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Nuclear Instruments and Methods in Physics Research A 569 (2006) 425–428
NUCLEAR INSTRUMENTS & METHODS IN PHYSICS RESEARCH Section A
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Optimization of temporal basis functions in dynamic PET imaging

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Available online 15 September 2006

Abstract

In this paper we introduce and evaluate a completely data-driven method to optimize both the linear expansion coefficients and the used temporal basis functions in dynamic PET reconstruction from list-mode data.

We present the first results of our method using simulated 2D PET data. The time activity curves are modeled as a conic combination of B-splines. The B-splines are optimized with respect to their knot locations. We have combined the newly introduced method with our previously developed dynamic MLEM algorithm in order to further improve the likelihood. The results show that even one iteration of our newly developed algorithm can drastically increase the likelihood and the resulting images better represent the underlying TACs.
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PACS: 02.30.Zz; 87.58.Fg; 87.57.Gg

Keywords: Dynamic PET; B-splines; Maximum likelihood

1. Introduction

The goal of dynamic positron emission tomography (PET) imaging is to determine the spatio-temporal activity distribution in the patients body. For reconstruction purposes the activity density is parameterized as a linear combination of spatio-temporal basis functions. Commonly used basis functions are image elements (voxels/pixels) discretely changing over time. Such reconstructions, consisting of a series of static images, are referred to as being time binned.

In sinogram format the data is acquired as a time series of static sinograms and conventionally the different time frames are reconstructed independently. Modeling of the time activity curves (TACs) however has proven to be beneficial [1].

In list-mode format all detected coincidences are stored one by one in a list. Even when the data are acquired in list-mode format the data are commonly binned in a number of time frames and then reconstructed independently. However, time binning inevitably compromises the available temporal resolution of the list-mode data (typically 1 ms). Therefore, dynamic reconstruction algorithms that exploit the high temporal resolution of list-mode data have been of interest for years. Snyder [2] developed a list-mode Maximum Likelihood Expectation Maximization (MLEM) algorithm for rate functions described by convolution of the input function with a basis of exponential functions. More general basis functions are useful because they do not require any assumptions on the underlying physiological process. A MLEM algorithm for general basis functions was described in Ref. [3]. One important class of such general basis functions are the B-spline basis functions. B-spline basis functions have some interesting properties that can be exploited during reconstruction and therefore became popular in dynamic emission-computed tomography [4–6]. The rate functions are then linear combinations of the B-spline basis functions. The two most commonly used B-splines are the first order and the cubic or fourth order splines. First order B-splines are rectangular basis functions and the classical time-framed reconstruction approaches therefore use a first order B-spline basis. Reconstructions using cubic

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doi:10.1016/j.nima.2006.08.078

splines reduce the bias and variance of the reconstructed images as compared to time-framed reconstructions [5,7]. All the aforementioned approaches using general basis functions have in common that the reconstruction task is defined as finding the optimal linear expansion coefficients in the time activity model. Studies using temporal B-splines that also try to optimize the temporal basis functions in an adaptive way show an even further decrease of the bias and variance. The B-splines can effectively be optimized through their defining knot positions. Previously developed frameworks used ad hoc methods based on the head-curve [5] or on intermediate reconstructed TACs [7] to redistribute the knots.

In this paper a strategy to optimize the temporal basis functions during dynamic PET reconstruction is introduced. The algorithm tries to optimize both the linear expansion coefficients and the used basis functions in order to maximize the log-likelihood of the data. Our implementation uses B-splines as temporal basis functions which are optimized through their defining knot positions. The general framework however is applicable for other temporal bases as well.

2. Theory

2.1. General framework

The activity distribution is parametrized on spatio-temporal basis functions $I_s(\boldsymbol{r})\beta_{s,t}(\tau)$, with $I_s(\boldsymbol{r})$ the indicator function of the sth spatial basis function and $\beta_{s,t}(\tau)$ is the tth temporal basis function defined on the sth spatial basis function. The measured list-mode data are samples of an inhomogeneous Poisson process. At coincidence bin b of the PET camera we observe an inhomogeneous Poisson process with rate density given by

$$\bar{y}_b(\tau) = \int_\Omega p_b(\boldsymbol{r})\lambda(\boldsymbol{r},\tau)\,\mathrm{d}\boldsymbol{r} = \sum_{s,t}^{S,T} p_{s,b} w_{s,t}\beta_{s,t}(\tau) \tag{1}$$

where $w_{s,t}$ are the linear expansion coefficients, $p_b(\boldsymbol{r})$ the sensitivity pattern of coincidence bin b. $p_{s,b} = \int_\Omega p_b(\boldsymbol{r})I_s(\boldsymbol{r})\,\mathrm{d}\boldsymbol{r}$ is the probability that an emission from the sth spatial segment is detected at bin b. The detections at the different coincidence bins are assumed independent and the log-likelihood of the measured data becomes

$$L(\boldsymbol{\lambda}(\boldsymbol{w},\boldsymbol{\beta})) = -\sum_s P_s \int_{\tau_i}^{\tau_f} \lambda_s(\tau)\,\mathrm{d}\tau + \sum_{\text{events}} \log \bar{y}_{b_e}(\tau_e) \tag{2}$$

where we have dropped the constant terms, τ_i and τ_f denote the start and end times of the acquisition. and $P_s = \sum_b p_{s,b}$ is the sensitivity of the detector for emissions from the sth-segment.

The reconstruction task now consists of finding the $(\boldsymbol{w},\boldsymbol{\beta})$ that maximizes the data log-likelihood i.e.

$$(\hat{\boldsymbol{w}},\hat{\boldsymbol{\beta}}) = \arg\max_{(\boldsymbol{w},\boldsymbol{\beta})} L(\boldsymbol{\lambda}(\boldsymbol{w},\boldsymbol{\beta})). \tag{3}$$

2.2. Classic dynamic reconstruction: MLEM_a

The classical dynamic reconstruction does not attempt to optimize the temporal basis functions but only estimates the linear expansion coefficients, i.e.

$$L(\boldsymbol{\lambda}(\boldsymbol{w},\boldsymbol{\beta})) \equiv L(\boldsymbol{\lambda}(\boldsymbol{w})). \tag{4}$$

The optimization problem in the linear expansion coefficients $w_{s,t}$ uses our previously developed dynamic MLEM iteration scheme [7]. The maximizer of the expectation has an analytical expression and we get the dynamic MLEM iteration scheme:

$$w_{s,t}^{\text{new}} = \frac{w_{s,t}^{\text{old}}}{S_{s,t}} \sum_{\text{events}} p_{s,b_e}\beta_{s,t}^n(\tau_e)\frac{1}{\bar{y}_{b_e}(\tau_e)} \tag{5}$$

with $S_{s,t} = P_s \int \beta_{s,t}^n(\tau)\,\mathrm{d}\tau$, the generalized dynamic sensitivity. This is the normal listmode MLEM for 4D reconstruction [1,7]. We will refer to it as an MLEM_a iteration step.

2.3. Dynamic reconstruction using adaptive basis functions: MLEM_b

As in the MLEM_a algorithm we can separate the optimization of Eq. (2) into a set of smaller dimensional optimization problems using the EM algorithm. Because we also want to optimize the basis functions, the log-likelihood of the expectation is only partially separable and there is no closed form expression for the optimizer of the S T-dimensional optimization problems. Several approaches for numerical optimization can be considered. The evaluation of the S objective functions and their derivatives with respect to its T variables is straight forward, however they require a projection and back projection of all data. Therefore, we stored time-binned approximations of the objective functions per EM iteration and the optimization within one EM iteration was performed using these approximative objective functions. This approximation reduces the computational cost considerably and makes the computational cost of one MLEM_b iteration comparable with one MLEM_a iteration.

2.4. Global scheme

The total reconstruction scheme is briefly outlined here. We start off with an initial image $(\boldsymbol{w}_0,\boldsymbol{\beta}_0)$ and start the EM iterations. Depending on the iteration number i we can decide if we only want to improve the linear expansion coefficients using the MLEM_a algorithm or if we also want to optimize the basis functions using the MLEM_b algorithm. We allow the combination of the two methods because the MLEM_b algorithm is only approximative, and thus the reconstruction should be concluded with a few MLEM_a iterations in order to reconstruct an image with the optimal linear expansion coefficients in combination with the respective approximative optimal basis functions. Moreover, MLEM_b could suffer from local extrema and instabilities which can be prevented by a good starting

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