A Machine Learning Approach to Denoising Particle Detector Observations in Nuclear Physics

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Introduction

Modern Nuclear Physics experimental setups run experiments with higher beam intensity resulting in increased noise in detector components used for particle track reconstruction. Increased uncorrelated signals (noise) result in decreased particle reconstruction efficiency. In this work, we investigate the usage of Machine Learning, specifically Convolutional Neural Network Auto-Encoders (CAE), for denoising raw hits from drift chambers in the CLAS12 detector at Jefferson Lab. During the denoising phase, it is important to remove as much noise as possible while retaining the valid hits to avoid losing crucial information about the experiment. We show that using CAE, it is possible to remove noise hits while retaining up to 94% of valid tracks for a beam current of 110 nA while for lower beam currents ($45-55$ nA), we get up to 98% efficiency. Studies on experimental conditions with increasing noise show that CAE performs better than conventional tracking algorithms in isolating hits belonging to tracks, indicating that machine learning can lead to significantly shorter times for conducting physics experiments.

Methodology

A CAE is used to denoise raw data from CLAS12 drift chambers.

- The input and output of the data are matrices of 36x112, representing hits in one sector of the DC.
- Training data was extracted from experimental data processed with conventional reconstruction process. Raw hits, including noise, are used as input to the network and reconstructed hits, belonging to a track, as output.
- Once trained, the network is able to remove noise from new, unseen before, events (e.g, Figure 3).

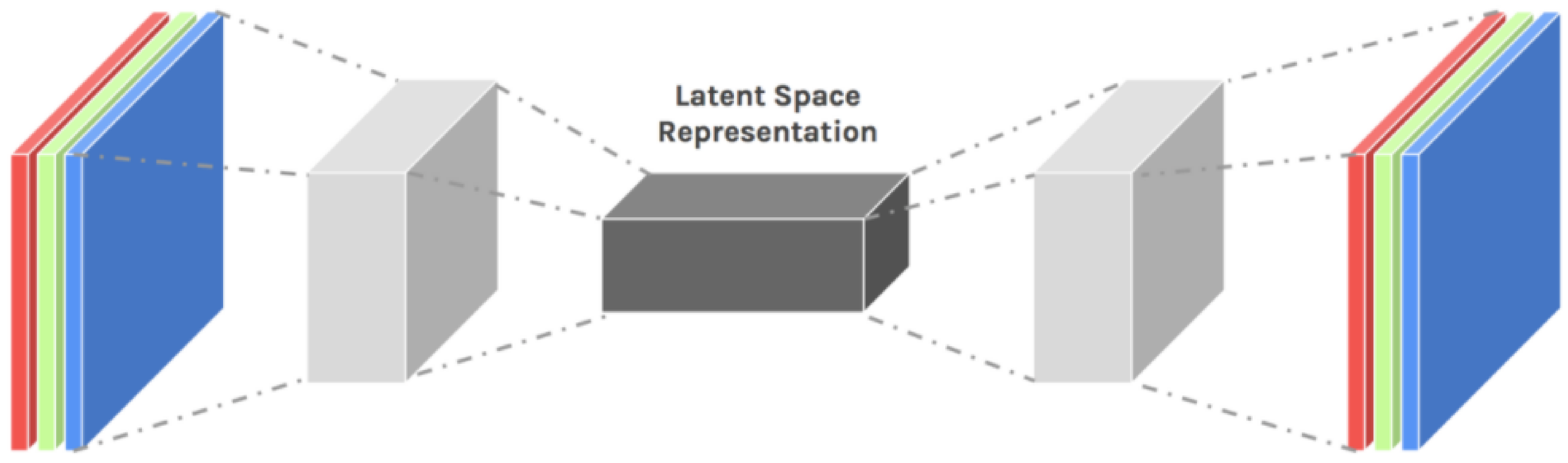

Fig. 1: Architecture of denoising CAE

Overview

The CEBAF Large Acceptance Spectrometer at 12 GeV (CLAS12) is located at Hall B, one of the experimental halls at the Jefferson Lab in Newport News, VA, serving a variety of physics experiments with different running conditions. The forward part of CLAS12 is built around a superconducting toroidal magnet (Figure 2). The six coils of the toroid divide the detector azimuthally into six sectors. Each sector contains three multi-layer drift chamber (DC) for reconstructing the trajectories of charged particles originating from a fixed target. One sector is composed of three drift chambers (called "regions"), each consisting of two sections (called "super-layers").

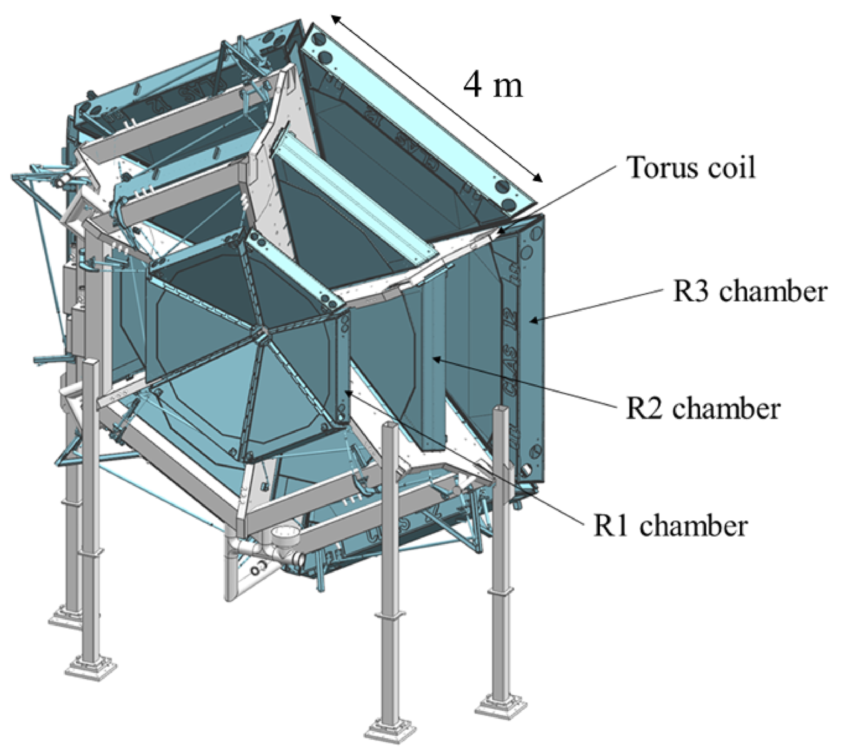

Fig. 2: View of CLAS12 detector showing Drift Chambers and Toroidal Magnet

- The Drift Chambers are used for tracking charged particles. Each super-layer has six layers of wires (12 wire planes in each "region") and each layer of wires has 112 hexagonal cells.
- Figure 3 presents some example events shown for one sector at a time. The top row depicts raw hits detected on a sector while the bottom depicts only those belonging to identified tracks. Hits present in the top row but missing on the bottom comprise the noise hits of the event.
- The efficiency of track reconstruction relies on cleanly identifying segments (clusters) in each super-layer. With increased noise, which arises from running with high beam intensity, removal of noise hits with conventional algorithms becomes less efficient, and with loss of segment the tracking efficiency suffers.
- With this work, we study how Convolutional Auto-Encoders can improve the segment finding algorithm by removing uncorrelated hits from noisy raw data.

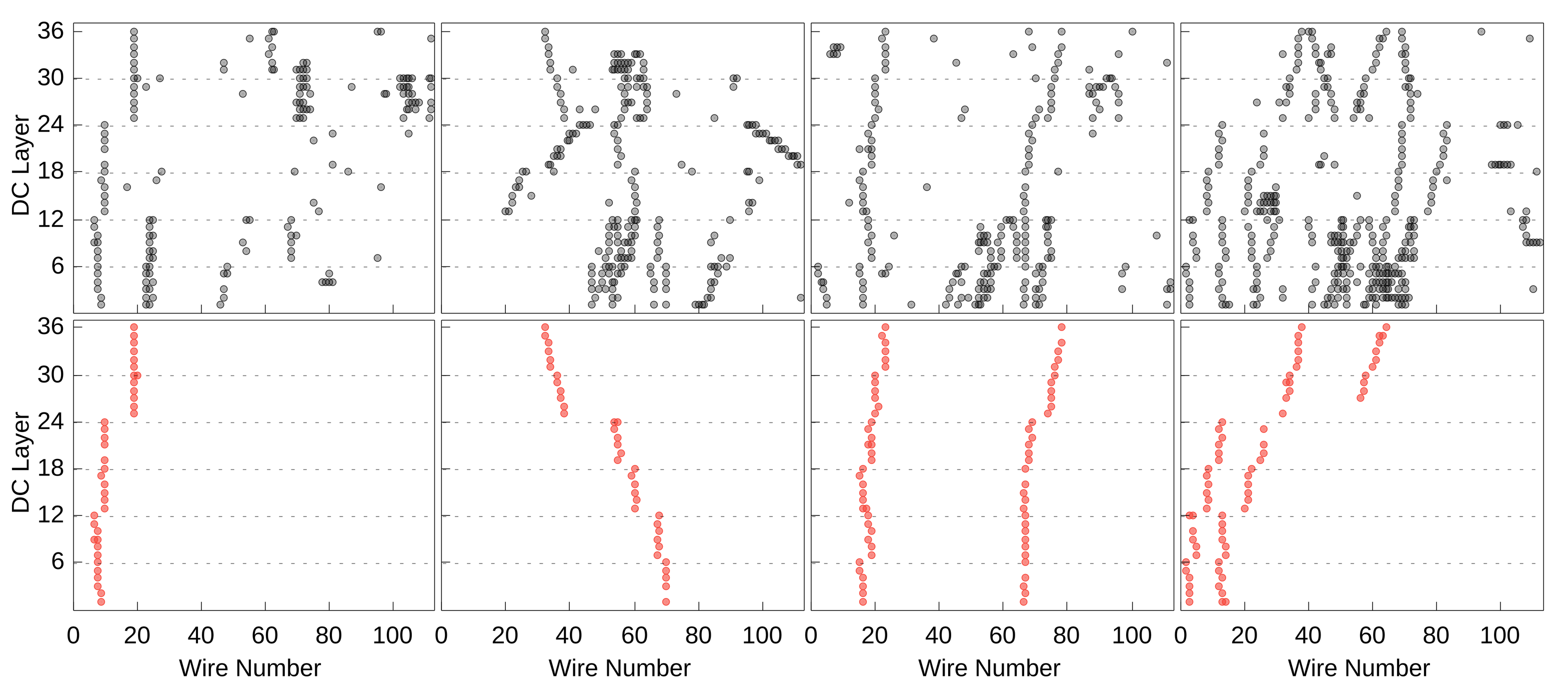

Fig. 3: Example events from drift chambers

Results

- Increased reconstruction efficiency: 86% at beam current 150nA using our methods compared to 88% at 45nA for conventional method (Figure 4)
- Same efficiency for 3 times higher beam current resulting in 3 times less time for experiments.
- Huge increase in number of reconstructed protons under the missing mass peak (Figure 5).

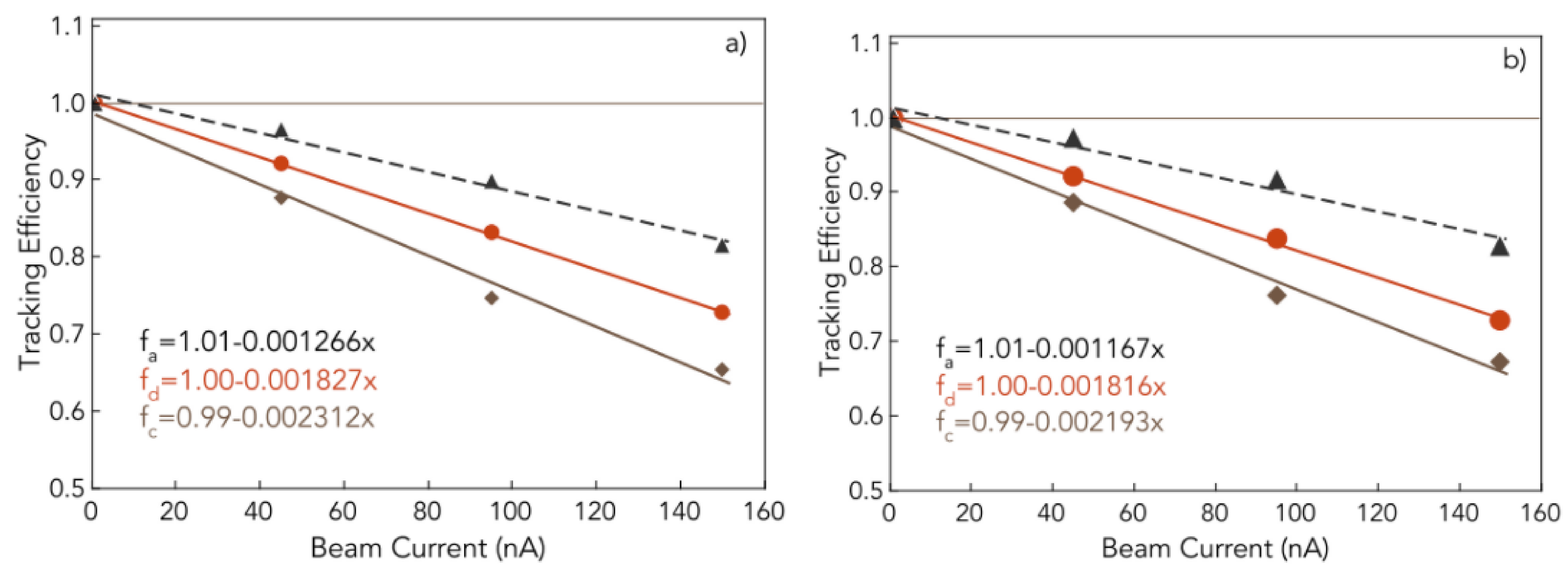

Fig. 4: Tracking efficiency as a function of luminosity (beam current) for positive (a) and negative particle (b). The efficiency is shown for conventional algorithm running on background merged files (diamonds), denoised files (circles) and denoised files using the ML component already part of CLAS12 from our previous work(triangles).

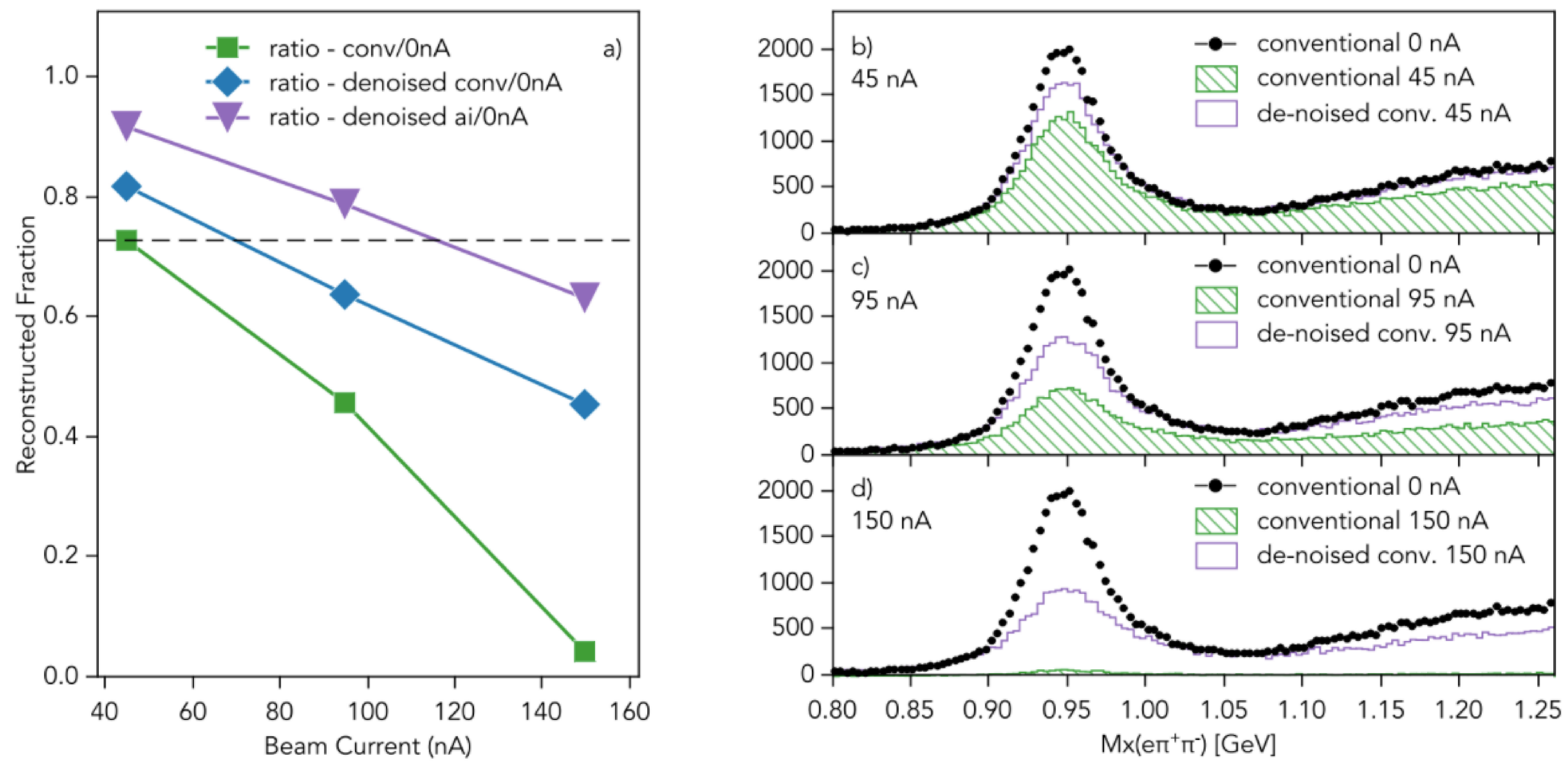

Fig. 5: Number of reconstructed protons from missing mass for data reconstructed with conventional tracking (squares), de-noised data with conventional tracking (diamonds) and denoised data sample reconstructed with AI assisted tracking algorithm (triangles) (a). Reconstructed missing mass distributions for data reconstructed with conventional tracking (filled), and de-noised data sample reconstructed with AI assisted algorithm (solid line). Missing mass distribution for data sample before background merging (0 nA) is shown (circles) for reference.

Acknowledgments

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