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# Enhancement of dynamic myocardial perfusion PET images based on low-rank plus sparse decomposition

Lijun Lu[a], Xiaomian Ma[b], Hassan Mohy-ud-Din[c], Jianhua Ma[a], Qianjin Feng[a,*], Arman Rahmim[d,e], Wufan Chen[a,*]

[a] School of Biomedical Engineering and Guangdong Provincial Key Laboratory of Medical Image Processing, Southern Medical University, Guangzhou, Guangdong 510515, China
[b] School of Software, Guangdong Food and Drug Vocational College, Guangzhou, Guangdong 510520, China
[c] Shaukat Khanum Memorial Cancer Hospital and Research Center, Lahore, Pakistan
[d] Department of Radiology, Johns Hopkins University, Baltimore, MD 21287, USA
[e] Department of Electrical and Computer Engineering, Johns Hopkins University, Baltimore, MD 21218, USA

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ABSTRACT

*Background and objective*: The absolute quantification of dynamic myocardial perfusion (MP) PET imaging is challenged by the limited spatial resolution of individual frame images due to division of the data into shorter frames. This study aims to develop a method for restoration and enhancement of dynamic PET images.

*Methods*: We propose that the image restoration model should be based on multiple constraints rather than a single constraint, given the fact that the image characteristic is hardly described by a single constraint alone. At the same time, it may be possible, but not optimal, to regularize the image with multiple constraints simultaneously. Fortunately, MP PET images can be decomposed into a superposition of background vs. dynamic components via low-rank plus sparse (L + S) decomposition. Thus, we propose an L + S decomposition based MP PET image restoration model and express it as a convex optimization problem. An iterative soft thresholding algorithm was developed to solve the problem. Using realistic dynamic $^{82}$Rb MP PET scan data, we optimized and compared its performance with other restoration methods.

*Results*: The proposed method resulted in substantial visual as well as quantitative accuracy improvements in terms of noise versus bias performance, as demonstrated in extensive $^{82}$Rb MP PET simulations. In particular, the myocardium defect in the MP PET images had improved visual as well as contrast versus noise tradeoff. The proposed algorithm was also applied on an 8-min clinical cardiac $^{82}$Rb MP PET study performed on the GE Discovery PET/CT, and demonstrated improved quantitative accuracy (CNR and SNR) compared to other algorithms.

*Conclusions*: The proposed method is effective for restoration and enhancement of dynamic PET images.



## 1. Introduction

Myocardial perfusion (MP) PET imaging can provide improved diagnostic accuracy, location of disease and quantification of blood flow over conventional SPECT imaging [1-3]. In particular, dynamic MP PET imaging offers the very notable capability to measure changes in the bio-distribution of radiopharmaceuticals within the myocardial region over time [4-6]. This offers a powerful mean to estimate the kinetic parameters (e.g. the tracer transport rate $K_1$ and subsequently myocardial blood flow (MBF)) by using the various kinetic modeling techniques. However, the dynamic MP PET imaging is primarily limited to research and remains underutilized in the clinical setting. The main challenge is the increased noise with limited durations of each frame, which will ultimately impact the quantification [7].

Individual PET image reconstruction is finished by statistical reconstruction methods, such as maximum likelihood (ML) method [8]. However, the ML often results in high noise at low counts. This problem [9] is further aggravated in dynamic scans. Strategies have been explored to improve the reconstruction accuracy of the dynamic frames for kinetic parameter estimation [10-15]. Reconstruction-strategies (e.g. 4D reconstruction) exploit

* Corresponding authors.
*E-mail addresses:* lulijun@smu.edu.cn (L. Lu), fengqj99@fimmu.com (Q. Feng), chenwf@smu.edu.cn (W. Chen).

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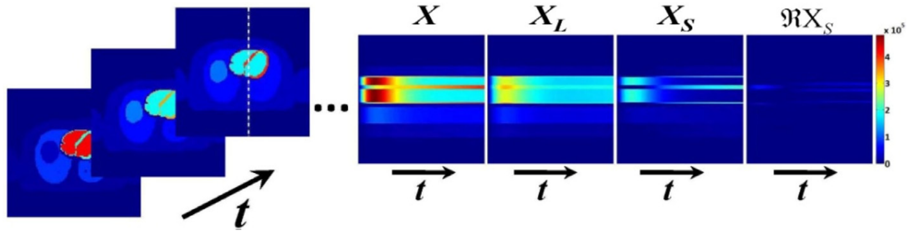


**Fig. 1.** The dynamic MP PET images (left) and corresponding data sets (right). Each column of X consists of the specific pixels along the dotted line shown in left, and it varies as time (t) changes. $X_L$ represents the background (low-rank) component of X that changes slowly, and $X_S$ is the dynamic (sparse) component of $X$ that captures the dynamic changes in the frames.

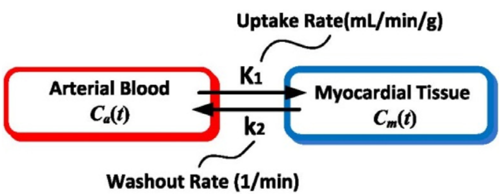


**Fig. 2.** One-tissue compartment model for kinetic modeling of $^{82}$Rb MP PET imaging. This model has only one compartment in myocardial tissue and exchanges radiotracer between arterial blood compartment and myocardial compartment by $K_1$ and $k_2$.

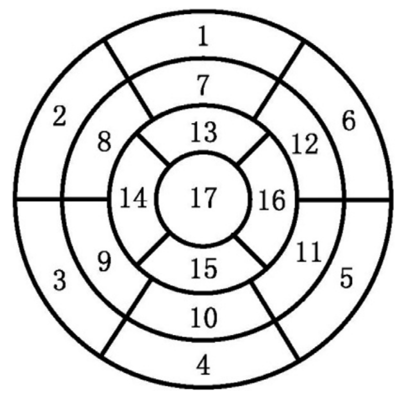


**Fig. 4.** The polar plot of the 17 myocardial segments for tomographic imaging of the heart.

the spatiotemporal correlation in dynamic PET scans to improve the precision of parametric image. However, 4D methods can be algorithmically and computationally intensive and require further optimization efforts [16-18].

In contrast to reconstruction-based strategies, post-reconstruction or restoration strategies process the dynamic frames already reconstructed with filtered back projection (FBP) or ML, thus being more readily applicable to clinical data [19]. Gaussian filter can be used for image smoothing while resulting in edge blurring. Edge-preserving filters [20] have been proposed to reduce the noise while preserving edges. More recently, nonlocal means type filter methods have been developed for image denoising [21-23]. For example, Dutta et al. [21] proposed non-local means method for dynamic PET denoising. Chun et al. [22] proposed non-local means methods combining the side information of CT. Chan et al. [23] proposed an anatomically guided median non-local means filter combining the non-local means method and anatomical regional information.

Alternatively, techniques consider using the sparse characteristic of PET images [24-25]. The total variation regularization has been incorporated into PET reconstruction both in image space [26-27] or measurement space [28]. Multidimensional wavelet denoising was proposed to restore the dynamic cardiac PET images [29-30]. Su and Shoghi [31] proposed wavelet-based noise reduction technique which can reduce the noise more efficiency at high noise levels. Le Pogam et al. [32] proposed a strategy that combines the complementary wavelet and coverlet transform accounting for directional properties of the image. Nonetheless, all these methods exploit the characteristic that the spatial or temporal signals of dynamic PET images are sparse (either in direct representation or transform-domain).

There are approaches performing PCA or KLT on the dynamic PET data. For example, Kao et al. [33] performed PCA on the dynamic sinogram to reduce the noise. Wernick et al. [34] proposed to first apply KLT on the standard datasets, and then reconstruct the uncorrelated dynamic data independently, resulting fast yet accurate reconstruction. Furthermore, Matthews et al. [35] used SVD, as applied to initially reconstructed images, to derive the temporal

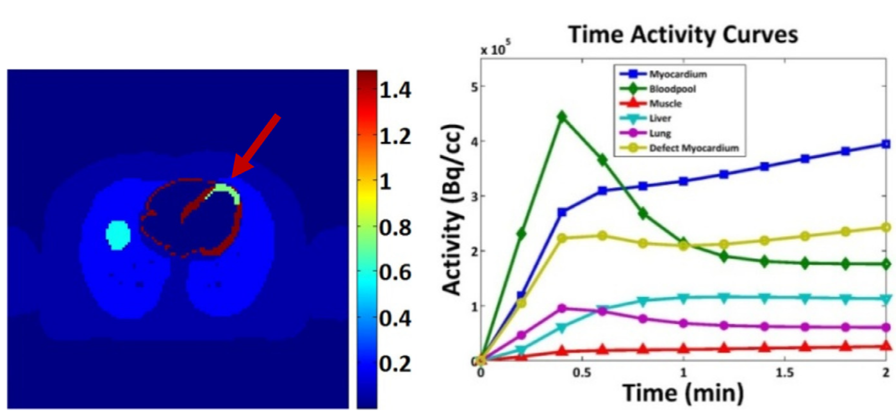


**Fig. 3.** (Left) $K_1$ parametric image and (right) TACs generated using one-tissue compartmental model. (The defect myocardium is labeled with the red arrow). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)