Acoustic Imaging for Nucleation events in a Scintillating Bubble Chamber Dark Matter

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Abstract

One of the longest-standing fundamental questions in physics is the nature of dark matter. To address this problem, the Dahl Group's goal, in collaboration with the Scintillating Bubble Chamber (SBC) Collaboration, is to introduce and develop new nuclear recoil detection technology that combines two existing technologies: bubble chamber electron recoil rejection and liquid scintillator event-by-event energy resolution. This technique searches for WIMPs (Weakly Interacting Massive Particles), a leading dark matter candidate that would interact with normal matter by scattering elastically off atomic nuclei. The SBC Collaboration has suggested that a scintillating liquid argon bubble chamber be operated and analyzed at Fermilab for dark matter and neutrino studies.

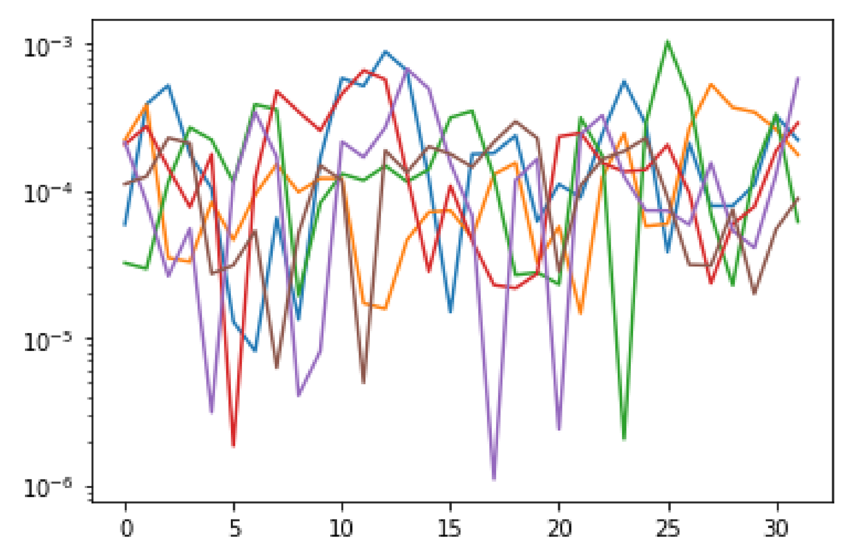
This contribution to the development of a scintillating liquid argon bubble chamber focuses on nuclear recoil sensitivity calibration to identify the lowest energy nuclear recoils while simultaneously excluding electron recoil events and background events. The Neutron Therapy Facility at Fermilab will be aid in developing reliable antimony-beryllium neutron sources, which are explored and modeled both experimentally and initially via simulations to ideal sources for optimal calibration.

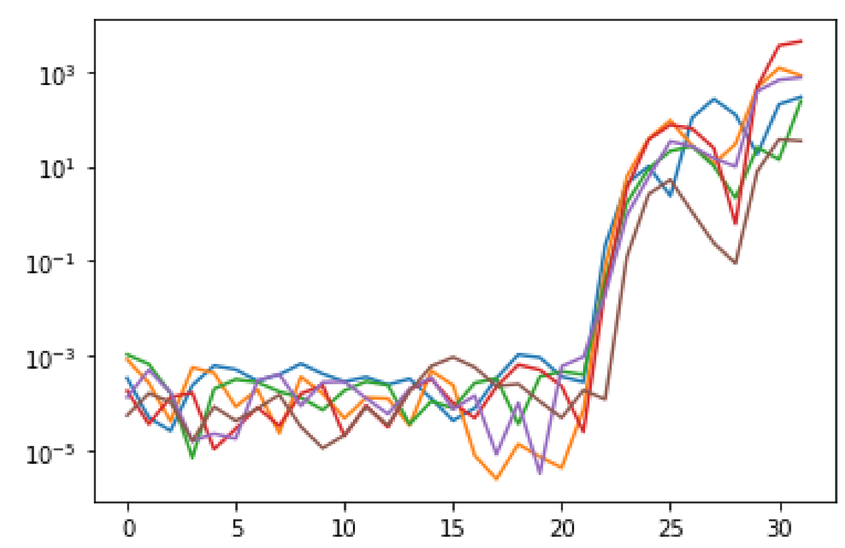
In addition to nuclear recoil sensitivity calibration, this research also explores the potential of acoustic imaging for bubble chamber technology. The goal is to eliminate the need for LED pulsing and cameras in future detectors by using acoustic imaging technology. This approach could provide a solution to scintillation contamination from chamber materials, which fluoresce with long lifetimes and interfere with scintillation data while using a camera trigger. An acoustic trigger could detect bubbles in the dark, collect scintillation data, and then pulse the LEDs to take pictures, ultimately improving the accuracy and sensitivity of nuclear recoil detection.

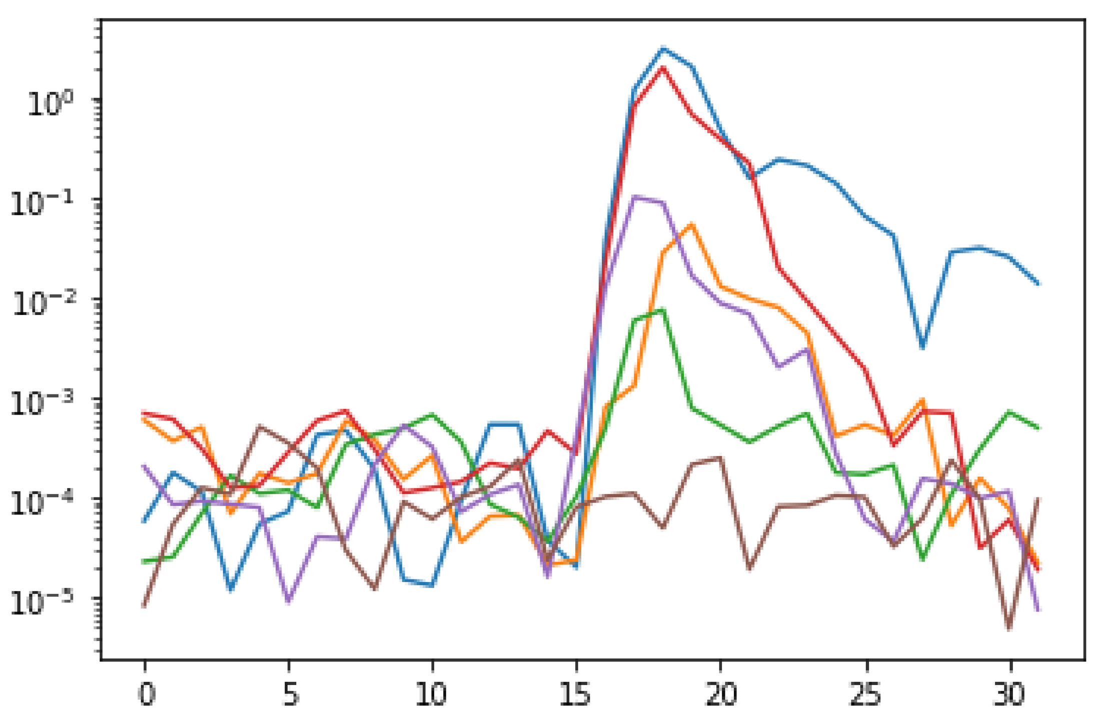
Introduction

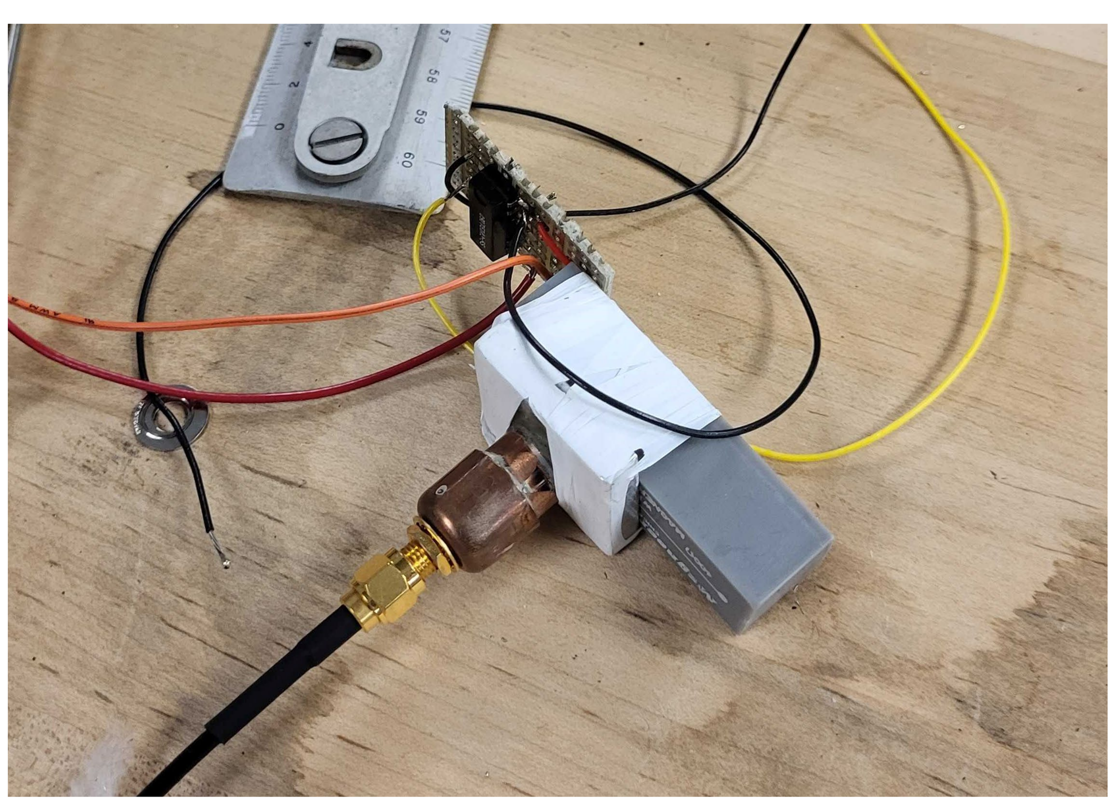
Understanding dark matter and its behavior is of the highest priority and is at the forefront of global particle physics. For nearly a decade now, observations of the universe have suggested the existence of invisible or dark matter, yet our understanding of its nature remains minimal. Dark matter is a hypothetical form of matter that is thought to make up approximately 85% of the universe's mass. Despite its name, dark matter does not actually emit or absorb light, making it invisible to telescopes. However, its presence can be inferred through its gravitational effects on visible matter, such as the rotation curves of galaxies and the large-scale structure of the universe. Dark matter consists of roughly 27% of the universe, 6 times that of visible matter, which means to say that the building blocks of our universe are in the unseen. Discovery and insight into the nature of dark matter would predict new particles, address theoretical limitations of the Standard Model, and advance our understanding of the fundamental foundations of our universe.

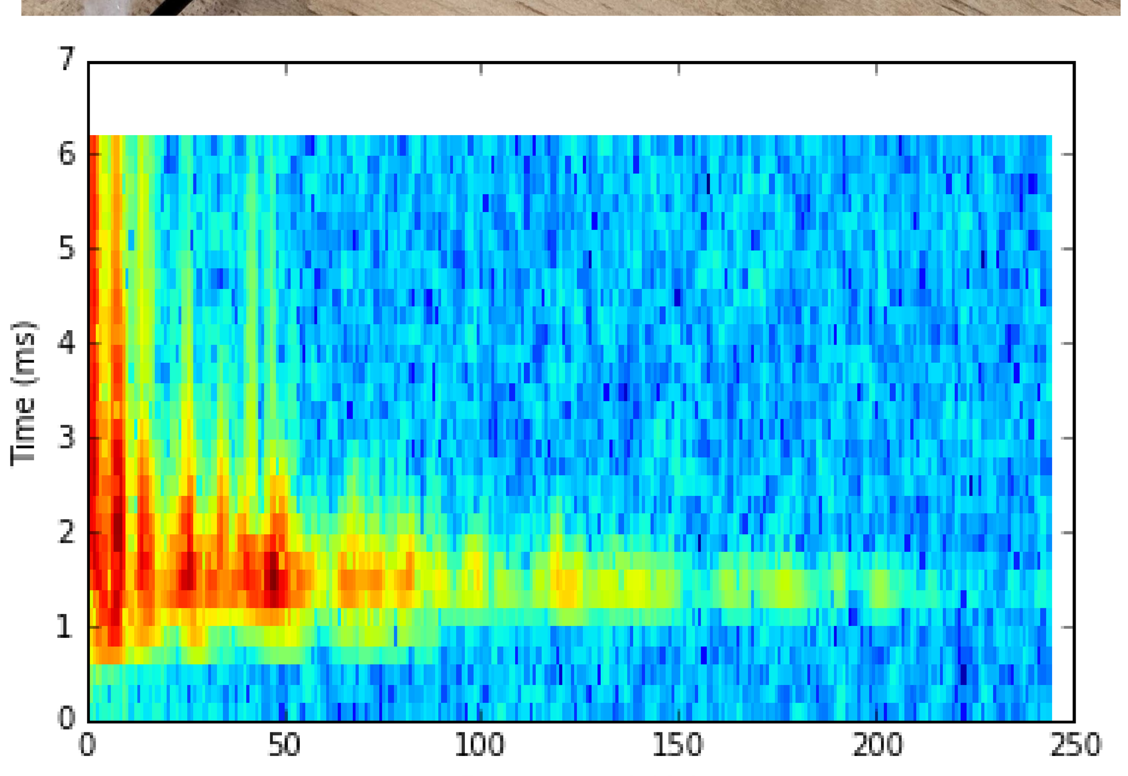
The study of dark matter is a highly active field of research, and many experiments are currently underway to directly detect dark matter particles and study their properties. Understanding the nature of dark matter is crucial for understanding the overall structure and evolution of the universe, as well as the behavior of gravity on cosmological scales. In addition, the discovery of new particles or new forms of matter would have far-reaching implications for our understanding of the fundamental laws of physics and the origins of the universe.











Figures

Figures 1-3. Amplitude vs Time graph for six frequency ranges recorded for selected positive, background, and negative trigger events respective. Each waveform represents a frequency bracket and its behavior over time, useful for finding important frequency ranges.

Figure 4: The setup for recording and data collection of the mechanical relay using the Red Pitaya.

Figure 5: Spectrogram of a positive trigger event showing frequency (kHz) vs Time (ms) with a resolution of 257 x 32. The time windows are overlapping and Hanning windowed, and providing important columns by hand resulted in a significant improvement. This spectrogram is an example of using a mechanical relay as a consistent sound source for acoustic event recognition.

Methodology

The data collection process for the acoustic event recognition project involves the recording of synchronized audio and triggering events from a mechanical relay. The data is collected in sets that consist of positive event triggers (relay clicks), negative event triggers (distracting noise), and background event triggers (background noise). The recorded audio is then pre-processed for feature extraction and training. For the data collection, we are using a Red Pitaya as our hardware platform. The Red Pitaya is a versatile and cost-effective device that is ideal for our needs. It features a Dual-Core ARM Cortex-A9 MPCore processor and a Xilinx Zynq 7010 FPGA, which provides us with a high level of flexibility and control over our data acquisition and processing. The Red Pitaya also has a sample rate of 125MS/s and an ADC resolution of 10 bits, which allows us to capture high-quality acoustic signals. The fast response time and good discrimination are crucial for a good trigger, and the Red Pitaya meets these requirements. We need to identify clicking sound events from a timed mechanical relay, and these events have a very short duration, typically less than 10ms. The Red Pitaya's high sample rate and FPGA allow us to capture and process these events with the necessary speed and accuracy. Additionally, we can use the FPGA to perform real-time signal processing and feature extraction, which is critical for our machine learning model.

The pre-processing stage involves the cleaning of the raw audio data to improve the accuracy of the feature extraction process. The data is first filtered using a bandpass filter to remove any noise outside the frequency range of interest. The pre-processing stage also includes the Hanning windowing, which is a technique used to reduce spectral leakage during the Fourier transform process. The windowing function is applied to each time window, which reduces the amplitude of the edges of the window to zero, resulting in a smoother frequency analysis. Feature extraction involves the extraction of relevant features from the pre-processed audio data. The features extracted include the spectral features of the audio, such as the frequency, amplitude, and duration of the events. The most important features are identified using manual visualization of the data, which allows for the selection of meaningful data/frequency ranges, yielding significant improvement.

Training involves the use of machine learning algorithms to learn from the extracted features and predict the occurrence of future events. The data is split into training and testing sets, with a portion of the data reserved for testing the accuracy of the trained model. The decision tree algorithm is used for this project, and a shallow decision tree with only a few levels deep is used for live FFT analysis to look for features in a spectrogram to trigger on. Evaluation involves the evaluation of the trained model's accuracy using the testing set of data. The evaluation metrics used include precision, recall, and F1-score. The model's performance is also evaluated using receiver operating characteristic (ROC) curves to measure the model's ability to discriminate between positive and negative events. The machine learning model development stage involves the optimization of the model's hyperparameters to improve its accuracy. The hyperparameters include the depth of the decision tree and the number of samples used for training. The goal is to develop a model that can accurately recognize acoustic events within a short response time, ideally within 10ms.

The project's future development involves the use of the trained model in bubble nucleation event recognition in a scintillating liquid argon bubble chamber. The training process will be expanded to include less controlled and synchronized data to make it more applicable to the situation that will occur in the bubble chamber. Additionally, the hardware used will be optimized to improve the model's response time and discrimination ability.

Conclusions

The decision tree model we have developed has shown high accuracy in recognizing evaluation data for the mechanical relay, which is expected as the evaluation and training data are very similar. As this is ongoing research, we plan to expand our evaluation and training data to encompass a larger variety and more realistic scenarios. We anticipate that this will enhance the performance of our model, making it more applicable to the target application of bubble nucleation events in the future.

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