anatomical information of CT data to supplement functional information of PET data in a co-aligned imaging space.

PET image can derive quantitative functional parameters for assessing metabolism of abnormal structures such as tumours. Standardised uptake value (SUV) which is to normalise PET images by injected tracer dose and patient body weight, has been widely accepted in oncology to provide approximate estimate of metabolic rate of glucose consumption in identifying malignant lesions by using the tracer of FDG. The use of lean body mass (LBM) has been proposed to address the inaccurate estimation of body mass with the use of body weight in deriving SUV [4]. PET Response Criterion (PERCIST) has been well accepted in deriving metabolic changes of malignant lesions in assessing treatment response. It suggests that the use of a volume of interest (VOI) reference placed on the right lobe of liver, or the descending aorta in the case of abnormality in the liver. These two structures were considered to have stable SUV among the population of PET studies. The average pixel values of the VOI reference from PET image was then used in thresholding PET data to separate malignant lesions from non-lesions. It is of great benefits to automate the PERCIST-based thresholding for objective evaluation of treatment response and reduce operator-dependent bias.

There are extensive literatures which present the automatic segmentation of anatomical structures needed in PERCIST such as the liver [5], and also the aorta [6]. Our recent work [7] has demonstrated a framework of automated liver segmentation specifically for optimised PERCIST with the use of multi-atlas registration of liver. However, the presented framework cannot be applied for the segmentation of the descending aorta when liver is abnormal. Furthermore, the descending aorta is a small structure which introduces greater challenges in the VOI placement when compared to the liver. In this paper, we propose a descending aorta segmentation algorithm for its application to the PERCIST-based thresholding framework. A
fully automatic approach to the segmentation of the descending aorta with the use of multi-atlas registration coupled with weighted decision function was applied. The resultant segmentation was then used as a VOI reference for PERCIST thresholding of PET.

II. METHODS

A. Overview of the proposed descending aorta segmentation

Fig. 1 illustrates the overview of our proposed segmentation process of the descending aorta. Initially CT images were pre-processed to remove the bed/linen artifacts automatically by adaptive thresholding and image subtraction from a bed template [8]. Empty spaces were then removed to reduce the computation. After that, the range of descending aorta was estimated by identifying the lung structures in the CT image. Then multi-atlas registration followed by the weighted decision function [6] was applied to the detected range to segment the descending aorta. In addition, the segmented result (label) of the descending aorta was transferred to the co-registered PET images and a VOI reference with the 1cm diameter and 2cm height was placed within the label volume. Finally, by using the VOI reference, a PERCIST-based threshold was calculated and used to separate the structures of high metabolic value in the SUV_{LBM} normalised map of the PET counterpart.

B. Patient Data

Whole body PET-CT studies were acquired from the department of PET and Nuclear Medicine, Royal Prince Alfred hospital with a Siemens Biograph TruePoint PET-CT scanner or a mCT PET-CT scanner. All the studies have either 326 slices or 368 slices at a slice thickness of 3 mm to cover the body from the top of the head to the upper thigh of the human body. PET slice had a 200×200 matrix at pixel size of 4.07 mm² and CT slice had a 512×512 matrix at the pixel size of 0.98 mm². In total, 30 randomly selected patient studies (anonymised) were used in the evaluation, consisting of 5 studies with abnormal activities in the liver and further 25 non-small lung cancer studies. No abnormalities were observed in the descending aorta for all the studies. For the construction of the training data, additional 10 patients with no abnormalities in the lung and the aorta regions were used.

C. Training Set Construction

In our training set, labels of the descending aorta were semi-automatically segmented from 10 CT studies by an experienced operator using geodesic contour modelling in the medical imaging interaction toolkit [9]. Segmentation was done in transaxial slices from the bottom of the aortic arch to the bottom of the lungs. Under segmented descending aorta was preferred when the boundary was unclear from the low-contrast CT images.

D. Descending Aorta Segmentation

1) Descending Aorta Localisation

Lung structures were segmented from whole-body CT image initially for estimating the spatial range of descending aorta. These lung structures cover the thorax region of the body where the descending aorta structure is localised within the lung pairs. In the segmentation of the lungs, an adaptive thresholding was applied on the CT data to separate air from
other tissue structures. Left and right lungs were then separated by identifying the two largest connected regions [10]. Cropped thorax image covers the range of the descending aorta.

2) Multi-Atlas based Segmentation with Weighted Decision Function

The multi-atlas based descending aorta segmentation with decision function was adopted from [6]. In our study, we have $N$ descending aorta atlases $A_1$, $A_2$, ..., $A_N$, and its corresponding manually delineated labels $S_1$, $S_2$, ..., $S_N$. Let cropped thorax image $U$ be the target image and $S$ be the label from the segmentation results. All the atlases were registered to $U$ using affine translation followed by B-Spline registration from the Elastix toolkit [11], resulting in transformation parameters $u_i$, $u_{i+1}$, ..., $u_N$. These parameters were then used to map the labels $S_i$, $S_{i+1}$, ..., $S_N$ to $U$. After the transformations, difference $D_i$ between $U$ and each of the transformed atlases were calculated and used as weight functions $\lambda$ for each pixel $p$ according to:

$$\lambda_i(p) = \frac{1}{D_i(p) \times g \sigma(p) + \epsilon}.$$  \hspace{1cm} (1)

Here, $g$ is a Gaussian filter with $\sigma$ equal to 4 and $\epsilon$ is a constant set to 0.001 in order to avoid division by 0. The probabilistic label $S_p$ was generated by computing the average of the weighting functions where:

$$S_p(p) = \frac{1}{\sum_{i=1}^{N} \lambda_i(p)} \sum_{i=1}^{N} \lambda_i(p) S_i(u_i(p)).$$  \hspace{1cm} (2)

The resulting probabilistic label represents the weighted decision function, which was then subject to a Gaussian filter with $\sigma$ equals to 4. The filtered result was then thresholded at 50% of its pixel values. The largest connected component (pixels) was extracted as the final segmented label. In our experiments $N$ was set to 10.

E. VOI Reference Segmentation

From the segmented label of the descending aorta in Section D, the VOI reference was placed inside this label by centring the VOI at a slice located at 20% from the top of the label in the transaxial view. For each of the slices in the VOI reference, a circle was placed using the centroid of the pixels in the label, so as to the VOI reference is equally distant from the boundary of the labels. The VOI reference which is defined as a 1cm diameter over 2cm height is only a fraction in volume of the entire label, thus ensuring the complete placement of the VOI reference even with errors in the descending aorta segmentation label.

F. PERCIST-based Thresholding

The value of $LBM$, according to [12], was calculated using the body parameters of weight (kg), height (m), age (year old) and gender (1 for male, 0 for female):

$$LBM (kg) = weight - \{weight \times (1.2 \times weight / height^2) + 0.23 \times age - 10.8 \times Gender - 5.4\} / 100$$  \hspace{1cm} (3)

The derived $LBM$ was then applied to convert PET image to $SUV_{LBM}$ map according to [13] where:

$$SUV_{LBM} = \frac{C_{ref}(t)}{\text{Injected dose} / LBM}.$$  \hspace{1cm} (4)

Here, $C_{ref}(t)$ is the radioactivity concentration at time $t$, expressed in kBq/ml and injected dose in MBq. The VOI reference from the PET was then used to derive the value of a threshold according to [14]:

$$Th - SUV_{LBM} = (2 \times \text{mean}) + (2 \times SD)$$  \hspace{1cm} (5)

where mean and standard deviation $SD$ were calculated from the pixels within the segmented VOI reference.
III. RESULTS AND DISCUSSIONS

A. Descending Aorta Segmentation

Fig. 2 shows the results of the descending aorta segmentations together with the VOI references in selected challenging cases among the 30 PET-CT studies. In all the cases, descending aortas were correctly identified and segmented according to our visual inspection. However, as expected in a completely automated approach, some cases resulted in slight over-segmentation. Fig 2(b) is a case when a small portion of the segmentation label is outside the descending aorta and occupies part of the mediastinum. Another over-segmentation result is shown in Fig 2(c), where the abnormality seen in the left lung’s diaphragm resulted in registration errors which translated to the descending aorta segmentation to include part of the ribs, as depicted in the coronal view. Nevertheless, even with such over segmentations, the placement of the VOI references were always completely within the descending aorta. Further, in all the investigated cases, segmentation errors where always from over-segmentation and not under, which are an important attribute in the VOI reference segmentation. This is attributed to the fact that our weighted decision function was set to 50% which gives preference to over estimation of the atlas registration.

Fig. 3 illustrates the importance of the weighted decision function in the final segmentation results of the descending aorta. On the right is the sum of the labels of the registration results prior to the weighting function. Blue line indicates the 50% common region among the 10 atlas labels. The middle result shows the Gaussian smoothed probabilistic label calculated from the weighted decision function where the red line indicates the 50% common region. From the left image, we can clearly see that the weighted decision function corrects the under segmentation results from the multi-atlas result, especially in the top-right and bottom-right corners. Such correction ensures that under segmentation is always avoided.

As a further test to the accuracy of the VOI reference estimation, we measured the homogeneity of the voxels residing in the VOI reference in PET. It is expected that if the VOI reference is entirely within the descending aorta, it will consists of homogeneous pixel values and thus have low SUV$_{LBM}$ standard deviation from the mean. For each study, we calculated the standard deviation and plotted the results in Fig. 4. Among our 30 studies, the average standard deviations SUV$_{LBM}$ was within 13.3 ± 5.2% to its mean, which was within the expected variation of SUV$_{LBM}$ found in the descending aorta structure from our experiments.

B. Thresholding of PET Image

The segmented VOI references were used in the PERCIST-based thresholding to calculate the SUV$_{LBM}$ normalised PET. Fig. 5 shows an example of an aligned PET-CT study with mapped descending aorta (blue line) and its corresponding VOI reference (red line). Visually in both the PET and CT, the VOI reference resides completely within the descending aorta.

Figure 3. An example of the stages in descending aorta segmentation. (a) shows the CT image of the descending aorta with the segmentation labels from the weighted decision function from (b) and from only the multi-atlas registration (c).
Figure 5. A PET-CT study demonstrating the segmentation of the descending aorta and its use in the placement of the VOI reference for subsequent PERCIST-based thresholding. Here in both PET and CT, we can clearly depict the VOI reference (red outline) from the descending aorta segmentation (blue outline) in orthogonal views of coronal (a), sagittal (b) and axial (c), respectively from left to right.

Fig. 6 illustrates an example of using the VOI reference in the calculation of SUV_{LBM} thresholding for two PET-CT studies with liver tumour(s). The results of the SUV_{LBM} thresholding were able to depict all the abnormalities for all studies, which were consistent to the findings in the physician’s reports.

C. Computational Cost

The whole-body PET-CT segmentation process took in average of 36±3 minutes running on a consumer PC equipped with Core i7 3.40 GHz CPU and 16.0GB of memory. The biggest time consuming task was the multi-atlas registration which took an average of 30minutes (approx. 83% of the total time). We used 10 atlases in our multi-atlas registration thus resulting in this high computation time.

IV. CONCLUSION AND FUTURE WORK

In this study, we developed a fully automatic multi-atlas segmentation of the descending aorta from low-contrast CT in PET-CT studies. The segment results were then used in the calculation of the PERCIST-based thresholding in the normalization of PET counterpart. In our 30 clinical PET-CT studies, we correctly place the VOI reference within the descending aorta, demonstrating reliability and robustness of our algorithm. We will also further evaluate the performance of our method using greater number of clinical studies, and its integration to PERCIST-based thresholding using the liver VOI reference. Our current solution targeted the robustness and reliability of our segmentation. This resulted in high computation cost which we will attempt to reduce in our future study by code optimisations.

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REFERENCES