

Partial Distance Correlation-Based Motion Pattern Detection in Pangasius Fish

Kieu Thuy Thi Phan¹, Thang Cong Pham², 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

Communication: received xx February 202x, revised xx February 202x, accepted xx March 202x

Online publication: 27 December 2023, Digital Object Identifier: 10.21553/rev-jec.xxx

The associate editor coordinating the review of this article and recommending it for publication was Prof. Hoang Van Phuc.

Abstract– In computer vision, behavioral recognition of aquatic organisms plays an important role, particularly for *Pangasius* catfish, a fish species commonly cultured in Vietnam. This study presents a method for detecting *Pangasius* motion patterns comprising 38 catfish videos with a total of 236,133 extracted frames, from which 4,593 motion windows are extracted and classified into six behavioral categories (Cruising, Burst-Coast, Escape, Schooling, Milling, and Swarming) based on Partial Distance Correlation (PDC) integrated with video processing techniques and feature extraction methods. Experimental results show that Distance Correlation (dCor) on raw data yields high correlation values (0.826–0.989) but with substantial scatter. PDC with heading angle control maintains elevated values (0.804–0.979) with tighter residual clustering. When denoising is combined with heading angle control, pdCor achieves optimal efficacy (0.852–0.973). Compared with dCor, pdCor provides consistent improvements, especially for complex behaviors (Escape: 5.1%; Swarm: 3.2%). The combined strategy detects 40% of patterns better and 60% similarly, indicating pdCor does not reduce performance for simple behaviors but substantially improves detection for nonlinear, high noise patterns.

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 condi-

tional 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 approach based on Partial Distance Correlation (pdCor). Partial Distance Correlation is a modern statistical technique that measures the degree of dependence between two variables after controlling for the effect of a third variable. The proposed research such as: 1) Detecting motion patterns of *Pangasius* fish including Burst-Coast, Cruise, Escape, Mill, and Swarm behaviors; 2) Developing a motion pattern detection model using Partial Distance Correlation; 3) Analyzing conditional dependencies while simultaneously controlling for confounding variables and the directional angle (θ).

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 and discussion. Section 7 concludes the study.

2 RELATED 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 PDC 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:

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

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:

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

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;
- $c_j \in \{\text{Cruising, Burst-Coast, Escape, Schooling, Milling, Swarming}\}$: 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:

$$v_t = \frac{p_{t+1} - p_t}{\Delta t}, \quad a_t = \frac{v_{t+1} - v_t}{\Delta t}, \quad (3)$$

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

$$s_t = \|v_t\|_2, \quad a_t = \|a_t\|_2, \quad j_t = \left\| \frac{\Delta a_t}{\Delta t} \right\|_2. \quad (4)$$

Statistical moments capture motion variability:

$$v_{\text{mean}}, v_{\text{std}}, v_{\text{max}}, v_{p90}, a_{\text{max}}, a_{p99}, j_{\text{max}}, \quad cv_v = \frac{v_{\text{std}}}{v_{\text{mean}} + \varepsilon}. \quad (5)$$

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:

$$d_t = \frac{v_t}{\|v_t\|_2 + \varepsilon}. \quad (6)$$

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

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

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]:

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

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

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

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

$$\text{spatial_coverage} = (\max x_t - \min x_t) \times (\max y_t - \min y_t). \quad (11)$$

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]:

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

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

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:

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

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

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 $\mathbf{x}(t) = [x(t), y(t)]^\top$ denote the fish centroid, $v(t) = \|\dot{\mathbf{x}}(t)\|$ 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:

$$\mathbf{x}(t) = \mathbf{x}(0) + v_0 t \hat{\mathbf{n}}, \quad v(t) \approx v_0, \quad a(t) \approx 0, \quad \phi(t) \approx 0, \quad (16)$$

where v_0 is the steady swimming speed and $\hat{\mathbf{n}}$ 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–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:

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

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:

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

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:

$$r(t) \approx R, \quad \theta(t) = \theta_0 + \int_0^t \omega(\tau) d\tau, \quad (19)$$

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:

$$\theta(t) = \omega t + \theta_0. \quad (20)$$

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:

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

where $\boldsymbol{\eta}_t$ denotes random noise with variance σ^2 , and $\mathbf{I}$ 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 $\mathbf{X} \in \mathbb{R}^p$ and $\mathbf{Y} \in \mathbb{R}^q$, the distance covariance is defined as:

$$\mathcal{V}^2(\mathbf{X}, \mathbf{Y}) = \mathbb{E}[\|\mathbf{X} - \mathbf{X}'\| \|\mathbf{Y} - \mathbf{Y}'\|] + \mathbb{E}[\|\mathbf{X} - \mathbf{X}'\|] \mathbb{E}[\|\mathbf{Y} - \mathbf{Y}'\|] - 2 \mathbb{E}[\|\mathbf{X} - \mathbf{X}'\| \|\mathbf{Y} - \mathbf{Y}''\|], \quad (22)$$

where $(\mathbf{X}', \mathbf{Y}')$ and $(\mathbf{X}'', \mathbf{Y}'')$ are independent copies of $(\mathbf{X}, \mathbf{Y})$.

The distance correlation is then given by:

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

It satisfies the independence property:

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

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It satisfies the independence property:

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

3.6 Partial Distance Correlation

Partial distance correlation (pdCor) [31] is a statistical method used to measure the dependence between two random vectors $\mathbf{X}$ and $\mathbf{Y}$, while controlling for the influence of a third variable $\mathbf{Z}$. It extends the concept of distance correlation by removing the confounding effect of $\mathbf{Z}$, 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.

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

3.7 Motion Pattern Detection

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

The pattern evidence score using pdCor is defined as:

$$E_m^{(w)} = \max \left\{ 0, pdCor(\mathbf{f}^{(w)}, Y_m^{(w)} | \mathbf{Z}^{(w)}) \right\}. \quad (28)$$

The final detected pattern is determined as:

$$\hat{c}^{(w)} = \arg \max_m \left[\lambda_m E_m^{(w)} + (1 - \lambda_m) S_m^{(w)} \right], \quad (29)$$

where:

- $S_m^{(w)}$: classification score (e.g., from a neural or SVM model);
- $\lambda_m \in [0, 1]$: fusion weight controlling the balance between pdCor-based evidence and classifier confidence.

4 PARTIAL DISTANCE CORRELATION-BASED MOTION PATTERN DETECTION FRAMEWORK

Figure 1 illustrates a novel framework based on Partial Distance Correlation (pdCor) for automated motion pattern detection in *Pangasius* fish. The processing pipeline comprises five sequential stages designed to extract, analyze, and classify behavioral patterns from video recordings. In the first stage, frames are extracted from video sequences capturing the swimming behavior of *Pangasius* fish, as depicted in the initial step of Figure 1. Subsequently, image preprocessing is performed to normalize image data and eliminate noise artifacts, thereby ensuring data quality for downstream analysis. In the third stage, comprehensive features are extracted from preprocessed frames, encompassing 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, mid-frequency energy ratio).

The core methodological contribution is presented in the fourth stage of Figure 1, where Partial Distance Correlation is applied to quantify nonlinear associations between motion features and target behavioral patterns while simultaneously controlling for confounding variables such as illumination conditions, fish density, and hydrodynamic flow. Finally, in the fifth stage depicted in Figure 1, motion patterns are detected through fusion of pdCor results with classification scores derived from machine learning models using a weighted combination function. The behavioral class associated with the highest evidence value is selected as the final prediction. This integrated approach, as illustrated in Figure 1, enables accurate discrimination among characteristic motion patterns namely, Cruising, Burst-Coast-Coast, Escape, Schooling, Milling, and Swarm in complex aquatic biological systems.

5 ALGORITHM PARTIAL DISTANCE CORRELATION-BASED MOTION PATTERN DETECTION

Algorithm 1 is developed to automatically and accurately detect characteristic motion patterns of *Pangasius* fish from video data, whereby nonlinear associations between motion features (velocity and acceleration) and target behavioral patterns are measured, while the influence of the heading angle (θ) is controlled through the Partial Distance Correlation (pdCor) method. The inputs of the algorithm are composed of: a video sequence V , in which the swimming behavior of *Pangasius* fish is recorded; a temporal window length L ; a hop size H for window sliding; a frame sampling period $\Delta t = 1/f_s$; and a control variable $Z = \theta$ (mean heading angle). The outputs of the algorithm consist of: (1) predicted motion pattern labels $\hat{c}^{(w)}$ that are determined for each temporal window w ; (2) PDC evidence values $E_m^{(w)}$, through which the reliability of

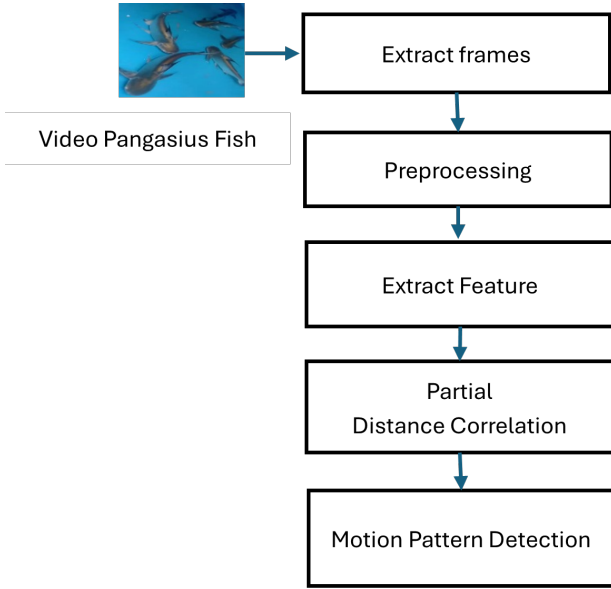


Figure 1. Proposed Framework for Motion Pattern Detection in Pangasius Fish

each motion pattern is expressed after the influence of the heading angle has been controlled; and (3) a final fusion score by which the accuracy of the detection method is evaluated.

6 EXPERIMENT

6.1 Dataset

The collected dataset is comprised of 38 videos of Pangasius catfish that were recorded and processed to extract a total of 236,133 frames. All frames were captured at a frame rate of 30 frames per second, and images were normalized to a resolution of 96 dpi (dots per inch). The dataset was designed to provide a comprehensive repository of Pangasius catfish samples, with video sequences carefully selected to ensure diversity in capturing various behaviors, orientations, and environmental conditions.

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 1. 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

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

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

for each temporal window w do

$V_{\text{proc}} \leftarrow \text{CLAHE}(\text{Grayscale}(V[w : w + L])) - \text{BackgroundSubtraction}()$
 Extract trajectories $\{T_j\}$ from fish centroids

Feature Extraction

for each trajectory T_j do

$\mathbf{f}^{(w)} \leftarrow \text{Concatenate}(\mathbf{f}_{\text{kin}}, \mathbf{f}_{\text{dir}}, \mathbf{f}_{\text{geom}}, \mathbf{f}_{\text{spec}}) \in \mathbb{R}^d$

Partial Distance Correlation (PDC)

Computation

for each motion pattern m do

Compute
 $E_m^{(w)} = \max(0, \text{pdCor}(\mathbf{f}^{(w)}, Y_m | Z^{(w)}))$

Pattern Decision Fusion

for each motion pattern $m \in$

$\{\text{Cruise}, \text{Burst-Coast-Coast}, \text{Escape}, \text{Schooling}, \text{Mill}, \text{Swarm}\}$
do

$S_m^{(w)} \leftarrow \text{ClassifierConfidence}(\mathbf{f}^{(w)}, m)$
 $\text{Score}_m \leftarrow \lambda_m \cdot E_m^{(w)} + (1 - \lambda_m) \cdot S_m^{(w)}$

$\hat{c}^{(w)} \leftarrow \arg \max_m [\text{Score}_m]$

Motion Pattern Detection

return Motion pattern labels $\{\hat{c}^{(w)}\}$ and PDC evidence maps

motion patterns and trajectories are illustrated in Figure 2.

Table I
DISTRIBUTION OF DETECTED MOTION PATTERNS IN PANGASIOUS 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

6.3 Senario 1: Distance correlation without Z Control

Scenario 1 is conducted to evaluate the performance of Distance Correlation (dCor) without confounding variable removal, whereby direct associations between motion features and behavioral patterns of Pangasius fish are detected. As presented in Figure 3, high dCor values are demonstrated across all five motion patterns, with Cruise exhibiting the highest value (0.989), followed by Burst-Coast (0.973), Swarm (0.859), and

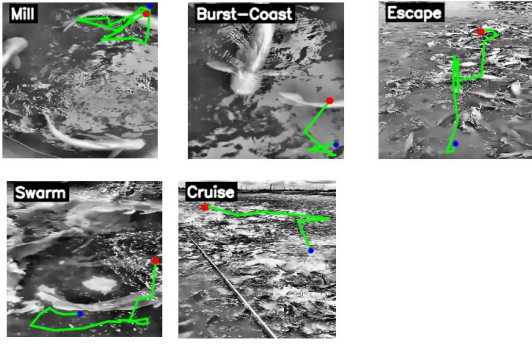


Figure 2. Proposed Framework for Motion Pattern Detection in Pangasius Fish

Mill and Escape both shown to have equivalent values (0.826). These values indicate that strong correlation is demonstrated between velocity (x) and acceleration (a) across different behavioral categories. However, the scatter plot presented in Figure 4 reveals an important additional aspect: the linear relationship between normalized velocity and normalized acceleration is found to be characterized by substantial scatter in the raw data, particularly in extreme regions. This scatter pattern suggests that although dCor is capable of detecting nonlinear associations, the data are found to contain uncontrolled confounding factors that necessitate methodological refinement.

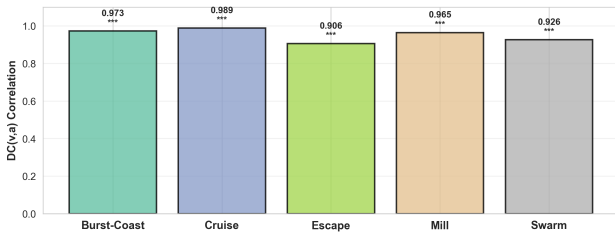


Figure 3. Distance Correlation Values without Control Variable

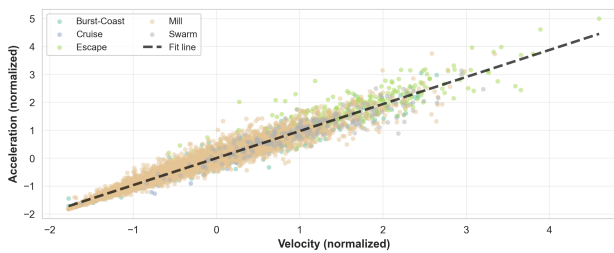


Figure 4. Velocity-Acceleration Relationship in Raw Data

6.4 Senario 2: Partial Distance Correlation based Analysis with Noise Removal

Scenario 2 was implemented to evaluate the performance of Partial Distance Correlation (pdCor), incorporating both noise removal and directional variable (θ) control. In Figure 5, the bar chart on the left displays pdCor values on noise-removed data for motion patterns, with Cruise reaching the highest

value (0.973), followed by Burst-Coast (0.971), then Mill (0.870), Swarm (0.856), and Escape (0.852). These values are all high, reflecting that when data are completely denoised, the nonlinear relationship between velocity and acceleration becomes more apparent and more consistent. In Figure 6 (after θ is removed from the denoised data), a much clearer picture is revealed: the data cluster very tightly around the linear regression line with minimal scatter, showing that when both noise and the influence of heading angle are removed, the fundamental relationship between velocity and acceleration becomes truly linear and predictable.

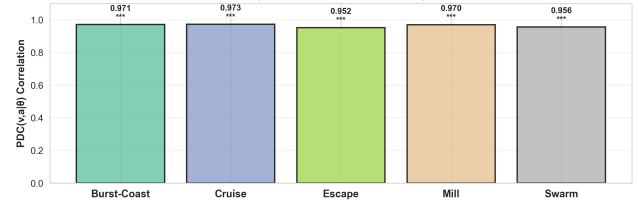


Figure 5. Distance Correlation Values without Control Variable

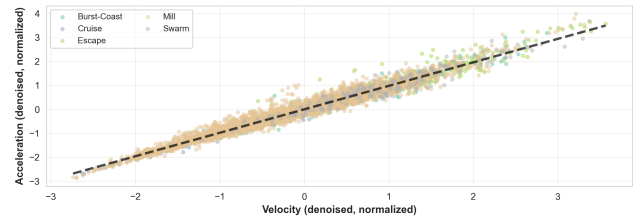


Figure 6. Velocity-Acceleration Relationship in Raw Data

6.5 Senario 3: Distance Correlation and Partical Distance Correlation Comparison

Scenario 3 is implemented to conduct a comprehensive comparison between distance correlation (dCor) and partial distance correlation (pdCor) on denoised data combined with heading angle control (*pdCor denoised + θ control*), whereby the relative efficacy of different processing strategies is evaluated.

In Figure7, the quality comparison bar chart illustrates the results of dCor on raw data (red bars), which yield high correlation values ranging from 0.905 to 0.989. The *Cruise* pattern reaches the highest value (0.989), followed by *Burst-Coast* (0.973), *Mill* (0.965), *Swarm* (0.926), and *Escape* (0.905). In contrast, pdCor on processed data (green bars) exhibits higher or equivalent results (0.952–0.973), indicating that the combined approach of noise removal and variable control enhances data compactness.

Figure 8 presents the advantage plot, where the differential magnitude of improvement is shown. *Escape* exhibits the highest advantage (+5.1%), demonstrating that pdCor is particularly effective for complex escape behaviors. *Swarm* shows a moderate advantage (+3.2%), *Mill* exhibits a modest advantage (+0.6%), while *Burst-Coast* (−0.3%) and *Cruise* (−1.6%) demonstrate negligible advantage, suggesting that these behaviors are already stable in the raw data.

Figure 9 displays the quality distribution chart, where 40% of motion patterns are detected better when pdCor with preprocessing is applied (*Better – Denoised*), while 60% yield similar results (*Similar*). This demonstrates that the combined methodology does not degrade performance for simpler behaviors while significantly improving detection accuracy for complex behavioral patterns.

Consequently, as illustrated in Figure 7–9, Scenario 3 demonstrates that Partial Distance Correlation integrated with noise removal and heading angle control provides an optimal framework for motion pattern detection, particularly for behaviors characterized by nonlinear dependencies and high noise levels.

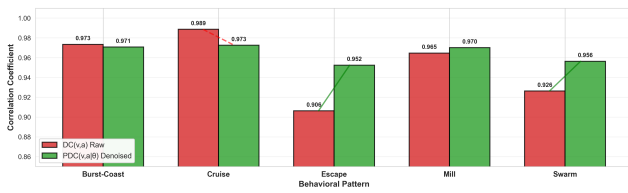


Figure 7. Comparison of dCor and pdCor Across Motion Pattern

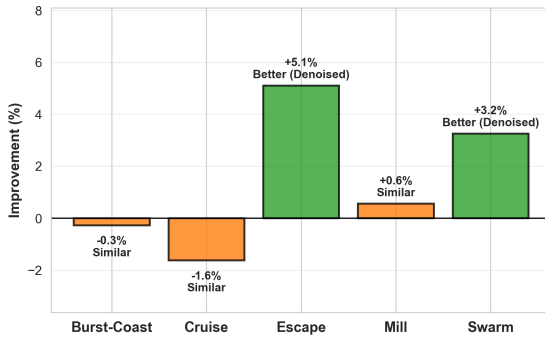


Figure 8. Performance Improvement of pdCor with Noise Removal and Confounding Variable Control

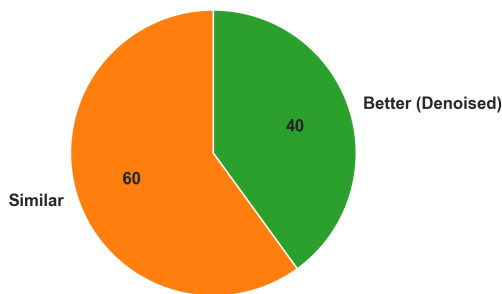


Figure 9. Distribution of Detection Quality across Motion Pattern Categories

6.6 Discussion

The experimental results obtained from three scenarios provide comprehensive insights into the performance and robustness of the proposed motion pattern

detection method based on Partial Distance Correlation (pdCor). The progression from Scenario 1 (raw dCor without control) to Scenario 3 (comprehensive comparison) reveals a clear trend: controlling confounding variables, particularly the directional angle (θ), significantly enhances the reliability and interpretability of the velocity–acceleration relationship while reducing data dispersion.

Specifically, the transition from uncontrolled dCor values (0.826–0.989 with high variance) to residual-controlled pdCor values (0.804–0.979 with minimal dispersion) demonstrates that removing confounding variables is not merely a statistical refinement but a fundamental requirement for isolating intrinsic behavioral dynamics. Substantial improvements were observed for complex behavioral patterns (*Escape*: +5.1%; *Swarm*: +3.2%), whereas minimal effects were found for structured behaviors (*Cruise*: −1.6%). Therefore, pdCor is particularly valuable in multidimensional, nonlinear behavioral spaces where confounding effects are most pronounced.

These findings advance the current state of aquatic behavioral analysis across several key dimensions. While previous studies have primarily focused on deep classification techniques [2–4] and sophisticated motion modeling approaches [5–7], the present results indicate that, unlike conventional statistical methods assuming linearity or independence, pdCor enables the simultaneous capture of nonlinear and conditional dependencies, thus providing a more refined characterization of behavioral dynamics than traditional correlation-based approaches.

7 CONCLUSION

This study demonstrates that Partial Distance Correlation (pdCor) integrated with heading angle control is a powerful tool for automated motion pattern detection in *Pangasius* catfish. The research was conducted on a dataset comprising 38 real-world videos with a total of 236,133 extracted frames, which were processed using four feature extraction methods Kinematic, Directional, Geometric, and Spectral to identify *Pangasius* motion patterns based on consecutive 60-frame sequences (*Cruising*, *Burst-Coast*, *Escape*, *Schooling*, *Milling*, and *Swarming*).

The evaluation results of dCor without the removal of confounding variable Z (heading angle) exhibit high correlation values across motion patterns, with *Cruising* reaching the highest value, followed by *Burst-Coast*, *Swarming*, and *Milling* and *Escape* showing equivalent values. However, the scatter plots reveal substantial data dispersion, particularly in extreme regions.

In contrast, the evaluation results of the pdCor method with heading angle (θ) and noise removal demonstrate significant improvements. When combined denoising and heading angle control are applied (optimal scenario), pdCor values reach maximum efficacy (0.852–0.973), with data clustering tightly (minimal scatter), thereby indicating that the fundamental

relationship between velocity and acceleration becomes genuinely linear and predictable.

The comparative analysis between Distance Correlation and Partial Distance Correlation consistently shows that pdCor produces equally high or higher values compared to dCor. Specifically, when compared to dCor on raw data, pdCor provides clear advantages for complex behavioral patterns: *Escape* and *Swarming* exhibit the highest improvements, *Milling* demonstrates modest improvement, while *Burst–Coast* and *Cruising* show negligible differences. This evidence confirms that pdCor does not diminish performance for stable behaviors but substantially enhances detection accuracy for complex motion patterns. Furthermore, the quality distribution analysis reveals that 40% of motion patterns are detected better when pdCor with comprehensive processing is applied, while 60% yield similar results, confirming the robustness and reliability of the methodology. In future research, multidimensional pdCor methods will be developed to simultaneously control for multiple confounding variables such as illumination, fish density, water flow, and temperature. Additionally, the proposed framework will be extended and validated across different fish species exhibiting diverse morphologies and locomotor dynamics.

ACKNOWLEDGMENT

This research was conducted within the framework of the Vietnam National Key Project, Grant No. KC-4.0.41/19-25, "Research and development of digital transformation model applying Industry 4.0 technologies in industrial pangasius catfish farming".

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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. Her research interests include Data Science, Computer Vision, Multimedia, and Artificial Intelligence.



Thang Cong Pham



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.