International Journal of Computer Theory and Engineering, Vol. 3, No. 2, April 2011
ISSN: 1793-8201

Implementation of Radial Basis Function for fMRI Registration

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Abstract—**This paper presents functional magnetic resonance imaging (fMRI) slice registration. Radial basis function (RBF) network is used for registering auditory cortex slices. Training the network is done with co-ordinates of the selective points (feature points) from two images at a time (source and target images). The input layer is given with coordinates of the selective points of the source image and in the output layer, the labeling is given as the coordinates of the selective points of the target image. Accuracy of registration depends on the amount of distortion present.**

Index Terms*—*Radial basis function, functional magnetic resonance imaging, Heschl's gyrus, auditory cortex

I. Introduction

Image registration involves spatially transforming the target image to align with the reference image. One of the images is referred to as the reference or source and the second image is referred to as the target or sensed. Image registration is an important task in scanned medical images. Registration helps in 3D volume reconstruction. Images taken from different equipment can be registered to compensate missing information. In X-ray computed tomography (CT), magnetic resonance imaging (MRI) is anatomical imaging with high spatial resolutions. The physiological information is limited. In single photon emission computed tomography (SPECT) and positron emission tomography (PET) physiological information can be provided.. It would be advantageous to combine images from multi-modality images so that the resulting image can provide both physiological and anatomical information with high spatial resolution for use in clinical diagnosis and therapy [1]..

In general, the registration method consists of the following steps:

- Feature detection. Salient and distinctive objects (closed-boundary regions, edges, contours, line intersections, corners) are manually automatically detected. These features can be represented by their point representatives (centers of gravity, line endings, distinctive points), which are called control points (CPs).
- Feature matching. The correspondence between the features detected in the sensed image and those detected in the reference image is established. Various feature descriptors and similarity measures along with spatial relationships among the features are used.
- Transform model estimation. The type and parameters of the mapping functions, aligning the sensed image with the reference image, are estimated. The parameters of the mapping functions are computed by means of the established feature correspondence.
- Image resampling and transformation. The sensed image is transformed by means of the mapping functions. Image values in non-integer coordinates are computed by the appropriate interpolation technique.

Registration of medical image data sets is the problem of identifying a set of geometric transformations which map the coordinate system of one data set to that of the others. Depending on the nature of the input modalities, identification between uni-modal and multi-modal cases should be done according to whether the images being registered are of the same type or not. The multimodal registration [6] scenario is more challenging since the corresponding anatomical structures will have differing intensity properties.

When designing a registration framework, one needs to decide on the nature of the transformations that will be used to bring images into agreement. One must also evaluate the quality of alignment given an estimate of the aligning [10] transformation.

Objective functions or similarity measures are special-purpose functions that are designed to provide these essential numerical scores. The goal of a registration problem can then be interpreted as the optimization of such functions over the set of possible transformations. In general, these problems correspond to multidimensional non-convex optimization problems where we cannot automatically get the solution. Thus an initial estimate of the aligning transformation is needed before the search begins. Statistical methods include maximum likelihood, maximum mutual information, and minimum joint entropy methods [9].

Similarity measures are representative of a significant group of currently used registration algorithms. Many registration approaches either directly employ or approximate one of these measures. While the analysis presented here carries straightforwardly to registration of multiple data sets, for simplicity. The goal of registration is to find an estimate of an aligning transformation which optimizes some objective function of the observed data sets.

The maximum likelihood (ML) method of parameter estimation has served as the basis for many registration algorithms [8]. Its popularity in parameter estimation can be

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ISSN: 1793-8201

explained by the fact that as the sample size increases, ML becomes the smallest variance unbiased estimator. Analysis of the method is however useful for comparison purposes. According to the classical ML approach, the entire manifold of joint models is known and available for the optimization task [7]. According to the ML criterion, obtain estimates by varying some parameters of a probabilistic model that is being evaluated on a set of observed data. In the case of registration problem, the optimal geometrical transformation that explains the observations according to the ML criterion satisfies the (normalized) log-likelihood criterion

II. Materials and Methods

A. Neural Network Structures

The neural network with Radial basis function [2][3] is used for learning the images [4][5]. The number of neurons in the input layer is 4 number of neurons in the output layer is 6.

Input layer description

Node 1 = x coordinate of point in image 2(target image)
Node 2 = y coordinate of point in image 2(target image)
Node 3 = x coordinate of point in image 1(image to be registered with target image)
Node 4 = y coordinate of point in image 1(image to be registered with target image)

Output layer description

Node 1= vertical shift
Node 2= upward(1) or downward(2)
Node 3=horizontal shift
Node 4= left(1) or right(2)
Node 5= angle with respect to axis passing through centre of the image
Node 6= left(1) or right(2)

The hidden layer has been trained with different number of nodes increasing from 2 neurons.

Table 1 shows the direction of rotation among pixel coordinates of source (reference) and target (sensed) image. The size of the image is 63 rows by 63 columns. The term 'T' coordinate in target image and 'S is the pixel coordinate in the source image. Curved arrow to the right is the clockwise direction and the curved arrow to the left is the counter clockwise direction.

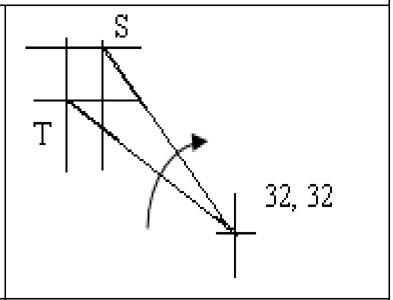
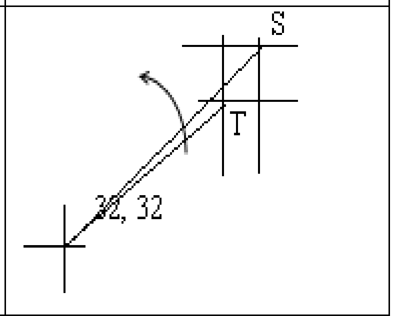
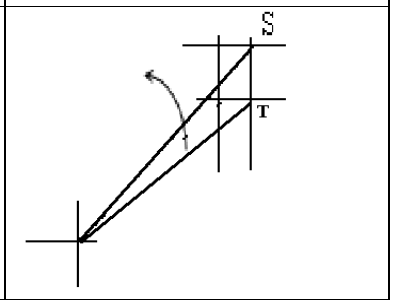
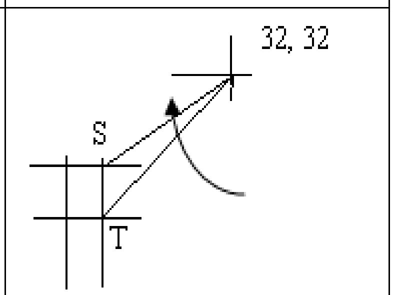
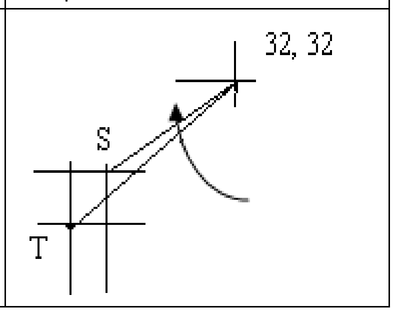
Table 2 presents 10 sample pixel coordinates that is used for training the network. For testing the network, the same sample points and new points are presented.

The description of Table is as follows.
Column 1 = pattern number
Column 2= x coordinate of points in target image
Column 3= y coordinate of points in target image
Column 4= x coordinate of points in source image
Column 5= y coordinate of points in source image
Column 6= shift in rows
Column 7= Upward or downward translation
Column 8= shift in columns
Column 9 = Horizontal translation
Column 10= Rotation of source pixel coordinate with respect to corresponding target pixel coordinate
Column 11= Clock wise or counterclockwise rotation

B. Radial Basis function

The concept of distance measure is used to associate the input and output pattern vectors. Radial Basis Functions (RBFs) are capable of producing approximations to an unknown function 'f' from a set of input data. The approximation is produced by passing an input point through a set of basis functions, each of which contains one of the RBF centers.

TABLE 1 DIRECTION OF ROTATION

1	
2	
3	
4	
5	

Training RBF [11]

Step 1: Apply Radial Basis Function.
No. of Input = 4
No. of Patterns = 10
No. of Centres = 3

Calculate RBF as
RBF = exp (-X)
Calculate Matrix as
G = RBF
$A = G^T * G$
Calculate
$B = A^{-1}$
Calculate
$E = B * G^T$
Step 2: Calculate the Final Weight.
F = E * D
Step 3: Store the Final Weights in a File.

Testing RBF
Step 1:. Read the Input
Step 2: Read the final weights
Step 2: Calculate.
Numerals = F * E
Step 3: Check the output and calculate entropy

III. Image Registration

Characteristic points in image 1(Reference image) and image 2(image to be aligned with reference image) are defined. Characteristic points are important points through maximum alignment can be done. By this, unnecessary points choosing can be avoided and hence the RBF can learn with less number of patterns. During training, the x, y coordinates of the characteristic points of image 1 and image 2 are inputs in the input layer and the horizontal, vertical shifts along with angle are given in the output layer.

Implementation steps:
Training
Step 1: Identify characteristic points in image 1 and image 2.
Step 2: Calculate horizontal shift, vertical shift and rotation angle.
Step 3: Generate training patterns with the information obtained in step 1 and step 2.
Step 4: Train RBF with training patterns.
Testing
Step 5: Present the same set of characteristic points and obtain values in the output layer. Find the error between obtained and actual values.

TABLE 2 Patterns used for training and testing RBF

	Input pattern				*Target pattern*					
	Reference image		*Image to be aligned*		*Translation (pixel)*				*Rotation (degrees)*	
Pattern number	*x*	*y*	*x*	*y*	*Vertical shift*	*Upward(1) Downward(2)*	*Horizontal shift*	*Left(1) Right(2)*	*Angle rotated*	*Direction CW(2) / CCW(1)*
1	3	14	1	17	2	1	1	2	3.05	2
2	5	41	3	42	2	1	1	2	0.59	1
3	22	47	19	48	3	1	1	2	5.4	1
4	34	47	32	48	2	1	1	2	7.59	2
5	38	18	36	18	2	1	0	0	7.25	1
6	28	6	27	7	1	1	1	2	2.56	2
7	48	14	47	15	1	1	1	2	0.2	2
8	49	45	48	45	1	1	0	0	1.68	1
9	36	62	35	62	1	1	0	0	1.88	1
10	13	57	12	58	1	1	1	2	0.33	1

IV. Results and Discussions

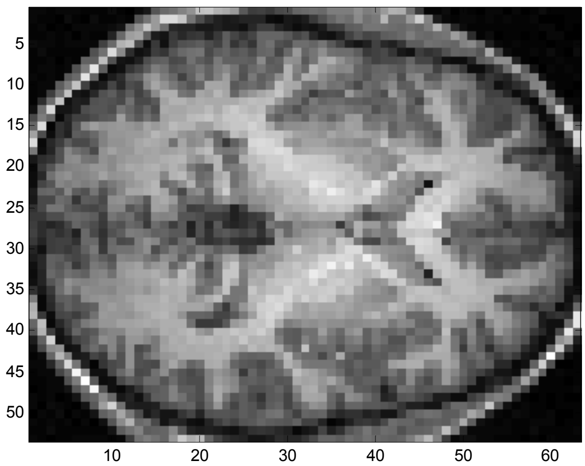


Fig.1 Heschl's gyrus, auditory cortex(image to be aligned)

The fMRI have been obtained with standard setup conditions. The magnetic resonance imaging of a subject was performed with a 1.5-T Siemens Magnetom Vision system using a gradient-echo echoplanar (EPI) sequence (TE 76 ms, TR 2.4 s, flip angle 90 , field of view 256 - 256 mm, matrix size 64 * 64, 42 slices, slice thickness 3 mm, gap 1 mm), and a standard head coil. A checkerboard visual stimulus flashing at 8 Hz rate (task condition, 24 s) was alternated with a sound (control condition, 24 s). In total, 110 samples (3-D volumes) were acquired.

Figure 1 shows the Heschl's gyrus, auditory cortex (image to be aligned) image slice. This image is rotated through 10^o clockwise. This is treated as the reference image(Figure 2). Figure 3 shows the final alignment of source with target. Figure 4 presents the summed error during testing using RBF for the 10 patterns given in Table 2. Figure 5 presents the registration error along vertical shift, along horizontal shift and along rotation. The registration can be reduced hen the number of centers change. It can be by increasing or decreasing the number of centers. The RBF network trained by the coordinates approach presented in this paper can be used as a general network for registering other fMRI images. By presenting the paired coordinates from both the reference and image to be aligned, the amount of shifts and rotation can be obtained. Based on the values obtained in the output layer of the network, a block size of 3 X 3 pixels around the concerned coordinates can be considered and all the shifts and rotations should be applied in an opposite direction for proper alignment. If only few pairs of coordinates are considered for alignment, then aligned image is not smooth. Hence more pairs of coordinates need to be considered.

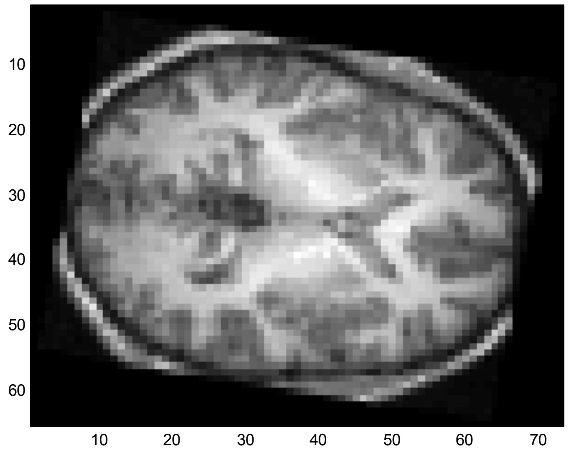


Fig. 2 Heschl's gyrus, auditory cortex (10o rotated)(Reference image)

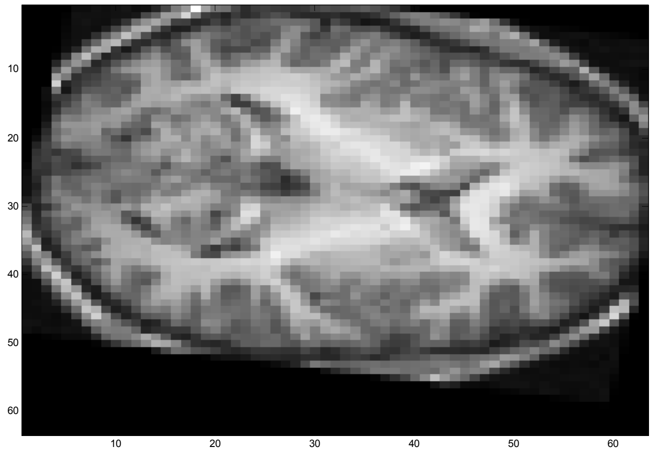


Fig.3 Final alignment

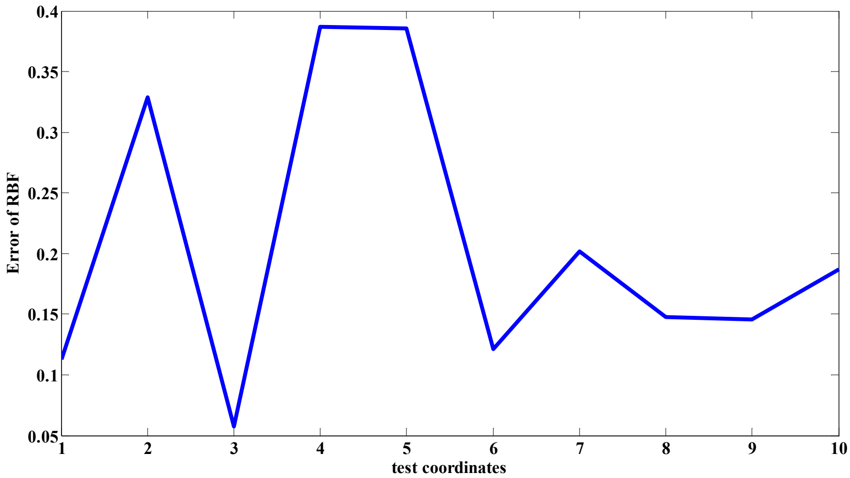


Fig.4 Training error by RBF

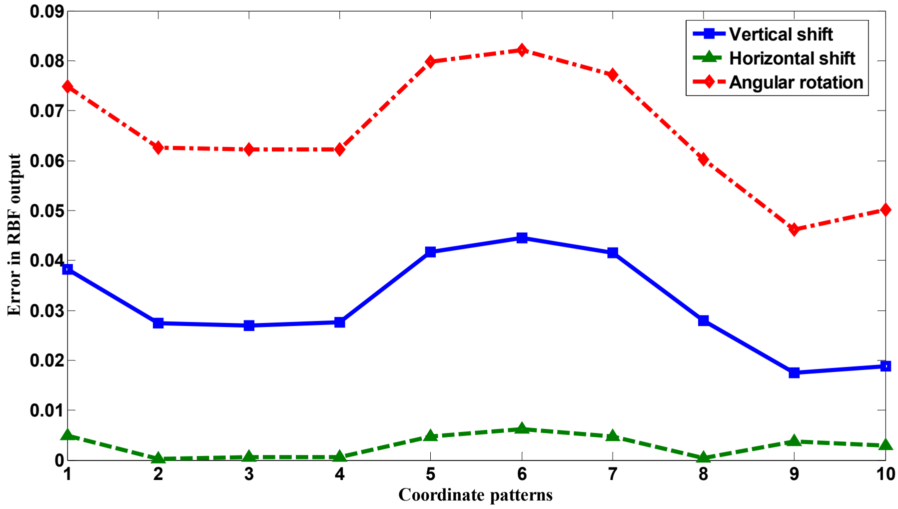


Fig.5 Registration error

V. Conclusions

This paper describes implementation of RBF for registration of **Heschl's gyrus, auditory cortex** image slice. RBF take least time to learn the alignment of characteristic points. RBF maps the coordinates of source image with coordinates of target image.

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