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Full Length Research Paper

A cultural algorithm based particle swarm optimization approach to linear brushless DC motor PID controller

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This paper presents a new hybrid Cultural Algorithm (CA) based particle swarm optimization (PSO) that converges to a significantly more accurate solution then existing particle swarm optimization and which has also been applied to the linear brushless DC motor PID controller design. The utility of hybrid CA based PSO is demonstrated by determining the optimal proportional-integral-derivative (PID) controller parameters for speed control of a linear brushless DC motor and then compared with basic PSO method. The proposed hybrid approach has superior features including stable convergence characteristic and good computational efficiency, reducing the steady-state error (Ess), rise time (Tr), settling time (Ts) and maximum overshoot (Mp) in speed control of a linear brushless DC motor. The comparative experimental results has demonstrated the feasibility and effectiveness of the proposed novel approach.

Key words: Proportional-integral-derivative controller, cultural algorithm, particle swarm optimization, DC motor, step response.

INTRODUCTION

Several heuristic tools have evolved in the past decades that facilitate solving optimization problems that were previously difficult or impossible to solve. These tools include evolutionary computation, simulated annealing, tabu search, particle swarm and so forth. Reports of applications of each of these tools have been widely published. Recently, these new heuristic tools have been combined among themselves and with knowledge elements as well as with more traditional approaches such as statistical analysis to solve extremely challenging problems. Traditional methods of optimization are not robust to dynamic changes in the environment and often require a complete restart in order to provide a solution (for example dynamic programming). In this paper, a hybrid cultural algorithm (CA) based particle swarm optimization (PSO) approach to optimally design a proportional-integral-derivative (PID) controller for a brushless DC motor is proposed.

Generally, CA-PSO is characterized as a simple concept, easy to implement and computationally efficient. Unlike the other heuristic techniques, CA-PSO has a flexible and well-balanced mechanism to enhance the global and local exploration abilities.

OVERVIEW OF CULTURAL ALGORITHM (CA)

The CA is a class of computational models derived from observing the cultural evolution process in nature (Reynolds et al., 2010). As a dual inheritance system, cultural algorithm has two basic components: ‘population space and belief space’. First, individuals in the ‘population space’ are evaluated with a performance function obj(). An acceptance function accept() will then determine which individuals are to impact the ‘belief space’. Experiences of those chosen elites will be used to update the knowledge/beliefs of the, and from then, together with old individuals, individuals are ‘selected’ and form a new generation of population. The two feedback paths of information, one through the accept() and influence() functions, and the other through individual experience and the obj() function create a system of dual

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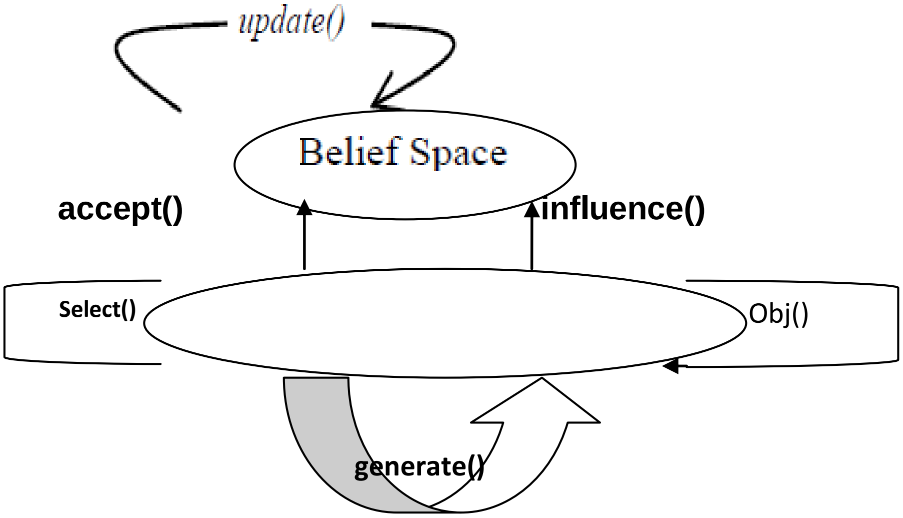


Figure 1. Framework of cultural algorithm.

inheritance of both ‘belief space’ through function update() which represents the evolution of beliefs. Next, the beliefs are used to influence the evolution of the population. New individuals are ‘generated’ under the ‘influence’ of the beliefs population and belief. The population component and the belief space interact with and support each other in a manner analogous to the evolution of human culture. The basic framework is shown in Figure 1 (Reynolds et al., 2010). A CA is a dual inheritance system that characterizes evolution in human culture at both the macro-evolutionary level which takes place within the belief space, and at the micro-evolutionary level which occurs in the population space.

Knowledge produced in the population space at the micro-evolutionary level is selectively accepted or passed to the belief space and used to adjust the knowledge structures there. This knowledge can then be used to influence the changes made by the population in the next generation.

PID CONTROLLER

The PID controller is the most common form of feedback. It was an essential element of early governors and it became the standard tool when process control emerged in the 1940s. In process control today, more than 95% of the control loops are of PID type, most loops are actually PI control. PID controllers are today found in all areas where control is used; most of the industries employ proportional-integral-derivative (PID) controllers because it is ‘simple in construction’:

i) Designing easy.
ii) Reduce the instability.
iii) Robust in performance.
iv) Zero steady state error.
v) Less over shoot.
vi) Less rise time.
vii) Redesigning is easy as changing of three parameter values.

Equation 1 shows the ‘transfer function’ of PID controller:

$$C(s) = K_p + \frac{Ki}{s} + K_d s \tag{1}$$

Where

Kp: Proportional gain.
Ki: Integral gain.
Kd: Derivative gain.

Tuning a control loop is the adjustment of its control parameters like Ki, Kp and Kd to the optimum values for the desired control response. Stability (bounded oscillation) is a basic requirement, PID controllers often provide acceptable control even in the absence of tuning, but performance can generally be improved by careful tuning and performance may be unacceptable with poor tuning.

PID controller for DC motor

There are mainly two types of DC motors used in industry. The first one is the conventional DC motor where the flux is produced by the current through the field

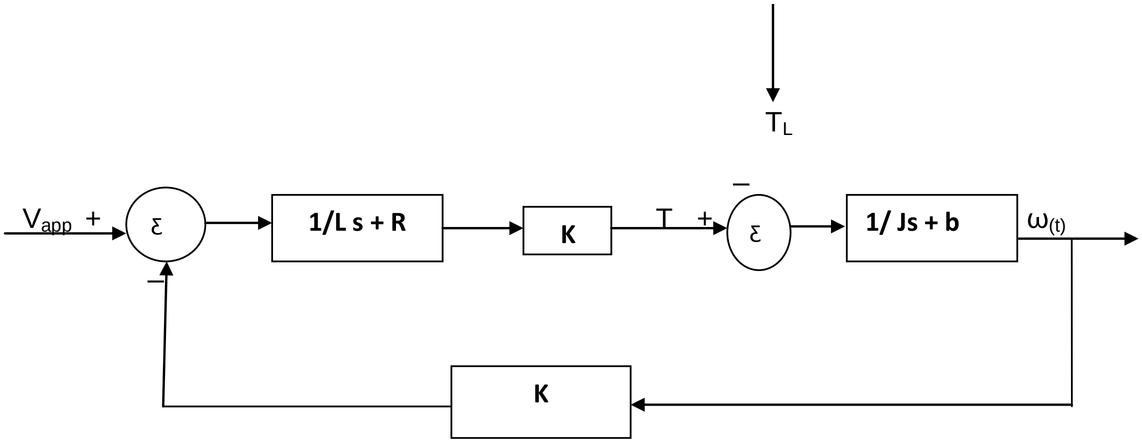


Figure 2. Block diagram of DC motor.

coil of the stationary pole structure. The second type is the brushless DC motor (BLDC motor) where the permanent magnet provides the necessary air gap flux instead of the wire-wound field poles (Tipsuwanporn et al., 2002). This kind of motor not only has the advantages of DC motor such as better velocity capability and no mechanical commutator but also has the advantage of AC motor such as simple structure, higher reliability and free maintenance. In addition, brushless DC motor has the following advantages:

i) Smaller volume.
ii) High force.
iii) Simple system structure.

So it is widely applied in areas which needs high performance drive (Li et al., 2004). From the control point of view, DC motor exhibit excellent control characteristics because of the decoupled nature of the field and armature mmf's recently, many modern control methodologies such as nonlinear control (Hemati et al., 1990), optimal control (Pelczewski and Kunz, 1990), variable structure control (Lin et al., 1999) and adaptive control (Cerruto et al., 1995) have been widely proposed for linear brushless permanent magnet DC motor. However, these approaches are either complex in theatrical bases or difficult to implement (Lin and Jan, 2002). PID control with its three term functionality covering treatment to both transient and steady-states response offers the simplest and yet most efficient solution to many real world control problems (Ang et al., 2005). In spite of the simple structure and robustness of this method, optimally tuning gains of PID controllers have been quite difficult.

Yu and Hwang (2004) have presented a LQR method to optimally tune the PID gains. In this method, the response of the system is near optimal but it requires mathematical calculation and solving equations. The characteristic equations of BLDC motors can be represented as:

$$v_{app}(t) = L\frac{di(t)}{dt} + R.i(t) + v_{emf}(t) \tag{2}$$

$$v_{emf} = K.\omega(t) \tag{3}$$

$$T(t) = K.i(t) \tag{4}$$

$$T(t) = J\frac{d\omega(t)}{d(t)} + D.\omega(t) \tag{5}$$

Where $v_{app}(t)$ is the applied voltage, $\omega(t)$ is the motor speed, L is the inductance of the stator, i(t) is the current of the circuit, R is the resistance of the stator, v_{emf} (t) is the back electromotive force, T is the torque of motor, D is the viscous coefficient, J is the moment of inertia, Kt is the motor torque constant and K_b is the back electromotive force constant ($K_t = K_b = k$).

Block diagram and transfer function of DC motor

Figure 2 shows the block diagram of the brush less DC motor. Transfer function for DC motor's speed control is:

$$\frac{w(t)}{V(t)} = \frac{K}{(Js+b)(Ls+R)+K^2}$$

Where,

Input (V): source voltage, *output (ω): rotating speed and *the rotor and shaft are assumed to be rigid.

Figure 3 shows the actual closed loop step response of DC-motor.

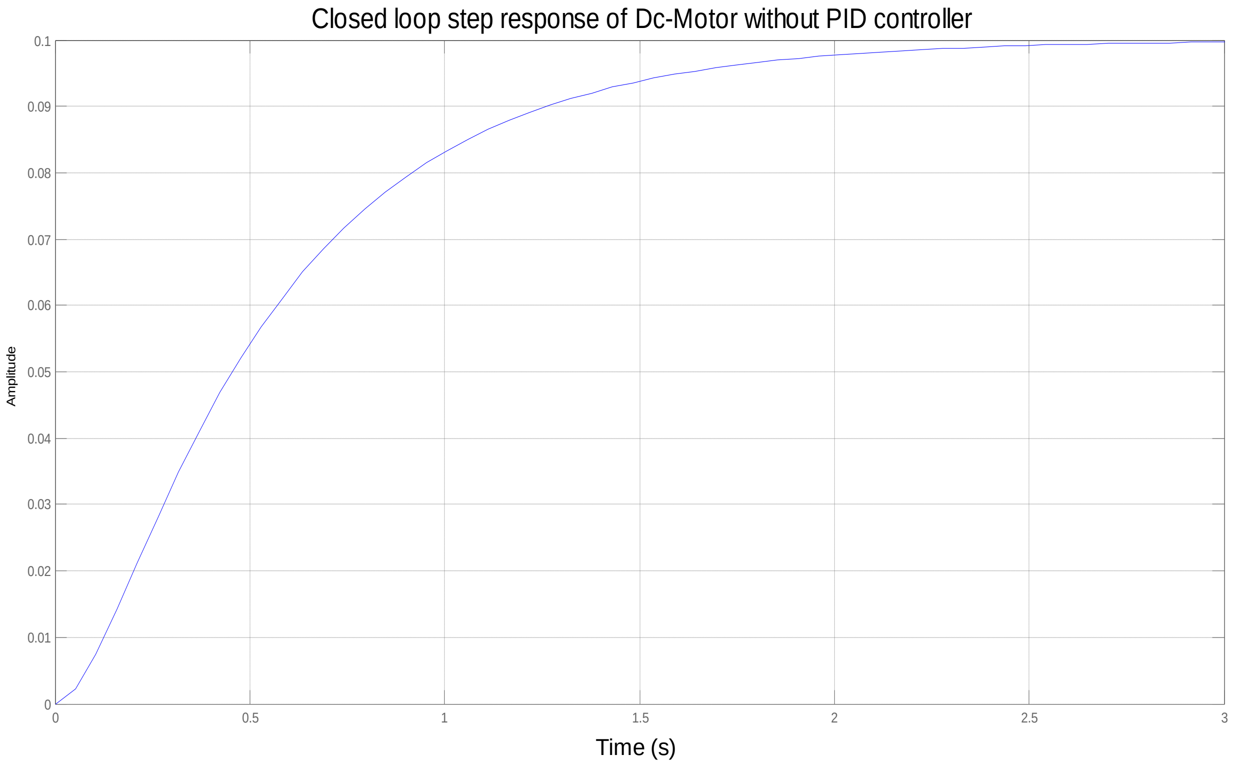


Figure 3. The closed loop step response.

Table 1. Parameter of motor.

Parameters	Symbols	Units	Values
Electrical resistance	*R*	ohm	1
Electrical inductance	*L*	*H*	0.5
Electromotive force constant	$K_e = K_t$	Nm/Amp	0.01
Moment of inertia of rotor	*J*	Kgm^2/s^2	0.01
Damping ratio of mechanical system	*b*	Nms	0.1

*input (V): source voltage, *output (ω): rotating speed and *The rotor and shaft are assumed to be rigid.

DC motor parameter values

The parameters and their values used to calculate transfer function of the motor used for simulation are in Table 1.

IMPLEMENTATION OF PSO METHOD

Mathematical model of PSO is defined as follows (Kennedy and Eberhart, 1995; Eberhart and Shi, 1998): Assume that the population of particles is *n* and the searching space is D-dimensional; the position and the velocity of the ith particle in the d-dimensional search space can be represented as $x_i = (x_{i1}, \ldots, x_{id})$ and $v_i = (v_{i1}, ..., v_{id})$ $(i = 1, \ldots, n)$. Each particle's own best position (pbest) $P_p^k(i)$ represents the best position found so far at time *k*. The best position of the whole swarm (gbest) at time *k* is represented as P_g^k. At each generation, the velocity and position of each particle is updated by the following formula:

$$v_i^{k+1} = wv_i^k + C_1 r_1 (P_p^k(i) - x_i^k) + C_2 r_2 (P_g^k - x_i^k)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1}$$

Where *w* is the inertia moment, C_1 and C_2 are cognitive

Table 2. Parameters used in CA-PSO.

Parameters	Values
Population size	50
C1	2
C2	2
No of iterations	100

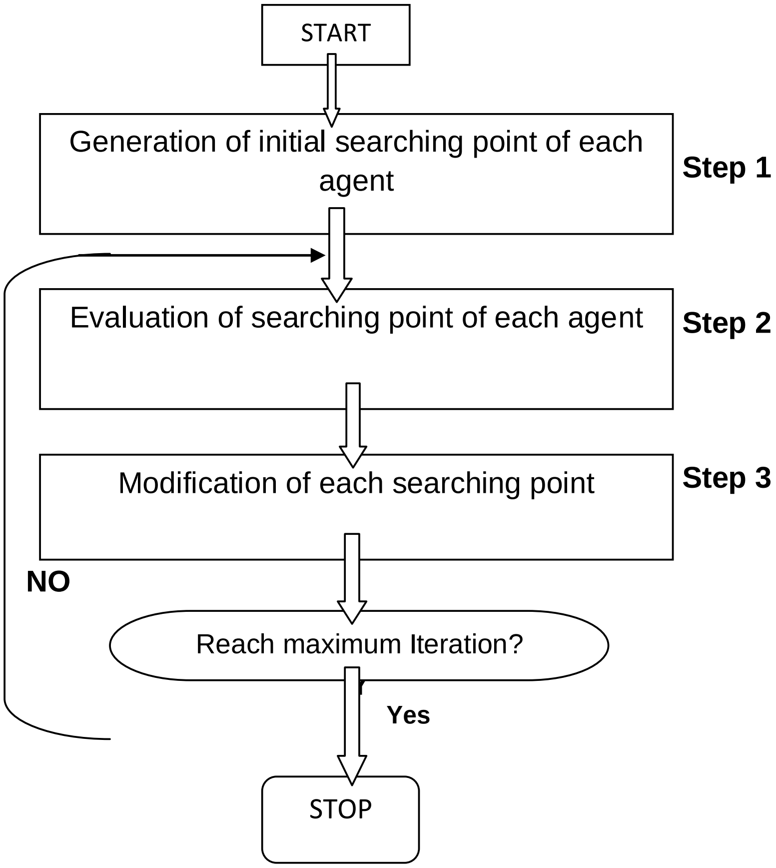


Figure 4. Flow chart of PSO-PID.

and social acceleration constants (Gaing, 2004), both r_1 and r_2 are independent random numbers uniformly distributed in the range of [0, 1].

Table 2 shows the PSO parameters that are used to verify the performance of the PSO-PID controller parameters:

A) Flow chart of PSO (Figure 4).
B) Optimal PSO-PID response.

Table 3 lists the performance of the PSO-PID controller of DC-motor with PSO algorithm. The step response of DC motor in PSO based PID controller is shown in Figure 5. Figure 6 shows the evolution curve with PSO method.

IMPLEMENTATION OF CULTURAL ALGORITHM

Table 4 shows the CA based PSO parameters that are used to verify the performance of the CA-PID controller parameters:

A) Optimal CA-PID response.

Table 5 lists the performance of the CA-PID controller.

Figure 7 shows the system step response with CA-PSO method. Figure 8 shows the evolution curve with CA

Table 3. Performance of the PSO-PID controller.

Parameters	Symbols	Values obtained
Proportional gain	P	23.8480
Integral gain	I	3.5227
Derivative gain	D	0
Maximum overshoot	M_p	0
Steady state error	E_{ss}	0.0997
Settling time	T_s	10 s
Rise time	T_r	0.5 s

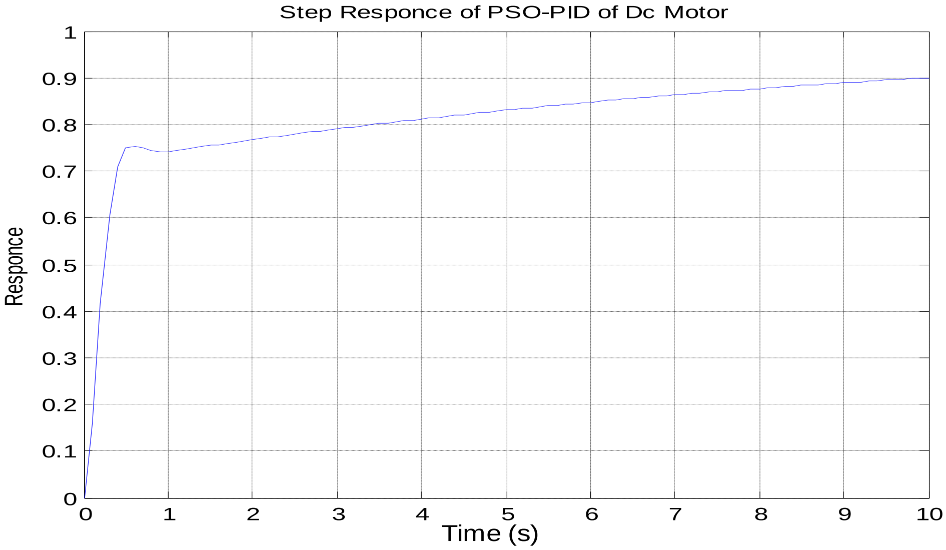


Figure 5. Step response of PSO-PID of DC motor.

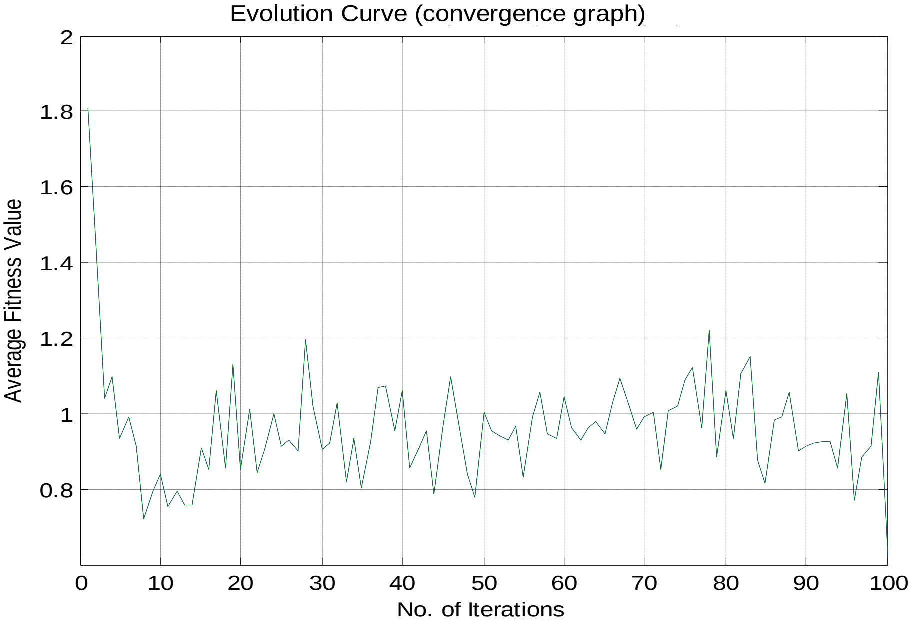


Figure 6. Convergence graph of PSO- PID of Dc motor.

Table 4. Parameters used in CA-PSO.

Parameters	Values
Population size	50
C_1	2
C_2	2
No of iterations	100
K_v	0.1

Table 5. CA-PSO performance.

Parameters	Symbol	Values obtained
Proportional gain	P	14.7031
Integral gain	I	59.8389
Derivative gain	D	17.9709
Maximum overshoot	M_p	0.01
Steady state error	E_{ss}	0.000020251
Settling time	T_s	0.4 s
Rise time	T_r	0.3 s

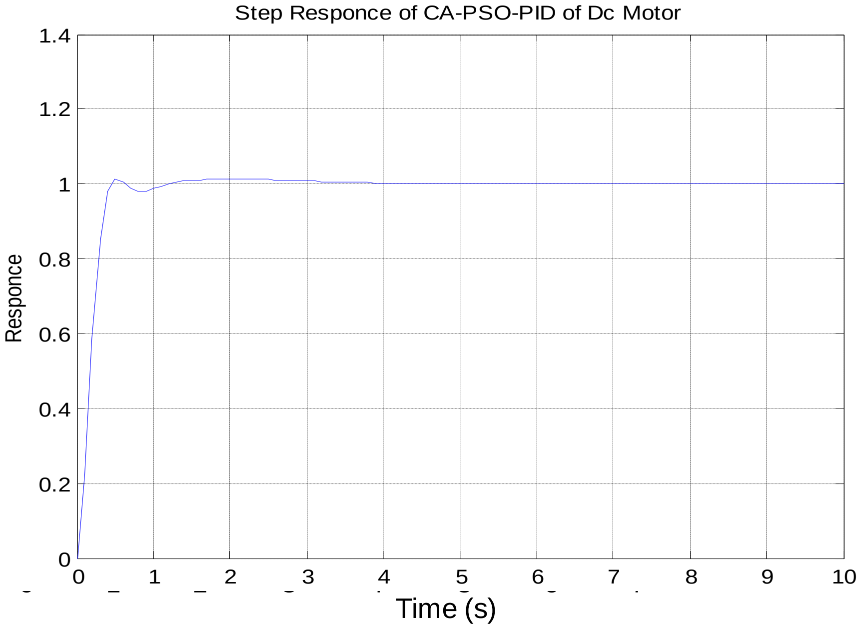


Figure 7. The system step response with CA-PSO method.

based PSO.

B) Comparison of CA-PSO with basic PSO.

To show the effectiveness of the proposed method, a comparison of the designed PID controller is made with the basic PSO method. Same PSO parameters are used as that of 'cultural algorithm'. Figure 9 shows series of the comparative experimental results and the effectiveness of our proposed hybrid can be clearly demonstrated.

Conclusion

In this paper the algorithm of basic particle swarm optimization algorithm is modified and the culture-based

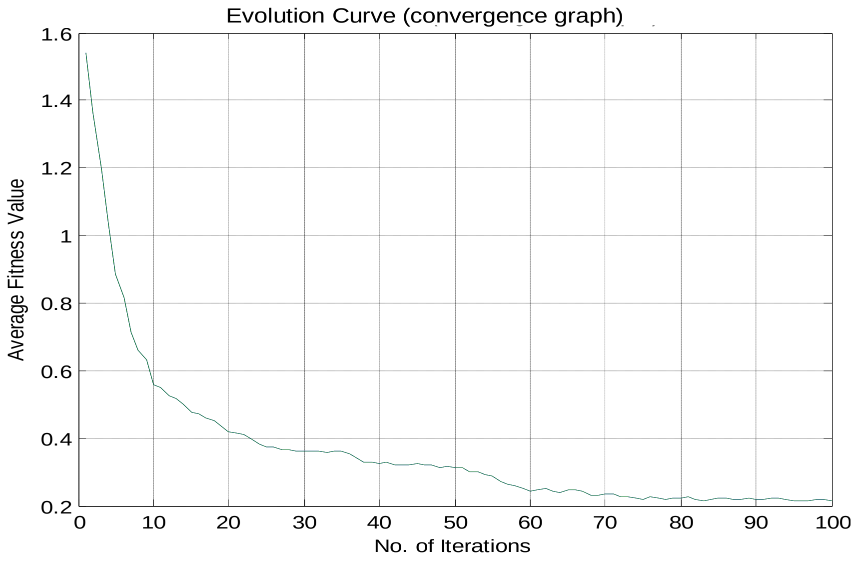
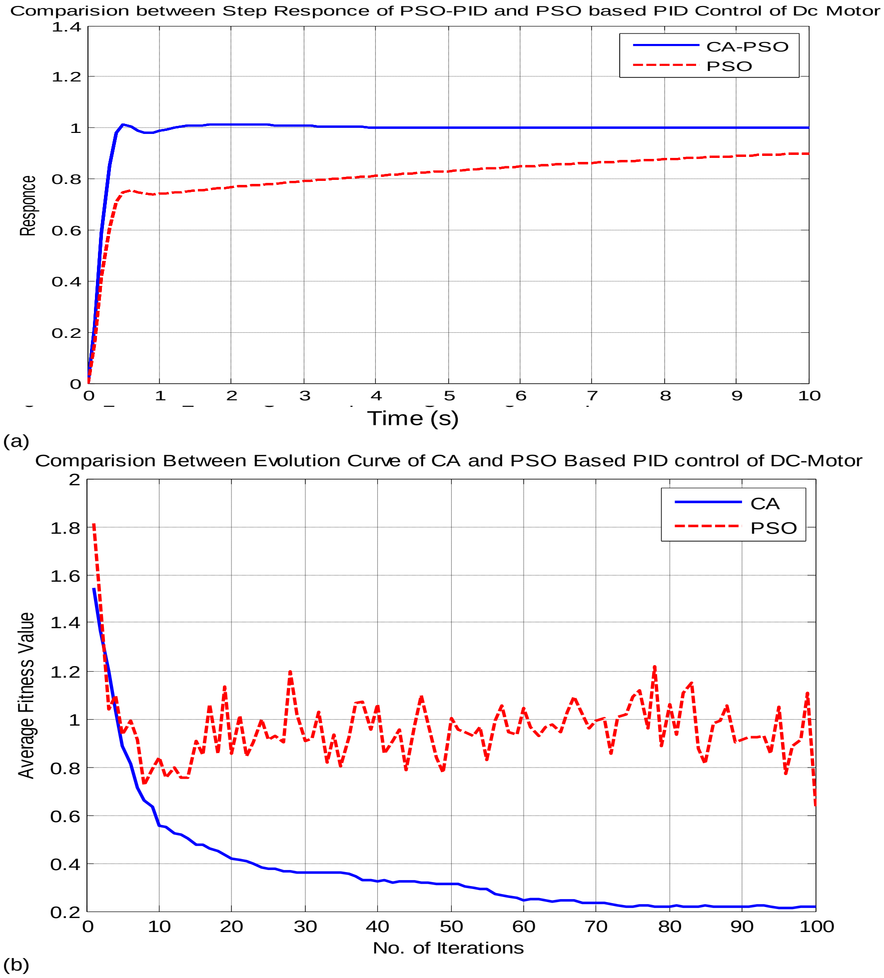


Figure 8. Evolution curve with CA based PSO.



(a)

(b)

Figure 9. Comparative results among different approaches. Comparison between CA-PSO and PSO (a) and comparison between CA and PSO (b).

particle swarm optimization is proposed. The new algorithm based on culture frame through the respective evolution in two different spaces and the mutual information correspondence can better overcome the PSO's shortcoming to be easy to fall into the local optimum. Theoretically, from the aforementioned PID parameter optimization test indicated that the function implemented with CA-PSO can more quickly find the best solution than PSO with less iterating step. Because two spatial bases certain correspondence agreement to exchange the superior particle, increased the particle multiplicity, avoided falling into the partial optimal solution and enhanced the validity of basic particle swarm optimization algorithm.

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