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ORIGINAL ARTICLE

Spread enhancement for firefly algorithm with application to control mechanism of exoskeleton system

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ABSTRACT – Firefly algorithm (FA) is a swarm intelligence based algorithm for global optimization and has widely been used in solving problems in many areas. The FA is good at exploring the search space and locating the global optimum, but it always gets trapped at local optimum especially in case of high dimensional problems. In order to overcome such drawbacks of FA, this paper proposes a modified variant of FA, referred to as spread enhancement strategy for firefly algorithm (SE-FA), by devising a nonlinear adaptive spread mechanism for the control parameters of the algorithm. The performance of the proposed algorithm is compared with the original FA and one variant of FA on six benchmark functions. Experimental and statistical results of the approach show better solutions in terms of reliability and convergence speed than the original FA especially in the case of high-dimensional problems. The algorithms are further tested with control of dynamic systems. The systems considered comprise assistive exoskeletons mechanism for upper and lower extremities. The performance results are evaluated in comparison to the original firefly and invasive weed algorithms. It is demonstrated that the proposed approaches are superior over the individual algorithms in terms of efficiency, convergence speed and quality of the optimal solution achieved.

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Introduction

Swarm-intelligence based algorithms full under bio-inspired optimization algorithms where the intelligence is attributed to the social behaviour of animals and insects in nature. In recent years, many researchers have adopted swarm intelligence algorithms to solve hard optimization problems and they have shown great potential in solving complex engineering optimization problems [21]. Numerous swarm-based algorithms have been developed, and these include particle swarm optimization (PSO), ant colony optimization (ACO), bacteria foraging optimization (BFO), and bat algorithm (BA). Inspired by the flashing pattern of a swarm of fireflies, Yang [23] proposed a new swarm intelligence based algorithm called firefly algorithm (FA).

Yang [22, 23] proves that FA is very efficient in dealing with multimodal problems as well as performs better than other bio-inspired optimization algorithms. That is why, it has attracted much attention to solve problems in various applications including single objective problems [7, 15, 16, 17, 18] and also multi objective problems [13, 25]. Although FA has similarities with other swarm intelligence algorithms, it is much simpler in concept and implementation.

Some drawbacks of the algorithm have been found regarding the capability of the algorithm in higher dimension problems [20] as well as getting trapped in local optima [3]. Thus, improved versions have been developed to address such issues [3, 4, 19, 20], and applied to discrete, combinatorial and continuous optimization problems. Alternatively, hybridization has also been attempted to improve performance of the algorithm in terms of search capabilities and better accuracy. Several works have been reported such as hybrid with levy flight [24], ACO [2], differential evolution [1] and genetic algorithm [3].

Assistive robotic devices are increasingly needed to facilitate mobility and rehabilitation requirements of elderly and disabled [14]. Therefore, research interest in upper and lower extremities robot assistance has intensified in the academic and industrial sectors. Exoskeleton is an assistive device designed for mobility and for rehabilitation purpose [5]. Significant research within academic and industrial sectors in the area of exoskeleton mobility and robot assistance for medical and rehabilitation applications [5 – 6]. The proposed algorithms are used to devise control mechanisms for lower and upper extremities. The bio-inspired algorithms are applied to optimise the controller to achieve preferable manoeuvrability of the model.

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In this paper, a new variant of firefly with nonlinear adaptive strategy to modify and improve the original algorithm is proposed. The modified algorithm is named spread enhancement strategy for firefly algorithm (SE-FA). The organization of the paper is as follows: Section II introduces the classical FA algorithm and its parameters, Section III describes the adaptive variants and introduces the proposed algorithm. Section IV describes the experimental set-up and presents performance investigations with benchmark functions. Section V presents analysis and evaluation of the results. The latter section investigates the application of the proposed algorithms on practical engineering applications. The proposed algorithms are applied to optimise the control parameters of position tracking control of human arm and lower limb exoskeleton model. Finally, conclusion drawn from the work are presented in section VI.

Firefly algorithm

Firefly algorithm (FA) is one of the bio-inspired optimization algorithms and in the family of swarm intelligence based optimization algorithms developed by Yang [22-24]. It is a population-based metaheuristic algorithm inspired by the social behaviour of a group of fireflies that interact and communicate via the phenomenon of bioluminescence produced in the insect body.

Yang also suggests that each firefly will produce its own light intensity that determines the brightness of the firefly. The variation of light intensity produced is associated with the encoded objective function. As the attractiveness of firefly is proportional to the light intensity produced by each firefly, the distance, r could be defined as the distance between any two fireflies. For a firefly to move to another brighter firefly, assuming that a firefly j is more attractive than firefly i, Yang suggests that the movement of firefly i, towards firefly j is determined by

$$x_{i+1} = x_i + \beta_0 e^{-\gamma r^2}(x_j - x_i) + \alpha\epsilon_i \tag{1}$$

where the third term is the randomization term which consists of randomization coefficient, α with the vector of random variable, ϵ_i from Gaussian distribution and β_0 is the parameter value of attractiveness coefficient at r = 0.

Spread enhancement for firefly algorithm

The proposed algorithm presented here is purposely to solve several issues of the classical algorithm. The classical algorithm's parameters are all predetermined and do not change after each generation. Yan et al. [20] noted that it works well on functions with low dimension and narrow variable ranges. However, the algorithm will not perform well in complex situations such as increment of the dimension and variable ranges. Moreover, the fireflies get easily trapped in local optimum as the search space is wider and the problem dimension is larger. As a result, the accuracy of optimization result is not high in such situations.

Therefore, the algorithm outlines several strategies to minimise the impact of these drawbacks. On the other hand, it also aims to improve the exploration and intensification of the firefly search. The proposed strategies introduce time-varying weight in the process of renewal of the firefly location, transform the predetermined parameter into time-varying nonlinear step size and add synergy to local search in the algorithm.

In the original FA, most of the parameter values in the equation of movement renewal are set and predetermined. Therefore, in order to improve the performance of the algorithm, in each process of movement renewal, those parameters change, whether increase or decrease, nonlinearly with time. The aim of the changes made is to enhance the search and local exploration, and avoid excessive pace of any local extreme point. It helps the algorithm to jump out of a local optimum at the beginning and leads to fast movement to the global best value at the end of the generations. The modification is by determining the inertia weight ω_{iter} as a nonlinear function of the present iteration number ($iter$) at each time step. The formulation of the nonlinear adaptive weight function thus proposed is as follows:

$$\omega_{iter} = \left[\frac{(iter_{max} - iter)^n}{(iter_{max})^n}\right] \times (\omega_f - \omega_i) + \omega_f \tag{2}$$

where $iter_{max}$ is the maximum number of iterations/generations in a given run, n is the nonlinear modulation index and $\omega(t)$ is inertia weight with ω_f as the final parameter value and ω_i as the initial parameter value. The inertia weight will be the parameter of the algorithm such as absorption coefficient, $\gamma(t)$ and randomization coefficient, $\alpha(t)$ and inertia weight of firefly position renewal, $\delta(t)$.

The synergy of local search is done by exploiting the neighbourhood condition. Hence, the score of information index, $S_i(iter)$ is introduced for the fireflies with nonlinear spread enhancement strategy to pay more attention to local search and find better global optimum solution. The index is formulated as:

$$S_i = \left[\frac{f(x_{worst}(iter)) - f(x_i(iter))}{f(x_{worst}(iter)) - f(x_{best}(iter))}\right] \times [q_i - q_f] + q_f \tag{3}$$

Table 1. Benchmark functions used in the tests.

No	Function	Benchmark Formulation	Search Space
f_1	Sphere	$f_1(x) = \sum_{i=1}^{D} x_i^2$	$[-10,10]^D$
f_2	Schwefel's Problem 2.22	$f_2(x) = \sum_{i=1}^{D} \lvert x_i \rvert + \prod_{i=1}^{D} \lvert x_i \rvert$	$[-10,10]^D$
f_3	Schwefels's Problem 1.2	$f_3(x) = \sum_{i=1}^{D} (\sum_{j=1}^{i} x_j)^2$	$[-65,65]^D$
f_4	Rastringin	$f_4(x) = \sum_{i=1}^{D} \{x_i^2 - 10\cos(2\pi x_i) + 10\}$	$[-5.12, 5.12]^D$
f_5	Ackley	$f_5(x) = -20\exp\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\right) - \exp\left(\frac{1}{D}\sum_{i=1}^{D}\cos 2\pi x_i\right) + 20 + e$	$[-32,32]^D$
f_6	Griewank	$f_6(x) = \frac{1}{4000}\sum_{i=1}^{D} x_i^2 - \prod_{i=1}^{D}\frac{x_i}{\sqrt{i}} + 1$	$[-600, 600]^D$

Table 2. The FA variants used.

Algorithm	Parameters	Reference
Classical FA	$\beta_o = 1.0, \alpha = 0.2, \gamma = 1.0$	[23, 24]
IWFA	$\beta_o = 1.0, \alpha = 0.2, \gamma = 1.0,$ $\omega_{initial} = 1.0, \omega_{final} = 0.4$	[19]
SE-FA	$\beta_o = 1.0,$ $\alpha_{initial} = 1.0, \alpha_{final} = 0.01,$ $\gamma_{inital} = 0.01,$ $\gamma_{final} = 1.0, \omega_{initial} = 1.0, \omega_{final} = 0.4$	

where $x_{worst}(iter)$ and $x_{best}(iter)$ are the worst and best positions at iteration (iter), respectively with q_i as the lowest factor value and q_f as the highest factor value set at the initialization stage. The index will adjust the proposed nonlinear adaptation strategies. Hence, the adjustment mechanism of the nonlinear adaptive strategies is expressed mathematically as:

$$x_{i+1} = \delta(t)x_t + S_i(t)\beta e^{-\gamma(t)r^2}(x_j - x_i) + S_i(t)\alpha(t) \tag{4}$$

The above shows the adaptation of position of the fireflies after each iteration / generation in a given run of the experiment. With these nonlinear adjustments, the modified firefly algorithm will have better balance between the global search and local search capabilities, and thus will avoid getting trapped into local optimum, and this will increase the speed of convergence to better optimum solution.

Methodology

In this paper, the performance of SE-FA compared to the classical FA is assessed with six benchmark functions as shown in Table 1. The performance evaluation measurements used in the comparative assessment include the quality of the final solution and the convergence speed towards optimum solution. Furthermore, the proposed algorithms are also used to devise control mechanisms for lower and upper extremities. A set-point tracking position control is developed as the control mechanism. The bio-inspired algorithms are applied to optimise the controller to achieve preferable manoeuvrability of the model. Performances of the proposed algorithms with the control strategy are evaluated and analysed.

The experimental testing hardware platform comprises a personal computer (PC) with processor CPU Intel (R) Core (TM) i5-2400 with operating systems Window 7 Professional, frequency of 3.10 GHz and memory installed of 4.00 GB RAM. The program is coded in MATLAB R2013a.

Benchmark functions and experimental analysis

The proposed algorithm, SE-FA is extensively compared with the classical FA and one variant of FA known as inertia weight FA (IWFA) [19]. Yafei et al. [19] introduced inertia weight (IW) at updating fireflies during iteration period to lead to improved solutions. Adopting such idea, the adaptive dynamic step size of the firefly parameters is proposed here. For a fair comparison of all the competitive algorithms, the same population size of fireflies is used as proposed by Yang [24]. Table 1 shows the parameter set of all the algorithms during initialization for the tested problems.

The performance of SE-FA compared to the classical FA and IWFA is assessed with six benchmark functions as shown in Table 2. The benchmark functions consist of three unimodal functions (De Jong, f_1, Schwefel's Problem 2.22, f_2 and Schwefel's Problem 1.2, f_3) and three multimodal functions (Rastringin, f_4, Ackley, f_5 and Griewank, f_6).

Table 3. Test with benchmark functions in 10 dimensions.

	FA		IWFA		SE-FA	
	Mean Value	Standard Deviation	Mean Value	Standard Deviation	Mean Value	Standard Deviation
f_1	1.22e+02	2.05e+01	1.30e-06	1.47e-06	1.05e-12	7.47e-13
f_2	2.83e+01	2.90e+00	2.03e-03	1.77e-03	2.63e-06	1.00e-06
f_3	1.12e+02	2.24e+01	5.18e-05	8.86e-05	2.94e-12	4.21e-12
f_4	5.98e+01	7.28e+00	7.81e-05	1.65e-04	1.99e-10	1.15e-10
f_5	1.95e+00	2.47e+00	1.08e-02	1.18e-02	5.09e-09	5.29e-09
f_6	1.39e+02	2.36e+01	1.89e-03	3.23e-03	1.95e-13	1.82e-13

Table 4. Test with benchmark functions in 30 dimensions.

	FA		IWFA		SE-FA	
	Mean Value	Standard Deviation	Mean Value	Standard Deviation	Mean Value	Standard Deviation
f_1	6.20e+02	5.36e+01	1.27e-06	3.23e-06	4.13e-12	4.34e-12
f_2	5.29e+06	1.03e+07	1.74e-03	1.31e-03	1.14e-05	7.57e-06
f_3	8.72e+02	1.19e+02	7.14e-05	1.46e-04	4.63e-11	1.06e-10
f_4	3.32e+02	1.11e+01	3.54e-05	4.87e-05	1.75e-09	2.99e-09
f_5	2.15e+00	3.20e+00	8.49e-03	7.32e-03	6.71e-09	6.33e-09
f_6	6.06e-02	7.37e+01	1.71e-03	2.83e-03	2.70e-13	2.02e-13

The number of function evaluations (NFE) is used in the tests as a measurement of computational time instead of the number of generations. 30 independent runs of the three algorithms are carried out on each of the benchmark functions and the mean value of the best value of benchmark function solution and their respective standard deviation are noted. The problems are considered in 10 and 30 dimensions.

The performance evaluation measurements used in the comparative assessment include the quality of the final solution, the convergence speed towards optimum solution, the successful rate (reliability of hitting the optimum threshold) and statistical significance test. Such comparison reflects the superiority of the proposed approach as tabulated in Tables 3 – 4, and these are discussed below.

Comparison of the quality of optimum solutions for the algorithms in dimensions 10 and 30 is shown in Tables III and IV. The results obtained are in terms of mean fitness value and standard deviation for 30 independent runs of each algorithm. The maximum number of NFE for each algorithm is predetermined as 3000. The best solution value in each case is marked in bold. Based on the results obtained, it is noted that the algorithms successfully located the optimum points of all the benchmark functions. However, the mean result obtained with SE-FA was better than the other algorithms. This demonstrates that SE-FA achieves better performance than the other algorithms, in terms of convergence to the optimum solution.

Both classical FA and IWFA seem to have got trapped to the local optimum especially in case of Schwefel's Problem 1.2, Ackley and Griewank function in 30 dimensions. IWFA showed some improvement as compared with the classical FA; however, both algorithms could not jump out of the local optimum. On the other hand, SE-FA improved the situation and also showed exploitation of local search. SE-FA also showed faster convergence and tendency to get better result as the number of NFE increased.

Application to control of assistive exoskeleton

Human arm model of upper extremities and lower limb exoskeleton model for lower extremities are used in this experiment. The proposed algorithms are used to devise control mechanisms for lower and upper extremities. A set-point tracking position control using proportional, integral and derivative (PID) control is developed as the control mechanism. Performances of the proposed algorithms with the control strategy are evaluated and analysed. For the experiment, the basic criteria used were thus as follows:

Maximum number of population, $n_{max} = 30$.
Maximum number of iterations, $it_{max} = 30$
(NFE = 900).

In this section, the proposed algorithms are employed for upper limb exoskeleton exercise. A lot of the research work has been reported using bio-inspired algorithms in the design and development of upper limb exoskeleton. For example, Hassan and

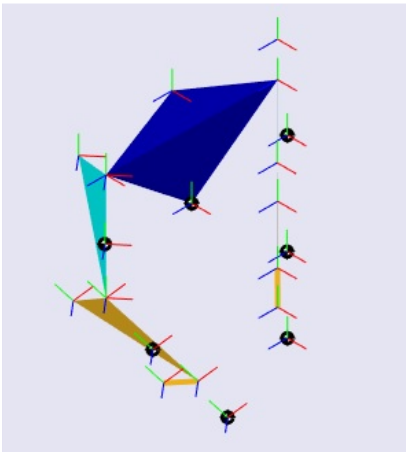

Figure 1. The human arm model.

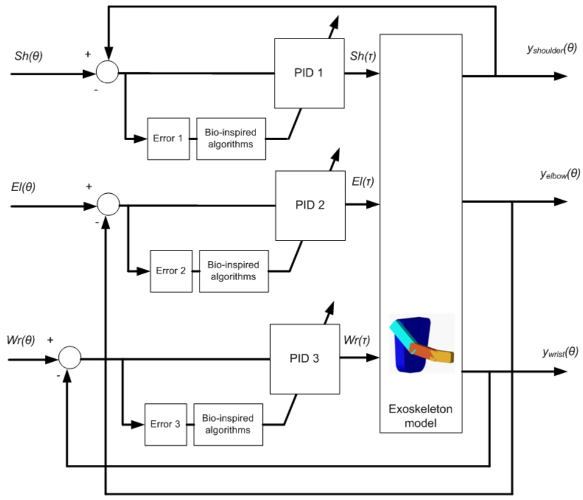

Figure 2. The controller of the upper limb exoskeleton system.

Karam [8] used PSO in designing the structure of rehabilitation robot arm. Khan et al. [9] also employed PSO in determining the control gains of upper limb assist exoskeleton robot. Simulation were performed for only one human arm. The algorithms were used to tune and optimise the controller to determine the best gains for the system. The performance of the control system with the used optimisation algorithms is evaluated. The error and torque characteristics are also monitored. For all the tests, the algorithms used the same population size, n and NFE for a fair comparative evaluation.

In the simulations, the elbow and shoulder joints were actuated individually. In this experiment, wrist was considered static and hence, the wrist movement was followed based on the elbow movement. In this case, the tracking was based on the movement of elbow and arm. The starting point was standing position in normal condition. Both shoulder and elbow were initialised to zero position. Zero position refers to human in standing where both elbow and shoulder are in straight downward position. For this experiment, the shoulder moved in outward rotation while the elbow was raised by moving in flexion and extension condition. From the experiments, SE-FA achieved better result by producing the lowest cost function value as compared to FA and IWO algorithms.

Lower Limb Exoskeleton Movement

In this section, control mechanisms for lower-extremities exoskeleton assistance are devised and evaluated with the proposed algorithms. The lower limb exoskeleton system model as described by Ghassaq et al. [5] is used in this experiment. The exoskeleton system is to control and balance both lower limb exoskeleton and humanoid movement in a walking cycle. The humanoid model structure has been developed by [5] in MATLAB 2012 / Simulink linked with Visual Nastran 4D (VN4D) environment. For simulated walking, a specific trajectory of the knee joint movement is set using Clinical Gait Analysis (CGA) data with reference to Kirtley [10]. The algorithm can be used to find optimal parameters of exoskeleton design and also to fine tune the control structure used for the exoskeleton. Long et al. [11], used GA to optimise a sliding mode controller in lower limb exoskeleton application.

In this research, PID control is developed for knee joint movement. The bio-inspired algorithms are used to optimise and minimise the orientation error for the knee joints while the exoskeleton system is in walking phase. The proposed optimisation algorithms are used to fine tune the controller gains to minimise the error, e(t). The block diagram of the PID control used for the lower limb exoskeleton is shown in Figure 3.

The simulation focused on the trajectory of right and left knee and the ability of the controller to move the exoskeleton model accordingly. The output of the controller is the knee torque of the model which is fed to the humanoid. In Figure 8, the Error 1 and 2 need to be minimised, and the proposed algorithms as the optimisation tools in the controller. Furthermore, SE-FA achieved better result by producing the lowest cost function value as compared to FA and IWO algorithms.

Table 8 shows the minimum and maximum torque profiles of the right and left knee joints of both humanoid and exoskeleton during walking phase. Samples of the torque profile are shown in Figure 4 for the case of torque profiles for both humanoid and exoskeleton of the SE-FA. Most of the algorithms achieved good results as they showed that the average torque of exoskeleton was less than 30 Nm. This is

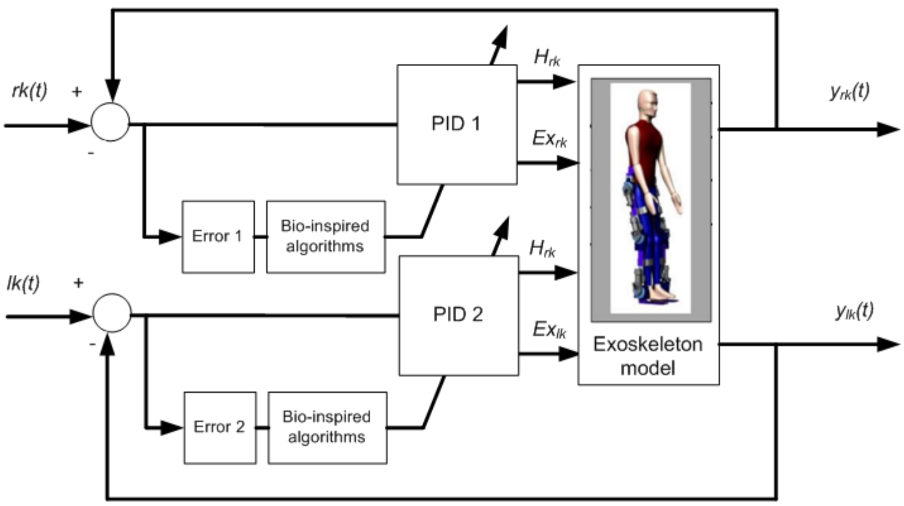

Figure 3. Lower limb exoskeleton with controller.

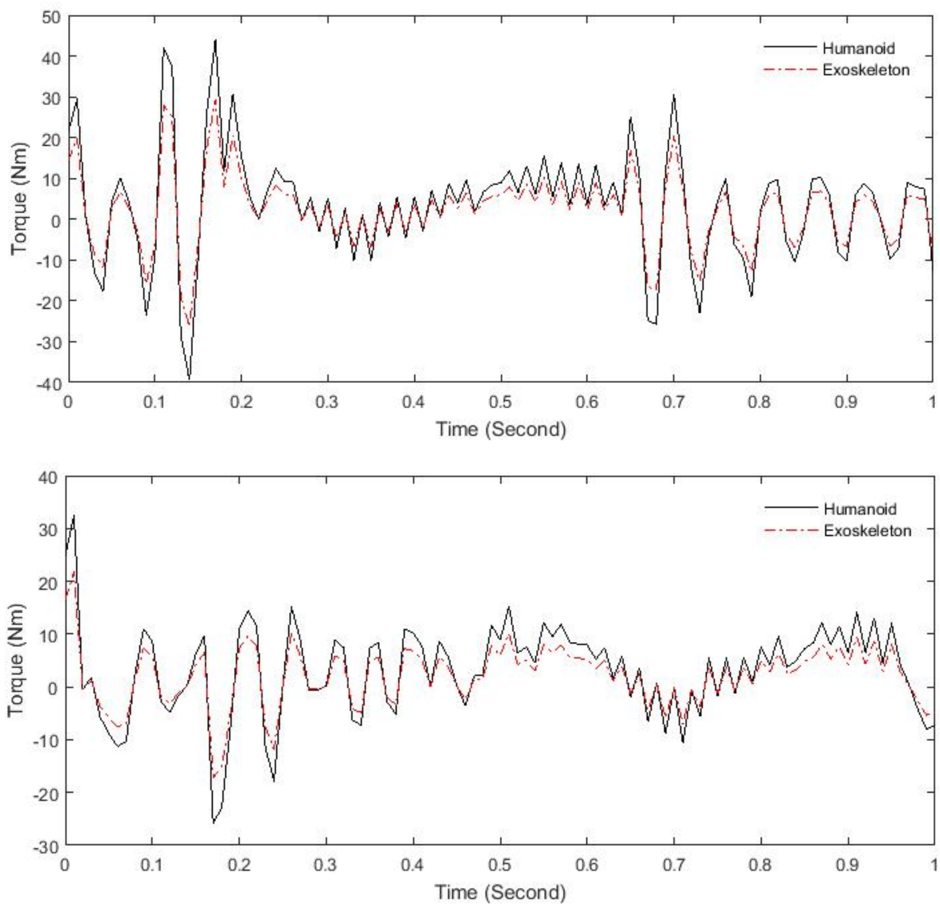

Figure 4. Torque profile for SE-FA, 1(a) Right leg, 1(b) Left leg.

because, according to Low [12], the maximum assistive torque for exoskeleton in the application to support knee joint is advised to be lower than 60 Nm.

Conclusion

This paper has presented an improved variant of firefly algorithm by using nonlinear adaptation of the step size of the algorithm parameters. The present formulation scheme attempts to improve the exploration and exploitation abilities of the search space to avoid premature convergence and achieve better optimum solution. It has been demonstrated in tests with six benchmark functions in high dimensions that the proposed SE-FA has outperformed the classical FA and IWFA in terms of quality of optimum value, convergence speed and successful rate. The proposed bio-inspired optimisation algorithms have

Table 5. The human arm movement used in the experiment.

		Shoulder rotation	Elbow flexion
Range of motion	Actual	-80o – 100o	0o – 145o
	Experiment	0o – 40o	0o – 45o

Table 6. The optimized control parameter of human arm model.

	FA	SE-FA	IWO
f(x)	4.387E-02	3.074E-02	3.630E-02
time, t	1.081E+03	1.145E+03	1.142E+03
x1	483.321	397.505	352.290
x2	484.666	38.042	355.445
x3	258.553	499.949	218.787
x4	326.401	477.913	404.934
x5	449.641	378.743	482.203
x6	64.304	463.003	1.084
x7	308.661	50.335	179.289
x8	440.777	128.142	120.782
x9	103.620	188.722	108.247

Table 7. The optimized control parameters of lower limb exoskeleton.

Algorithm	f(x)	time, t	x1	x2	x3	x4	x5	x6
FA	1.19277	1.22E+05	5.00	2.12	0.19	5.00	1.40	0.23
SE-FA	1.15880	2.36E+05	4.14	1.80	0.22	4.79	2.82	0.28
IWO	1.29199	1.99E+05	3.40	1.24	0.21	2.79	2.22	0.28

Table 8. The minimum and maximum torque profile of right and left knee joint torque.

Algorithm	Humanoid				Exoskeleton			
	Right		Left		Right		Left	
	min	max	min	max	min	max	min	max
FA	-21.317	41.858	-14.211	27.905	-32.896	30.000	-21.930	20.000
SE-FA	-39.390	44.086	-26.260	29.391	-25.812	32.529	-17.208	21.686
IWO	-34.732	40.856	-23.154	27.237	-27.487	33.518	-18.325	22.346

been employed in two engineering applications. Application of the optimisation algorithms to optimise parameters of PID control for trajectory tracking of upper and lower extremity exoskeletons. The performance comparison has been made based on ability of the algorithms to achieve best fitness and convergence to optimal solution. The test results obtained have shown that the proposed algorithm has provided significant improvement to the original algorithm, and is more reliable, achieves better results and significantly outperforms the original algorithms.

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