

GlobalPID Algorithms Based on Machine Learning for STCF

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CONTENTS

• Introduction

• Identification For Charged Particles

• Identification For Neutral Particles

- GlobalPID Software
- Summary

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The Super Tau Charm Facility (STCF) is an important option for China's future accelerator-based

291 cn

particle physics large-scale scientific facility.



Particle identification (PID) is one of the most important and commonly used tools for the physics

analysis in STCF.

The PID algorithm performance is crutial for exploiting the potential of

STCF detectors.

| ITk • <0.25%X ₀ /layer • σ _{xy} <100 μm | Cylindrical µRWELL CMOS MAPS |
|--|---------------------------------|
| $\begin{array}{l} \text{MDC} \\ \bullet \sigma_{xy} < 130 \ \mu\text{m} \\ \bullet \sigma_{p}/p \sim 0.5\% \ @ \ 1 \ GeV \\ \bullet dE/dx {\sim} 6\% \end{array}$ | Cylindrical Drift chamber |
| PID • π/K (and K/p) 3-4σ separation up to 2GeV/c | RICH with MPGD DIRC-like TOF |
| EMC E range: $0.025 - 3.5 \text{GeV}$ σ_{E} (%) @ 1 GeV Barrel: 2.5 Endcap: 4 Pos. Res. : 5 mm | pCsI + APD |
| MUD • 0.4 - 2 GeV • π suppression >30 | RPC + scintillator |

- $\pi/K(K/p)$ 3-4 σ separation up to 2Gev/c
- μ/π up to 2Gev/c, π suppression ~ 3%
- Good discrimination power for $\gamma/n/K_L^0$



Better particle identification usually requires the combination of information

from multiple sub-detectors.

- Single sub-detector is often sub-optimal
- Usually difficult for traditional PID algorithms to combine all sub-detectors 4

The data-driven machine learning (ML) has provided a powerful toolbox for PID.

- Advantage: Extracting effective information from large amounts of interrelate data
- Widely applied and opening up new possibilities in high-energy physics experiments.
- Achieved outstanding results in the field of PID.
 - LHCb、BelleII、CMS and ALICE
 - Main methods : Boosted Decision Tree (BDT) and Neural Networks (NN)

■ Innovated and developed a Global Particle Identification (GlobalPID) software algorithm

based on the ML techniques.

- Targeting at particle identification problem at the STCF experiment
- Exploration the physical potential

- Achieve optimal PID performance
- To boost the progress of physics analysis work

- Identification of charged particles $(e/\mu/\pi/K/p)$
- Combine all sub-detectors reconstruction information
- * Taking **BDT** (based on XGBoost) as a baseline model
- * Other ML algorithms tested as well :
 - MLP, SVM, Transformer
- Charged hadrons discrimination
- e.g. DTOF raw information: The hit position and time of Cherenkov photons on the sensor
- Based on classical convolutional neural network (CNN) on PID detectors
 - Improve hadron discrimination power
 - As the input for charged particleID



- Neutral particle $(\gamma/K_L^0/n)$ identification
- Fully utilize energy deposition, time response within the ECAL and MUD hit pattern
- * A convolutional neural network is developed for neutral particle identification

Identification For Charged Particles



Data Sample

- The quality of the data samples
 - * High statistics
 - * large momentum and angle coverage
- Data production
 - * Based on OSCAR simulation and reconstruction
 - * MC single charged track using ParticleGun
 - * 50000 tracks for each type ($e\pm$, $\mu\pm$, $\pi\pm$, $K\pm$, $p\pm$)
 - * $p \in (0.2, 2.4) \text{Gev/c}, \theta \in (20^\circ, 160^\circ), \text{ phi} = 0^\circ$
- Pre-processing
 - * Flatten momentum and θ spectrum to avoid bias due to p/ θ distribution
 - * Train:Validation:Test = 8:1:1





Training and Tuning : Feature Selection

- Selecting a subset of the most informative features from large amount of interrelated sub-detectors information can help stabilize the model training process
- Tracker/dEdx/RICH/DTOF/ECAL/MUD reconstructed variables have been collected
- **45** features are kept, feature importance distribution of the features is obtained (Full list of variables please see backup slides)



Training and Tuning : Optimal Hyperparameters

- Target: automated optimization of BDT hyperparameters
 - * Reduce manual intervention and time costs
 - * Improve model efficiency and reliability
- Optimal hyperparameters are obtained based on GridSearchCV
 - Discrimination power between charged particles are used as criteria
 - * Search range of max_depth: [200,1200]
 - Search range of n_estimators: [3,15]
- Selected hyperparameters
 - * max_depth: 7
 - * n_estimators: 800

• Tunning of hyper-parameters



Performance

- BDT model(based on XGBoost) is trained and optimized to discriminate (e, μ , π , k, P)
- Preliminary results have been obtained
 - * Good performance for leptons
 - * Hadron performance is sub-optimal at the moment. Expecting better performance with updated

PID reconstruction algorithms



Performance

0.7

0.6

0.4

0.2

0.9

0.8

0.7

0.5

0.3

0.2

-0.6

-0.4

-0.2

0 cosθ

The signal efficiency for e and μ

0.2 0.4

0.6

0.8



• The signal efficiency and background misidentification rate(no more than 1%) for π at different momentum and angles.

STCF DTOF based on classical convolutional neural network π/k discrimination Zhipeng Yao

The DTOF is located on the end cap of the STCF PID system and is based on an total internal reflection Cherenkov time-of-flight detector.

* Using the hit position and time of Cherenkov photons on the photomultiplier tube, a twodimensional pixel map is constructed and a convolutional neural network is developed for π/k discrimination, further enhancing the PID performance of the DTOF.



The darker areas in the image indicate a higher probability of Cherenkov photons being detected at the corresponding channel at the given time. The overall image represents the topological structure of Cherenkov photons produced by different particles.

STCF DTOF based on classical convolutional neural network π/k discrimination Zhipeng Yao

• model : EfficientNetV2-S Accuracy = 99.46%

| Stage | Operator | Stride | #Channels | #Layers |
|-------|------------------------|--------|-----------|---------|
| 0 | Conv3x3 | 2 | 24 | 1 |
| 1 | Fused-MBConv1, k3x3 | 1 | 24 | 2 |
| 2 | Fused-MBConv4, k3x3 | 2 | 48 | 4 |
| 3 | Fused-MBConv4, k3x3 | 2 | 64 | 4 |
| 4 | MBConv4, k3x3, SE0.25 | 2 | 128 | 6 |
| 5 | MBConv6, k3x3, SE0.25 | 1 | 160 | 9 |
| 6 | MBConv6, k3x3, SE0.25 | 2 | 256 | 15 |
| 7 | Conv1x1 & Pooling & FC | - | 1280 | 1 |

• The signal efficiency and background misidentification

rate for pions/kaons at different momentum and angles.



- Using EfficientNetV2-S as the baseline model and optimizing
- Training:Adding momentum and position information of particle hits in the DTOF outside of the fully connected layers



• The signal efficiency for pions (the background no more than 3%)

14

Identification For Neutral Particles



Data Sample

Energy deposition pixel map (71*136) :

- X-coordinate : Position information
 - Left endcap / Right endcap (0-9/61-70)
 - Barrel (10-60)
- Y-coordinate: CrystallD
- Value: Energy deposition inside the crystal



• Energy deposition pixel map



Neutral Particle Data Sample:

- $\gamma/K_L/n$
- Generated by ParticleGun
- 100,000(Each type)
- $P \in (0, 2.0) \text{ Gev/c}, \theta = 90^{\circ}, \varphi = 0^{\circ}$

CNN



The initial implementation of a global neutral particle discriminator based on CNN

- CNN consists of alternating convolutional and pooling layers, ending with fully connected layers
 - * Convolutional Layer: Use convolutional kernels to extract new hidden features
 - * Pooling Layer: Reduce data dimensionality, prevent overfitting, and reduce resource usage
 - * Fully Connected Layer: Add MUD information in the future

Performance

Analyzing the energy deposition distribution in ECAL (preliminary)

•Neutron:

- Signal efficiency is controlled to be above 80%.
 - •Background misidentification ~20%, mainly for KL

•Gamma:

- *Good photon discrimination performance*
- Signal efficiency > 90%

•K_:

- Signal efficiency > 70%
- Background misidentification ~20%, mainly for Neutron



The neutron and K_L identification capability still needs improvement

GlobalPID Software

- The BDT model and GlobalPID algorithm have been integrated into OSCAR software and is available OSCAR for analysis and research. **GlobalPID**
 - * For the identification of charged particles
 - * Pre-trained model is integrated, and made transparent to users
 - Based on C-API of XGBoost, Provided simple interface and user manual for users



- Development of the ML-based software packages for hadron and neutron particle identification.
- The GlobalPID packages integration : All the software packages will be transferred into the **ONNX** framework.

Applications

Core Software

EDM

Database

External Library/Tools

Geant4

GenFit

Reconstructi

Analysis Visulization

Data I/O

VertexFit

ROOT

CERNLIB

Generator

Simulation

SNIPER

Geometry

Podio

DD4hep

Summary

- To fully exploit the performance of the STCF detector, a novel GlobalPID algorithm based on machine learning is developing.
- Based on a data-driven method, BDT is used as a baseline to discriminate charged particles at STCF.
 - * Extract features from many correlated variables(integrating all sub-detector information)
 - * Provides charged particle identification performance in different PID modes
 - * Drive the fast simulation work
- Integrate PID system information and use CNN to achieve hadron discrimination.
- A global neutral particle identifier based on CNN is initially implemented.
- Preliminary results for the identification of charged and neutral particles have been obtained, but need to be further checked and validated.
- The GlobalPID software package has been completed for charged particles identification and is available for analysis and research.

More study is needed to do:

- * Add time response and MUD information to neutral particle identification
- * Further study the variables used for PID
- * Try other machine learning techniques
- * Upgradation and result verification for GlobalPID software package









• Features

| | 特征量信息 | 说明 | | 特征量信息 | 说明 |
|-----------------------|-----------------|----------------------------------|---------------|-----------------------|--|
| ReconstructinParticle | 'charge' | 重建粒子的电荷 | DEDX | 'dEdXsepE/MU/PI/K/P' | 基于五种粒子假设下的chi2值 |
| | 'momentum.x' | | | | |
| | 'momentum.y' | 粒子在xyz方向上的动量 | RecECALShower | 'numHits' | 在ECAL里的击中数目 |
| | 'momentum.z' | | | energy', | 重建粒子的能量 |
| | <u> </u> | | | 'eSeed' | 种子的能量 |
| RecRICHLikelihood | 'likelihood_e' | 该粒于假设为电于的可能性 | | e3x3 | 3*3晶体内的能重沉积 |
| | likelihood_mu | 该松丁悢旼万muon的可能性 | | e5x5 | |
| | likelihood_k | 该松丁假区为Kaon的可能性 该粒子俚设步kaon的可能性 | | position.x | Shower的X坐你 |
| | 'likelihood_p' | 该粒了限设为Kdoll的可能性 | | position z' | Shower的z处标 |
| | incentrood_p | 风松1 IK 区外的100mm14 船庄 | | 'secondMoment' | 一阶矩阵 |
| DTOFPid | 'logL e' | 粒子分别在五种粒子假设下的 | 可能性 | 'LateralMoment' | 横向矩阵 |
| | 'logL_mu' | | | 'ZernikeMoment{2,0} ' | Zernike2*0矩阵 |
| | 'logL_pi' | | | 'ZernikeMoment {4,2}' | Zernike4*2矩阵 |
| | 'logL_k' | | | | |
| | 'logL_p' | | | | |
| | (. | | MUDTrack | 'theta' | 在极方向上的夹角 |
| TrackerRecTrack | 'helixPar_d0' | | | 'phi' | 在xy半面上的夹角 |
| | | | | • hitNum′ | 在u子探测器里的击甲数 |
| | (halivDar phi) | | | RPCHitNum | 在电阻板至(RPC)中的击中 左朔虹闪烁体探测照上的土中 |
| | nelixPar_phi | | | PSHITNUM 'maxHit' | 在 望 科 内 炼 冲 休 测 奋 上 的 击 中 右 县 十 主 由 粉 昕 左 早 的 主 由 粉 |
| | 'helixPar cna' | | | 'maxHitlaver' | 有限八山干奴川江云的山干奴 有最名主由粉日的巨粉 |
| | | | | maximulayer | 日取少山十致日时公数 |
| | 'helixPar zO' | | | | |
| | — | | | | |
| | 'helixPar_tanl' | | | | |
| 2024/4/46 | | Ve | | | 22 |







• Efficiency distribution









25

• The signal efficiency of Proton







26

• DE/dx Sepa.











- Based on the selected features, various models are studied and tested:
 - Boosted decision tree based on XGBoost and LightGBM
 - Deep neural network
 - Support vector machine
- Model optimization is based on a combination of grid search and bayasian optimization



BDT (XGBoost) is chosen given its performance and tranparency max depth: 7 n estimators: 400