Crystal Identification in Dual-Layer-Offset DOI-PET Detectors Using Stratified Peak Tracking Based on SVD and Mean-Shift Algorithm

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Abstract—An Anger-logic based pixelated PET detector block requires a crystal position map (CPM) to assign the position of each detected event to a most probable crystal index. Accurate assignments are crucial to PET imaging performance. In this paper, we present a novel automatic approach to generate the CPMs for dual-layer offset (DLO) PET detectors using a stratified peak tracking method. In which, the top and bottom layers are distinguished by their intensity difference and the peaks of the top and bottom layers are tracked based on a singular value decomposition (SVD) and mean-shift algorithm in succession. The CPM is created by classifying each pixel to its nearest peak and assigning the pixel with the crystal index of that peak. A Matlab-based graphical user interface program was developed including the automatic algorithm and a manual interaction procedure. The algorithm was tested for three DLO PET detector blocks. Results show that the proposed method exhibits good performance as well as robustness for all the three blocks. Compared to the existing methods, our approach can directly distinguish the layer and crystal indices using the information of intensity and offset grid pattern.

Index Terms—Crystal position map, DOI-PET detector, mean-shift, peak tracking, singular value decomposition (SVD).

I. INTRODUCTION

SILICON photomultipliers (SiPMs) have many advantages, including magnetic-field insensitivity, compact size, high gain, high quantum efficiency, low working voltage and good timing performance [1], [2]. They are promising sensors for positron emission tomography (PET) systems. Our group is developing a SiPM based brain-PET system which is planned to be inserted into a 3T clinical magnetic resonance imaging (MRI) system. The brain-PET insert scanner should be obliquely incident gamma-rays which increases the parallax error. Therefore, the depth-of-interaction (DOI) encoding ability of the detectors is critical for high performance imaging. DOI information can be obtained by multiple ways such as light sharing technique [3], dual-end readout [4] and pulse shape discrimination [5], [6], etc. In our project, we have developed DOI detector blocks using dual-layer offset (DLO) design, which is a kind of light sharing technique [7]. The DLO design has better sampling density than the conventional design and would achieve better image performance for a whole system [8].

One traditional way for PET detectors to decode the positions is using the Anger-logic. Each event has a coordinate \((x, y)\) which is a pseudo-position of the gamma interaction [9]. A crystal position map (CPM) also called look up table (LUT) should be pre-generated from the detector’s flood histogram to assign each \((x, y)\) to a specific crystal index. The accuracy of the CPMs is crucial to the detector’s intrinsic spatial resolution.

The most primitive method to generate the CPM is manual segmentation. However, it is not accurate enough and time consuming, especially for a whole system consisting of thousands of crystals. Several automatic or semi-automatic approaches were proposed to perform an appropriate segmentation of the flood histograms. A statistical model based on likelihood boundaries of Gaussian mixture models (GMMs) was presented by Stonger [10] and Yoshida [11]. Approaches based on neural networks were implemented by Hu [12] and Wang [13]. A Fourier template and non-rigid registration based method was proposed by Chaudhari [14], [15]. Moreover, a principal component analysis based algorithm [16] and a probabilistic graphical model based algorithm [17] were also proposed to build CPMs. We also developed a neighborhood standard deviation based algorithm [18] for an animal PET system [19]. However, most of these methods were geared to non-DOI detectors. Dealing with DLO detectors, the layers distinction and crystal indices generation would be a problem for these methods. The GMM-based method has been employed for DOI-PET detectors by Yoshida [11]. However, it is time-consuming and impractical for large dimension position histograms, because a large number of parameters for the GMMs must be estimated. In this paper, a novel method using stratified peak tracking is proposed.
II. MATERIAL AND METHODS

A. The DLO Detector & Flood Histogram

One of the home-made DLO-LYSO array is shown in Fig. 1(a) & (b). The crystal with all surfaces polished has a size of 2 × 2 × 7 mm$^3$ (SIPAT, China). The top layer (15 × 15 array, size 31.6 × 31.6 × 7 mm$^3$) was placed half crystal offset in two dimensions on the bottom layer (16 × 16 array, size 33.6 × 33.6 × 7 mm$^3$) as shown in Fig. 1(c). Enhanced specular reflector (ESR, 3M) was used between the crystals to achieve high crystal discrimination. The bottom layer was coupled to an 8 × 8 SiPM array as shown in Fig. 1(d). The SiPM pixel (MicroFB-30035-SMT, SensL Inc.) consists of 4774 of 35 × 35 µm$^2$ microcells with a size of 4 × 4 mm$^2$ and a sensitive area of 3.16 × 3.16 mm$^2$. The SiPM array has an overall dimension of 33.7 × 33.7 mm$^2$ with 0.2 mm gaps between adjacent SiPM elements. The output channels of the SiPM array were directly fed to a front-end ASIC called EXYT [20] and multiplexed by on-chip resistor networks to generate 3 analog outputs including an energy (E) and two positions (X and Y). Two 8 × 8 SiPM arrays were fabricated on a same printed circuit board to share a same 8 channel ADC chip (AD9637). In this study, only one of them was used.

The detector was covered by a light-tight box and worked at room temperature (about 25°C) without cooling and with a voltage of 28.5 V for SiPMs. A $^{22}$Na point source with an activity of about 3 µCi was placed at about 3 cm from the top of the detector block. Fig. 2 shows the flood histogram with a half-hour acquisition. The crystals are clearly distinguished except for a small amount of crystals overlapping at the edges of the block. The crystals in the top layer have more counts than the crystals in the bottom layer due to the gamma-ray attenuation effect.

B. Method Flowchart Description

A novel automatic method to generate the CPMs for the DLO detectors using a stratified peak tracking was developed. The flowchart of the method is described in Fig. 3. The peaks of the top layer are tracked firstly using the following
procedure: 1) the original flood histogram ($I_0$) is squared, the result is denoted as $I_1$; 2) the image $I_1$ is decomposed using a singular value decomposition (SVD) algorithm, and then a principal component image (PCI) of the top layer is generated using the largest eigenvalue denoted as $I_3$; 3) average horizontal and vertical peaks of the projections of the PCI are determined and employed as the initial peaks of the top layer; 4) true peaks of the top layer are tracked by the mean-shift algorithm \[21\]. Then, the peaks of the bottom layer are tracked as below: 1) a template image of the top layer is created using the peaks of the top layer and a Gaussian kernel denoted as $I_4$; 2) image $I_4$ is subtracted from $I_0$, the result is denoted as $I_5$; 3) initial peaks of the bottom layer are created using the peaks of the top layer; 4) true peaks of the bottom layer are tracked by the mean-shift algorithm. At last, the CPM is generated using all the peaks with a distance-based method.

C. Details of the Program

To simplify the description of the following algorithms, we use the specific numbers that the DLO block consists of a $15 \times 15$ array in the top layer and a $16 \times 16$ array in the bottom layer and the flood histogram $I_0$ with size of $512 \times 512$ pixels.

The first step is to increase distinction between the top and bottom layers. The square image $I_1$ is generated, i.e. $I_1 = I_0 \ast I_0$. An example of $I_1$ is shown in Fig. 4, which gives prominence to the top layer.

Singular value decomposition and only keeping some components with large eigenvalues has been used in image compression. In this paper, SVD is employed to create a principal component image (PCI) of the top layer.

The SVD of $I_1$ is shown in equation (1).

$$ I_1 = U \Sigma V $$  \hspace{1cm} (1)

where, $U/V$ is an $512 \times 512$ matrix formed by the normalized eigenvectors of $I_1 I_1' (I_1' I_1)$ associated with the eigenvalues $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_{512}$, and $\Sigma = \text{diag} [\sigma_1, \sigma_2, \ldots, \sigma_{512}]$ is a diagonal matrix ($\sigma_i = \sqrt{\lambda_i}$). A new diagonal matrix ($\Sigma'$) only with the largest eigenvalue and the other eigenvalues set to 0 is created, i.e. $\Sigma' = \text{diag} [\sigma_1, 0, \ldots, 0]$. The PCI image of the top layer $I_2$ can be created by equation (2).

$$ I_2 = U \Sigma' V $$  \hspace{1cm} (2)

A typical result of image $I_2$, as shown in Fig. 5, has a neat $15 \times 15$ lattice, indeed, highlights the average vertical and horizontal grid lines of the top layer.

Then, the projection profiles of $I_2$ along the X and Y directions are obtained as shown in Fig. 6. A local maximum identification method is used to find 15 peaks individually from these one-dimensional projections. The method is described as follows: I) the index of the maximum value of the projection is determined; II) the projection around the index is assigned to 0; III) go to step I until finding 15 indices. After all the peak locations are determined, the initial peaks of the top layer are created. An example is shown in Fig. 7.

The mean-shift algorithm has been proposed as a method for cluster analysis, which is an iterative procedure that shifts each data point to the centroid position of data points in its neighborhood \[21\]. There are different kinds of kernels can
be employed for the mean-shift algorithm. In this paper, the simplest one so-called flat kernel is used. Let $K$ be a flat kernel that is the characteristic function of the $\lambda$-ball as shown in equation (3) ($\lambda = 6$ in the following calculation):

$$K(x) = \begin{cases} 1 & \text{if } \|x\| \leq \lambda \\ 0 & \text{if } \|x\| > \lambda \end{cases}$$

(3)

The sample mean at point $x$ is calculated by equation (4):

$$m(x) = \frac{\sum_{s \in S} K(s - x)I_1(s)}{\sum_{s \in S} K(s - x)}$$

(4)

where, $s$ is any point position in the 2D coordinate set $S$, and $I_1(s)$ is the intensity at point $s$. The data point $x$ is moved to its sample mean $m(x)$, i.e. $x$ is updated by $m(x)$. This movement is repeated until convergence.

To increase the robustness of the algorithm, an average mean-shift is performed in advance. The $15 \times 15$ initial peaks are divided into $3 \times 3$ groups with $5 \times 5$ initial peaks in each group. The center position of each group is iterated using equation (5), and the initial peak positions of each group are iteratively updated using equation (5):

$$c_j = \frac{1}{25} \sum_{i=1}^{25} x_{i,j}$$

$$m(c_j) = \frac{1}{25} \sum_{i=1}^{25} m(x_{i,j})$$

$$x_{i,j} = x_{i,j} + (m(c_j) - c_j), \quad i = 1 \sim 25; j = 1 \sim 9$$

(5)

where, $c_j$ is the center position of group $j$, and $x_{i,j}(i = 1-25)$ are the peak positions of group $j$.

After this step, all the peak positions are continually iterated by mean-shift algorithm individually until convergence. At last, each initial peak of the top layer is moved to its true peak position. Fig. 8(a) shows the mean-shift procedure and Fig. 8(b) shows the mean-shift result of the example flood histogram.

A binary image with an intensity of 1 at the true top-peak locations and 0 otherwise is created. The binary image is convolved with a 2D spatial Gaussian filter. The convolved image is denoted as $I_1$ as shown in Fig. 9(a). The intensity of $I_1$ is adjusted to 70% of $I_0$. Then, a new image denoted as $I_4$ is obtained by subtracting $I_3$ from $I_0$, which mainly includes the responses of the bottom layer as shown in Fig. 9 (b).

If the peaks of image $I_4$ are clearly distinguished, the same process can be used for assigning the initial peaks of the bottom layer. As the crystal responses at the edges of the bottom layer cannot be well distinguished, a more robust method is introduced using the peaks of the top layer to locate the initial peaks of the bottom layer. Due to the half crystal offset design, the crystal responses in the top and bottom layers are in a staggered arrangement. Based on this prior knowledge,
the algorithm is developed as follows: 1) the center of each adjacent four true peaks of the top layer is assigned as one initial peak of the bottom layer. From this, a \(14 \times 14\) initial peaks of the bottom layer could be created as shown in the dotted box in Fig. 10(a). 2) The initial peaks at the edges are then determined and extrapolated from the coordinate information of the newly generated peak-matrix. For example, for the upper edge peaks in the first row, their column coordinates are assigned as those of the second row and the row coordinates are subtracted 20 from the second row. The results of the initial peaks of the bottom layer are shown in Fig. 10(a). The mean-shift algorithm is also employed to identify the true peaks of the bottom layer, as shown in Fig. 10(b).

After this step, all the peaks of the crystal responses are tracked and each peak includes the information of the layer, column and row number. To generate the CPM, distances from each pixel in the flood histogram to the peaks are calculated. Each pixel is assigned to a unique crystal with the minimum distance value. To speed up the algorithm, a rough estimation process is proposed. For the pixel \((i, j)\), its estimated peak index is \([\text{round}(i \times 15/512), \text{round}(j \times 15/512)]\) in the top layer and \([\text{round}(i \times 16/512), \text{round}(j \times 16/512)]\) in the bottom layer. Only the distances for a \(5 \times 5\) peak array with the center of the estimated peak are calculated in the top and bottom layers.

D. Manual Correction

None of the automatic segmentation methods can completely succeed for all flood histograms. Manual correction should be added for minor modification of the incorrect
parts. In our automatic methods, the peaks of the top layer and the bottom layer may converge to an error position in the situation of flood histogram with serious distortion. In this work, an easily operable graphical user interface (GUI) program including the automatic algorithm and the manual correction procedure was developed based on Matlab2012a. There are two interaction steps in the manual correction procedure: 1) after the true peaks of the top layer are tracked, the flood histogram with the identified peaks (displayed as crosses) is visually inspected by the operator. If any of them is uncorrected, the operator only needs to click on the point near the crystal response without peak (cross) on the flood histogram with the mouse, the nearest initial peak to the clicked point will be replaced with the click point. Then, the mean-shift algorithm is carried out to move this point to its desired location; 2) the same process is carried out to the bottom layer.

III. RESULTS

A. Crystal Position Maps

The proposed method was tested for 3 home-made DLO PET detector blocks with energy resolutions around 15%. All the CPMs could be generated automatically. The average computation time for generating a CPM is 55.6 s on a Lenovo laptop computer (Intel(R) Core(TM) i7-5500U @2.40GHz, 8.0 GB RAM), and only 0.74 s is expended for the stratified peak tracking. Fig. 11 shows the segmentation results of the three detector blocks. The segmentation boundaries surrounding the peaks display the pixels with the equivalent distances to its two closest peaks. The segmentation results were checked visually, and 100% could be accepted without further manual modification.

IV. DISCUSSIONS

In this paper, an automatic crystal position map generating approach was proposed using a stratified peak tracking method based on the SVD decomposition and mean-shift algorithm. A simple GUI program including the automatic algorithm and the manual correction procedure was developed. Compared to the other methods, our approach is an optimal design for dual-layer offset PET detectors, which can directly distinguish the layer information and crystal indices by using the intensity difference and offset grid pattern.

The algorithm procedure presented here is a practical implementation for our built-up DLO detectors with same length crystals for both layers (7 mm), which leads to the count distinction between the two layers. Some groups have provided DLO detectors with longer bottom crystals than top crystals to get similar crystal efficiency for both layers [22]. For this design, the layers cannot be separated in the flood histogram with the source irradiating from the top of detectors. Thus the algorithm will fail. However, since Lutetium based scintillators are the most widely used materials in PET detectors, and the Lutetium intrinsic radiation could be used as an approximate flood source [23], our algorithm could work with a minor modification. The bottom layer has a higher Lutetium background sensitivity than the top layer, thus the bottom peaks can be tracked firstly. Even for a non Lu-based detector module, the algorithm will also be workable by irradiating a source from the bottom side.
Moreover, the presented program can also be employed to generate CPMs for single layer detectors by using one time of SVD and mean-shift procedure.

V. CONCLUSIONS

In conclusion, we developed an optimal algorithm for the DLO PET detectors. The algorithm produced accurate delineation of crystals from flood histograms obtained from three DLO PET detectors developed in our lab. The proposed method is promising and expected to be applied easily to DLO PET detectors and potentially should facilitate accurate system characterization. More tests will be carried out in the future.

REFERENCES


