Automatic Detection of PET Lesions

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Abstract

We propose a method to handle the automatic detection of PET lesions based on asymmetry feature measurement after segmenting the PET images. It is an essentially initial step in automatic diagnosis and content-based retrieval applications. Our technique includes six steps: Image alignment, segmentation, image reflection & subtraction, thresholding, background removal using morphological filtering and segment back-mapping. Compared with existing per-pixel asymmetry detection methods, our method can provide fewer false positives and more accurate results.

Keywords: PET, Symmetry, Automatic diagnosis.

1. Introduction

Hospital and clinical environments are already embracing digital processing, which is playing a very important role in heath care services. A variety of imaging modalities form an essential and inseparable component to diagnose various disease states which manifest themselves as structural or functional changes. These modalities can be divided into two main categories, structural imaging modalities such as X-ray, Computer Tomography (CT), Magnetic Resonance Imaging (MRI), Ultrasound Imaging, Microscopic Imaging and functional imaging such as Single Photon Emission CT (SPECT), and Positron Emission Tomography (PET).

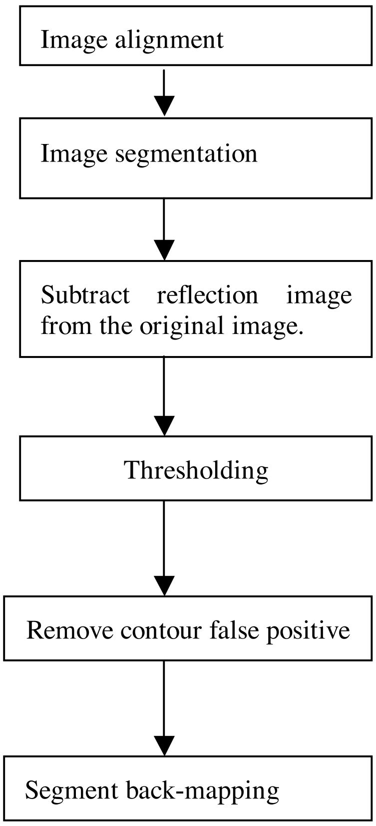
By the use of digital medical images, image retrieval of large medical database becomes feasible. Traditional image retrieval systems are based on textual description, which can be subjective and some visual feature information that is difficult to describe. To automatically index images, content-based image retrieval has been proposed. Content-based image retrieval systems are based on three major visual features: color, texture, and shape, and to a lesser extent some other image features like icons, geometrical, topological and knowledge features. There are excellent surveys for content-based image retrieval Yoshitaka, Ichikawa (1999) and Rui and Huang (1999).

The image retrieval schemes described above have been applied to the structure medical imaging field. For example Ng, Cheung and Fu (1995) showed a query example of Medical Image Retrieval by Color Content, Korn et al (1998) defined a method of fast searching for Content-based mammography tumour retrieval by shape. Balestrieri et al (2001) proposed a computer-aided diagnosis scheme which can search for mass lesions based on contour and texture features. In Zhang and Dickinson (1998), they developed a prototype of a dental radiograph image database retrieval system indexed by shape-based content. In Orphanoudakis, Chronaki and Vamvaka (1996), a system for medical image retrieval based on geometric and texture features using ROI-based attribute match was developed. Keim (1999) proposed an index structure based on geometric features for 3D volumetric CT/MRI image retrieval. Liu et al (2001) applied 3D brain CT image retrieval based on semantic features using statistical bilateral asymmetry measures for normal and pathological human brains. In the popular area of cardiac image content-based retrieval, Robison et al (1996) proposed a sensitive shape similarity measure which used a non-rigid mapping similarity measure to implement cardiac MRI image retrieval based on orientation-sensitive shape. In Chu et al (1995,1998), a method of medical image retrieval was proposed by interpreting spatial relationship among objects.

The content-based medical image retrieval approaches mentioned above are not specifically tailored for functional images. Unlike the anatomical imaging techniques, biomedical functional imaging techniques allow us to see dynamic processes quantitatively in the living human body (Feng et al., 1997). However, these have relatively low signal to noise ratio and low resolution that limits the use of anatomical content feature such as shape for PET image indexing. In our research group's previous work, Cai, Feng (2000), a prototype design for PET image retrieval system using physiological kinetic features was proposed, but this system can only retrieve the tumour with a known time tissue activity curve (TTAC) then only can be applied to dynamic images. Batty et al (2002) presented a PET brain image retrieval method using detection and measurement of asymmetrical features, However their method is based on a per-pixel approach, and on noisy PET images this can lead to many false positive, necessitating a large error threshold and hence lowered sensitivity. In this paper, we use asymmetry feature detection on segmented PET images to automatically extract pathological lesions, which is an essential initial step in automatic diagnosis and content-based retrieval applications. This paper is organized as follows: In section 2, an overview is given of PET lesion detection based on asymmetrical feature measurement. In section 3, the clinical case studies and related experimental results are described. Finally, conclusions and further work are presented in section 4.

2. Asymmetry measurement to detect brain lesions

As flowchart 1 described, our method is based on six steps to automatically detect the asymmetrical brain features. Because normally, a brain image is symmetrical around the middle plane. And for each sagittal slice of brain PET image, its left and right parts are symmetrical or similar around the mid-sagittal line.



Flowchart 1. Six steps of Asymmetry measurement

Step one is image alignment, to calculate asymmetry in the later steps, we first need to ensure that the middle symmetrical line of the PET image is centred and vertical. In this paper we use a moment based approach.

We start with a binary valued thresholded version of the original image. The translation and rotation of the image are then calculated by a moment analysis of the binary image. The image is then aligned using this result.

Step two is segmentation. The segmentation method used is fully automatic. This algorithm has been demonstrated to be affective in segmenting anatomical features even in noisy resolution PET imaging. The details of the segmentation algorithm used are provided in Parker (2001). Currently each PET data set plane is segmented using a two-dimensional segmentation.

In step three, we create a reflection image of the original segmented image and then subtract it from the original segmented image.

In step four, the difference image is thresholded to detect significant asymmetries.

In step five of the proposed technique we remove false positive detections from the boundary of the brain. This is done by masking a symmetrical background mask. The background segment is easily detected as the segment touching the image edges. The background mask is made symmetrical by ORing together the original background mask and its reflection. And then perform a morphological operation where the boundary is dilated by five pixels (five pixels are determined from experiment). At this stage significantly asymmetrical features have been detected.

In last step, the features in the final asymmetry detection result are mapped back to the corresponding segments in the original segmented image to select the segments corresponding to pathological lesions.

3. Results

To test the efficiency of our method, we used two clinical brain FDG-PET studies, one is a normal patient (plane 15, last time image), and the other is a pathological image with an obvious tumour (plane 19, last time image).

Figure 1 illustrates the results of image alignment. Figure 1-a and figure1-b are the rotated and shifted original datasets. Figure 1-c and figure 1-d are normal image and tumour image after image alignment respectively.

Figure 2-a and Figure 2-b are the generated symmetrical background mask of the normal image and tumour image.

The normal image asymmetry detection is showed in Figure 3. Figure 3-a shows the original per-pixel image. Figure 3-b shows the approximation image of the normal data set after segmentation.

Figure 3-c and figure 3-d illustrate the absolute difference between reflection image and original image for per-pixel asymmetry detections without using segmentation and the asymmetry detections using segmentation respectively.

Figure 3-e for per-pixel image and figure 3-f for segmented image show the thresholded difference image with threshold value is 0.15.

Finally, the result of asymmetry feature detection for the normal image after the false detections on the border have been removed by the background mask is shown in Figure 3-g based on per-pixel approach and Figure3-h based on segmentation image. It can be seen that there are many more false positives in figure 3-g than figure 3-h.

For the tumour image detection, Figure 4-a and figure 4-b show the original per-pixel image and approximation image after segmentation respectively.

The results of per-pixel unsegmented asymmetry detection and segmented asymmetry detection without threshold are shown in Figure 4-c and figure 4-d respectively.

Figure 4-e and figure 4-f illustrate the thresholded difference images with threshold number is 0.15 for the per-pixel unsegmented asymmetry detection and segmented asymmetry detection respectively.

After the false detections on the border have been removed by the background mask, Figure 4-g and Figure 4-h showed the final asymmetry feature detection result for the per-pixel unsegmented image and segmented image respectively. It is obviously that there are fewer false positives in Figure 4-h than in figure 4-g.

The final tumour extraction result is shown in figure 4-i.

4. Conclusion and Further work

In this paper, we proposed a content-based retrieval technique using asymmetric feature detection after segmentation. By comparing per-pixel asymmetry feature detection with our segmented image asymmetry detection, the latter one is shown to provide fewer false positive in the PET data examples presented. The preliminary results presented in this paper produces some interesting results. In the future, we will extend this technique to apply to 3-D PET image and provide a larger test data set for evaluating other pathologies.

5. References

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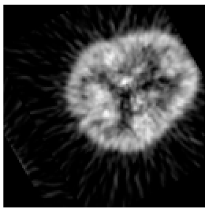
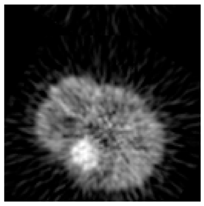
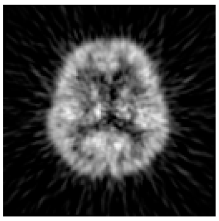
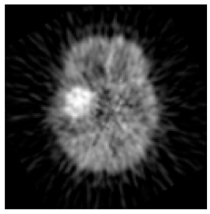
	Normal image	Tumour image
Un-alignment images	 a	 b
Alignment images	 c	 d

Figure 1. Image alignment

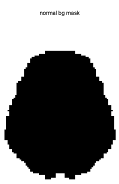
 a	 b

Figure 2. Symmetrical background mask of normal image(a) and tumour image(b)

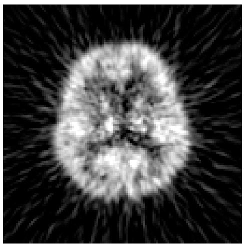
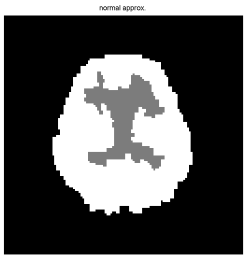
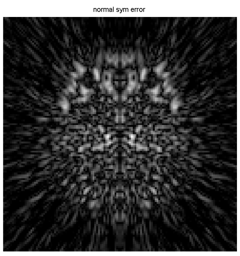
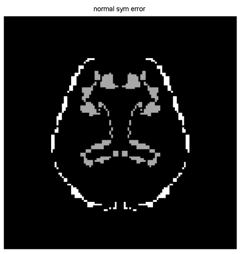
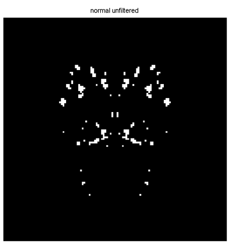
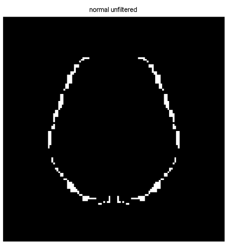
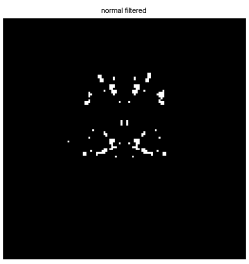
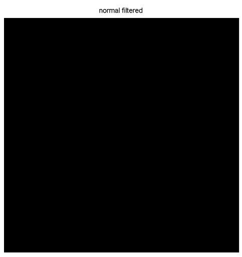
	Results from unsegmented image	Result from Segmented approximation image
Original image where its midsagittal line aligned and vertically	 a	 b
Absolute difference images between the original image (a,b) and their own vertical reflection.	 c	 d
Thresholded images of the difference images (c,d) with Threshold value =0.15	 e	 f
Thresholded with contour false detection removal	 g	 h

Figure 3. Asymmetry feature detection for PET image without tumour

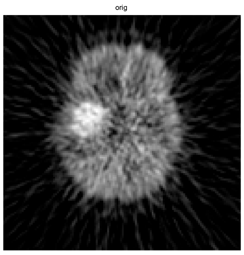
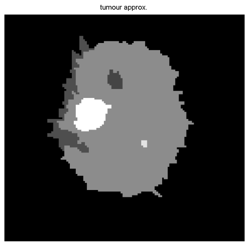
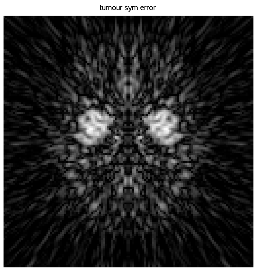
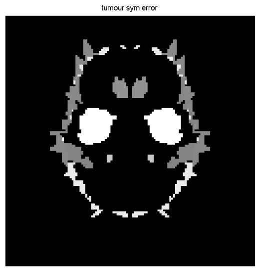
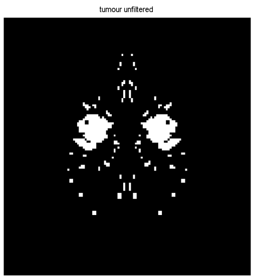
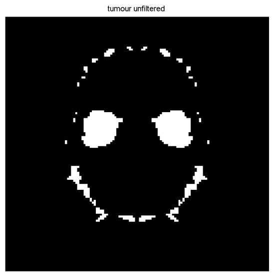
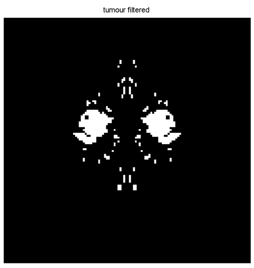
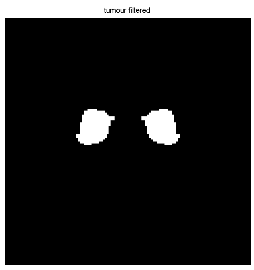
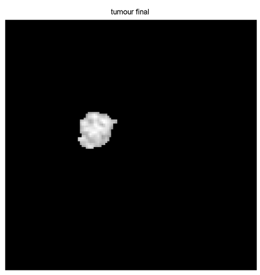
	Result from unsegmented image	Result from segmented approximation image
Original images where its midsagittal line aligned and vertically	 a	 b
Absolute difference images between the original image (a ,b) and their own vertical reflection.	 c	 d
Thresholded images of the difference images (c,d) with Threshold value =0.15	 e	 f
Thresholded with contour false detection removal	 g	 h
Segment back-mapping		 i

Figure 4. Asymmetry feature detection for PET image with tumour