Robust Low-Dose CT Perfusion Deconvolution via Non-Local Tensor Total Variation

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Introduction: Stroke and cerebrovascular diseases are the leading cause of serious, long-term disability in the United States. Computed tomography perfusion (CTP) is one of the most widely accepted imaging modality for stroke care. However, the high radiation exposure of CTP has lead to increased cancer risk. Tensor total variation (TTV)[1] has been proposed to stabilize the quantification of perfusion parameters by integrating the anatomical structure correlation. Yet the locality limitation of the neighborhood region has led to noticeable absence or inflation of the delicate structures which are critical indicators for the clinical diagnosis. In this work, we propose a non-local tensor total variation (NL-TTV) deconvolution method to by incorporating the long-range dependency and the global connections in the spatio-temporal domain.

Materials and Methods: In CT perfusion, the dynamic blood flow parameters such as the cerebral blood flow (CBF), cerebral blood volume (CBV) and the mean transit time (MTT) can be estimated from the flow-scaled residue function K. In the proposed NL-TTV framework, we impose a regularizer on the long-range similarity of anatomical structure using non-local TV[2] by solving the optimization problem: $\widehat{K} = \mathrm{argmin}_{K\in\mathbb{R}^{T\times N}}\left(\frac{1}{2}||AK - C||_2^2 + ||K||_{NL\_TTV}\right)$, where K is the flow-scaled residue function we want to find, $A \in \mathbb{R}^{T\times T}$ is the Toeplitz matrix of arterial input function, $C \in \mathbb{R}^{T\times N}$ is the contrast concentration curves. Specifically, the regularization term $||K||_{NL-TTV} = \sum_i \sqrt{\sum_j \big(K(i) - K(j)\big)^2 w(i,j)}$ which assigns weight $w(i,j) = \frac{1}{Z(x)} e^{-\frac{||K(N_x)-K(N_y)||_2^2}{\sigma^2}}$, where the normalization factor $Z(i) = \sum_y w(i,j)$. An iterative algorithm consisting of the adaptive gradient descent of K in the first term and proximal map in the NL-TTV term are used to solve the above optimization problem.

Results and Discussion: The evaluation is performed on 22 subjects (12 with cerebral deficits) using GE Lightspeed Pro-16 scanners. Fig. 1 shows the CBF maps and the enlarged region of interest (ROI) of one subject with cerebral deficits computed using four baseline methods, namely the standard singular value decomposition (sSVD), block-circulant SVD (bSVD), Tikhonov regularization, tensor total variation (TTV), and our proposed non-local tensor total variation (NL-TTV) algorithms. While the baseline methods demonstrate significant over-estimation due to the instability of the residue functions at low-dose and lack of sufficient spatial contextual information to stabilize the deconvolution, the proposed NL-TTV demonstrates its superb capability of estimating the accurate blood flow dynamics, by leveraging the global and long-range similarity between the tissue structure in the brain. Table 1 shows the peak signal-to-noise ratio (PSNR) where NL-TTV outperforms the baseline methods with statistical significance ($p<0.05$).

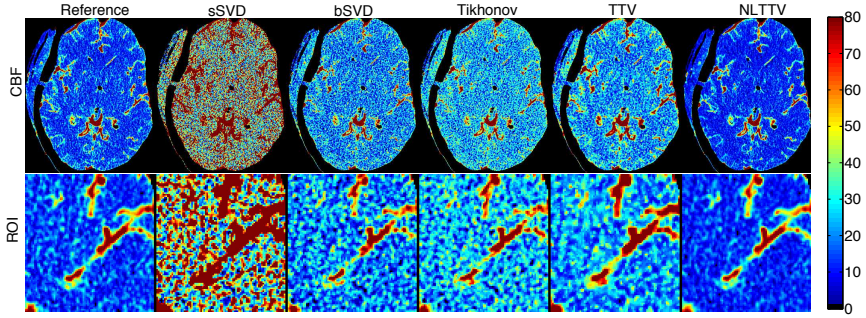

Figure 1. Cerebral blood flow (CBF) maps of a subject with right frontoparietal craniotomy due to ischemia in the right anterior cerebral artery (RACA) and right middle cerebral artery (RMCA) territories.

Method	PSNR
sSVD	9.82
bSVD	19.68
Tikhonov	19.84
TTV	22.20
NL-TTV	25.79

Table 1. Peak signal-to-noise ratio of five algorithms.

Conclusions: A robust and accurate deconvolution algorithm for low-dose CT perfusion is proposed and evaluated on clinical dataset with significant boost in estimation accuracy. This proposed method leverages the global and long-range structural similarity of the anatomical and dynamic information in the tissue to stabilize the spatio-temporal residue functions. Future work includes improving the computational efficiency via parallel computing, and generalizing the method to other imaging modalities such as magnetic resonance perfusion (MRP), arterial spin labeling (ASL) MRI.

References: [1] Fang, R. IEEE TMI, 2015. [2] Mignotte, M. Pattern recognition letters 29:16, 2008, 2206–2212