

MOEDAL

<u>Monopole and Exotics</u> <u>Detector at the LHC</u>

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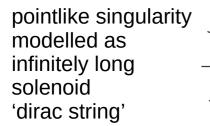
- MoEDAL Physics
- MoEDAL Detector
- Machine learning for MoEDAL

Magnetic Monopoles

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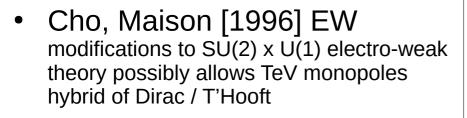
Many different predictions;

Dirac monopole [1931]



• T'Hooft-Polyakov [1973] GUT

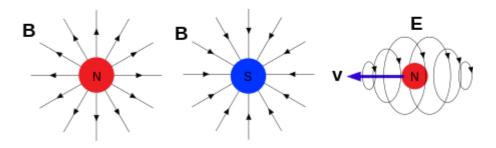
Topological soliton in fundamental gauge fields in theories with broken symmetries.



• Dyons, magnetic and electric

Common properties;

• Acts like particle with magnetic charge. EM interaction with much stronger coupling! $g_D \sim 68.5e$



- Mass ~ varies by theory, uncertain Unconstrained for Dirac monopoles EW 4~10TeV, Tevatron > 600GeV
- Explains charge Quantisation, possibly baryon asymmetry, early cosmos
- Stable if topological solitons

= Heavy, Stable, Highly Ionising

Exotics and HIPs

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Monopole signal = Heavy, Stable, Highly Ionising Similar exotics;

- Stable Massive particles SUSY; stops, staus, gluinos (esp. if parity conserved)
- Multi-Charged particles eg, double charged Higgs Bilepton
- High momentum + low velocity, high ionisation, indicates heavy charged BSM object

at inglier energies are nom ref. 5. vertical ballos indicate boundaries different approximations discussed in the text. The short dotted line " μ^- " illustrate the "Barkas effect," the dependence of stopping power of charge at very low energies [6].

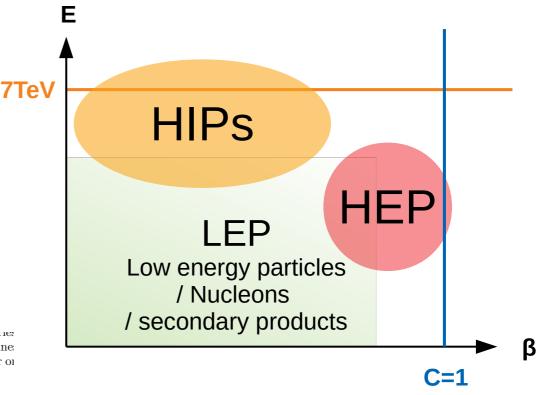
27.2.2. Stopping power at intermediate energies :

The mean rate of energy loss by moderately relativistic charged heav $M_1/\delta x$, is well-described by the "Bethe-Bloch" equation,

$$\mathsf{Lep}\left\langle \frac{dE}{dx} \right\rangle = \mathsf{Hep}\left\{ \frac{1}{2}\ln \frac{2m_e c^2 \beta^2 \gamma^2 T_{\max}}{I^2} - \beta^2 - \frac{\delta(\beta\gamma)}{2} \right] \,.$$

It describes the mean rate of energy loss in the region 0.1 $\lesssim \beta\gamma \lesssim$ intermediate-Z materials with an accuracy of a few %. At the lower projectile velocity becomes comparable to atomic electron "velocities" (S

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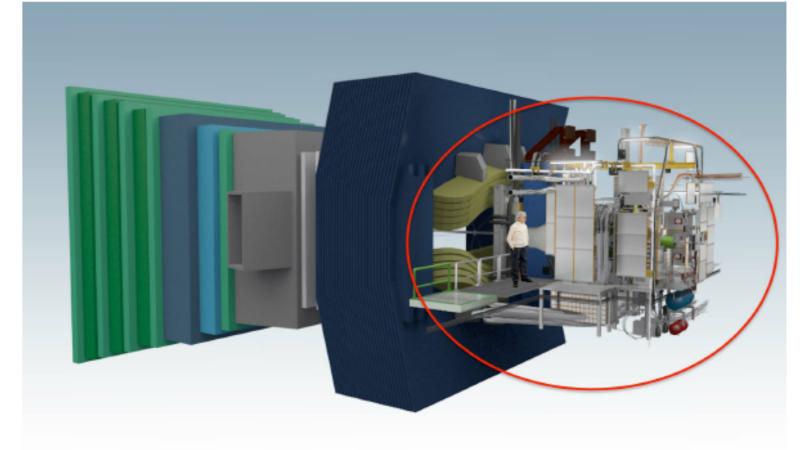


- Detectors optimised triggering on ~ light speed particles, minimally ionising / penetrating
- High bunch crossing rate, most events discarded
- Rare HIP signal, can look like v. common backgrounds

MoEDAL detector

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LHC IP:8



LHCb

MMTs

Aluminium ferromagnetic monopole trappers

NTD array + VHCC

Ionisation detectors (rest of this talk)

MoEDAL

Timepix Radiation environment monitoring

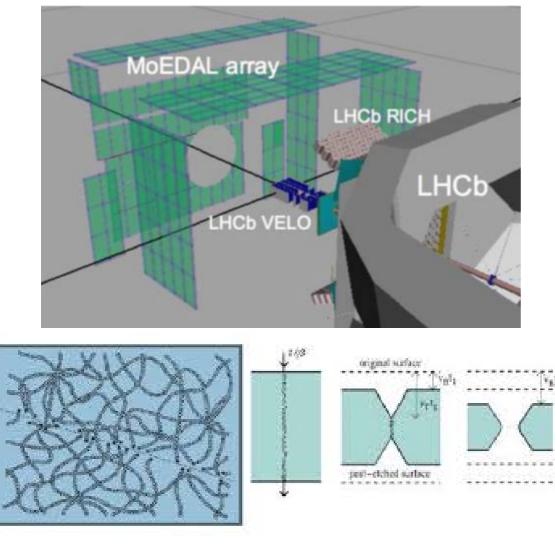
MAPP

Millicharged particle detector

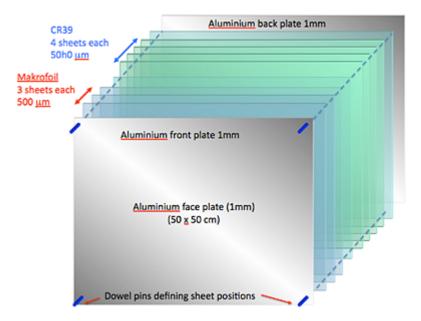
Moedal: NTD arrays

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Stacked Arrays of ionisation sensitive polymer solid state nuclear track detectors (NTDs) Sensitive to Heavily Ionising Particles, low sensitivity to standard model particles

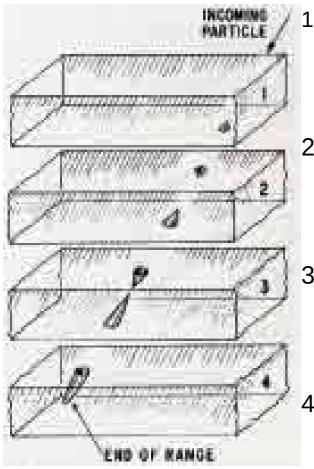


NANOSCOPIC ---> MICROSCOPIC



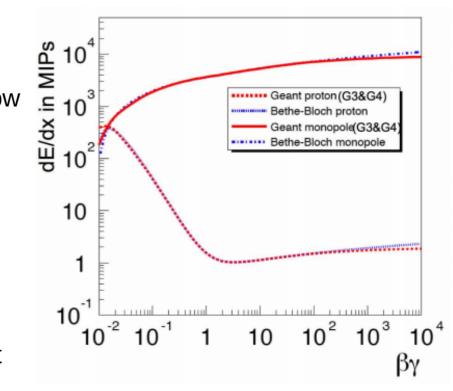
- Ionising particles break polymer chains in NTD foil in localised region
- Leaves latent 'Ion track'
- Chemical etching process occurs faster along ion tracks than bulk medium
- Forms 'etch-pits' where ionising particles entered and exited the foil

Standard Model Ionisation Behavior



Courtesy INF Bologna

- Initial High energy causes minimal ionisation. Doesn't show up as etch pit
- Particle loses energy, lower velocity, efficient 'electronic' ionisation. 'Ranging in'
- Reaches peak energy loss larger etch-pits form at point of entry and exit
- 4. Energy loss, 'electronic' ionisation ceases, etch-pit formation stops.
 'Ranging out'



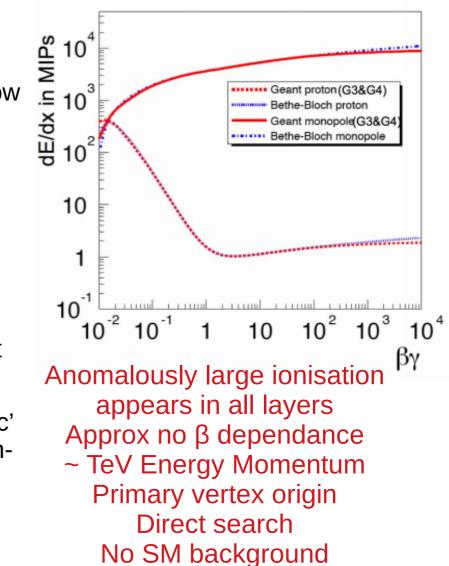
Particles in NTD stack

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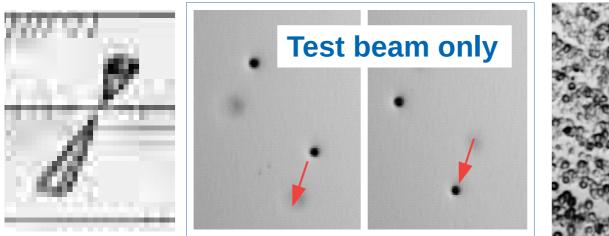
#1: Training / Modelling

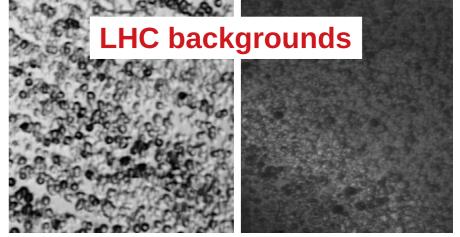
Theoretical parameter space LHC nuclear spallation Showers, detector systematics Non-Linear chemical etching process

multiple β dependant Particle – Polymer interactions HIP goes through all β regimes



- Large variability, huge uncertainties, many parameters. First principles modelling / Monte-Carlo impractical
- No 'real' magnetic monopole examples to train from
- Can simulate HIP signal in given foil layer with calibrated heavy ion beam
- Different ions for different parts of possible energy spectrum
- Realistic signal examples require presence of real background





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#2: Background density

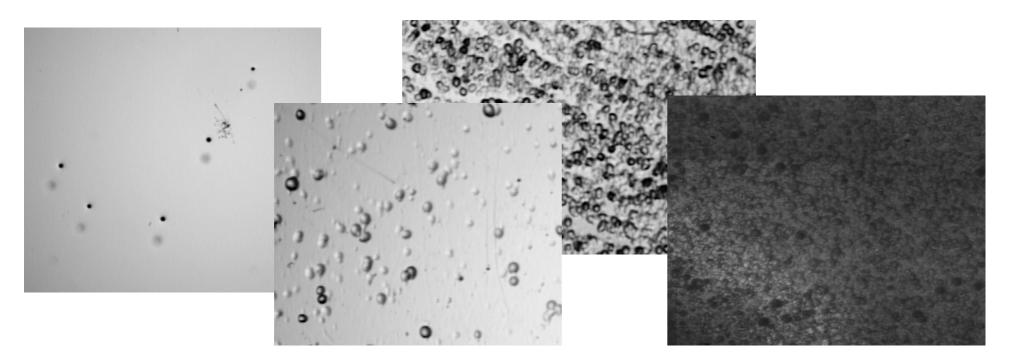
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CR39, Heavy ion test beam

LHC Exposure

Makrofol, heavy ion test beam + 8 months LHC background

2yrs LHC background pile-up



- Problem changes as density increases,
- Images represent ~mm²
 Millions of etch-pits in each cm²
- O(100) m² macroscopic foil area Trillions of etch-pits total

- Foil structure altered by γ rays changes detector response
- Etch-pit clusters merge under etching
- Foil thickness fluctuates

#3: Accurate identification

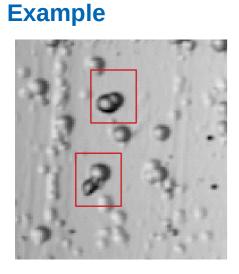
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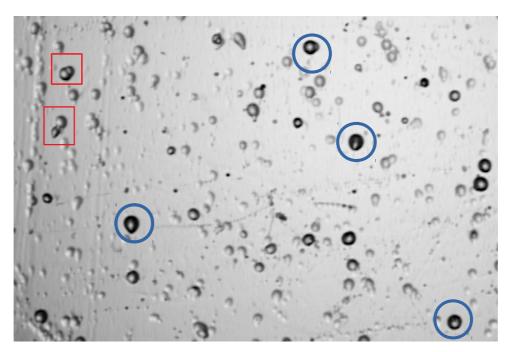
Want to find peak ionisation events

Need robust ~99% signal efficiency and ~99% background rejection

- LHC particle flux; all different SM ionisation behaviour happening
- Pits start to cluster and overlap
- Accurate ID requires detailed 3D inspection. Incompatible with rapid automated scanning
- Supervised learning requires accurate labelling. Have to locate

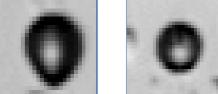


Entry Exit pair? Background cluster?









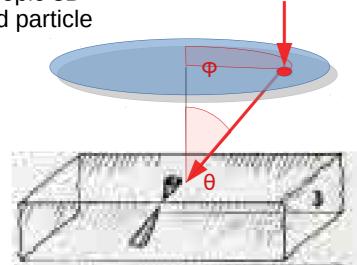
Strong Visual Symmetry between different physics objects / backgrounds

3D Dark-field imaging

 Want to probe microscopic 3D structure to understand particle event interpretation

VS

 Want to rapidly scan macroscopic area with minimal motion and large field of view



- CAN parametrise illumination angle
- LED grid, passing through Fresnell lens. Allows control of θ, φ
- Retain microscopic focal plain alignment over macroscopic area

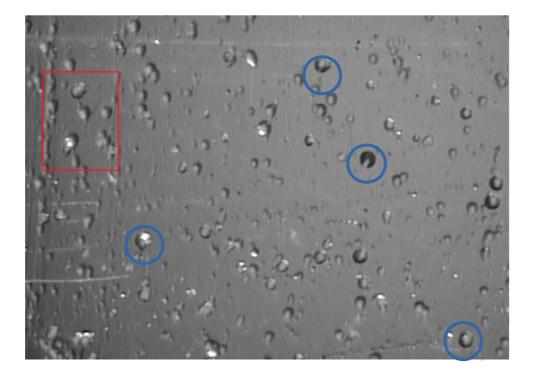
Example

X, Y, Phi becomes 3d data-space

Animation In-phase rotation common origin

Opposite phase possible entry exit

ML / CNN sees all angles at once



Entry exit pairs look different to overlapping bkg Resolve different 3D structures

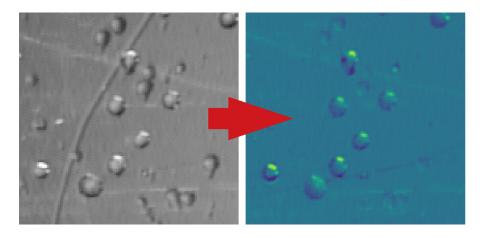
Spot anomalies eg; connected entry exit or heavy ionisations that etch all the way through

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ML – Training / Analysis



"Normalisation" - Redefine relative to local zero, 'clean' up low ionisation pits / de-clutter. Remove systematic imaging biases + non-etch pit visual backgrounds





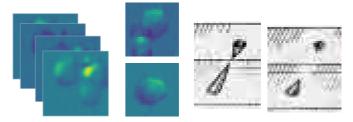
Convolution kernel search for patterns of interest in 3D data space



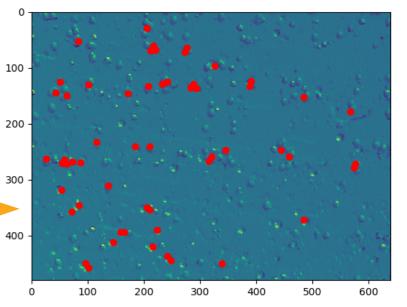


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Build supervised ML dataset from preselection. Train sub-classifiers, eg, entry exit asymmetry ~ dE/dx - can replace initial search with learnt models



Pre-select etch-pits, reject trivial backgrounds, reduce labelling, storage, requirement ~ 1000



ML – Ensemble + inference

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Candidate

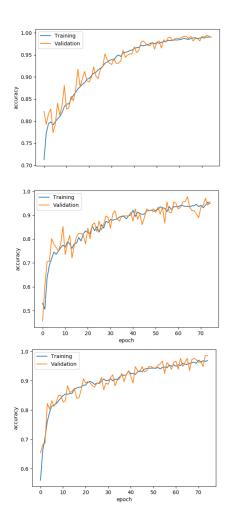
Top Surface Bottom Surface

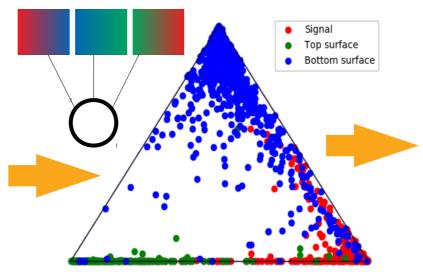
500

 Train specialist experts to handle specific sub-classifications eg, B vs C Eg, top / bottom surface biased ionisation indicating SM range in/out

100

200





- Combine in Ensemble
- Hetrogenous vs Homogenus (classifiers trained on different tasks with different data)
- Geometric combination $C' = C_1 * C_2$ vs arithmetic $C' = aC_1 + bC_2$

Can use in inference to label new areas of foil,

300

Can extend further and use a dense neural network to form the ensemble