NeuroImage 82 (2013) 1–12

Contents lists available at SciVerse ScienceDirect

NeuroImage

journal homepage: www.elsevier.com/locate/ynimg

Diffusion imaging quality control via entropy of principal direction distribution

Mahshid Farzinfar [a,*], Ipek Oguz [a,b], Rachel G. Smith [b], Audrey R. Verde [a], Cheryl Dietrich [a], Aditya Gupta [a,e], Maria L. Escolar [e], Joseph Piven [a,b], Sonia Pujol [f], Clement Vachet [a,b,d], Sylvain Gouttard [d], Guido Gerig [d], Stephen Dager [g], Robert C. McKinstry [h], Sarah Paterson [i], Alan C. Evans [j]
The IBIS network, Martin A. Styner [a,b,c]

[a] Department of Psychiatry, University of North Carolina, Chapel Hill, USA
[b] Carolina Institute for Developmental Disabilities at University of North Carolina, Chapel Hill, USA
[c] Department of Computer Science, University of North Carolina, Chapel Hill, USA
[d] Scientific Computing and Imaging Institute, School of Computing, University of Utah, Salt Lake City, UT, USA
[e] Children's Hospital of Pittsburgh, University of Pittsburgh, Pittsburgh, PA, USA
[f] Surgical Planning Laboratory, Brigham and Women's Hospital, Harvard Medical School, Boston, MA, USA
[g] Dept. of Radiology, University of Washington, Seattle, USA
[h] Dept. of Radiology, Washington University, St. Louis, USA
[i] Department of Pediatrics, Childrens Hospital of Philadelphia, PA, USA
[j] McConnell Brain Imaging Center, Montreal Neurological Institute, Montreal, Canada

ARTICLE INFO

Article history:
Accepted 3 May 2013
Available online 17 May 2013

Keywords:
Diffusion magnetic resonance imaging
Diffusion tensor imaging
Quality assessment
Entropy

ABSTRACT

Diffusion MR imaging has received increasing attention in the neuroimaging community, as it yields new insights into the microstructural organization of white matter that are not available with conventional MRI techniques. While the technology has enormous potential, diffusion MRI suffers from a unique and complex set of image quality problems, limiting the sensitivity of studies and reducing the accuracy of findings. Furthermore, the acquisition time for diffusion MRI is longer than conventional MRI due to the need for multiple acquisitions to obtain directionally encoded Diffusion Weighted Images (DWI). This leads to increased motion artifacts, reduced signal-to-noise ratio (SNR), and increased proneness to a wide variety of artifacts, including eddy-current and motion artifacts, "venetian blind" artifacts, as well as slice-wise and gradient-wise inconsistencies. Such artifacts mandate stringent Quality Control (QC) schemes in the processing of diffusion MRI data. Most existing QC procedures are conducted in the DWI domain and/or on a voxel level, but our own experiments show that these methods often do not fully detect and eliminate certain types of artifacts, often only visible when investigating groups of DWI's or a derived diffusion model, such as the most-employed diffusion tensor imaging (DTI). Here, we propose a novel regional QC measure in the DTI domain that employs the entropy of the regional distribution of the principal directions (PD). The PD entropy quantifies the scattering and spread of the principal diffusion directions and is invariant to the patient's position in the scanner. High entropy value indicates that the PDs are distributed relatively uniformly, while low entropy value indicates the presence of clusters in the PD distribution. The novel QC measure is intended to complement the existing set of QC procedures by detecting and correcting residual artifacts. Such residual artifacts cause directional bias in the measured PD and here called dominant direction artifacts. Experiments show that our automatic method can reliably detect and potentially correct such artifacts, especially the ones caused by the vibrations of the scanner table during the scan. The results further indicate the usefulness of this method for general quality assessment in DTI studies.

Introduction

Diffusion magnetic resonance imaging has become an increasingly relevant neuroimaging technique because of its ability to investigate microstructural features of white matter non-invasively and in-vivo, particularly in studies of normal, developing, aging and pathological human brain (Bach et al., 2011; Hsu et al., 2008; Johansen-Berg and Rushworth, 2009; Le Bihan et al., 1986; Solano-Castiella et al., 2010; Unrath et al., 2010). Within the brain, diffusion of water molecules inside the tissues differs from "Brownian motion" and reflects interactions of molecules with many obstacles such as cell membranes, fibers and macro molecules. Diffusion Tensor Imaging (DTI) measures the rate and directionality of water displacement in various brain tissues via a Gaussian model of diffusion. The tensor in DTI is estimated using a set

* Corresponding author.

1053-8119/$ – see front matter © 2013 Elsevier Inc. All rights reserved.
http://dx.doi.org/10.1016/j.neuroimage.2013.05.022

of diffusion sensitized MR images, known as Diffusion Weighted Images (DWIs), by using several (at least six) non-collinear diffusion sensitizing gradients (Basser et al., 1994). Several tensor properties are commonly employed to analyze DTI, such as Fractional Anisotropy (FA) and PD, which characterize the shape and the principal direction of the resulting tensor. As of late, plenty of research has been conducted regarding diffusion tensor models resulting in several useful estimation techniques such as linear least square (LLS), non-linear least square, weighted least square (WLS) based on the log Rician probability distribution (Salvador et al., 2005) and Maximum Likelihood estimate using log-likelihood function of the Rician distribution (Fillard et al., 2007). While the use of the tensor model is currently predominant in clinical applications of diffusion MRI, DTI is unable to characterize fiber crossing within a voxel. Consequently, the need for investigating the non-tensor models has increased particularly for tractography (Basser et al., 2000; Mori et al., 1999) and fiber-driven analysis.

As theoretical work characterizing DTI grows, it is essential to increase their practical usability from a clinical environment perspective (Pierpaoli and Basser, 1996; Tournier et al., 2011). Inherently, DWI images suffer from diverse artifacts as a result of limitation or malfunction in the hardware or software of the scanning device. In addition, severe artifacts may also originate from physiological noise such as bulk head motion or respiratory motion. These difficulties cause propagated bias of diffusion tensor property estimation. Thus, it is essential to establish appropriate image quality assessment techniques on both DWI and DTI data.

DWI-based image quality control techniques can detect and potentially correct artifacts such as inter-slice abrupt differences in signal intensities, venetian-blind (Liu et al., 2010), eddy current induced distortion (Andersson and Skare, 2002; Reese et al., 2003), susceptibility (Andersson et al., 2003; Jezzard et al., 1999) and drop-out signal intensities (Tournier et al., 2011) which can be caused by mechanical vibration artifact (Gallichan et al., 2010) (see Fig. 1). The standard approach to correct drop-out, venetian-blind and inter-slice change based artifacts is to exclude the affected DWI images prior to the DTI estimation (Liu et al., 2010). It is noteworthy that such correction via exclusion of DWIs can lead to a biased estimate of the resulting tensor's properties and principal direction.

In order to reduce the influence of artifacts and the inherent noisy characteristics in DWIs, methods for denoising DWI or DTI data have been proposed (Tristán-Vega and Aja-Fernández, 2010) based on joint information from all DWIs and the correlation between them to filter the DWI images. Another possibility is to apply regularization of tensor images, in addition to estimating the tensor model (Wang et al., 2004). Alternatively, a maximum-a-posterior framework estimation can be used to couple tensor estimation and regularization to better capture information from noisy images (Fillard et al., 2007). Additionally, methods have been proposed that detect and reduce the influence of outliers as part of an iterative DTI estimation process that gives lower weights to artifactual data (Chang et al., 2005).

While these approaches are applicable in many general DTI settings, they may fail for more systematic artifacts resulting from mechanical vibration. These artifacts are known to occur mostly in some 3 Tesla Siemens scanners for subjects weighing less than 30 kg. Although the pre-processing hardware fix described in Liu and Liu (2011) corrects some of these artifacts, a substantial number of subjects remain artifactual. Strong diffusion gradients cause low-frequency mechanical resonance of the diffusion MRI system (Hiltunen et al., 2006; Mukherjee et al., 2008). This low frequency mechanical resonance leads to uneven distribution of vibrations within parts of the scanner and patient table, and hence uneven brain tissue movement. These vibration artifacts present as an area of signal loss in the DWIs and a subsequent directional bias in the estimated tensors. The directional bias is visually evident in color-coded FA images with local orientation of the principal tensor direction (see Fig. 2). The vibration artifact is hypothesized to be mainly due to substantial local echo shift in k-space, which exceeds the k-space window (Mohammadi et al., 2011). The movement-related signal-loss occurs most likely due to physical resonance of the scanner with longer time vibration when it is excited by strong left-right gradients (Gallichan et al., 2010). Therefore, not only the quality of DWIs is affected, but also the diffusion-related measurements are disrupted.

As a post-processing step of quality control to correct vibration artifacts, an improved DTI estimation approach was proposed (Gallichan et al., 2010). A co-regressor is used based on an empirical approximation to influence the artifacts in diffusion-tensor fit. This approximation assumes that the artifacts result from diffusion gradients in the left–right direction and also using the co-regressor restricts performance of correcting these artifacts. More recently, as a systematic technique for correcting these artifacts (Mohammadi et al., 2011), an approach was proposed using phase-encoding (PE) reversal by combining two images with reversed PE direction, each weighted by a function of its local tensor fit error. The disadvantage of this approach is that systematic correction causes limitations and difficulties during image acquisition which makes it less applicable.

In this work, we investigate artifacts that introduce a directional bias in the measured principal direction of diffusion (see Figs. 2 and 3), called dominant direction artifacts in the remainder of this paper. Upon visual inspection, such artifacts may be apparent in DWIs as local signal intensity drop-out or may not be apparent in DWIs. We propose a novel DT-MRI quality control measure to detect these artifacts by assessing the orientational bias of the diffusion tensor model and refurbishing DWIs using an entropy-based measurement on the orientational distribution of principal directions. The main difference between our approach and other vibration correction approaches (Gallichan et al., 2010; Mohammadi et al., 2011) is that these approaches adjust major vibration-induced drop-out signal intensities in DWIs. However, we show that these artifacts may not be visually apparent in DWIs. Thus, it would be

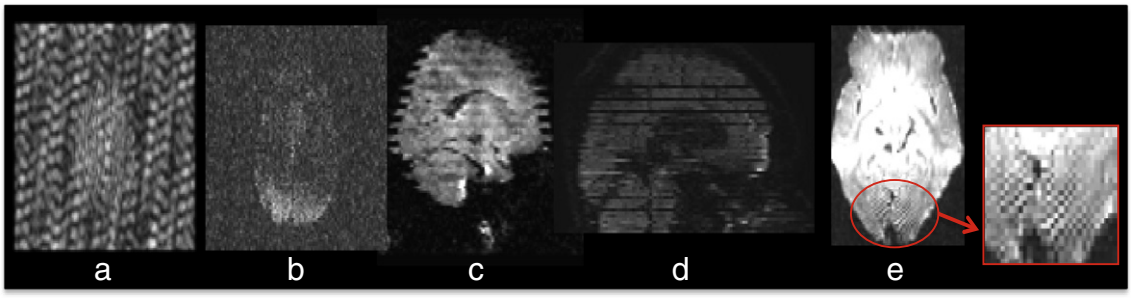

Fig. 1. Examples of intensity artifacts detected. (a) An electromagnetic interference-like artifact, (b) severe signal loss in the anterior and middle regions, (c) Venetian blind artifact, (d) inter-slice and intra-slice intensity artifact and (e) checkerboard artifact.