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Priors-guided slice-wise adaptive outlier cleaning for arterial spin labeling perfusion MRI☆

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ABSTRACT

Background: Due to the low signal-to-noise-ratio (SNR) and unavoidable head motions, the pairwise subtraction perfusion signal extraction process in arterial spin labeling (ASL) perfusion MRI can produce extreme outliers.
Comparison with existing methods: We previously proposed an adaptive outlier cleaning (AOC) algorithm for ASL MRI. While it performed well even for clinical ASL data, two issues still exist. One is that if the reference is already dominated by noise, outlier cleaning using low correlation with the mean as a rejection criterion will actually reject the less noisy samples but keep the more noisy ones. The other is that it is sub-optimal to reject the entire outlier volumes without considering the quality of each constituent slices. To address both problems, a prior-guided and slice-wise AOC algorithm was proposed in this study.
New Methods: The reference of AOC was initiated to be a pseudo cerebral blood flow (CBF) map based on prior knowledge and outlier rejection was performed at each slice. ASL data from the ADNI database (www.adni-info.org) were used to validate the method. Image preprocessing was performed using ASLtbx.
Results: The proposed method outperformed the original AOC and SCORE in terms of higher SNR and test-retest stability of the resultant CBF maps.
Conclusion: ASL CBF can be substantially improved using prior-guided and slice-wise outlier rejection. The proposed method will benefit the ever since increasing ASL user community for both clinical and scientific brain research.

1. Introduction

Arterial spin labeling (ASL) perfusion MRI is a technique for measuring regional cerebral blood flow (CBF) noninvasively (Detre et al., 1992; Williams et al., 1992). In ASL, arterial blood water is labeled with radio-frequency (RF) pulses in locations proximal to the tissue of interest, and perfusion is determined by pair-wise comparison of the brain images acquired after labeling with separate images acquired with control labeling using various subtraction approaches (Aguirre et al., 2002; Lu et al., 2006; Liu and Wong, 2005). Limited by the longitudinal relaxation rate (T1) of blood water and the post-labeling transmit process, only a small fraction of tissue water can be labeled, resulting in a very low SNR (Wong, 1999). To improve SNR, a series of ASL images are usually acquired to take the mean perfusion map for final CBF quantification. However, outlier image volumes out of the small number of total can significantly affect the mean CBF map. Advanced acquisition strategy such as background suppression (Maleki et al., 2012; Mani et al., 1997) can greatly improve signal-to-noise ratio and motion effects. Prospective motion correction (Zun et al., 2014) can correct motions online. But those techniques are not available in every

Abbreviations: ASL, arterial spin labeling; CBF, cerebral blood flow; SNR, signal to noise ratio; AOC, adaptive outlier cleaning; PAOC, prior-guided AOC; PET, positron emission tomography; PASL, pulsed ASL; CSF, Cerebrospinal fluid; SCORE, Structural Correlation based Outlier Rejection; GM, grey matter; WM, white matter; PAOCSL, slice-wise PAOC; MNI, Montreal Neurological Institute; ICC, intraclass correlation coefficient

☆ Part of data used in preparation of this article were obtained from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database (adni.loni.ucla.edu). As such, the investigators within the ADNI contributed to the design and implementation of ADNI and/or provided data but did not participate in analysis or writing of this report. A complete listing of ADNI investigators can be found at: http://adni.loni.usc.edu/wp-content/uploads/how_to_apply/ADNI_Acknowledgement_List.pdf.

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ASL imaging in many large scale studies such as Coronary Artery Risk Development in Young Adults (CARDIA) (ref: Dolui et al., 2016) and Alzheimer's Disease Neuroimaging Initiative (ADNI) (ref: Wang et al., 2013). In the literature, various outlier cleaning methods have been proposed. In (Wang et al., 2008), we defined outliers based on amplitude and successive difference of head motions and the mean and standard deviation of the whole brain CBF time series. (Tan et al. 2009) then used the mean and standard deviation of each CBF volume to identify outlier volumes. In 2013, we developed an adaptive outlier cleaning algorithm (AOC) for ASL MRI (Wang et al., 2013; Ze Wang et al., 2013). A common problem with all these methods is that the reference CBF map used for identifying outliers is the intermediate mean of the remaining CBF images, which may be initially contaminated by the outliers and will favor outliers and reject non-outliers. Additionally, most of existing methods are designed for removing the outlier image volumes (3D images) without considering whether they contain non-outlier voxels or not. Simply discarding the entire volume is certainly not an optimal way because it will reduce the sample size and then SNR for the non-outlier voxels. Meanwhile, outlier CBF image slices may exist in the non-outlier CBF image volumes. A third concern is that the rejection criterion is purely distance (or correlation) based without incorporating prior knowledge about CBF distribution. The method by Tan et al. (2009) can reject outlier slices but the method is still subject to other concerns as listed above. Maumet et al. (Maumet et al., 2014) proposed an M-estimator based method to clamp the perfusion signal at each voxel before taking the average. The empirical hard threshold used for clamping, however, may not be accurate at all in ASL especially given the low SNR. Recently, Dolui et al. (Sudipto Dolui et al., 2015; Dolui et al., 2017) proposed a new method to improved AOC by iteratively defining potential outlier as the CBF volume with high correlation to the reference mean. The CBF volume was discarded as actual outlier if discarding the volume reduced spatial variance in the reference CBF map obtained after removing the potential outlier from the averaging process. Although the method was demonstrated to perform considerable better compared to alternative methods, the method discarded whole volumes and also did not consider prior information about CBF distribution. The purpose of this study was to amend those volume-wise AOC strategies with prior guidance and a slice-wise workflow. For ease of description, we dubbed the new AOC method as prior-guided AOC (PAOC) hereafter. Part of the method and results has been presented in a conference abstract Wang (2016) and the code for the method is freely available from https://cfn.upenn.edu/~zewang/ASLtbx.php.

2. Materials and method

2.1. Subjects

Longitudinal ASL data acquired 3 months apart were obtained from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database (adni.loni.usc.edu) and were used in the preparation of this article. The ADNI was launched in 2003 as a public-private partnership, led by principal investigator Michael W. Weiner, MD. The primary goal of ADNI is to test whether serial magnetic resonance imaging (MRI), positron emission tomography (PET), other biological markers, and clinical and neuropsychological assessment can be combined to characterize the progression of mild cognitive impairment (MCI) and early Alzheimer's disease (AD). ASL was included as one MR modality of ADNI since the phase II of the project. Because of the ease of implementation and operations, the product Siemens PASL sequence was chosen to acquire the data. Data for the current manuscript were limited to scans from cognitively normal elderly controls (EC) from ADNI 2 in the ASL MRI substudy as of May, 2015. This cohort included 19 EC [age: 74.7 ± 6.6 yrs (mean ± standard deviation), Mini-Mental Status Examination (MMSE): 29.2 ± 1.1, 9 males, 10 females]. Full inclusion and exclusion criteria for ADNI are described at www.adni-info.org.

2.2. Image acquisition parameters

High-resolution structural MRI images were acquired using a 3D MPRAGE T1-weighted sequence with the following parameters: TR/TE/TI = 2300/2.98/900 ms, 176 sagittal slices, within plane FOV = 256 × 240 mm2, voxel size = 1.1 × 1.1 × 1.2 mm (Aguirre et al., 2002), flip angle = 9°, bandwidth = 240 Hz/pix. Resting ASL data were acquired using the Siemens product PICORE sequence (Wong et al., 1997), which is a pulsed ASL (PASL) sequence using the Q2TIPs (Luh et al., 1999) technique for defining the spin bolus. The acquisition parameters were: TR/TE = 3400/12 ms, TI1/TI2 = 700/1900 ms, FOV = 256 mm, 24 sequential 4 mm thick slices with a 25% gap between the adjacent slices, partial Fourier factor = 6/8, bandwidth = 2368 Hz/pix, imaging matrix = 64 × 64. The first volume of the 105 ASL acquisitions was used as the M0 image.

2.3. Image preprocessing

ASL images were preprocessed using state-of-art procedures implemented in ASLtbx (Wang et al., 2008; Wang, 2012). The raw images were first motion corrected using the ASL-specific motion correction method to avoid the systematic label/control labeling induced spurious motions (Wang, 2012). The mean EPI images were coregistered to the high-resolution T1 images using SPM12 (Wellcome Department of Imaging Neuroscience, London, UK, http://www.fil.ion.ucl.ac.uk/spm). Residual motions, mean CSF signal, global signal were then regressed out of each voxel using simple regression (Wang, 2012). ASL raw images (control (C) images and label (L) images) were subsequently smoothed with an isotropic Gaussian kernel with full-width-half-maximum = 6 mm. Perfusion-weighted images were extracted from the adjacent C and L images with simple subtraction, which were subsequently converted into quantitative CBF using the same routine as in (Wang et al., 2013). T1-weighted structural images were segmented into GM, WM, and CSF tissue probability maps (TPMs) using the new segmentation tool in SPM12, which were subsequently resliced to the native ASL image space after registering the T1 map with the mean raw ASL image. GM and WM masks were then created by thresholding the GM/WM probability maps with a threshold of 0.4. After CBF calculations, the CBF time series were cleaned using the proposed algorithms: prior-guided AOC (PAOC) applied to image volumes, and slice-wise PAOC (PAOCSL). The performance of the proposed algorithms were compared with the Structural Correlation based Outlier Rejection (SCORE) algorithm (Sudipto Dolui et al., 2015; Dolui et al., 2017). Other methods in the literature were not included because SCORE was shown to perform considerably better than those methods based on several criteria in (Sudipto Dolui et al., 2015; Dolui et al., 2017).

2.4. PAOC, PAOCSL and validations

Fig. 1 shows the flowchart of PAOCSL. The algorithm can be modified to a volume-wise PAOC after removing the slice-wise loop. A pseudo CBF map was introduced as the prior-guided CBF reference based on the common finding of that a CBF map resembles a grey matter density. Specifically, the pseudo CBF was created using a weighted sum of the GM and WM tissue probability maps obtained from segmenting the structural images. The relative weighing of the two tissue types was controlled by a constant $\beta > 1$ to ensure higher value in GM compared to WM with zero value in CSF (1.8 in this paper). Note that the reference map. can be replaced with an M0 map after masking out CSF which is bright in an M0 map unlike CBF. A mean CBF map obtained from otherwise good quality data can also be used as a reference. The slice (or volume) which was least correlated with the reference image was identified as a potential outlier and was removed by the algorithm as true outlier if exclusion of that from the averaging process resulted in reduced spatial variation within each tissue type (similar to SCORE (15)). Note that exclusion of a slice or volume from