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Medical Image Registration Based on Feed-forward Neural Networks and Directional Discrete Cosine Transform

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Abstract: ***Registration is used to align two or more pictures taken, for example, at different times, from different sensors, or from different viewpoints. All large systems which evaluate images require the registration of images, which considered as an intermediate step. Examples of systems where image registration is a significant component include change detection using multiple images acquired at different times, fusion of image data from multiple sensor types, environmental monitoring, image mosaicing, weather forecasting, creating super resolution images, integrating information into Geographic Information Systems (GIS) and medical image analysis. In this research, the concentration is on registration of medical images. Analysis of multi-temporal medical images requires proper geometric alignment of the image to compare corresponding regions in each image volume. The proposed image registration technique consists of two steps. In the first step the feature extraction method is performed by using Directional Discrete Cosine Transform (DDCT). Finally the feed forward neural networks based image registration technique is performed .Comparison study in registration process between Directional Discrete Cosine Transform (DDCT) and Traditional Discrete Cosine Transform (DCT) is performed. Experiments have shown that the proposed method provides more accurate results for registration process when using DDCT than traditional DCT.***

Keywords: Image registration, affine transformation, neural networks, discrete cosine transform, Directional Discrete Cosine Transform.

1. Introduction

Image registration is a procedure to determine the spatial best fit between two images that overlap the same scene, and a fundamental stage in many image processing applications such as medical image analysis [1] and remote sensing.

Registration techniques can be classified into two large categories: 1) Feature based methods and 2) Area based methods [2]. Feature based techniques is performed by extracting characteristic features from images and use these features to carry out the registration. On the other hand, in some medical images it is hard to extract strong features described above due to a lack of strong details in the image. In order to perform registration on these types of medical images, an area-based method is used to extract the features.

To register two images, a transformation must be found so that each point in one image can be mapped to a point in the second. In this research, affine transformation that is composed of scaling, a translation, and a rotation is assumed. An affine transformation is any transformation that preserves collinearity i.e., all points lying on a line initially still lie on a line after transformation and ratios of distances e.g., the midpoint of a line segment remains the midpoint after transformation.

Image registration based on neural networks is a relatively new approach and requires further considerations and research. In this paper the extraction of image features using DDCT is performed and feed them into a feed-forward neural network (FFNN) to find the affine transformation parameters of a test image with respect to a reference image. A comparison study between the registration process when using DDCT for image feature extraction and that given in [3] when using Traditional DCT is done to complete our study.

This paper is organized as follows. In section 2, the new image registration scheme based on DDCT is presented. Experimental results are shown in section 3. Finally some conclusions and remarks are given in section 4.

2. THE REGISTRATION PROBLEM

One of the problems that face the doctor is magnetic resonance imaging (MRI) images registration because it plays an important role in clinical diagnosis and therapy planning. In MRI image registration two or more images taken, at different times, from different sensors, or from different viewpoints need to be aligned to compare corresponding regions in each image volume.

In this paper, this problem is taken into account and two separate phases are used to solve the MRI image registration problem. Following give the details of the two phases used.

2.1 Affine Transformation

Image registration may be viewed as a mapping between two images through several parameters. Let us define two images as 2D arrays of intensity denoted by $I_1(x, y)$

and $I_2(x, y)$. An affine transformation is typically defined with respect to four basic parameters, t_x, t_y, s, θ which map a point (x_1, y_1) of the first image to a point (x_2, y_2) of the second image as follows:

$$\begin{pmatrix} x_2 \\ y_2 \end{pmatrix} = \begin{pmatrix} t_x \\ t_y \end{pmatrix} + s \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix} \begin{pmatrix} x_1 \\ y_1 \end{pmatrix}$$

Where t_x, t_y are the translation parameters, s is the scale factor and θ is the rotation angle.

2.2 Feature Extraction Method

In the proposed scheme, the goal of the feature extraction phase is to minimize the sample space while retaining sensitivity to the variance in the samples with respect to the affine transformation parameters evaluated. It is for this reason that most feature extraction techniques, which are invariant to affine transformations, are inappropriate for registration purposes. In this work, the two methods for feature extraction used are DCT and DDCT. Following gives a description for each method.

2.2.1 Discrete cosine transform

Discrete cosine transform (DCT) is an important transform extensively used for image compression [4]. The 1D discrete cosine transform X(k) of a sequence x(n) of length N is defined as [5]:

$$X(k) = \propto \sum_{n=0}^{N-1} x(n) \cos\left(\frac{\pi(2n+1)k}{2N}\right), 0 \le k \le N-1$$

Where

$$\propto(k) \begin{cases} \sqrt{\frac{1}{N}} & k = 0 \\ \sqrt{\frac{2}{N}} & k \ne 0 \end{cases}$$

The first transform coefficient $X(0)$ is the average of all samples in the sequence and is known as DC coefficient, and other transform coefficients are known as AC coefficients $\{X(k), k = 1,2, \dots, N-1\}$. The 2D DCT is implemented by separable 1D transform in horizontal and vertical directions.

One of the main characteristic of DCT is its ability to convert the energy of the image into a few coefficients [6] by cluster high value coefficients in the upper left corner and low value right of the image. Thus, applying DCT on the image and taking the first K significant coefficients extracted in a zigzag order started from the upper left corner from the transformed image can be used as feature vector that represent the image. This vector sequence will be fed to the classifier. The Number K of the coefficients to retain is chosen experimentally. The higher number of taken coefficients makes the quality better for the representation.

As indicated, the 2D DCT provides best results for image in which horizontal and/or vertical edges are dominating. Edges other than horizontal and vertical direction are also very important and these edge orientations vary greatly from one image to another. In this situation, directional Discrete Cosine Transform (DDCT) is the best choice than the traditional DCT to avoid many non-zero AC components in the frequency domain [7]. In the DDCT, first DCT is applied along the dominating direction within the image and then the second DCT is applied after the rearrangement of the coefficients as discussed in section 2.2.2.

2.2.2 Directional Discrete Cosine Transform

There are eight directional modes 0, 1, 3, 4, 5, 6, 7 and 8. Modes 0 and 1 are similar to traditional vertical and horizontal DCT. Mode 3 is named as diagonal down-left, mode 4 as diagonal down-right, Mode 5 as vertical-right, Mode 6 as horizontal-down, Mode 7 as vertical-left, and Mode 8 as horizontal-up. Any one of the eight directional modes can be applied to any block size of an image. For instance, Fig. 1 shows six directional modes (Modes 3–8) for block size N=8.

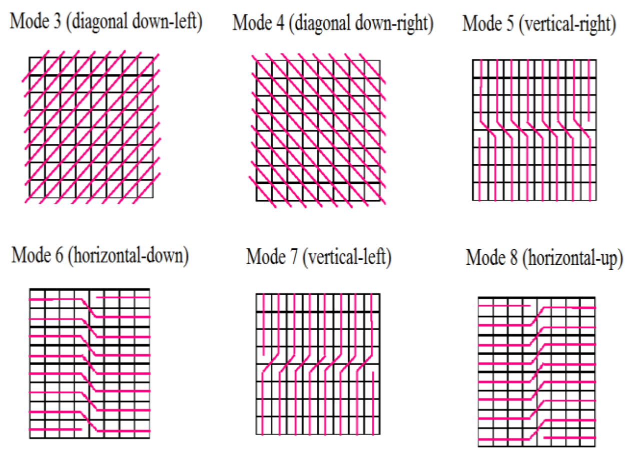

Figure 1: Six directional modes for the block size 8x8 (The vertical and horizontal modes are not included here)

It is easy to find that Mode 4 can be obtained by flipping Mode 3 either horizontally or vertically; Mode 6 can be obtained by transposing Mode 5, and Mode 7/8 can be obtained by flipping Mode 5/6 either horizontally or vertically. Thus mode 3 (diagonal down-left direction) and mode 5 (vertical-right) are the essential modes. The DDCT of modes 3 and 5 are given as follows:

Mode 3 DDCT:

Step 1: Consider an 4×4 image block as shown in Figure 2(a), X00, X01, …, X33 are the pixels in the 2D spatial domain.

Step 2: 1D- DCT is performed for the 4X4 block in diagonal down-left position with lengths L=1, 2, 3, 4, 3, 2, 1 as shown in figure 2(b).

Step 3: The coefficients of step2 after 1D DCT are arranged vertically as shown in figure 2(c).

Step 4: Apply Horizontal 1D- DCT for lengths L=7, 5, 3 and 1, the coefficients are arranged in the same pattern as shown in the figure 2(d).

Step 5: After Step 4, move all 2D (4X4) Directional DCT coefficients to the left followed by zigzag scan as shown in figure 2(e).

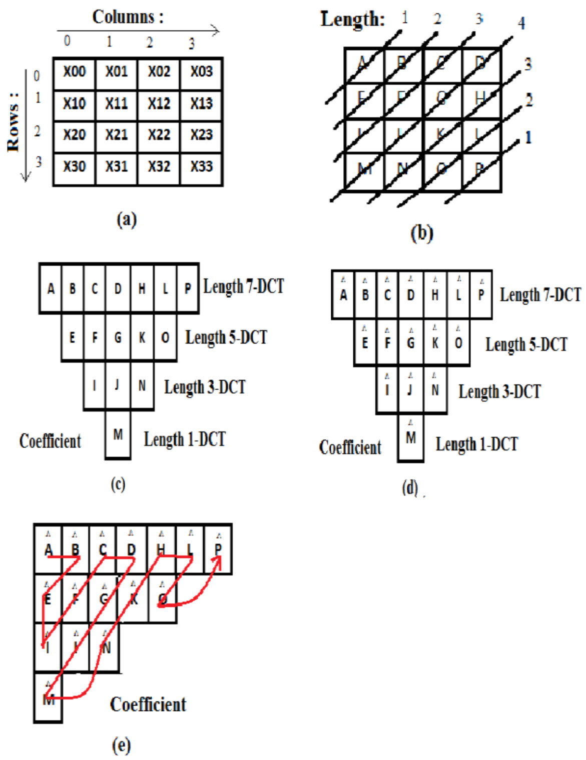

Figure 2: (a) Pixels in the 2D spatial domain for a 4X4 block, (b) DCT performed for 4X4 block for Diagonal Down Left for lengths = 1, 2, 3, 4, 3, 2 and 1, (c) Coefficients of 1D DCT arranged vertically for step 4, (d) 1D DCT applied horizontally for lengths = 7, 5, 3 and 1, (e) Move all 2D (4X4) directional DCT coefficients to the left followed by zigzag scan.

Mode 5 DDCT:

Step 1: Consider an 4×4 image block as shown in Figure 3(a), X00, X01, …, X33 are the pixels in the 2D spatial domain.

Step 2: 1D DCT is performed for the 4X4 block in vertical-right position with lengths L= 2,4,4,4,2 as shown in Figure 3(b).

Step 3: The coefficients of step 2 after 1 D DCT are arranged vertically in the same pattern as shown in step 3.

Step 4: Apply horizontal 1 D DCT for lengths L= 5, 5, 3 and 3. The coefficients are arranged the same pattern shown in figure 3(c).

Step 5: After Step 4, move all 2D (4X4) Directional DCT coefficients to the left followed by zigzag scan as shown in figure 3(e).

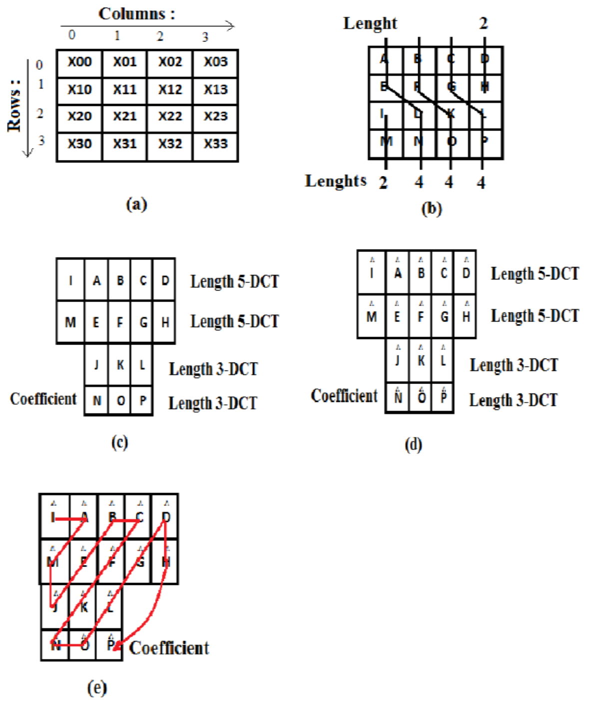

Figure 3: (a) Pixels in the 2D spatial domain for a 4X4 block, (b) DCT performed for 4X4 block for Vertical Right for lengths 2,4,4,4 and 2, (c) Coefficients of 1D DCT arranged vertically for step 4, (d) 1D DCT applied horizontally for lengths = 5, 5, 3 and 3, (e) Move all 2D (4X4) directional DCT coefficients to the left followed by zigzag scan.

2.3 NNs BASED REGISTRATION

A typical neural network based image registration scheme consists of two separate phases [8] as shown in Figure 4. In the pre-registration phase a reference image is scaled, rotated and translated by several amount of values to generate a set of affine transformed images. Then DDCT coefficients are calculated from the image, and a sub-sample of the 2D DDCT plane is extracted in a zigzag manner and fed as input to a feed-forward neural network (NN) with corresponding affine transformation parameters values at the output in a training stage.

Once a trained neural network is available the registration phase is straightforward: extract the same global features from a test image with unknown affine transformation parameters, feed them to the network, and read the estimated parameter values at the output.

Feed-forward neural networks structure consist of three layers namely, an input layer, hidden layer, and an output layer. The network structure is shown in Fig. 5. The network given a set of initial weights, the input sample data and the output is computed. The modification of the weights is obtained based on the difference between the output and its expected value.

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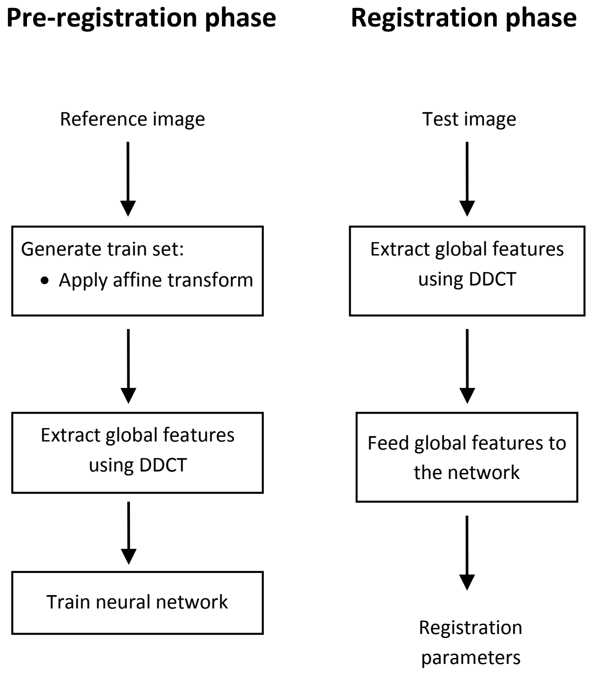


Figure 4: Neural network based on registration scheme

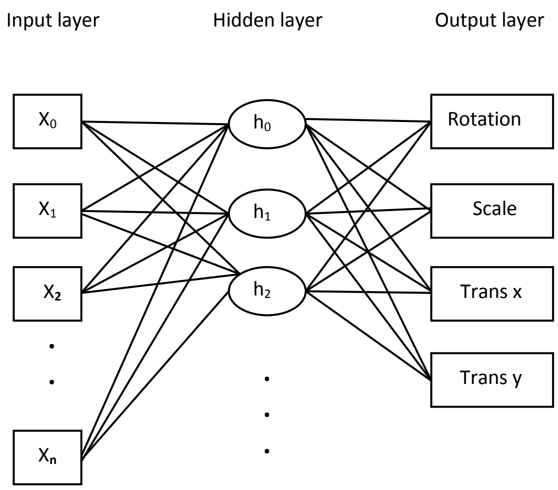


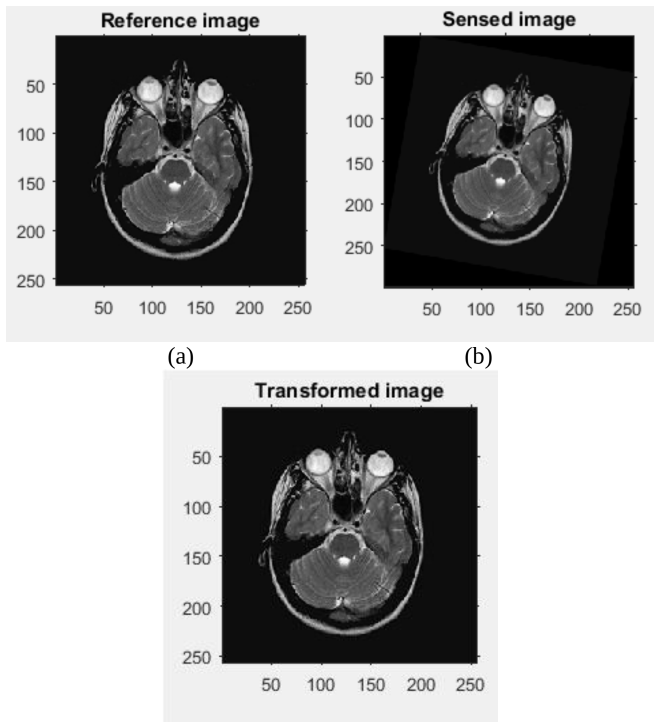
Figure 5: Structure of the feed-forward NN

3. Experimental results

A pair of 256 x 256 MRI images of the brain was used in order to test the proposed registration method. Fig. 6 shows one of the original image and a sensed image containing translation, rotation and scaling.

The training set used in the study consisting of 300 images extracted from the reference image, each image is translated, rotated and scaled randomly within a predefined range. The range of affine transformation parameter values used for training and test sets were shown in Table 1. The feature vector for each affine transformed image is the cut out in a zigzag order taken from the lowest frequency band in each 144 (12x12) DDCT plane. Similarly, a test-set of 60 images was generated from the sensed image.

As mentioned in section 2.3, image registration process based on feed-forward NN scheme is consists of two separate phases. In the first phase, the feed-forward neural network is used for training 300 feature vectors obtained from the reference image. The feed-forward neural network used contained 144 inputs (feature vector), 4 outputs (corresponding affine parameters) and 40 neurons in the hidden layer. The FFNN had a tangent-sigmoid transfer function for the hidden layer neurons and a linear function for the output layer neurons, and was trained using the Levenberg-Marquardt method [9].



(a) (b)

(c)

Figure 6: (a) The original images, (b) a sensed image containing translation, rotation and scaling, and (c) a transformed image.

The second phase is used to evaluate the performance of the proposed registration approach by applying the other 60 feature vectors obtained also from the sensed image.

The performance of the image registration process based on feed-forward NN scheme is shown in table 2. It was found that the root mean square error when using DDCT of mode 8 is less than that when using traditional DCT. Then the performance in registration process when using DDCT with mode 8 is better than that when using traditional DCT; see figure7. Experimentally it was found that mode 8 is suitable for image registration process under study. The other modes may be suitable for other type of images.

Table 1: Affine transformation parameter values used in experiments

Affine parameter	Discrete parameter

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Rotation (degrees)	[-12, 12]
Scale (percent)	[0.9, 1.1]
Vertical translation (pixels)	[-5, 5]
Horizontal translation (pixels)	[-5, 5]

Table 2: RMSE resulted by DDCT coefficients and Traditional DCT

Parameter RMSE / Method	θ	S	Tx	Ty
DDCT mode 8	0.1509	0.0367	0.2329	0.2220
Traditional DCT	0.2037	0.0427	0.2668	0.2358

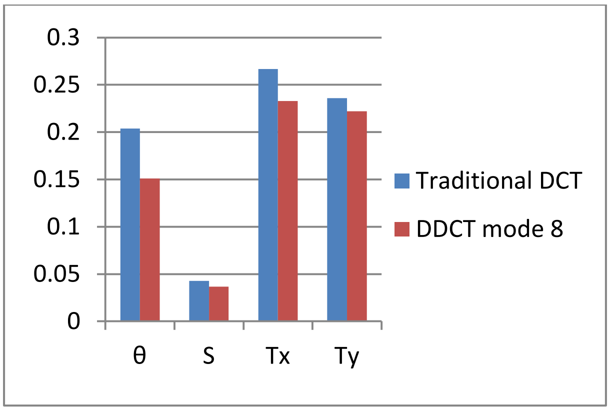

Figure 7: performance of the registration process when using DDCT and traditional DCT in feature vectors extraction

4. CONCLUSION

In this paper, a novel image registration scheme based on feed-forward neural networks and Directional DCT is presented. The proposed method uses transform based approach as well as area based approach with no requirement for control-point or distinct features identification. Comparison experiments for feature extraction based image registration among DDCT and DCT are performed. Simulation studies have shown that the registration method based on DDCT has more accurate performance than traditional DCT. Therefore the general conclusion is that DDCT should be preferred for image registration problems because it takes image orientation features into account which improve performance and accuracy.

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