ABSTRACT

In order to assess brain perfusion, one of the available methods is the estimation of parameters such as cerebral blood flow (CBF), cerebral blood volume (CBV) and mean transit time (MTT) from Dynamic Susceptibility Contrast MRI (DSC-MRI). This estimation requires both high temporal and spatial resolution to capture the rapid tracer kinetic and detect small impairments and reliably discriminate boundaries. With this in mind, we propose a compressed sensing approach to decrease the acquisition time without sacrificing the reconstruction, especially in the region affected by the tracer. Within the framework of a TV-L1-L2 minimization for solving the reconstruction from partial Fourier data, we introduce a novel baseline-constraining term weighting the difference of the reconstructed volume from the baseline in all regions where no perfusion is apparent. We show that the proposed reconstruction scheme is able to provide accurate estimation of the tracer kinetics (the necessary step for estimating CBF, CBV and MTT) in the volume even at high acceleration (x16), with a RMSE of 11, a third of what achievable without the baseline constraint.

Index Terms— compressed sensing, MRI, dynamic susceptibility, DSC-MRI, contrast kinetics, multiple sclerosis

1. Introduction

A well evaluated technique to assess brain perfusion is the Dynamic Susceptibility Contrast-MRI (DSC-MRI). This method is based on a set of T2*-weighted images acquired before, during and after the injection of a contrast agent (gadolinium-DTPA). The reduction of the transverse tissue relaxation time (T2*) caused by the tracer can be detected as an attenuation in the MRI signal (see Fig. 1). DSC-MRI allows the analysis of several perfusion parameters, namely the cerebral blood flow (CBF), the cerebral blood volume (CBV) and the mean transit time (MTT) [1, 2, 3]. The most used technique to extract these parameters involves several steps, the crucial one being a deconvolution operation. DSC-MRI requires, namely, high temporal resolution to better describe the rapid tracer kinetic, high spatial resolution to detect small impairments and reliably discriminate boundaries, and high signal-to-noise ratios to reduce the ill-conditioning problem of the deconvolution step. With such impacting constraints, DSC-MRI could potentially gain from lower data acquisition requirements. Clinically, faster sampling could allow accurate arterial input function estimation or applications of tracer kinetic models requiring higher temporal resolution than currently available. Compressed Sensing (CS) is a novel technique used to decrease the acquisition time or increase reconstruction fidelity [4, 5]. CS allows to overcome the limit of Shannon theorem by reconstructing the signal from a small sample set of measurements under the sparsity hypothesis of the signal itself. To increase the impact of CS, a wavelet transform may be used, since it sparsifies the representation of the signal.

The application of CS to DSC and its influence on quantitative parameter estimation is gaining attention, but it is just beginning to be explored [6]. However, the sparsity of the contrast agent distribution, its impact on the acquisition, and the ability to reconstruct the contrast kinetics on the small regions involved by its passage have not been investigated yet. On one side, the tracer transit will change each slice’s intensity profile from one temporal sample to the next one, on the other the mutual information between two temporal samples is extremely redundant. We try to exploit this redundancy to constrain the reconstruction, so to concentrate the influence of the information gathered from different temporal samples to be focused near the most perfused area, that will experience a larger attenuation in the MR signal. By this means, it is possible to further reduce the data (undersampling) needed for the reconstruction, resulting in a smaller acquisition time, without causing data loss when compared to the standard method applied to a traditional non-dynamic MRI.

2. Methods

The main idea in this work is the efficient application of compressed sensing theory to DSC-MRI real data, exploiting the fact that the majority of voxels are not involved by the fast kinetics of the tracer. Building on the reconstruction scheme developed in [7], we introduce a spatial mask as suggested in [8] so to use the information of the data already reconstructed...
2.1. Baseline constrained reconstruction

The reconstruction scheme from partial Fourier data Rec-PF proposed in [7] from undersampled MRI uses an alternating direction method to minimize the objective function:

\[ O(u) = \sum_i \| D_i u \|_2 + \tau \sum_i |\psi_i^T u| + \lambda /2 \cdot \| F_p u - f_p \|_2^2. \]  

(1)

Given an \( N \times N \) image represented as a row vector \( u \) in the space domain, and indicating with \( D_i \) the discrete differential operator, the first term \( \sum_i \| D_i u \|_2 \) represents the total variation (TV) of the image, that is a first order gradient containing structure edges information, and whose minimization enforces a piecewise smooth estimate of the image. Indicating with \( \psi_i \) the discrete wavelet transform matrix [9], the second term \( \sum_i |\psi_i^T u| \) is the \( \ell_1 \)-norm of the wavelet representation of the image: this term is widely used in compressed sensing applications since it promotes the signal sparsity [5]. Indicating with \( F_p \) the \( p \times N^2 \) compressed sensing matrix mapping the image into \( p < N^2 \) acquired frequencies, the term \( \| F_p u - f_p \|_2^2 \), being the \( \ell_2 \)-norm in the Fourier domain, expresses the fidelity of the reconstruction to all of the partial Fourier data acquired.

Given a spatial mask \( M \) containing the regions which intensities are expected to change due to the contrast agent, a baseline image \( u^0 \) acquired at time \( t = 0 \), and an image \( u^T \) to be reconstructed at time \( t = T > 0 \) acquiring \( p \ll N^2 \) samples of the K-space, we add to the Eq. 1 a fourth term penalizing the distance of the reconstructed image \( u^T \) from \( u^0 \). We then add a term to Eq. 1:

\[ \sum_i \| \psi_i^T u^0_i - \psi_i^T u^T_i \|_2, \quad i \notin M \]  

(2)

In order to increase the smoothness of the reconstructed image, we use a relaxed version of Eq.2, where a weighted average between \( u^0 \) and \( u^T \) is computed for each \( i \notin M \). We can therefore minimize the following objective function with an alternate iterative scheme [8], obtaining a baseline constrained reconstruction from partial Fourier data (BCRec-PF):

\[ \mathcal{O}_B(u) = O(u) + \| \xi^b - \psi^T u \|^2. \]  

(3)

where \( \xi \in \mathbb{R}^n \) represents the constraints (in the wavelet domain) that the pixels of the reconstructed image need to satisfy, depending on their inclusion inside the spatial mask \( M \):

\[ \xi^b = \begin{cases} \psi^T u^0_i & i \in M \\ \psi^T (\alpha u^T_i + (1 - \alpha) u^0_i) & i \notin M \end{cases} \]  

(4)

where \( 0 < \alpha < 1 \), \( u^T \) is the reconstructed image at the current time point \( T \). By this means we minimize the difference between the reconstructed image and the baseline only in the estimated stationary region. The minimization of \( \mathcal{O}_B(u) \) can be carried out with the iterative scheme proposed in [7], adding the least square expansion of \( \| \xi^b - \psi^T u \|^2 \).

2.2. Spatial mask definition

In all preliminary studies on Shepp-Logan phantom stacks [8], spatial maps \( M \) used in Eq. 4 were fixed and known a priori. With this approach, instead, we estimate adaptively the spatial mask, alternately performing full and undersampled scans.

Before the infusion of the tracer at time \( t_0 \), at least two full scans are usually acquired. Their average yields the baseline image \( u^0 \), i.e., the description of the system in its stationary state. When the image \( u^T \) at time \( t = T > t_0 \) has to be reconstructed, and the baseline \( u^0 \) and some reconstructed image \( u^{T-1} \) are available, the corresponding mask \( M_T \) is estimated similarly to what has been proposed in [10], by setting a threshold \( \theta \):

\[ M_T = \| u^0 - u^{T-1} \|_2 > \theta \]  

(5)

2.3. Haemodynamics parameters

Haemodynamics parameters can be estimated from DSC-MRI data, under the hypothesis that it is possible to describe the concentration of the tracer \( C_{VOI}(t) \) in a volume of interest (VOI) as the application of a transport function \( h(t) \), seen as the impulsive response of the system, depending on the blood
flow and on the vascular structure, to the arterial input function $C_{AIF}(t)$:

$$C_{VOI}(t) = C_{AIF}(t) \otimes h(t).$$  \hspace{1cm} (6)$$

From the knowledge of $C_{VOI}(t)$, $C_{AIF}(t)$ and $h(t)$, it is possible to estimate a number of clinically useful haemodynamics parameters as mean transit time (MTT) of a tracer particle within the VOI, the cerebral blood volume (CBV) representing the percentage of blood vessel tissue in the VOI, and the cerebral blood flow (CBF), representing the speed in which the nutrients reach the tissue. Unfortunately, $h(t)$ is usually unknown, and must be estimated with a deconvolution approach. A preliminary step to the deconvolution is the recovering of a smooth tracer’s concentration; this is achieved by first transforming the attenuation signal $S(t)$ of the DSC-MRI in the corresponding noisy concentration signal $C_{raw}(t)$:

$$C_{raw}(t) = -\frac{1}{TE} \ln \left( \frac{S(t)}{S_0} \right),$$

where $TE$ is the sequence echo time, $S(t)$ represents the intensity signal and $S_0$ is the baseline intensity. Then, the concentration signal $C_{raw}(t)$ is fit through a weighted non-linear least square estimator, with a monovariate gamma-function to provide the smooth concentration $C_{VOI}(t)$ [11]. A correct reconstruction of $S(t)$ is therefore of paramount importance for a correct estimation of CBF, CBV and MTT.

3. Data

In order to evaluate the performance of the original method proposed in [7] and those proposed here, we use a stack of $256 \times 256 \times 12$ voxels DSC-MRI images, resolution $0.9 \times 0.9 \times 6 \text{ mm}$, obtained with EPI sequence, TR = 1.635s, TE = 40ms, 100 time samples (corresponding to about 120 seconds), acquired from a relapsing-remitting multiple sclerosis patient [11].

To simulate the sampling of images with a smaller time step than what actually used in the image acquisition, the data are interpolated by using cubic splines (Fig. 2).

4. Results

After choosing the value $\theta = 50$ and $\alpha = 0.6$ optimizing their value on simulated data, we tested the reconstruction performance of Rec-PF against the proposed BCRec-PF applying different undersampling levels on $S(t)$, by taking 1/4, 1/8 and 1/16 (corresponding to acceleration factors of 4, 8 and 16) of the complete K-space domain. The reconstruction error has been calculated as the average pixel-wise root mean square error, then averaged over all time. Being $u^t$ the estimated reconstruction, and $u^t$ the original image at time $t$, we have:

$$\text{RMSE} = \frac{1}{T} \sum_{t=1}^{T} \left( \frac{1}{N} \sum_{i} (u^t_i - u_i^t)^2 \right).$$  \hspace{1cm} (7)$$

Results are reported in Tab. 1.

<table>
<thead>
<tr>
<th>Method</th>
<th>BCRec-PF</th>
<th>Rec-PF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acceleration 4</td>
<td>5.90</td>
<td>11.40</td>
</tr>
<tr>
<td>Acceleration 8</td>
<td>9.57</td>
<td>28.40</td>
</tr>
<tr>
<td>Acceleration 16</td>
<td>11.13</td>
<td>32.68</td>
</tr>
</tbody>
</table>

In order to evaluate the ability of the reconstruction algorithms to preserve the tracer kinetics information (usually involving small regions of the image), the reconstructed temporal patterns $S(t)$ in 16 selected regions of interest (ROI) of dimension $3 \times 3$ pixels have been analyzed: 8 regions correspond to perfused areas and 8 to non-perfused areas, as shown in Fig.2. The reconstruction performance on these regions are qualitatively reported in Fig. 3, whereas the estimated CBV parametric maps are reported in Fig. 4.

5. Conclusions

In this paper we describe a reconstruction algorithm from partial Fourier data, that building on a previous TV-L1-L2 minimization scheme introduces a novel term constraining the reconstructed image to assume values close to the baseline intensity for all voxels that are estimated as non-perfused. We additionally define a temporal adaptive way to update the spatial mask that constrains the minimization process. It is worth noting that within the perfusion mask no regularity constraints are imposed, making the method able to follow the perfusion kinetics, at the possible expense of smooth estimates.

We tested this proposed baseline constrained reconstruction...
Fig. 3. Representative reconstruction of the $S(t)$ in a representative region for different acceleration with the proposed BCRec-PF and the Rec-PF methods: the original intensity signal (solid blue line), reconstructed signal (solid red), and reconstructed signal confidence interval (dotted green) are reported.

from partial Fourier data (BCRec-PF) on real DSC-MRI data acquired from a multiple sclerosis patient, showing that the perfusion pattern exhibits small reconstruction error within the estimated mask, and that the overall reconstruction error is lower than what was achieved by the original Rec-PF algorithm.

6. References


