Bayesian perfusion estimation with PASL-MRI

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Abstract
Arterial Spin Labeling (ASL) is currently used for non invasively quantify brain perfusion. In the non parametric commonest approach, the magnetization function at each inversion time \( T_I \) is estimated for a set alternated tagged and non tagged MRI images. This strategy is needed to minimize the effect of the drift and noise signals present in the MRI images by averaging the data to make it possible the detection of the weak magnetization differences between tagged and non tagged images. In this paper a novel flexible approach is proposed where the averaging procedure is not explicitly considered. The magnetization estimation problem is formulated in a Bayesian framework where spatio-temporal priors are used to deal with the ill-posed nature of the reconstruction task. The rigid alternating tagging strategy constraint imposed by the traditional ASL estimation approach is no longer needed making it possible to achieve smaller acquisition times without compromise the reconstruction quality.

Test with synthetic and real data are performed to assess the performance of the algorithm. These tests show that the proposed algorithms outperforms the traditional methods used.

1 Introduction
Perfusion is the process by which the nutrients in the blood stream are delivered to the tissues, through the capillary bed. This can be defined as volume of blood per time unit and per unit volume of tissue. It is a parameter whom knowledge provides very useful information about the condition of a certain organ[3].

Arterial Spin Labeling (ASL) Magnetic Resonance Imaging (MRI) technique relies on the detection of magnetically labeled water molecules. It offers a non-invasive way of generating perfusion images that are potentially quantitative [2]. In this technique, the main objective is to produce a control image and a labeled image, in which the static signal tissues are identical. To obtain the labeled image, water protons in the blood supplying the region are saturated or inverted by an inversion pulse, and after a certain time interval, called the Inversion Time (TI). In this time period, the labeled water molecules of the blood stream reach the capillaries of the tissues, exchanging magnetization with the tissue water molecules, from which the perfusion signal is measured. Subtracting the labeled image and the control image eliminates stationary tissue contribution, leaving the local magnetization by the labeled molecules[5].

Currently, there are three major methods for executing the subtraction of the controlled and labeled image. They are (a) simple pair-wise subtraction, (b) surround subtraction, in which the difference is calculated between each image and the average of its two nearest neighbors and (c) a subtraction of sinc-interpolated control and tag images[4].

Since the images resulting from ASL have intrinsically low Signal-to-Noise Ratio (SNR), substantial signal averaging is performed, which reflects in increased acquisition times. This limitation is especially critical when multiple TI points should be sampled in order to perform quantitative parameter estimation. In this case, a trade-off exists between the number of TI points sampled and the number of averages collected at each point[1].

The method proposed in this article intends to decrease the number of images acquired and yet improve the image SNR, which might allow that various TI points might be acquired without increasing the acquisition time.

2 Algorithm
The algorithm proposed here is designed in a Bayesian framework with the following observation model

\[
Y = F + D + v\Delta M + \Gamma
\]

where \( Y \) represents a \((n \times m \times l)\) 3 dimensional matrix (a stack of \( l \) images of \( n \times m \) pixels), \( F \) is the

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base morphological MRI image of the brain (common to all images of the sequence), \( D \) represents the Drift, \( \Delta M \) is the magnetization difference measured in the ASL model and \( \Gamma \sim N(0, \sigma^2) \) represents the Additive White Gaussian Noise (AWGN). The binary vector \( v \) contains the labeling marks indicating which image within the sequence is tagged.

The estimation of \( \Delta M \) given the observations \( Y \) and the vector \( v \) is a ill-posed problem and prior information is needed to regularize the solution. Therefore, the maximum a posteriori (MAP) estimation problem can be formulated as follows

\[
(\Delta M, \hat{F}, \hat{D}) = \arg \max_{\Delta M, F, D} \log p(Y|\Delta M, F, D, v) + \log p(\Delta M|v) + \log p(F|v)p(D|v)
\]

(2)

3 Results
To test the algorithm, a mask was created, simulating a human brain with two different regions. A sequence of images was then created with alternating labeling sequence and noise was added.

A sequence of Monte-Carlo tests were performed, with values of \( \sigma = 1 \), the value of the background image, \( F = 10000 \). The mean value obtained for SNR of the background image and for \( \Delta M \) were, respectively, 80.0228\,dB and –2.20135\,dB.

After processing, for the image obtained through simple averaging, the SNR of the magnetization image, \( \Delta M \) was 12.221\,dB. The Improved SNR is therefore ISNR = 14.4231\,dB. The mean error obtained was 23, 40\%. Using the Surround Subtraction method, the final SNR of \( \Delta M \) equals 12.2796\,dB, which represents a SNR gain of 14.4810\,dB. The mean error was 23, 07\%.

Using the approach proposed in this paper, the SNR of the processed image is approximated to 15.6200\,dB, and represents a SNR gain of 17.8214\,dB and the mean error was 15, 12\%. Considering the values obtained for the different methods used, it is clear that this new approach improves the SNR of the processed image, when compared to the most common approaches used nowadays, with an increment of approximately 3\,dB. In the figure 3 are displayed the images obtained using the three processing methods. The method has also been applied to real data with satisfactory results (figure3).

4 Conclusions
The results for the new approach proposed in this paper have revealed a major improvement in both the SNR of the final image, as well as the overall mean error, when compared with two of the main methods used in ASL processing nowadays. Quantitatively, it improves the SNR in 3\,dB and decreases overall mean error in approximately 8\%. When applied to real data, images processed with this new approach revealed less influence of noise and it’s easier to distinguish the contours of the different regions of the brain, as well as a smoothing of areas of same intensity.

These are important results, that might allow the decreasing of the long acquisition times necessary today in order to acquire data at multiple TI, without compromising image quality.

References


