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Path planning of an elongated undulating fin using mutant particle swarm optimization

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ABSTRACT

This paper proposes a mutant particle swarm optimization algorithm (M-PSO) to optimize the power energy of a bio-mimetic robotic fish that comprises sixteen undulating fin-rays equipped to a fish robot. The main objective is to obtain the shortest path for the fish robot to achieve the desired position while minimizing power consumption. The proposed M-PSO is a recent generation of particle swarm optimization (PSO) that employs the removal of the worst particles to accelerate the swarm, enabling particles to escape local minima and improve the propulsive efficiency of the fish robot. Simulation results demonstrate that the developed M-PSO consumes less energy and requires less time compared to the original PSO and genetic algorithm (GA). Moreover, the M-PSO was tested on a robotic fish navigating an unknown environment characterized by complex spatiotemporal parameters, showcasing its superiority over other methods in all case studies.

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1. INTRODUCTION

The autonomous underwater vehicle (AUV) has been widely used in various areas, including diving investigation, fish surveillance, submarine cable installation, and measuring turbulence in the thermocline. Bionic fish robots, also known as autonomous underwater vehicles, possess propulsive ability and adaptability, enabling them to operate with great efficiency and high maneuverability in complex spatiotemporal environments [1]–[3]. Underwater vehicles propel themselves through water by employing various means of propulsion, including a stream, a propeller, and frame or fin system [4]. Consequently, this propulsion requires the utilization of battery-supplied electricity. However, due to the limitations of battery capacity, reducing the energy cost of a robotic fish poses a significant challenge for researchers.

The utilization of paths with minimum power consumption has been shown to significantly enhance the swimming performance of the robotic fish [5]–[8]. The optimization objective is to minimize both the traveling time and energy consumption required to reach the desired target. Hu and Zhou [9] proposed, a model based on ionic polymer-metal composites (IPMC) has been proposed to predict the energy cost of a propelled fish robot. Additionally, a real-time model has been introduced in [10] to monitor and manage the battery usage of a fish robot. Zhu *et al.* [11] present an energy conversion approach that converts wave energy into electricity, thereby reducing the power consumption of a fish robot. To prolong the lifespan of an artificial fish, Shen and Guo [12] introduce fuzzy logic algorithm to select a cluster head for power optimization. In our previous research [13], we investigated the use of reinforcement learning to optimize the convergence speed of a swimming gait controller based on central pattern generator (CPG) in order to reduce the battery-supplied electricity for the fish robot.

While the aforementioned methods are effective in monitoring and managing the energy consumption of robotic fish, they often struggle to solve power optimization problems that involve multiple variables and a non-linear objective function. To address this challenge, evolutionary algorithms have been employed to discover energy-optimal trajectories for bio-mimetic robotic fish [14]–[17]. Nguyen *et al.* [18], used the particle swarm optimization (PSO) algorithm to optimize the parameters of CPG in order to improve the propulsive force of the undulating fin, resulting in save power consumption. However, a major drawback of the metaheuristics is their susceptibility to becoming trapped in local minima.

In the paper, a novel variant of PSO was investigated to address the issue of local optimization and determine the optimum path for an elongated undulating fin in both known and unknown environments. Section 2 introduces an energy model for the robotic fish and establishes the objective function. In section 3, we present mutant particle swarm optimization algorithm (M-PSO), a state-of-the-art PSO generation, and its application in path planning for the sixteen-fin robot. Section 4 presents simulation results and a comparative analysis of metaheuristic algorithms in optimizing the power consumption of the fish robot. Finally, section 5 provides a conclusion.

2. PROBLEM DESCRIPTION

The undulating fin structure of the bio-mimetic robotic fish is formed by connecting sixteen neighboring fin rays with a flexible thin film. The distance of a fin ray and its adjacent one is 32 mm, and the fin width measures 150 mm. The CAD mechanical design of the fish robot is depicted in Figure 1 [19].

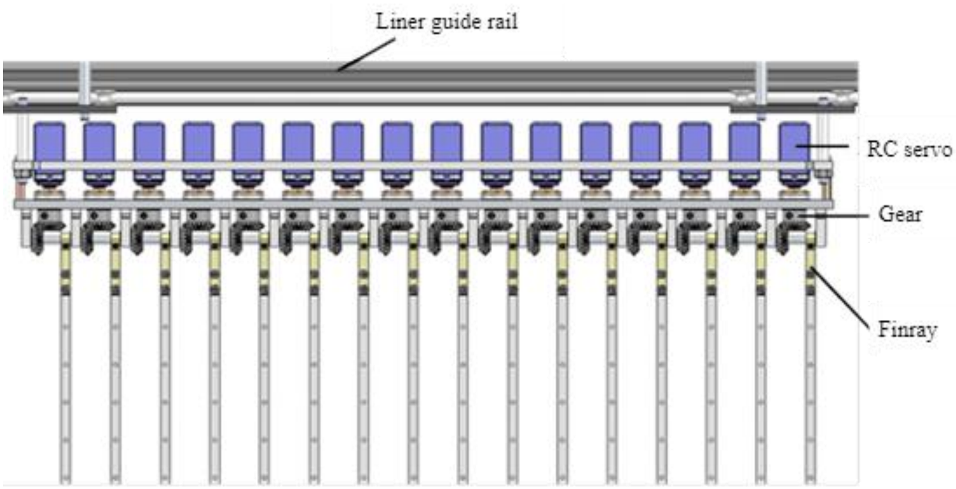

Figure 1. CAD model of the fish robot

Sixteen fin rays are controlled by sixteen radio control (RC) servomotors. The electrical-dynamic model of a motor is expressed as [20]:

$$L\frac{d}{dt}I_u = -RI_u - 2\pi\lambda_M v + U_u \tag{1}$$

$$2\pi J_m\frac{dv}{dt} = \lambda_M I_u - Q \tag{2}$$

where L_u and R_u are the armature inductance and resistance of the servo motor, respectively; U_u is the control voltage supplied to the armature component of the motor; λ_M denotes the motor torque factor; v is the angular velocity of the servo motor; J_m is the inertia torque of the motor shaft and fin ray; Q is the external load torque induced by the ambient impact affecting the fin ray.

Since the value of the armature inductance is much less than that of the armature resistance (L ≪ R), In (1) can be approximated by:

$$U_u = RI_u + 2\pi\lambda_M v \tag{3}$$

The external load torque Q and the propulsive force generated by each fin-ray can be defined as [20]:

$$Q = \rho . D^5 . \lambda_Q(J_0) . |v| . v \quad (4)$$

$$F = \rho . D^4 . \lambda_T(J_0) . |v| . v \quad (5)$$

where ρ is the specific gravity of fluid, D is the thickness of each fin-ray, λ_Q is the torque coefficient of the fin-ray, and J_0 is the propulsion rate.

Generally, the energy consumption of each RC servomotor is calculated as:

$$E = U_u . I_u = R {I_u}^2 + 2\pi\lambda_M v I_u = E_1 + E_2 \quad (6)$$

where E is the electricity used by RC servomotor; $E_1 = R_u {I_u}^2$ is the loss power because of the armature resistance; $E_2 = 2\pi\lambda_M v I_u$ is the power converted to mechanical energy. Since $E_1 \ll E_2$, $E_1 \approx 0$. In (6) can be rewritten as follows:

$$E = U_u . I_u \approx 2\pi\lambda_M v I_u \quad (7)$$

From (2):

$$I_u = \frac{2\pi J_m}{\lambda_M}\dot{v} + \frac{Q}{\lambda_M} \quad (8)$$

Substituting (8) into (7), it yields:

$$E = E_3 + E_4 = (2\pi)^2 . J_m . v . \dot{v} + 2\pi Q . v \quad (9)$$

It can be observed from (9) that E_3 is the power required for the acceleration of the fin-rays, and E_4 is the loss power produced by the interaction between the fin- rays and fuid. The loss power of i^{th} RC servo motor can be approximately calculated as:

$$E^i = 2\pi . Q . v^i = 2\pi . \rho . D^5 . \lambda_Q(J_0) . (v^i)^2 \left|v^i\right| \quad (10)$$

Using (5), (9), and (10) the energy consumption of the i^{th} fin ray can be considered as a function of the thrust force F_i:

$$E^i = \frac{2\pi\lambda_Q(J_0)}{\sqrt{\rho} D |\lambda_T(J_0)|^{1.5}} \left|F^i\right|^{1.5} \quad (11)$$

where F^i is the propulsive force of the i^{th} fin-ray.

An energy optimization problem can be posed as minimizing the following energy consumption function:

$$E_0 = \alpha \int_{t_0}^{t_f} \sum_{i=0}^{16} |F^i|^{1.5} \, dt \quad (12)$$

where t_0 and t_f is initial and final time to find a trajectory; $\alpha = \frac{2\pi\lambda_Q(J_0)}{\sqrt{\rho} D |\lambda_T(J_0)|^{1.5}} = const$

3. APPLICATION M-PSO FOR PATH PLANNING OF BIOMIMETIC ROBOT

This section starts with the inspiration of one of the well-known swarm intelligence techniques called PSO. Following that, a novel variant of PSO, namely mutant particle swarm optimization (M-PSO), has been proposed in order to improve the non-linear optimal solutions. Finally, the proposed M-PSO method has been employed to recognize the energy-efficient trajectory for a biomimetic robot.

3.1. The mutant PSO

PSO was first proposed by Kennedy and Eberhart in 1995 as a swarm intelligence algorithm inspired by the social and cognitive behavior of animal species such as fish or birds [21]–[23]. According to the problem hypothesis, each individual has a position, velocity, and a communication channel. Each particle arbitrarily "flies" pass a seeking environment with multiple dimensions, evaluating its position relative to an objective function at each iteration. The next location of particle is determined by considering both its own best position and the best position of the particle within its neighborhood. Mathematically, these updated positions for each particle in the seeking environment can be represented using the following pair of algebraic equations [24], [25].

$$Q_{x,y}^{r+1} = \varepsilon . Q_{x,y}^{r} + a_1.\gamma_1\left(X_{bestx,y}^{r} - P_{x,y}^{r}\right) + a_2.\gamma_2\left(Y_{besty}^{r} - P_{x,y}^{r}\right) \quad (13)$$

$$P_{x,y}^{r+1} = P_{x,y}^{r} + Q_{x,y}^{r+1} \quad (14)$$

where a_1 and a_2 are two acceleration cofficients, γ_1 and γ_2 are two random numbers with the value in [0 1]; whereas ε is an inertia weight. In (13), $X_{bestx,y}^{r}$ is the best y^{th} component of x^{th} particle, whereas Y_{besty}^{r} is the y^{th} component of the best particle of swarm up to iteration r.

It is also observed from (13) that the velocity of each individual decreases after a particular number of iterations. As a result, it becomes challenging for the particles to undergo significant changes in their position, which can lead to getting trapped in local optima. To address this issue, a more recent variant of PSO, called M-PSO, has been introduced with the aim of enhancing the individuals' acceleration.

In fact, the M-PSO will replaces the worst particles by the mutant particles that is randomly formed by choosing the X_{best} components of individuals of the original PSO. The vector of mutant component has the size similar to each individual, known as M_{best}. For a population of NxD, where n is the swam's size and d is the number of dimensions of each individual, M_{best} can be formed as follows:

For $m = 1 : d$
$M_{best\_m} = X_{best}(rand(n,1), m)$
end

where $rand(n,1)$ is a function uniformly generating an integer in the range of [0 n].

3.2. Application M-PSO for path planning of a biomimetic robot

The proposed M-PSO algorithm to find the optimum route for a fish-like robot is expressed by the following steps in Algorithm 1:

Algorithm 1. Application M-PSO

Step 1: set ε, a_1, a_2 and initialize the propulsive force $F_i(t)$
Step 2: calculate the state all particles of the swarm using initialized positions of each particle $F_i(t)$ in $t \in (t_0, t_f)$.
Step 3: calculate the fitness function by Eq. (11) for all particles of the swarm, and then assess the objective function of each individual $Q_y^r = f(H_y^r)$, $\forall y$, the best particle index is obtained as g
Step 4: select ${X_{best\_y}}^r = P_y^r$, $\forall r$ and ${Y_{best}}^r = P_g^r$
Step 5: set iteration number $r = 1$
Step 6: the velocity and position of each particle are renewed by Eqs. (13) and (14)
Step 7: assess the updated objective function of each individual $Q_y^{r+1} = f(P_y^{r+1})$, $\forall y$ and the best particle index is recognized as g_1
Step 8: update X_{best} of each particle $\forall y$
  If $Q_y^{r+1} < Q_y^r$ then ${X_{best\_y}}^{r+1} = P_y^{r+1}$ else ${X_{best\_y}}^{r+1} = {X_{best\_y}}^r$
  Update M_{best} of population and the corresponding particle of X_{best}
  If $Q_{worst}^{r+1} < Q_m^r$ then $X_{best\_worst}^{r+1} = M_{best}^{r+1}$ where $Q_m^r = f(M_{best}^r)$
  Update Y_{best} of population
  If $Q_{g1}^{r+1} < Q_g^r$ then $Y_{best}^{r+1} < X_{best\_g1}^{r+1}$ and set $g = g_1$ else $Y_{best}^{r+1} < Y_{best}^r$
Step 9: if $r < ite_{max}$ then $r = r + 1$ and go to step 6 else go to step 10
Step 10: obtain the optimum energy consumption as Y_{best}^r

4. RESULT AND DISCUSSION

In this section, the energy optimization methods are employed on a sixteen-fin robotic fish with a kinematic coordinate system as illustrated in Figure 2. Here, l_i represents the length of a fin ray, $O_i(i = 1,2,3,\ldots,16)$ is the joint attacking point, and h_i presents each fin ray's centroid. The fin rays are connected each other by the origin of the axis coordinate system.

Assuming that the undulating fin swims 10 m in the X direction, 4 m in the Y direction with the fixed value in the Z direction, z=10 m. The operating period of the system is 10 s from the initial time. Using Runge-Kutta 4th method for calculating performance index, state, and cost, the bionic robot-fish consumes

413.252 W to reach the desired target. However, the energy consumption reduces to 410.927 W after using the M-PSO algorithm. The optimal route is computed by using M-PSO is shown in Figure 3.

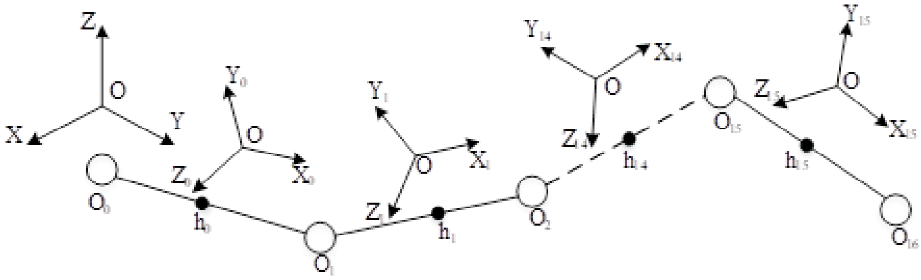

Figure 2. Dynamic coordinate system of the sixteen-fin fish robot

Table 1 gives a comparison of the different metaheuristic algorithms in term of aspects such as the total of energy consumption, the position of the tested robot. It can be seen from Table 1 that three swarm intelligence algorithms are capable of optimizing the energy consumption. However, the proposed M-PSO method consumes the minimum battery usage (410.927 W) comparing to the genetic algorithm (GA) (411.236 W) and PSO (411.042 W). Furthermore, the M-PSO also find shorter path for the bio-mimic robotic fish, at point (9.9352, 4.02492), to reach the desired target.

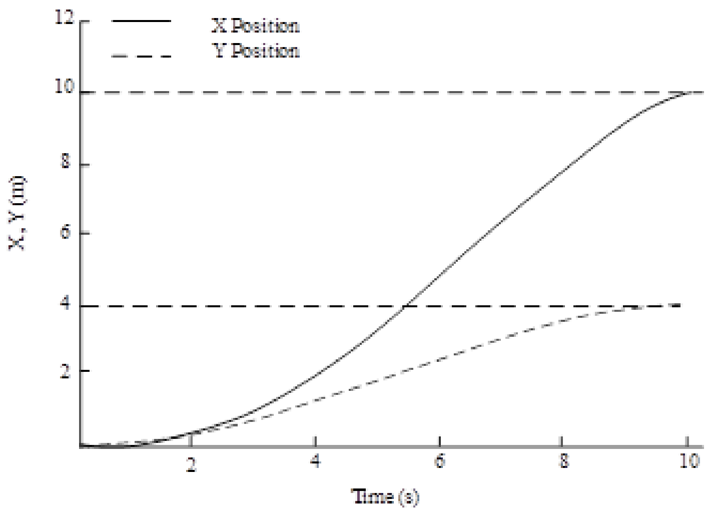

Figure 3. The near-optimal trajectory employed by M-PSO

Table 1. Results of energy consumption by using three different optimizers

Algorithm	Position (m)	Energy (W)
GA	(10.3408, 3.82641)	411.236
PSO	(10.1943, 4.1124)	411.042
M-PSO	(9.9352, 4.02492)	410.927

To demonstrate the superiority of the proposed method in solving the optimization problems, the power consumption is considered as the robotic fish swims in an unknown environment, characterized by a complex and strong current that significantly effects on its route. These influences are assumed as a lumped energy disturbance that can be modelled by:

$$E_{\Delta}(t) = \begin{cases} \frac{\rho}{d^2} & |d| \leq r_{max} \\ 0 & Otherwise \end{cases} \tag{15}$$

where $E_{\Delta}(t)$ represents the electricity consumed by the source Δ at a position located at a distance d from it. The coefficient ρ is a constant, and r_{max} denotes the maximum radius within which the energy from source Δ has an effective influence.

In term of a complicated environment, the proposed method is used to find the shortest route with minimizing the battery usage. It means the following objective function need to be minimized:

$$E_0 = \alpha \int_{t_0}^{tf} \sum_{i=1}^{16} |F_i|^{1.5} dt + \sum_{j=1}^{k} E_{\Delta}(d) \tag{16}$$

where k is the maximum number of the energy sources in the environment.

Assuming the fish robot moves 10 m in x direction and 4 m in y direction within 10 s. The near-optimal trajectory obtained by using the GA, PSO and M-PSO optimizers is shown in Figure 4. From Figure 4, we can see three swarm intelligence techniques all can seek appropriately similar optimal paths in a complex environment. To achieve desired goal; nevertheless, the M-PSO method consumes a lower battery usage in a shorter time than that is obtained by the GA and PSO. The detailed results about the position and energy consumption of the fish robot moving in a turbulent underwater environment is presented in Table 2. It can be observed from Table 2, the M-PSO only uses 493.112 W of the power energy, whereas the value is 493.483 W for the GA and 493.257 W for the PSO, respectively. Overall, the simulation results demonstrate the merits of the proposed M-PSO method in finding the shortest trajectory with minimizing battery usage as compared to other meta-heuristic algorithms.

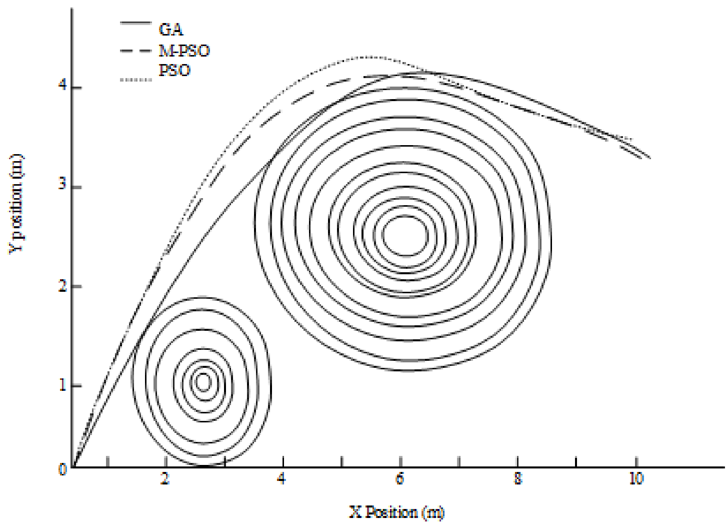

Figure 4. The near-optimal trajectory employed by GA, PSO and M-PSO in a turbulent environment

Table 2. Energy consumption by using three metaheuristic optimizers in a complicated environment

Algorithm	Position (m)	Energy (W)
GA	(10.1279, 4.22641)	493.483
PSO	(10.0917, 4.1916)	493.257
M-PSO	(10.0023, 4.01164)	493.112

5. CONCLUSION

For bio-mimic robotic fish, it is very important to reduce the energy consumption in order to enhance the performance efficiency and save the manufacturing cost. Energy minimization can be employed by using the optimization algorithms. In this paper, three different meta-heuristic methods, including the GA, PSO and M-PSO were applied to find the shortest route with minimizing power energy consumption of RC servo motors. The simulation results shown that the proposed M-PSO method performs better than the GA and PSO in the energy consumption. Moreover, the overlapped energy sources are also considered as the robotic fish moving a complicated environment, demonstrates the outperform of the proposed M-PSO algorithm compared to the previous methods in the power consumption optimization.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Thi Thom Hoang	✓	✓	✓	✓	✓				✓	✓				
Thi Huong Le		✓							✓	✓				

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

[1] G. V. Lauder, "Fish locomotion: recent advances and new directions," *Annual Review of Marine Science*, vol. 7, no. 1, pp. 521–545, Jan. 2015, doi: 10.1146/annurev-marine-010814-015614.
[2] J. E. Colgate and K. M. Lynch, "Mechanics and control of swimming: a review," *IEEE Journal of Oceanic Engineering*, vol. 29, no. 3, pp. 660–673, 2004, doi: 10.1109/JOE.2004.833208.
[3] C. Ren, X. Zhi, Y. Pu, and F. Zhang, "A multi-scale UAV image matching method applied to large-scale landslide reconstruction," *Mathematical Biosciences and Engineering*, vol. 18, no. 3, pp. 2274–2287, Mar. 2021, doi: 10.3934/MBE.2021115.
[4] K. H. LOW, "Maneuvering of biomimetic fish by integrating a buoyancy body with modular undulating fins," *International Journal of Humanoid Robotics*, vol. 04, no. 04, pp. 671–695, Dec. 2007, doi: 10.1142/S0219843607001217.
[5] D. Xu, L. Yu, Z. Lv, J. Zhang, D. Fan, and W. Dai, "Energy consumption optimization for the formation of multiple robotic fishes using particle swarm optimization," *Energies (Basel)*, vol. 11, no. 8, Aug. 2018, doi: 10.3390/en11082023.
[6] Q. Tian, T. Wang, Y. Wang, Z. Wang, and C. Liu, "A two-level optimization algorithm for path planning of bionic robotic fish in the three-dimensional environment with ocean currents and moving obstacles," *Ocean Engineering*, vol. 266, p. 112829, 2022, doi: https://doi.org/10.1016/j.oceaneng.2022.112829.
[7] W. Yang *et al.*, "Improved artificial potential field and dynamic window method for amphibious robot fish path planning," *Applied Sciences (Switzerland)*, vol. 11, no. 5, pp. 1–15, Mar. 2021, doi: 10.3390/app11052114.
[8] Y. Mu, J. Qiao, J. Liu, D. An, and Y. Wei, "Path planning with multiple constraints and path following based on model predictive control for robotic fish," *Information Processing in Agriculture*, vol. 9, no. 1, pp. 91–99, 2022, doi: https://doi.org/10.1016/j.inpa.2021.12.005.
[9] Q. Hu and H. Zhou, "IPMC propelled biomimetics robotic fish energy consumption model construction and its application to energy-saving control," in *2009 IEEE International Conference on Robotics and Biomimetics (ROBIO)*, 2009, pp. 2151–2156. doi: 10.1109/ROBIO.2009.5420483.
[10] M. C. C. Wang, W. Wang, G. Xie, and H. Shi, "Real-time energy monitoring and management system and its application on bionic robotic fish," in *Proceeding of the 11th World Congress on Intelligent Control and Automation*, 2014, pp. 3256–3261. doi: 10.1109/WCICA.2014.7053253.
[11] W. Zhu, X. Wang, M. Xu, J. Yang, T. Si, and S. Zhang, "A wave energy conversion mechanism applied in robotic fish," in *2013 IEEE/ASME International Conference on Advanced Intelligent Mechatronics*, 2013, pp. 319–324. doi: 10.1109/AIM.2013.6584111.
[12] Y. Shen and B. Guo, "Energy-efficient cluster-head selection with fuzzy logic for robotic fish swarm," in *2015 12th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD)*, 2015, pp. 513–518. doi: 10.1109/FSKD.2015.7381995.
[13] V. D. Nguyen, D. Q. Vo, V. T. Duong, H. H. Nguyen, and T. T. Nguyen, "Reinforcement learning-based optimization of locomotion controller using multiple coupled CPG oscillators for elongated undulating fin propulsion," *Mathematical Biosciences and Engineering*, vol. 19, no. 1, pp. 738–758, 2022, doi: 10.3934/mbe.2022033.
[14] M. P. Aghababa, M. H. Amrollahi, and M. Borjkhani, "Application of GA, PSO, and ACO algorithms to path planning of autonomous underwater vehicles," *Journal of Marine Science and Application*, vol. 11, no. 3, pp. 378–386, 2012, doi: 10.1007/s11804-012-1146-x.
[15] G. Yang and R. Zhang, "Path planning of AUV in turbulent ocean environments used adapted inertia-weight PSO," in *2009 Fifth International Conference on Natural Computation*, 2009, pp. 299–302. doi: 10.1109/ICNC.2009.355.

[16] S. Mirjalili, J. S. Dong, and A. Lewis, "Ant colony optimizer: theory, literature review, and application in AUV path planning," in *Nature-Inspired Optimizers: Theories, Literature Reviews and Applications, Cham: Springer International Publishing*, 2020, pp. 7–21. doi: 10.1007/978-3-030-12127-3_2.
[17] W. Guo and Z. W. Peng, "Path planning of bionic robot fish based on genetic algorithm," *Applied Mechanics and Materials,* vol. 530–531, pp. 1058–1062, 2014, doi: 10.4028/www.scientific.net/AMM.530-531.1058.
[18] V. D. Nguyen *et al.*, "Force optimization of elongated undulating fin robot using improved PSO-based CPG," *Computational Intelligence and Neuroscience*, vol. 2022, pp. 1–11, Mar. 2022, doi: 10.1155/2022/2763865.
[19] V. H. Nguyen, C. A. T. Pham, V. D. Nguyen, H. L. Phan, and T. T. Nguyen, "Computational study on upward force generation of gymnotiform undulating fin," *Lecture Notes in Electrical Engineering*, vol. 554, pp. 914–923, 2020, doi: 10.1007/978-3-030-14907-9_88.
[20] T. I. Fossen, "Guidance and control of ocean vehicles," University of Trondheim, Norway, Printed by John Wiley & Sons, Chichester, England, ISBN: 0 471 94113 1, Doctors Thesis, 1999.
[21] J. Kennedy, "Swarm Intelligence," in *Handbook of nature-inspired and innovative computing: integrating classical models with emerging technologies, A. Y. Zomaya, Ed.*, Boston, MA: Springer US, 2006, pp. 187–219. doi: 10.1007/0-387-27705-6_6.
[22] Y. del Valle, G. K. Venayagamoorthy, S. Mohagheghi, J.-C. Hernandez, and R. G. Harley, "particle swarm optimization: basic concepts, variants and applications in power systems," *IEEE Transactions on Evolutionary Computation*, vol. 12, no. 2, pp. 171–195, 2008, doi: 10.1109/TEVC.2007.896686.
[23] M.-Y. Cho and T. T. Hoang, "Feature selection and parameters optimization of SVM using particle swarm optimization for fault classification in power distribution systems," *Computational Intelligence and Neuroscience*, vol. 2017, pp. 1–9, 2017, doi: 10.1155/2017/4135465.
[24] H. T. Thom, C. M. Yuan, and V. Q. Tuan, "A novel perturbed particle swarm optimization-based support vector machine for fault diagnosis in power distribution systems," *Turkish Journal of Electrical Engineering and Computer Sciences*, vol. 26, no. 1, pp. 518–529, 2018, doi: 10.3906/elk-1705-241.
[25] T. T. Hoang and T. H. Le, "Intelligent fault diagnosis for power distribution system-comparative studies," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS),* vol. 25, no. 2, pp. 601–609, Feb. 2022, doi: 10.11591/ijeecs.v25.i2.pp601-609.

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