PET/CT画像を利用した脳腫瘍のコンピュータ診断支援システム*

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Computer Aided Diagnosis System of Brain Tumors in PET/CT Images*

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In this paper, we proposed a computer aided diagnosis system (CADs) that supports to detect the existence of tumor in the area of the brain from a given FDG-PET/CT image. Firstly, tilt correction was applied to brain image based on a computation of the mid-sagittal plane in the head. Secondly, tumor detection was performed by detecting asymmetrical regions between images of the left and right cerebral hemispheres. In this step, an improved SURF algorithm was utilized to detect the asymmetrical regions between the left and right sides in a 2D axial slice of the brain image. In cases where the 2D axial slice data was identified as symmetrical, one supplementary method based on typical illegal shape identification was applied so that the symmetrical tumor could be detected. 80 cases (10 cases with brain tumors and 70 normal cases) were tested in this experiment. The results showed this system could detect brain tumors effectively and was capable of identifying a health brain pattern and mostly avoided the incorrect identification of tumors.

1. Introduction

Tumor is one of the diseases that scares people the most. Brain tumor may be considered among the most difficult tumors to treat, as it involves the organ which is not only in control of the body, but is also responsible for the self-definition of the person. During surgery or any kind of treatment, eloquent areas must not be affected in order to minimize iatrogenic risks. Therefore good diagnosis and planning of treatment choices is essential. This is why imaging technology is now of paramount importance in the evaluation of brain tumors[1]. During a wide variety of images which is available to support the physician's actions at different levels, Positron emission tomography / Computed tomography (PET/CT) is an important tool for tumor detection of brain in three dimensions. PET can provide quantitative informa-

tion on blood flow and glucose metabolism, CT can provide the anatomic structure of human brain. In addition, as image scanning becomes more widely utilized and the number of images which neuroradiologists have to diagnose has increased rapidly, the burden of a neuroradiologist increases considerably. Consequently, neuroradiologists have been demanding the new approach of "computer aided diagnosis" due to their heavy workloads in the field of neuroradiology.

Computer aided diagnosis has become one of the major research subjects in medical imaging and diagnostic radiology. The basic concept of computer aided diagnosis was proposed by the University of Chicago, in the mid-1980s, whose idea it was to provide a computer output as a "second opinion" to assist radiologists in interpreting images, so that the accuracy and consistency of radiological diagnosis could be improved, and also the image reading time could be reduced[2–4]. Since then, a number of researchers have developed computer aided diagnostic schemes for detection and classification of various kinds of abnormalities such as breast diseases[5–9], lung diseases[10–13] and the other pathologies in some organs[14–18].

In recent years, various kinds of computer aided diagnosis methods have been developed in the neuroradiology involving with PET/CT images. A com-

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mon automatic method is based on dynamic definitions of threshold values to isolate the lesion[19,20]. Zhu et al.[21] and Boudraa et al.[22] respectively proposed a new method based on Fuzzy C-Means to detect brain tumors in PET imaging; Gao et al.[23] presented a method via additive color mixtures to identify tumors using PET brain images in their research. Amir Fazlollahi et al.[24] proposed a soft segmentation approach to automatically detect brain tumors in 18F-FDOPA PET images using PET/MRI fusion by a tumor growth model. A statistical segmentation algorithm was proposed by Yong Xia et al.[25] which incorporates the prior anatomical knowledge represented by probabilistic brain atlas into the variational bayes inference to delineate the different part in brain.

In this research, a new method which achieved computer aided diagnosis of brain tumor in PET /CT image was proposed. After tilt correction using CT images, Speeded-Up Robust Features (SURF) algorithm is applied for the detection of brain tumor. Then a supplementary method based on typical illegal shape identification is utilized to re-detect the image judged as negative in the first step in order to detect the tumor which is probably missed diagnosis and symmetrical with the middle line of brain. This new method was not only capable of detecting and locating the tumors in brain but also identifying a health brain pattern and mostly avoided the incorrect identification of tumors, which indicated this system could provide efficient auxiliary diagnostic information for radiologists and remove their burden.

This paper is organized as follows. **2.** gives an introduction of imaging characteristics of tumors of the brain in PET scanning. **3.** describes the methodology which gives a description of tilt correction, asymmetrical region detection, typical illegal shape identification and detailed introduction of our proposed methodology. **4.** presents the experimental results obtained using the proposed CADs and the discussion about the advantage and limitation of this CADs. Finally, the conclusions are drawn in **5.**

2. Imaging Characteristics of Tumors of the Brain in PET/CT Scanning

2.1 PET Scanning

Functional imaging obtained by PET, which depicts the spatial distribution of metabolic or biochemical activities in the body, can be used to make a diagnosis of a tumor. During cancer inspection by a PET scan, drugs called FDG (Fluorodeoxyglucose: a glucose-mimicking radioactive element) are injected into a patient. And the gamma rays emitted from the patient are photographed by the nuclear imaging system. The PET images show the various level of absorption (SUV: Standard Uptake Value) of the FDG throughout the body. We distinguished normal and

pathological regions through the absorption levels of FDG by tissues and lesions[26].

A normal human brain exhibits an approximate bilateral symmetry with respect to the mid-sagittal plane bisecting the brain[23]. However, pathological brains with tumors often depart drastically from this bilateral symmetry. For the PET image of brain, because gray matter is sensitive to FDG uptake[27], the outside of brain with gray matter shows high SUV, and the inside of brain around the Hippocampus shows relatively low SUV. Brain tumor prevents the FDG's absorption of surrounding gray matter so that the symmetry between left brain and right brain is destroyed, as shown in Fig.1 (a) and (b). We name this kind of brain tumor as Type A, which is the common and typical pattern in brain tumor. In this case, the edge of abnormal region has smooth effect.

There are few tumors which are located inside of brain and don't make influence to grey matter great. The tumor's shape is obvious because of its high SUV in the background of low level of absorption of FDG, as shown in the Fig.1 (c). This kind of tumor is usually with obvious sharpening effect of edge. We name this type of brain tumor as Type B which includes symmetrical tumor and asymmetrical tumor.

2.2 CT Scanning

Structural imaging obtained through a CT scan provides structural information of human bodies, which can help precisely determine positions of the lesions. In the diagnosis of a tumor in the brain, it is necessary to make a tilt correction to an image of the head. In PET/CT scanning, PET and CT are synchronous tomography imaging, therefore, PET and CT images has been fused perfectly and presents the same tilt angle regarding the location of the head. Due to its higher resolution and not being influenced by a tumor's existence as severely as in a PET image, CT images are utilized for tilt correction in head in this research.

3. Methodology

According to the imaging characteristics of a brain tumor in a PET/CT scanning, we propose a computer aided diagnosis system for supporting to detect the existence of a brain tumor. During the scanning process, a person's head can tilt, this leads to a false interpretation by a CAD system or a doctor. Therefore, it is necessary to make a tilt correction to the image of the brain before diagnosis. In the diagnostic phase, 2 steps are utilized for the detecting the tumors of two patterns. Firstly, tumor detection is achieved by asymmetrical region detection in a 2D axial image. In this step, an improved SURF algorithm is proposed based on interest point detection, interest point matching and asymmetrical region identification. After this step, the most tumors could be detected. But a relatively few cases where the tumor is symmetrical with the middle line of brain can exist

Fig. 1 Left column is PET image, right column is CT image. In (a) and (b), PET images present an asymmetry due to the tumor; In (c), the PET image shows a tumor located in the middle line of the brain.

Fig. 2 Processing flow in computer aided diagnosis system

in the data which would be identified as negative in the first step. Therefore, in the second step, a supplementary method of tumor detection based on typical illegal shape identification is proposed to re-detect the image judged as negative in the first step in order to detect the tumor which is missed diagnosis. The processing flow is shown in Fig. 2.

3.1 Tilt Correction

There are two types of tilt to consider in a head scanning: tilt angle in the axial plane, known as β , and tilt angle in the coronal plane, known as α .

Fig. 3 Examples of tilt angle β in the axial plane for a CT scan (middle) and PET scan (right)

Fig. 4 Examples of tilt angle α in the coronal plane for a CT scan (middle) and PET scan (right)

- β is the angle between the mid-sagittal plane and a vertical line in the axial plane (see Fig. 3).
- α is the angle between the mid-sagittal plane and a vertical line in the coronal plane (see Fig. 4).

Let f and π be an image of a head and its symmetry plane, respectively. The function of plane π could be represented as:

$$\pi = Ax + By + Cz + D \quad (1)$$

In this function, A , B , and C are defined by the angles α and β such that:

$$A = \cos(\alpha) \times \cos(\beta) \quad (2)$$

$$B = \cos(\alpha) \times \sin(\beta) \quad (3)$$

$$C = \sin(\alpha) \quad (4)$$

D is the distance from the coordinate origin to plane π . In Fig. 5, α is the angle between the normal vector of plane π and plane xy ; β is the angle between the x -axis and the projection of the normal vector to plane xy . Here, β and α correspond to the examples shown in Figs. 3, 4, respectively.

At first the mid-sagittal plane in 3D image of the head is calculated. Finding the mid-sagittal plane can be treated as a rigid registration problem between the original image f and its reflected image r [28,29]. Our problem is a particular case of monomodal registration: both images differ by only a geometric transformation, and therefore, have the same contrast. In the following, we use the normalized sum of the squared intensity difference as a similarity measure, which coincides with the normalized cross-correlation.

Fig. 5 Definition of a plane in a coordinate system

$$\mu(\alpha, \beta, D) = 1 - \frac{\sum_{\Omega} \|f(p) - r(p')\|^2}{2 \sum_{\Omega} \|f(p)\|^2} \quad (5)$$

The point symmetry of point $p(x, y, z)$ with plane π is $P'(x', y', z')$:

$$x' = x - \frac{2A(Ax + By + Cz + D)}{A^2 + B^2 + C^2} \quad (6)$$

$$y' = y - \frac{2A(Ax + By + Cz + D)}{A^2 + B^2 + C^2} \quad (7)$$

$$z' = z - \frac{2A(Ax + By + Cz + D)}{A^2 + B^2 + C^2} \quad (8)$$

where $P'(x', y', z')$ is a point in image r .

When $\mu = \max \mu$, the degree of similarity between images f and r will be optimal and the mid-sagittal plane is located. The optimization is performed using Powell's method. After the computation of the mid-sagittal plane, a transformation is performed on the 3D brain images to achieve a tilt correction and align them with the coordinate system[30].

3.2 Asymmetrical Region Detection

Asymmetrical region detection means finding asymmetrical parts between the left and right cerebral hemisphere in a 2D axial image. An improved SURF algorithm is used for this step.

SURF (Speeded-Up Robust Feature) is a robust local feature detector, first presented by Herbert Bay et al. in 2006, that can be used in computer vision tasks like object recognition or 3D reconstruction. SURF could achieve 3 functions: 1) interest point detection 2) interest point description using the distribution of the intensity content within the interest point neighborhoods; 3) interest point matching[31]. We made an appropriate improvement to the SURF algorithm and adopted it into the process of asymmetrical region detection in PET brain images.

3.2.1 Interest Point Detection and Description

At first, each axial image was divided into a left part and a right part with respect to the middle line, and then the right part was mirrored. The left part and mirrored right part were used as the reference image and the observation image of the input data of

Fig. 6 Input data as process of key point detection and matching by SURF

the interest point detection and matching by SURF. As shown in Fig. 6.

Detection of an interest point by SURF is based on the theory of scale space, which uses the determinant of Hessian matrix to search for a local maximum. Given a point $u = (x, y)$ in an image I , the hessian matrix $H(u, \sigma)$ in u at scale σ is defined as follows:

$$H(u, \sigma) = \begin{bmatrix} L_{xx}(u, \sigma) & L_{xy}(u, \sigma) \\ L_{yx}(u, \sigma) & L_{yy}(u, \sigma) \end{bmatrix} \quad (9)$$

Where $L_{xx}(u, \sigma), L_{xy}, L_{yy}$ is the convolutions of the Gaussian second order derivative $\frac{\partial^2}{\partial \chi^2} g(\sigma)$ with the image I in point u , and similar for $L_{xy}(u, \sigma)$ and $L_{yy}(u, \sigma)$ [31]. The determinant of Hessian matrix is

$$\text{Det}(H) = L_{xx} \times L_{yy} - L_{xy}^2 \quad (10)$$

Bay et al proposed box filters to approximate second order Gaussian partial derivatives. Therefore, the (10) could be expressed as:

$$\text{Det}(H_{\text{approx}}) = D_{xx} \times D_{yy} - (0.9 \times D_{xy})^2 \quad (11)$$

After constructing a multi-scale image pyramid and then searching for the interest point on a different scale and precisely locating the interest point, the stable interest point could be obtained.

A description of an interest point contained two parts: orientation assignment and feature vector generation, which were both done on the scale σ of a feature point. Each interest point was described with a 64-dimensional vector.

3.2.2 Interest Point Matching and Fuzzy Symmetrical Region Detection

In the interest point matching step, Euclidean distance is used to determine whether the two vectors correspond to the same interest point in the left half and mirrored half. The nearest neighbor is defined as the interest point with the minimum Euclidean distance (Fig. 7). In this study, the brain image has already been tilt corrected, therefore, for each interest point we only need to choose the interest point in the adjacent area of the corresponding image, instead of scanning and matching all the interest point of an image. This can effectively reduce the mismatch rate

Fig. 7 Interest point detection and matching. Symmetrical interest points were connected by horizontal line.

and improve the efficiency of the algorithm.

For 2D PET images of the brain, all the interest points are represented by I , then

$$I = I_s + I_u \quad (12)$$

Where I_s is an interest point which has matching interest point. For the pair of interest points which are matched, it means the surroundings of matched interest points are symmetrical and tumor does not exist. I_u is an interest point which does not have a matching interest point in the other half of the picture. For I_u , the surrounding region maybe asymmetrical and the tumor probably exist. Due to less than perfect bilateral symmetry in brain, fuzzy symmetry region detection algorithm is utilized to detect tumor around this interest point.

- (1) At first, the procession of detecting tumor is from left side to right side of brain. (The slice of view is from side of the head.) For the interest point in the left side of brain image, which has not a matched one in the right side, we defined the circle region with a center point of this interest point and a radius of 20 pixels as the preliminary detection region. In Figs. 8, 9, the circles in the left side are preliminary detection region.
- (2) Finding the symmetrical circle region of a preliminary detection area with respect to the middle line. The circles in the right side are a symmetrical circles. We call this pair circle as pair-region of the preliminary detection.
- (3) Brain segmentation. The normal brain shows a high standardized uptake value (SUV) in a PET image[26], especially gray matter, which could achieve very high FDG uptake[27]. Therefore, the gray matter of brain can be extracted by threshold processing and region growing in PET imaging data. Finally a binary image is obtained by binarizing processing. In Figs. 8, 9, the blotting out part is binary image of gray

Fig. 8 Asymmetrical region detection in a normal case

Fig. 9 Asymmetrical region detection in an abnormal case

Fig. 10 The pair-region. SL is the area of foreground in left circle region, SR is the area of foreground in right circle

matter.

- (4) Mapping the pair-region onto a binary brain image. Computing the area of a foreground (the blotting out part) in the pair-region respectively. If the difference of the area of foreground between the two circles reaches the predetermined threshold, the pair-region is labeled asymmetrical regions and positive, a tumor candidate. If the difference fails the threshold, the pair-region is labeled negative and healthy. Shown in Fig. 10. If $|SL - SR| \geq \text{predetermined threshold}$, pair region was identified as positive; If $|SL - SR| < \text{predetermined threshold}$, pair region was identified as negative. Where SL is the area of foreground in left circle region, SR is the area of foreground in right circle, see Fig. 10.
- (5) Then the procession of detecting tumor is from right side to left side of brain. The procedure and parameter setting are same with steps above.

3.3 Typical Illegal Shape Identification

Most tumors could be detected by the criterion of asymmetrical characteristics of the brain in a PET scanning. However, there is possibility that very few symmetrical tumors are not detected by the first method and identified as negative, such as the tumors located in the middle of brain, or two tumors located in the left and right cerebral hemisphere respectively and symmetrical with the middle line. This kind of tumor usually has the characteristic of obvious sharp-

ening effect of edge. For this case, a supplementary method based on typical illegal shape identification was designed to re-detect the image judged as negative in the first step in order to detect the tumor which is missed diagnosis.

3.3.1 Edge Detection

Canny detector is utilized to extract the edges in the whole brain image. Canny detector firstly does a Gaussian filter to the images, and then traces edges through the image using hysteresis thresholding. Since the tumor has an obvious sharpening effect of edge, Canny detector could maintain the integrity of the edge of a tumor as much as possible, including the curved edge. For normal tissue in brain, due to the less sharpening effect of edge than tumor, their edges are usually shown as short line segment, long horizontal line segment or long vertical line segment after processed by Canny detector, curved egde of normal tissue could not be identified, as shown in Fig. 11 (b) and Fig. 12 (b).

3.3.2 Rectangle Identification

- Each edge is shown in a rectangle which was obtained by contour tracing algorithm. Shown in Fig. 11 (c) and Fig. 12 (c). Due to the integrity of the edge of a tumor was extracted as much as possible because of its obvious sharpening effect of edge, tumor's edge should be encompassed in a relatively large rectangle; while for normal tissue, due to the less sharpening effect of edge than tumor, the rectangle of normal while for a rectangle of normal tissue's edge, long boundary will not appear both in the horizontal and vertical position, thus the rectangle is relative small or narrow.
- If both length of boundary at horizontal and vertical position in a rectangle reach the pre-determined threshold, the region is judged as tumor, or else, as negative, it is a normal object.

4. Experimental Results and Discussion

4.1 Image Data

All PET/CT images used in this study were obtained from Atsuchi Neurosurgical Hospital PET Center. The use of these images was allowed by the ethics committee of this hospital. The data was stored in DICOM format and the resolution was 168×168 pixels for the PET images and 512×512 pixels for the CT images. The diagnosis of the cases was as follows: 10 cases with tumor in the brain and 70 normal cases. See Tables 1, 2. About the parameters settings, we decide the parameter by empiric with the sufficient margin.

4.2 Experimental Results and Analysis

Of the 420 slices in 10 cases with brain tumors and of 3165 slices in 70 normal cases, 42 slices con-

Fig. 11 (a) is an original brain image with a tumor located around the middle line; (b) is the edge image after Canny detector; (c) is the image after rectangle identification of brain inside

Fig. 12 (a) is an original normal brain image; (b) is the edge image after Canny detector; (c) is the image after rectangle identification of brain

Table 1 List of abnormal case data used in evaluation

ID of abnormal case	Number of all slices	Number of slices with tumor of asymmetrical characteristics/ number of slices detected as positive	Number of slices with tumor of typical illegal shape characteristics/ number of slices detected as positive
1	40	10/10	—
2	36	3/2	—
3	38	9/5	—
4	39	3/2	—
5	48	1/1	—
6	54	3/1	—
7	47	4/3	—
8	41	2/2	—
9	40	2/1	—
10	37	4/4	1/1
Total	420	41/31	1/1

Table 2 List of normal case data used in evaluation

Number of normal cases	Number of normal slices
70	3165

tained brain tumor. 1 slice contained a symmetrical tumor which is located in the middle line of brain (Fig. 11), the other 41 slices contained asymmetrical

Table 3 Results of tumor automated diagnosis with slice as statistical unit

–	Only asymmetrical region detection	Only typical illegal shape detection	Combination of two methods in CADS
True positive	31	1	32
False positive	15	0	15
True negative	3528	3543	3528
False negative	11	41	10
Sensitivity and Specificity of CADS			
Sensitivity	0.7619	Specificity	0.9958

Table 4 Results of tumor automated diagnosis with individuality as statistical unit

–	Only asymmetrical region detection	Only typical illegal shape detection	Combination of two methods in CADS
True positive	10	1	10
False positive	10	0	10
True negative	60	70	60
False negative	0	9	0
Sensitivity and Specificity of CADS			
Sensitivity	1.00	Specificity	0.8571

tumor. 32 slices were correctly identified with tumor (true positive), 15 slices were incorrectly identified with tumor (false positive), 3528 slices were correctly identified with no tumor (true negative), and 10 slices were incorrectly identified with no tumor (false negative). Shown in Table 3.

If the statistical unit is individuality, as shown in Table 4, all 10 cases with brain tumors could be detected (true positive). Of 70 normal cases, 60 cases were correctly identified with no tumor (true negative), 10 cases were incorrectly identified with tumor (false positive).

The sensitivity is 1.0 with the individuality as the statistical unit, and 0.7619 with the slice as the statistical unit. This indicates to us the new CADS is capable of identifying if the patient had a brain tumor, but not fully able to recognize all slices caused by tumors. The most common error occurred when the image was ambiguous so that the tumor's intensity was similar to the brain tissue. Due to the nature of PET imaging with high noise to signal ratio,

some slices with a tumor were too ambiguous to detect asymmetrical regions successfully.

The specificity is 0.8571 with the case as the statistical unit, and 0.9958 with the slice as the statistical unit. This indicates that this method was capable of identifying a health brain pattern and mostly avoided incorrect identification of tumor. The error happened where the brain showed extremely blurring symmetry in its structure so that the normal brain pattern was identified incorrectly.

In Tables 3, 4, the experimental result of each method utilized exclusive to the dataset is listed. It shows the first method is keen to detect the existence of asymmetrical tumor, but it could not detect symmetrical tumor. The second method is capable of finding the tumors with obvious sharpening effect of edge but it is not sensitive to detect the asymmetrical tumor so that a lot of false negative will be induced. Therefore we combine the two methods together in CADS. Firstly, tumor detection is achieved by asymmetrical region detection in a 2D axial image. Then the supplementary method based on typical illegal shape identification is applied to re-detect the image judged as negative in the first method so that it could reduce the number of false negative.

4.3 Discussion

4.3.1 Comparative Experiment

The proposed method is a fully automatic computer aided diagnosis system to support the detecting the existence of tumor in the brain from PET/CT images. If the common method of mirroring operator is utilized for tumor detection, the result is not satisfying as shown in the Figs.13, 14, Tables 5, 6. About comparative method, without title correction, the main brain part is segmented by the same method with the part 3.2.2 (3). Then subtraction operator is applied to the segment brain image and its mirroring image.

In experiment using mirroring method, a large number of false positive were created due to not perfectly symmetry between the left and right cerebral hemisphere and head tilt during scanning.

Fig.13 shows the experimental result of CADS and mirroring method in an abnormal case. Fig.13 (b) is the result of CADS, only asymmetrical regions are labeled with circles. Fig.13 (c) is the result of mirroring method. Although tumor region (the big detected region) is detected by mirroring method, many false positive regions (the small detected regions) also are produced.

Fig.14 shows the experimental result of CADS and mirroring method in a normal slice. Fig.14 (b) is the result of CADS, abnormal region is not found in the slice and this slice is labeled as negative; Fig.14 (c) is the result of mirroring method, many false positive regions are produced in the slice and this slice is labeled as positive (all the detected regions are false positive).

Fig. 13 Experimental results of two methods in an abnormal case. (a) is an original image with brain tumor; (b) is the experimental result of new CADS, asymmetrical regions are labeled with circles; (c) is the experimental result of mirroring method. Although asymmetrical regions are detected (the big detected region), many false positive regions also are produced (the small detected regions)

Fig. 14 Experimental results of two methods in a normal case. (a) is a normal original image; (b) is the experimental result of new CADS, no positive region is labeled; (c) is the experimental result of mirroring method, many false positive regions also are produced (all the detected regions are the false positive)

In mirroring method, false positive appears in almost every slice (Table 6); Although this method's sensitivity is very high (both 1.0 with the individuality and slice as the statistical unit), however, it is almost meaningless because of its so low specificity (0.1278 with the slice as the statistical unit and 0.0857 with the individuality as the statistical unit). It means this method could not reduce the burden of reading image for radiologist because of a large number of normal slice targeted as abnormal.

Comparing with the mirroring method, the new CADS's advantage is capable to detect the existence of brain tumor, meanwhile resist the number of false positive, so it achieves an effective balance between sensitivity and specificity. Therefore the new CADS could assist radiologists in interpreting image and provide efficient auxiliary diagnostic information for radiologists, so that the accuracy and consistency of radiological diagnosis could be improved, and also the image reading time could be reduced and reading burden could be removed.

4.3.2 Adaptable Pattern and Limitation

This CADS is consist of two diagnosis methods: asymmetrical region detection and typical illegal shape identification. The adaptable pattern of method is following and Table 7:

- Method of asymmetrical region detection. It is capable of detecting most brain tumors, including tumors in Type A and asymmetrical tumors

Table 5 Results of tumor automated diagnosis with slice as statistical unit in comparative experiment

Statistical unit	True positive	False positive	True negative	False negative
Slice	32	3099	454	0
Sensitivity	1.0	Specificity	0.1278	

Table 6 Results of tumor automated diagnosis with individuality as statistical unit in comparative experiment

Statistical unit	True positive	False positive	True negative	False negative
Individuality	10	64	6	0
Sensitivity	1.0	Specificity	0.0857	

Table 7 Description of adaptable patterns in method

	Method of asymmetrical region detection	Method of illegal shape identification
Which type of tumor is aimed at	Type A and asymmetrical tumor in Type B	Symmetrical tumor in Type B
Characteristic in PET imaging	Asymmetry of brain in 2D slice	Obvious sharpeing effect of edge in tumor
Role in this CADS	Major	Complementary

in Type B (Mentioned in 2.1). It plays a major role in this CADS.

- Method of illegal shape identification. It is capable of detecting symmetrical tumors in Type B. It plays a complementary role in this CADS.

In addition, there is a limitation in this study. The number of experimental dataset is small; especially, from cooperative hospital we obtained the only 1 case with symmetrical tumor which locates in the middle line of brain. In the future we will improve the accuracy of experiment with more cooperation with hospital, such as obtaining more image data for experiment and achieving cross validation.

5. Conclusion

In this research, we developed and configured a computer aided diagnosis system to support detecting the existence of tumors in the brain from PET/CT images. We made use of the PET/CT scanning image, in which the CT imaging data was used to make

the tilt correction, while the PET imaging data was used to detect brain tumors. Tumor detection was first accomplished by examining the asymmetrical region in a slice of the brain. During this diagnostic stage, an improved SURF algorithm was used to extract and match interest point from the left hemisphere and right hemisphere, and then detect the asymmetrical regions of a brain image. After that, a supplementary diagnosis based on typical illegal shape identification is applied. Experimental results showed that this system could detect tumors and avoid incorrect identification of tumors in health data, which indicated this method could assist radiologists in interpreting image and provide efficient auxiliary diagnostic information for radiologists, so that the accuracy and consistency of radiological diagnosis could be improved, and also the image reading time could be reduced and image reading burden could be removed.

This research will serve as a base for future studies of CAD systems for brain tumors. In the future, more methods will be included to enhance the accuracy and precision of algorithm and experiment with more cooperation and communication with hospital.

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