A NOISE SUPPRESSION APPROACH IN THE QUANTITATIVE ANALYSIS OF DCE IMAGES

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Target audience: MRI Researchers interested in innovative image and signal processing methods.

Purpose: Quantitative analysis of dynamic contrast-enhanced (DCE) images may be achieved by estimating T_1 and spin density (S_0) from fully sampled k-space datasets acquired using multiple flip angles. Fast 3D imaging techniques with fewer flip angles are commonly used to reduce scan time, and averaging over multiple (repetitive) acquisitions is used to increase accuracy. However averaging can lead to unsatisfactory quantitative results due to its sensitivity to motion, especially in the head and neck region. Thus a quantitative DCE analysis approach with reduced motion-sensitivity and noise-susceptibility is desired. First a non-local means (NLM) spatial filtering for noise-reduction in a single acquisition is introduced [1]. Second, further noise suppression by incorporating a model-based filtering originated from the sparse coding theory with a joint-dictionary is proposed [2,3]. The joint-dictionary also extrapolates the small number of acquired flip angles to a larger number of virtual flip angles, which essentially improves quantification performance. Finally, a model-based full dictionary is constructed based on a method proposed by Dan Ma et al [4] to retrieve the T_1 from the extrapolated dataset and S_0 by least square estimation.

Method: Signal intensity at a given flip angle *a* is given by $S(a) = S_0 (1- e^{-TR/T1})\sin(a)/(1- \cos(a)e^{-TR/T1})$, where S_0 is the equilibrium longitudinal magnetization. This equation can be rewritten as $S(a)/\sin(a)=m*S(a)/\tan(a)+S_0(1-m)$, where $m=e^{-TR/T1}$.Conventionally T_1 and S_0 are first estimated by a linear fitting procedure (such as TOPPCAT [5]) from the averaged data (e.g. NEX=5), and the T_1 relaxation rate $R_1(t)$ are calculated at each pixel over time from changes in the signal intensity relative to baseline (S(t)-S(0)). K^{trans} and vascular volume maps are then calculated using Patlak analysis, based on the Tofts-Kermode model for contrast agent distribution modified to take into account the presence of separate extracellular and intravascular compartments [5]. Alternatively, we propose to estimate T_1 and S_0 (with NEX=1) using sparse coding and dictionary. NLM is involved to spatially suppress the noise while keeping the details in the images on the single raw signal acquisition (e.g. NEX=1). Sparse representation is a generalized approach that represents any kind of data using sparse combination of terms of an over-complete base, which is called dictionary and can be trained by some training samples. Despite favors of sparse representation stemming from theoretical analysis, its applications in MRI is still limited. The model-based filtering based on the sparse coding method is realized by using training set generated with the signal model, and is used to further reduce signal noise and increase resolution along the flip angles by constructing a joint-dictionary , which is a low resolution dictionary (LRD) cascaded with a high resolution dictionary (HRD). The joint-dictionary is generated by dictionary learning algorithms [2, 3].The sparse resolutions (in the sense of l_0) of LRD are acquired by solving the linear equation accordingly. The reconstructed high resolution and high SNR signal is obtained by applying the corresponding sparse solutions of LRD to the HRD and is used to retrieve the T1 value at each voxel by finding the matched index from the full dictionary, which is composed of signals generated from the signal model equation by varying T_1 value with fixed S_0. S_0 is estimated by least square error from the estimated T1 and the reconstructed signal.

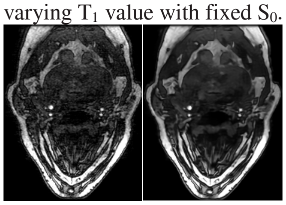

Fig. 1 Left: original image, right: image after using NLM.

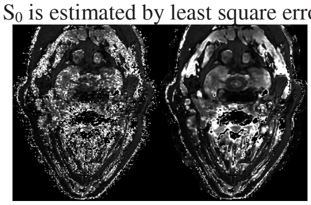

Fig. 2 T1 map estimated using TOPPCAT on images of Fig. 1

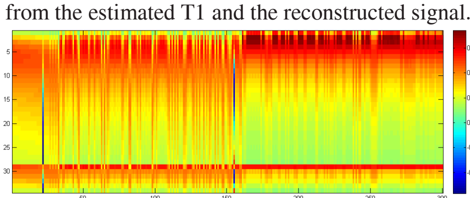

Fig. 3 The trained dictionary. The upper rows is HRD (from row 1 to 28) and lower rows is LRD (from row 29

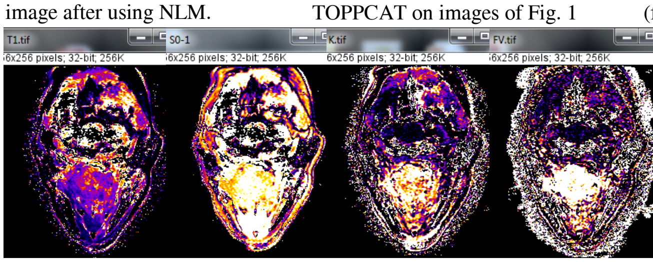

Fig. 4 Maps of T_1, S_0, K_{trans} and FV (Fractional Plasma Volume) generated by TOPPCAT with NEX=5 (from left to right).

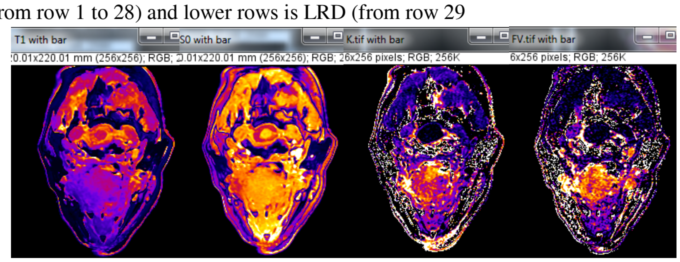

Fig. 5 Maps of T_1, S_0, K_{trans} and FV generated by the proposed method with NEX=1 (from left to right).

Results: The comparison between the original image and the image spatially filtered by NLM is shown in Fig. 1, and the generated respective T1 maps with TOPCAT are shown in Fig. 2. The training dataset was produced by varying T_1 uniformly distributed between 50 and 6000 ms (50:10:6000) with S_0=1000. Samples for HRD and LRD have 28 flip angles (1:1:26, 28, 30) and 6 flip angles (5, 10, 12, 15, 20, 30) respectively, generated from the model equation with corresponding parameters of HRD and LRD. Total sample number is 596. A dictionary with 300 atoms is trained using K-SVD (A signal approximation with respect to the dictionary vs. varying number of atoms using OMP [2] need to be obtained in future) , and optimized for sparsity $K = 3$ (the nonzero elements in the sparse solution). The dictionary matrix is hereafter (28+6)*300. Fig. 3 shows the learned joint-dictionary. The whole samples were used to construct the full dictionary too. Fig. 4 demonstrates the results of vascular measurements obtained by TOPPCAT on signal with NEX=5 from a healthy volunteer, and Fig. 5 contains the corresponding results obtained with our methods from the same volunteer.

Conclusion and Discussions: A new quantitative DCE analysis approach is proposed and demonstrated on a healthy volunteer. This method improved quantitative analysis by sparse encoding and dictionary, which reduced its susceptibility to noise and sensitivity to motion. Currently the parameter of NLM is tuned manually, and an automatic noise level estimation is under investigating.

References: [1] Buades, A. CVPR 2005, Vol.2, 60-65. [2] Elad, M. Sparse and Redundant Representations, Springer, 2010. [3] Yang, J. et al. IEEE Trans. Image Processing, vol. 21, 3467-3478, 2012. [4] Dan Ma et al, Nature 495,187–192, 2013. [5] Barboriak, D. A User's Guide to TOPPCAT.