Brain Perfusion with MRI: Arterial Input Function Localization with the Support of MR Angiography

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INTRODUCTION:

In perfusion weighted imaging (PWI), the cerebral blood flow (CBF) calculation starts with the selection of arterial input function (AIF). AIF is the tracer concentration in time for an artery that is supposed to supply blood to the tissue of which the residue function will be calculated. CBF is the initial value of the tissue residue function that is obtained through deconvolution of the signal intensity-time curve of the tissue with the AIF. CBF image is produced by deconvolving the tissue time curves of all pixels and their corresponding AIFs. The selection of the AIF is therefore the most important step in this process since CBF is determined by various characteristics of the AIF curve, such as time of arrival of the contrast material in the artery, time to peak, steepness, full width at half maximum and the signal intensity difference between the peak and the baseline. Ideally, each tissue voxel in a perfusion volume has a unique arterial input. But it is widely accepted that it is impossible to verify AIF selection for every voxel.

In perfusion weighted images, the anatomic locations of the arteries are not clearly visible. The conventional AIF selection technique is to locate a region on a perfusion image that is supposed to include an artery and select the pixels of which time curves meet the criteria of steepness, narrowness and high signal intensity change. However, these required criteria might be indicating only a pulsation of the boundary of an artery, and this would result in CBF underestimation. The irregular shape and positioning of arteries further complicates AIF selection by using MR perfusion images. In this study, we alternatively employ MR angiography (MRA) images for more accurate results in localizing the arteries. With this method we achieve automated multiple AIF selection, through which regional CBF images on various brain slices are calculated.
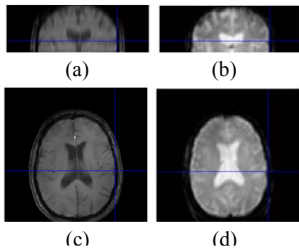
METHOD:

Patient Study

MRA and MR perfusion images of the same brain slices were generated for each patient. Both images corresponding to the same axial slice were identified. The perfusion images were registered to MRA images by using Statistical Parameter Mapping (SPM) software. MRA and perfusion images of a sample slice are shown in Fig. 1.

AIF Selection by Using Probability Density Functions

In this study we used multivariate Gaussian probability density functions in order to segment out arteries. An expert radiologist defined the training set by labeling the known pixels as white matter, gray matter, cerebrospinal fluid and artery. The pixels around the boundaries of the arteries were labeled as a separate group representing the

pulsation artifacts. The intensity values of these pixels from the registered MRA image (Fig. 2(a)) and the slopes (Fig. 2(b)) of the perfusion curves of the same pixels constitute the two dimensional training set. The scatter plot of the training set of these tissues is shown in Fig. 3. This training set was used to calculate the probability density functions depicted in Fig. 4.
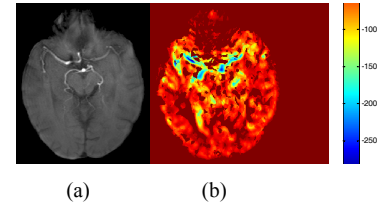
Fig.1. MRA image of the sample slice: (a) coronal and (c) axial view; MR perfusion image of the same slice: (b) coronal and (d) axial view.

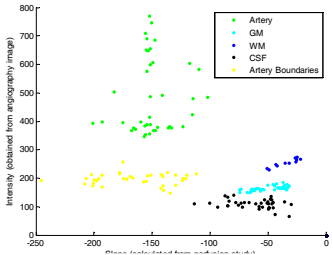Fig 2. (a) MRA image and (b) slope image.

Fig. 3. Scatter plot of the training set (Tissue types were shown in different colors).
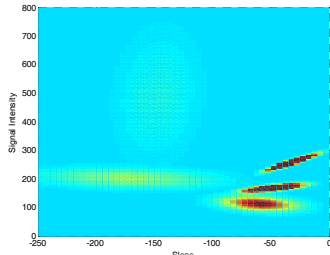

Fig. 4. Scatter plot of the training set (Tissue types were shown in different colors).

The resulting two dimensional probability density functions yield a more precise artery segmentation compared to a single intensity thresholding on the angiography image or on the slope image calculated from the perfusion time series. In this way, we segmented out right and left middle, posterior, and anterior cerebral arteries (mcerR and mcerL, pcer, and acer, respectively) as shown in Fig. 5. Each of these arteries is assumed to feed a certain region of the brain slice (Fig. 6).

RESULTS:

We determined an AIF for each segmented artery by taking the average of the perfusion curves of the pixels belonging to that segment, and generated a CBF image of each region (rCBF) by using the corresponding AIF (Fig. 7(a), (b), (c), (d)). Finally we produced a complex CBF (cCBF) image comprising all rCBF images (Fig. 7 (e)).
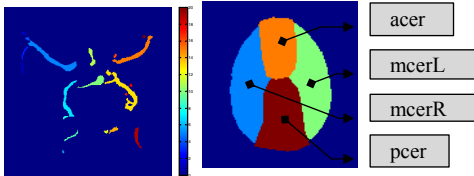

Fig. 5. Segmented arteries.

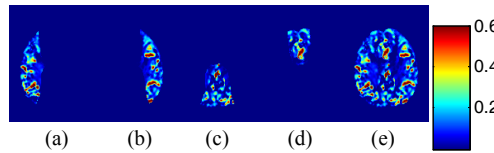Fig. 6. The slice was divided into regions that are fed by different arteries.

Fig. 7. The rCBF images computed by using AIFs chosen from (a) mcerR, (b) mcerL, (c) pcer, and (d) acer; (e) cCBF image.
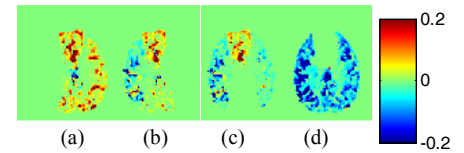

Fig. 8. (a) cCBF- sCBF$_{mcerR}$, (b) cCBF- sCBF$_{mcerL}$, (c) cCBF- sCBF$_{pcer}$, and (d) cCBF- sCBF$_{acer}$.

The CBF image of the brain slice entirely computed with a single AIF chosen from one of the above mentioned arteries, (sCBF images: sCBF$_{mcerR}$, sCBF$_{mcerL}$, sCBF$_{pcer}$, sCBF$_{acer}$), were compared with the cCBF image. The CBF differences, computed by subtracting each sCBF image from the cCBF image, are shown in Fig. 9.

CONCLUSION:

In this study, we utilized MRA and perfusion images to establish two dimensional probability density functions to be used for artery segmentation. We obtained more precise results compared to intensity thresholding on an MRA image or on a slope image calculated from the perfusion images. Automated artery segmentation employed in this work enables the radiologists to make use of multiple AIFs in calculating CBF.