Fusion Bacterial Foraging and Particle Swarm Optimization Algorithm For An Autonomous Hovercraft Control

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Fusion Bacterial Foraging and Particle Swarm Optimization Algorithm For An Autonomous Hovercraft Control

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Keywords: Bacterial Foraging (BF) Algorithm, Particle Swarm Optimization (PSO), PD like Fuzzy, Hovercraft, Integral of Time Multiplied Square Error (ITSE).

1. Introduction

In recent years, many researchers have focused on using nonlinear control to build an autonomous hovercraft [1–6] that can work well on various surfaces such as water, sand beach, ice and especially on muddy land. Most of these available controllers of the real hovercraft models are just based on the traditional PD controller and very few methods of optimizing the controller parameters are introduced for this system. The main aim of this paper is to propose a new way to optimize the proportional and derivative gains of the PD like fuzzy controller of the hovercraft.

Based on an expert knowledge system, fuzzy logic controllers (FLC) have the advantage of solving problems by using flexible if-then rules. Many works [7-14] have utilized this technique to solve various control system topics and achieved significantly better results than other methods. Hence, this research also applies this approach to the control system of hovercraft models. In this paper, we design a set of fuzzy triangular membership functions and optimizes scaling factors (SF) as the inputs of fuzzy controller. Although evolutionary algorithms [15, 16] such as particle swarm optimization (PSO), simulated annealing (SA) and genetic algorithm (GA), can easily detect the local minima but it is difficult to detect the global optimization. PSO algorithms [17-21] are a population-based heuristic algorithm that is invented based on observing animal swarm social behavior to detect accurate targets in multi-dimensional space. PSO uses individual particles to perform searches. To finding the optimal solution, each particle decides its search direction based on its best previous location (cognitive part) and all other members' best locations (social part). In 2002, K. M. Passino [22], inspired from the behavior of *Escherichia-coli* bacteria, firstly proposed a bionic algorithm that is very effective for distributed optimization and control design. Although, BF algorithm is very effective in local search, it is easily tapped or delayed in reaching global solution because of the random search directions during chemotaxis process that is the movement of an organism or entity in response to a chemical stimulus.

Although, BF algorithm is very effective in local searches, it is easily tapped or delayed in reaching global solution because of the random search directions during the movement of an organism or entity in response to a chemical stimulus called chemotaxis process.

To avoid local optima traps and improve the optimal performance in engineering application research, several PSO-based algorithms are used to solve the problems, for instance: GA and PSO [23], PSO and SA [24], hybrid PSO-Differential Evolution [25], Direct Search method and hybrid PSO [26], hybrid swarm intelligence approach [27]. Also, combining PSO with BF has emerged as one of the most efficient optimization methods, which can be applied successfully in many fields, including mathematical optimization [28], RFID network planning [29], medical care [30] and traditional PID control [31-36] in electric power systems. The above techniques can expand the optimal convergence pace by taking the advantages while eliminating the weakness of the solo algorithms.

Thus, we employed a fusion algorithm, called fusion bacterial foraging and particle swarm optimization (named hereafter fBF-PSO), to increase the convergence speed in shorter operating generation and adjust the global search efficiency. We use PD like fuzzy control to improve hovercraft system stability. The fBF-PSO technique is also used to improve the performance of this PD like fuzzy control by minimizing the ITSE fitness cost function [37-39]. The proposed controller can obtain high-performance control of the Hovercraft in terms of higher accuracy, quick response, high stability and smoother maneuvers. To the best of our knowledge, this is the first paper that combines the advantages of PSO and BF method in designing an effective and optimal PD like fuzzy controller for a real hovercraft model. In section 2, we describe the hovercraft configuration. In section 3, optimization algorithm and control strategy are introduced. In section 4, numerical simulation control of a real hovercraft model is presented. Finally, conclusions are discussed in section 5.

2. Autonomous Hovercraft configuration

The air cushion vehicle, which is usually called as hovercraft, is composed of rotors and a cushion. Blower (rotor duct fan) is used to provide a large volume of air inside the air cushion, which is larger than the atmospheric pressure. Therefore, the hovercraft can float and is capable of travelling over ice, water, land, mud… [1-6, 13]. A tilt servo motor, which is located at the rear, is usually employed to steer the hovercraft. Although many modern technologies are used [1-6, 13], there is still a need for a more advanced hovercraft maneuvering system. Especially, faster response and higher reliability are of great interest. Figure 1 shows a popular hovercraft model used in this research, which has a single tilt servo motor, a propeller settled along z-axis and a blower attached along y-axis.

The dynamic hovercraft model in this paper is referenced from [1, 6 and 13] with right hand coordinate systems. X-axis is used to position in the lateral direction whilst Y-axis is along its body. As shown in the figure 1, the Z-axis is vertical and its positive direction is downward. The hovercraft's kinematics can be briefly described as follow:

$$\begin{cases} \dot{x} = p\cos\varphi - s\sin\varphi \\ \dot{y} = q\cos\varphi - s\sin\varphi \\ \dot{\varphi} = \omega \end{cases} \tag{1}$$

where $\boldsymbol{\omega} \in \boldsymbol{R}$ represents the angular velocity. $\boldsymbol{p},\boldsymbol{q},\boldsymbol{s} \in \boldsymbol{R}$ are defined as linear velocities in surge direction, sway direction and steering, respectively. From this above equation, we can derive the kinetic and potential energies of the hovercraft to compute L'agrange $L=T\text{-}V$. Then we can apply Euler-Lagrange formulation on equation 2:

$$\boldsymbol{M}(\boldsymbol{q})\dot{\boldsymbol{q}} + \boldsymbol{C}(\boldsymbol{q},\dot{\boldsymbol{q}})\boldsymbol{q} = \begin{bmatrix} \boldsymbol{F} \\ \boldsymbol{T}_q \\ \boldsymbol{0} \end{bmatrix} \tag{2}$$

where $\boldsymbol{T_q} \in \boldsymbol{R}$ represents the torque in yaw and $\boldsymbol{F} \in \boldsymbol{R}$ is the control force in the surge direction. The torque control, which is perpendicular to the center of the hovercraft propeller, is a function of $\boldsymbol{F} \in \boldsymbol{R}$.

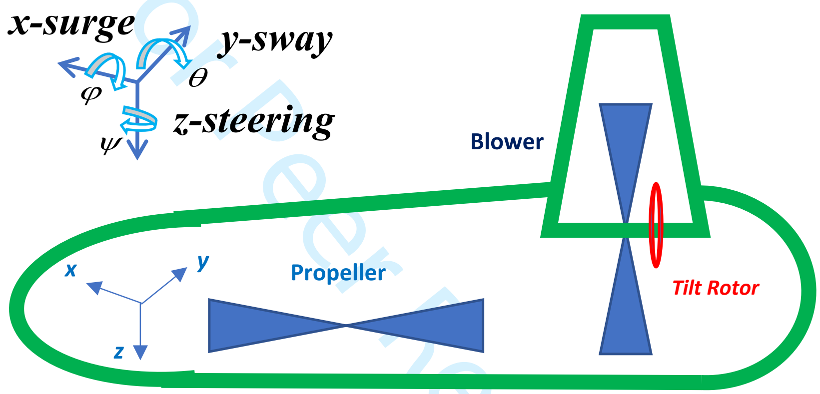


Figure 1. The Hovercraft prototype model.

3. Optimization Algorithms and Control Strategy

3.1.1. PD controller

The PD controller, which is implemented in this article, is high efficiency despite having a simplistic structure. Its design can reduce the settling time whereas improve the system stability. For the ith area, the PD controller combined gain, $K(s)$, is computed from the following equation 3:

$$\boldsymbol{G}_{(s)} = \boldsymbol{K_P} + \boldsymbol{K_D s} \tag{3}$$

Where, K_P and K_D are the conventional PD controller proportional and derivative gains, respectively.

3.1.2. Fuzzy Logic Controller (FLC)

The FLC dynamic behavior are based on a set of linguistic rules and originated from expert knowledge [7-9]. Designer needs to decide the input and output variables for building a suitable set of fuzzy rules. In this article, the error *e(t)* and the error rate *de(t)* are chosen as input variables, while the control output is also signal input to the system and considered as c_i. Then, the relationship between these two inputs and one output variables are investigated. The error and error rate as well as the fuzzy rules determine the online change of the system output c_i. We then need to fuzzify and defuzzify *e(t), de(t)* and c_i parameters. Fig. 2 illustrate the fuzzy inference system employed in this work. The center of area method defuzzification and Mamdani's MIN–MAX inference engine is utilized. Seven linguistic triangular membership functions for the two inputs and one output are assigned: positive big PB, positive medium PM, positive small PS, zero ZE, negative small NS, negative medium NM, and negative big NB. Table 1 explains the Fuzzy controller rules.

3.1.3 PD like Fuzzy controller

An intelligent control apply to autonomous hovercraft is the PD like Fuzzy controller. In that, FLC could be used as a classical PD controller, and overcome the disadvantages of the PD Controller. It is necessary to select the input and output variables and proper controller rules, as illustrated on equation 4:

$$\boldsymbol{u_{(t)} = K_P e_{(t)} + K_D de_{(t)}} \tag{4}$$

Where *e(t)* is the error, and *de(t)* is the change in error. In the following subsections, the proposed optimization algorithms are presented to optimize the SF as inputs to a fuzzy controller.

Table 1. Rule base of Fuzzy Logic Controllers

Control signal CI(t)		***Input e(t)***						
		NB	**NM**	**NS**	**ZE**	**PS**	**PM**	**PB**
Input de(t)	**NB**	**ZE**	PS	PM	PM	**PB**	**PB**	**PB**
	NM	NS	**ZE**	PS	PM	PM	**PB**	**PB**
	NS	NM	NS	**ZE**	PS	PM	PM	**PB**
	ZE	NM	NM	NS	**ZE**	PS	PM	PM
	PS	**NB**	NM	NM	NS	**ZE**	PS	PM
	PM	**NB**	**NB**	NM	NM	NS	**ZE**	PS
	PB	**NB**	**NB**	**NB**	NM	NM	NS	**ZE**

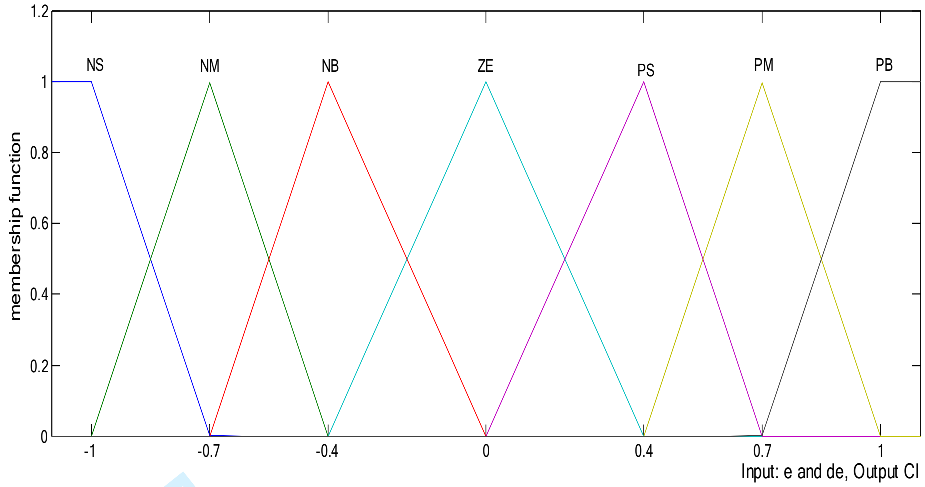


Figure 2. Fuzzy membership function.

3.2.1. PSO Algorithm

Recently, the PSO has emerged as the one of the most well-known and powerful tools for optimization [17-21]. We try to adapt PSO algorithm for the hovercraft control. Specifically, PSO algorithm is combined with another effective optimization algorithm to optimally tune the PD controller gains. In order to follow along with learning rates c_1 and c_2, the inertia weight □ is a user-defined parameter. It manages the relationship of the previous values of particle velocities to the current value. The PSO implementation process is illustrated by the flow chart in Fig. 3. The PSO mathematical equations (5) and equation (6) are briefly described as follows:

$$\boldsymbol{V(t+1) = \omega V(t) + c_1 r_1 (Pbest(t) - P(t)) + c_2 r_2 (Gbest(t) - P(t))} \quad (5)$$

$$\boldsymbol{P(t+1) = P(t) + V(t+1)} \quad (6)$$

Where V is particle velocity, P is the current position, Pbest is local best position and Gbest is global best position; ω is the inertia weighting factor, c_1 and c_2 as learning rates. The variables r_1 and r_2 are uniformly distributed random numbers [0, 1].

3.2.2. BF optimization

The BF optimization derives from searching for information on the Escherichia (E-coli) bacteria [22] capabilities to survive in the natural changing environment. During the evolution process, fitness criteria rely on their mobile behavior to maintain a proper foraging strategy as well as reshape or eliminate their poor strategy when they are searching for food. Bacteria with good foraging strategies are then replicated in the next generation by the evaluation chain. The E-coli bacteria foraging progression to global searching capability is simplify described by four significant steps of Chemo-tactic, Swarming, Reproduction and Elimination–Dispersal. First, Chemo-tactic (θ_k) process illustrates the E-coli bacteria motion by two different methods; one can swim until a fixed time is reached while the other can tumble to alternate between two lifetime modes of operation. Where, θ_k symbolizes the *k-th* bacterium, N_k is the size of the step taken in the random direction specified by the tumble and Δ is a length of the random direction unit vector, as shown in equation (7). Second, Swarming step (J_{cc}): bacteria move to follow the nutrient gradient produced by the nutrient consuming group. Bacteria will release an attractant when they reach high nutrient areas and form concentric patterns of higher density bacteria. Mathematically, swarming can be described by equation (8). Where q is the number of variables to be optimized, which are present in each bacterium and $\theta = [\theta_1, \theta_2, \ldots, \theta_q]^T$ is a point in the p-dimensional search domain; d_a and e_a are the attractive coefficients; h_r and e_r are repellant coefficients. Third, Reproduction (N_r) step**: t**o maintain the constant population, the healthier bacteria split into two and the less healthy bacteria die. As shown in equation (9), Sr is the number of population members that have had enough nutrients to reproduce (split in two) without mutation. Finally, Elimination and Dispersal step: may occur when local significant increases in heat kill bacteria that are currently in nutrient-rich regions. Bacteria can be dispersed by an abrupt flow of water. Elimination and dispersal events may destroy chemotactic progress, but they may also promote chemotaxis, since they place bacteria near food sources. Soon after BF algorithm was invented, it has been widely used for optimization in numerous science and technology fields.

$$\boldsymbol{\theta_k = \theta_k + N_k * \Delta_k} \tag{7}$$

$$\boldsymbol{J_c = -\, d_a exp\Big[-e_a \textstyle\sum_{m=1}^{q}\big(\theta_m - \theta_m^i\big)^2\Big] + h_r exp\Big[-e_r \textstyle\sum_{m=1}^{q}\big(\theta_m - \theta_m^i\big)^2\Big]} \tag{8}$$

$$\boldsymbol{S_r = S/2} \tag{9}$$

3.2.3. Fusion Bacterial Foraging-Particle Swarm Optimization algorithm

Several studies [28-36] combined the ability of PSO to exchange social information with the ability of BF to eliminate and disperse old problems into new solutions**.** This combination was called fBF-PSO, which has the combined strength of the two algorithms. To achieve optimal convergence, the proposed fBF-PSO algorithm is derived from the specified search directions of bacteria tumbling, which are oriented simultaneously by the individual and global best locations, and the identified ideas of PSO is updating position and velocity. This means that the proposed algorithm utilizes a PSO velocity calculation to precisely determine the updated chemotaxis drop direction within the BF algorithm. This allows tumble's unity-length random order to be adapted to the best global as well as the best individual position.

Several parameters must be evaluated, including: "iterations, inertia weight, learning rates, the number of bacteria, chemotactic steps, limit swimming distance, reproduction steps, elimination-dispersal events, and probability that each bacterium is eliminated". These are referred to in [16-19, 22, 28-36] and in our own experimental controller designs. Hence, we combine fBF-PSO and the PD like Fuzzy control for building the hovercraft controller. This algorithm is then implemented to find the SF as the best optimization parameters of the proposed controller. In the control diagram illustrated in Fig. 3, the tracking error *e(t)* and differential tracking error *de(t)* are employed as inputs of the fuzzy inference system. Two main parameters K_P (proportional gain) and K_D (derivative gain) of the PD like Fuzzy control are then optimally tuned with the integral of time multiplied square error (ITSE) performance index [37-39]. After this, the results are compared qualitatively and quantitatively in terms of the ITSE minimum value: the settling time, the rising time, the overshoot and the tracking error, as demonstrated in equation (9):

$$\boldsymbol{ITSE = \int_0^{\infty} e^2(t)\, t\, \mathrm{d}t} \tag{9}$$

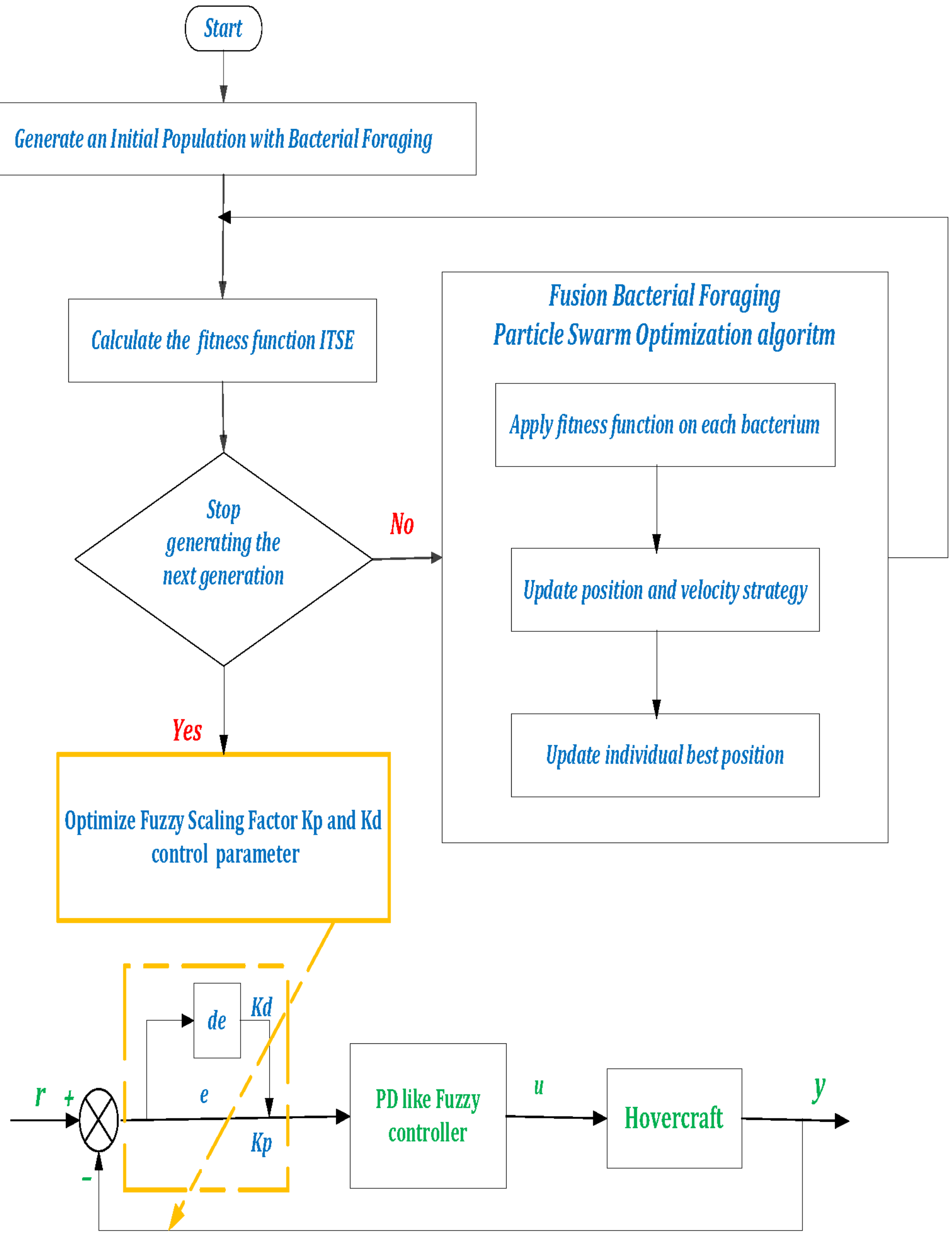


Figure 3. The fBF-PSO algorithm diagram.

4. Numerical Peformance

In this section, MATLAB/Simulink software is used to evaluate the performance of the proposed controller designs for autonomous Hovercraft mathematical models. These models were derived from the previous research [1, 6 and 13] with the mass of Hovercraft $m = 2.1\ kg$ and the inertia moment $I = 0.000257$. The simulation sampling time is 0.01 second. Numerical simulation results are operated in the stochastic optimization space. The proposed optimizations are simply set on 50 iterations. The PD gains of the proposed controllers are set in range ϵ [0, 100]. The significant optimal parameters of each optimization algorithm are chosen and displayed in the Table 2.

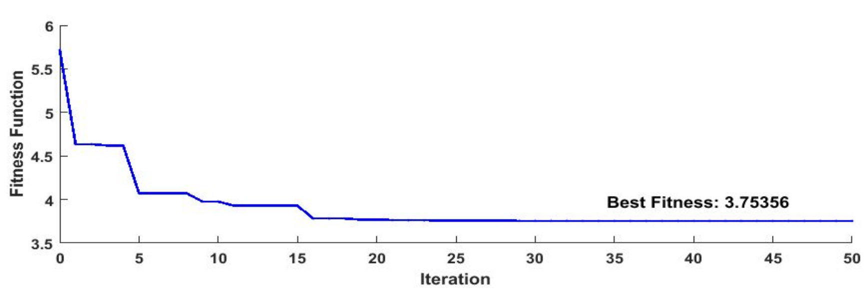
Table 2. Algorithms parameters setup

Parameters	PSO	BF	fBF-PSO
Dimension of search space	2	2	2
Generation or Iteration	50	50	50
Acceleration coefficient, c_1	1.22	-	1.22
Acceleration coefficient, c_2	1.22	-	1.22
Inertia weighting factor	0.92	-	0.92
Number of bacteria	-	50	50
Number of chemotactic steps	-	10	10
Limits the length of a swim	-	5	5
Number of reproduction steps	-	5	5
Number of elimination-dispersal events	-	3	3
Probability of each bacteria getting eliminated or dispersed	-	0.2	0.2

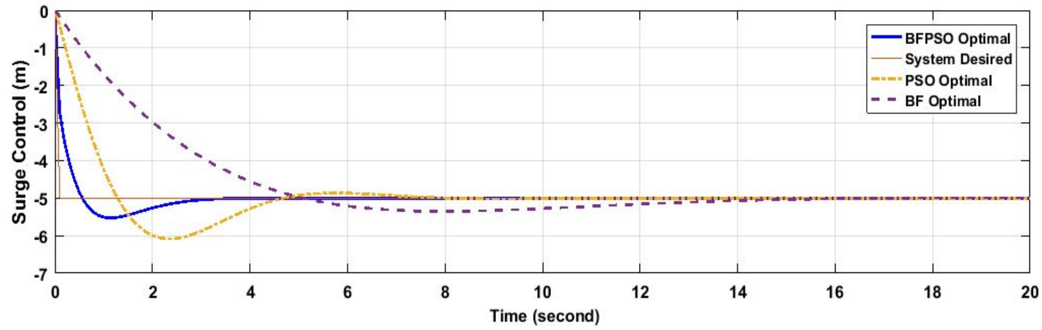
To compare the fBF-PSO with the standard BF and conventional PSO, this paper investigate the performances of three channels of autonomous hovercraft motions: surge position x in Figure 4, sway position y in Figure 5 and yaw steering angle in Figure 6, respectively. The numerical performances display that the fBF-PSO methodology achieved the significant stability and dominance in performance response compare to the solo BF or the single PSO algorithm. All presented results proved that fBF-PSO achieved the optimal control including: response time, less error, just after the third second at all, and were illustrated on the Table 3. Generally, all optimal controller designs achieve the high-quality performance in terms of stability, precision and reliability.

Table 3. The fBF-PSO proposed method tuning gain results

	Surge position x (5 m)	*Sway position y (5 m)*	*Steering-Yaw angle (10 degree)*
Generation	*50*	*50*	*50*
K_P	*78.324*	*45.783*	*34.569*
K_D	*50.671*	*88.123*	*77.257*
Settling time (s)	*2.943*	*2.818*	*3.154*
Overshoot (%)	*10.12*	*1.05*	*0.93*
Elapsed time (s)	***21009.3397***	***29053.3585***	***25266.4916***

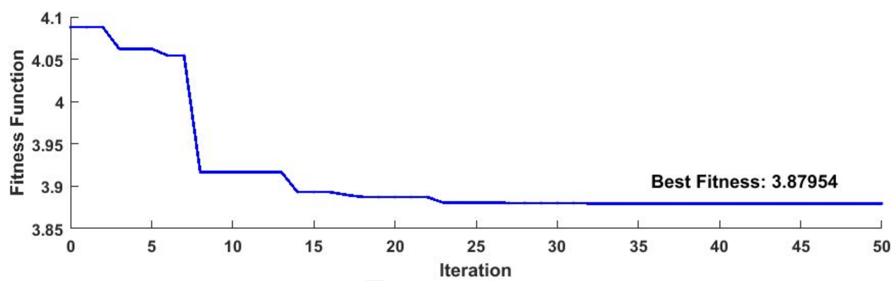


(a)

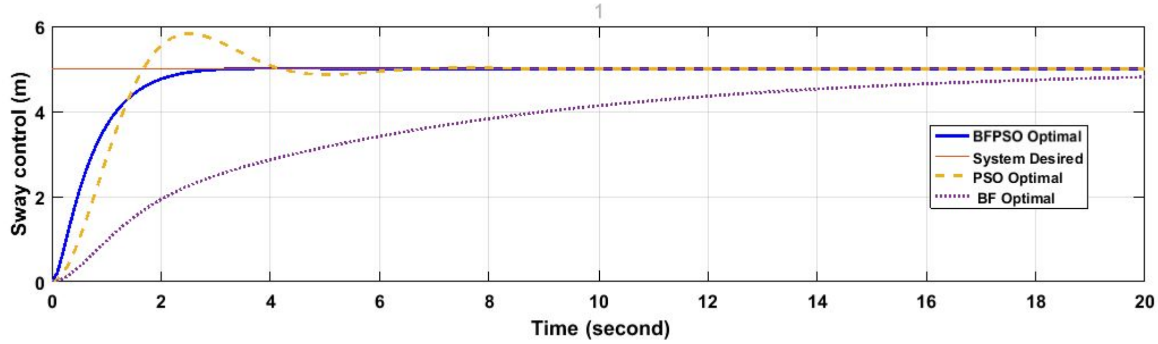


(b)

Figure 4. Hovercraft Surge control. (a) fBFPSO algorithm fitness value, (b) The proposed algorithm.

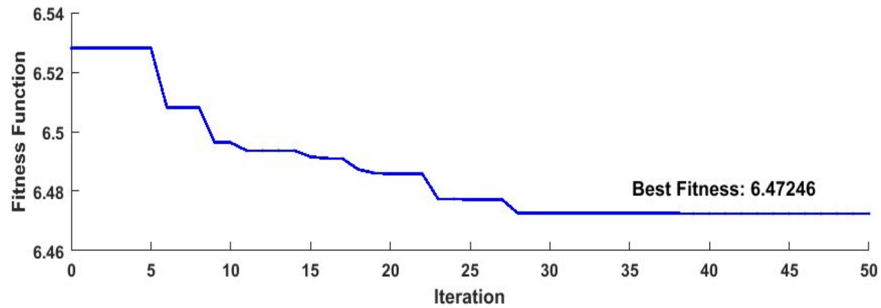


(a)

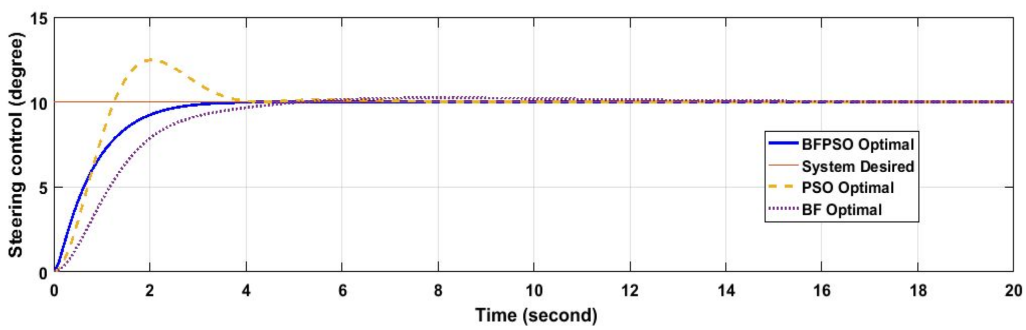


(b)

Figure 5. Hovercraft Sway control. (a) fBFPSO algorithm fitness value, (b) The proposed algorithm



(a)



(b)

Figure 6. Hovercraft Steering angle control. (a) fBFPSO algorithm fitness value, (b) The proposed algorithm.

5. Conclusions

The paper presents a successful design of three numerical optimal controllers to pilot an autonomous hovercraft. The fBF-PSO algorithm that employs both the ability to exchange social information of the PSO algorithm and the capability of finding new BF solutions via the elimination and dispersal step is proposed in order to find the optimal PD like Fuzzy controller parameters for the hovercraft pilot models: surge, sway and steering control. The proposed controller obtains optimal pilot performance after the third second when compared with the other single optimal controller designs, PSO or BF. Furthermore, it provides fastest response, high reliability as well as stability than available controllers for the realistic hovercraft mathematical models. A path planning algorithm for hovercraft model with obstacle avoidance and wind disturbances will be developed in future. In addition, the real hovercraft model with the proposed control technique will be implemented for testing and optimization.

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