FIPS: A Functional Image Processing System for PET Dynamic Studies

Dagan Feng[1,2], Weidong Cai[1,2], and Roger Fulton[1,3]

[1] Center of DSP for Multimedia Applications,

Dept. of Electronic & Information Engineering, Hong Kong Polytechnic University

[2] Biomedical and Multimedia Information Technology (BMIT) Group,

Basser Dept. of Computer Science, The University of Sydney, Australia

[3] Dept. of PET and Nuclear Medicine, Royal Prince Alfred Hospital, Australia

Address correspondence to Prof. Dagan Feng

Professor & Deputy Director,

Center of DSP for Multimedia Applications

The Hong Kong Polytechnic University

Director, Biomedical & Multimedia Information Technology (BMIT) Group

The University of Sydney

NSW 2006, Australia

Telephone: (+61-2) 9351-2103

Facsimile: (+61-2) 9351-3838

E-mail: feng@cs.usyd.edu.au or enfeng@polyu.edu.hk

Running Title: A Functional Image Processing System for PET

ABSTRACT

Positron emission tomography (PET) imaging can provide quantitative physiological information, in addition to qualitative information. However, most of PET image handling software packages have not included modeling and quantitative analysis functions. In this paper, based on some of our systematic studies on biomedical functional image data processing and modeling, we developed a functional image processing system (FIPS), which is a completely interactive window-based processing system including features for brain PET dynamic studies. The system contains several special modules: (1) Basic image statistical analysis; (2) Optimal PET image sampling schedule (OISS) design; (3) Physiological knowledge-based clustering analysis (KCA); (4) Dynamic image data compression; (5) Most of the major fast algorithms for generation of functional images; etc. This system would therefore be very useful for the design of proper data acquisition protocol for brain PET dynamic studies, functional imaging data analysis, compression, modeling, and simulation.

I. INTRODUCTION

Functional imaging techniques such as positron emission tomography (PET) have matured into a crucial and powerful tool for modern biomedical research and clinical diagnosis [1]. One of the major advantages of PET imaging is that it can provide quantitative physiological information, in addition to qualitative information. However, most of the PET image handling software packages have not included modeling and quantitative analysis functions yet. In this paper, based on our systematic studies on biomedical functional image data processing and modeling, we developed a functional image processing system, called FIPS.

II. SYSTEM OVERVIEW

FIPS is an interactive window-based processing system including features for brain PET dynamic studies. The software was implemented in C programming language and IDL on a SUN Ultra-2 workstation running Solaris 2.5, as well as on an Intel Pentium-based platform using RedHat Linux 5.1. The system contains several special modules: (1) Basic image statistical analysis, such as tissue time activity curve (TTAC) and plasma time activity curve (PTAC) viewer, dynamic image sequence player, profile, histogram, and surface etc; (2) Optimal PET image sampling schedule (OISS) design [2][3]; (3) Physiological knowledge-based clustering analysis (KCA); (4) Dynamic image data compression [4]; (5) Most of the major fast algorithms for generation of functional images, such as the Patlak graphic approach (PGA) [5], the linear least squares method (LLS) [6], and the generalized linear least squares algorithm (GLLS) [7] etc. Fig.1 illustrates the system structure of the FIPS. Some of the functional modules and related research are described and summarized in the following sections.

A. *Optimal PET Image Sampling Schedule*

An optimal image sampling schedule (OISS) for dynamic PET has recently been derived theoretically and investigated by computer simulation and clinical studies [2][3]. It has been demonstrated that the use of OISS is an effective way to reduce image storage requirements while providing comparable parameter estimates.

Finding the optimal image sampling schedule involves minimising the determinant of the convariance matrix of the estimated parameters, or conversely maximising the determinant of the Fisher information matrix by rearranging the sample intervals, using the minimum number of required samples. It has been shown [2] that the minimum number of temporal frames required is equal to the number of model parameters to be estimated. For example, for the five-parameter FDG model, only five temporal frames are sufficient to obtain parameter estimates of equivalent statistical accuracy and reliability to the conventional technique which typical requires the acquisition of more than twenty temporal frames [8]. Since fewer temporal image frames need to be reconstructed, the computational burden is substantially reduced. Fig.2 is a graphic interface of the FIPS system. The image on the right-bottom corner illustrates an example of the OISS for the five-parameter FDG model.

B. *Knowledge-based Clustering Analysis (KCA)*

In general, a time activity curve (TAC) can be obtained from each pixel in dynamic PET image. However, many TACs may have similar kinetics. Based on domain specific physiological kinetic knowledge related to dynamic PET images and physiological tracer kinetic modeling, a physiological knowledge-based clustering analysis algorithm (KCA) has been developed [4] to classify image-wide TACs, $C_i(t)$ (where i=1,2,…,R, and R is the total number of image pixels), into S cluster groups C_j (where j=1,2,…,S, and S<<R) by measurement of the magnitude of natural association (similarity characteristics). Each pixel TAC is classified as belonging to one of the cluster groups. An index table indexed by cluster group contains the mean TAC for each cluster group. This KCA module can be used as a processing tool to extract physiological information from dynamic image data.

C. *Dynamic Image Data Compression*

We have recently proposed a three-stage technique for dynamic image data compression [4]. Firstly, we apply the optimal image sampling schedule (OISS) design to reduce the number of temporal frames. In order to obtain more accurate and precise results from clinical dynamic PET data, the OISS with five-parameter FDG model (OISS-5) was used to correct for the cerebral blood volume (CBV) and partial volume (PV) effects [9]. Secondly, the physiological knowledge-based clustering analysis algorithm can be used to further compress the reduced set of temporal PET image frames into a single indexed image. In this stage, noisy background pixels were removed prior to cluster analysis to improve reliability. Finally, we compress and store the indexed image using the portable network graphics (PNG) format. Details of this three-stage compression technique can be found in [4]. This compression algorithm can reduce image storage space by more than 95% without sacrificing image quality. It could benefit to the current expansion in medical imaging, and image data management.

D. *Fast Algorithms for Generation of Parametric Images*

With the recent development of high spatial and temporal resolution PET, a number of parametric imaging algorithms have been developed [6], but most of which involve certain strong assumptions or require considerable computational time. The generalized linear least squares (GLLS) algorithm has been shown to offer some advantages over other methods for parameter estimation in non-uniformly sampled biomedical systems [7]. We found that, compared with existing algorithms [6], the GLLS algorithm: (1) can directly estimate continuous model parameters; (2) does not require initial parameter values; (3) is generally applicable to a variety of models with different structures; (4) can estimate individual model parameters as well as physiological parameters; (5) requires very little computing time; and (6) can produce unbiased estimates [7]. Details of the GLLS algorithm can be found in [7]. The GLLS algorithm has been integrated into the FIPS system, as part of the fast-parametric-image-algorithm module. We also integrate the famous Patlak graphical approach (PGA) [5] and linear least squares (LLS) algorithm [6] etc. into the FIPS system. In the left-bottom side of Fig.2, we can see the parametric image of the local cerebral metabolic rates of glucose (LCMRGlc) generated by using the GLLS algorithm.

III. Conclusions

Based on some of our systematic studies on biomedical functional image data processing and modeling, we developed a functional image processing system (FIPS), which integrates several special modules for brain PET dynamic studies, such as the optimal PET image sampling schedule (OISS) design, the knowledge-based clustering analysis (KCA), the generalized linear least squares (GLLS) fast algorithm, the three-stage algorithm for dynamic image data compression and some image statistical analysis functions etc. In addition, the development of some special modules, including physiological knowledge-based image smoothing, image segmentation, extracting PTAC from dynamic PET, and data visualization etc., is actively conducted in our group. The FIPS is expected to be very useful in brain PET functional imaging data acquisition, analysis, compression, modeling, and simulation.

Acknowledgments

This research is supported by the RGC and ARC Grants. The authors are grateful to the National PET /Cyclotron Center, Taipei Veterans General Hospital Taiwan for their kind assistance.

References

[1] D. Feng, D. Ho, H. Iida, and K. Chen, "Techniques for functional imaging," invited chapter, in: C.T. Leondes ed., *Medical Imaging Systems Techniques and Applications: General Anatomy*, Amsterdam: Gordon and Breach Science Publishers, pp.85-145, 1997.

[2] X. Li, D. Feng, and K. Chen, "Optimal image sampling schedule: A new effective way to reduce dynamic image storage space and functional image processing time," *IEEE Trans. Med. Imag.,* vol. 15, pp. 710-719, 1996.

[3] K. Ho-Shon, D. Feng, R. A. Hawkins, S. Meikle, M. Fulham, and X. Li, "Optimised sampling and parameter estimation for quantification in whole body PET," *IEEE Trans. Biomed. Eng.,* vol. 43, pp. 1021-1028, 1996.

[4] D. Ho, D. Feng, and K. Chen, "Dynamic image data compression in spatial and temporal domains: Theory and algorithm," *IEEE Trans. Info. Tech. Biomed.*, vol. 1, no.4, pp. 219-228, 1997.

[5] C. S. Patlak, R. G. Blasberg, and J. Fenstermacher, "Graphical evaluation of blood to brain transfer constants from multiple-time uptake data," *J. Cereb. Blood Flow Metab.*, vol. 3, pp. 1-7, 1983.

[6] D. Feng, D. Ho, K. Chen, L. C. Wu, J. K. Wang, R. S. Liu, and S. H. Yeh, "An evaluation of the algorithms for determining local cerebral metabolic rates of glucose using positron emission tomography dynamic data," *IEEE Trans. Med. Imag.*, vol. 14, pp. 697-710, 1995.

[7] D. Feng, S. C. Huang, Z. Wang, and D. Ho, “An unbiased parametric imaging algorithm for non-uniformly sampled biomedical system parameter estimation,” *IEEE Trans. Med. Imag.*, vol. 15, pp. 512-518, 1996.

[8] D. Feng, W. Cai and R. Fulton, “An optimal image sampling schedule design for cerebral blood volume and partial volume correction in neurologic FDG-PET studies”, The 29th Annual Scientific Meeting of A&NZ Society of Nuclear Medicine, April 4-8, 1998, Melbourne, Australia, *Australia and New Zealand Journal of Medicine*, vol.28, No.3, pp361, 1998.

[9] W. Cai, D. Feng, and R. Fulton, “Clinical investigation of a knowledge-based data compression algorithm for dynamic neurologic FDG-PET images,” *The 20th Annual International Conference of IEEE Engineering in Medicine & Biology Society*, Oct 29-Nov 1, 1998, Hong Kong, pp.1270 – 1273.

[10] D. Feng, D. Ho, K.K. Lau and W.C. Siu, “GLLS for optimally sampled continuous dynmaic system modeling: Theory and algorithm”, In: R. E. Carson, et al. ed., *Quantitative Functional Brain Imaging with Positron Emission Tomography*, San Diego: Academic Press, pp. 339-345, 1998.

Fig.1. The system structure of the functional image processing system (FIPS).

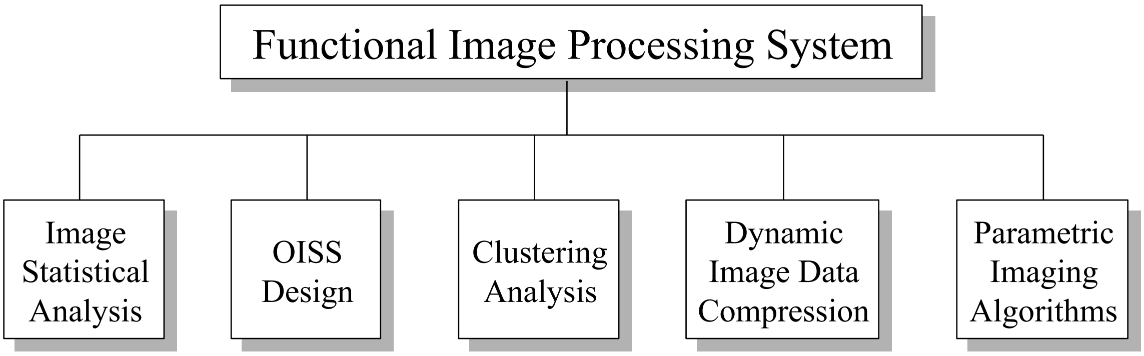

Fig.2.Illustration of an interface of the FIPS system. The image on the right-bottom corner shows an example of compressing 22 brain PET FDG image frames obtained from the traditional sampling schedule into 5 frames according to the OISS design. The image on the left-bottom side illustrates a parametric image of the local cerebral metabolic rates of glucose (LCMRGlc) generated using the build-in fast GLLS algorithm.