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# Low-dose cerebral perfusion computed tomography image restoration via low-rank and total variation regularizations

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ABSTRACT

Cerebral perfusion X-ray computed tomography (PCT) is an important functional imaging modality for evaluating cerebrovascular diseases and has been widely used in clinics over the past decades. However, due to the protocol of PCT imaging with repeated dynamic sequential scans, the associative radiation dose unavoidably increases as compared with that used in conventional CT examinations. Minimizing the radiation exposure in PCT examination is a major task in the CT field. In this paper, considering the rich similarity redundancy information among enhanced sequential PCT images, we propose a low-dose PCT image restoration model by incorporating the low-rank and sparse matrix characteristic of sequential PCT images. Specifically, the sequential PCT images were first stacked into a matrix (i.e., low-rank matrix), and then a non-convex spectral norm/regularization and a spatio-temporal total variation norm/regularization were then built on the low-rank matrix to describe the low rank and sparsity of the sequential PCT images, respectively. Subsequently, an improved split Bregman method was adopted to minimize the associative objective function with a reasonable convergence rate. Both qualitative and quantitative studies were conducted using a digital phantom and clinical cerebral PCT datasets to evaluate the present method. Experimental results show that the presented method can achieve images with several noticeable advantages over the existing methods in terms of noise reduction and universal quality index. More importantly, the present method can produce more accurate kinetic enhanced details and diagnostic hemodynamic parameter maps.



## 1. Introduction

Acute stroke is a leading cause of morbidity and mortality worldwide. Cerebral perfusion computed tomography (PCT) is an effective diagnostic tool for evaluating acute ischemic stroke by calculating several perfusion parameters, such as mean transmit time (MTT), cerebral blood volume (CBV), and cerebral blood flow (CBF) [1,2]. In acute stroke examination with a standard PCT scanning protocol, the dynamic acquisition of sequential CT sections in cine mode should be performed for approximately 1 min [3,4]. Hence, its associative excessive radiation exposure radiation remarkably exceeds that used in conventional CT examination, which has raised significant concern from patients. Minimizing X-ray exposure in cerebral PCT examinations has been one of the major endeavors in CT fields [5–9].

To date, various techniques that optimize cerebral PCT scanning protocol for dose reduction have been explored, including low-mAs and/or kVp exposure control [7,9–12] or decreasing the image acquisition frequency in enhanced scans [13,14]. Notably, low-mAs exposure control is a straightforward and cost-effective means to reduce radiation dose in clinic. However, excessive quantum noise in low-mAs projection data acquisition would unavoidably lead to degraded images and hemodynamic parameter maps. To address this ill-posed problem, many approaches have been reported, including projection and image filtering techniques [5,15–17], sequential-images iterative reconstruction [6], and parameter maps estimation by an iterative scheme with a strong regularization [18–20]. For example, Ma et al. presented an iterative image reconstruction method based on maximum a posteriori with a pre-contrast scan induced edge-preserving prior [6]. Fang et al.

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presented a robust low-dose CT perfusion deconvolution method via tensor total-variation regularization [19]. Meanwhile, a major drawback of sequential-image or parameter map iterative reconstruction methods is the computational load caused by multiple re- and back-projection operations in image or parameter map domains. Although most projection filtering techniques can suppress noise and streak artifacts with less computational burden, they usually sacrifice structural details without considering accurate noise modeling over all projections. In addition, noise distribution of low-dose CT images is usually non-stationary and unknown. As a result, it is a difficult task to design an advanced structure preserving image filter in practice. In general, a successful CT image iterative reconstruction approach needs incorporating specific prior information of desired image. A typical example is the sparsity prior of image in a transform domain including the discrete gradient transform and wavelets transform, which has been studied in perfusion CT [14], cone-beam CT [21] and spectral CT [22].

Recently, instead of simple sparsity of vectors, researchers have paid attention to explore the low-rank characteristic of matrices. The related techniques have demonstrated impressive performance in video restoration [23,24], and medical imaging including four-dimensional CT [25], spectral CT [26], and dynamic magnetic resonance imaging (MRI) [27]. In this paper, with the facts that the rich similarity redundancy information exists among enhanced sequential PCT images, we propose a low-dose PCT image restoration model by incorporating the low-rank and sparse matrix characteristic of sequential PCT images. More specifically, the sequential PCT images were first stacked into a matrix (i.e., low-rank matrix), and then a non-convex spectral norm/regularization and a spatio-temporal total variation (TV) norm/regularization were built on the low-rank matrix to describe the low-rank and sparsity of the sequence PCT images, respectively. An improved split Bregman algorithm was developed to minimize the present objective function. Qualitative and quantitative evaluations were carried out on both the digital phantom and clinical cerebral PCT datasets in terms of several evaluation metrics.

The remaining parts of the paper are organized as follows. Section 2 describes the process of dynamic PCT imaging, the low-rank matrix recovery model, the present PCT image restoration model, and the associative optimization algorithm. The experimental setup and evaluation metrics are also presented in this section. Evaluation results are presented in Section 3. Finally, the discussion and conclusion are given in Sections 4 and 5, respectively.

## 2. Methods and materials

### 2.1. Brief review of dynamic PCT imaging

In clinic, PCT examination of brain regions is performed as follows: first, the pre-contrast unenhanced CT scan of the whole brain is performed. Then, following an intravenous injection of iodinated contrast agent, continuous enhanced dynamic scan of the selected slices of brain in a cine mode is performed. The obtained dynamic measurement can be viewed as a temporal sequence of 2D spatial images. Finally, several nondeconvolution and deconvolution methods [28] can be used to process the obtained sequential PCT images for obtaining quantitative hemodynamic information, such as MTT, CBV, and CBF.

### 2.2. Overview of the low-rank and sparsity modeling for sequential PCT image restoration

#### 2.2.1. Low-rank matrix recovery

Low-rank matrix recovery is currently a hot topic in image processing which can be regarded as a rank regularized minimization problem [29] from the given observation matrix $M$ corrupted by errors $E$, i.e.,

$$\min_X \frac{1}{2}\|X-M\|_F^2+\lambda\,\mathrm{rank}(X) \tag{1}$$

where rank($X$) represents the rank of the desired objective matrix $X$; $\|\cdot\|_F$ denotes the Frobenious norm; and $\lambda$ is a hyper-parameter to balance the first (i.e., fidelity term) and the second (i.e., penalty term) terms. Due to the form of rank penalty, directly minimizing the objective function in Eq. (1) is a difficult task. To address this issue, similar to [27], the rank penalty can be relaxed to be a nuclear norm representation with $\|X\|_*=\sum_i\sigma_i$, where $\sigma_i$ are the singular values of $X$. Through this relaxation, the recovery of the low-rank matrix $X$ can be simplified as follows:

$$\min_X \frac{1}{2}\|X-M\|_F^2+\lambda\|X\|_*. \tag{2}$$

Recht et al. have shown that this approach perfectly recovers the matrix $X$ with a high probability, if the random measurement ensemble is used and the number of measurements exceeds a constant times the number of degrees of freedom [29].

#### 2.2.2. LR-TV model for PCT image restoration

In PCT imaging, rich similarity redundancy information existing among the enhanced sequential PCT images leads to the low-rank matrix characteristic of the stacked sequential images. Specifically, the sequential PCT images can be represented as a matrix that has linearly dependent rows, i.e., low-rank. An illustration of the low-rank characteristic of the sequential PCT images is shown in Fig. 1. Moreover, the sparsity of the sequential PCT images, which corresponds to the enhanced perfusion information, can also be exploited along with the low-rank matrix characteristic to further improve image quality. Hence, we pose the PCT image restoration problem as a regularized matrix recovery problem with low-rank and TV (sparsity) constrains, which is referred to as "LR-TV" for simplicity. Mathematically, the LR-TV model for PCT image restoration can be formulated as:

$$\begin{aligned}&\min_X \ \frac{1}{2}\|X-M\|_F^2\\ &\ s.t.\ \ \mathrm{rank}(X)\le K_1,\ \ \left\|\left(\sum_{i=0}^{2}\left|\Phi_i^T X\Psi_i\right|^2\right)^{\frac{1}{2}}\right\|_{\ell_0}\le K_2\end{aligned} \tag{3}$$

where $M$ is the noisy PCT sequence, $X=[x_1,\ldots,x_j,\ldots,x_{N_t}]$, $x_j$

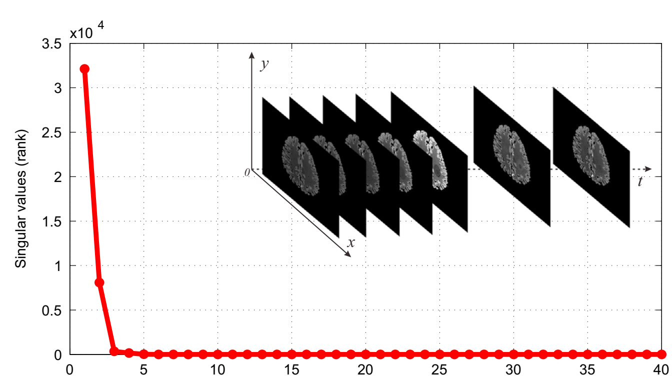


**Fig. 1.** Justification of the low-rank characteristic of the sequential PCT images with $N_t$=40. It can be seen that the matrix is low-rank because only a few singular values are not close to zero.