Ghost Artifact Removal Using Texture Analysis in Spinal Cord Diffusion Tensor Images

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Background and Objective

Diffusion Tensor Imaging (DTI) of the spinal cord is an extremely promising technique for examining the spinal cord in-vivo. However the DTI methods typically use Echo Planar Imaging (EPI) readouts which are very sensitive to phase shifts occurring during long echo train acquisition. This causes ghosting in the resultant images [2]. Ghosting artifacts caused by echo misalignment are a systematic problem and are also a function of the instability of the main magnetic field B_0 and a system timing error associated with the scanner hardware [3]. Various efforts have been made to reduce the ghosting artifacts such as using reference scan based techniques. However, these techniques are sensitive to the subject's motion or other dynamic changes (e.g. hardware instability, blood flow and CSF flow artifact) [4]. The purpose of this study is to (a) evaluate the validity and reliability of an automatic post processing method for identifying and segmenting spinal cord regions from ghost regions in b0 DTI images, (b) examine reproducibility of methods used for ghost artifacts detection, and (c) investigate statistical measures to differentiate ghost from true cord signal in segmented DTI data with and without Spinal Cord Injury (SCI).

Methods & Materials

Subjects: A total of 12 subjects (7 healthy and 5 spinal cord injury patients) were recruited for this study with a mean age of 11.18 years. Subjects and parents provided written assent and consent approved by the institutional review board. The inclusion criteria used for recruitment of the spinal cord injury group were: stable cervical-level spinal cord injury as evidenced by no neurological change in the past three months and initial injury date of at least 6 months prior to imaging.

Imaging: The MRI scans were performed using a 3.0T Siemens Verio MR scanner (Siemens Healthcare, Erlanger, Germany) with 4-channel neck matrix and 8-channel spine matrix coils. Inner FOV (iFOV) DTI images as well as T1 and T2-weighted images were acquired axially covering the entire spinal cord (2 slabs). The iFOV DTI sequence used in this study was a single shot EPI sequence for diffusion weighted imaging with spatially 2D selective RF excitation and view angle tilting (VAT) which allows for higher resolution and reduced geometric distortion. This sequence has been shown to be very reliable in DTI images of the spinal cord [4]. The imaging parameters included: Diffusion direction = 20; Number of b0 scans=6; field of view size=250mm, TR=7900ms, TE=110ms, slice thickness=6mm, flip angle=90° and number of averages=3. Cardiac gating was not used in this study as it increases scan time and is not desirable in pediatric studies.

Data Analysis: Following data acquisition a multi-stage post-processing pipeline was performed to remove ghost artifact from the DTI images. The method consists of three stages, namely, segmentation, feature extraction and classification. First, segmentation was performed using mathematical morphological processing to select regions of interests (ROIs) including the spinal canal and the ghost from the background of the b0 images. The accuracy of the proposed segmented method was then compared with the ROIs drawn manually by an independent board certified radiologist. The ROIs were specifically drawn to minimize the effects of partial volume artifact which is caused by image co-registration. Next, texture features were extracted from segmented regions to differentiate the ghost from the true cord data. Twenty one features including five features based on the histogram of the image (mean, variance, skewness, kurtosis and entropy) and 16 feature vector elements, incorporating four statistical measures (contrast, correlation, homogeneity and energy) calculated from co-occurrence matrices in directions of 0°, 45°, 90° and 135° were extracted. Mutual Information (MI) was examined to extract features with maximal dependence on the target class as defined by an independent board certified radiologist and with minimal redundancy between extracted features. Ten features with a high value of MI shown in Table 1 were selected as final features. Finally, a trained classifier, Adaptive Neuro-Fuzzy Interface System (ANFIS) written in MATLAB was implemented to discriminate between segmented cord and ghost regions in b0 images of DTI data based on textural features extracted for each region. This is one of the widely used supervised learning algorithms that have been utilized successfully in several medical imaging applications [5]. It includes an input layer, three hidden layers and one output layer. The input layer is composed of a number of neurons equal to the dimensions of the feature vector (ten neurons). With respect to the hidden layers, several topologies with different numbers of neurons were tested. Statistical analysis was performed to evaluate the effectiveness of this method.

Results & Conclusion

The experiments were carried on 50 b0 images of DTI data which consist of ghost artifacts. 100 regions including 50 true cords and 50 ghost cords were processed using the proposed pipeline. The effectiveness of the proposed segmentation method compared with drawn ROIs was presented in terms of sensitivity, specificity and accuracy. This approach was able to detect the desired regions (true cord and ghost cord) from background regions (surrounding tissues) by sensitivity, specificity and accuracy of 0.99, 0.98 and 0.98, respectively. Figure 2 represents the output of ANFIS classifier tested on 25 images included 10 ghost cords (with target class of 2) and 15 true cords (with target class of 1). Outputs higher than 1.5 were considered as ghost cord and less than 1.5 were considered as true cord.

The results obtained from the classifier showed a sensitivity of 0.91, specificity of 0.79, and accuracy of 0.84 which assures that the proposed method would be viable for use in clinical practice for the detection of ghost in DTI images.

In conclusion, an automatic method to detect and segment spinal cord regions from ghost regions in DTI scans was implemented and tested. Such techniques are extremely valuable for accurate detection characterization and interpretation of the DTI metrics in normal and spinal cord injury patients.

References: (1) Hailong Li. MRI 2013; 31:1022-1028. (2) Emmanuel Durand, JMRM 2001; 46:198–201. (3) Yoon-Chul Kim, JMRI 2008; 27:239–245. (4) Barakat N, AJNR 2012; 33:1127–33. (5) F. Behloul, IEEE TRANSACTIONS ON MEDICAL IMAGING 2001; 20(12): 1302-1313.

Table 1 *Selected features using mutual information method.*

	Calculated from histogram of the image			*Calculated from co-occurrence matrices*						
Feature	*Varience*	*Kurtosis*	*Entropy*	*Correlation*	*Energy*	*Energy*	*Contrast*	*Energy*	*Homogeneity*	*Energy*
Direction	-	-	-	*0°*	*0°*	*45°*	*90°*	*90°*	*90°*	*135°*

(a) (b) (c) (d)

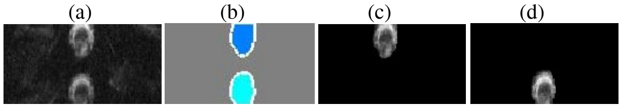

Figure 1. (a)Axial b0 image of a control subject at spinal cord level of C6-C7 ,(b) segmented regions ,(c) Ghost located in the anterior and (d) cord located in the posterior region of the image.

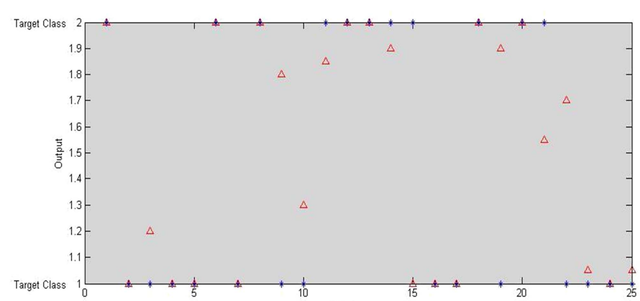

Figure 2. The output of ANFIS classifier tested on 25 images.