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ScienceDirect
Computerized Medical Imaging and Graphics 31 (2007) 157–165
Computerized Medical Imaging and Graphics
www.elsevier.com/locate/compmedimag

Assessment of glucose metabolism from the projections using the wavelet technique in small animal pet imaging

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Received 2 November 2005; received in revised form 13 December 2006; accepted 15 December 2006

Abstract

The dynamic positron emission tomography (PET) images are usually modeled to extract the physiological parameters. However, to avoid reconstruction of the dynamic sequence of images with subjective data filtering, it is advantageous to apply the kinetic modeling in the projection space and to reconstruct single parametric image slices. Using the advantage of the wavelets to compress the data and to filter the noise in the sinogram, we applied the graphical analysis method (Patlak) to generate a single parametric sinogram (WAV-SINO) from PET data acquired in seven normal rats measured with fluorodeoxyglucose (FDG) in the heart. The same data set was analysed with the graphical method in the spatial domain from the sinograms (USUAL-SINO), and also from images reconstructed with non-filtered backprojection (USUAL-nFBP) and filtered backprojection (USUAL-FBP). The myocardial metabolic rates for glucose (MMRG) obtained with USUAL-nFBP, USUAL-FBP, USUAL-SINO and WAV-SINO were found to be, respectively, 7.54, 6.75, 6.52 and 6.98 μmol/100 g/min. While the variance with respect to USUAL-FBP was about 142% for USUAL-nFBP, 99.6% for USUAL-SINO and 101.9% for WAV-SINO, the spatial resolution as assessed from the profiles through the myocardial walls of the reconstructed images was 112% for USUAL-FBP and 105% for WAV-SINO relative to the high resolution USUAL-nFBP. The WAV-SINO parametric images showed slightly better visual quality than those obtained from the spatial domain. Finally, the wavelet filtering technique allowed to reduce the computing time, the storage space and particularly the variance in the MMRG parametric images while preserving the spatial resolution.

Keywords: Positron emission tomography; Kinetic modeling; Glucose metabolism; Cardiology; FDG; Image analysis; Wavelets; Micropet; Small animal; Rat

1. Introduction

The capital role of a parametric image in positron emission tomography (PET) imaging is to provide the functional information and the accurate physiological parameters of a specific radiotracer in a tissue. Unfortunately, the limitations of PET imaging are the low signal-to-noise ratio due to the detection system, the limited injected dose of the tracer and the reduced time of acquisition. Several efforts have been made to reduce errors produced during image processing and data analysis. The image reconstruction methods such as filtered backprojection (FBP) [1], maximum likelihood expectation maximization (MLEM), and ordered subsets expectation maximization (OSEM) [2,3] also include subjective filtering. The disadvantage of FBP is the cutoff frequency which is not well defined, the sinusoids of the Fourier transform which are not adapted to represent spatially inhomogeneous data and data with poor statistics. In regard to MLEM and OSEM, the limitations are the amplification of noise and the slow convergence with the increasing number of iterations in the search of a better spatial resolution.

Recently, the wavelet transform has emerged as a powerful and efficient tool for data analysis and has shown potential in several applications, for example, in medical imaging, the wavelets have been used in tomographic image reconstruction [4–7], in noise filtering [8–12], in image segmentation [13–15] and in image compression [9,15,16]. Wavelets have also been found to be useful in digital mammography for both image enhancement and the detection of microcalcification [17–19]. The multiresolution algorithms developed by Mallat [20] and applied by both Turkheimer et al. [21–23] and Cselenyi et al. [24] in PET brain studies have several advantages over conventional filtering techniques to decrease the noise sensitivity of parametric estimation procedures. The present application of wavelets to the analysis of PET cardiac data in the rat with fluorodeoxyglucose

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doi:10.1016/j.compmedimag.2006.12.003

(FDG) directly from the sinograms using the graphical analysis method [25] was a comparative study to our earlier work where the data were analysed in the image domain [26]. Using the wavelets to compress the data and to filter the noise, the dynamic PET projections were transformed in the wavelets domain, then the correlated signals in the approximation and details matrices were considered for kinetic modeling, and finally the data were transformed back to the spatial domain and a single parametric sinogram was reconstructed.

2. Theory

2.1. Wavelets

2.1.1. Multiresolution analysis

The discrete wavelet generated from one single function called the mother wavelet Ψ by dilatation and translations is defined as:

$$\psi_{i,j}(x) = 2^{i/2}\psi(2^i x - j) \tag{1a}$$

for each $i \in Z$, 2^i being the resolution, and for each translation $j \in Z$.

The dilated and translated version of the scaling function ϕ is defined as:

$$\phi_{i,j}(x) = 2^{i/2}\phi(2^i x - j) \tag{1b}$$

Different wavelets were constructed by Meyer [27], Daubechies [28], Battle [29], Lemarie [30] and others. All these examples correspond to a multiresolution analysis, a mathematical tool introduced by Mallat [20], which is particularly well adapted to the use of wavelet technique in image analysis. The wavelets used in this work were those designed by Battle and Lemarie.

2.1.2. Battle–Lemarie filters

The analytical expression of the Fourier transform of the scale function ϕ was designed by Battle and Lemarie [29,30]:

$$\hat{\phi}(\omega) = \frac{1}{\omega^n \sqrt{S_{2n}(\omega)}} \tag{2a}$$

with:

$$S_n(\omega) = \sum_{k=-\infty}^{+\infty} \frac{1}{(\omega + 2k\pi)^n}$$

where ω is the frequency. In this expression, the wavelet was generated from spline polynomials of order m, where m is odd and $n = m + 1$ in (2a). Note that the hat above the letters accounts for the Fourier transform. The wavelet function $\hat{\psi}$ is deduced from the scale function $\hat{\phi}$ as:

$$\hat{\psi}(\omega) = \frac{\exp(-\mathrm{i}\omega/2)}{\omega^n} \sqrt{\frac{S_{2n}((\omega/2) + \pi)}{S_{2n}(\omega) S_{2n}(\omega/2)}} \tag{2b}$$

The Fourier transform of the quadrature mirror filters (QMF) is given by:

$$\hat{\phi}(2\omega) = \hat{l}(\omega)\hat{\phi}(\omega) \tag{3a}$$

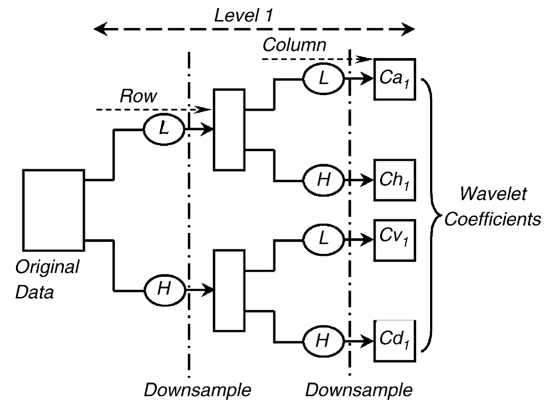

Fig. 1. Diagram illustrating the different steps of image decomposition with the wavelets. The original data are first convolved with low (L) and high (H) pass filters followed with decimations to give coefficients for approximations (Ca), horizontal details (Ch), vertical details (Cv) and diagonal details (Cd).

and

$$\hat{l}(\omega) = \sqrt{\frac{S_{2n}(\omega)}{2^{2n} S_{2n}(2\omega)}} \tag{3b}$$

The filter h is the modulated version of the filter l and is given by:

$$h_k = (-1)^k l_{1-k} \tag{3c}$$

In the multiresolution method, any arbitrary function $f(x)$ can be basically represented as [31]:

$$f(x) = \sum_{i \in Z}\sum_{j \in Z} a_{i,j}\phi_{i,j}(x) + \sum_{i \in Z}\sum_{j \in Z} d_{i,j}\psi_{i,j}(x) \tag{4}$$

The estimation of the coefficients $a_{i,j}$ and $d_{i,j}$ is carried out through an iterative decomposition algorithm [20,31]:

$$a_{i,j} = \sum_{k \in Z} l_{2j-k} a_{i-1,k}; \qquad d_{i,j} = \sum_{k \in Z} h_{2j-k} a_{i-1,k} \tag{5}$$

In order to have exact reconstruction, the filters have to verify [31]:

$$\tilde{l}(n) = l(-n); \qquad \tilde{h}(n) = h(-n) \tag{6}$$

l and h are the decomposition filters, and $\tilde{l}$ and $\tilde{h}$ are the reconstruction filters. The filters used to process the PET data in the present work were those of Battle–Lemarie of length 22 [26].

The algorithms of multiresolution analysis consist in decomposing the original image at different scales using a low-pass filter l, associated with the scale function ϕ, and a high-pass filter h, associated with the wavelet function ψ. The decomposition is along the vertical and horizontal directions as sketched in Fig. 1, leading to four new images representing the low frequencies (approximation image) and the high frequencies (horizontal, vertical and diagonal images). The resulting low frequency image can also be subsequently decomposed with the same low-pass and high-pass filters to produce four images, and so forth. At each level of decomposition, the first image is called the approximation image and the others are called the details