DIRECT ESTIMATION OF PERMEABILITY MAPS FOR LOW-DOSE CT PERFUSION

Ruogu Fang[1], *Ajay Gupta*[2], *Pina C. Sanelli*[3]

School of Computing and Information Sciences, Florida International University, Miami, FL
Department of Radiology, Weill Cornell Medical College, New York, NY
Department of Radiology, Northwell Health, Manhasset, NY

ABSTRACT

With the goal of achieving low radiation exposure from medical imaging, computed tomography perfusion (CTP) introduces challenging problems for both image reconstruction and perfusion parameter estimation in the qualitative and quantitative analyses. Conventional approaches address the reconstruction and the estimation processes separately. Since the hemodynamic parameter maps have much lower dimensionality than the original sinogram data, estimating hemodynamic parameters directly from sinogram will further reduce radiation exposure and save computational resources to reconstruct the intermediate time-series images. In this work, we propose the first direct estimation framework for CTP that integrates the time-series image reconstruction, contrast conversion, hematocrit correction and hemodynamic parameter estimation in one optimization function, which is solved using an efficient algorithm. Evaluations on the digital brain perfusion phantom and a clinical acute stroke subject demonstrate that the proposed direct estimation framework boosts the estimation accuracy remarkably in CTP scanning with lower radiation exposure.

Index Terms— Direct Estimation, Computed Tomography Perfusion, Total Variation, Hemodynamic Parameter

1. INTRODUCTION

Computed tomography (CT) remains the most widely used imaging modality for stroke, the leading cause of long-term disability and the second leading cause of death worldwide [1]. However, when coupled with CT perfusion (CTP), the excessive radiation exposure used in this repetitive scanning protocol to assess diagnosis and prognosis has the potential for severe short- and long-term health hazards. Low radiation dose CTP has been an active area of research [2, 3, 4] with the goal of reducing radiation exposure and improving medical safety, while maintaining accurate imaging information for clinical decision-making. The ultimate goal of CTP is to estimate the hemodynamic parameters (such as K^{trans}, abbreviated as K_t, and v_p in the Patlak Model [5]) from the CT time-series data, which are reconstructed from the sinogram.

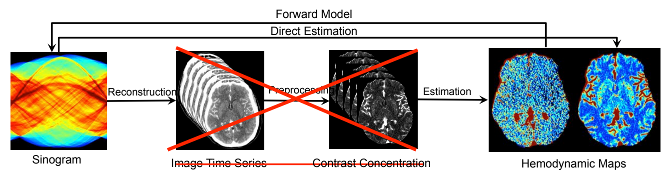

Fig. 1. Direction hemodynamic parameter estimation for computed tomography perfusion.

There are mainly two types of classical approaches to achieve low radiation dose CTP by improving (1) reconstruction stage, including spatio-temporal filtering and exploiting sparsity in the time-series images [6]; (2) estimation stage, such as dictionary-learning [2] and spatio-temporal tensor total variation on the residue impulse functions [3].

While these methods have achieved different levels of success, they typically separate the optimization of the two stages by reconstructing the time-series images first, then fitting the hemodynamic model to derive the parameter maps. As the hemodynamic maps have much lower dimensionality than the original sinogram data, direct estimation of hemodynamic parameter maps from sinogram data will further reduce the radiation dosage and save computational resources to reconstruct intermediate time-series images. Recent works have proposed to directly estimate the hemodynamic parameters for dynamic contrast enhanced MRI, Positron Emission Tomography (PET) and Single-Photon Emission Computed Tomography (SPECT) [7, 8, 9, 10, 11, 12]. To the best of our knowledge, direct estimation of hemodynamic parameters in CTP has not been explored. This work is the first attempt to integrate the reconstruction and estimation processes for low-radiation dose CTP.

In this paper, we propose a theoretically novel and computationally efficient optimization framework to directly estimate the hemodynamic parameters (K_t and V_p) in CTP, as illustrated in Fig. 1. Unlike the classical approaches which reconstruct the time-series CT images first, then estimate the parameter maps by fitting the Patlak model, we formulate the problem as a linear model with L_1 total variation regularization and uses a fast iterative shrinkage-thresholding algorithm (FISTA) to efficiently find the optimal solution.

2. METHODOLOGY

The conventional hemodynamic parameter estimation starts with the sinogram from the scanner, where time-series CT images are reconstructed from each frame of the sinogram. Then CT values in the time-series images are converted to contrast concentration by subtracting the baseline image, followed by hematocrit correction to account for the total cells in the blood. Finally the Patlak model is used to estimate the hemodynamic parameters K_t and V_p from the corrected contrast concentration signals by linear regression for each voxel respectively. The conventional model is summarized in the left column of Fig. 2.

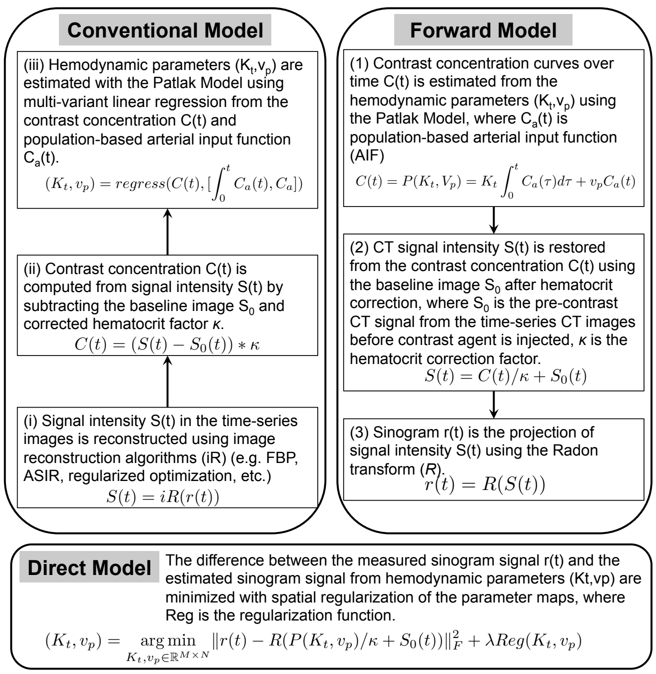

Fig. 2. Computational steps in the forward model and the conventional pipeline of hemodynamic parameter estimation in CT perfusion.

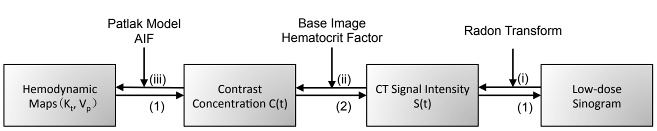

Fig. 3. The forward model of hemodynamic parameter maps estimation from low-dose sinogram in CT perfusion.

To directly estimate the hemodynamic parameters from the sinogram, we invert the process of parameter estimation to formulate the forward model, as demonstrated in Fig. 3. We assume the Radon transform for the reconstruction and the Patlak model for the parameter estimation [5]. The corresponding computational steps of the forward model is summarized in the right column in Fig. 2.

The classical approach to estimate the hemodynamic parameters in low-dose CTP generally imposes regularization on the reconstruction and the estimation stage separately. In this paper, we propose a direct estimation framework with regularized optimization on the final hemodynamic maps only. By integrating the three computation steps in the forward model into one joint step, assuming we already know the hemodynamic parameter maps K_t and v_p for all the voxels, the sinogram $r'(t)$ can be estimated for each time point t. By minimizing the difference between the measured sinogram $r(t)$ with the estimated sinogram $r'(t)$, with proper regularization on the hemodynamic maps directly, we can skip the computationally-expensive step and the potential errors introduced in reconstructing the time-series images and the contrast concentration signals. The direct mode is illustrated in the bottom box in Fig. 2. Please note that for this generic direct estimation model, the regularization function can have a wide selection, while in this work, we use the sparsity in the gradient domain, i.e. total variation of the hemodynamic parameter maps, as shown in Eq. (1).

$$(K_t, v_p) = \underset{K_t, v_p \in \mathbb{R}^{M \times N}}{\arg\min} \|r(t) - R(P(K_t, v_p)/\kappa + S_0(t))\|_F^2 + \lambda_1 \|K_t\|_{TV} + \lambda_2 \|v_p\|_{TV} \quad (1)$$

In Eq. (1), we want to compute K_t and v_p, which are the hemodynamic parameters of the Patlak model. $r(t)$ is the measured sinogram signal, κ is the hematocrit correction factor, $S_0(t)$ is the pre-contrast signal or baseline image, R is the Radon transform, P is the Patlak model, $\|.\|_{TV}$ is the L_1 total variation regularizer, as in [13, 14], and λ_1, λ_2 are the weighting parameter for the regularizer.

This above problem can be solved efficiently using any l_1 solver such as ADMM[15] or FISTA[16]. Note that the Radon transform, preprocessing (contrast conversion and hematocrit correction), and linear regression can be represented by operators and do not need to be explicit matrices.

3. EXPERIMENTAL RESULTS

In this section, we evaluate the efficacy of the proposed direct estimation framework on both simulated and clinical CTP data. We conduct experiments to compare with two baseline methods: the conventional Filtered Back Projection (FBP), and Total Variation (TV)-based compressed sensing reconstruction [17]. These two CT image reconstruction algorithms are coupled with multi-variant regression to generate the hemodynamic parameter maps using the Patlak model.

Our ground truth images consist of clinical CTP datasets on an acute stroke patient and a digital brain perfusion phantom. The clinical stroke subject is of size $512 \times 512 \times 4$ with 118 time points. The digital brain perfusion phantom is obtained from the author's website[1], with regions of ischemic

[1] https://www5.cs.fau.de/research/data/digital-brain-perfusion-phantom/

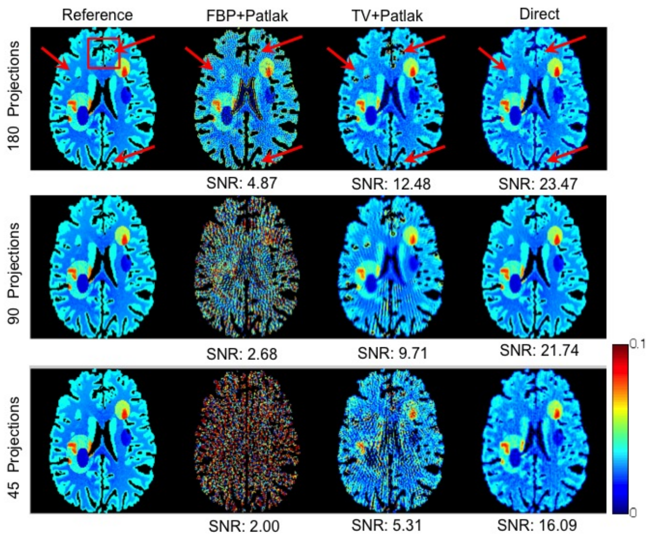

Fig. 4. Kt maps estimated from digital brain perfusion phantom from 180, 90, and 45 projection angles for FBP+linear regression (2nd column), TV reconstruction+linear regression (3rd column) and direct estimation (4th column) in comparison with ground truth (1st column). Arrows in the first row highlights the artifacts in the FBP and TV-based indirect estimation.

penumbra and infarct core delineated manually on two hemispheres at different locations. The size of the digital perfusion phantom is 256×256 with 50 time points at 1 s intervals.

In this paper, we use FISTA [16] to solve Eq. (1). The numerical accuracy is reported using the Signal to Noise Ratio (SNR) in dB. We select the regularization parameters on a validation dataset, where $\lambda_1 = 0.05$, $\lambda_2 = 0.01$, while the parameter L in the FISTA algorithm is set to 4. In order to fairly compare with the baseline methods, we tune the parameters in the indirect reconstruction algorithms coupled with linear regression to their best performance.

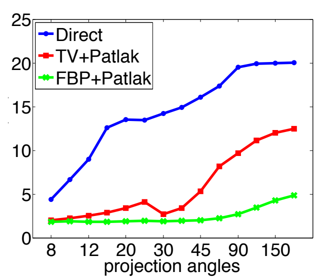

Fig. 6. Comparison of parameter estimation accuracy in limited projection angle settings using three methods: Direct estimation, TV+Patlak and FBP+Patlak. The evaluation metric is signal-to-noise ratio (SNR).

We first demonstrate the experimental results in the digital brain perfusion phantom. In Fig. 4, the K_t maps are estimated with 180, 90 and 45 projection angles, with a region of interest near the artery enlarged in Fig. 5. Note that the contrast concentration is far more sensitive than the reconstructed images to projection angles because the baseline image is subtracted and the range of the contrast concentration is much smaller. For reduced number of projection angles, FBP reconstruction with linear regression shows notably high noise level and streak artifacts. While the TV reconstruction algorithm coupled with linear regression demonstrates improved visual results, the streak artifacts and the noise are still present and visible, especially artifacts at boundaries in Fig. 5 and in the 45 angle setting, leading to missing of micro-structures in the brain. In comparison, the proposed direct estimation not only eliminates the streak artifacts and noise, but also preserves the micro-structures and clear-cut boundaries between tissue classes.

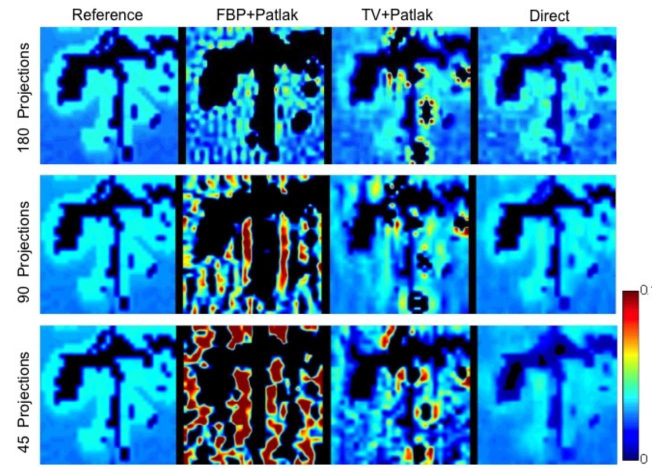

Fig. 5. The red box region of interest (ROI) of Kt maps in Fig. 4 estimated from digital brain perfusion phantom from 180, 90 and 45 projection angles for ground truth (1st column), FBP+linear regression (2nd column), TV reconstruction+linear regression (3rd column) and direct estimation (4th column) in comparison with ground truth (1st column).

Fig. 6 shows quantitative comparison of three methods in terms of parameter estimation accuracy at different number of projections angles for the Kt map in the digital brain perfusion phantom. From the figure, we observe that direct estimation outperforms FBP and TV-based reconstruction coupled with linear regression for the Patlak model in limited projection angle settings. Another observation is that as the number of projection angles decrease, direct estimation is more robust in terms of estimation accuracy. While the estimation accuracy of TV-based reconstruction coupled with linear regression drastically goes from 11.1 dB to 2.7 dB as the number of projections decrease from 120 to 30 angles, direct estimation remains more stable when the estimation accuracy slightly drops from 19.9 dB to 14.2 dB.

In clinical data of an acute stroke subject and a normal subject, the artifacts and noise due to tracer delay, electronic noise and recording error will make the task more challenging. Fig. 7 shows the Kt and Vp maps of an acute stroke subject presenting with a right sided perfusion abnormality (left in the image) at 90 projection angles. While FBP reconstruction with linear regression totally failed to estimate the cor-

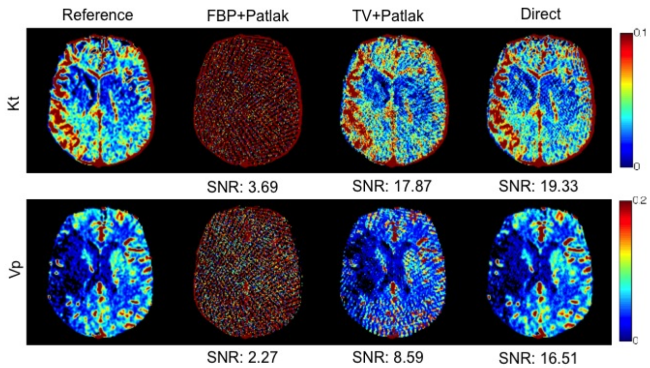

Fig. 7. Kt and Vp maps estimated from a clinical stroke subject with from 90 projection angles using FBP+linear regression (2nd column), TV-minimization+linear regression (3rd column) and direct estimation (4th column).

rect perfusion parameters, TV-based reconstruction with linear regression for Patlak model has obvious artifacts. Direct estimation outperforms both methods in restoring the hemodynamic parameters.

4. CONCLUSION

In this paper, we have proposed a novel direct estimation method for hemodynamic parameter quantification in limited-data computed tomography perfusion, and have demonstrated that it can accurately restore the perfusion parameters in Patlak model in digital brain perfusion data and a clinical acute stroke subject, outperforming the TV-regularized reconstruction with linear regression. Higher spatio-temporal resolution and improved coverage may be achieved when applied to 3D CTP. Future work can evaluate the method's flexibility with model selection for reconstruction and hemodynamic parameter estimation.

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