LIST MODE RECONSTRUCTION FOR PET WITH MOTION COMPENSATION: A SIMULATION STUDY

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ABSTRACT

Motion artifacts can be a significant factor that limits the image quality in high-resolution PET. Surveillance systems have been developed to track the movements of the subject during a scan. Development of reconstruction algorithms that are able to compensate for the subject motion will increase the potential of PET. In this paper we present a list mode likelihood reconstruction algorithm with the ability of motion compensation. The subject motion is explicitly modeled in the likelihood function. The detections of each detector pair are modeled as a Poisson process with time-varying rate function. The proposed method has several advantages over the existing methods. It uses all detected events and does not introduce any interpolation error. Computer simulations show that the proposed method can compensate simulated subject movements and that the reconstructed images have no visible motion artifacts.

1. INTRODUCTION

Recent developments in PET detector technology have dramatically increased PET resolution, which results small movements of the subject can be a significant factor that limits the image quality. It has been demonstrated that head movement can significantly degrade the image resolution in human brain imaging. Motion is not a problem in *in vivo* animal imaging when it is performed in anesthetized animals; however, anesthesia can cause substantial alterations in physiology and metabolism. In particular, it is extremely difficult or impossible to assess brain function in animals that are in an artificial coma. Development of reconstruction algorithms with motion compensation will allow imaging of awake animals, which will make it possible to understand the brain changes that result in the behavioral phenotype of bioengineered animals.

The basic approach is to use a position monitoring system to track the subject movements and to compensate the motion in reconstruction algorithms. Several motion tracking systems have been studied for PET imaging. Daube-Witherspoon *et al.* [1] reported a radio frequency based measuring system. Other researchers [2, 3, 4, 5] have focused on optical systems such as Polaris (Northern Digital, Inc.; Waterloo, Canada). These systems are capable of measuring rigid body motion in six degrees of freedom.

Methods for correcting motion have also been developed. However, they primarily focused on correction of interframe movements. The detected events are first gated into different frames with the aid of some external signal, such as belly-belt for respiratory motion, ECG signal for cardiac motion, or signal from a position tracking system [6, 7]. Each frame is then reconstructed individually and summed together after proper transformation (rigid and/or nonrigid) according to the subject movement. There are several problems with the multiple acquisition frame approach. First, if the subject has too much movement (awake animals and uncooperative patients), it can result in many low-count frames. Second, if the object is partially outside the transaxial field of view (FOV) of the scanner in a frame, that frame can not be individually reconstructed. Third, interpolation error can be introduced when transforming each individually reconstructed image. In the case of respiratory gated and cardiac gated studies, reconstruction of each frame is necessary because the motion vectors have to be estimated from the reconstructed images. However, when the motion information is obtained from a position monitoring system (such as in brain imaging), reconstruction of individual frames is unnecessary.

An alternative approach proposed by Daube-Whiterspoon *et al.* [1] and Meikle *et al.* [8] is event-by-event rebinning, where each event is rebinned into a fixed sinogram (with respect to the subject coordinate system) by proper translation and/or rotation according the measured movement. This approach is attractive since it has the potential to be implemented in real time in hardware [9]. However, it has a normalization problem if the movements are not confined to in-plane translations and rotations. In addition, round-off error can be introduced in the rebinning procedure.

Another method proposed by Meikle *et al.* [8] is to post-

This work was supported by the Director, Office of Science, Office of Biological and Environmental Research, Medical Sciences Division, of the U.S. Department of Energy under contract no. DE-AC03-76SF00098, and by the National Institutes of Health under grant P01 HL25840.

process the motion blurred reconstruction using deconvolution. This method has not attracted much attention because the deconvolution unnecessarily amplifies the noise in PET data compared to other motion compensation techniques. Moreover, when the movements include significant rotation, spatially variant deconvolution filters have to be used, which not only increase the computational cost, but can also introduce other artifacts.

Here we propose a list mode likelihood reconstruction algorithm that can compensate for rigid motion. We assume the motion information is measured using an external tracking device. The method does not generate multiple frames, nor rebin the events, and hence eliminates interpolation errors. It also solves the normalization problem of the event-by-event rebinning method.

2. LIKELIHOOD FUNCTION OF LIST MODE DATA WITH MOTION

For static PET imaging with no motion, PET data are generally modeled as a collection of independent Poisson random variables. By treating the detections of each detector pair separately, we have derived the log-likelihood function for list mode data [10]:

$$L(\boldsymbol{x}) = \sum_{k=1}^{K} \log \sum_{j=1}^{N} p(i_k, j) x_j - \sum_{j=1}^{N} \varepsilon_j x_j,$$

where x_j is the mean activity inside the $j\text{th}$ voxel of the unknown image, $p(i,j)$ is the probability of detecting an event from the $j\text{th}$ voxel in the $i\text{th}$ detector pair, i_k is the index of the detector pair of the $k\text{th}$ detection, $\varepsilon_j \equiv \sum_i p(i,j)$, K is the total number of detections, and N is the total number of image voxels. Randoms and scatters can also be included in this model.

When the object is moving during the scan, the mean detection of each detector pair is changing over time, and so does the detection probability $p(i,j)$. Therefore, we model the detections of each detector pair as a Poisson process with time-varying rate function $\lambda_i^*(t)$

$$\lambda_i^*(t) = \sum_j p(i,j,t) x_j,$$

where $p(i,j,t)$ is the time-dependent detection probability. It can be factored into

$$p(i,j,t) = n_i a_i(t) g(i,j,t),$$

where n_i is the detecting efficiency of the ith detector pair, $a_i(t)$ is the attenuation factor of the ith detector pair at time t, and $g(i,j,t)$ is the geometric probability of detecting an event from the jth voxel at the ith detector pair at time t. Here we assume that the activity in the object is constant during the scan and that the time-dependency of the attenuation and the geometric probability is due to the movements of the object.

For a Poisson process with rate function $\lambda(t)$, with N events observed from time T_0 to T_1 and event arrival times $t_1, \ldots, t_k, \ldots, t_N$, the likelihood function is [11]

$$\begin{aligned} &\mathsf{P}(t_1, \ldots, t_k, \ldots, t_N | \lambda(t)) \\ &\quad = \left(\prod_{k=1}^{N} \lambda(t_k) \right) \exp \left\{ - \int_{T_0}^{T_1} \lambda(u) du \right\}. \end{aligned}$$

For $N = 0$, the product is defined as unity.

Combining the detections in all detector pairs and assuming that the detections between different detector pairs are independent, the log likelihood is therefore given by

$$\begin{aligned} L(\boldsymbol{x}) &= \sum_k \log \lambda_{i_k}^*(t_k) - \sum_i \int \lambda_i^*(u) du \\ &= \sum_k \log \sum_j n_{i_k} a_{i_k}(t_k) g(i_k, j, t_k) x_j \\ &\qquad - \sum_i \int \sum_j n_i a_i(u) g(i,j,u) x_j du \\ &= \sum_k \log \sum_j n_{i_k} a_{i_k}(t_k) g(i_k, j, t_k) x_j - \sum_j \varepsilon_j^* x_j \end{aligned}$$

where i_k is the index of the detector pair of the kth event, and $\varepsilon_j^* \equiv \sum_i n_i \int a_i(u) g(i,j,u) du$ is the sensitivity of the jth voxel. The major difference between ε_j^* and ε_j is the integral over time. Note that the summation is over all possible detector pairs, not just those have detections.

Once we compute ε_j^*, we can use the same algorithm that we have developed for regular list mode reconstruction [10] to find the maximum likelihood estimate. To control the noise in reconstructed images, we used the same quadratic prior function. Readers are referred to [10] for details of the algorithm.

There are several advantages of the proposed method over the existing methods. First, the proposed method can use all detected events, unlike the rebinning method where events that are not inside the original sinogram space have to be discarded. Second, the method works even if the object is *always* partially outside the FOV of the scanner, as long as $\varepsilon_j^* > 0$ for all voxels. In contrast, the multiple frame approach would fail if the object is partially outside the transaxial FOV. Third, no interpolation error is introduced.

3. COMPUTER SIMULATIONS AND RESULTS

We developed a Monte Carlo program to simulate the photon detection in a PET scanner with arbitrary subject movements. Each movement is defined in six degrees of freedom (three for translation and three for rotation). When an event is generated, the program first traces each photon until it exits the object. Then the photon's position and direction are transformed according to the corresponding object location and orientation, and the program continues the trace until it is detected by a detector or travels outside the scanner. A coincident event is recorded when both photons are detected. Here we did not simulate random and scatter events. The object self-attenuation was also ignored. These factors will be included in future studies. We modeled the detector crystal as LSO with an attenuation coefficient of 0.082 mm^{-1}.

We first simulated seven point sources in a warm cylinder. The objects (point sources and cylinder) underwent a continuous rotation around the x-axis in the transaxial direction. The rotation was modeled by seven equally spaced discrete positions (Fig. 1). The PET system simulated was a Concorde microPET rodent system (Concorde, Knoxville, TN). The diameter and length of the cylinder are both 50mm. The total number of events detected during the whole scan was about 1 million.

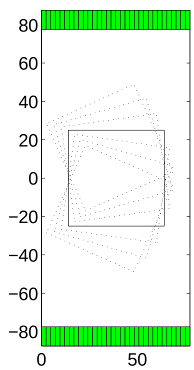
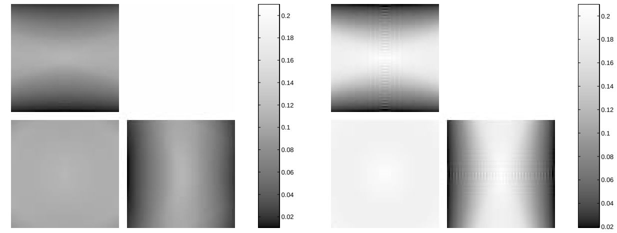


Fig. 1. The side view of the seven positions of the cylinder in the PET. The axis of rotation is the x-axis (out from the paper). The angles are -24°, -16°, -8°, 0°, 8°, 16°, 24°. The seven point sources are located inside the cylinder with one at the center and six near the boundary. The scales are in mm.



(a) (b)

Fig. 2. The efficiency images: (a) the efficiency images of the cylinder scan with rotation; (b) the efficiency images of a static (no motion) scan. The voxels are 1mm cubic voxels. In each group, the images are the top view slice (top), the front view slice (lower left), and the side view slice (lower right) through the center of the image volume. All the images are in the same color scale.

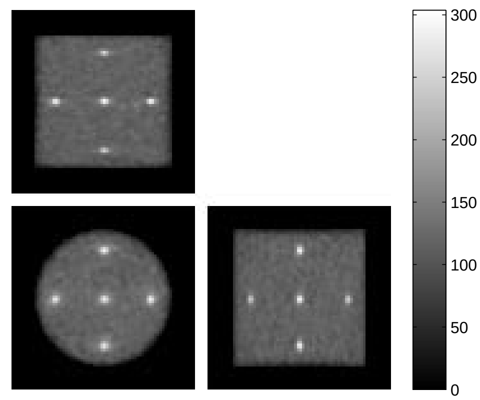


Fig. 3. The reconstructed image of the seven point sources inside a warm cylinder. The images are the top view slice (top), the front view slice (lower left), and the side view slice (lower right) through the center of the image volume. All the images are in the same color scale.

Fig. 2 shows the detecting efficiency image ε_j^* for the scan with comparison to that of a static scan without motion. It shows that the rotation reduces the detection efficiency in the center of the image volume. Fig. 3 shows the reconstructed image using 1mm cubic voxels. The reconstruction volume was a cylindrical region that was 4mm larger than the source in all dimensions. The smoothing parameter was 0.01. All the point sources are well defined with no visible motion artifacts.

Second, we demonstrated the ability of the proposed method to reconstruct an object that is larger than the transaxial FOV of the scanner. We simulated a long cylinder (diameter = 18mm, length = 125mm) that was placed in the transaxial direction. The transaxial FOV of the scanner is 104mm. In order to scan the whole cylinder, it must be moved during the scan. We simulated the movement using two positions as shown in Fig. 4. The multiple frame approach cannot be used here because of the missing data in each frame.

In Fig. 5 we show the efficiency image of this simulated scan. The two ends along the x-axis of the image have less efficiencies because they had been partially outside the FOV. The reconstructed image is shown in Fig. 6. It shows no visible artifacts caused by the missing data, despite the fact that the object was always partially outside the FOV.

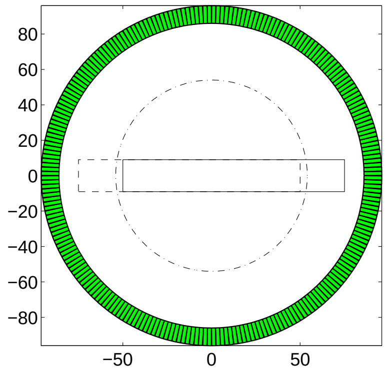


Fig. 4. The configuration of the long cylinder simulation. The dashed dotted circle indicates the FOV of the scanner. The solid box indicates the position of the cylinder during the first half of the scan, and the dashed line indicates the position in the second half of the scan.

Fig. 5. The center transaxial slice of the efficiency image of the long cylinder scan shown in Fig. 4.

4. DISCUSSION

We have proposed a list mode likelihood reconstruction method for PET with compensation of motion. The proposed method can incorporate all detected events in reconstruction and does not require interpolation. It works even if the object is partially outside the FOV as long as no portion of the object has zero detection sensitivity.

In this paper we have assumed the motion vectors are exact. Real motion tracking systems have finite resolution and noise, which can degrade the performance of the algorithm. We are currently studying these effects. Future work will also include more realistic modeling of the photon detection, such as randoms and scatters, and will extend the method to dynamic reconstruction.

Another direction in which we are working is to reduce the computational cost. While computation of $a_i(t)$ and $g(i,j,t)$ is the same as a regular (static) list mode reconstruction, computation of the efficiency ε_j can be time-consuming, and it is required for each scan because of the variation of the movements. In this paper we computed a backprojection for each object position. One possible method to reduce the computation cost is to rebin the normalization factors before backprojection. However, this will introduce rebinning errors in the efficiency image, and the effects of such errors need further study.

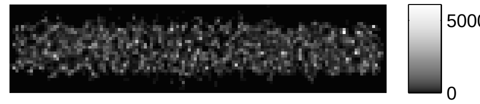


Fig. 6. The center transaxial slice of the reconstruction of the long cylinder.

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