A neural network approach for orienting heavy-ion collision events[†]

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It has been recognized that at relativistic energies, a strong linear response relation exists between the higher-order mean square anisotropic flows and multipole deformations.[1)] This implies that anisotropic flows will serve as a sensitive probe for the nuclear deformations. Considering the presence of statistical effects, we focused on orienting individual events from a microscopic perspective.

Utilizing the isospin-dependent Boltzmann-Uehling-Uhlenbeck (IBUU) transport model, ultra-central collisions ($b < 1$ fm) occurring between stable prolate nuclei of ^{238}U were simulated at 1 GeV/nucleon with random orientations. The collision orientation is represented by Euler angles as $\Omega(\varphi, \theta, 0) = R_z(\varphi)R_y(\theta)R_x(0)$, with $\varphi_{1,2} = \theta_{1,2} = 0$ denoting the body-body collision whose long axis coincides with the x-axis of the laboratory. By filtering out events with spectators from the projectiles, we have

$$\theta_2 \in \begin{cases} [\theta_1, 180° - \theta_1] & \theta_1 < 90° \\ [180° - \theta_1, \theta_1] & \theta_1 \geq 90° \end{cases} \tag{1}$$

and

$$\varphi_2 = \varphi_1 \tag{2}$$

with $\theta_1 \in [0°, 180°]$ and $\varphi_1 \in [0°, 180°]$, and the subscripts 1 and 2 respectively corresponding to the target and the projectile. All orientations are ultimately categorized into six cases, as indicated in Table 1.

Table 1. The initial collision orientations corresponding to the six classification cases.

Case	θ_1 (Target)	θ_2 (Projectile)
1	$[0°, 30°] \cup [150°, 180°]$	$[0°, 30°] \cup [150°, 180°]$
2	$[0°, 30°] \cup [150°, 180°]$	$[30°, 60°] \cup [120°, 150°]$
3	$[0°, 30°] \cup [150°, 180°]$	$[60°, 120°]$
4	$[30°, 60°] \cup [120°, 150°]$	$[30°, 60°] \cup [120°, 150°]$
5	$[30°, 60°] \cup [120°, 150°]$	$[60°, 120°]$
6	$[60°, 120°]$	$[60°, 120°]$

Commonly used observables generated via IBUU simulations are input to a neural network to map the classification of orientations. As shown in Fig. 1, the network called the convolutional orientation classifier (COF) includes inputs such as the anisotropic flows in transverse momentum-rapidity space $v_n(p_t, y_0)$ with $n = 1, 2, 3, 4$, the average anisotropic flow of individual events $\langle v_n \rangle$, the multiplicities of charged particles M_τ with $\tau = p, \pi^-, \pi^+, \Delta^-, \Delta^+, \Delta^{++}$ labeling the types of particles, and the counts of emitted particles at different angles $\theta_\perp(\phi)$ in the transverse(longitudinal) plane. The classification accuracy of the COF network exceeds 70% on both the training and validation sets whose output-channel probability distributions on the actual cases are displayed in Fig. 2. Additionally, we observed that the observables corresponding to different COF channels are consistent with the real classification cases.

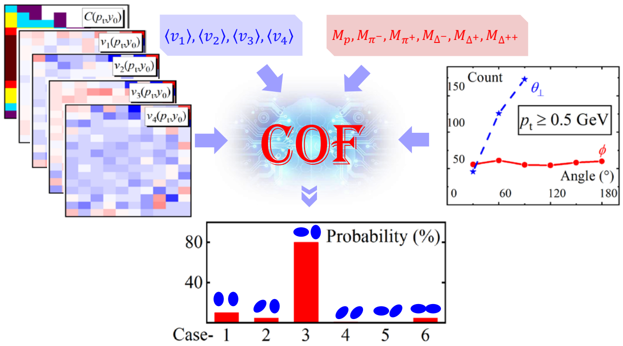

Fig. 1. Schematic of the structure of the convolutional orientation filter (COF) neural network.

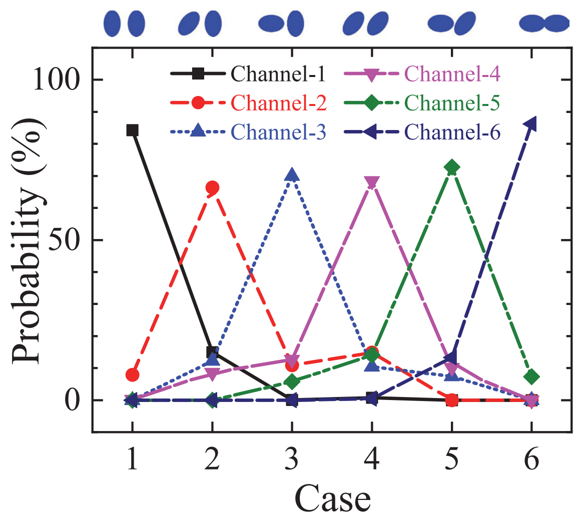

Fig. 2. The probability distribution of the actual case at different predicted channels.

Reference
1) G. Giacalone, J. Jia, and C. Zhang, Phys. Rev. Lett. **127**, 242301 (2021).

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