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Crystal identification in positron emission tomography using nonrigid registration to a Fourier-based template

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Abstract

Modern Positron Emission Tomography (PET) detectors typically are made from 2D modular arrays of scintillation crystals. Their characteristic flood field response (or flood histogram) must be segmented in order to correctly determine the crystal of annihilation photon interaction in the system. Crystal identification information thus generated is also needed for accurate system modeling as well as for detailed detector characterization and performance studies. In this paper, we present a semi-automatic general purpose template-guided scheme for segmentation of flood histograms. We first generate a template image that exploits the spatial frequency information in the given flood histogram using Fourier-space analysis. This template image is a lower order approximation of the flood histogram, and can be segmented with horizontal and vertical lines drawn midway between adjacent peaks in the histogram. The template is then registered to the given flood histogram by a diffeomorphic polynomial-based warping scheme that is capable of iteratively minimizing intensity differences. The displacement field thus calculated is applied to the segmentation of the template resulting in a segmentation of the given flood histogram. We evaluate our segmentation scheme for a photomultiplier tube-based PET detector, a detector with readout by a position-sensitive avalanche photodiode (PSAPD) and a detector consisting of a stack of photomultiplier tubes and scintillator arrays. Further, we quantitatively compare the performance of the proposed method to that of a manual segmentation scheme using reconstructed images of a line source phantom. We also present an adaptive method for distortion reduction in flood histograms obtained for PET detectors that use PSAPDs.

Keywords

crystal identification; flood histogram; segmentation; PET; nonrigid registration; PSAPD; PSPMT

1. Introduction

Positron Emission Tomography (PET) cameras currently used for clinical as well as pre-clinical applications are frequently made up of 2D modular detector arrays of scintillation crystals (Humm et al. 2003, Phelps 2004). Incident annihilation photons interact in these scintillation crystals producing a proportionate number of optical photons that are routed

Both authors have contributed equally to this work

towards the front and back face of the crystals due to thin reflector sheets placed between adjacent crystals (Cherry et al. 2003). All crystals of the detector array can be read out simultaneously either by a single position-sensitive photodetector device or an array of discrete detector elements that are optically coupled to the rear end of the array (Muehllehner and Karp 2006).

When the detector array is irradiated with an annihilation photon flood source, the output electronic signals from the photodetectors can be used to create a two dimensional distribution of the horizontal (X) and vertical (Y) positions of the detected events. This probabilistic map, where each peak corresponds to a single crystal in the detector array, is called the *flood histogram*. For conventional block detectors that use a stack of four single-channel photomultiplier tubes (PMTs) or for those based on multi-channel position sensitive PMTs (PSPMTs) with multiplexed readout, the X and Y positions, typically, are computed using Anger's method (Anger 1964, Siegel et al. 1996). However, for detectors that use position sensitive avalanche photodiodes (PSAPD), a pincushion distortion results when Anger's equations are used (Shah et al. 2002, Olcott et al. 2005). A mathematical description of the charge sharing mechanism that leads to the pincushioning effect was given by Despres et al. (2007). This work proposed a correction method, but concluded that the recovery of corner and edge crystals was largely limited by the underlying physics. A new positioning algorithm for reducing the pincushion distortion was developed by Zhang et al. (2007). This method, while demonstrating desirable performance for certain PSAPD designs, overestimates the pincushioning effect in other cases and leads to *barrel* distortions. This phenomenon may be attributed to the different resistive readout schemes used in the manufacturing process of PSAPDs that tend to produce different orders of pincushioning in the flood histogram (Despres et al. 2007).

For detailed characterization of PET detectors in a scanner and consequently, for accurate system modeling and image reconstruction, parameters like energy resolution, timing resolution and light collection need to be measured for each crystal in the system. This is because individual crystals even in the same detector array can have different detection efficiencies, varying energy deposition characteristics, and diverse optical photon collection properties (Dahlbom and Hoffman 1988). In addition, there may be variations across detector blocks. For characterization measurements, a look-up table (LUT) that delineates events in one crystal from those in adjacent crystals is created. This is done by segmenting the flood histograms of each detector block into regions equal in number to the total number of crystals in that block, such that each region contains one peak. Events are assigned to the crystals based on their X and Y signals and the corresponding value in the LUT. This procedure facilitates performance analysis for individual crystals in detector arrays, and provides normalization data needed for system modeling. It is crucial that the LUT be reasonably accurate since imprecisions may affect scanner spatial resolution (Cutler and Hoffman 1994). Sensitivity may also be impaired since mispositioned events will be subject to incorrect detection energy windows.

Modern PET scanners typically have thousands of crystals (e.g. the microPET II small animal PET scanner has a total of 17,640 crystals, while the Siemens Biograph four-ring clinical PET scanner has 32,448 crystals). The most time consuming method for segmentation of flood histograms is to manually select the peaks by clicking at appropriate points on the computer screen and then use the binary file thus created (1 corresponding to pixels clicked and 0 otherwise) as an input to a standard segmentation method, e.g. the watershed method (Vincent and Soille 1991). A semi-automatic method where the manual process was replaced by background subtraction of the flood histogram followed by spatial filtering for noise removal and peak identification by intensity-based thresholding was developed by Mao (1999). This method, however, was not robust for identification of edge crystals due to the hard thresholding

condition and hence, considerable time was needed for manually correcting the segmentation. An approach using Gaussian mixture models (GMM) for segmenting flood histograms from multilayer GSO-based depth-of-interaction (DOI) capable detectors was proposed by Yoshida et al.(2004). Their approach performed well for complex flood histograms of individual blocks, but was impractical for the flood histogram of the whole detector because a large number of parameters for the GMM must be estimated. A method based on neural networks and self-organizing maps for the small animal YAP-(S)PET scanner (Del Guerra et al. 1998) was implemented by Lazerrini et al.(2004). A similar approach was taken by Hu et al. (2006) for the Inveon scanner. These methods were able to achieve high accuracy for their specific detector designs, but suffered from instability due to inconsistencies in training data. Segmentation methods directly based on absolute intensities of the individual spots in the original flood histogram are likely to fail. This is because individual crystals in the detector array may have dissimilar efficiencies and as a consequence, may produce spots of largely varying intensities in the flood histogram. Choosing an appropriate threshold needed for segmentation is then non-trivial.

In this paper, we present a general purpose scheme for segmenting flood histograms measured from PET detectors that use 2D detector arrays. We also propose an adaptive method for distortion correction of flood histograms obtained from PSAPDs that renders them suitable for segmentation using the proposed scheme. For the segmentation process, we start with an intensity correction step based on Fourier methods. Further, the Discrete Fourier Transform (DFT) of the corrected image is exploited to derive a template image that is a lower order spatial approximation of the flood histogram. In this process, knowledge about the total number of crystals in the array is incorporated. The template image is such that it lends itself to segmentation by horizontal and vertical lines between adjacent peaks. A scheme based on intensity matching is used to register the template to the flood histogram (in this case, the target). Diffeomorphism constraints are imposed on the warp leading to an invertible transformation. This invertibility of the mapping ensures that there is a one-to-one correspondence between the template and target, and hence, no ambiguity in assigning intensity values will be encountered. The segmentation derived from the template is then transformed into the target coordinates using the calculated warping function, resulting in the segmentation of the flood histogram. We also report on a tool for manual correction we have developed which allows the user to modify the underlying flood histogram for the sake of segmentation in aberrant cases, e.g. when a complete horizontal or vertical line is missing from the map.

This paper is organized as follows. We first present formulae for computing flood histograms for PET detectors using PSPMTs and PSAPDs that include an adaptive method for PSAPD-based detectors that leads to reduced spatial distortions. We then describe the generalized Fourier domain analysis used to obtain the template image from the detector flood histogram. Further, for registering the template to the target, we formulate the warping as a constrained optimization problem and present a method to solve it. We demonstrate the application of our segmentation scheme for a PSPMT-based detector module, a PSAPD-based detector evaluated for use in a high resolution PET scanner (Yang et al. 2006), and the PET component of the UC Davis dedicated breast PET/CT scanner that uses a (4×4) array of segmented LSO blocks and PSPMTs (Doshi et al. 2001, Wu et al. 2006). Photographs and a design drawing of the detector configurations are shown in Figure 1. These three examples were chosen to cover a wide range of proposed and existing PET camera designs. Further, for quantitative analysis of performance we show results from a spatial resolution study conducted using the UC Davis dedicated breast PET scanner and evaluate the performance of the proposed method against that from manual segmentation. Manual segmentation involves clicking once on each peak in the flood histograms of the two detector heads on a computer screen followed by a watershed method based segmentation.

2. Materials and methods

2.1. Formulae for the generation of flood histograms

Flood histograms for conventional block detectors that use four single-channel PMTs are generated using Anger's equations given in Table 1, column 1. For detectors with multi-channel PSPMTs, the modified Anger formulae are given in Table 1, column 2 (Siegel et al. 1996). In these formulae A , B , C and D are used to denote the four output signals and (X, Y) represents the 2D position of an event. The labels A , B , C and D are assigned in a clockwise manner starting at the top right hand corner.

For PSAPD-based detectors, the two existing formulae used to compute the flood histogram are indicated in Table 2, row 1. A , B , C and D again represent the four output signals in the same orientation as they were for the PMT-based detectors and (X, Y) again indicates the 2D position of an event. Use of the Anger equations produces the well-known pincushion distortion, while Zhang's method may lead to a barrel distortion. These two are opposing effects, and thus, a linear combination of the two schemes, as indicated in the second row of Table 2, is expected to yield outcomes with the least distortion. In these proposed adaptive formulae, we have allowed for α to take on a value between 0 and 1 since the pincushioning effect need not be an exact inverse of the barrel one. The special cases $\alpha = 0$ and $\alpha = 1$ correspond to the Zhang's method and Anger's method respectively.

2.2. Measurement of flood histograms for PET detectors

2.2.1. The single PSPMT-based detector block—The PSPMT used in the detector was from Hamamatsu Corporation, Bridgewater, NJ, USA (part #R7600-00-C12). The anode signals from the PSPMT were mapped to four position-encoding signals using a resistive network (Seidel et al. 1999). The PSPMT was coupled by optical grease (Bicron, Saint-Gobain Ceramics & Plastics Inc., Paris, France) to a 14×14 array of $(1.5 \times 1.5 \times 20)$ mm³ unpolished Lutetium Oxyorthosilicate (LSO) scintillation crystals (Agile Engineering, Knoxville, TN, USA). Electronic collimation was achieved using a setup previously reported (Yang et al. 2006) with a 1.67 MBq ²²Na point source with diameter 0.5 mm. The detector array was irradiated from one side along its longer axis at distances of 2 mm and 18 mm from the PSPMT for 5 min each, and data were measured in coincidence mode. This arrangement allowed for evaluating the robustness of our method to depth-dependent effects that are a well-known characteristic of flood histograms in PET detectors with single-ended readout (Yang et al. 2007). Singles mode data were also measured without collimation with the ²²Na source irradiating the array from one side at distance 5 cm. The flood histogram acquired in coincidence mode with electronic collimation at 2 mm from the PSPMT is used to demonstrate step-by-step the outcomes of the proposed segmentation method.

2.2.2. The PSAPD-based detector—The PSAPD used for this detector was manufactured at Radiation Monitoring Devices Inc. (RMD), Watertown, MA, USA and had an approximate active area of (14×14) mm² (Shah et al. 2002). The device had four anodes for the determination of position and energy and a single cathode for timing measurement. The total energy of a particular event was determined by summing the corresponding measurements from the four anodes. The array used in this case was a (9×9) stack of $(1.5 \times 1.5 \times 30)$ mm³ unpolished LSO crystals. The detector was cooled to 0°C and the flood histogram shown in this paper was measured by irradiating the array for a 5 min duration in coincidence mode with electronic collimation at 10 mm from the PSAPD employing the same setup used for the PSPMT-based detector. We also examined the performance of the proposed method for high resolution PET detectors that used (8×8) mm² PSAPDs coupled to a (7×7) array of $(0.9225 \times 0.9225 \times 20)$ mm³ unpolished LSO crystals (Yang et al. 2008). In this case, the detector was cooled to 0°C and data were measured in coincidence mode.

2.2.3. The PET component of the UC Davis dedicated breast PET/CT system—

The PET camera in this case consists of two flat-panel detector heads that rotate around the pendant breast in the prone PET/CT scanner geometry (Wu et al. 2006). Each of the heads consist of a (4×4) array of position-sensitive photomultiplier tubes (PSPMT) coupled individually via a lightguide to a (9×9) array of $(3 \times 3 \times 20)$ mm³ LSO crystals. This design provides an example of a stack of photodetectors and arrays that constitute a single detector head. The flood histogram in this case was measured for 10 min using LSO background.

2.3. Generating a template from the flood histogram

Due to crystal-to-crystal variability in the detector array, individual elements may not produce spots with similar intensities in the flood histogram. To account for this effect, we first need to automatically correct intensities over the whole image. The method proposed in Section 2.3.1 addresses this issue. The second step for the generation of the template is to use the horizontal and vertical patterns in the flood histogram effectively to achieve a reasonable approximation of the peak locations in it. A procedure developed for this is discussed in Section 2.3.2. For our discussion, let $\mathbf{T} \in \mathbb{R}^{M \times N}$ denote the flood histogram with M rows and N columns to be segmented and let K_x and K_y denote the number of crystals in the detector array in the X and Y directions respectively. For illustration of the intermediate steps, we use a flood histogram generated from the single PSPMT-based detector.

2.3.1. Intensity correction using the Fourier Transform—Using the Discrete Fourier Transform (DFT), we represent $\mathbf{T} = \mathbf{F}_M \mathbf{\Lambda} \mathbf{F}_N^T$, where $\mathbf{F}_M \in \mathbb{C}^{M \times M}$ and $\mathbf{F}_N \in \mathbb{C}^{N \times N}$ denote the Fourier matrices, and $\mathbf{\Lambda} \in \mathbb{C}^{M \times N}$ is the matrix of Fourier coefficients. We define a mask in the Fourier domain for low-pass filtering that retains only (7×7) lower order coefficients in $\mathbf{\Lambda}$ (Jain 1989). The dimensions of this low-pass filter mask were chosen empirically. We then compute the inverse DFT of this masked image and take its absolute value, $\mathbf{W}$, which is an overly smoothed version of $\mathbf{T}$ but represents regions of high and low intensity. The intensity corrected image $\mathbf{T}_I$ is obtained by performing a pixel-by-pixel division of $\mathbf{T}$ by $\mathbf{W}$. Figure 2 (a) shows the uncorrected flood histogram $\mathbf{T}$, and Figure 2(b) is $\mathbf{W}$, the low-pass filtered version of 2(a). After scaling $\mathbf{T}$ by $\mathbf{W}$, the resultant $\mathbf{T}_I$ is shown in Figure 2(c). High intensity values in the top portion of $\mathbf{T}$ are due to proximity to the radiation source. After correction, we observe an enhancement in the intensity of the spots, especially in the lower half of $\mathbf{T}_I$, as desired.

2.3.2. Obtaining the template—The flood histogram has dominant horizontal and vertical spatial components. Horizontal patterns in the image will correspond to vertical ones in the Fourier domain. Similarly, vertical bands in space would correspond to horizontal patterns in frequency domain. Starting with $\mathbf{T}_I$, we first obtain its DFT, denoted here by $\mathbf{\Lambda}_I$. We then create a mask in the frequency domain that has an intensity value of 1 along the lines with spatial frequency along X or $\lambda_x = 0$ and spatial frequency along Y or $\lambda_y = 0$, and 0 otherwise. Further, we perform a pixel-by-pixel multiplication of this mask with $\mathbf{\Lambda}_I$ followed by an inverse DFT of the resultant, which we called $\mathbf{T}_R$. The image $\mathbf{T}_R$, shown in Figure 3(a), indeed, highlights the vertical and horizontal grid lines of $\mathbf{T}$. We then obtain projections of $\mathbf{T}_R$ along the X and Y directions. From these one-dimensional projections, we use a scheme based on first and second derivative properties of the underlying functions for finding K_x and K_y peaks in the X and Y directions respectively. In this peak identification method, the inflection points for each projection are determined by finding zero-crossings of its first derivative, and then choosing those inflection points where its second derivative is negative. Once the peak locations are determined, a binary image with an intensity of 1 at the peak locations and 0 otherwise is created. The binary image is then smoothed by convolving it with a 2D spatial Gaussian filter whose standard deviation is set to be one third of the shortest distance between adjacent peaks in the X or Y directions. This smoothing procedure reduces the computational burden on the registration scheme we present in Section 2.4. The template image thus obtained (denoted by

S) is shown in Figure 3(b). A segmentation of **S** into 196 discrete regions generated from drawing horizontal and vertical lines midway between the peaks is shown in Figure 3(c). The pseudo-color denotes the region labels 1 to 196.

2.4. Intensity-based warping procedure

For registering image **S** to image **T**, we use an intensity-based warping scheme with polynomial bases. The objective of our registration scheme is to find a deformation field $\mathbf{u}(\mathbf{x})$ such that the root mean square (RMS) error between the target image $\mathbf{T}(\mathbf{x})$ and the deformed template image $\mathbf{S}(\mathbf{x} - \mathbf{u}(\mathbf{x}))$ is minimized. We found that the spatial deformation in **T** from **S** can be modeled accurately by polynomial warps of fifth or lesser order. The RMS cost functional in our case is given by

$$\mathbf{C}(\mathbf{u}(\mathbf{x})) = \|\mathbf{S}(\mathbf{x} - \mathbf{u}(\mathbf{x})) - \mathbf{T}(\mathbf{x})\|^2, \quad (1)$$

where $\mathbf{x} = [x_1, x_2]$ and $\mathbf{u}(\mathbf{x}) = [u_1(x_1, x_2), u_2(x_1, x_2)]$ are 2D vector valued variables and functions, and x_1 and x_2 , and u_1 and u_2 are the coordinate components of $\mathbf{x}$ and $\mathbf{u}$ respectively. By writing the deformation fields in terms of polynomials, we get

$$u_1(x_1, x_2) = \sum_{r=0}^n \sum_{q=0}^r a_q^r x_1^{r-q} x_2^q, \quad (2)$$

$$u_2(x_1, x_2) = \sum_{r=0}^n \sum_{q=0}^r b_q^r x_1^{r-q} x_2^q, \quad (3)$$

where n is the rank of the polynomial bases and a_q^r and b_q^r are coefficients of the polynomial bases. In order to minimize $\mathbf{C}(\mathbf{u}(\mathbf{x}))$ in (1) as a function of the polynomial coefficients, we use the conjugate gradient algorithm with the Armijo line search (Luenberger 1984, Armijo 1966). The gradient of the cost function $\mathbf{C}$ with respect to the coefficients a_q^r was computed as follows:

$$\frac{\partial \mathbf{C}}{\partial a_q^r} = \frac{\partial}{\partial a_q^r} \int (\mathbf{S}(\mathbf{x} - \mathbf{u}(\mathbf{x})) - \mathbf{T}(\mathbf{x}))^2 d\mathbf{x}, \quad (4)$$

$$= \int 2(\mathbf{S}(\mathbf{x} - \mathbf{u}(\mathbf{x})) - \mathbf{T}(\mathbf{x})) \frac{\partial \mathbf{S}(\mathbf{x} - \mathbf{u}(\mathbf{x}))}{\partial (x_1 - u_1(\mathbf{x}))} (-1) x_1^{k-r} x_2^r d\mathbf{x}. \quad (5)$$

Here $\frac{\partial \mathbf{S}(\mathbf{x} - \mathbf{u}(\mathbf{x}))}{\partial (x_1 - u_1(\mathbf{x}))}$ is $\nabla_{x_1} \mathbf{S}$ interpolated at $\mathbf{x} - \mathbf{u}(\mathbf{x})$. The derivative of the cost function with respect to the coefficients b_q^r is computed in a similar manner. Since the order of polynomial used is very low, the resulting displacement is sufficiently smooth and regularizers such as linear elastic energy are not required in practice. To test the invertibility of the deformation field, we compute the Jacobian of the resulting mapping $\mathbf{x} \mapsto \mathbf{x} - \mathbf{u}(\mathbf{x})$ and make sure that it is positive definite at every step (Jost 2002). If this is not the case, a lower order polynomial basis is chosen to approximate the transform. The resulting displacement thus calculated is then applied to the segmentation of **S** to get the segmented version for **T**. The segmentation results along with examples for the PSPMT-based detector are shown in Section 3.1.

2.5. Tool for manual correction

There are unusual cases where human involvement may be required in the segmentation process. An example is when a whole vertical or horizontal line of peaks, or both, are missing from the flood histogram. For these cases, we have developed a tool for manual correction to assist in the segmentation process. Using a graphical user interface (GUI), we allow users to click points where they expected to see peaks in a given flood histogram. The X and Y information of the clicked points is used to create a pseudo-target for registration, in which the points manually chosen are superimposed onto the original flood histogram after 2D Gaussian smoothing. All steps outlined to generate the segmentation are then repeated with the target replaced by the pseudo-target. The GUI was implemented in MATLAB and the *ginput* command is used for reading the locations of the manually clicked points. The complete procedure for segmentation is shown in Figure 4.

2.6. Resolution phantom study

A ‘hot’ rod (inner diameter = 0.3 mm, length = 7 cm) filled with ^{18}F FDG was placed in a ‘warm’ cylinder (diameter = 4.4 cm, length = 6 cm). The concentration ratio between the rod and the background was maintained at 400:1. This phantom was imaged using the UC Davis dedicated breast PET scanner. Flood histograms obtained from each of the two rotating heads of the scanner were first segmented by an unbiased volunteer who was ‘blind’ to the outcomes of the automatic method. The manual segmentation scheme involved clicking once on each of the $2 \times 1296 = 2592$ spots corresponding to the flood histograms of the two heads on a computer screen. After this procedure, a binary file based on the clicked locations was created and the watershed method was used for segmentation. The same flood histograms were segmented automatically using the proposed method. No manual correction was needed. Data were reconstructed using single-slice rebinning (Daube-Witherspoon and Muehllehner 1987), followed by 2D filtered backprojection.

3. Results

3.1. Segmentation of the PSPMT-based detector

The measured flood histogram shown in Figure 2(a) was used to obtain the template in Figure 3(b). The algorithm was implemented in MATLAB® (The MathWorks, Inc., MI, USA). The total time required for generating the template for this case on a Intel Xeon, 2.33 GHz computer was 0.2 sec. The template was then registered to the target in Figure 2(c) using fifth-order polynomial warping. Outcomes of the warping process are shown in Figure 5. The estimated transform was used to generate the modified target shown in Figure 5(a). Figure 5(b) shows the overlay of the estimated segmentation boundaries on flood histogram under consideration. We repeated the segmentation process for another flood histogram obtained when the source was collimated at a depth of 18 mm from the PSPMT. Our results in this case are shown in Figure 5(c). The flood histogram obtained from a singles mode measurement was also segmented and our results are shown in Figure 5(d). The procedure for segmentation for Figures 5(c) and (d) was the same as that for Figure 5(b), and hence, intermediate results are not shown. The computation time for obtaining the final segmentation in each case was around 47 sec for the (256×256) images. The proposed method indeed was able to segment all 196 crystals with reasonable accuracy in each of the three cases.

3.2. Segmentation for the PSAPD-based PET detector

3.2.1. Preprocessing for distortion correction for PSAPD flood histograms—

Flood histogram data were measured using the setup outlined in Section 2.2.2. The formulae shown in Section 2.1 were used for generating the flood histograms shown in Figure 6. The four corner crystals have fewer events than other crystals. This can be attributed partly to their

coupling efficiencies with the PSAPD as they only partially overlap with the active area of the PSAPD, and partly to low intercrystal scatter since they have only two neighbors. Figure 6(a) and 6(b) show the pincushion distortion encountered when using Anger's equations and the barrel distortions resulting from using Zhang's formulae respectively. The results from the proposed adaptive method with $\alpha = 0.7$ are shown in Figure 6(c). The adaptive scheme, indeed, does produce a histogram with a reduction in spatial distortions compared to Anger's and Zhang's methods and is suitable for use with the proposed segmentation scheme.

3.2.2. Segmentation results—We repeated the segmentation procedure using Figure 6(c) as our target. The target flood histogram was first intensity-corrected. A template generated by our method was then registered to Figure 6(c). The segmentation obtained is shown in Figure 7(a). We observed that there was no ambiguity in the mapping because of the missing or low-efficiency crystals. The total computation time in this case for the (256×256) image was 20 sec. All 81 crystals were accurately segmented as determined from visual inspection.

3.2.3. Segmentation of the flood histograms generated using Anger's or Zhang's method—Once the distortion corrected flood histogram is segmented as outlined above, labels for all events (every (X_c, Y_c)) in the flood histogram were looked up. These labels were then transferred to the coordinate systems of the flood histograms obtained using Anger's scheme or Zhang's method by using the corresponding (X_a, Y_a) and (X_b, Y_b) values respectively. There were pixels in the resultant images where labels were undefined. These were pixels where no events were registered. We estimated the labels at these pixels using median filtering with a (3×3) neighbourhood (Huang et al. 1979) followed by nearest neighbour interpolation to generate the corresponding segmentation. Our results are indicated in Figures 7(b) and (c), where we show the estimated segmentation boundaries overlaid on the flood histograms of Figures 6(a) and (b). In each case, all 81 crystals were segmented accurately as determined by visual inspection.

3.2.4. Segmentation of detectors that use (8×8) mm² PSAPDs—We applied the proposed distortion correction and segmentation scheme to data measured from these detectors. Analogous to our results from the (14×14) mm² PSAPDs, our adaptive formulae - in this case, with $\alpha = 0.65$ - produced flood histograms with reduced distortions. All 49 crystals could automatically be segmented using the proposed method (results not shown).

3.3. Segmentation of the flood histogram from the PET component of the dedicated breast PET/CT

For the segmentation of the flood histogram in this case, we required an additional pre-processing step to segment the 16 individual flood histograms from the assemblage, following which, each segment was processed separately.

3.3.1. Intensity correction and pre-processing—We started with the intensity correction step for the flood histogram of the whole detector block (shown in Figure 8(a)). The low-pass filtered image generated for this procedure is shown in Figure 8(b). We segmented this image into 16 regions using projections along X and Y and our peak-identification method. Figure 8(c) shows the corrected flood histogram with segmented region boundaries. Each region was treated as a separate flood histogram for further analysis.

3.3.2. Segmentation of individual histograms and merger—All 16 flood histograms were processed and a segmentation for each was generated. Since the warping was diffeomorphic, there was no ambiguity for allotment of segmented regions and for the merger of individual segmentations generated. Figure 9(a) shows our results. These were generated in 124 sec. Figures 9(b) and 9(c) show commonly encountered problems in PET camera designs.

A few peaks are missing from the histogram owing to improper coupling or are merged and hence, inseparable. Because we have enforced the requirement that segmented regions must equal the number of crystals in the arrays, the proposed method not only isolates regions where the missing crystals might be present but also distributes the merged peaks based on the horizontal or vertical information from other peaks in the histogram.

3.4. Tool for manual correction in unusual cases

In this subsection, we show an example of a flood histogram that had a missing horizontal line of peaks. This histogram was obtained for one of the detectors from the UC Davis dedicated breast PET system where the coupling was suboptimal. Data are present in the histogram corresponding to the decoupled area, except with lower counts. Figure 10(a) shows the map. The manual tool was used to estimate the missing crystal positions and an overlay of the flood histogram with peaks corresponding to the line of occluded crystals is shown in Figure 10(b). This, now, was our pseudo-target. The boundaries of the resultant segmentation overlaid on the flood histogram are shown in Figure 10(c). The segmentation generated is able to classify all 81 peaks in the flood histogram.

3.5. Resolution phantom study

Figure 11 shows the reconstructed images and the corresponding radial and tangential profiles obtained from the line-source in warm background experiment. The measured average resolutions are indicated in Table 3. These values were obtained by averaging the radial or tangential resolutions over 30 horizontal slices with spacing 1.8 mm through the reconstructed images. No significant variation in spatial resolution as a function of axial position was seen for either method, indicating that the spatial distortion caused by the geometrical approximation introduced by single-slice rebinning was not a major contributor to the reconstructed spatial resolution (Sossi et al. 1994). The manual segmentation procedure lasted 1 hour and 28 min. The same flood histograms were segmented automatically using the proposed method in 4 min and 10 sec. No statistically significant difference in the reconstructed radial and tangential resolutions obtained from the two segmentation schemes was seen. Thus, no degradation in spatial resolution is caused by the proposed method.

4. Discussion

Crystal identification for PET scanners is necessary for detailed system characterization and quantitative studies, but this process can be both time consuming and tedious. A generic solution to the crystal identification problem is proposed in this paper using a template-guided segmentation scheme. This scheme is especially efficient because the dependence of crystal identification accuracy on absolute intensities of spots in the flood histogram is substantially reduced. Our segmentation approach can broadly be divided into two processes, (I) the generation of a Fourier-based template image, and (II) the registration of the template to the flood histogram to be segmented. With a good initial template, the burden on the registration process was reduced with lower order polynomial bases modeling the underlying spatial variations. Bending energy or elastic energy constraints can potentially be incorporated into our method, if warranted. However, in our experience, this is not required. We acknowledge that our choice of a diffeomorphic warping scheme for removing ambiguity in the warped space may be considered a matter of convenience and not a necessity. Other methods for registration can easily be employed with our template. In imaging scenarios where relatively small changes occur in detector flood histograms over time, the template image can be stored and reused while only the registration step needs to be repeated.

The template image in this paper was segmented using horizontal and vertical lines drawn between adjacent peaks. However, an alternative approach of defining ‘islands’ around the

spots in the histogram may be followed (Dahlbom and Hoffman 1988), if desirable. In this case, we would generate our initial segmentation by defining circles around the spots in the template and then transform this segmentation to the target coordinate system using the calculated warping field. However, while a one-to-one mapping is guaranteed by our proposed method, the topology may not be preserved, or in other words, circles need not be circles when transformed. In this case, one may still be able to track points from the template to the target and produce a circle around a spot whose radius is a mean of the distances of the points that were on the circle and the warped peak location. However, this process will need rigorous evaluation.

A manual tool that allows the user to create a modified pseudo-flood histogram by clicking on position estimates of the missing crystals is proposed. The tool also provides the user flexibility in aberrant cases where undesirable segmentation is generated by the automatic method. For commercial scanners, such detectors are likely to be replaced. These failed detectors may be identified by examining if our peak-finding procedure is able to clearly delineate all crystals.

A composite method for PSAPDs that leads to significant reduction in spatial distortion was presented. For a specific application using PSAPDs, α may be varied over the $[0, 1]$ range and an optimal value may be determined for that application. The adaptability of the α parameter is expected to allow for compensating effects arising from the manufacturing variability and performance differences for individual PSAPDs. An example of this is described in Section 3.2, where the adaptive formulae were used for both a (14×14) mm² PSAPD and a (8×8) mm² PSAPD. These two devices have different resistance values between the back contacts due to their different sizes (Shah et al. 2002). Furthermore, the junction capacitance changes with PSAPD size (Karplus et al. 2006). In spite of this design variability, the adaptive formulae with different α values in the two cases yielded flood histograms that could be segmented automatically by the proposed method. We also expect better uniformity for photon counts in individual crystals of the detector array when using the proposed method compared to Anger's method due to reduced distortions (Zhang et al. 2007).

Our segmentation results for PSPMT-based detectors indicate that the proposed algorithm was able to segment the 196 regions automatically and fairly accurately as determined by visual inspection. Crystal identification at the two depths in coincidence mode and singles mode also indicates that the proposed method would not only be useful for detectors with single-ended readouts, but also for detectors with dual-ended readouts capable of measuring DOI where the PSPMT alone performs the task of X-Y crystal identification (Chaudhari et al. 2008). The computation time in MATLAB for this case with severe nonlinearities was 47 sec. In the future, we plan to implement our method in C and expect to achieve a segmentation result in less than 10 sec. For PSAPD-based detectors, we have developed a procedure not only for generating a segmentation of the distortion corrected flood histogram, but also for segmenting flood histograms generated using either Anger's or Zhang's equations. This extension will especially be useful for existing PET scanners based on PSAPDs which have already implemented Anger's or Zhang's method as a part of their data processing software. For the dedicated breast PET/CT detectors, results of the proposed method by visual inspection were accurate. Thus, our segmentation scheme was suitable for various configurations of PET detectors.

For quantitative analysis, a spatial resolution study was performed. The performance of the proposed method was evaluated against manual segmentation, which in this case, may be considered as a gold standard. We did not expect the proposed method to yield higher spatial resolution than manual segmentation, rather that it would be no worse. Our findings confirm that this indeed is the case. The major advantage of using the proposed method is in speed and in the required human effort. The proposed scheme produced a segmentation fully automatically and is more than 20 times faster than the manual segmentation method for our

dedicated scanner that consisted of a total of 2592 crystals. This time saving will potentially be huge when tens of thousands of crystals need to be segmented in modern PET scanners. Thus, the proposed segmentation scheme provides an efficient and accurate method for routine PET scanner characterization studies and for quality control.

5. Conclusions

The semi-automatic segmentation scheme presented here produced accurate delineation of crystals from flood histograms obtained from PMT-based and PSAPD-based PET detectors, including those with stacked detector geometries. While providing manual control necessary for exceptional cases, our scheme attempted to keep human involvement to the bare minimum. The adaptive method proposed in this paper for the generation of PSAPD flood histograms resulted in reduced spatial distortions and was found to be beneficial for crystal identification. We conclude that the proposed segmentation method can easily be applied to a wide variety of PET cameras designs and potentially should facilitate accurate and accelerated system characterization.

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Figure 1. PET detectors used for demonstration of the proposed method; (a) PSPMT-based detector with a single-ended readout, (b) PSAPD-based detector with a single-ended readout, and (c) a design drawing a single head of the UC Davis dedicated breast PET camera and a single PET detector from the (4×4) array (adapted from (Doshi et al. 2000)).

Figure 2. Fourier-based intensity correction; (a) the uncorrected flood histogram $\mathbf{T}$ for the PSPMT-based detector, (b) a low-pass filtered version $\mathbf{W}$ of (a), (c) the intensity corrected flood histogram $\mathbf{T}_I$

Figure 3.

Fourier-based template generation; (a) a filtered version of Figure 2(c) keeping coefficients only along the $\lambda_x = 0$ and $\lambda_y = 0$ lines in frequency domain, (b) the estimated template image, (c) a segmentation of (b) into 196 non-overlapping regions. The black lines denote region boundaries.

Figure 4.
A flowchart of the flood histogram segmentation process

Figure 5.

Segmentation results for the 14×14 array; (a) the warped template, (b) an overlay of the segmentation boundaries on the flood histogram for source depth = 2 mm from the PSPMT using the calculated warping transform, (c) estimated segmentation boundaries for the flood histogram generated for a source depth of 18 mm overlaid on the underlying map, (d) segmentation boundaries for a flood histogram in singles mode

Figure 6. Flood histograms obtained for a (9×9) array of $(1.5 \times 1.5 \times 20)$ mm³ unpolished LSO crystals; (a) using Anger's equations, (b) using Zhang's method, and (c) using the proposed adaptive approach with $\alpha = 0.7$

Figure 7.

Segmentation of the PSAPD flood histograms; (a) an overlay of the segmentation boundaries on the distortion corrected flood histogram, (b) estimated segmentation region boundaries overlaid on the flood histogram obtained from Anger's equations (Figure 6(a)) after transferring labels, (c) estimated segmentation region boundaries overlaid on the flood histogram obtained from Zhang's method (Figure 6(b)).

Figure 8.

Intensity correction and segmentation of the flood histogram from the dedicated breast PET/CT scanner; (a) the uncorrected histogram, (b) the low-pass filtered image used for intensity correction and segmentation, (c) intensity-corrected histogram showing the boundaries of segmented regions.

Figure 9. Segmentation of the dedicated breast PET detector; (a) the segmentation generated, (b) magnified flood histogram with a missing peak with overlaid segmentation, (c) magnified flood histogram with merged peaks with overlaid segmentation.

Figure 10. Target modification using manual correction; (a) the flood histogram obtained from a (9×9) array, (b) the pseudo-target obtained by manual correction, (c) region boundaries after segmentation of (a).

Figure 11.

Results from the phantom study; (a) a horizontal section from phantom images reconstructed using manual segmentation, (b) the same horizontal section reconstructed using the automatic segmentation method, (c) radial profiles through a single slice in the reconstructed image, (d) tangential profiles through a single slice of the reconstructed images.

Table 1

Formulae used for event positioning for PMTs.

Conventional block detectors	Multichannel PSPMTs
$X_1 = \frac{(A+B)-(C+D)}{A+B+C+D}$	$X_2 = \frac{A}{A+B}$
$Y_1 = \frac{(A+D)-(B+C)}{A+B+C+D}$	$Y_2 = \frac{C}{C+D}$

Table 2

Formulae used for event positioning for PSAPDs.

Anger's equations	Zhang's method
$X_a = \frac{(A+B)-(C+D)}{A+B+C+D}$	$X_b = \frac{A-C}{A+C} \cos(\pi/4) + \frac{B-D}{B+D} \sin(\pi/4)$
$Y_a = \frac{(A+D)-(B+C)}{A+B+C+D}$	$Y_b = \frac{A-C}{A+C} \sin(\pi/4) - \frac{B-D}{B+D} \cos(\pi/4)$
Adaptive method: $X_c = \alpha X_a + (1 - \alpha)X_b$, where $\alpha \in [0,1]$, $Y_c = \alpha Y_a + (1 - \alpha)Y_b$.	

Table 3

Average spatial resolution obtained from manual segmentation and the proposed method. The numbers in the brackets are standard deviations over the 30 horizontal slices.

Method	Radial (mm)	Tangential (mm)
Manual	4.32(0.32)	4.25(0.27)
Proposed	4.27(0.30)	4.13(0.17)