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Identification of ghost artifact using texture analysis in pediatric spinal cord diffusion tensor images

Mahdi Alizadeh[a,b,*], Chris J. Conklin[a], Devon M. Middleton[a], Pallav Shah[c], Sona Saksena[a], Laura Krisa[d], Jürgen Finsterbusch[e], Scott H. Faro[f], M.J. Mulcahey[d], Feroze B. Mohamed[a]

[a] Jefferson Integrated Magnetic Resonance Imaging Center, Department of Radiology, Thomas Jefferson University, Philadelphia, PA, United States
[b] Department of Neurosurgery, Thomas Jefferson University, Philadelphia, PA, United States
[c] Department of Radiology, Temple University, Philadelphia, PA, United States
[d] Department of Occupational Therapy, Thomas Jefferson University, Philadelphia, PA, United States
[e] Department of Systems Neuroscience, University Medical Center Hamburg-Eppendorf, Hamburg, Germany
[f] Department of Radiology, Johns Hopkins University, Baltimore, MD, United States

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ABSTRACT

Purpose: Ghost artifacts are a major contributor to degradation of spinal cord diffusion tensor images. A multi-stage post-processing pipeline was designed, implemented and validated to automatically remove ghost artifacts arising from reduced field of view diffusion tensor imaging (DTI) of the pediatric spinal cord.
Method: A total of 12 pediatric subjects including 7 healthy subjects (mean age = 11.34 years) with no evidence of spinal cord injury or pathology and 5 patients (mean age = 10.96 years) with cervical spinal cord injury were studied. Ghost/true cords, labeled as region of interests (ROIs), in non-diffusion weighted b0 images were segmented automatically using mathematical morphological processing. Initially, 21 texture features were extracted from each segmented ROI including 5 first-order features based on the histogram of the image (mean, variance, skewness, kurtosis and entropy) and 16s-order 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°. Next, ten features with a high value of mutual information (MI) relative to the pre-defined target class and within the features were selected as final features which were input to a trained classifier (adaptive neuro-fuzzy interface system) to separate the true cord from the ghost cord.
Results: The implemented pipeline was successfully able to separate the ghost artifacts from true cord structures. The results obtained from the classifier showed a sensitivity of 91%, specificity of 79%, and accuracy of 84% in separating the true cord from ghost artifacts.
Conclusion: The results show that the proposed method is promising for the automatic detection of ghost cords present in DTI images of the spinal cord. This step is crucial towards development of accurate, automatic DTI spinal cord post processing pipelines.

1. Introduction

Diffusion tensor imaging (DTI) allows the characterization of physical properties of tissues by measuring three-dimensional water diffusion in vivo. To this end, the unique characteristic architecture of the spinal cord may allow DTI to localize white matter, separate white from gray matter and assess structural damage of the cord [1]. It has been reported that DTI parameters of the cervical spinal cord can be obtained in children with spinal cord injury (SCI) with moderate-to-strong reliability and that the indices had moderate-to-good concurrent validity against MRI and the International Standards for Neurological Classification of Spinal Cord Injury (ISNCSCI) motor, sensory and anorectal examinations [2–5].

In recent years, DTI acquisition of the spinal cord has been significantly enhanced using inner field of view (iFoV) pulse sequence techniques [2]. This sequence is based on a single shot Echo Planar Imaging (EPI) sequence and uses spatially selective 2D RF excitation for obtaining high resolution images of the spinal cord while mitigating contamination from physiologic noise [2–4]. However, EPI is very sensitive to phase shifts occurring during long echo trains which gives

* Corresponding author at: Department of Neurosurgery and Jefferson Integrated Magnetic Resonance Imaging Center, Department of Radiology, Thomas Jefferson University, Philadelphia, PA 19107, United States.
E-mail address: mahdi.alizadeh.2@jefferson.edu (M. Alizadeh).

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rise to ghost artifacts [6,7]. Ghosting artifact caused by echo misalignment is a systemic problem and is a function of the instability of the main magnetic field B_0 and system timing error associated with the scanner hardware (e.g. eddy current causes by physical *x*, *y* and *z* gradients) [8]. In DTI acquisitions these ghost artifacts occur in various diffusion gradient directions as shadows of the original structure. This can reduce the visualization of the true spinal cord structure and can increase ambiguity of the true location of the cord.

Several methods for correcting echo misalignment have been suggested in literature. Currently, reference scan based techniques are primarily used on clinical MRI scanners. These techniques perform a calibration scan to determine the on-axis gradient/data acquisition time delay and then use small gradients to align echoes [6–9]. However, reference scans are sensitive to dynamic changes such as subject motion and introduce complexities in MRI pulse sequence design [10]. Another way to reduce ghosting artifact is using parallel imaging techniques [8,10]. This technique needs multi-coil sensitivity information for image reconstruction. To calculate sensitivity maps before the EPI scan, a reference or calibration scan is needed, but since patient motion or other dynamic changes (e.g. hardware instability, blood flow) may occur after calibration the results tend to be inconsistent and can be vary between patients [10]. Image based correction techniques such as filtering the images reconstructed from the even and odd echoes separately or applying the motion correction methods have also been studied, but these techniques require access to the raw k-space data [9].

In this paper, a multi-stage post-processing pipeline with a focus on texture analysis was developed and tested to remove ghost artifact from the DTI images. To the best of our knowledge, this is first study using a computer aided system in detecting ghost artifact in spinal cord diffusion tensor images. The method consists of three core stages: segmentation, feature extraction and classification. Initially, segmentation was performed using a mathematical morphological processing algorithm to select regions of interests (ROIs) including the true cords (TCs) and the ghost cords (GCs) from the background of the b0 images. Next, texture features with maximal dependence on the target class as defined by an independent board certified neuroradiologist and with minimal redundancy between features were selected. Finally, a trained classifier Adaptive Neuro-Fuzzy Interface System (ANFIS) was implemented to differentiate between segmented cord and ghost regions. Removal of the ghost from these images will reduce unnecessary tensor estimations which in turn reduces the processing time and enable accurate quantification of the DTI parameters. Furthermore, automatic identification of the ghosts in the images grants the ability to automate the DTI post processing pipeline thereby eliminating errors caused by human interaction.

2. Methods

2.1. Overview

The framework of ghosting artifact detection on DTI data consists of five steps, including data acquisition, preprocessing and the three aforementioned stages of ghost removal, as summarized in Fig. 1. After data acquisition, a preprocessing step (using median filter) was implemented to correct images to the noise and image heterogeneity for segmentation accuracy. Following this, segmentation was performed using mathematical morphological processing to select ROIs including TCs and GCs, which will be referred to as sub-images (step 3). Next, twenty-one statistical texture features were extracted using co-occurrence matrix of each sub-image in directions of 0°, 45°, 90° and 135°, and from the histogram vector obtained from sub-images (step 4). This aligns the 21 channels to a feature vector and uses Mutual Information (MI) to select features with maximal dependence on the target class and with minimal redundancy between extracted features. Finally, in step 5, a classification strategy based on AFNIS was implemented to separate GCs from TCs.

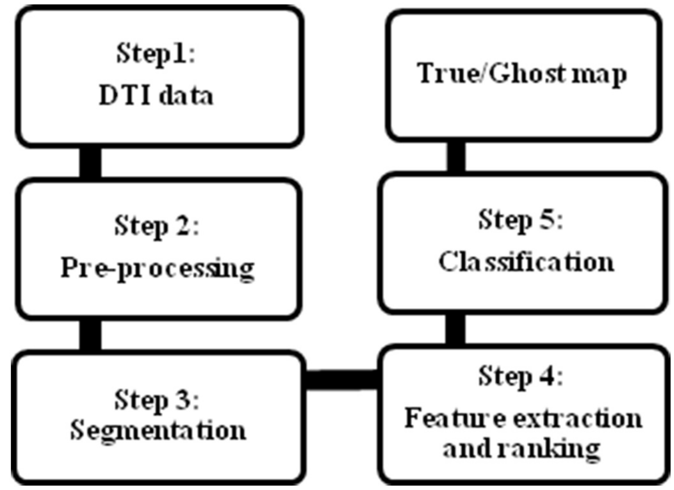

Fig. 1. General Framework of the ghost artifact detection scheme based on DTI data (b0 images).

2.2. Subjects and data acquisition

A total of 12 subjects (age range 8–15 years) were recruited and scanned: 7 healthy subjects (mean age = 11.34 years) with no evidence of spinal cord injury or pathology and 5 patients (mean age = 10.96 years) with cervical spinal cord injury. Subjects and parents provided written informed assent and consent of the institutional review board approved protocol. The inclusion criteria used for recruitment of the spinal cord injury group were: subjects had stable spinal cord injury as evidenced by no neurological change in the past three months and were at least 6 months post-spinal cord injury. The MRI scans were performed on a 3.0 T Siemens Verio MR scanner (Siemens Healthcare, Erlangen, Germany) with 4-channel neck matrix and 8-channel spine matrix coils.

DTI scans based on a 2D radiofrequency (RF) reduced field of view (rFOV) pulse sequence using a tilted excitation plane were collected axially from C1 to upper-mid thoracic depending on subject height in the same anatomical location prescribed for the T2-weighted images [2,4,5]. The rFOV sequence was based on a double refocused echo-planar imaging (EPI) sequence with 2D–selective RF excitations which allows for a higher in-plane resolution with fewer geometric distortions, eddy current and physiologic based artifacts [22]. Manual shim and fat saturation volume adjustments were also performed before data acquisition to confine the adjustment volume to the anatomy of interest as much as possible to limit residual distortions and chemical-shift artifacts. The imaging parameters included: Matrix size = 58 × 204, Diffusion directions = 20; Number of b0 scans = 6; field of view size = 250 mm, TR = 7900 ms, TE = 110 ms, slice thickness = 6 mm, b-value = 800 s/mm^2, flip angle = 90° and number of averages = 3. Cardiac gating was not used in this study as it increases scan time, which is not desirable in pediatric studies.

2.3. Preprocessing and segmentation

Initially, noise reduction of the images was achieved using a 2-D median filter with a 3 × 3 window size as well as 12 to 8-bit image compression to make the spinal canal more homogeneous (and reduce the sensitivity of noise bias). The choice of window size was estimated by experimenting with various window sizes (e.g., 3 × 3 and 5 × 5) using the standard median filter. The output images were then visually evaluated for improvement of cord/CSF and spinal canal/background boundaries. A window size of 3 × 3 was found optimal and chosen for the analysis pipeline.

Note, that the pre-processed images were only used for segmentation step. Next, morphological processing was applied to segment and