



# KINEMATIC EDGE DETECTION USING FIR FILTERS

S. Caiazza, M. Berggren, J. List, M. Wittel



# INTRODUCTION

## Derived from the PhD theses:

- S. Caiazza: [The GridGEM module for the ILD TPC & A new algorithm for kinematic edge determination](#)
- M. Chera-Wittel: [Particle Flow: From First Principles to Gaugino Property Determination at the ILC](#)

## Initial publication report

- M. Chera-Wittel: [Publication report @ ILD group meeting](#)

## Kinematic Edge Detection Using Finite Impulse Response Filters

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\* *DESY*

### Abstract

Various physics observables can be determined from the localisation of distinct edge-like features in distributions of measurement values. In this paper, we address the observation that neither differentiating nor fitting the measured distributions is robust against significant fluctuations in the experimental data. We propose the application of Finite Impulse Response (FIR) filters instead. To demonstrate the method, we consider the typical case in particle physics in which the precise localisation of kinematic edges, often blurred by e.g. background contributions and detector effects, is crucial for determining particle masses. We show that even for binned data, typical for high energy physics, the optimal FIR filter kernel can be approximated by the *first derivative of a Gaussian* (FDOG). We study two highly complementary supersymmetric scenarios that, if realised in nature, could be observed at a future high-energy  $e^+e^-$  collider such as the International Linear Collider (ILC) or the Compact Linear Collider (CLIC). The first scenario considers the production of  $\tilde{e}^\pm$ -pairs while the second focuses on the  $\tilde{\chi}_1^\pm$  and  $\tilde{\chi}_2^0$ -pair production. We demonstrate that the FIR filter method for edge extraction is superior to previously employed methods in terms of robustness and precision.

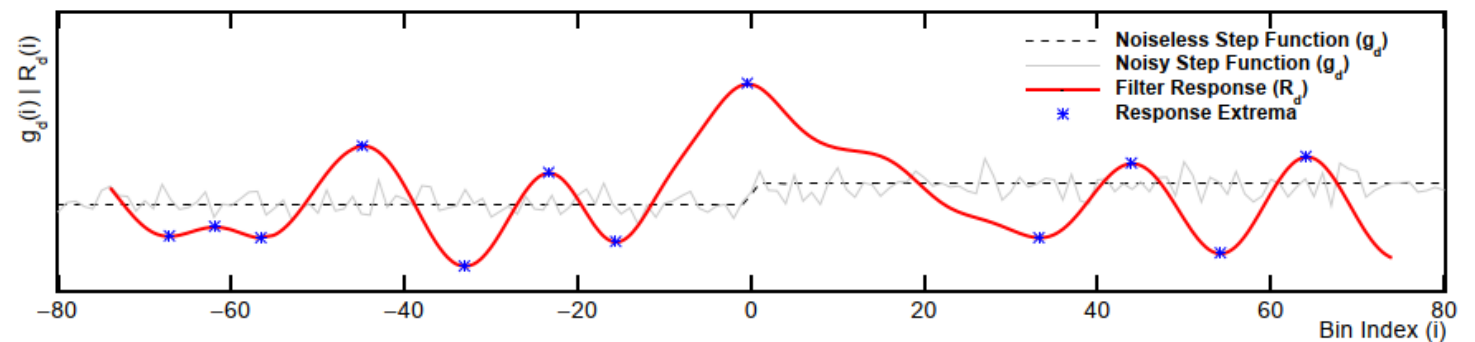
# PUBLICATION SUMMARY

## Abstract

- How to use numerical analysis techniques typical of image and signal processing to identify with the highest precision the position of an edge-like feature in a discrete distribution like a histogram

## Content structure

- Introduction
- Theoretical basis, description of the algorithm and of the characterization procedure
- Description of the two ILD scenarios which provide a suitable testing ground
- Application of the algorithm to those two analysis
- Conclusions



# REVIEW SUMMARY

## **Review process**

- ILD referees: D. Jeans and R. Ete
- First submitted Apr. 18, 2019. First review round May 2019
- Second submission June 11, 2020. Second review round June 2020

## **Relevant contributions from the review process**

- Identify and explain better the key messages.
- Identify further observables to deliver a clearer message.
- The key points and the numerical results of the benchmark remained the same

# KEYPOINTS

## What is it and when to use it

- A numerical algorithm to measure the position of the flex point of a function reducing the effect of noise or statistical fluctuations
- Best used when there is no analytic function modelling the distribution without arbitrary assumptions
- E.g. The position of kinematic edges when the initial state or the resolution effects cannot be described by an analytic function (that is almost always)

## How do we estimate the errors

- Characterizing the method on analytic test functions to understand its performance
- Data-driven approach to evaluate the statistical errors
- With a set of Montecarlo tests to evaluate the systematic errors and calibrate the measurement

## How can this technique improve the results of an analysis

- Apply the algorithm to two ILD benchmark scenarios already analyzed with other methods
- Improved resolution in the determination of the  $s$ -electron masses in the STC4 scenario
- Improved stability in the determination of the charginos and neutralinos masses in the Point 5 scenario

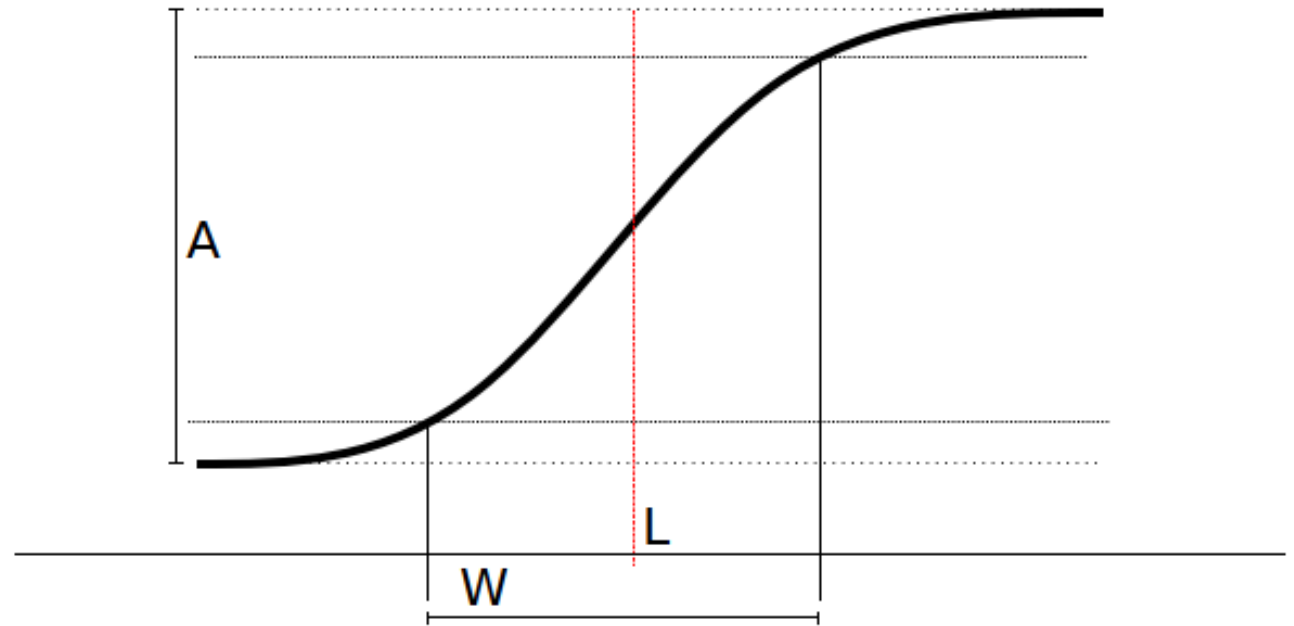
# RELEVANT CHANGES: SEC. 2

## Properly defined the characterizing parameters of the benchmark functions

- For all presented benchmarks we will use a Gaussian smoothed step
- The width is the distance between the 10<sup>th</sup> and the 90<sup>th</sup> percentile
- The signal for the definition of the SNR is the maximum value of the analytic derivative

## Clarified that the algorithm applies to discrete functions in general, not just histograms

- Consistently used the word grid spacing, rather than binning unless explicitly referring to histograms



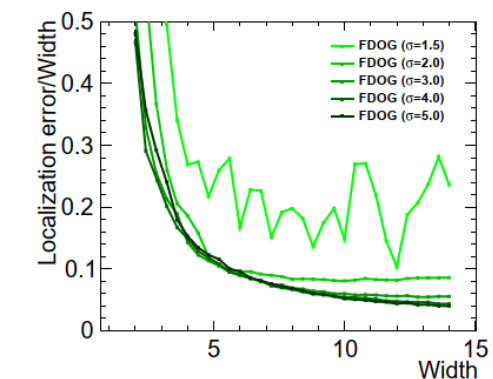
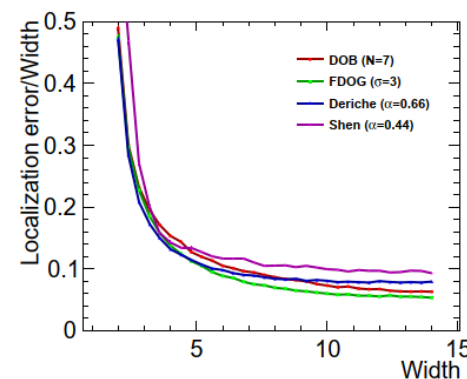
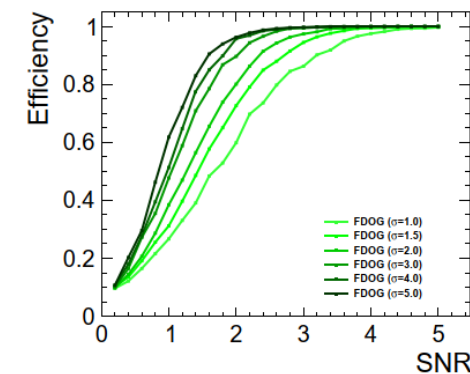
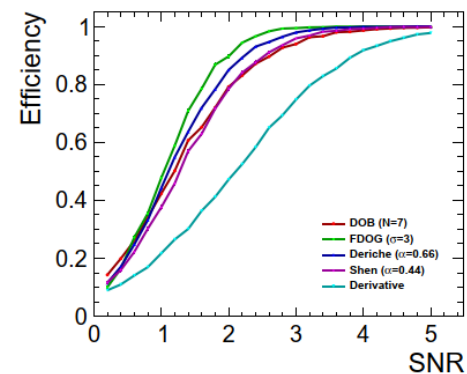
# RELEVANT CHANGES: SEC. 2

## Always showing the benchmark results for the same function set

- Previously for some benchmarks we were comparing different parameterization of the same filter, elsewhere we compared different filters with similar scale.
- Now for all the benchmark we show both type of comparison

## Using the new benchmark observable $\sigma_L/W$

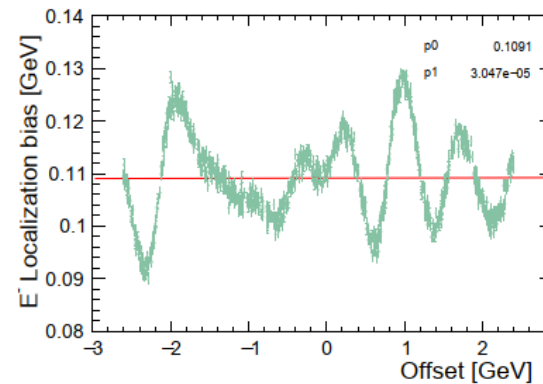
- Simulates the effect of changing the binning resolution
- Useful to transition to the histograms case



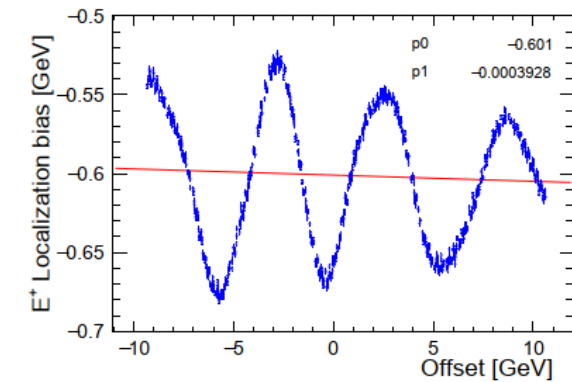
# RELEVANT CHANGES: SEC 4

## Clarified the details of the calibration

- Clarified the source of the characteristic modulation in the calibration plots.
- Improved the explanation of the calibration procedure



(a) Low-momentum edge calibration



(b) High-momentum edge calibration



# SUBMISSION PLANS

Circulate the draft until  
Dec. 9<sup>th</sup>

- Please submit any comment or feedback you may have

Obtain the PSB approval

Submit to arXiv

Submit to NIM A

Thanks to D. Jeans and R. Ete whose feedback improved the publication consistently