Machine learning-based cerebral blood flow quantification for ASL MRI

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Introduction. CBF quantification in arterial spin labeled (ASL) MRI has typically assumed a fixed oscillating label/control paradigm: -1 1 -1 … (-1 for labeling(L), 1 for control(C)). However, due to the fluctuations in arterial blood flow, head motion, and hardware imperfections, the total amount of labeled blood water spins is most likely not constant between label and control pairs. Intuitively, a better CBF quantification practice should consider such fluctuations. In this study, we presented a novel approach to estimate the real ASLf from the acquired data using the support-vector-machine (SVM) [1] learning-based ASL data classification and use it to improve CBF quantification.

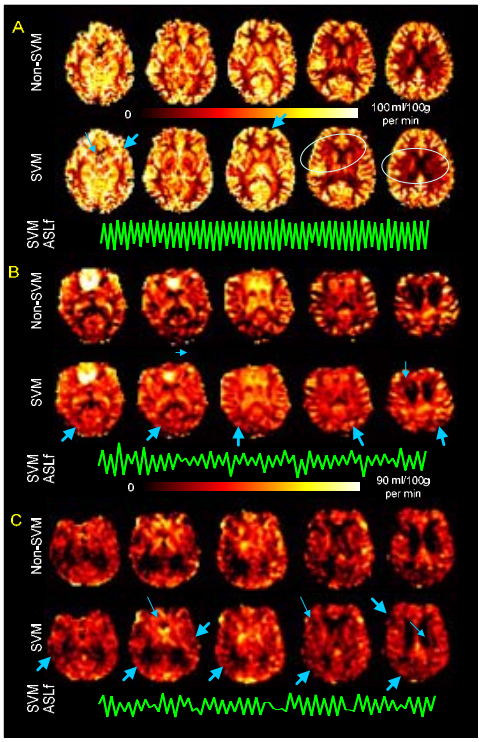

Fig. 3. ASLf and CBF maps of A) a normal subject, B) and C) AD patients. Non-SVM means regular CBF quantification without removal of ASLf variations. The color bars on the top and bottom are for the CBF map in Fig 3A, Fig3B-C, respectively.

Materials and Methods. ASL data were acquired in a 3-T Siemens whole-body scanner from 13 healthy subjects twice with 1.5 to 2 months apart with signed IRB approved consent forms. A continuous ASL (CASL) sequence was used with parameters: TR/TE/label time/post-label delay=3.8sec/17msec/2 sec/1sec, matrix=64x64, 12 sequential slices with a thickness of 7mm (2.35 mm gap), 50 L/C pairs. Previously published CASL data from 2 patients with Alzheimer's Disease (AD) [2] were also used to evaluate the proposed method.

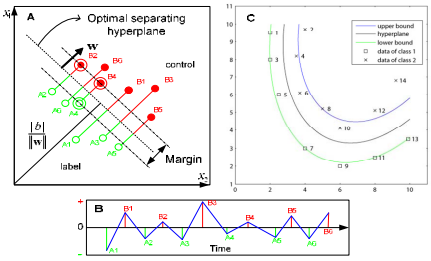

Fig. 1. Illustration of linear A) and nonlinear C) SVM-based ASL data quantification. B) the distance of each ASL image to the separating plane in A is grouped into the ASLf. Similar procedures can be used to extract ASLf from the nonlinear SVM classifier shown in Fig 1C.

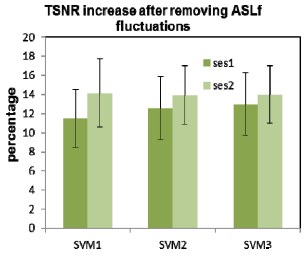

Fig. 2. Mean TSNR increases due to the removal of ASLf variations.

ASL data were preprocessed as described in [2], and then mapped into the eigen-space [3,4]. Both linear (SVM1) and nonlinear SVMs (SVM2 and 3) were used to classify the L images from the C images and to extract ASLf (Fig 1). As illustrated in Fig. 1A and 1B (for illustration simplicity, only 2 voxels were assumed there), ASLf was extracted as a collection of the signed distance (Fig. 1B) of each sample to the separating plane in Fig. 1A [3]. In the case of that the data is not linearly separable (see Fig. 1C), a nonlinear function can be used to transform the original data into a new feature space so that they can be separated in that space. Once the separating plane (the curve in the middle in Fig. 1C) is located, ASLf can be extracted accordingly using the same process as mentioned above. In this study, a polynomial function $K(\mathbf{x},\mathbf{z}) = (s \cdot \mathbf{x} \cdot \mathbf{z} + c)^q$ where $\mathbf{x}$ and $\mathbf{z}$ are vectors in the same feature space, s (0.5 here) and q (2 for SVM2 and 3 for SVM3) are scalar parameters, c is $(\mathbf{x} \cdot \mathbf{x}/k)^{-1}$ (k is the dimension of the feature space). Correlations between ASLf and motion time courses were checked. ASLf was orthogonized to the ideal oscillating labeling function to get the residuals, which were then regressed out from ASL image. CBF images were calculated from both the non-ASLf variation cleaned and cleaned data for comparisons. TSNR was calculated from the resulting CBF image series. TSNR of SVM results were divided by that of the regular CBF calculations and averaged across the brain to get an aggregate TSNR ratio in order to assess the TSNR improvement due to the removal ASLf variations.

Results and discussions. ASLf presented no correlations with motion time courses; neither did the ASLf fluctuations and the motion time courses, suggesting that ASLf fluctuations were not caused by head motions. Fig. 2 shows that removing the SVM-identified ASLf variations yielded significant mean TSNR increases (across 13 subject, $p<0.006$) as compared to regular CBF calculation based on an ideal ASLf. No significant difference was found between linear SVM (SVM1) and nonlinear SVM (2 and 3) for improving TSNR. Fig. 3 shows the quantification results for a normal subject and 2 AD patients. To save space, only the results of SVM3 were shown here (SVM 1 and 2 yielded similar but slightly less improved results). As marked by arrows and ovals, subtle spatial improvement was found in the normal control's data (Fig. 3A) because there were not much spin labeling variations as indicated by the ASLf. For AD patients (Fig. 3B and 3C), large fluctuations were demonstrated in the extracted ASLf, which were correlated with head motions, and remarkable CBF map improvement (part of them was marked by arrows though the improvement is almost in the whole brain) was demonstrated after removing those ASLf variations. In summary, we proposed a novel approach to estimate the spin labeling fluctuations and by removing them we demonstrated significantly increased TSNR and markedly improved CBF maps.

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Reference [1] Burges, C.J.C., Data Mining and Knowledge Discovery, 1998. **2**: p. 121-167. [2] Wang, Z., et al, Mag Res Img, 26, 261-269, 2008. [3] Wang, Z., et al., NeuroImage, 2007. **36**(4): p. 1139-1151. [4] Wang, Z. NeuroImage, 46, 608-615, 2009.