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Outlier detection based on the neural network for tensor estimation

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ABSTRACT

Rationale and objectives: Diffusion weighted imaging (DWI) is always influenced by both thermal noise and spatially/temporally varying artifacts such as subject motion and cardiac pulsation. Motion artifacts are particularly prevalent, especially when scanning an uncooperative population with several disorders. Some motion between acquisitions can be corrected by co-registration approaches. However, automated and accurate motion outlier detection of brain DWIs is an integral component of the analysis and interpretation of tensor estimation. Many different and innovative methods have been proposed to improve upon this technology. In this study, we proposed a classifier work frame, which can classify DWIs as normal images or motion artifacts.

Materials and methods: The procedure contains the following stages: first, we used the wavelet transform to extract features from the original DWIs; second, the principle component analysis was used to reduce the features; third, the forward neural network (FNN) was employed to construct the classifier; fourth, a Rossler-based chaotic particle swarm optimization method was proposed to train the FNN; fifth, the cost matrix was determined as the false negative (FN) which was 10 times larger than the false position (FP); and finally, the K-fold cross validation was chosen to avoid overfitting. We applied this method on 60 DWI datasets, including 50 training datasets and 10 test datasets.

Results: The experimental results based on our DWI database showed that the proposed method can effectively extract the global feature from images and achieve better performance in tensor estimation by automatic unvoxelwise outlier rejection compared with manual and visual inspection, and previous voxelwise outlier rejection methods. We found that the motion artifact detection accuracy on both the training and test datasets was over 95.8%, while the computation time per DWI slice was only 0.0149 s.

Conclusion: The proposed method could potentially remove the influence of unexpected motion artifacts in DWI acquisitions and should be applicable to other magnetic resonance imaging.

1. Introduction

Diffusion tensor imaging (DTI) has become an important magnetic resonance imaging (MRI) procedure for imaging tissues with micro fabric structures in vivo, especially to investigate the integrity of brain white matter, and provide critical information for clinical diagnosis and biomedical research [1–3]. Currently, clinical research in the DTI field is undergoing a rapid expansion to depict white matter connectivity and microstructural features of human brain tissues that weave these sites together into a system with spatially interacting neural elements [4], and it is increasingly applied to brain studies of normal development, aging and pathological changes from various diseases [5]. In particular, diffusion tensor maps are typically computed by fitting the signal intensities from diffusion weighted images as a function of their corresponding b-matrices according to the multivariate least squares regression modal proposed by Basser et al. [1]. However, the signal in diffusion weighted imaging (DWI) is influenced not only by thermal noise, but also by spatially and temporally varying artifacts. All these factors might result in a very low signal-to-noise ratio (SNR) in the DWI dataset and lead to substantial influence on accuracy of the artificial tensor estimation [6,7]. Motion between acquisitions can be corrected by image registration approaches, but individually damaged images are generally uncorrectable, especially in scans of an uncooperative population [8,9]. Therefore, it is important to detect and remove corrupted images and outliers. Currently, most DTI quality control procedures are conducted manually by visually checking the DWI dataset slice by slice (Liu et al., 2010). In clinical practice, if images were corrupted by severe artifacts, they should be removed or be weighted less in subsequent tensor calculation. In theory, we only need six DWIs to calculate a tensor. However, in order to enhance the SNR of DTI, typically 32–128

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measurements are obtained to improve the robustness of the estimated tensor [10]. Hence, we can usually afford to reject a small subset of the dataset to get tensor estimation and to also not scarify the SNR significantly. Recently, investigators have also developed various algorithms to address this issue by automatically identifying outliers for essential motion correction in DTI tensor estimation. However, the results often suffer from low consistency across different datasets, lack of agreement between different researchers, and difficulty judging motion artifacts by qualitative inspection. The challenge is to identify and reject such images with motion artifacts from the redundant source images in DWIs quickly, accurately and automatically. The traditional tensor estimation method does not work well, although the DTI community is aware of the detrimental effects of the outlier, while some robust tensor estimation methods could identify potential outliers with low weight, in which the computation cost of the iteration procedure is enormous [11,12].

In this study, an automatic algorithm was proposed to improve the accuracy, sensitivity and robustness of the tensor estimation by targeting the most common artifacts in DWIs. The proposed method performs a standard pipeline of processing typical DTI data prior to tensor estimation. The procedure consists of three stages: feature extraction, feature dimension reduction, and forward neural network (FNN)-based classification. The wavelet transform is an effective tool for feature extraction because it allows for the analysis of images at various levels of resolution [13,14]. In order to further reduce the feature vector dimensions and increase the discriminative power, the principal component analysis (PCA) method was employed [15]. Subsequently, the FNN was chosen as the classifier because it is a powerful tool among supervised classifiers and it can classify nonlinear separable patterns and approximate an arbitrary continuous function. Recently, particle swarm optimization (PSO) algorithm is available to train the FNN. PSO is well-known for its lower computational cost, low memory store, and robust convergence to global minima [16]. In order to improve the performance of PSO, we used a chaotic PSO (CPSO) method [17,18] to find the optimal parameters for FNN. The performance of the CPSO method has been compared with that of adaptive back-propagation (BP), adaptive genetic algorithm (GA) and canonical PSO methods. The method has been tested on 60 adult DWI datasets, which were manually inspected for non-recovery datasets. We specifically investigated the ability of the proposed method to provide reliable and rapid tensor estimation in the presence of artifacts resulting from motion artifacts. The experimental results showed that the proposed method could extract the useful features from brain DWIs effectively and achieve good performance in outlier detection. The potential motion outliers could then be successfully excluded from the subsequent tensor estimation procedure.

This article is organized into the following sections. Section 2 presents an optimized tensor estimation model based on automatic outlier rejection using the FNN method, including a wavelet transform-based feature extraction and a PCA technique-based feature dimension reduction, and a CPSO method to eliminate the adverse effects in DWIs. In Section 3, experimental results on real DWI datasets are presented to investigate the ability of the algorithm to provide reliable tensor estimation. The final section is devoted to the discussion and conclusions.

2. Methods

2.1. Feature extraction

The wavelet transform (WT) is applicable to various fields especially in image classification [19,20]. Discrete wavelet transform (DWT) is a powerful implementation of the wavelet transform. The basic fundamental principle of DWT is introduced as follows: suppose $x(t)$ is a square-integrable function, then the continuous WT of $x(t)$ relative to a given wavelet $\psi(t)$ is defined as

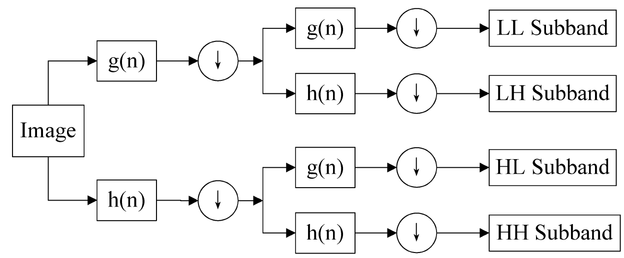

Fig. 1. Schematic diagram of 2D DWT.

$$W_{\psi}(a,b)=\int_{-\infty}^{\infty}x(t)\psi_{a,b}(t)dt \quad (1)$$

where

$$\psi_{a,b}(t)=\frac{1}{\sqrt{a}}\psi\left(\frac{t-a}{b}\right) \quad (2)$$

Here, wavelet $\psi_{a,b}(t)$ is calculated from the mother wavelet $\psi(t)$ by translation and dilation: a is the dilation factor and b is the translation parameter (both real positive numbers).

Eq. (1) can be discretized by restraining a and b to a discrete lattice ($a=2^b$ and $a>0$) to give the DWT, which can be expressed as follows:

$$\begin{aligned} ca_{j,k}(n)&=DS[\textstyle\sum_n x(n)g_j^*(n-2^jk)] \\ cd_{j,k}(n)&=DS[\textstyle\sum_n x(n)h_j^*(n-2^jk)] \end{aligned} \quad (3)$$

Here, coefficients $ca_{j,k}$ and $cd_{j,k}$ refer to the approximation components and the detail components respectively. The functions $g(n)$ and $h(n)$ denote the low-pass filter and high-pass filter respectively. The subscripts j and k represent the wavelet scale and translation factors respectively.

In applying this technique to DWIs, the DWT is applied separately in each dimension. Fig. 1 illustrates the schematic diagram of 2D DWT. As a result, there are 4 sub-band (LL, LH, HH, HL) images on each scale. The sub-band LL is used for the next 2D DWT. The LL sub-band can be regarded as the approximation component of the image, while the LH, HL, and HH sub-bands can be regarded as the detailed components of the image. As the level of the decomposition increased, we obtained more compact yet coarser approximation components. Thus, wavelets provide a simple hierarchical framework for interpreting the image information. Feature extraction with Level-1 and level-2 decompositions is still huge for further processing. In our algorithm, level-3 decomposition via the Harr wavelet was utilized to the extract features.

2.2. Principal component analysis (PCA)

Classification methods often begin with the dimension reduction procedures where data are approximated by points in a lower-dimensional space. The wavelet coefficients obtained from DWT are considered to be the input features, but the dimensionality is too large for computation. There are two general approaches for performing dimensionality reduction: feature extraction and feature selection. Feature extraction transforms the existing features into a lower dimensional space, while feature selection selects a subset of the existing features without a transformation. In this paper we chose the feature extraction and dimension reduction method since our goal pertains to the final classification accuracy rather than the physical features.