A Total Variation spatial prior for the estimation of perfusion and transit time maps in PASL-MRI

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Introduction: Maps of perfusion and arterial transit time can be measured quantitatively using pulsed Arterial Spin Labeling (PASL), by fitting a kinetic model to magnetization difference images acquired at multiple inversion times. Model estimation can be successfully performed using Bayesian methods, which incorporate *a priori* physiological information regarding the parameters [1,2,3]. Due to the intrinsically very low signal-to-noise ratio (SNR) of PASL data, a single value for each physiological parameter is often obtained by averaging the data over large regions-of-interest (ROI). However, it would be desirable to obtain spatial maps with sufficient resolution [4]. Prior knowledge regarding spatial structure can also be incorporated in a Bayesian framework [5]. Here, Total Variation (TV) regularization is implemented as a spatial prior for parameter estimation [6] and is compared with the common Quadratic Form of the Euclidean Distance (QFED) based prior [7].

Methods: A two-compartment kinetic model was used to describe the magnetization difference (ΔM) collected at multiple inversion times (TI), as a function of the model parameters, perfusion (f) and Arterial Transit Time (ATT) (Δt) [8]. A Bayesian framework based on the *maximum a posteriori* criterion was designed in order to estimate the physiological parameters, including three prior terms describing *a priori* knowledge about the parameters: (i) information about the physiological distributions of the parameters; (ii) spatial prior based on the quadratic form of the Euclidean distance (QFED) between the parameter values in neighboring voxels [7]; and (iii) spatial prior based on Total Variation (TV) regularization, an edge preserving prior [6]. The two types of spatial priors were considered in addition to the physiological prior and were compared to the physiological prior only and to each other. A four-element neighborhood is considered for the spatial correlation [6]. The model parameters were defined by a multivariate Normal distribution with the values shown in Table 1, derived from data found in the literature.

Both synthetic and real PASL data were used to test the performance of the proposed method. Synthetic data were generated based on 64x64 perfusion and ATT maps (test objects). Four different test objects were considered (Figure 1): (1) a realistic brain mask (700 voxels) with homogeneous gray (GM) and white (WM) matter regions, for perfusion, and three hypothetical arterial territories, for ATT (*simple*); (2) same object as in (1) smoothed by application of a Gaussian filter (SD = 0.6) (*smooth*), (3) same object as in (1) with a slow (~8%) anterior to posterior gradient (*gradient*) and (4) same object as in (1) with a hypo- and a hyper-perfusion region simulating hypothetical lesions (*pathology*). Monte Carlo simulations were performed at six noise levels (10, 50, 75, 100, 125 and 150% of PASL maximum signal over the curve). Real PASL data were collected from 7 healthy volunteers on a 3T Siemens Verio system using a Q2TIPS PICORE sequence (TR/TE=2500/50 ms). The acquisition slab contained 9 contiguous axial slices, positioned parallel to the AC-PC line, with a resolution of 3.5x3.5x5.0mm^3. The tag-control pairs were sampled uniformly at TI's between 0.2 and 2.4s in steps of 2s, with 8 repetitions each. For each ΔM map, the noise was measured as the standard deviation of the signal over a ROI in the background. Parameter estimation was performed based on the full ΔM data (8 repetitions), as well as with reduced numbers of repetitions (2, 4 and 6).

Results: The normalized mean squared errors (NMSE) of perfusion and ATT estimation obtained for synthetic data, at a noise level of 100%, are shown in Figure 2. In general, the use of the TV prior produced the lowest errors, both relative to using the physiological prior only or the QFED spatial prior. The QFED prior performed best for the estimation of perfusion in the *smooth* test object. Figure 3 shows the normalized mean squared differences of the estimation results, obtained with different numbers of repetitions of the data, relative to the full data. The TV prior produced relatively lower errors compared with the physiological only prior. However, the QFED based prior showed the lowest error differences. This is probably explained by the fact that the errors obtained with this prior in the full data are higher than with the TV prior (as expected from the simulations), yielding lower relative errors with increased noise. Figure 4 shows the perfusion and ATT maps obtained using the 3 sets of priors, for one subject. All methods were able to identify the expected brain regions, namely gray and white matter in perfusion maps and posterior to anterior variation in ATT maps. However, the TV prior provided the clearest maps, with the QFED maps being smoother and the ones without spatial prior noisier.

Discussion: In this work, a Total Variation (TV) based spatial prior was proposed for the estimation of perfusion and ATT maps from PASL data. It was shown to produce more accurate results than a QFED based prior or the use of no spatial information, when realistic test objects exhibiting abrupt transitions between tissues or arterial territories were considered. In fact, commonly used QFED priors are usually useful for images with slow transitions (such as the *smooth* test object, for which QFED performed best), while TV is an edge preserving prior and is therefore more indicated for images with piecewise constant spatial structure (such as the *simple*, *gradient* and *pathology* test objects, for which TV performed best). Estimation results in real data also showed good performance of the TV prior in the identification of the expected perfusion and ATT brain regions, in particular when the noise in the data was manipulated by reducing the number of repetitions considered.

Table 1: Prior information of the parameters.

Parameter	Region	Mean	Standard Deviation
f(s^{-1})	GM	0.0120	0.0040
	WM	0.0040	0.0015
Δt (s)	Anterior	0.5	0.1
	Medial	0.7	
	Posterior	0.9	

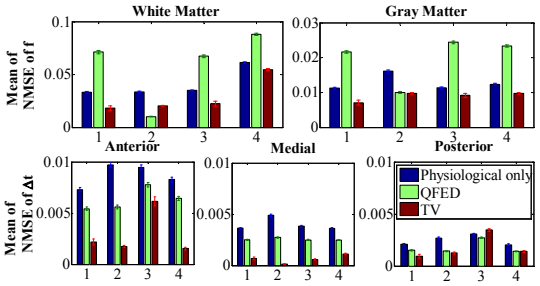

Fig.2: Estimation errors for Monte Carlo simulations at 100% noise. **1**–*Simple*, **2**–*Smooth*, **3**–*Gradient*, **4**– *Pathology*.

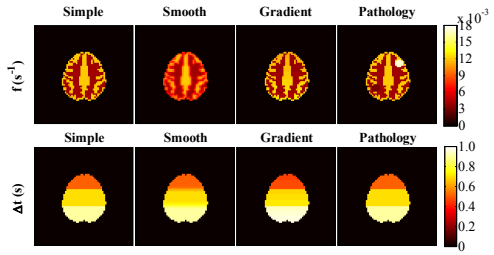

Fig.1: Test objects used in Monte Carlo simulations.

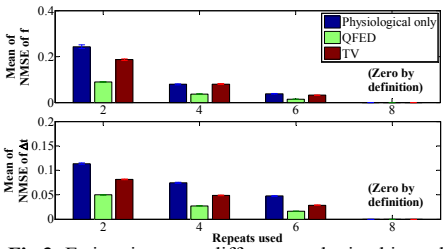

Fig.3: Estimation error differences obtained in real data, as a function of the number of repetitions.

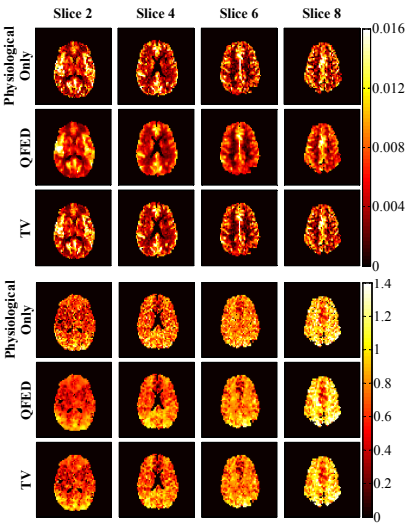

Fig.4: Maps of perfusion (top, s^{-1}) and ATT (bottom, s), for one subject.

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