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Medical Image Registration using Cascaded Pulse Coupled Neural Networks

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Abstract: This study presented a novel image registration algorithm for Magnet Resonance Image (MRI) using cascaded Pulse Coupled Neural Networks (PCNNs). Firstly, the two unregistrated images' barycenters and foveation points are extracted respectively. Next, obtaining some clustering centers of the extracted foveations via fuzzy C-Means clustering (FCM) algorithm. Finally, using barycenter as coordinate origin and the corresponding clustering centers of foveations as characteristics to build coordinate system and attain the correlative registration parameters. The experimental results show that registration accuracy of the proposed algorithm is 95.7%. Meanwhile, it is robust and effective for MR image registration.

Key words: Pulse coupled neural networks, magnet resonance image registration, foveations, fuzzy C-Means clustering

INTRODUCTION

In last decades, medical images have been widely applied in physic and other correlative fields, such as clinical diagnosis, pathology analysis and healing examinations etc. Comparing to traditional CT image, MR image has some inherent advantages. For instance, it can obtain clear parenchyma images using proton to achieve biological vivo imaging (Matsopoulos *et al*., 1994). Therefore, the investigation of multimodal MR image has attracted more attentions because of the increasing clinical demands (Wang and Ma, 2008). Although image fusion is a critical aspect in MRI, image Registration is the prerequisite for image fusion. For this reason, MR image registration becomes the key process to the subsequent image analysis and clinical applications (Li and Ragini, 2011).

Image registration is to overlay images (two or more) of the same scene taken at changeable times, from various viewpoints, or by different sensors. Currently, kinds of achievements have been made in image registration and various registration methods have been presented according to their nature (Zitova and Flusser, 2003; Ravichandran and Ravindran, 2007). Generally speaking, the purpose of medical image registration is to attain the maximal similarity of pixel intensity using appropriate optimization methods. However, the registration results of these optimization methods are hardly satisfied, particularly when there are translation, scale and rotation bias conditions (Mouravliansky *et al*., 1998). With this in mind, a novel MR image registration algorithm is proposed because of the great foveation points detection ability of PCNN.

The foveation points detection is a movement process that human eyes move restlessly to get the information from an object (Tanaka *et al*., 1999). These foveation points are generally corners and, to the lesser extent, the edges (Kinser, 1999). The corners and edges of the PCNN segments are similar to the foveation points, which results in its perfect foveations detection ability of PCNN, combining with its translation, rotation, scale, distortion and intensity signal invariance (Johnson, 1994), which is original motivation of the proposed algorithm. The new algorithm has been applied to the MR image registration successfully and has strong anti-noise performance.

CASCADED PCNN MODEL DESCRIPTION

Simplified PCNN model: The cascaded PCNN model included two parts: the simplified PCNN model and modified PCNN model. The PCNN was originally presented by Eckhorn in order to explain the synchronous neuronal burst phenomena in the cat and other little mammals' visual cortex (Eckhorn *et al*., 1990). With the progress in research, PCNN has been widely applied in the image processing realm (Gu *et al*., 2004; Ranganath and Kuntimad, 1999; Karvonen, 2004). The

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neuron consists of three parts: dendritic tree receptive field, the linking modulation field and the pulse generator field. Now, the common PCNN used in the image processing is a model improved by Lindblad and Kinser on the basis of Eckhorn's original model (Lindblad and Kinser, 1998). The adjustment of this model parameters is very inconvenient in every computational iteration, therefore, in this paper, we will employ a simplified PCNN model for ameliorating. The single neuron model of simplified PCNN is shown as Fig. 1.

The mathematic expressions of the simplified PCNN system can be described as follows:

$$F_{ij} = I_{ij} \tag{1}$$

$$L_{ij}(n) = \sum w_{ijkl} Y_{kl}(n-1) \tag{2}$$

$$U_{ij}(n) = F_{ij}(n)\,(1+\beta L_{ij}(n)) \tag{3}$$

$$Y_{ij}[n] = \begin{cases} 1, U_{ij}[n] > \theta_{ij}[n] \\ 0, U_{ij}[n] \le \theta_{ij}[n] \end{cases} \tag{4}$$

$$\theta_{ij}(n) = \exp(-\alpha_\theta)\,\theta_{ij}(n\text{-}1) \tag{5}$$

where, F_{ij}, I_{ij}, L_{ij}, U_{ij}, θ_{ij} and Y_{ij} are the feeding input, external input stimulus (neuron corresponding pixel value), linking input, internal activity, dynamic threshold and output of the neuron ij, respectively; the linking coefficient w_{ijkl} among surrounding neurons is local gaussians; the constant β is the linking strength; α_θ is decay coefficient; n represent iterations. In addition, the neuron neighborhood size is 3×3, each neuron can fire and create pulse only once during a pulsing cycle in the simplified model.

The whole behaviors of the PCNN can be described as: each pixel in input image is treated as a neuron and its intensity is an external stimulation input I_{ij}. The initial state of all neurons is zero, the internal activity U_{ij} is equal to the external stimulation input I_{ij} at first iteration. The threshold θ_{ij} of all neuron begin to attenuate from initial state and one neuron will fire and output a pulse, while its threshold decreases to less than U_{ij}. Meanwhile, the threshold θ_{ij} of this neuron rapidly increases to ensure it will not be re-activated in this pulsing period. Moreover, the neighboring neurons stimulate its neighboring neurons to be fired in succession and will yield a pulse wave propagating faraway at activation areas. For image processing, those adjacent pixels with similar intensity will incline to synchronously fire.

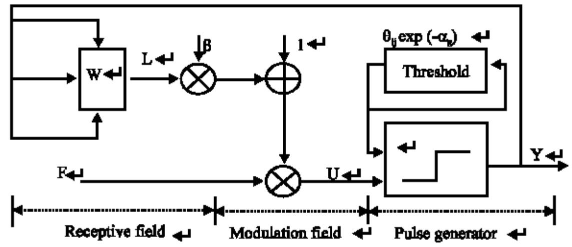

Fig. 1: Simplified PCNN neuron model

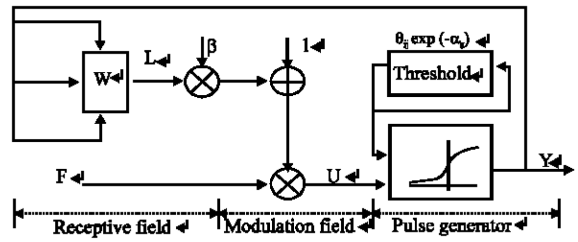

Fig. 2: Modified PCNN neuron model

Modified PCNN model: Image foveation point detection is actually the process of object peak detection. The simplified PCNN model, its each output is only 0 and 1, which is quite simple to select maximum points of object. Thus, there will generate a large number of foveation points which is very unfavorable to subsequent clustering and characteristic points selection. Nevertheless, the modified PCNN model is very helpful to overcome this shortcoming because its output is analogue value, from 0 to 1, i.e., using the sigmoidal pulse generator to substitute step function output of simplified PCNN model. Then, high quality foveations could be obtained by setting an appropriate threshold. We call this model the modified PCNN, its sigmoidal pulse generator function is expressed with Eq. 6:

$$Y_{ij}(n) = \frac{1}{1+\exp[-\gamma\,(U_{ij}[n]-\theta_{ij}[n])]} \tag{6}$$

The single neuron model of modified PCNN is shown in Fig. 2.

The difference of modified PCNN's from the above simplified PCNN model is its pulse generator, its output is sigmoidal function. The working mechanism can be explained with Eq. 1-6. In Eq. 6, parameter γ is for the sigmoidal function and the others mean as same as in the above simplified PCNN, including its dynamic behavior.

PCNN FOVEATIONS DETECTION ALGORITHM AND EXPERIMENTAL RESULTS

Modified PCNN'S foveations detection algorithm: The foveation point detection algorithm relies heavily on the inherent ability to segment an image of the PCNN. The original image, as an input to PCNN and each iteration will produce a binary image. After several iterations, segmentation result outputs a series of binary images and a specific binary image as the best result has to be screened from these binary images. Usually, the pixels corresponding to image background are first fired and others are the required object pixels. In the process of image foveation point detection processing, only object pixels will be considered in the next step.

The main idea of the object foveation point detection is related to 4 procedures, i.e., 1 input images preprocessing, including reference image and transformed image; 2 segment input image using simplified PCNN and find out object of input image after several iterations; 3 filter object image-the final fired binary image and 4 detect the object image peak with modified PCNN model by setting 0.8 as the threshold.

The detection algorithm flowchart is shown in Fig. 3.

Experimental results: Two experiments are presented here to exhibit the effectiveness of foveations algorithm. First, we obtain a gray level image from Harvard medical school image library (http://www.med.harvard.edu/ AANLIB/). The reference image is a brain tissue MR image with 256×256 pixels, the transformed image is reference image which is rotated 10 degree clockwise. Based on the description of foveations algorithm earlier, the experimental results are shown as follows:

Figure 4a is original reference image, Fig. 4b is original transformed image and the corresponding gray images are given in Fig. 4c and d, respectively. The following step is image segmentation algorithm based on simplified PCNN to produce a series of segmented binary images, including the required object region image shown in Fig. 5 and 6.

From Fig. 5 and 6 we can see each iteration result of reference image, transformed image. The a1-a12 of Fig. 5 and 6 show the single iteration outputs and the corresponding b1-b12 show the accumulative effects of multiple iterations. The suffix number represents iteration time. Some regions of input images are not always motivated until the last iteration. According to the previous foveation point detection theory, we believe that these regions are the required object regions. Considering the invariant characteristics of PCNN in its inherent translation, rotation, scale and distortion, these foveation points will surely inherit the invariant characteristics of PCNN. This is the reason why we use foveation point as the characteristics to achieve the image registration besides the barycenter. Foveation point detection results are demonstrated in Fig. 7a and d.

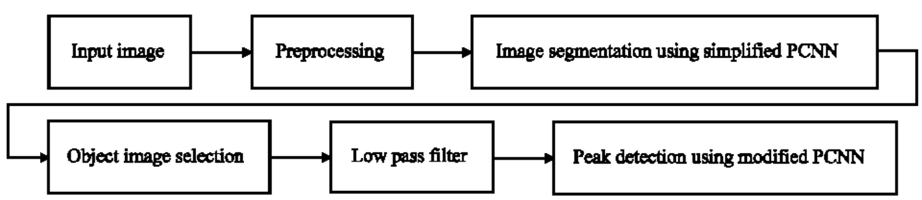

Fig. 3: The foveations detection algorithm flowchart

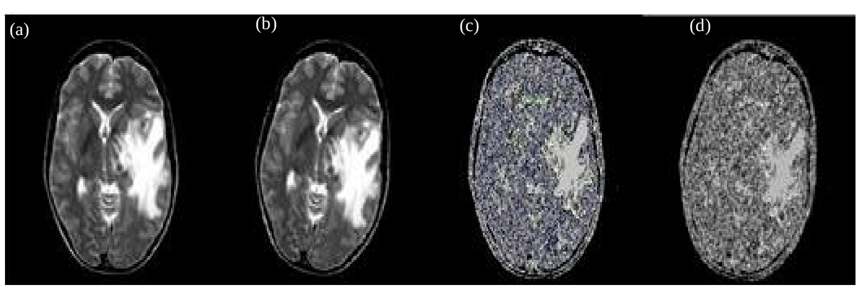

Fig. 4 (a-d): Reference image and transformed image

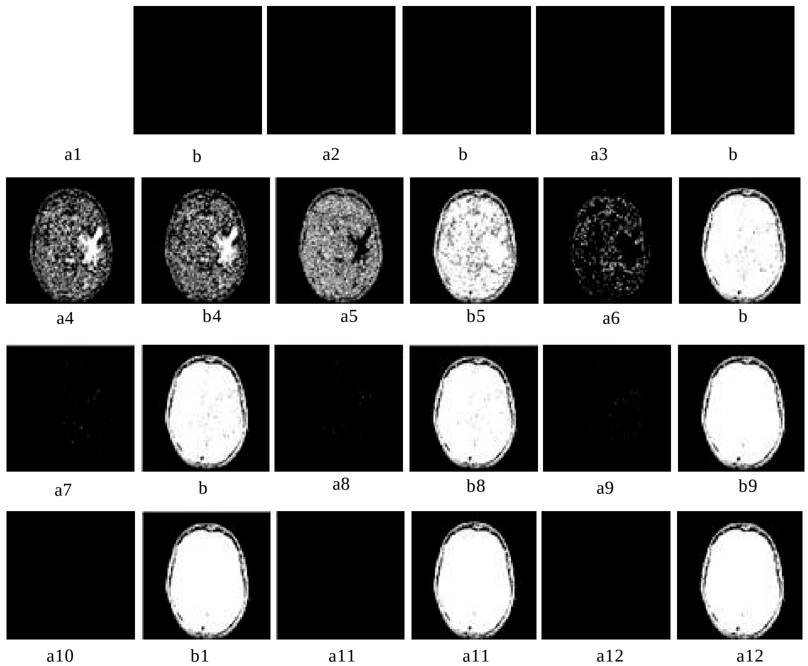

Fig. 5: Segmentation images of reference image

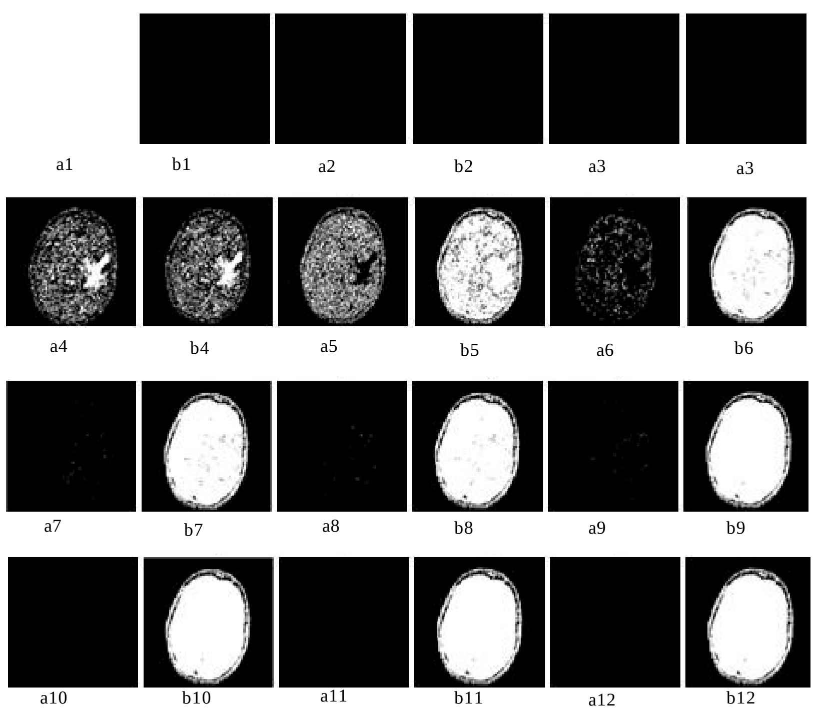

Fig. 6: Segmentation images of transformed image

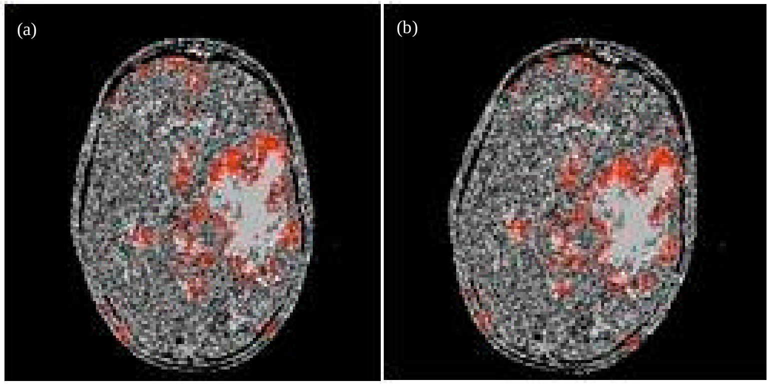

Fig. 7(a-b): Foveation detection results; (a) Foveation of reference image and (b) Foveation of transformed image

MR IMAGEREGISTRATIONALGORITHM

Registration algorithm description: In order to improve registration precision and implement registration process fast, we need to obtain certain clustering centers of these foveation points as the essential characteristics and combine with barycenter in physics that has also the invariant characteristics of translation and rotation to complete registration process. The main points of registration algorithm as follows:

Step 1: Obtain clustering centers of image foveation points using fuzzy C-Means clustering algorithm as characteristics

Step 2: Take barycenter as the coordinate origin and vertical downward direction as the positive direction to establish a coordinate system

Step 3: Divide the whole coordinate system into eight parts symmetrically

Step 4: Gather the number of clustering center in every part and remain one-to-one correspondence. Whenever it is a blank, the corresponding part should be marked zero; if there are more than one points, taking the center of these points. This is the key step and will affect the final registration precision

Step 5: Calculate angle difference of corresponding parts, using its average value as the final registration parameter

Figure 8 is the corresponding algorithm procedure.

Computing the registration parameters: The barycenter is the rotation center of an image and it has a fixed position which doesn't change with the changes of the whole image. Hence in this study, we pick out it as the coordinate origin. According to previous registration algorithm, the every clustering center is considered as a characteristic point of the reference image and transformed image. Although the translation transformation is synchronous with image rotation, for multimodal MR image, there is no singular translation except for image rotation induced translation. The translation of the image barycenter is very small among the multimodal MR images, can be negligible here. Therefore, the rotation angle becomes the focus. A tiny translation will not affect the registration result in the condition of little angle rotation occurring. After taking rotation operation, the transformed image will match reference image well.

The registration parameters will be computed following the steps below. Firstly, the whole object region barycenter is computed as coordinate origin and vertical downward direction as positive direction to establish a coordinate system. Secondly, dividing the whole coordinate system into eight parts symmetrically and connecting every clustering center to corresponding coordinate origin to calculate the angles relative to the positive direction. Finally, calculating the average of differences ($\Delta\alpha$) relative to positive direction as the final rotation parameter to achieve registration process. An example is shown in Fig. 9.

Simulation experiment results and analysis: On the basis of aforesaid, Fig. 7 obtaining the clustering centers of every foveation image as characteristics and labeled in blue star shape and the corresponding image barycenter is labeled by a red cross. Figure 10 clearly verifies the foveation points' invariance characteristics of translation and rotation.

In this study, the image barycenter is used as coordinate origin. Generally, it has a fixed position in the

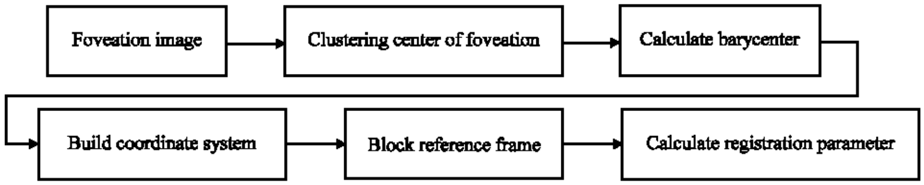

Fig. 8: Registration algorithm flowchart

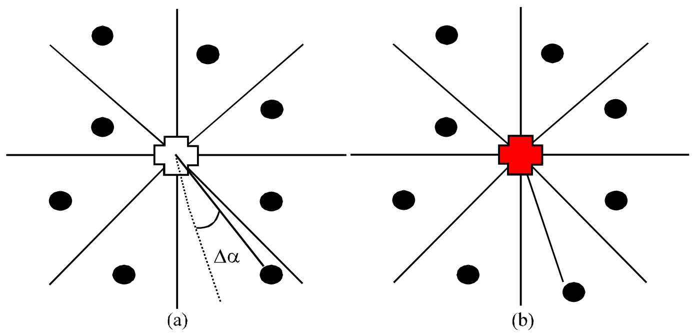

Fig. 9 (a-b): (a) The distribution for the barycenter and clustering centers of reference image and (b) The distribution of the barycenter and clustering centers of transformed image

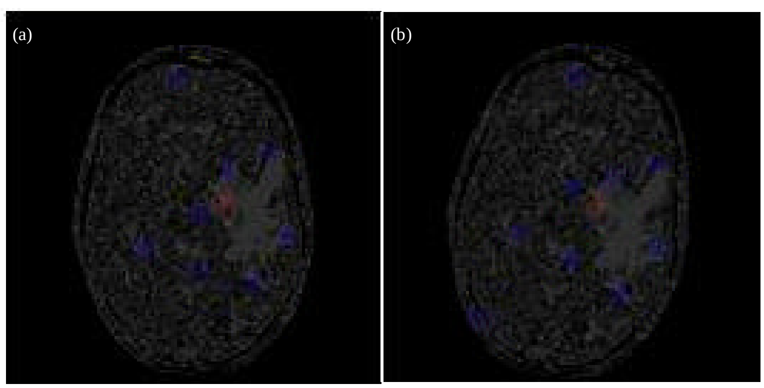

Fig. 10 (a-b): Characteristics of reference image and transformed image, respectively; (a) Referring image and (b) Fransformed image

Table 1: The registration result with rotation bias

Standard parameter	Angle degree differences of the corresponding parts, Eight parts (counterclockwise rotation from the positive direction): 1	2	3	4	5	6	7	8	Registration result (β)
10	7.5365	7.2142	0	6.1440	15.7367	23.2270	0.1136	7.0218	9.5706

image and is believed that both the translation Δx and Δy are equal to zero. The registration results are listed in Table 1, where the angle unit is degree. The rotation parameter is denoted as β.

The translation and rotation always appear synchronously but rotation angle is a main problem to multimodal MR image registration. Table 1 shows the typical result of registration which with certain rotation bias. Here, we select relative error and registration precision as the algorithm evaluation criteria, the evaluation parameter σ in Qiu's method is meaningless in the condition of only rotation bias (Qiu *et al*., 2007).

Table 2: The contrastive results

Algorithm	Registration precision (%)	Relative error (%)
The proposed method	95.7	4.3
Qiu's method	92.1	7.9

Comparing to Qiu's registration method, the proposed method reveals a significant superiority. Table 2 gives the contrastive results.

Although the result from the proposed method is satisfied, still some unsatisfied problems exist. Firstly, if the rotation angle is very small, we have to divide coordinate system into parts as more as possible for improving the registration precision. Then, FCM algorithm requires a large amount of calculations; especially there are a large number of foveation points. Finally, when difference of corresponding point in the same part is 45 degree or 135 degree, the rotation invariance of PCNN will become weaker (Muresan, 2003; Zhang and Wu, 2008), this is bound to affect the final registration precision. Researches, for solving these problems, should be carried out sooner in the interest of obtaining an improved registration algorithm.

CONCLUSIONS

Taking advantage of the invariant characteristics of translation, rotation and distortion in PCNN, this study proposed a novel MR image registration algorithm. Experimental results indicate that the proposed algorithm is very effective and has a strong robust. Moreover, it can independently select some foveations as the final characteristics according to object region traits.

For an image, its barycenter position is more relatively fixed and the foveations of object region will surely inherit PCNN's invariant characteristics, so the proposed algorithm is effective and steady. Besides medical images, this method can be applied to other types' images. With the development of clustering algorithms, this method will be further improved and computational load will be reduced greatly. At the same time, registration accuracy will also be enhanced significantly.

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