Nuclear Inst. and Methods in Physics Research, A 872 (2017) 74–79

Contents lists available at ScienceDirect

Nuclear Inst. and Methods in Physics Research, A

journal homepage: www.elsevier.com/locate/nima

Real time depth of interaction determination based on Fourier Transform and Support Vector Machine

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ARTICLE INFO

Keywords:
Depth of Interaction (DoI)
Fast Fourier Transform (FFT)
PET
SVM

ABSTRACT

The resolution of the PET scanners is limited by the parallax error due to the missing knowledge about Depth of Interaction (DoI) of the incident photons inside the scintillation crystal. In real time, a DoI calculator must fulfill a suitable event processing rate, which requires low complexity DoI algorithms. The DoI is obtained when the crystal within a phoswich detector is identified based on the shape of the scintillation light distribution. The main idea of this paper is to enhance the performance of crystal identification by using a Support Vector Machine (SVM) classifier and Discrete Fourier Transform (DFT) feature extractor. Besides, the paper introduces a complexity reduction method by merging the SVM classification phase and DFT in order to comply with the real-time rate. A real-time FPGA-based merged DFT-SVM DoI method has been implemented and validated to discriminate pulse-shapes of LSO-LuYAP scintillation crystals events. A correct assignment of 92.2% at rate of 6.2 Mevents/s is achieved for a sample of ∼100 000 pulses from LSO-LuYAP crystals read out using vacuum photomultipliers. Compared with recent DoI methods, the proposed method provides the highest performance and fulfills the required real-time rate of PET scanners

1. Introduction

One of the common nuclear imaging techniques is the Positron Emission Tomography (PET) [1,2] which provides three dimensional functional images of the biological systems. PET has many applications such as in the early detection, diagnosis and evaluation of diseases. The conventional PET scanner is composed of a ring of scintillator crystals, which absorb gamma rays and emit photons, connected to photon-sensing devices (i.e. sensors). The emitted photons hit the sensors that generate electrical pulses with certain decay constants, depending on the material of the crystals. The typical commercially available sensors are photomultiplier tubes (PMTs).

Distortion in high resolution PET images usually occurs due to the parallax-error (known as depth of interaction (DoI) error) [3], which can be eliminated by using Phosphor sandwich (phoswich) detectors [4]. The phoswich detector is a stack of two or more different scintillation crystals; with different decay constants, optically coupled to a single PMT [5]. By identifying the crystal in which the scintillation light has been produced, the PET photon's DoI is determined. This crystal identification (CI) process requires applying pulse shape discrimination (PSD) method, such as in [6–17].

The performance of the discriminator, which depends on photon counting efficiency and the fidelity of the detected photons, has in turn a strong effect on the PET image quality [18]. The fidelity of the detected photons is the degree of exactness with which the PET image is reconstructed. Recent PET systems use an on-chip discriminator, which captures multiple-event coincidence, for better imaging performance evaluation. In such case, the PET sensor consists of multiple blocks of scintillator matrices with PMT and on-chip discriminator, one slow control board and finally an optical link to send the data for further processing to the PC, as described in [19,20]. That configuration guarantees better image resolution if the discriminator follows the sensor detection rate and provides an efficient CI performance.

The rate of PET events varies from one system to another corresponding to the number of detectors and the hardware configuration. According to the ClearPET™ system [20,21], 1.5 M events/s is the required PSD real time rate. While the PET detector module, which was proposed in [19], supports up to 6 M events/s.

On the other hand, there are digitization parameters, which are the sampling rate, the number of used samples of scintillation pulses and cut off frequency of the anti-aliasing filter, that affect the performance

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http://dx.doi.org/10.1016/j.nima.2017.08.008
Received 19 May 2017; Received in revised form 1 August 2017; Accepted 3 August 2017
Available online 14 August 2017
0168-9002/

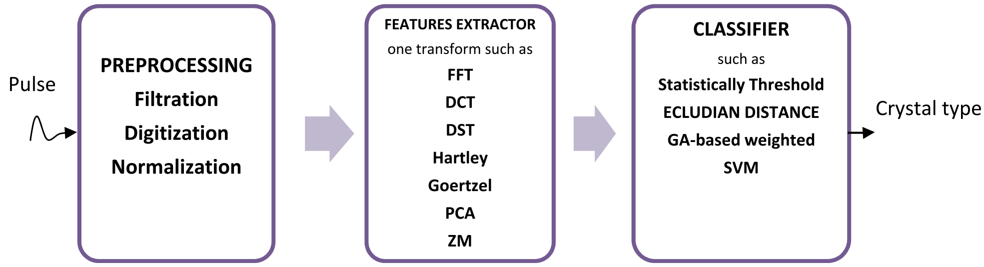

Fig. 1. Digital PSD scheme.

and the complexity of the PSD. Recent mathematical analysis of the frequency spectra, which is proposed in [22], selects optimally the digitization criterion and determines the most discriminated frequency in order to reduce the number of needed frequency components and required computations.

Furthermore, in order to achieve a high discrimination performance, complicated digital PSD algorithms were used [23,24]. These PSD techniques usually consist of three main processes as indicated in Fig. 1. The first step is preprocessing, which includes amplification, filtering, digitization, and normalization. The second step is the feature extraction, which can be performed by transforming the scintillation pulses to another domain. The Discrete Fourier Transform (DFT) is one of those transformers which were used in PSD algorithms. Finally, a classifier is applied to classify the scintillation pulses.

Despite of its high complexity, the DFT components were used as extracted features of the pulses, and classified by the statistically threshold metrics [11]. While the performance of the DFT based method can be enhanced by using the Support Vector Machine (SVM) classifier, the algorithm complexity will be increased. Moreover, SVM does not have a complex kernel that could directly manipulate the complex numbers of its input data sets. On the other hand, recent researches [25,26] suggested alternative methods to use the SVM with complex numbers.

The main objective of this work is to further improve the current performance of the widely adopted DFT DoI method by using the SVM as a classifier. In addition, the DFT and SVM are merged in order to reduce the PSD complexity. On the other hand, most of DoI methods are utilized at low event rates and do not meet the on-chip requirements. As a result, the proposed merged DFT-SVM DoI method is a promising method for its high level of accuracy and efficient computation. Besides, the merged DFT-SVM method is easily realized on an FPGA and the entire pulse processing followed by the proposed method of discrimination can be equipped in a single chip to fulfill the real time requirements of PET scanners.

The rest of the paper is organized as follows. The mathematical proof of the merged DFT-SVM DoI method is discussed in Section 2. In Section 3, the proposed method is applied on LSO and LuYAP pulses, and the results are shown and discussed in Section 4. Finally, the conclusion is provided in Section 5.

2. Proposed merged DFT-SVM DoI method

The proposed method uses the DFT as a feature extractor and the SVM as a classifier in order to achieve a high discrimination performance in DoI applications. The SVM is composed of two phases; the learning phase and the classifying phase. The learning phase of the SVM is usually performed offline in a computer by software. On the other hand, the classification phase that includes a decision function for the classified target can be implemented in an FPGA. This decision function complexity is of $O(MN)$ multiplications and $O(MN)$ additions; for N features and M support vectors. Moreover, the DFT adds more computation complexity (i.e. $O(N\ log\ N)$ multiplications and additions) for computing its complex outputs of N frequency components. The proposed Merged DFT-SVM combines the DFT and SVM algorithms in a single step to reduce the computation complexity and achieve the required real time rate of PET systems. The following subsections discuss the DFT and SVM, and introduce the proposed method.

2.1. The discrete Fourier transform

The Fourier Transform (FT) converts the signal into a periodic sequence of complex valued components of frequency. In discrete form, the input signal p is represented by a finite series of uniformly distributed N samples. While, the DFT output (P) is the equivalent length series of uniformly distributed samples of the FT, and is given by,

$$P = DFT(p) = pW \tag{1}$$

where W is the transformation matrix given by:

$$W = \begin{pmatrix} w^0 & w^0 & w^0 & \cdots & w^0 \\ w^0 & w^1 & w^2 & \cdots & w^{(N-1)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ w^0 & w^{(N-1)} & w^{2(N-1)} & \cdots & w^{(N-1)(N-1)} \end{pmatrix}, \tag{2}$$

and $w^{(n)(k)} = e^{-i\frac{2\pi nk}{N}}$.

2.2. The support vector machine

SVM has a strong mathematical background and wide applications, such as image processing, applied statistics, computer vision, pattern recognition, and machine learning [27]. SVM is a supervised learning algorithm, which means it uses a training data set and a classification algorithm by which it determines if something belongs to a certain class. In other words, the goal of the SVM is trying to find the optimal separating hyperplane (i.e. decision boundary) that maximizes the margin between two or more classes of training data points. This hyperplane lies at the margin's midway and must

$$\begin{aligned} &\text{Minimize :} && \frac{1}{2}\left\|\vec{h}\right\|^2, \\ &\text{Subject to the constrains :} && y_i\left(\vec{h}\cdot\vec{V}_i + b\right) \geq 1. \end{aligned} \tag{3}$$

Then the solution of this problem is achieved by optimizing the following Lagrange equation:

$$L = \frac{1}{2}\|h\|^2 - \sum_i \alpha_i\left(y_i\left(\vec{h}\cdot\vec{S}_i + b\right) - 1\right) \tag{4}$$

where the input for this problem is a training set of pair samples (V, y), where V is the input features vectors, and y is the output result which indicates the class label ($y \in \{1, -1\}$).

On the other hand, the outputs of solving Eq. (4) are h, b and α's. h is the set of weights, one for each input feature, whose linear combination predicts the value of output y. While S's (called the support vectors) are the selected points from the input training features' data (V) that satisfy the maximum margin above and below the hyper-plane. The output b (i.e. bias), and alphas (i.e. Lagrange multiplier constants) are parameters which determine a unique maximal margin solution. The y_i's and α_i's correspond to the selected support vectors V_i's.

The classification of an unknown vector U is predicted by the decision function $d(U)$, which is positive for class 1 and negative for class 2, and is defined for kernel (H) as follows:

$$d(U) = sign\left(\sum_i H(U, S_i)\, y_i\alpha_i + b\right). \tag{5}$$