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Partial Distance Correlation-Based Motion Pattern Detection in Pangasius Fish

Kieu Thuy Thi Phan[1], **Thang Cong Pham**[2], **Hiep Xuan Huynh**[3,4*]

[1] University of Economics Ho Chi Minh City, Ho Chi Minh City, Vietnam
[2] The University of Da Nang – University of Science and Technology, Da Nang, Vietnam
[3] Can Tho University, Can Tho City, Vietnam
[4] CTU Leading Research Team on Automation, Artificial Intelligence, Information Technology and Digital Transformation (CTU-AIMED)

Correspondence: Hiep Xuan Huynh, hxhiep@ctu.edu.vn
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Abstract– **This paper proposes a motion-pattern detection framework for Pangasius catfish based on Partial Distance Correlation (pdCor) to analyze nonlinear dependence under realistic aquaculture conditions. Video sequences are segmented into temporal windows; after image preprocessing (grayscale/normalization, CLAHE, denoising, and sharpening), fish centroid trajectories are extracted. For each window, multi-group motion descriptors are computed, including kinematic features (velocity, acceleration, jerk), directional features (heading angle, angular speed), geometric trajectory measures (path efficiency, tortuosity, spatial entropy), and spectral attributes (spectral entropy, dominant frequency). To remove nuisance effects from illumination variation, school density, and especially the heading angle θ, pdCor is used to quantify conditional dependence between motion features and behavioral indicators, and each window is labeled by the class with the maximum pdCor-based evidence. The framework is evaluated on a real dataset of 38 outdoor videos covering five patterns (*Cruise*, *Burst–Coast*, *Escape*, *Mill*, and *Swarm*) under three experimental scenarios from raw dCor to denoised and confounder-controlled pdCor, with comparisons to other partial dependence measures. Results show that confounder control substantially reduces dispersion in the velocity–acceleration space and improves the stability and interpretability of dependence estimates across patterns, confirming the practical value of pdCor for Pangasius behavior analysis.**

Keywords– **Partial distance correlation; motion pattern detection; pangasius fish behavior; trajectory-based features; behavior analysis**

1 Introduction

In computer vision, motion pattern detection has become an essential research topic for analyzing behavioral dynamics. In aquaculture, the detection of underwater organism motion patterns, particularly those of Pangasius catfish, one of Vietnam's main cultured species [1], is vital for health monitoring, environmental management, and farming optimization. Recent studies have extracted motion cues from videos to analyze velocity, trajectory, direction, and fish density [2]. Object detection models such as YOLOv5 and CME-YOLOv5 have shown strong performance under dense and low-light conditions [3, 4]. Moreover, advanced simulation models including flexible-fin [5], fin-body coupling [6], and autonomous fin-control [7] provide a solid biomechanical foundation for swimming behavior analysis. These developments collectively establish a robust framework for understanding and modeling fish motion patterns in real-world aquaculture environments.

However, most existing works have been mainly based on deep learning classification of behaviors, while little attention has been given to the detection of motion patterns within trajectory data. In addition, no prior study has investigated nonlinear and conditional dependencies among motion variables, particularly when behaviors are influenced by environmental factors such as water flow, illumination, or group density.

In this study, we propose a novel pdCor-based framework for analyzing and detecting Pangasius motion patterns under realistic aquaculture conditions. The contributions are: (1) motion patterns (*Burst–Coast*, *Cruise*, *Escape*, *Mill*, *Swarm*) are detected and analyzed; (2) trajectory-derived motion escriptors are extracted and window labels are assigned using a maximum pdCor-evidence rule; and (3) conditional dependencies are evaluated under a control-variable set Z, with the heading angle θ emphasized as a dominant confounder.

The remainder of this paper is organized as follows: Section 2 presents a review of related work. Section 3 provides the theoretical background. Section 4 introduces the proposed model. Section 5 describes the algorithm for Pangasius motion pattern detection. Section 6 reports the experimental results. Section 7 concludes the study.

2 Realated Work

In the field of computer vision, extensive research has been devoted to the tracking and analysis of fish behavior from experimental videos. Deep learning techniques have been applied to detect behavioral patterns of fish in aquaculture tanks based on trajectory and temporal information [2]. To enhance detection accuracy under complex illumination conditions, optimized versions of the YOLOv5 network have been developed for dense or low light environments [3, 4]. Another important direction has been the simulation of fish motion to understand the hydrodynamic mechanisms of swimming. A flexible fin model was proposed to reproduce realistic locomotion in [5], while fin-body coupling motion was analyzed to evaluate propulsion efficiency [6]. More recently, an autonomous fin-control model has been introduced to accurately reconstruct natural swimming patterns [7]. Nevertheless, most existing studies have remained at the level of descriptive or classification-based behavior analysis, without investigating the dependency structures among motion variables under multivariate and nonlinear conditions.

The Partial Distance Correlation (pdCor) method was introduced by Székely and Rizzo [8] to quantify the dependence between two variables after controlling for the influence of a third variable, while preserving the ability to capture nonlinear relationships. In complex biological motion data, where noise and conditional variability are often present, pdCor has been regarded as a robust and informative statistical measure. Several extensions of the pdCor framework have recently been proposed to improve modeling capability. A multivariate regression formulation, termed Partial Least Distance Square Regression (PLDSR), was introduced to integrate pdCor into highly correlated data environments [9]. Moreover, a conditional correlation expansion has been developed to identify genuine dependencies among variables with higher precision [10]. Beyond traditional statistical domains, pdCor has also been integrated into computer vision pipelines to interpret the relationships between deep features in convolutional neural networks, thereby improving transparency and explainability of deep learning models [11].

Although pdCor has been successfully applied across multiple disciplines, its integration into computer vision systems for fish behavior analysis particularly in aquatic environments has not yet been explored. In this study, a new approach is proposed in which pdCor is embedded within a vision-based motion analysis pipeline to enable interpretable detection of Pangasius motion patterns and to uncover conditional dependencies among behavioral descriptors.

3 Motion Pattern and Partial Distance Correlation

3.1 Motion Trajectory

The trajectory of fish j over a temporal window is defined as a sequence of centroid positions extracted from video frames [12, 13]. Let the trajectory be denoted as

$$\mathcal{T}_j = \{p_j^{(i)}\}_{i=1}^{L}, \quad p_j^{(i)} = (x_j^{(i)}, y_j^{(i)}) \in \mathbb{R}^2, \tag{1}$$

where $p_j^{(i)}$ represents the centroid position of fish j at frame i, L is the number of frames in the temporal window, and (x, y) denote the spatial coordinates.

3.2 Motion Pattern

A motion pattern is formally defined as a multidimensional characterization of fish behavior within a temporal window. The motion pattern $\mathcal{M}_j$ is represented as a tuple

$$\mathcal{M}_j = (\mathcal{T}_j, \mathcal{V}_j, f_j, c_j), \tag{2}$$

where:

- $\mathcal{T}_j$: the trajectory sequence of fish j;
- $\mathcal{V}_j = \{v_j^{(i)}\}_{i=1}^{L-1}$: the velocity sequence;
- $f_j \in \mathbb{R}^d$: the feature vector encompassing kinematic, dynamic, and collective descriptors;
- $c_j \in \{\text{Cruising}, \text{Burst–Coast}, \text{Escape}, \text{Schooling}, \text{Milling}, \text{Swarming}\}$: the motion pattern label.

3.3 Feature Extraction

3.3.1 Kinematic Features: Kinematic features [14, 15] are computed from the speed and acceleration sequences and are designed to capture the basic characteristics of swimming motion

$$v_t = \frac{p_{t+1} - p_t}{\Delta t}, \qquad a_t = \frac{v_{t+1} - v_t}{\Delta t}, \tag{3}$$

where $\Delta t = 1/f_s$ is the frame period. Derived quantities include speed, acceleration magnitude, and jerk

$$s_t = \|v_t\|_2, \qquad a_t = \|a_t\|_2, \qquad j_t = \left\| \frac{\Delta a_t}{\Delta t} \right\|_2. \tag{4}$$

To quantify motion variability, we extract the following statistical features

$$v_{\text{mean}}, v_{\text{std}}, v_{\text{max}}, v_{p90}, a_{\text{max}}, a_{p99}, j_{\text{max}}, cv_v. \tag{5}$$

These features quantify the intensity and temporal variation of fish movement, widely adopted in biomechanical and animal behavior analysis.

3.3.2 Directional Features: The normalized direction vector [16] is given by

$$d_t = \frac{v_t}{\|v_t\|_2 + \varepsilon}. \tag{6}$$

The change in orientation between frames describes local turning dynamics [17]

$$\phi_t = \arccos(\langle d_t, d_{t+1} \rangle), \qquad \omega_t = \frac{\phi_t}{\Delta t}. \tag{7}$$

Mean and percentile statistics of ϕ_t and ω_t indicate the stability and turning aggressiveness of motion, which are crucial for differentiating *Cruising* (straight) and *Milling/Swarming* (chaotic) behaviors.

3.3.3 Geometric Trajectory Features: Spatial organization is characterized by the ratio between path length and displacement [18, 19]:

$$\text{efficiency} = \frac{\|p_L - p_1\|_2}{\sum_{t=1}^{L-1} \|p_{t+1} - p_t\|_2 + \varepsilon}, \tag{8}$$

$$\text{tortuosity} = \frac{\sum_{t=1}^{L-1} \|p_{t+1} - p_t\|_2}{\|p_L - p_1\|_2 + \varepsilon}. \tag{9}$$

Spatial entropy and coverage are computed over an 8×8 grid of positions [20]:

$$\text{entropy}_{\text{traj}} = -\sum_{i,j} p_{ij} \log p_{ij}, \tag{10}$$

$$\begin{aligned}\text{spatial\_coverage} &= (\max x_t - \min x_t) \\ &\quad \times (\max y_t - \min y_t).\end{aligned} \tag{11}$$

These features measure how widely and evenly the fish explores space, reflecting collective dispersion and schooling behaviors.

3.3.4 Spectral Features: Temporal regularity and periodicity of motion are analyzed via the Fast Fourier Transform (FFT) of the speed signal [21]:

$$S(f) = \text{FFT}(s_t - \bar{s_t}), \tag{12}$$

$$\text{PSD}(f) = |S(f)|^2. \tag{13}$$

The dominant frequency f_{peak} and the energy ratio at mid-frequency bands (1.0–2.5 Hz) describe *Burst–Coast–Coast* patterns, while the spectral entropy [22] is defined as:

$$\text{entropy}_{\text{spec}} = -\sum_{f>0} p(f) \log p(f), \tag{14}$$

$$p(f) = \frac{\text{PSD}(f)}{\sum_f \text{PSD}(f) + \varepsilon}. \tag{15}$$

3.4 Fish Motion Patterns

Fish motion patterns can be modeled as simplified dynamic systems describing velocity, acceleration, and angular orientation under hydrodynamic constraints [19–25]. Let $\mathrm{x}(t) = [x(t), y(t)]^\top$ denote the fish centroid, $v(t) = \|\dot{\mathrm{x}}(t)\|$ the instantaneous speed, and $\phi(t)$ the heading angle.

3.4.1 Cruise Pattern: During cruising, fish maintain a nearly constant velocity with minimal heading changes, reflecting a stable and energy-efficient locomotion strategy. The kinematic model for cruise behavior [23, 24] is expressed as:

$$\begin{aligned} \mathrm{x}(t) &= \mathrm{x}(0) + v_0\, t\, \hat{\mathrm{n}}, \\ v(t) &\approx v_0, \\ a(t) &\approx 0, \\ \phi(t) &\approx 0, \end{aligned} \tag{16}$$

where v_0 is the steady swimming speed and $\hat{\mathrm{n}}$ is the unit direction vector. This motion corresponds to low kinetic variation, high path efficiency, and minimal directional entropy, indicative of streamlined and goal-directed movement.

3.4.2 Burst–Coast Pattern: The *Burst–Coast* pattern alternates between a tail-driven acceleration phase and a passive coasting phase dominated by drag [25, 26]. The velocity profile over time can be modeled as:

$$v(t) = \begin{cases} v_0 + at, & t \in \text{Burst phase}, \\ v_{\max} e^{-\gamma(t-t_b)}, & t \in \text{Coast phase}, \end{cases} \tag{17}$$

where a is the active acceleration, γ the hydrodynamic damping coefficient, and t_b the Burst termination time. v_0 and $v_{\max}$ denote the initial and peak velocities, respectively. This pattern produces quasi-periodic oscillations in the spectral domain with dominant frequency $f_{\text{peak}} \in [1, 2.5]$ Hz.

3.4.3 Escape Pattern: The escape response is triggered by threats, involving a rapid C-shaped body bend followed by a high-speed propulsion [27, 28]. The body curvature angle $\theta(t)$ is modeled as a damped sinusoidal function

$$\theta(t) = A e^{-\beta t} \sin(\omega t), \tag{18}$$

where A is the initial bend amplitude, β the damping factor (viscous dissipation), and ω the oscillation frequency. This model yields large instantaneous angular velocities ω_t and acceleration peaks $a_{\max}$, characteristic of escape maneuvers.

3.4.4 Mill Pattern: In the *Mill* pattern, fish swim collectively around a common center with nearly constant radius [24]. For each individual fish, the radial and angular components of motion are described as

$$r(t) \approx R, \qquad \theta(t) = \theta_0 + \int_0^t \omega(\tau)\, d\tau, \tag{19}$$

where R is the radius of rotation, $\omega(t)$ the angular velocity, and θ_0 the initial angular position. If angular velocity is constant, the angular position simplifies to

$$\theta(t) = \omega t + \theta_0. \tag{20}$$

3.4.5 Swarm Pattern: The *Swarm* pattern represents dense but disorganized group motion without a common orientation [29, 30]. Individual displacement can be modeled as a stochastic process

$$\mathrm{x}(t + \Delta t) = \mathrm{x}(t) + \boldsymbol{\eta}_t, \qquad \boldsymbol{\eta}_t \sim \mathcal{N}(0, \sigma^2 \mathrm{I}), \tag{21}$$

where $\boldsymbol{\eta}_t$ denotes random noise with variance σ^2, and I is the identity matrix. This produces high spatial and spectral entropy, reflecting chaotic local interactions within the swarm.

3.5 Distance Correlation

Distance correlation is a statistical measure designed to detect both linear and nonlinear associations between random vectors. Unlike Pearson correlation, which only captures linear dependence, distance correlation is zero if and only if the variables are independent.

Given two random vectors $\mathrm{X} \in \mathbb{R}^p$ and $\mathrm{Y} \in \mathbb{R}^q$, the distance covariance is defined as

$$\begin{aligned}\mathcal{V}^2(X,Y) &= \mathbb{E}\left[\|X-X'\|\,\|Y-Y'\|\right]\\ &\quad+\mathbb{E}\left[\|X-X'\|\right]\mathbb{E}\left[\|Y-Y'\|\right]\\ &\quad-2\,\mathbb{E}\left[\|X-X'\|\,\|Y-Y''\|\right],\end{aligned} \tag{22}$$

where (X',Y') and (X'',Y'') are independent copies of (X,Y).

The distance correlation is then given by

$$dCor(X,Y)=\frac{\mathcal{V}(X,Y)}{\sqrt{\mathcal{V}(X,X)\,\mathcal{V}(Y,Y)}},\quad dCor(X,Y)\in[0,1]. \tag{23}$$

It satisfies the independence property

$$dCor(X,Y)=0 \iff X\perp Y. \tag{24}$$

The distance correlation is then given by

$$dCor(X,Y)=\frac{\mathcal{V}(X,Y)}{\sqrt{\mathcal{V}(X,X)\,\mathcal{V}(Y,Y)}},\quad dCor(X,Y)\in[0,1]. \tag{25}$$

It satisfies the independence property:

$$dCor(X,Y)=0 \iff X\perp Y. \tag{26}$$

3.6 Partial Distance Correlation

Partial distance correlation (pdCor) [31] is a statistical method used to measure the dependence between two random vectors X and Y, while controlling for the influence of a third variable Z. It extends the concept of distance correlation by removing the confounding effect of Z, making it especially useful in complex systems such as biological motion analysis, where variables like illumination, water flow, or population density may distort direct relationships.

$$pdCor(X,Y\mid Z)=\frac{\mathcal{V}(X,Y)-\dfrac{\mathcal{V}(X,Z)\,\mathcal{V}(Y,Z)}{\mathcal{V}(Z,Z)}}{\sqrt{\left(\mathcal{V}(X,X)-\dfrac{\mathcal{V}(X,Z)^2}{\mathcal{V}(Z,Z)}\right)}}\times\frac{1}{\sqrt{\left(\mathcal{V}(Y,Y)-\dfrac{\mathcal{V}(Y,Z)^2}{\mathcal{V}(Z,Z)}\right)}}. \tag{27}$$

3.7 Motion Pattern Detection

For each temporal window w, the detection procedure is formulated as follows. Let $f^{(w)}$ denote the feature vector and $Y_m^{(w)}$ the indicator (or soft score) for motion pattern m.

The pattern evidence score using partial distance correlation is defined as

$$E_m^{(w)}=\max\left\{0,\ pdCor\left(f^{(w)},Y_m^{(w)}\mid Z^{(w)}\right)\right\}, \tag{28}$$

where $Z^{(w)}$ denotes the nuisance (control) variables for window w.

The final detected pattern is then obtained by selecting the label with the largest pdCor-based evidence

$$\hat{c}^{(w)}=\arg\max_m E_m^{(w)}. \tag{29}$$

4 Partial Distance Correlation-Based Motion Pattern Detection Framework

Figure 1 illustrates a novel processing framework based on Partial Distance Correlation (pdCor) for the automated detection of motion patterns in Pangasius fish. The processing pipeline is organized into five sequential stages, which are designed to extract, analyze, and classify behavioral patterns from video data. In the first stage, image frames are extracted from video sequences in which the swimming behavior of Pangasius is recorded.Next, image preprocessing is performed to normalize and clean the data by converting frames to grayscale, enhancing local contrast using CLAHE, reducing noise with Non-Local Means denoising, and sharpening edges via an unsharp masking technique. In this way, the influence of illumination conditions and observation noise is reduced, and data quality is ensured for subsequent analysis steps. In the third stage, comprehensive features are extracted from the preprocessed frames, including kinematic descriptors (velocity, acceleration, jerk), directional features (heading angle, angular velocity), geometric trajectory characteristics (path efficiency, tortuosity, spatial entropy), and spectral attributes (spectral entropy, dominant frequency, and mid-frequency energy ratio). In the fourth stage, Partial Distance Correlation (pdCor) is applied to quantify nonlinear relationships between motion features and target behavioral patterns, while confounding factors such as illumination conditions, fish density, and related environmental variables are controlled. Finally, in the fifth stage, motion patterns are detected directly from the pdCor values: for each temporal window, the behavioral class whose label exhibits the highest pdCor value with the corresponding motion feature vector is assigned to that window. This pdCor-based decision mechanism enables clear discrimination among characteristic motion patterns such as Cruising, Burst–Coast, Escape, Schooling, Milling, and Swarm under intensive Pangasius farming conditions.

5 Algorithm Partial distance correlation-based Motion Pattern Detection

Algorithm 1 is developed to automatically detect characteristic motion patterns of *Pangasius* fish from video data, where nonlinear associations between trajectory-derived motion descriptors and behavioral pattern indicators are quantified while confounding effects are controlled using Partial Distance Correlation (pdCor). The inputs of the algorithm include a video sequence V, a temporal window length L, a hop size H, a sampling period $\Delta t = 1/f_s$, and a control-variable set $\mathbf{Z}^{(w)}$ (where θ is used as the primary control variable, i.e., the mean heading angle). For each temporal window w, frames are preprocessed and centroid trajectories $\{\mathcal{T}_j^{(w)}\}$ are extracted. Motion descriptors $\mathbf{f}_j^{(w)}$ are then computed for each fish and aggregated into a window-level feature representation $\mathbf{f}^{(w)}$ (e.g., by

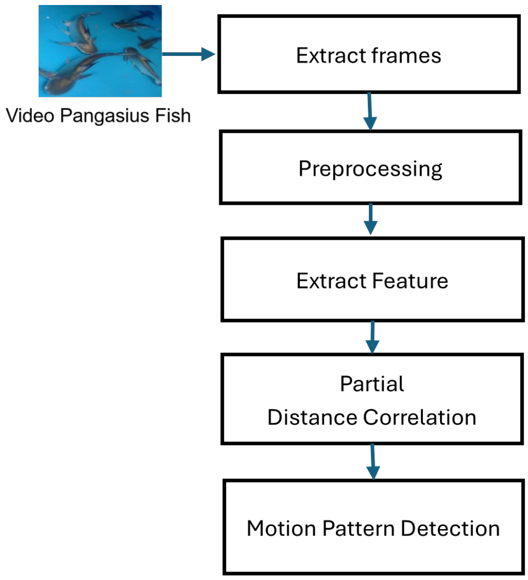

Figure 1. Proposed Framework for Motion Pattern Detection in Pangasius Fish.

averaging across individuals), after which pdCor-based evidence values $E_m^{(w)} = \max\{0, \mathrm{pdCor}(\mathbf{f}^{(w)}, Y_m \mid \mathbf{Z}^{(w)})\}$ are obtained for each motion pattern m. The predicted label $\hat{c}^{(w)}$ is finally determined by the maximum-evidence rule $\hat{c}^{(w)} = \arg\max_m E_m^{(w)}$. The outputs consist of the window-level motion pattern labels $\{\hat{c}^{(w)}\}$ and the corresponding pdCor evidence values $\{E_m^{(w)}\}$.

Algorithm 1: Motion Pattern Detection using Partial Distance Correlation (pdCor)

Input: Video sequence V of Pangasius fish; temporal window length L; hop size H; frame sampling period Δt; control variables Z

Output: Detected motion pattern labels $\hat{c}^{(w)}$

Preprocessing & Trajectory Extraction

$\mathcal{I}^{(w)} \leftarrow \mathrm{Preprocess}(V[w : w + L])$ (gray, resize, CLAHE, denoise, unsharp);

$\{\mathcal{T}_j^{(w)}\}_{j=1}^{J_w} \leftarrow \mathrm{TrackCentroids}(\mathcal{I}^{(w)})$;;

$\mathrm{Z}^{(w)} \leftarrow \mathrm{ExtractControls}(\mathcal{I}^{(w)}, \{\mathcal{T}_j^{(w)}\})$;;

Feature Extraction

foreach *fish* j **do**

  $\mathrm{f}_j^{(w)} \leftarrow \mathrm{Features}(\mathcal{T}_j^{(w)})$ (kin, dir, geom, spec);

Form sample matrix $\mathrm{F}^{(w)} = [\mathrm{f}_1^{(w)}, \ldots, \mathrm{f}_{J_w}^{(w)}]^\top$;;

Partial Distance Correlation (pdCor) Computation

for *each motion pattern* m **do**

  Compute $E_m^{(w)} = \max\left(0, \mathrm{pdCor}(\mathrm{f}^{(w)}, Y_m \mid \mathrm{Z}^{(w)})\right)$

Pattern Decision

$\hat{c}^{(w)} \leftarrow \arg\max_m E_m^{(w)}$

Motion Pattern Detection

return return $\{\hat{c}^{(w)}\}, \{E_m^{(w)}\}$;

6 Experiment

6.1 Dataset

The dataset was collected from 38 videos of Pangasius catfish recorded in outdoor grow-out ponds and holding tanks, faithfully reflecting real production conditions in which characteristic motion patterns frequently occur, such as the startled escape response *Escape* (fish are startled, burst rapidly, and disperse), organized circular swimming *Mill* near pond banks or feeding areas, and dense but disordered surface activity *Swarm* when fish crowd the water surface. The videos were captured using bank-mounted or hand-held cameras positioned approximately 0.5–2 m above the water surface, with oblique top-down viewing angles of about 30°–60°, allowing clear observation of both the school and its surrounding environment. Original video resolutions ranged from HD (1280×720) to Full HD (1920×1080); all frames were subsequently normalized to 96 dpi, and the frame rate was 25 frames per second (fps). Each video has a duration of approximately 1–5 minutes and was recorded under diverse natural lighting conditions (bright sun, partial shade, overcast sky, strong surface reflections), so that a wide range of postures, swimming directions, school densities, and environmental states in Pangasius ponds is represented.

6.2 Motion Patterns in Pangasius Fish

The motion patterns were derived from the Pangasius catfish video dataset, in which a total of 4,593 motion windows were identified and classified into five distinct behavioral classes, as presented in Table I. Each motion pattern was generated based on sequences of 60 consecutive frames extracted from video recordings captured at 30 frames per second. The distribution of these motion patterns was found to be strongly skewed toward the “Mill” behavior, represented by 3,511 windows accounting for 76.4% of the entire dataset. The remaining behaviors were distributed as follows: the “Burst–Coast” motion was detected in 479 windows (10.4%), the “Escape” behavior was observed in 349 windows (7.6%), the “Swarm” motion was identified in 220 windows (4.8%), and the “Cruise” behavior was recorded in only 34 windows (0.7%). The extracted motion patterns and trajectories are illustrated in Figure 2.

6.3 Scenario 1: Distance Correlation without Confounder Control

Scenario 1 was conducted to examine the direct dependence between velocity (x) and acceleration (a) using distance correlation (dCor) without controlling any nuisance variables. As shown in Figure 3, consistently high dCor values were obtained across the five motion patterns, with *Cruise* achieving the

Table I
Distribution of Detected Motion Patterns in Pangasius Fish

Motion Pattern	Number of Windows	Percentage (%)
Mill	3,511	76.4
Burst-Coast	479	10.4
Escape	349	7.6
Swarm	220	4.8
Cruise	34	0.7
Total	**4,593**	**100.0**

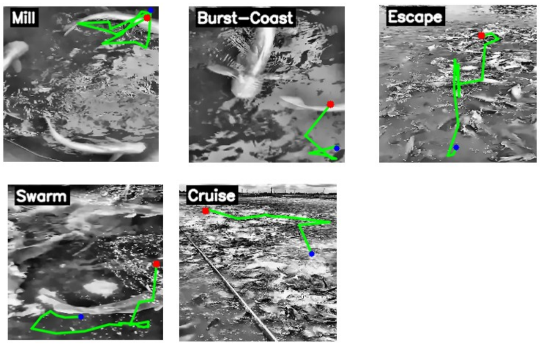

Figure 2. Proposed Framework for Motion Pattern Detection in Pangasius Fish.

highest value (0.989), followed by *Burst–Coast* (0.973), *Swarm* (0.859), and both *Mill* and *Escape* (0.826). These results indicate that a strong (possibly nonlinear) dependence between x and a exists across behavioral categories. However, the scatter distribution in Figure 4 remains widely dispersed with noticeable extreme regions, suggesting that the observed dependence is influenced by unmodeled nuisance factors and measurement noise. Therefore, although dCor is effective for detecting dependence in raw signals, additional refinement is required to isolate the intrinsic kinematic relationship.

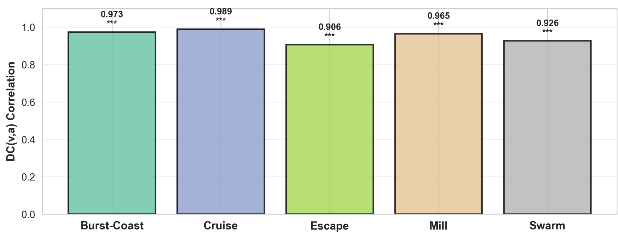

Figure 3. Distance Correlation Values without Control Variable.

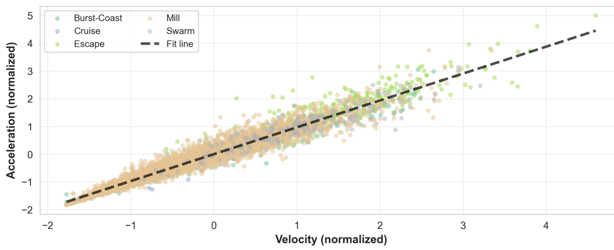

Figure 4. Scatter plot of velocity versus acceleration.

6.4 Scenario 2: Partial Distance Correlation-Based Analysis with Noise Removal

Scenario 2 was designed to evaluate pdCor under two key refinements: (i) denoising and (ii) explicit control of the heading-angle variable θ. First, pdCor values computed on denoised data (Figure 5) remain high for all patterns, with *Cruise* (0.973) and *Burst–Coast* (0.971) being the highest, followed by *Mill* (0.870), *Swarm* (0.856), and *Escape* (0.852). This indicates that the velocity–acceleration dependence is preserved and becomes more consistent after noise suppression. More importantly, after the effect of θ is removed, the residual velocity–acceleration relationship (Figure 6) clusters tightly around the linear regression line with markedly reduced dispersion. This confirms that θ acts as a dominant confounder in the x–a interaction, and that controlling θ is critical for improving interpretability and stability.

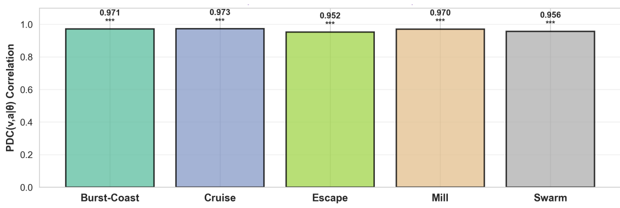

Figure 5. PdCor values across motion patterns on denoised data.

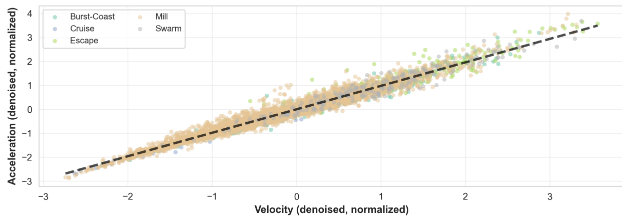

Figure 6. Residual velocity–acceleration scatter after controlling the heading angle θ (denoised data).

6.5 Scenario 3: Comprehensive Comparison of Dependence Measures under Control

Scenario 3 was designed to provide a comprehensive comparison of four dependence measures, namely dCor, pdCor, Partial Pearson, and Partial Spearman, on data balanced using the *undersampling* strategy. As shown in Figure 7, all measures yielded very high dependence values (above 0.90), confirming a strong coupling between the two kinematic features X (mean velocity) and Y (mean acceleration). The highest value was produced by dCor, reflecting unconditional dependence when the nuisance effect of the confounder Z was not removed, whereas more conservative estimates were obtained by the partial measures (pdCor, Partial Pearson, and Partial Spearman) after controlling for Z. Nevertheless, only a minor reduction was observed, indicating that the X–Y relationship remained robust after the confounding effect was accounted for. In addition, the pattern-wise comparison (Figure 8) showed that high dependence was consistently preserved across most motion patterns (approximately 0.88–0.98), supporting the view that the velocity–acceleration dependence constitutes an intrinsic and consistent kinematic property rather than being dominated by any specific behavioral group. Notably, a pronounced decrease of Partial Spearman was observed in low-variability regimes (e.g., *Cruise*), despite data balancing, suggesting potential instability of rank-based partial measures when many tied ranks or limited dispersion are present, while distance-based measures (dCor/pdCor) exhibited better stability. In this context, dCor/pdCor were indicated as suitable choices for nonlinear dependence analysis under confounder control, particularly for behavioral data that are heterogeneous and prone to observational noise.

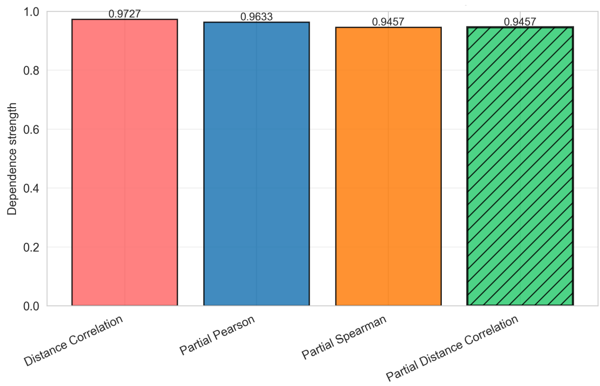

Figure 7. Comparison of four dependence measures between mean velocity and mean acceleration.

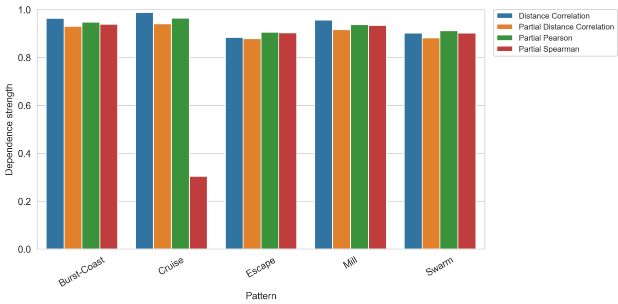

Figure 8. Four dependence measures across motion patterns.

7 Conclusion

A motion-pattern detection framework for Pangasius fish has been proposed based on Partial Distance Correlation (pdCor) to analyze nonlinear dependence under realistic aquaculture conditions in which multiple nuisance factors are present. A complete processing pipeline has been constructed, including frame extraction, image preprocessing, centroid-trajectory construction, and multi-group motion feature extraction (kinematic, directional, geometric-trajectory, and spectral descriptors). To isolate intrinsic behavioral dynamics, pdCor has been used to quantify the conditional dependence between motion features and behavioral pattern indicators while confounding variables are controlled, with particular emphasis placed on the heading angle θ. A direct pdCor-based decision mechanism has then been adopted, by which each temporal window has been assigned the behavioral class with the maximum pdCor evidence score, enabling discrimination among characteristic motion patterns, namely *Cruise*, *Burst–Coast*, *Escape*, *Mill*, and *Swarm*. The effectiveness of the proposed framework has been validated through three experimental scenarios, progressing from uncontrolled raw dependence analysis (dCor), to pdCor combined with denoising and confounder removal, and finally to a comprehensive comparison with other partial dependence measures. The results have indicated that, although high dependence can be detected by dCor in the uncontrolled setting, the velocity–acceleration space remains highly dispersed, reflecting a mixture of observation noise and contextual effects. When denoising and θ control are incorporated, the residual relationship becomes more compact and more interpretable, by which it is confirmed that confounder control is a fundamental requirement for stable behavioral analysis on real Pangasius data. Therefore, pdCor is regarded as a feasible and interpretable tool for motion-pattern analysis and recognition of Pangasius fish in intensive farming environments. In future work, the control-variable set Z will be extended in a multivariate manner (e.g., illumination indices and school-density indicators), and statistical reliability will be strengthened by confidence-interval estimation and dataset expansion to mitigate the impact of class imbalance.

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Kieu Thuy Thi Phan received her Bachelor's degree in Computer Engineering and her Master's degree in Information Systems from Can Tho University, Vietnam. She is currently pursuing her Ph.D. degree at the University of Science and Technology – The University of Danang (DUT), Vietnam. Her research interests include Data Science, Computer Vision, Multimedia, and Artificial Intelligence.

Thang Cong Pham received the Bachelor's degree in 2012 and the Engineering (Specialist) degree in 2013 from Tula State University, Russia, and the Ph.D. degree in Engineering Sciences from the same university in 2016. He did a postdoctoral fellowship at the Centre of Deep Learning and Bayesian Methods, National Research University Higher School of Economics, Moscow, Russia. He is currently an Associate Professor of Computer Science at the Faculty of Information Technology, The University of Danang – University of Science and Technology, Danang, Vietnam. His research interests include data mining, machine learning, image and signal processing, statistical image analysis, optimization methods, and edge-preserving filtering of random fields.

Hiep Xuan Huynh received the Engineer degree from Can Tho University (CTU), the master's degree from the l'Institut de la Francophonie pour l'Informatique (IFI), the Ph.D. degree from the Polytechnics School of Nantes University (Polytech'Nantes), and the Habilitation à Diriger des Recherches (HDR) degree from the l'Université de Bretagne Occidentale (UBO), all in computer science. He is currently a Full Professor of computer science with the College of Information and Communication Technology, Can Tho University, Vietnam. His research interests include Data Mining/KDD/AI/QA, Internet of Things, Cybersecurity, Edge Computing, Blockchains applying in agriculture, aquaculture, and environmental issues. Actually, he keep responsible head of the Leading Research Team on Automation, Artificial Intelligence, Information Technology, and Digital Transformation (CTU-AIMED) of Can Tho University.