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Transformation parameter estimation using parallel output based neural network

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ABSTRACT

One of the challenging tasks in image registration is to estimate transformation parameters automatically and efficiently. In this paper, we propose a task decomposition based parallel trained neural network to estimate transformation parameters as well as order of transformations. This parameter estimation problem can be divided into several subproblems like rotation, translation and scaling estimation. Each subproblem or module consists of decomposed input datasets, as well as a part of the output vector. Each module is trained in parallel for some specific and fixed input–output vector pattern. Feature vectors are used as input dataset of the proposed neural network. 2D PCA (two dimensional principal component analysis) feature extraction technique is used to build feature vector. This modular technique requires effectively less computation time in comparison to non-modular network. Moreover, this technique can robustly estimate different transformational parameters. The added advantage of this technique is that it can identify order of the transformation. Experimental results justify the effectiveness of the proposed technique.

1. Introductionintroduction

Medical images are nowadays widely used for diagnosis, treatment and supervising disease progression. The term medical image spreads over a vast area of different types of images, with different applications. Medical researchers use different medical images to investigate disease processes and to understand different developments as well as ageing. Multiple images of a common subject are captured at different times, or from different imaging modalities. Medical image registration primarily deals with the technique to align two or more images of inter-modality or intra-modality.

Different tomographic images such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Single Photon Emission Computed Tomography (SPECT), and Positron Emission Tomography (PET) are popular medical imaging techniques to analyze and register. Over the last decade, research on automatic rigid registration methods of medical images has been widely explored. Registration can be divided into two domains i.e. spatial domain and frequency domain. Spatial domain can be categorized mainly as intensity based and feature based [1–3]. Intensity based methods mainly deal with image intensities to estimate the transformation parameters such as rotation, scaling, translation etc. [4–6]. Image features [7] are used to determine corresponding feature pairs from the pair of images and then the transformation parameters are determined. In [8] authors propose SURF (speeded up robust features) algorithm based on feature information. Translation, rotation, and scale all have their counterpart in the Fourier domain. Fast Fourier transform-based (FFT) based methods [9,10] use not only the feature information but also spatial information of an image. In [11], authors use a FFT-based method, which is an extension on phase correlation technique to estimate transformational parameters. The pseudopolar based method [12] is an extension of FFT based method that is able to recover large rotations and scaling factors. Soft computing based techniques such as neural network, genetic algorithm, fuzzy logic etc. are recently being extensively explored. An artificial neural network (ANN) is a nonlinear mathematical or computational model based on the principles of biological neural networks. They can be used to model complex relationships between inputs and outputs or to establish patterns in data. Registration methods using neural networks have been reported [13,14]. In [15], principal component analysis (PCA) has been used in neural network for CT-MR and MR-MR registration.

Nowadays parallel artificial neural network (ANN) offers an effective technique to solve complex problems. It has several

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advantages over ANN encompassing increase in computational speed, ensuring accuracy etc. Main difficulty in creating a parallel ANN involves appropriate use of parallelism in a network. Moreover, the overhead of cross processor communication would result in negligible net performance increase. To overcome this problem, we propose a network with parallel output. The network consists of several modules and each module consists of some exclusive part of the input vector and part of the output. Each module is independent of other module i.e. no interprocessor communication is required to train the network. The advantage of this network model is that the overhead of cross-processor communication is eliminated.

In previous works [15,12], transformational parameters are estimated but the order of transformations is not established. In this article, we propose a method to estimate the transformational parameters as well as corresponding order using 2D PCA and parallel trained ANN. Feature vectors are calculated using 2D PCA and passed as input vector to output parallelism based ANN. Experimental results indicate that this method outperforms prior work [15,12], in terms of accuracy.

The rest of the paper is organized as follows: Prior techniques related to spatial image registration, 2D PCA and parallel trained ANN, which are used as prerequisite for the proposed algorithm are presented in Section 2. The proposed algorithm is presented in Section 3. Experimental results and comparison with other methods are discussed in Section 4 and final conclusions are provided in Section 5.

2. Relevant techniques for the proposed method

In this section we provide a brief introduction to rigid transformation, 2D PCA and parallel ANN.

2.1. Rigid geometric transformation

All the mapping models fall into two basic categories: rigid (global) and nonrigid (elastic) transformations. In rigid transformation, transformed image has exactly the same shape as that of the pre-transformed image. Transformations such as rotation, translation, reflection, scaling are rigid in nature. In affine transform, the relationship between the two sets of image coordinates, with (x', y') being the new coordinate and (x, y) being the old coordinate, is often modeled as

$$\begin{pmatrix} x\prime \\ y\prime \\ 1 \end{pmatrix} = \begin{pmatrix} m_1 & m_2 & m_3 \\ m_4 & m_5 & m_6 \\ 0 & 0 & 1 \end{pmatrix} \cdot \begin{pmatrix} x \\ y \\ 1 \end{pmatrix}$$

i.e. *new coordinate* = T' * *old coordinate*

$$T\prime = RST \tag{1}$$

where, order may be different. R is the image rotation about the image center by an angle θ anticlockwise represented by,

$$R = \begin{pmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{pmatrix}$$

S is the scaling effect with S_x and S_y representing scaling factors along X and Y axes respectively, i.e.,

$$S = \begin{pmatrix} S_x & 0 \\ 0 & S_y \end{pmatrix}$$

and T_x and T_y representing translation factors along X and Y coordinate axes respectively, i.e.,

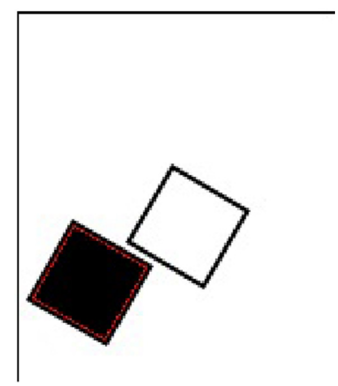

Fig. 1. Effect of different order of transformations.

$$x\prime = x + T_x$$

$$y\prime = y + T_y$$

Here, (x, y) are the coordinates of the pre-image and (x', y') are the coordinates of the image after translation.

In case of composite transformations, the order plays a big role. A rotation followed by a sequence of translation and a scaling will not give the same results as a translation followed by a rotation and then by a scaling. As an example, the transformational parameters are applied on an object are rotation (R) (30°), translation (T) (70, 70) and scaling (S) (scaling factor is 2 in along both x and y direction) one after another i.e. RTS. The result is reported in Fig. 1 as black rectangle. Now, if the order is changed keeping the parameters same then the result varies. The white rectangle in Fig. 1 represents the order as translation (T), rotation (R) and scaling (S) i.e. *TRS*. From Fig. 1 it is apparent that different orders offer different results.

2.2. Feature extraction using two dimensional PCA

Principal component analysis or PCA is a statistical procedure used to determine the covariance structure of a set of variables. Basically, it allows us to identify the principal directions along which the data vary. PCA is used as a classical feature extraction technique [16].

Here, the two dimensional image is converted to 1D vector and then the covariance matrix is calculated. But, according to Wiskott et al. [17] PCA cannot capture any small invariance in the training data unless it is explicitly provided. To overcome this problem, Yang et al. [16] propose an updated version named 2D PCA. It is operative on 2D matrices rather than 1D vectors. An image covariance matrix can be directly constructed from the original image data. Let X be the original image of size $m \times n$ and Y be the n-dimensional unitary column vector. By the linear transformation

$$V = XY \tag{2}$$

we can project image X onto Y. Covariance matrix of the projected feature vector of the training sample can be represented as

$$C_x = E(V - EV)(V - EV)^T$$

or,

$$= E[(X - EX)Y][(X - EX)Y]^T \tag{3}$$

Now, trace can characterise the total scatter of the projected vector.

So trace of C_x is

$$t_r(C_x) = Y^T[E(X - EX)^T(X - EX)]Y \tag{4}$$