

Individually optimized ASL background suppression using a real-time feedback loop on the scanner

¹Kirsten Koolstra, ¹Marius Staring, ²Paul de Bruin, ³Matthias J.P. van Osch

¹Division of Image Processing, Radiology, Leiden University Medical Center, the Netherlands

²Philips, Best, the Netherlands

³C.J. Gorter Center for High Field MRI, Radiology, Leiden University Medical Center, the Netherlands

Introduction

Suppression of background signal in ASL leads to perfusion images with higher signal-to-noise ratio (SNR) compared to ASL without background suppression (BGS)¹. BGS is obtained by applying multiple inversion pulses before and during the post-label delay (PLD). The optimal inversion times, and therefore the quality of the BGS, depends on the relaxation times of the underlying tissue (T_1 , T_2) and on imperfections of the scanner's magnetic fields (B_0 , B_1^+). Although this results in inter-subject differences, current ASL protocols make use of one set of predefined inversion times for all subjects, primarily because these inter-scan variations are not known at the moment of scanning. This means that the quality of the resulting perfusion images is not optimal for all subjects. In this work, we develop and implement a feedback loop that optimizes the timings of ASL BGS pulses real-time on the scanner, generating individually optimized perfusion images for each subject.

Methods

MR Data acquisition: Experiments were performed in 2 healthy volunteers with informed consent obtained, using a 3T MR system (Philips, The Netherlands) with a 32-channel head coil. PCASL data were acquired with a single-shot EPI readout: label duration/PLD = 2050/1750 ms, TE/TR=17/4000 ms, initial inversion times = 683/1948/2980/3597 ms. Initial inversion times were optimized via simulations for suppression of CSF, gray matter, white matter and corpus callosum.

Feedback mechanism: Directly after each dynamic scan, acquired label and control images were sent to an external computer via the remote connection software eXTernal Control (XTC) (Philips, The Netherlands). On this computer, we developed a Python processing framework that receives and processes the images in real time. Updated inversion times were sent back to the scanner computer, where we implemented a parameter import functionality during scanning. This closes the feedback loop, shown in Fig. 1A.

Optimization of inversion times: Four inversion times (2 during labelling, 2 during PLD) were optimized in real time, such that the signal in the label image was minimized while maximizing the perfusion signal to avoid magnitude subtraction errors for near-optimal BGS, i.e.

$$\hat{\mathbf{T}} = \underset{\mathbf{T}}{\operatorname{argmin}} \|\mathbf{m}_{\text{label}}(\mathbf{T})\|_2 - \lambda \|\mathbf{m}_{\text{control}} - \mathbf{m}_{\text{label}}\|_2,$$

with $\mathbf{m}_{\text{label/control}}$ the label/control image obtained with inversion times $\mathbf{T} = [T_1, T_2, T_3, T_4]^T$. The optimization was done using the Nelder-Mead method² and was terminated after 80 dynamics (~10 min).

Results

Figures 1B,C show the parameter updates and the corresponding inversion times during the feedback loop scan in 1 volunteer. Figures 1D,E show the cost function and the label images. Figure 2 shows the averaged ASL images over the last 10 dynamics of the feedback loop scan, with and without regularization, compared to a scan with and without standard BGS. Figure 3 shows the results for a stimulus scan at the end of a feedback loop scan, showing a signal increase in the visual cortex both in averaged perfusion and control images.

Discussion

The developed feedback loop mechanism was able to increase the temporal SNR of the perfusion images by 23% compared to 15% for standard BGS (with respect to no BGS). Regularization prevents the feedback loop scan to converge to a local minimum, which otherwise leads to magnitude subtraction artifacts. The improved BGS with the regularized feedback loop leads to a control image that directly shows the perfusion signal. This patient-optimized approach could therefore be a first step towards subtractionless ASL to allow twice the temporal resolution when monitoring neuronal activation.

References

- [1] Maleki N, et al. (2012). Optimization of background suppression for arterial spin labeling perfusion imaging. *MAGMA*. 25(2):127-33.
- [2] Nelder J, et al. (1965). A simplex method for function minimization". *The Computer Journal*. 7 (4): 308–313.

Figures

Figure 1. Implementation of the feedback loop on the scanner. **(A)** Schematic overview of the feedback mechanism for the PCASL sequence. **(B)** Parameter updates with respect to the initial guess are sent to the scanner after each dynamic scan. **(C)** Inversion times used for each of the dynamic scans. **(D)** The 2-norm of the label image decreases with the dynamic scan number. **(E)** The corresponding label images.

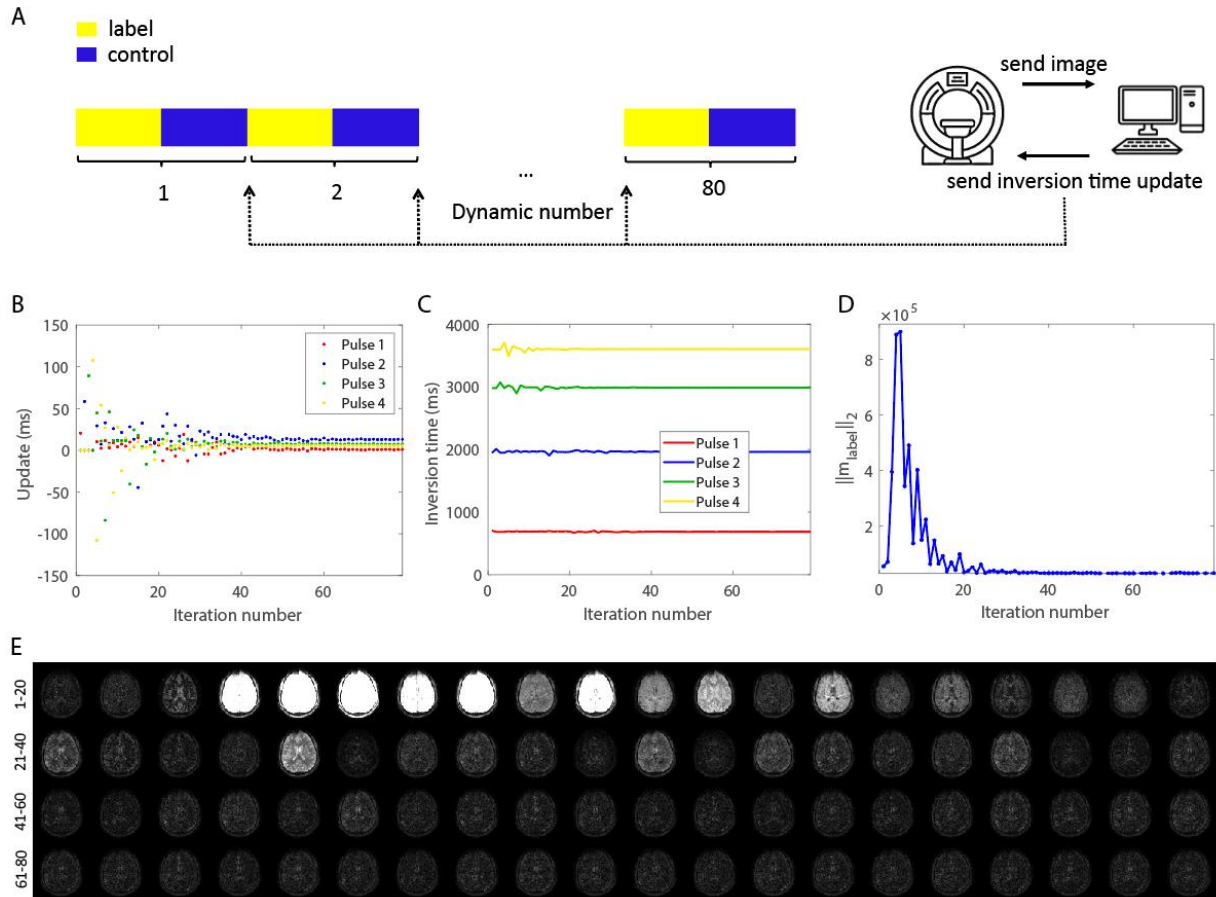


Figure 2. Averaged label, control and perfusion images over 10 dynamics for different amount of BGS. Standard BGS results in a perfusion image with higher temporal SNR compared to without BGS. Optimized BGS ($\lambda = 0$) with the feedback loop results in a lower quality perfusion image compared to standard BGS due to magnitude subtraction errors. Regularized optimization ($\lambda = 5$) circumvents this, resulting in the highest temporal SNR perfusion signal, which can furthermore directly be observed in the control image.

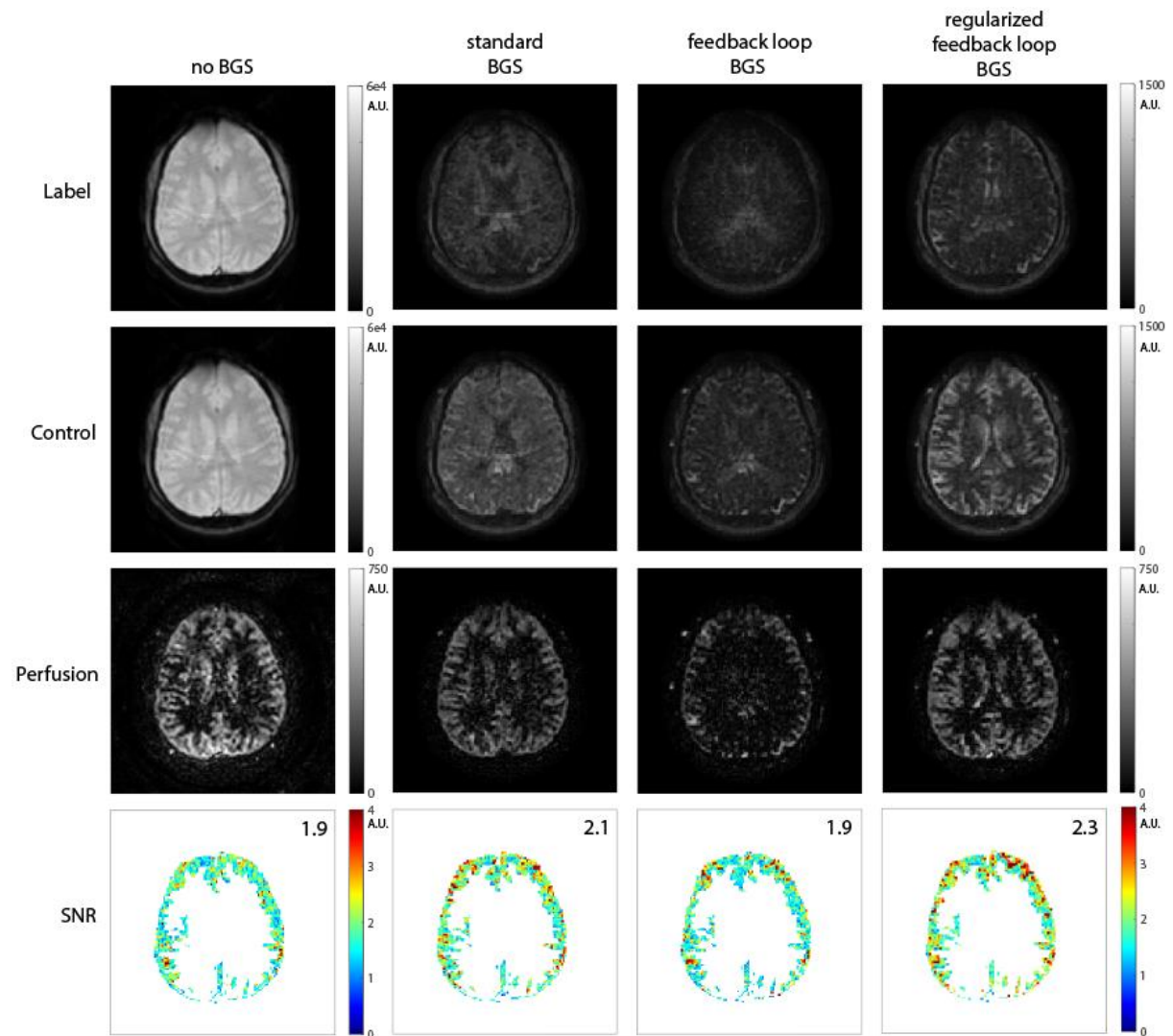


Figure 3. Neuronal activation measured by performing a stimulus at the end of a feedback loop scan. **(A)** The mean perfusion signal in an ROI in the visual cortex shows activation shortly after presenting the checkerboard (S), followed by a period of rest (R). **(B)** The visual cortex (dashed rectangle) shows an increase in the perfusion signal, which can directly be observed in the control images (all averaged over 5 neighboring dynamics), allowing to track the neuronal activation at twice the temporal resolution.

