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Denoising of dynamic PET images using a multi-scale transform and non-local means filter

Hajer Jomaa [a,*], Rostom Mabrouk [b], Nawres Khlifa [a], Frédéric Morain-Nicolier [c]

[a] *Laboratoire de Biophysique et Technologies Médicales, Université de Tunis El Manar, Tunis, Tunisia*
[b] *Brain Research Centre, University of British Columbia, Vancouver, Canada*
[c] *Centre de Recherche en STIC, Université de Reims Champagne-Ardenne, IUT de Troyes, France*

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The quantification of positron emission tomography (PET) images requires a time activity curve (TAC) to provide an accurate estimation of kinetic parameters. However, the low signals to noise ratio (SNR), the important level of noise, and the low spatial resolution of PET image make the extraction of the TAC a challenging task. In this study, we present a new method based on multi-scale and non-local means method (MNLM) to reduce noise in dynamic PET sequences of small animal heart. MNLM filter takes into account the temporal correlation between images in the dynamic measurement and benefits from the complementary properties of both the Shearlet transform and the wavelet transform to provide best reduction. The method was tested on dynamic digital mouse phantom and a preclinical rat study ($n = 6$). Based on a comparative study with three major algorithms reviewed on the state of the art, the data analysis proved the significance of the MNLM filter. In simulated data, the major finding of the study showed that at the highest noise level (7.68%), the model gave the best result (Chi-square = 4.06). Furthermore, it presented a notable gain in terms of PSNR and SSIM plot. In real data, the MNLM showed a better result in the computation of the contrast metric with a value of 27.04 ∓ 12.1 and the highest SNR with a value of 74.38 ∓ 9.2. This approach proved a better potential and could be considered as a valuable candidate to reduce noise in clinical system.

1. Introduction

Positron emission tomography (PET) is a powerful functional imaging modality which enables *in vivo* examination of organs' functions. PET allows the quantification of the cerebral blood flow, receptor binding, and bimolecular metabolism in the body. Recently, stand-alone or combined to anatomical modality use of PET has emerged as an extremely interesting technique for studying some patho-physiologic phenomena. The quantification of PET images helps the understanding of some specific physiological and biochemical processes like the global and local myocardium metabolic rate for glucose (MMRGlu). Cardiac PET image with [^{18}F]-fluorodeoxyglucose ([^{18}F]-FDG) is commonly performed to assess MMRGlu in the heart cells [1,2]. Mathematical modeling techniques, such as graphical or compartmental analyses, are generally applied to derive parameters of interest. Importantly, the quantification of PET images uses both the plasma time activity curves (TACs) and the target tissue TAC, as input functions of a mathematical model [3,4]. The tissue TAC is commonly obtained from the time course of the voxel or the mean over a region of interest (ROI) radioactivity in the image and the plasma TAC is obtained either from the blood sampling or from the image [5]. The blood sampling is a long, inaccurate and risky procedure in clinical studies. Therefore, different techniques like image derived input functions (IDIF) [2] and population-based input functions (PBIF) [6] were investigated to substitute the arterial blood sampling. Although, in many cases, these methods have succeeded, they are still considered as unreliable techniques because of the need to a few blood samples or the dependence on the image quality. Nevertheless, the estimation of the input function (IF) is a critical element and by consequence the quantification of PET images is still a difficult task given their low signals to noise ratio (SNR). Indeed, in addition to the Poisson–Gaussian mixed noise [7,8], these images suffer from the partial volume effect [9], the low spatial resolution, and the low contrast [10–12]. All these physical degradations limit the quality of PET image and consequently the corresponding (TAC). Undoubtedly, the quality of PET images has an impact on the TACs quality and therefore on the assessment of the parameters of inter-

* Corresponding author.
E-mail address: jomaahajer@gmail.com (H. Jomaa).

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est. In order to achieve a better derived PET TACs quality and hence gaining insight of metabolic mechanism, many techniques were proposed. To reduce the noise in PET images, the Gaussian filter was firstly used in the reconstruction algorithms, as a simple technique [13]. Although, this filter gives a good result in homogenous regions, it blurred the edges and degrades the spatial resolution. To overcome the modest performance of the Gaussian filter, investigators [14] have extended its proprieties to develop the Bilateral filter where noise is reduced while ROI-edges are preserved. However, its major disadvantage was smoothen-up the textures and the edges since its coefficients are calculated without considering the entire region. To overcome these limitations, other researchers [15] have suggested to refer to kinetic information to enhance the performance of this filter. They incorporated the similarity between the voxel-wise TACs employing the scheme of Bilateral filter. Other works [7] extended the filter to the trilateral filter and explored it to avoid the loss of some quantitative information. Recently, a more sophisticated filter namely non-local means (NLM), was applied to the PET images. With various extensions including anatomical knowledge [16] and a segmentation step [17], the NLM filter has proved its ability to reduce noise while preserving the structures and the details. Notably, other researchers exploited multi-scale transform such as wavelets [18,19] and curvelets [12] to decrease the noise in PET images. The wavelets were investigated to correct the quantitative and qualitative information in PET images [20–22] and they are still used by many researchers in recent works [23–25]. These transformations allowed the separation of the signal from noise and succeeded to improve the SNR with significant gains. With wavelet decomposition, at each scale, they analyzed the noise level separately with adaptive denoising algorithm. However, wavelets do not lead to a good representation of the anisotropic elements in images. Therefore, another multi-scale transform like curvelets were proposed to guarantee better performance by extending the wavelet properties [12]. Moreover, several attempts to denoise dynamic PET image were proposed by using the temporal information from dynamic PET image [21,26,27]. These methods incorporated both spatial and temporal characteristics of the PET image with different spatial algorithms. Recently, several authors [28] have developed an iterative deconvolution and HYPR denoising method to directly improve the image derived input functions of the PET image. In this paper, we propose a new framework of noise reduction in dynamic PET sequences of small animal heart based on multi-scale and non-local means method (MNLM). We extended the NLM filter to take into account the temporal correlation between images in the dynamic measurement. We exploited in addition both the Shearlet transform and the wavelet transform to benefit from their complementary properties. In our earlier work [29], we applied the extended version of the NLM (ENLM) on preclinical dynamic PET data. In this work, we continued our approach by adding a new framework based on another multi-scale transform and with a new combination between this transform and the ENLM. To evaluate the performance of the proposed technique, we use simulated phantom and preclinical rat study data. We compared denoising algorithm with three states of the art techniques for PET images: the Gaussian filter, the wavelet thresholding and the NLM algorithm. The results showed a significant reduction of noise with the preservation of the ROI-edges and the fine details. Qualitatively, both SNR and contrast were enhanced in comparison to the original data.

2. Materials and methods

2.1. Denoising model

In our framework, we will introduce our approach in details by focusing on the following parts.

2.1.1. The wavelet transform for PET denoising

The undecimated wavelet transform (UWT) is a powerful transform for denoising technique due to the translation invariance. This propriety makes the UWT of a translated version of an image the same as the translated version of the UWT of this image. In PET image, UWT was widely used by many researchers [23,24,30]. Its major advantage is to reduce noise in frequency domain with shift-invariant properties. Due to its multi-scale representation and separate decomposition, the UWT facilitates the noise reduction because of its ability to separate signal and noise. It decomposed the image into high frequencies and low frequencies. Accordingly, it is considered as an adaptive denoising algorithm which attempts to reduce noise and preserve data at each wavelet scale. In this paper, the UWT was used to decompose the image into two levels where we defined the 'BiorSplines' as a Biorthogonal Wavelet family. Then, we filtered horizontal, vertical, and diagonal details with the extended NLM (ENLM) instead of the traditional technique (thresholding). We used the 'à trous' algorithm [31]to obtain the passage from one resolution to the next one without decimate coefficients at every transformation level. It permits the avoidance of the pseudo Gibbs phenomenon which appears as dark artifacts presented around bright features in the image. In fact, the original image and both the approximation coefficients and detail coefficients have the same length at each level.

2.1.2. The extended NLM filter

The NLM filter was initially introduced by Buades et al. [32]. The details of the algorithm are described in Appendix A.

In this work, we extended the NLM filter (ENLM) to exploit the PET images proprieties. Notably, dynamic PET pixel is accumulated into a varying temporal map of a tracer distribution. A short time bins in the earliest time scan (~5–10 s) which allows to capture the rapid change of the kinetic tracer after its administration and a large time bins (300–600 s) in the latest dynamic frames to evaluate the uptake of the tracer in the myocardium. Accordingly, the latest images of the sequence are less damaged by noise than the earliest ones. Consequently, the noise is less important in the image $t+1$ then the image t. Additionally, the PET dynamic images are characterized by evident spatiotemporal redundancy between the different frames of the sequence. These proprieties are then used to extend the NLM filter. The similarity degree was computed using these relationships between the different images. The extended version of the NLM filter consisted in computing the similarity coefficients, in the image t, using pixels in the image $t+1$. We extended the definition of the weight $w(i, j)$ of the image t by using the same position at the next image $t+1$. The principle of this extension is illustrated in Fig. 1. Mathematically, the extended NLM filtered intensity, $x_{ENLM}(i)$, of the pixel i, is given by:

$$x_{\mathrm{ENLM}}(i,t) = \frac{1}{\sum_{j\in W_{(i,t+1)}} w(i,j)} \sum_{j\in W_{(i,t+1)}} w(i,j)x(j,t+1) \tag{1}$$

where

$$w(i,j) = \exp\left(-\sum_{k}\sum_{t}\frac{\left[x(N_i^k,t)-x(N_j^k,(t+1))\right]^2}{h^2}\right) \tag{2}$$

$w(i, j)$ is the weight that measures the similarity between the two pixels i and j. N_i and N_j are the respective neighborhoods surrounding the pixel i and j and W is a search window and t is the time point.