

Viability of Integrating Op-Amps for Event Detection in Time Projection Chambers

Zachary Castillo

Advisor: Dr. Dinesh Loomba

Undergraduate Honors Thesis

University of New Mexico Physics and Astronomy

May 2017

Contents

Abstract.....	3
Introduction	4
Experimental Set-Up	6
Electronics - Integrating Op-Amps, Arduinos, and DAQ Considerations	8
Theory of operation	10
Calculating the Strength of the Signal.....	11
Noise Considerations	12
Simulation	15
Detection Algorithm.....	17
Results.....	19
Discussion and Future Work	21
References	21
Appendix A – Table of DAQ Parameters	24
Appendix B – Noise of Arduino Zero	25
Appendix C – MATLAB Code	26

Abstract

The search for dark matter is well motivated, and has been underway for many years. However, the ultimate discovery of dark matter has been elusive, partly due to the ill-understood nature of dark matter. One hypothesized form of dark matter is known as Weakly Interacting Massive Particles, or WIMP for short. It is theorized that a WIMP can interact with ordinary matter via the weak force, and in doing so cause an elastic scattering with atomic nuclei. These scattering events result in ionization trails under the right conditions, and these ionization trails can be readily detected using a class of particle detectors known as time projection chambers (TPCs). The Directional Recoil Identification From Tracks (DRIFT) collaboration uses such a detector. Methods already exist for the associated electronics needed for detecting the signals from these tracks, but they are expensive and often proprietary. This thesis discusses the viability of using alternative and inexpensive electronics in the form of integrating op-amps, and Arduino micro controller boards or possibly other low cost digital acquisition devices such as the LabJack U3 or U6. Simulations are used to understand how the noise of the analog and digital electronics affect event detection. Results indicate that a preamplification of the charge is needed.

Introduction

One of the current outstanding problem in physics and cosmology is the resolution of the galaxy rotation curve problem. In essence, observable matter at the edges of galaxies orbit at a much faster rate than what is predicted from classical theory. This observation is considered to be the oldest and one of the most convincing indicators for Dark, or non-luminous, non-absorbing, matter [1]. Other evidence of dark matter is accepted among cosmologists, and its existence is well established [1]. Although dark matter does not interact with ordinary matter via the electromagnetic force, it is theorized to interact via the weak force, and the most likely candidates are referred to as Weakly Interacting Massive Particles (WIMPs).

Many experiments seek to directly detect WIMPs by observing elastic nuclear recoils inside the volumes of detectors. One such effort is the Directional Recoil Identification From Tracks (DRIFT) collaboration. Unlike most other dark matter experiments, DRIFT has the ability to convincingly measure the direction of WIMP induced nuclear recoils, in addition to the energy of these interactions [2]. Astrophysical models of galaxy formation and simulations indicate that the distribution of WIMPs does not co-rotate with the ordinary matter in the Galaxy. Because the Sun has motion with respect to the Galactic rest frame, the directional recoil rate of WIMP induced reactions should vary in time and be maximal around the direction of Solar motion. Exploiting this feature allows of the order of 10-100 events to confirm the existence of WIMPs, as opposed to approximately 10,000 events when only considering annual modulation. [3]

The DRIFT detector is a gas time projection chamber (TPC) which utilizes low pressure CS_2 . TPCs are a class of particle detectors which have been in use since the late 1970's [4]. The principle of operation of the DRIFT TPC is that an ionization trail of electrons due to nuclear recoils

are captured by electro negative molecules. These molecular ions are then drifted by an electric field to a readout plane. The electric field is created by a configuration known as field cage, which is a series of conducting bands connected via resistors to gradually step down the voltage difference between a high voltage cathode and a grounded anode readout plane. In the case of DRIFT, the readout plane is a collection of 448 20 μm diameter stainless steel wires crossed with 448 100 μm wires at a 2mm pitch or spacing. This arrangement results in a fiducial area of 0.803 m^2 . Deposited charge on the wires create signals which are converted to voltages by a preamplifier (Cremat CR-111), then amplified and shaped by a shaping amplifiers (CR-200). These electronics are located outside the detector volume. The processed signals are then acquired and digitized with National Instruments PCXI-6133 analog-to-digital converts (ADCs), which serve the purpose of data acquisition (DAQ). [3]

Researchers at the University of New Mexico have contributed to the DRIFT since 2006 by prototyping with smaller scale TPCs and alternative electronics as well as data analysis. This thesis is related to prototyping as it investigates the viability of alternative electronics and DAQs for event detection in TPCs. The inspiration for this research is the potential low cost of the components. Each Cremat chip in the DRIFT detector is approximately \$55, and a PCXI-6133 DAQ costs roughly \$3,400 at the time of writing. An alternative chip costs roughly \$10, and a DAQ can be bought for between \$25 and \$300, depending on the quality.

Experimental Set-Up

A 1 cubic meter vacuum vessel was used to control the pressure and type of gas used for preliminary data runs. The vacuum vessel houses a previously built cylindrical field cage which used a single wire at the readout plane. A single wire is used instead of a typically readout plane of 10s - 100s of wires so that the detection scheme can be thoroughly understood.

A radioactive Po-210 source was used to introduce ionizing alpha particles into the time projection chamber, perpendicular to the E field. The Po-210 source is located approximately 6.5 cm from the field cage and is collimated. The collimator is 1.96 cm in length and 0.25 cm diameter, reducing the angular distribution of the particles to less than 7.33 degrees.

The field cage is a cylinder that is approximately 12 in in length, with an inner diameter of 4.0 in. The walls of the field cage are made of 0.635 cm thick acrylic, and has 1.27 cm diameter holes at 2.54 cm spacing between centers to allow alpha radiation through. A series of eleven 56 Mega ohm resistors gradually step the voltage down from the negative high voltage cathode to the grounded anode, creating a near uniform electric field within the cylinder. The cathode was powered by using a high voltage DC power supply which was passed through a custom built low pass filter. The power supply was set to either 6.0 or 7.0 kV. The field cage with alpha source is shown in Figure 1.

The integrating IC and other analog electronics are mounted towards the right end of the field cage. The components before being mounted to the field cage are shown in Figure 2. The necessary connections to power the electronics and to measure the output are electrically connected to the outside of the vessel via BNC connections. The output of the signal can then connect via BNC cable to a digitizer, such as an Arduino, which is housed in a steel box. The steel

box provides shielding from stray electromagnetic radiation [5], and was modified to fit a BNC receptacle and allow a USB cable to be connected to the hardware.

The electronics can be understood in two stages. The first is analog in nature; charges are collected from the wire and integrated. The second stage is digital; the ADC digitizes the analog signal. Preliminary data was taken using an Arduino Uno.



Figure 1- The TPC in the vacuum vessel. The radiation source is the yellow puck towards the left in of the TPC (1). The electronics (2) are mounted on the right side of the field cage, and are pictured in Figure 2.

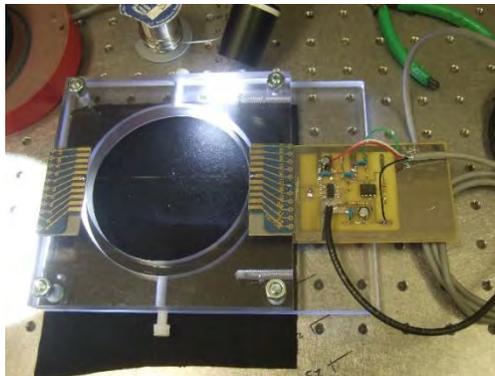


Figure 2 – The single wire readout plane and electronics.

Electronics - Integrating Op-Amps, Arduinos, and DAQ Considerations

Integrating Op-Amps

Operational amplifiers are ubiquitous in modern day electronics, and can perform arithmetic, differentiation, or integration on the input voltages through various feedback circuits. Additionally, op-amps are commonly used to amplify voltages. Op-amps are usually contained in integrated circuits (ICs) and are readily available from manufacturers. [7]

The Texas Instruments IVC 102 integrating IC is used in this project. This IC is low cost, approximately \$10 per chip, and allows several capacitor values to be used. [7] This feature is important when one considers the equation which describes an integrating op-amp:

$$V(t) = -\frac{1}{C} \int_0^t I(\tau) d\tau$$

Where C is the capacitance of the op-amp, I is the input current as a function of time, and τ is the integration variable.

It should be noted that lower values of the capacitance value result in larger output voltages. It should also be noted that the final measured output for the TPC is a positive voltage as opposed to a negative voltage because negative charges are collected.

A photo of the electronics used is pictured in figure 2. The purpose of the capacitors is to filter out any high frequency components due to the power supply. [7]

Arduinos and DAQs

Several factors need to be considered when selecting an Arduino or other DAQ. The voltage range, bit resolution, and sampling rate are of particular importance. These specifications are readily found in the manufactures specification sheets, although the digitization rate of

Arduino microcontrollers needs to be experimentally determined. This is because the digitization rate is related to the programable baud rate which is the rate at which the instrument transfers information over the communication channel. The bit resolution specifies the number of distinct values a DAQ can read and store, and is related to the resolution of the instrument according to

$$\Delta V = \frac{V_R}{2^B}$$

Where ΔV is the minimum change in voltage which can be measured, V_R is the voltage range of the DAQ, and B is the bit resolution. [8]

Arduinos, which are inexpensive microcontrollers, were considered as a low-cost data acquisition system. Arduinos exist in several models with a variety in the number of analog inputs and bit resolution for the ADC. The Arduino Uno and Arduino Zero are both discussed in this thesis. The Arduino Uno has an input range of 0-5 V with 10-bit resolution. The Arduino Zero has a range of 0 – 3.3 V with 12-bit resolution. The voltage resolution of these microcontrollers is then 4.88 mV and 0.806 mV respectively.

As mentioned earlier, the digitization rate of the Arduino micro controllers is related to the programmable baud rate. Additionally, the digitization rate is related to the complexity of the code programmed to the Arduino. To determine the digitization rate precisely, a signal generator was used with an oscilloscope to create a periodic signal such as a sine wave with a well-known frequency. This signal was supplied to the analog inputs of the Arduinos, and the data was saved to a PC. By counting the number of digitized points in one period of the signal, and then averaging over several periods, the digitization rate and error can be determined. The

digitization rate of either Arduino can be as large as 120 Hz when using all available analog inputs with a large baud rate and simple code.

In addition to Arduinos, there exist relatively inexpensive dedicated DAQ devices, such as the LabJack U3 and LabJack U6. These DAQs are also considered as potential means of data acquisition. A table of these four pieces of hardware with information such as price, resolution, and noise is shown in Appendix A.

Theory of operation

In an ideal model of a TPC experiment, the input voltage of the integrator is a series of short pulses in time, with an input of zero between pulses. Approximating the pulses as Dirac delta functions, the output of the integrator will be a stair step pattern, with the size of the steps being proportional to the size of the pulse, and the edge between steps corresponding to the time of the arrival of charge. This approximation is valid if the width of the pulse in time is much less than the sampling rate of the electronics used to digitize the output.

This approximation is justified with the following consideration. Alpha events enter the field cage with a velocity nearly perpendicular to the electric field, which is along the axis of the cylinder. Call the axis of the cylinder the z direction. The maximum angle that the alpha can have is determined by the inverse tangent of the ratio of the collimator's diameter to the length. The maximum extent of a potential ionization track along the z-axis is the diameter of the cylinder multiplied by the inverse tangent of the maximum angle, which is simply the ratio of the collimator's dimensions. The maximum extent of track along the z-direction is then approximately 1.3 cm with these considerations. CS_2 ions typically have a velocity of $50 \mu\text{m}/\mu\text{s}$ by

the time they reach the readout plane [9]. Assuming the maximum displacement along z , the time difference between the start and end of the track of CS_2 would be approximately 2.6 ns. This is certainly much less than the digitization rate of any DAQ that costs less \$500, which typically operate up to a few 100 kHz. In this setup, however, electrons are drifted directly, and the velocities are 1000 times higher, so the approximation is still valid.

Calculating the Strength of the Signal

In order to estimate the change in signal from a single ionization event, one needs to consider both the amount of charge which is deposited on the readout plane in the detector, and the electronics used to measure the charge. The number of charges which are deposited can be calculated by using the Stopping and Range of Ions in Matter (SRIM) software package, a commonly used tool in nuclear physics for the simulation of nuclear recoil tracks. SRIM includes a program known as TRIM (the Transport of Ions in Matter), which can calculate many phenomena that result from an ion's kinetic energy loss in matter. The phenomenon of interest for this discussion is the ionization distribution within the detector due to alpha radiation. The ionization distribution is the differential energy loss per length as a function of target depth. The total deposited energy is calculated by numerically integrating this distribution over the extent of the track within the detector. Dividing the energy by a gas dependent constant known as the W factor then gives the average number of ions and electrons produced by one radiation event. Finally, multiplication by the charge of a single electron gives the total charge produced because

of a single ionization event. This amount of charge gives an estimate to the maximum number of charges, in this case electrons, which could be deposited on a wire readout plane.

Using Po-210 alphas as the ionization, 171 Torr Nitrogen in the TPC, and by considering only the volume within the field cage, SRIM calculates that approximately 107,000 ionization pairs will be produced, or equivalently a total charge of 1.71 femto-Coulombs. Using the smallest possible capacitance of 10 pF for the IC, this amount of charge corresponds to a maximum change in voltage of 1.71 mV, assuming all the charge is deposited on a single wire. It should be noted that typical track lengths due to nuclear recoils from WIMP interactions are few mm in extent which corresponds to a few wires, so the actual change in voltage will be a fraction of this value at each wire when using a readout plane in an actual dark matter experiment. [9]

Noise Considerations

There are two distinct sources of noise in the experimental set up. The first is any type of input on the integrating IC that is not due to the collection of charges from ionization. These sources of noise may include stray charges within the TPC, mechanical vibration of the wires (known as microphonic noise), and leakage current from the printed circuit board. Allowing the HV source to be on for at least 24 hours eliminates the first potential source. The microphonic contribution is also small as determined by comparing the output of the circuit with the readout wire being connected for 24 hours, and without the wire connected. In effect, the noise is dominated by the leakage current in typical operation.

In practice, any op-amp will have some amount leakage current between the inputs of the op-amp. [6] The presence of this leakage current means that the integrating IC will produce

a gradually rising output, even in the absence of collected charges. The output is nearly linear, but the change in voltage over a set time interval is ultimately random and follows a Gaussian distribution due to statistical fluctuations in the leakage current. The parameters of this distribution can be determined by considering the change in voltage over a set time interval. By using a Tektronix TDS 3054C Oscilloscope to measure the change in voltage in a 1 second interval for 50 trials, the mean rise in voltage was measured to be 5.37 mV/s, with a standard deviation of 0.72 mV/s.

The second source of noise is digitization noise. Dedicated DAQ hardware is often quoted to have an error approximately +/- 1 bit [8]. However, Arduinos are not designed to be dedicated DAQs, and the digitized value may be several bits from the true input value. To make matters worse, the digitization error is worse depending on the programmable baud rate of the micro controller, and may not be the same across all input voltages. See Appendix for more details. In any case, the noise of the Arduino Zero is taken to be 5 bits at 1 standard deviation, and the noise for the Arduino Uno is taken to be 0.35 bits at 1 standard deviation.

As explained in more detail in the Detection Algorithm section, the relative change between data points is the value of interest when analyzing the signals. For this reason, I define the total noise in the system to be the combined effect of both the uncertainty from the output of the op-amp and the uncertainty due to digitization in one time interval. The total noise in a time interval is best understood through simulation since the resulting distribution will be discrete due to digitization, and some representative plots are presented in Appendix. However, some insight can be gained by approximating the digitizer to have a Gaussian distribution with a σ_D being standard deviation from a sample of discrete values at a constant voltage. It is well

known that errors add in quadrature if the errors are independent and Gaussian. This is a result of how Gaussian distributions are added, the means add as do the variances. Taking the noise due to the analog electronics to be $N(\mu\Delta t, (\sigma_a \Delta t)^2)$ and the noise to the ADC to be $N(0, \sigma_d^2)$, we have a result of $N(\mu\Delta t, (\sigma_a \Delta t)^2 + \sigma_d^2)$. In the preceding equations, Δt is the time between data acquisitions, and μ is the expected number of events per unit time. This consideration is useful since we see that noise can be reduced in two ways; either reducing the sampling time, or by reducing the noise of the digitizer.

The signal-to-noise of a measurement will be defined as the separation in magnitude between the expected change in voltage due to a signal, and the expected value of the total noise distribution in terms of the number of σ 's which specify the total noise distribution. For example, if a signal is expected to cause a change of 1 mV, and the noise distribution has a standard deviation of 0.1 mV and is centered at 0.005 mV, the signal-to-noise is 9.95σ . The signal-to-noise values for each DAQ is tabulated in Appendix A, and is calculated by considering simulated values

In addition to decreasing the noise by using a higher quality digitizer, an amplification technique using Gas Electron Multipliers (GEMs) can be used in the detector. GEMs are thin polymer electrodes with many holes, approximately 50-100 holes per mm^2 . An electric potential between the surfaces of the electrodes cause electrons passing through the holes to accelerate and cause an electron avalanche [10]. Within the TPCs of interest, amplification gains of over 1000 in the number of charges is easily obtainable when an appropriate potential is applied across the GEM.

Simulation

A simulation was programmed in MATLAB to test and analyze the efficacy of a detection algorithm within the constraints of typical choices of hardware. There are two primary steps in simulating a signal. The first is to simulate the output of the integrating IC, and the second is to digitize this nearly continuous signal while adding appropriate noise.

Four parameters are needed to simulate the analog signal. These parameters are the total average input voltage on the integrating IC, a parameter to describe the fluctuation in the average input, a voltage change due to ionization, and a rate to determine the frequency of ionization events. The first two parameters are taken to be the mean and standard deviation quoted in the Noise Considerations Section. The voltage change is taken to be 1.71 mV, as calculated in the Signal Strength Section. The event rate is chosen to be on the order of 0.1 to 1 events per second. An additional two parameters are used to simulate the gain of the GEM. Each event is multiplied by a random value drawn from a Gaussian distribution with a mean of 1000 and standard deviation of 200.

Another five parameters are needed to simulate the DAQ. These are the time between acquisitions, the number of resolvable bits, a parameter to describe the noise of the DAQ, and a minimum and maximum resolvable voltage.

A discrete time series is constructed first with a spacing equal to the acquisition rate, and a maximum value between 300 and 500 seconds. The signal may surpass the maximum resolvable voltage if the total time is too large. Two separate signals are created and then added together to simulate the output of the integrating IC. One of these signals is due to the integrated noisy input of the IC. A voltage value taken from a Gaussian distribution with a mean of 5.37mV/s

and standard deviation of 0.72mv/s is assigned to each point in the time series. This signal is then numerically integrated to simulate the operation of the integrating IC. The effect of ionization is created by considering the number of expected events between acquisitions. This is accomplished by using a Poisson random number generator, with the mean being the number of expected events in that time interval. The number of events is multiplied by 1.71 mV. A cumulative sum is then calculated, effectively performing the operation of integration over several delta functions. These two vectors are then added together.

The simulated analog signal must then be digitized with error due to digitization noise. This is done with the `digitize.m` and `noise.m` MATLAB functions. These are included in Appendix C. `digitize.m` essentially reassigns each value of the time series signal to largest bit value which is still smaller than the analog value. This digitized signal is then processed with the `noise.m` MATLAB function. `noise.m` reassigns each digital value to a value sampled from a Gaussian distribution with a mean of the digital value and a standard deviation motivated by typical performance of the considered DAQ. The result of `digitize.m` and `noise.m` are illustrated in Figure 3 for a linear signal.

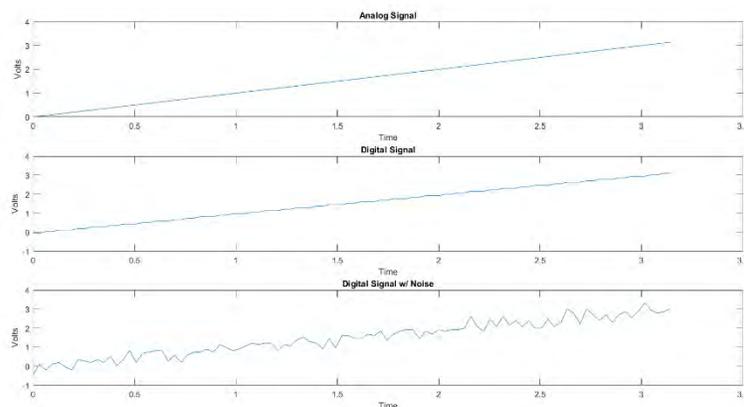


Figure 3 – Example of digitization process for a linear signal and a DAQ with large noise.

Detection Algorithm

As discussed in the Calculating Strength of Signal section, the expected change in signal is a sharp change in voltage. This is similar in concept to edge detection in image processing. Within the context of image processing, an edge is a discontinuity in intensity or brightness [11]. A preliminary step in identifying edges is to filter the data to suppress noise. A popular filter choice is a moving median filter because these filters are believed to outperform linear filters in this particular task. However, a careful analysis by Arias- Castro and Donoho shows that this is true only when the signal to noise is sufficiently large [12]. Fortunately, a two-stage median filtering approach can dramatically outperform linear filters in the presence of larger noise [12]. With this consideration in mind, two median filters are initially applied to the signals.

A median filter is a moving filter of a specified window length k . A window extending by the integer $\text{floor}(k/2)$ in each direction around each point is considered. The median value of the elements inside this window is then assigned to the point. For the purposes of this analysis, the first filter uses a window of length 3 data points, then a filter with a window length of 9 data points is applied.

After filtering, the signal is numerically differentiated by taking the difference between successive points. A threshold value for the derivative is set, and the value of the threshold is motivated by visual inspection of the final signal. Any point in the signal which passes the threshold is identified as an event candidate. Examples of the signal before median filtering, after

median filtering, and after taking the derivative are shown in Figure 4 for data simulated using a DAQ with 12-bits of resolutions over 2.4 Volts with low noise.

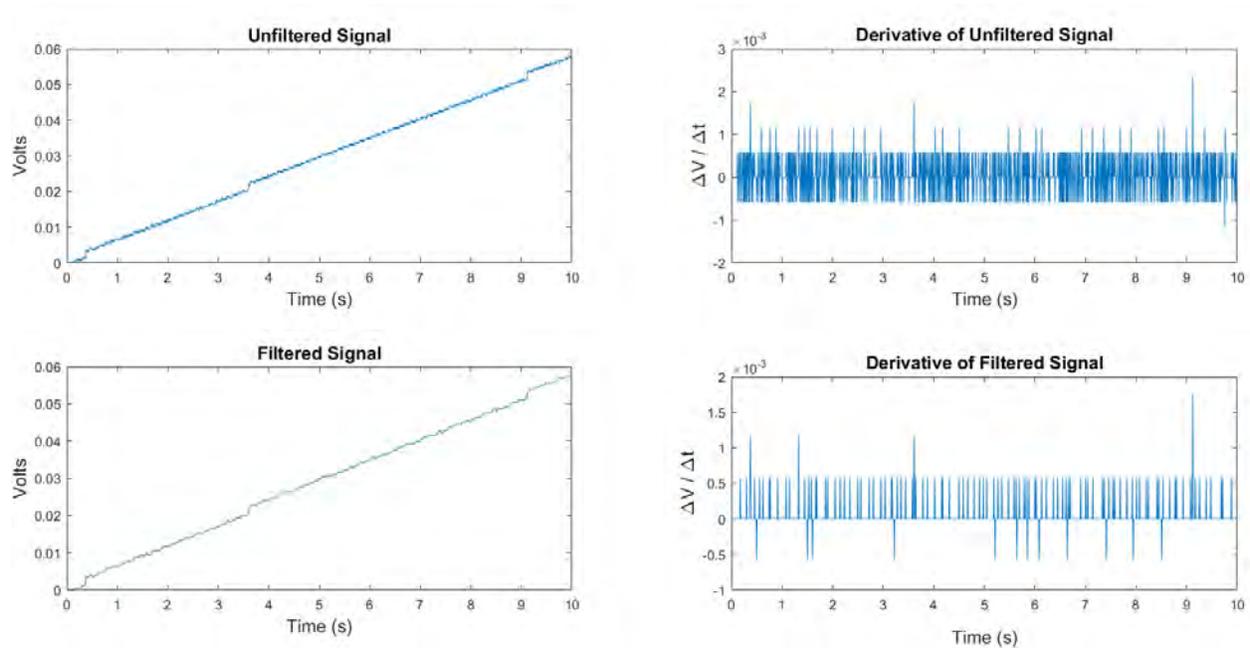


Figure 4 – Results of filtering and taking the derivative. It should be noted that a false positive would be identified after filtering near 1.5 seconds, indicating that the filtering parameters may still have room for optimizing. It should be noted that two possible cutoffs are possible in this case, one to include the four obvious possible peaks, and one to include only the largest peak.

Results

Figure 5 shows some simulated results of four different DAQs with an event rate of 0.1 events per second. The threshold for the derivative was set as high as possible without excluding obvious potential events, or in the case of the Arduinos, all the data.

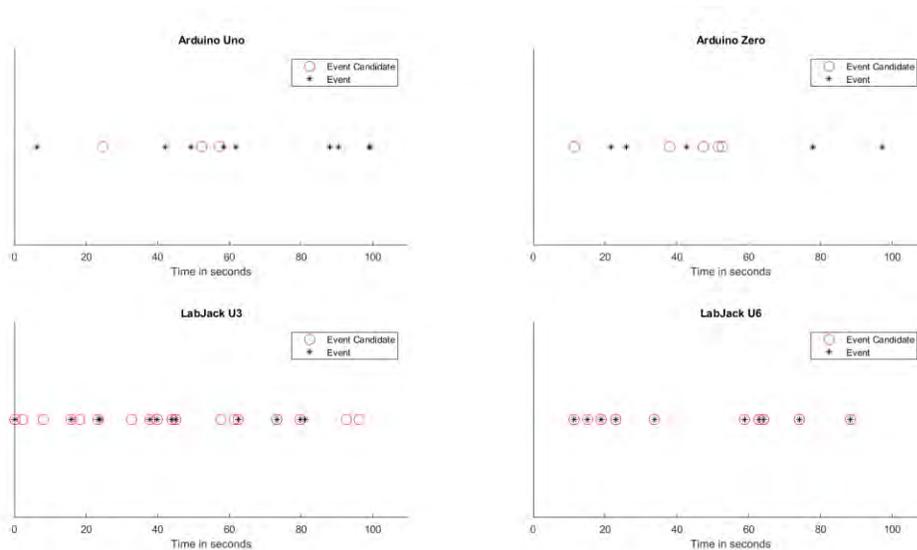


Figure 5-Typical results from the simulation. Simulated events are marked by stars, and identified event candidates are circled. Note that detection algorithm fails at identifying any events for both Arduinos. The algorithm identifies most events for the LabJack U3, but many false positives are identified as well. There is perfect success for the LabJack U6.

To better understand the extent of the misidentification of events for the LabJack U3, simulations were repeated until at least 100 events were considered. The Threshold 1 Candidates column shows the number of event candidates for a threshold at 1 mV in the case of the LabJack U3, and 2 μ v for the LabJack U6. The threshold for the second column was 1.5 mV. A second threshold

was not needed in the case of the LabJack U6 since the change in voltages due to events was so dramatic.

Table 1 – Event Candidates using LabJack DAQs

DAQ	Number of Events	Threshold 1 Candidates	Threshold 2 Candidates
LabJack U3	1036	2564	362
LabJack U6	1002	1002	-

Figure 6 is similar to Figure 5, with the exception that a GEM is used to amplifier the ionization charges by a factor of 1000. Results indicate perfect identification.

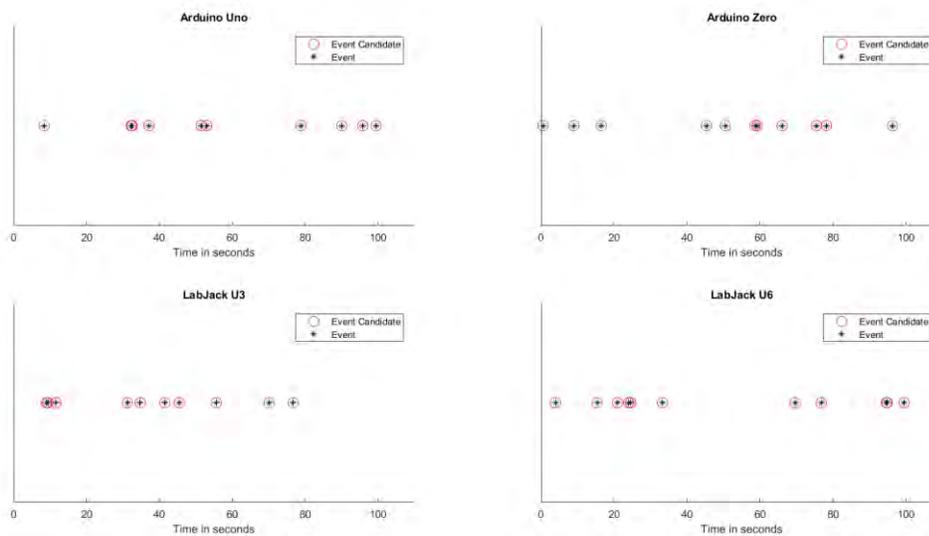


Figure 6 – Results from GEM consideration. The detection algorithm perfectly identified every event.

Discussion and Future Work

These simulations suggest that using only integrating op-amps with a low cost DAQ does not seem to be feasible given the current detection algorithm without GEM amplification. Although the LabJack U6 correctly identifies every simulated event, it is the most expensive option at \$300 per unit. It performs so well because of its large signal-to-noise separation at nearly 10σ . The LabJack U3 can identify the occasional event correctly, but suffers from significant under or over identification of events, as evident by table 1. A signal-to-noise separation of 3.8σ is not enough to reliably identify events. Based on the results from the LabJack U3 and U6, it is reasonable to conclude that the minimum acceptable signal-to-noise separation lies somewhere between 3.8σ and 10σ . However, Figure 5 indicates that using a GEM allows one to easily identify events using the described algorithm. This can be understood by the GEM causing a large signal-to-noise separation since the charges are amplified before reaching the electronics.

A demonstration of signal identification using GEMs with a wired grid is a natural continuation of this work. A very low cost option such as the Arduino Uno could be used, although the time resolution of approximately 0.01 seconds may be too coarse for some applications. Automated signal detection using software such as LabView would also be interesting.

References

[1] C. Patrignani et al. (Particle Data Group), Chin. Phys. C, 40, 100001, 393-401 (October 2016).

- [2] F. Mayet *et al*, "A review of the discovery reach of directional Dark Matter detection," *Physics Reports* 627, 1-49 (April 2016).
- [3] J.B.R. Battat *et al*, "Low threshold results and limits from the DRIFT directional dark matter detector," *Astroparticle Physics* 91, 65-74 (May 2017).
- [4] J.N Marx and D.R. Nygren, "The Time Projection Chamber," *Physics Today* 31, 46-53 (1978).
- [5] H. W. Ott, "Noise Reduction Techniques in Electronic Systems," A Wiley-Interscience Publication 1976.4
- [6] P. Scherz and S. Monk, "Practical Electronics for Inventors, Third Edition" McGraw-Hill 2013.
- [7] Texas Instruments, "Precision Switched Integrator Transimpedance Amplifier," Accessed May 2016. <http://www.ti.com/lit/ds/sbfs009/sbfs009.pdf>
- [8] LabJack Corp., "Noise and Resolution (App Note)," Accessed July 2016. <https://labjack.com/support/app-notes/noise-and-resolution>
- [9] D. Loomba. Personal Correspondence, April 2017.
- [10] F. Sauli, "The gas electron multiplier (GEM) : Operating principles and applications," *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, Volume 805, 2-24, (2016)
- [11] T. Lindeberg, "Edge detection", in Hazewinkel, Michiel, *Encyclopedia of Mathematics*, Springer 2001.

[12] E. Arias-Castro and D. Donoho, "Does median filtering truly preserve edges better than linear filtering?," *The Annals of Statistics* 37, 1172-1206 (2009).

Appendix A – Table of DAQ Parameters

DAQ	Acquisition rate for multiple channels	Voltage range	Bits	Noise at 1- σ	Signal-to-noise for 1.71 mV signal	Approximate cost
Arduino Uno	100 Hz	0 – 5 V	10	17 mV (0.35 bits)	0.47 σ	\$25
Arduino Zero	100 Hz	0 – 3.3 V	12	4 mV (4.96 bits)	0.30 σ	\$50
LabJack U3	120 Hz	0 – 2.4 V	12	0.19 mV (0.33 bits)	3.7 σ	\$100
LabJack U6	2780 Hz	-10 – 10 V	18	62.4 μ V (0.82 bits)	9.9 σ	\$300

Appendix B – Noise of Arduino Zero

The noise of the Arduinos was investigated using an HP 6114A Precision Power supply. This power supply can supply a voltage to within a tolerance of $50 \mu\text{V}$. A DC voltage was supplied to the analog inputs of the Arduino Zero. The Arduino programmed at a range of baud rates. 400 data points were measured for each baud rate, and the standard deviation was calculated. In the best case, the Arduino had a standard deviation of roughly 2.5 mV , which is nearly 3 bits of resolution.

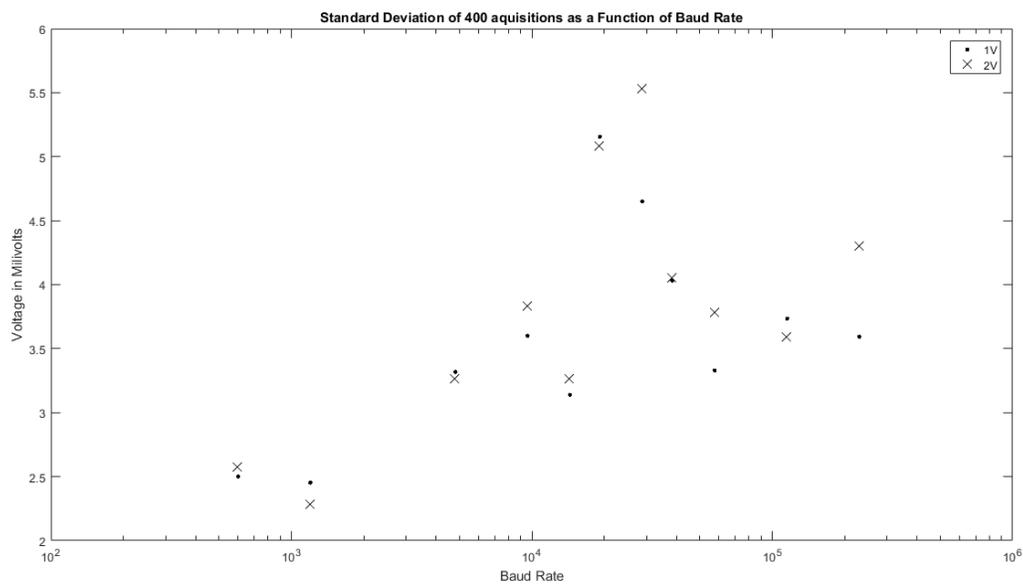


Figure 7 – Noise measurements of the Arduino Zero board using a precision power supply. There does not seem to be an obvious trend between baud rate and noise.

Appendix C – MATLAB Code

TPC_Simulation.mat:

```

%% Parameters
% DAQ Parameters
% Current Parameters are for the LabJack U3
deltaT = 62e-3; % time between acquisitions in seconds
timeInterval = 100; % total collection time in seconds
bits= 12; % integer
noiseDAQ = 0.33; % number of bits at 1 sigma
V1= 0; V2 = 2.4; % Lower and upper voltage values of DAQ

% Electronic Parameters
muOpAmp = 5.37e-3; % mean background voltage of leakage current V/s
noiseOpAmp = 0.72e-3; % Standard deviation of leakage current V/s
% Source Parameters
lambda = 0.3; % expected number of counts in one second
rate = lambda*deltaT; % expected number of counts in deltaT
vAlpha = 1.71e-3; % voltage change due to one event (mV)
    % Divide by deltaT so that correct value is integrated

%% Simulation

t = (0:deltaT:timeInterval)'; % Create time vector
L=length(t);

% This portion creates the exact signal with no digitization

% Create background voltage with noise:
v1 = normrnd(muOpAmp,noiseOpAmp,L,1);

% Create voltage changes due to events:
v2=zeros(size(v1));
% G = normrnd(100,0.2*100,[size(v2)]); % Gain from GEM
v2 = vAlpha*poissrnd(rate,size(v2)); %.*G;
v1 = deltaT*cumtrapz(v1);
v2 = cumsum(v2);

% Add signals to create simulated analog signal:
vSignal = v1+v2;

% This step digitizes the true signal
vDigital = digitize(vSignal, V1, V2, bits); % Digitize values
vDigital = noise(vDigital,V1,V2,bits,noiseDAQ); % Add noise to digitized
values

%% Detection

vFilter=movmedian(movmedian(vDigital,3),9); % Filter the data

%{
% Plotting the differentiated signal allows threshold to be set by eye
figure
plot(diff(vFilter))
%}
EventCan = diff(vFilter)>5e-3; % Event candidates return a value of 1

```

```

EventTrue = diff(v2) > 0; % True events return a value of 1
%% Plot
figure
hold on
% Plot event candidates with O's
plot(t(2:end),EventCan, 'Color',[1 0
0], 'Marker','o', 'LineStyle','none', 'MarkerSize',10)
% Plot true events with *'s
plot(t(2:end),EventCan./EventCan, 'k*', 'MarkerSize',10)
% Limit y-axis to values centered at 1
set(gca, 'YTick', []);
axis([0 1.1*max(t) 0.5 1.5])
legend('Event Candidate','Event')
xlabel('Time in seconds','FontSize',18)
title('Simulation with LabJack U3','FontSize',22)
hold off

```

digitize.m:

```

function [ y , volts ] = digitize( x, v1, v2, b)
% digitize - digitize analog signal
% x - input vector
% v1 - min resolvable voltage in same units as x
% v2 - max resolvable voltage in same units as x
% b - number of bits

vdig = (v2-v1) / (2^b - 1); % Minimum resolvable change in voltage
%bits = 0:2^b-1; % Bit values 0 thru 2^(# bits) -1
volts = v1:vdig:v2; % Resolvable voltages
y=zeros(size(x)); % Initialize digitized vector

for ii = 1:2^b
a = logical(x >= volts(ii)); % Find all values greater than current bit
y(a) = volts(ii); % Assign voltage value to those values
end

end

```

noise.m:

```

function [ y ] = noise( x, v1, v2, b, sig)
% noise1 - adds digitized noise to a digitized signal. Noise is
assumed to
% be Gaussian, with standard deviation of sig
% x - input vector
% v - voltage range
% b - number of bits
% sig - standard deviation in bits

% Convert bits to volts
sig = sig * (v2-v1)/(2^b);
xnoise=normrnd(x',sig);
y=digitize(xnoise,v1,v2,b);

end

```