Automated arterial input function selection using spatial information and feature space reduction

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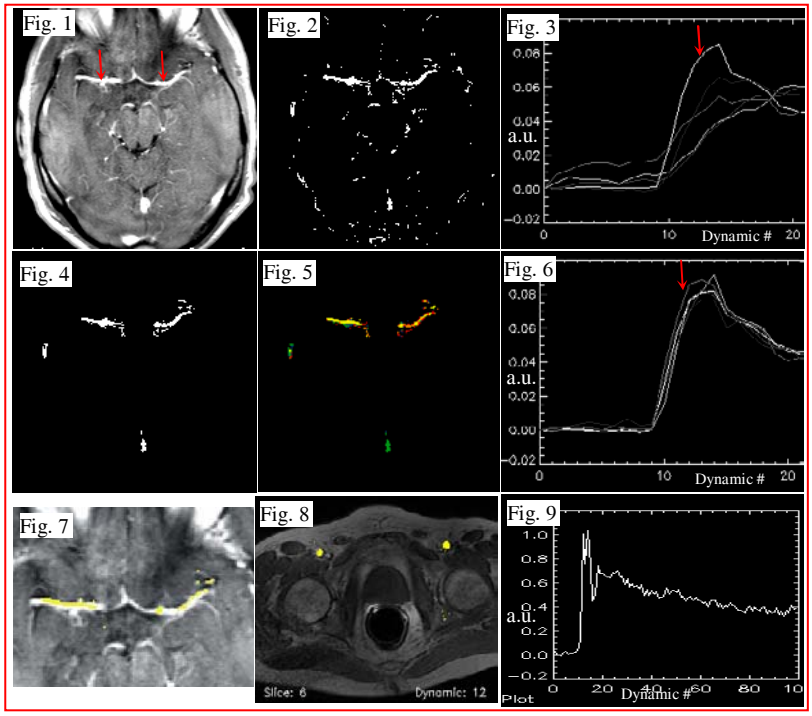
Introduction: pharmacokinetic analysis of T_1-weighted dynamic contrast enhanced MRI data (DCE) requires determination of the arterial input function (AIF) representing the delivery of intravascular tracer to tissue. This is typically accomplished by manual selection of concentration time curves (CTCs) in the image. This is, however, a time consuming and operator dependent (subjective) procedure. Several suggestions have been made in literature for a completely automated procedure for establishing the AIF [1, 2], but these do not take the spatial location of the CTCs into account. In this research we are interested in the **robust** and **automated** determination of the AIF in different anatomies, like brain, prostate and breast. Since the ensemble of target pixels from which the AIF is constructed are often spatially clustered (e.g. in relatively large arteries), we aim for clustering of target pixels **both** in the **spatial** domain and in **feature space**. To assure that the selection is robust against a range in temporal resolution and the number of dynamics of the DCE-MRI data, we propose to perform the clustering in feature space after **dimension reduction of the CTCs** using principal components analysis.



Methods: T_1 weighted DCE-MRI data were collected from brain (256x256, Δt=15.3 sec, 30 dyn.) and prostate (256x256, Δt=3.1 sec, 100 dyn.) using an Achieva 3.0 Tesla MR system (Philips Medical Systems, The Netherlands). The concentration of intravascular contrast agent at time t in a tissue voxel was estimated assuming a linear relationship between the contrast agent in the tissue and the changes in the longitudinal relaxation rate between the pre-contrast and post-contrast conditions. Pixels with satisfying CTCs were selected in the following way (partly following [1]). First, a mask was constructed to separate the signal of the anatomy from the background and 15% of the pixels within this mask, having the largest area under the CTC were selected. Secondly, the CTCs of the selected pixels were scaled to have a unity area under the curve and 25% of the curves with highly fluctuating time courses were excluded using a measure of roughness [1]. In the third step, the remaining curves were clustered into 5 classes using a kmeans clustering algorithm. However, as input for the kmeans we did not use the CTCs themselves, but a projection of the CTCs on the first 10 principal components that were obtained by principal component analysis on the covariance matrix of the range scaled, mean centered CTCs. This results in a 10 dimensional feature space as input for the kmeans, instead of a dimension equivalent to the number of dynamics. Only one of the classes is selected, based on the assumption that AIF's have a "fast" response. The selection criterion is the lowest first moment of the mean CTC of each cluster [3]. Since we are searching for relatively large arteries, the fifth step consists of spatial clustering. This was done by the calculation of a density map, in which the density of target pixels is calculated by counting neighbors. Then, pixels, including their neighborhood, were selected that had a density larger than .6 of the pixel with the highest density. This leads to a mask of spatially close target pixels. Finally, the remaining pixels were clustered for a second time with kmeans using the same procedure as before. The segment with the mean CTC with the lowest first moment was selected to calculate the AIF from.

Results: Fig. 1 shows a DCE-MRI image of the brain, acquired after injection of contrast agent. The red arrows point to areas which are targeted by an expert if manual AIF selection is performed. Fig. 2 shows the target pixels after the first round of kmeans (741 pixels selected of a total of 65k). The mean CTC of this segment is indicated with the red arrow in Fig. 3. The other curves are the mean CTCs of the clusters that were discarded. Significant scattering of target pixels is visible in Fig. 2, which is completely removed after spatial filtering (394 pixels remain), as shown in Fig. 4. The 5 clusters found by the second round of kmeans are color coded in Fig. 5. The yellow cluster (107 pixels) is selected on basis of its lowest first moment of the mean CTC of this segment (indicated with the red arrow in Fig. 6). This curve is the final AIF curve. The yellow cluster is projected on the DCE-MRI image in Fig. 7 to show the agreement with anatomy. In Fig. 8 and Fig. 9 we show the result of the procedure on prostate data with a much higher temporal resolution. The most prominent arteries are selected by the procedure (Fig. 8, yellow regions). The accompanying AIF curve is shown in Fig. 9.

Discussion / conclusion: For automated AIF selection procedures to be useful in clinical practice, they have to be robust and capable to deal with differences in the acquisition protocol. Experts who manually select AIF regions often search for large connected regions, e.g. clearly visible arteries, with similar CTCs. We have also done this, with an approach that takes into account the shape of the CTCs and their spatial location. Although an evaluation between user guided selection and automated selection is still needed, we believe that our method provides a robust selection of AIF curves in both brain and prostate. In future work we will focus on the second clustering in feature space, in order to obtain AIF curves which are separable more easily than the curves in Fig. 6. Also an extension to 3D will be investigated.

References: [1]: Mouridsen et al., MRM 55: 524-531 (2006), [2]: Murase, JMRI 2001 ;13(5):797-806, [3]: Alsop et al., 'Defining a local input function for perfusion quantification with bolus contrast MRI, Proc ISMRM, Hawaii, USA, 2002