Motion artifact correction in ASL images: an improved automated procedure

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***Abstract*—Arterial Spin Labelling (ASL) is a perfusion MRI technique with tremendous applications in the study of biological markers and prognostic factors of brain tumors and in the assessment of neural diseases; moreover, it is completely non-invasive as it uses the magnetically inverted blood of the patient as an endogenous tracer. Unfortunately this powerful method is only viable in very limited conditions due to its extreme sensitivity to artifacts originated by head motion, that are not effectively addressed by the current software solutions. This paper presents a motion correction procedure that addresses this issue and provides improved solutions to enhance ASL images of the brain in presence of severe head motion. Experimental results run on a motion-affected pCASL dataset show the concept and demonstrate the superiority of our proposed procedure compared to standard 3D registration.**

***Keywords*-Image Processing; Motion artifact correction; Magnetic Resonance Imaging; fMRI; Arterial Spin Labelling.**

I. Introduction

Arterial Spin Labelling (ASL) is a perfusion MRI technique that allows to measure cerebral blood flow (CBF) in a completely non-invasive way, as it uses the inflowing arterial blood of the patient labelled by magnetic inversion as an endogenous tracer [1]. The same brain volume is imaged before and after inverting the longitudinal magnetization of the arterial blood of the patient just upstream of the region of interest, generating a pair of control and label images, respectively; the magnetically inverted blood determines a localized variation of the MRI signal in the label image, so that the pairwise image subtraction of corresponding control and label returns a signal that is proportional to CBF. ASL has tremendous applications in the assessment of cerebrovascular disorders, in basic and clinical neuroscience, as well as in the study of biological markers of brain tumors. Furthermore, ASL combined with genetic studies provides new insights into the biological pathways and mechanisms of neuralgias and psychiatric illness [1] [2].

ASL technology has considerably improved in the past few years, increasing its utility as a diagnostic and research tool in neurological applications compared to traditional fMRI. Nevertheless, it intrinsically suffers from low Signal-to-Noise-Ratio (SNR) and it is extremely sensitive to artifacts arising from the head motion of the patient [3]; this dramatically impacts on the effective usability of the technique in the standard diagnostic applications.

In the usual practice, interleaved control and label pairs are acquired several times (namely dynamics) with the same acquisition conditions and then averaged over the dynamics in order to increase SNR. The CBF is therefore calculated from the subtraction of the average control and the average label image. Each image, either a control or a label, is a 3D volume acquired as a stack of 2D slices (see Figure 1 and 2 for examples).

Before averaging controls and labels over the dynamics, motion correction is usually performed through 3D rigid body registration of the images, as in BOLD fMRI scans [3]. A widely used approach is based on six-parameter-based rigid body transformation that minimizes the distance between each volume and the reference volume, that is typically the first image of the ASL series [4]. This approach suffers from several limitations in ASL images. Firstly, registration works towards the minimization of the intensity differences between the image to be registered and the reference; as a consequence, registering the images, that can be either controls or labels, against the first acquired image (generally a control) misinterprets the intensity difference originated by the ASL magnetic inversion [3]. This might improperly decrease not just the intensity differences generated by motion, but also the functional ASL perfusion signal, with disastrous consequences for the calculation of the CBF map. Secondly, ASL images are acquired slice by slice with a non negligible time delay between the acquisition of the different slices, and therefore they are not immune from inter-slice motion [5]: as a consequence, the slices of a single image do not line up as a real 3D volume, which impacts on the effectiveness of 3D registration.

The main contribution of this paper is to provide a comprehensive procedure able to address the unsolved issues in the correction of head motion in ASL brain imaging, overcoming the limitations of the current software solutions. The main steps are: (i) realignment of all the acquired volumes in order to correct the inter-slice motion in each image; (ii) rigid body registration of the re-aligned volumes, separately for controls and labels in order to avoid minimization of the labelling signal; (iii) selective averaging of registered pairs of controls and labels, removing intensity outliers due to

registration errors.

The effectiveness of our proposed procedure was established on ASL images affected by severe head motion and compared to standard motion correction approach based on 3D rigid registration.

II. Materials and Method

pCASL (pseudo-continuous ASL) brain imaging of a healthy volunteer was performed on a 3 T Achieva scanner (Philips) with a scan time of 4 min and 8 s, single shot echo planar imaging (EPI). Each scan included 17 slices of 7 mm thickness each with $3 \times 3mm^2$ resolution, sensitivity-encoded (SENSE), time of echo (TE) of 12.2 ms, repetition time (TR) of 4000 ms, slice-time 35 ms. The anonymized dataset was exported in Dicom from the MR scanner and loaded into our fully-automated motion correction program; this is implemented in ImageJ [6], a public domain and platform independent image processing program, extending the Imagej libraries [6] [7] with our own classes. The main steps of the proposed procedure are the following:

Inter-slice realignment of volumes. In order to correct inter-slice motion, each volume undergoes realignment. In turn, each slice of the volume is used as the reference with respect to which the next slice is rigidly aligned, so that the alignment proceeds by propagation. The central slice of the volume (the one with the highest amount of signal) is taken as anchor for the alignment technique, that proceeds from the center towards the extremes of the volume (first and last image of the stack, respectively). The 2D registration of each slice with respect to the propagating reference is based on a coarse-to-fine optimization strategy (pyramid approach), performing minimization of the difference of intensities of the two images according to a variation of the iterative Marquardt-Levenberg algorithm for non-linear least-square optimization (MLA) [8].

3D registration of realigned volumes. After realignment, the first control and label pair is co-registered and taken as a reference for the 3D registration of the images of the following dynamics. In order to preserve the intensity difference between control and label that is on the base of CBF calculation, in our approach the registration of the label against the control is limited to the first image pair; then all the controls are registered against a control reference and all the labels against a label reference, respectively. This is different from the standard registration procedures, that register all the images of the series (either controls and labels) against the first volume.

In order to minimize the influence of small intensity differences generated by noise, we applied an edge-based approach that takes into account only the most relevant signals of the images: first the edges of the images are detected through Sobel filtering, then 3D registration is applied to minimize the differences between each image and the corresponding reference. The technique applies a conjugate direction search to align the 3D volumes rigidly, adjusting the translation and rotation parameters towards the minimization of the difference between the volumes. The difference is measured in terms of intensity correlation.

Selective averaging In order to increase the Signal-to-Noise-Ratio (SNR), it is common practice to repeat the acquisition of control and label pairs several times (i.e. dynamics) and then average controls and labels over the dynamics; this increases the Signal-to-Noise-Ratio of a factor $\sqrt{N}$, where N is the number of averaged dynamics.

After 3D registration, mismatch of control and label images due to residual head motion typically generates signal outliers consisting in high and low signal spikes [3]. In our proposed procedure this issue is addressed by detecting pixel by pixel the signal outliers over the dynamics; the outliers are removed during the selective averaging procedure. First, the average avg and the standard deviation std of the signal over the N dynamics is calculated per each pixel of the image. Then, the outliers in the distribution of the pixel's signal over the dynamics are recognized as the values that are not included in the range $avg \pm 3 \cdot std$ and replaced by the value avg. The averaging of labels and controls is finally repeated without including the outliers.

III. Experimental validation

To quantitatively assess the effect of motion correction, we examined the pCASL dataset described in Section II and we extracted a limited number of temporally adjacent label and control scans that we could reasonably assume as not affected by head motion. As the reliability of this assumption decreases with time acquisition, we extracted 4 control/label pairs of 17 slices each, for a total number of 136 images. This motionless set of images was used as the ground truth for our validation. Then the motionless set was used to build a second set, where severe head motion was artificially introduced to simulate a subject moving the head from side to side during acquisition. The generation of artificial motion is necessary for a quantitative validation of the motion correction procedure, since it makes sure that the intensity difference between the motion affected and the motionless images is entirely due to head motion.

In order to simulate the worst motion conditions, both inter-slice and inter-volume motion were simulated [5]. In particular, we generated: (i) a 0.05 degrees rotation between each of the 136 slices; (ii) a 0.3 degrees rotation between each control and label volume. Therefore the resulting set was affected by an overall rotation of 9.2 degrees propagating from the first to the last acquired slice. Figure 1 shows a montage of some of the images of this set.

The validation procedure consisted in the following steps: (i) we run our motion correction algorithm, consisting on inter-slice realignment, 3D registration of labels and controls and selective averaging with outliers filtering, on the motion affected dataset. The output of this step, as

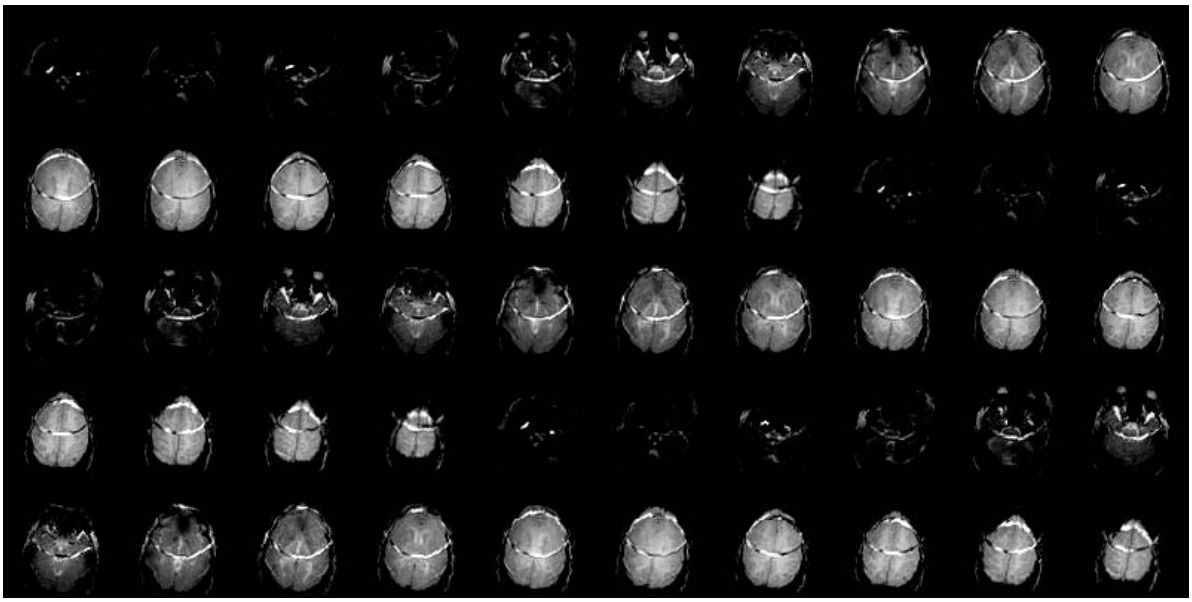

Figure 1: Motion simulated dataset, slice 1 to 50 of 136.

already explained, is a pair of motion corrected control and label images, of 17 slices each. These images are shown in Figure 2; (ii) we applied simple averaging of controls and labels to the motionless dataset and used the resulting averaged control and label pair as the ground truth of our evaluation; (iii) we assessed the success of motion correction pixel by pixel in terms of absolute difference between the corresponding motion corrected and motionless images, as it is reported in the following equation:

$$d = \left| \frac{Image_{motion} - Image_{motionless}}{Image_{motionless}} \right| \qquad (1)$$

The value d is calculated for each pixel as the absolute difference of the pixel's intensity in the motion corrected and the motionless image, respectively. This is a measure of the residual motion in the corrected images: the lowest d, the highest the success of the motion correction routine.

The obtained results, grouped for the control and the label, are reported in the first two boxplots of Figure 3. Our motion correction procedure was successful, with median value of the residual motion below 3%. The most of the residual motion values (three quarters of the total values, which corresponds to the highest horizontal line of the box), were below 22%.

Our proposed procedure was compared to the standard routine for fMRI motion correction; as already mentioned in Section I, this routine is based on 3D registration of all the images (controls and labels) against a reference consisting in the first volume of the time series [9], followed by simple averaging of all the label and control images separately, as in the standard practice for ASL. As for our technique, we first applied the standard registration routine to the simulated motion dataset and then measured the residual motion against the motionless images. Residual motion was calculated again on the same validation dataset used for our proposed procedure.

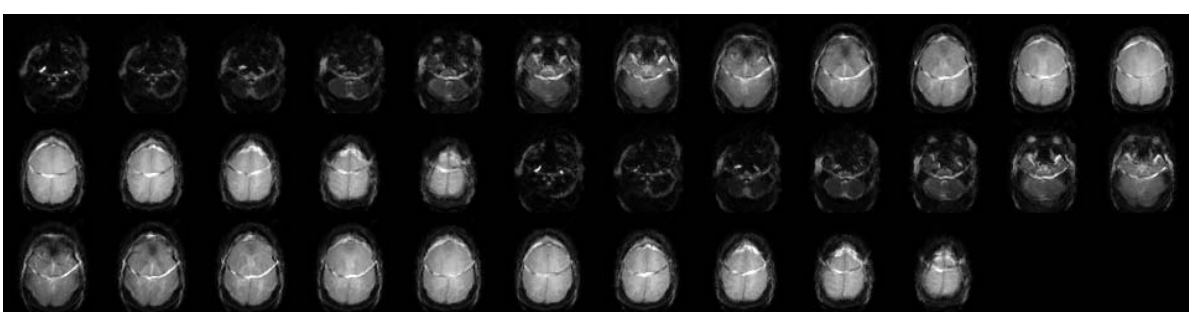

Figure 2: Output of the proposed motion correction procedure: averaged control image (first 17 slices of the sequence) and average label image.

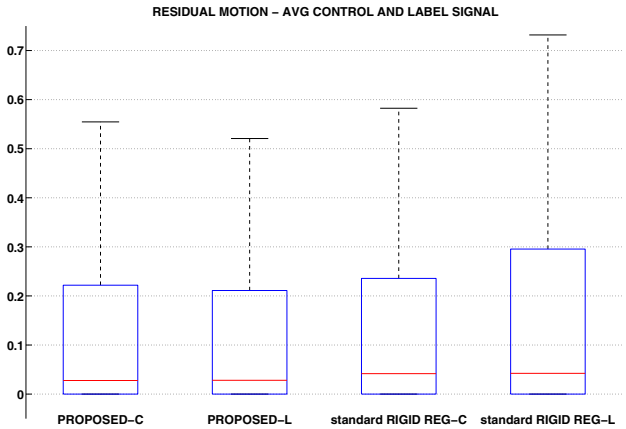

Figure 3: Residual motion of the average control and label image, respectively after applying our motion correction procedure and standard 3D rigid registration.

The obtained results are reported in the last two boxplots of Figure 3, separately for control and label. As shown by the boxplots, rigid registration performed worse than our technique: while the results on the control (that is less affected by motion since it temporally precedes the label) are quite comparable, the performance of rigid registration on the label was much lesser, with median residual motion above 4% and range of residual motion values upto 30% higher than our proposed procedure.

As explained in Section I, a map of the cerebral blood flow (CBF) of the patient is generated by the subtraction of the control and the label image. Figure 4 reports the residual motion calculated on the CBF maps respectively after applying our motion correction technique and after applying the routine based on rigid registration.

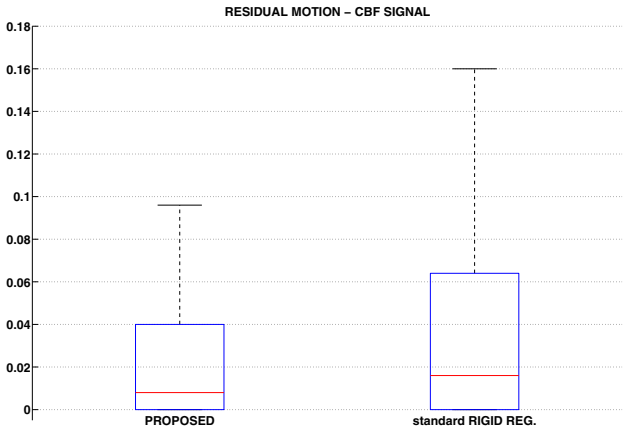

Figure 4: Residual motion of CBF map, respectively after applying the proposed motion correction procedure and a motion correction routine based on 3D rigid registration.

As it is visible from the figure, our technique obtained the best results, with median residual motion of about 0.8% and range of residual motion values upto 60% lower than the rigid registration routine.

IV. Conclusion and Future Work

This paper presented an automated motion correction technique for ASL images that addresses issues that are generally overlooked by the current software solutions; in particular: (i) rigid realignment of the slices of each acquired volume, in order to correct inter-slice motion; (ii) volumetric rigid registration of the realigned volumes, separately for controls and labels in order to avoid the improper minimization of the ASL labelling signal; (iii) improved averaging with selective filtering of intensity outliers. Experimental results on a pCASL dataset with severe head motion artificially generated demonstrate that our solution outperforms the traditional motion correction technique based on volumetric rigid registration.

As a future work, we plan to extend our proposed procedure taking into account an estimation of the movement of the head during image acquisition.

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