A Knowledge-based Image Smoothing Technique for Dynamic PET Studies

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Abstract

Many techniques have been proposed to reduce image noise in dynamic positron emission tomography (PET) imaging. However, these smoothing methods are usually based on the spatial domain and local statistical properties. Smoothing algorithms specifically designed for dynamic image data have not previously been investigated in detail. We present a knowledge-based smoothing technique that aims to diminish the noise and improve the quality of the dynamic images. By taking advantage of domain specific physiological kinetic knowledge, this technique can provide dynamic images with high noise reduction while preserving edges and subtle details.

I. INTRODUCTION

Dynamic positron emission tomography (PET) provides a powerful tool for the quantitative study of physiological processes and disease within the human body [1]. However, the finite spatial resolution of PET scanners and high noise result in poor image quality, thus degrading the precision of measurement and leading to errors in parameter estimation. Various smoothing techniques have been applied to remove noise from PET images [2-7]. Generally, they fall into two main categories. In the first category, the smoothing techniques such as direct Fourier inversion method [3], iterative reconstruction algorithms [4-5], improve image quality at or before the image reconstruction stage. In the second category the smoothing methods such as median filter [6], gradient inverse weighted method [7] and the sigma filter [8], are applied after the reconstruction. These methods are usually implemented in the two-dimension (2D) space domain, and normally involve some neighbour averaging, using a uniform-size, weighted-size or adaptive-size window. Recently, a feature-matching axial smoothing method [9] has been introduced for not only making use of the spatial correlations within the image plane, but also applying inter-slice three-dimension (3D) correlations. However, most of these techniques only make use of the spatial domain and local statistical properties. None of them fully addresses physiological information contained within the images. The physiological structure and properties of neighbouring pixels may be very different, such as the brain tissues and blood vessels. Conventional smoothing methods may therefore mix the contributions from adjacent tissue regions of different functional states.

In this paper, we develop a novel knowledge-based smoothing technique for reconstructed PET images. The approach is based on the domain specific physiological kinetic knowledge related to dynamic PET images and physiological tracer kinetic modelling. This technique is demonstrated by comparing with the conventional median filter method in terms of resolution loss and noise reduction in human brain clinical *[18F]2-fluoro-deoxy-glucose* (FDG) PET studies.

II. MATERIAL AND METHODS

A. *Physiological Tracer Kinetic Modeling*

Tracer kinetic modeling techniques with PET are widely applied to extract physiological information about dynamic processes in the human body. Generally, this information is defined in terms of a mathematical model $\mu(t|p)$ (where t = 1, 2,..., T and p is a set of the model parameters), whose parameters describe the delivery, transport and biochemical transformation of the tracer. The input function for the model is the plasma time activity curve (PTAC) obtained from the measurement of blood samples. Reconstructed PET images provide the physiological tissue time activity curve (TTAC), or the output function, denoted by $Z_i(t)$, where $t = 1, 2, \ldots, T$ are discrete sampling times of the PET measurements, and $i = 1, 2, \ldots, I$ corresponds to the i-th pixel in the imaging region. Application of the model on a pixel-by-pixel basis to measured PTAC and TTAC data using certain rapid parameter estimation algorithms, yields physiological parametric images.

B. *A Knowledge-based Image Smoothing Method*

The prior knowledge has the form of tracer kinetic model to a time series of PET tracer uptake measurements. In dynamic PET images, for each pixel in a cross-sectional image plane, a physiological TTAC (feature vector) can be extracted from a sequence of image frames. However, pixels in physiologically similar regions should have similar TTAC kinetics. Therefore, in our new knowledge-based smoothing method, an optimal clustering algorithm is applied to classify image-wide TTACs, $Z_i(t)$ (where $i=1,2,\ldots,I$, and I is the total number of the image pixels), into J cluster groups G_j (where $j=1,2,\ldots,J$, and $J<<I$)

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by measuring the magnitude of similarity characteristics within physiological kinetic activity domain. The similarity measure used was the Euclidean distance

$$D = \sqrt{\sum_{t=1}^{T}(Z_i(t) - \bar{Z}_{G_j}(t))^2} \qquad (1)$$

(where $\bar{Z}_{G_j}(t)$ is the mean TTAC within each group G_j) with an adaptive threshold

$$\tau = C \cdot \sigma_{\text{plane}} \qquad (2)$$

Here C is an empirically determined parameter, used as a smoothing controller (SC), and σ_{plane} is the standard deviation of the plane pixel values in the last frame. The σ_{plane} provides an indication of the overall variability in the pixel TTACs. TTACs with similar kinetics (i.e., $D \le \tau$) are classified into the same cluster, and conversely, TTACs with low degrees of similarity (i.e., $D > \tau$) are placed in different groups. All the clustering results are contained in a TTAC index table which is sequentially indexed by cluster group and each index will contain the mean TTAC cluster values for that group. Based on the TTAC index table, we can then re-produce the dynamic image sequence. The noisy TTACs for these pixels corresponding to a particular cluster can be replaced by the average or weighted average of the cluster TTACs, therefore a set of smoothed dynamic images can be generated.

Since the physiological TTACs are extracted from a sequence of twenty or more temporal image frames acquired with a conventional sampling schedule (CSS), the obtained TTAC feature vectors have high dimensions (20 or more), making the similarity measurement complex and inefficient. Therefore, before running the cluster algorithm, we apply our previous developed optimal image sampling schedule (OISS) *[10] to reduce the number of temporal image frames.* In the design of OISS, an objective function based on the Fisher Information Matrix [11], was used to discriminate between different experimental protocols and sampling schedules. It has been shown that the minimum number of image frames that needs to be recorded is equal to the number of parameters to be estimated. For dynamic PET imaging based on an OISS design with a five-parameter FDG model, only five image frames are needed. Therefore, the TTAC vector dimensions and the computational complexity of similarity measurement is considerably reduced. Pixels containing background noise and negative values were suppressed prior to cluster analysis.

C. Clinical Dynamic PET Studies

The proposed technique was applied to the dynamic clinical *[18F]2-fluoro-deoxy-glucose* (FDG), brain PET scans of three patients (one epileptic and two normals) using an eight-ring, fifteen-slice PET scanner (GE / Scanditronix PC4096 - 15WB). The PET scanning schedule in each scan was 10×0.2, 2×0.5, 2×1, 1×1.5, 1×3.5, 2×5, 1×10 and 3×30 minute scans. The dynamic PET data were corrected for attenuation, decay-corrected to the time of injection and then reconstructed using filtered back-projection with a Hanning filter. The reconstructed pixel size was 2mm×2mm. Each reconstructed slice consisted of 128×128 16-b pixels. For OISS with a five-parameter FDG model (OISS-5), the data were resampled into five scanning intervals (frames): 1×0.717, 1×2.483, 1×11.250, 1×60.933, and 1×44.617 minute scan [12].

III. RESULTS AND DISCUSSION

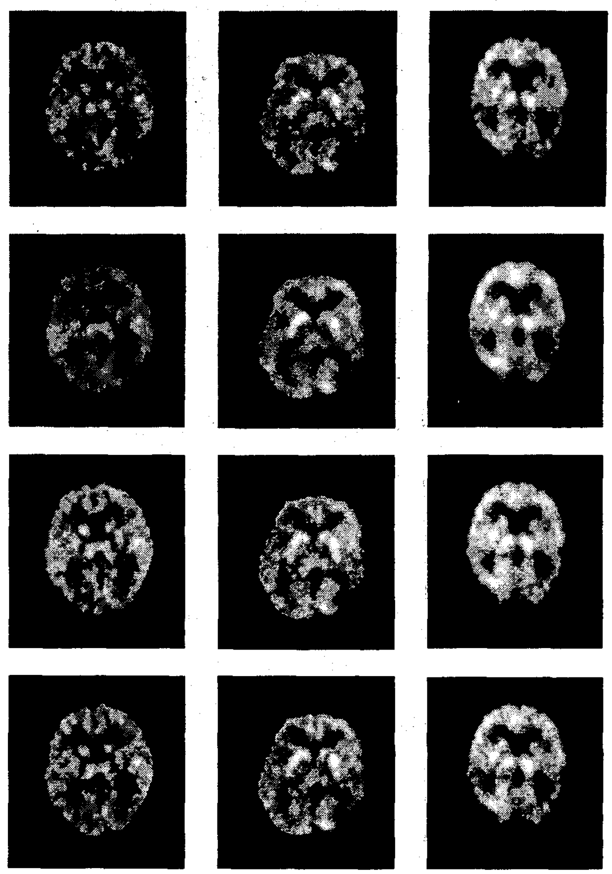
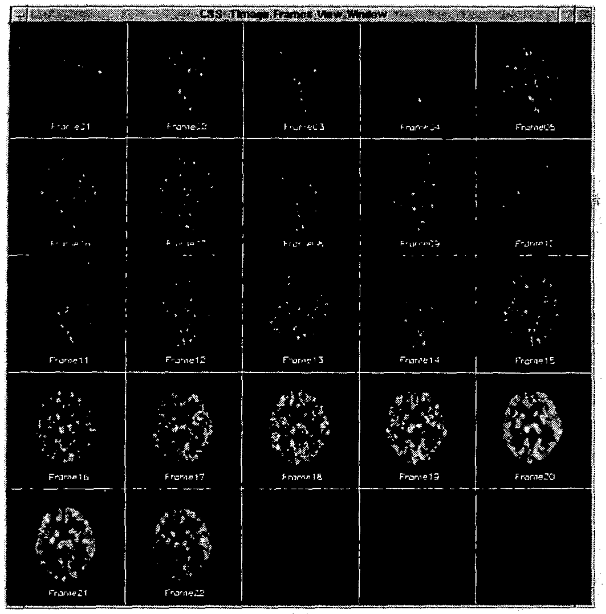
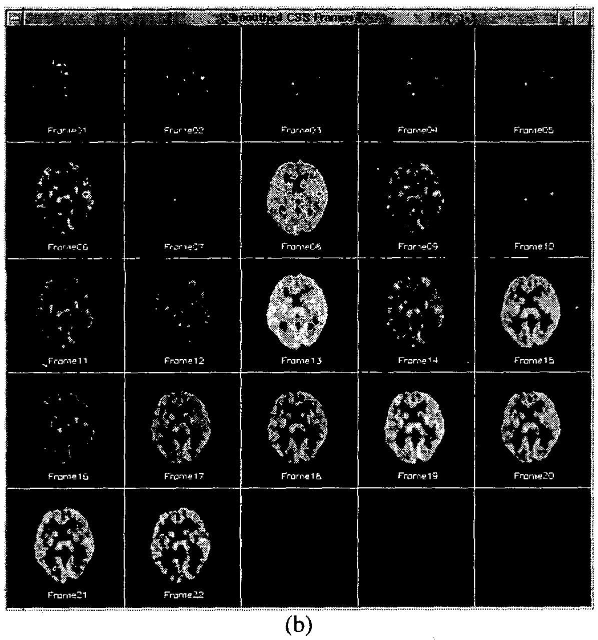


Figure 1. FDG-PET brain images smoothed using the median filter method and the proposed knowledge-based method. The first row: original images; the second row: smoothed images by the median filter method; the third row: smoothed images by our proposed knowledge-based smoothing technique (un-weighted average); the fourth row: smoothed images by our proposed technique (weighted average).

The resultant smoothed FDG-PET brain images using the conventional median filter method (with 5 x 5 window) and our proposed knowledge-based smoothing technique are compared and shown in Figure 1. The set of three different plane images (the last time frames) is from three different FDG-PET brain studies. Each column shows the results in a different study. The first row images represent original un-smoothed images; the second row images are smoothed by the median filter method; the third row images are smoothed by our proposed method with un-weighted average; and the fourth row column images are smoothed by our proposed method with weighted average. The results demonstrate that the proposed knowledge-based smoothing technique can give high noise reduction without blurring edges and concealing subtle details.



(a)



(b)

Figure 2. (a) The original noisy temporal image sequence; (b) the smoothed temporal image sequence using the proposed smoothing method.

Figure 2(b) shows a set of smoothed temporal image sequence using the proposed method. Comparing with the original noisy temporal image sequence in Figure 2(a), we can see that the proposed smoothing technique can not only provide much smoothed temporal image sequences, but also enhance the individual image frames, demonstrating features not seen in the original images, especiallv in the early images.

IV. CONCLUSION

In this paper, we proposed a novel knowledge-based smoothing method for dynamic PET image data, based on the domain specific physiological kinetic knowledge. The proposed technique has been investigated with clinical dynamic PET studies and appears to provide good noise reduction, while preserving edges and subtle details. We believe the technique may provide a useful alternative in dynamic PET to conventional smoothing approaches, and therefore it is worthy of further investigation.

V. ACKNOWLEDGMENTS

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VI. REFERENCES

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