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Investigating machine learning solutions for a 256 channel TCSPC camera with sub-70 ps single photon timing per channel at data rates >10 Gbps

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ABSTRACT: The development of a Time Correlated Single Photon Counting (TCSPC) camera with 256 channels has enabled several applications where single photon sensitivity is crucial, such as LiDAR, Fluorescent Lifetime IMaging (FLIM) and quantum information systems. The microchannel plate-based Multi-Anode Photo-Multiplier Tube (MAPMT) is a 16×16 array of 1.656 mm pitch pixels with an active anode area of $26.5 \times 26.5 \text{ mm}^2$. Each pixel can time single photons with an accuracy of 60 ps rms at a maximum photon rate of 480 KHz.

The timing electronics are capable of measuring 120 Mcps, producing huge volumes of data for processing, in the region of 10 Gbps per detector. Limitations in algorithmic data analysis techniques are critical for this application, hence this paper demonstrates a machine learning (ML) model which can determine the photon event coordinates with the objective of processing each one photon per 10 μs . The model applies calibrations for the detector and electronics such as amplitude walk, and charge measurement and channel to channel threshold variation. Optimisation of the model is detailed within the paper, including training hyperparameters, the clustering of coincident events and compression of the model through pruning techniques.

The ML model is trained and tested on a simulation of the microchannel plate (MCP) PMT with timing electronics configured for use as a TCSPC camera, utilising charge sharing techniques to further improve the spatial resolution of the detector. Further objectives of the research are to test the model on detector data, allowing assessment on the variance of accuracy between

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simulated and real data. Beyond this, assessment of the performance of this approach compared to algorithmic approaches and introduction of statistical reasoning of the robustness of the model will be completed.

KEYWORDS: Data processing methods; Pattern recognition, cluster finding, calibration and fitting methods; Analysis and statistical methods; Simulation methods and programs

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1 Introduction

The microchannel plate-based detector Multi-Anode Photo-Multiplier Tube (MAPMT) has an active anode area of $26.5 \times 26.5 \text{ mm}^2$, each pixel has a maximum photon rate of 480 KHz. The timing electronics of the detector are capable of measuring 120 Mega counts per second (Mcps). Hence, producing huge volumes of data, in the region of 10 Gbps per detector [1, 2].

This work aims to design novel algorithms using machine learning (ML) techniques to handle these data rates and process photon events in real time.

The microchannel plate (MCP)-based detector this work is modelled on has a 16×16 pixel anode layout, instrumented using PETsys TOFPET2d [3]. The MCP amplifies a single photoelectron output, as a charge cloud with an average gain of 1–10 million electrons, producing a charge distribution on the anode of the detector [4]. Each channel of the anode is connected to a channel of TOFPET2d providing information on 256 channels individually.

1.1 Data processing pipeline

To assess the feasibility of using machine learning models to resolve X , Y and t of photon events on the anode of the MAPMT, a data processing pipeline has been created. Currently this is being tested using data from a Monte-Carlo python simulation of the MAPMT, this has been built to accommodate for noise effects from the detector, such as the laser spot size, and detector calibrations. With the outputs of the simulation, the packets of pixel information are clustered into charge distributions using a python-built state machine, then the correctly clustered distributions are processed using a ML model to resolve for X_{photon} , Y_{photon} and T_{photon} . Each stage of this process are discussed in more detail in this paper.

1.2 Proof of principle implementation

Using machine learning methods to resolve for the photon event was explored firstly using a simplified case, this scenario allowed the simulation to output charge distributions rather than electronic packets which make up each charge distribution for each single photon event, hence the state machine was not needed as a pre-processing stage before the ML model as the packets were pre-clustered. Furthermore, there were no calibrations included in the simulation, so for each charge distribution simulated the output was, $N^*[X_{\text{pixel}}, Y_{\text{pixel}}, Q_{\text{pixel}}, t_{\text{pixel}}]$, where $N = \{1, 2, 3, \dots, 16\}$, where X_{pixel} and Y_{pixel} is the X and Y coordinate of each pixel in the 16×16 anode layout. Q_{pixel} is the total charge read on that pixel and t_{pixel} is the time the pixel information was attained.

With 200000 training samples (i.e. charge distributions) a neural network was trained which successfully determines the $X_{\text{photon}}, Y_{\text{photon}}$ coordinates. The architecture of the given network was a 1D convolutional layer followed by a couple of dense layers, all with relu activation functions using Keras backend on Tensorflow [5]. The convolutional network successfully determined the spatial coordinates of the photon event to a root mean squared error of 0.202 pixels, with a couple of thousand parameters. The network size is particularly of interest as the research objective is to implement the software into hardware to be instrumented with the detector, hence it is crucial to optimise the network in order to reduce the necessary resources.

This is a promising result as it implies the spatial resolution of the detectors can increase by over 4 times. The success of this result is especially important given our objective to increase the spatial resolution of the detector with charge sharing techniques, this proof implies that we would still be able to employ these techniques.

2 Detector calibrations

The preliminary Monte-Carlo simulation was a simplified version of the MAPMT detector, which used a naive model of the detector gain and charge footprint collected by the anode, to model the charge collected on each pixel. The TOFPET2d electronics do not have a direct measure of charge, they use a Time-over-Threshold (ToT) discrimination technique, where the output width of the integrated discriminators T_{ToT} is related to the charge collected on each pixel Q_{pixel} . Hence, the TOFPET2d channel number encodes pixel $X_{\text{pixel}}, Y_{\text{pixel}}$ and provides an independent time measurement (30 ps resolution) t_{pixel} for each pixel. Hence a calibration is required to convert the ToT back to a charge measurement, also this effect must be modelled to train the neural network to perform this calibration.

There is an additional systematic error introduced by the ToT discrimination technique, termed amplitude walk [6], which introduces a delay depending on the charge collected. Hence, another calibration is required to correct this to reconstruct the true event time $t_{\gamma} = t_{\text{pixel}} + t_{\text{AWC}}(T_{\text{ToT}})$.

To calibrate for charge, ToT and t_{γ} , using a fast voltage step (1 ns rise time) was injected to each TOFPET2d channel through a 2.2 pF capacitor, to produce a charge injection similar to the MAPMT output current pulse. To achieve a greater range of results for charge measurements between 1×10^5 to 5×10^6 electrons, attenuators of values 20 dB, 26 dB and 32 dB were used. The following plots demonstrate the logarithmic relationships found between charge, ToT and amplitude walk calibration. These functions are used within the Monte-Carlo simulation of the

detector to achieve realistic outputs. It is the objective of the machine learning model to learn these relationships so it can output X_{photon} , Y_{photon} , t_{γ} (figure 1).

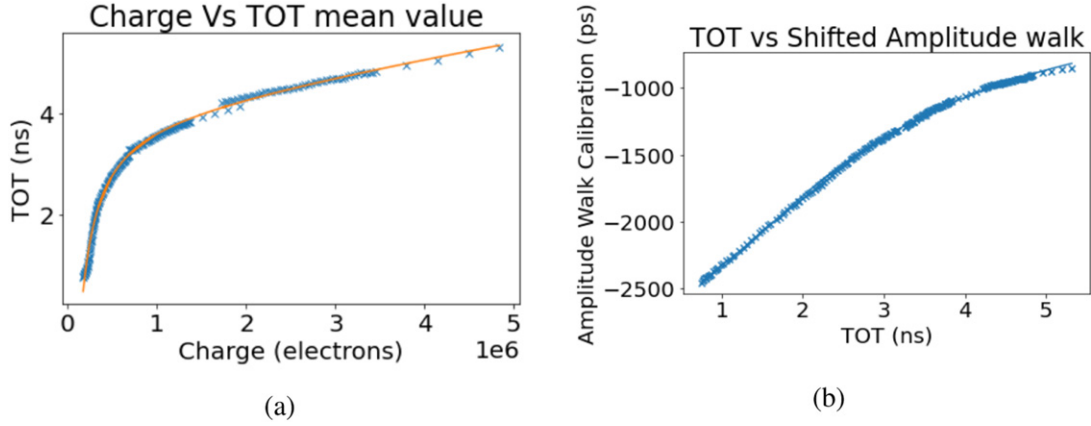


Figure 1. (a) Illustrates the logarithmic function between charge (Q_{pixel}) and ToT (T_{ToT}), (b) depicts the relationship between ToT and Amplitude Walk Calibration ($t_{\text{AWC}}(T_{\text{ToT}})$) with an attenuation of 26 dB.

3 Clustering coincident photon events

In simulating the data the t_{pixel} is generated for each packet in a cluster with a Gaussian distribution with a standard deviation of $\sigma = 60$ ps, experimentally the time between photon events is $\Delta T = 2$ to 2.5σ , hence packets from coincident photon events can overlap. To solve this a state machine was designed to cluster coincident events, this currently has an accuracy 94% of clusters correctly identified. The state machine works by clustering incoming packets based on the Euclidean distance of the previous packets X_{pixel} and Y_{pixel} values and the current packets spatial coordinates. Observation of the timing information of the packets is also useful in the state machine as this determines when a charge distribution is likely clustered, this cluster is kept and utilised as a training sample in the neural network. Further analysis will be completed in order to improve the accuracy of the state machine in the future, currently only the correctly clustered charge distribution are utilised as training data for the neural network.

4 Resolving X, Y, T with neural network architecture

Currently work is being done to optimise the convolutional neural network to determine the photon event coordinates given the calibrations within the simulation. Hence, the network has the additional task of learning the calibrations discussed. To address this the architecture of the convolutional neural network has been deepened, with two 2D convolutional layers with batch normalisation layers in-between, followed by four fully connected layers, all with relu activation functions. A preliminary result for resolving the photons spatial coordinates, suggests the model can predict the coordinates with an rms error of 0.8 pixels. Prior to the training the data was pre-processed and it was observed that sorting the packets by the X_{pixel} and Y_{pixel} values reduced

the number of epochs needed and reduced the loss. This needs to be tested on more data sets and then work will be done to achieve an optimised architecture of the network by employing pruning techniques. Beyond this, analytical comparison of the performance algorithmic methods compared to this processing pipeline can be made.

5 Further objectives

With the success of building a machine learning model that can effectively process photon events with the complication of pre-processing coincident events and outputting coordinates to minimal error whilst considering noise effects within the detector and electronics. Further work will be focused on exploring any adaptations the neural network would require when passed real detector data. Once real detector data has been collected, the neural network will be assessed on its performance when training with differing ratios of simulated and real detector data, it is predicted that the model will perform best with a hybrid approach, where the training set is comprised of both simulated and real detector data. Analysis of the models architecture and work into pruning the layers will be researched to optimise the software routine.

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