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Synergistic fibroblast optimization: a novel nature-inspired computing algorithm

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Abstract: The evolutionary algorithm, a subset of computational intelligence techniques, is a generic population-based stochastic optimization algorithm which uses a mechanism motivated by biological concepts. Bio-inspired computing can implement successful optimization methods and adaptation approaches, which are inspired by the natural evolution and collective behavior observed in species, respectively. Although all the meta-heuristic algorithms have different inspirational sources, their objective is to find the optimum (minimum or maximum), which is problem-specific. We propose and evaluate a novel synergistic fibroblast optimization (SFO) algorithm, which exhibits the behavior of a fibroblast cellular organism in the dermal wound-healing process. Various characteristics of benchmark suites are applied to validate the robustness, reliability, generalization, and comprehensibility of SFO in diverse and complex situations. The encouraging results suggest that the collaborative and self-adaptive behaviors of fibroblasts have intellectually found the optimum solution with several different features that can improve the effectiveness of optimization strategies for solving non-linear complicated problems.

Key words: Synergistic fibroblast optimization (SFO); Fitness analysis; Convergence; Benchmark suite; Monk's dataset
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1 Introduction

Evolutionary computation techniques are developed based on the characteristics of natural phenomena, including foraging behavior, evolution, cell and molecular phenomena, cognition and neurosystems, alignment phenomena in microscopes, nonbiological systems, and geo-science-based techniques. Since the 1970s, metaheuristic algorithms have evolved continuously to find an effective optimization approach to solve non-linear complex problems (Cruz et al., 2010; Mo, 2012). Optimization problems are common and there is always a requirement for solutions which are optimal or near-optimal. There are different methods which provide solutions to the intractable optimization problems, and one such intellectual model is the nature-inspired computational system (Marrow, 2000). Although all the heuristic algorithms have different inspirational sources, the common objective is to find the optimum. The aim of this study is to introduce a simulated synergistic fibroblast optimization (SFO) model that follows the theory of swarm intelligence. The intellect behavior of the fibroblast organism in the dermal wound-healing process has inspired the design and development of a novel SFO algorithm. Various characteristics of the fibroblast cellular organism, such as differentiation, proliferation, inflammation, migration, reorientation, alignment, extracellular matrix (ECM) synthesis, collaborative, goal-oriented, interaction,

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regeneration, self-adaptation, and evolution, have motivated the design and development of SFO, a heuristic optimization algorithm (DiMilla et al., 1991; Derrac et al., 2013). The goal of an introduced SFO is to find the optimum (minimum or maximum) solution that resolves real-time and uncertainty problems.

Fibroblast is a kind of cellular organism that migrates from one location to another in the wounded region of the skin (Stebbings, 2001). It is a ubiquitous stromal cell which is found in most mammalian connective tissue, and it plays a significant role in the dermal wound-healing process. When the skin gets injured, a cell swarm invades the injured region by the secretion of collagen protein to heal the wounds, encompassing diverse processes such as inflammation, formation of tissue, angiogenesis, contraction of tissue, and tissue remodeling. The crucial part in the inflammation event is the interaction of fibroblast cells through ECM. Trajectories of individual fibroblast are determined as they migrate towards the wounded region, under the combined influence of fibrin/collagen alignment and gradients in a paracrine chemo attractant produced by leukocytes. The degree of interaction among the cells depends on the population of the particles and includes the effect of crowding. Fibroblasts migrate from the normal tissue to the wounded region by the secretion of collagen protein that determines the formation of new tissue (Dallon et al., 2000; McDougall et al., 2006; Rodemann and Rennekampff, 2011).

The effect of collagen alignment is influenced by a number of parameters, such as fibroblast concentration, cellular speed, fibroblast sensitivity to chemoattractant concentration, and the chemoattractant diffusion coefficient, which regularize the new direction of swarm movement. While the cells move from the normal tissue to the wounded region, initially the motility speeds of the cells are reduced, but are steadily improved at the later stage. The speed and direction of the cell are normalized by the chemoattractant gradient, which improves fibroblast influx on the wound, and the diffusion co-efficient causes fibroblast density to spread a uniform distribution in the skin (DiMilla et al., 1991). Fibroblasts have invaded the injured region with the synthesis of collagen protein found in the ECM and the orientation of cells. In this research, an SFO computational model is constructed with foremost pre-eminent characteristics of the fibroblast that involves collaborative-, cognitive-, and self-adaptations that imitate the whole wound-healing process. The self-organizing and co-operative natures of the fibroblast to heal injury are associated greatly with the evolutionary algorithm strategy to discover the optimal solution in the problem space.

2 Literature review

Particle swarm optimization (PSO) is a swarm intelligence technique proposed by Eberhart and Kennedy (1995). It imitates the characteristics observed from birds flocking and fish schooling. The PSO algorithm has been used extensively to solve numerous nonlinear function optimization problems, provide solutions to complex optimization problems, develop real-time applications, and introduce various parameters and variations for fine tuning the behavior of PSO (Eberhart and Kennedy, 1995; Poli et al., 2007). The chronology of PSO evolution and comprehensive PSO-based methods surveyed by Sedighizadeh and Masehian (2009) illustrate that the PSO algorithm can be a suitable tool for solving various optimization problems considering its high efficiency in comparison with other evolutionary algorithms (such as genetic algorithm (GA)) and its simplicity. Tanweer et al. (2016) proposed human-learning principles to improve the performance of the PSO algorithm. It was tested on a black box optimization testbed to solve a selective class of problems under different budget settings and compared with nine different PSO variants. The results demonstrated that human-learning principles inspiring PSO offer more significant results than other variants of PSO. Tanweer et al. (2015) introduced a self-regulating PSO (SRPSO) algorithm, which has been evaluated using the 25 benchmark functions taken from CEC 2005 test suites. The performance of SRPSO was investigated with bare bones PSO (BBPSO) and comprehensive learning PSO (CLPSO), and the analysis results exemplified that SRPSO achieves a 95% confidence level, compared with other optimization algorithms in a non-parametric Friedman test. McCaffrey (2012) proposed a simulated protozoa optimization (SPO) technique, which mimics the foraging and reproductive behavior of unicellular organisms such as the paramecium caudatum. It was tested to solve five standard benchmark numeric minimization problems and compared with PSO, bacterial foraging optimization (BFO), and GA optimization (GAO). The experimental results revealed that SPO produces promising results that can be applicable to diverse problems and very large datasets. Niu et al. (2007) developed the multi-swarm cooperative PSO (M-CPSO) algorithm inspired by the phenomenon of symbiosis in natural ecosystems. It was investigated on several benchmark functions and the results revealed that the performance of M-CPSO is competitive with standard PSO. The convergence of a PSO algorithm analyzed by van den Bergh and Engelbrecht (2010) shows that the standard PSO is not guaranteed to the convergence of global optima, causing a stagnation problem. The authors suggested a few parameters to be incorporated to elucidate and modify the behavior of standard PSO. Izakian et al. (2010) applied a discrete PSO (DPSO) algorithm for the grid job scheduling problem. It was tested on 512 jobs and 16 machines and evaluated with popular metaheuristic algorithms such as GA, ant colony optimization (ACO), fuzzy PSO (FPSO), and continuous PSO (CPSO). The results illustrated that the proposed method is more efficient than other heuristic approaches. Snásel et al. (2013) introduced a new variant PSO algorithm, protoPSO, by incorporating protozoic behavior inspired by the protozoa organism. The fitness evaluation of the proposed algorithm was investigated to solve a test problem using well-known functions. The results showed that the novel optimization strategies would be able to solve some sets of problems. Improved binary PSO (IBPSO) applied for the feature selection method to classify the gene expression data was carried out by Chuang et al. (2008). Compared with *K*-nearest neighbors (*K*-NN), the proposed IBPSO method attains the highest classification accuracy in the 11 gene expression data test problems.

Differential evolution (DE) is a vector population based stochastic method introduced by Storn and Price (1997) for global optimization. Storn (2008) studied the current trends, applications, and open problems in DE. The authors concluded that DE is an efficient optimization technique for solving constrained, multi-objective, uncertain, and large-scale optimization problems. It can be used widely in the multi-disciplinary research field. Das (2011) surveyed the major variants and significant engineering applications of the DE algorithm, indicating that DE exhibits remarkable performance in solving complex real-world multi-objective, constrained, multi-modal, theoretical, large-scale, and uncertain optimization problems. Qin et al. (2009) proposed a new variant of the self-adaptive DE (SaDE) algorithm and investigated it on benchmark test suites of 26 bound constrained numerical optimization problems. The results signified that the novel method achieves better performance than conventional DE and several state-of-the-art parameter-adaptive DE variants. Khaparde et al. (2016) developed a new rotation mutation strategy in a DE algorithm. It was evaluated extensively on 26 testbeds taken from the CEC 2005 test suite. The results showed that the proposed method is slightly better than the standard DE algorithm in solving multi-model problems. Sajjadi et al. (2016) developed a novel predictive model based on an extreme learning machine (ELM) to ensure the economic and environment-friendly provision of heat load to consumers attached to a district heating system. Estimation and prediction of ELM results with conventional learning algorithms of genetic programming (GP) and artificial neural networks (ANN) showed that the introduced method is robust and performs better in most cases. Jana et al. (2013) introduced real parameter optimization based on a Levy distribution differential algorithm (LevyDE). It was tested on a CEC 2005 benchmark function set and the results showed that the efficiency of the LevyDE algorithm is better, compared with other standard algorithms. Balouek-Thomert et al. (2016) implemented a multi-objective DE method to optimize the workflow placement in a cloud environment. Experimental validation was conducted on a real-time testbed using cloud traces and the solution demonstrated its effectiveness. Shamekhi (2013) introduced a modified DE (modified DE/rand/1/bin) algorithm to improve the convergence speed of the original DE. The performance characteristics of the modified DE were investigated in different applications and compared with those of the original DE. The results showed that the proposed work achieves a better optimal point and a convergence rate 43% higher than that of the original DE algorithm. Pooranian et al.

(2015) proposed a hybrid PSO with the gravitational emulation local search (GELS) algorithm for an efficient task scheduling problem in grid computing, and demonstrated its effectiveness when compared with other metaheuristics. Khoshnevisan et al. (2015) proposed a hybrid method of life cycle assessment (LCA), multi-objective GA, and data envelopment analysis (DEA) to investigate LCA of cropping systems. The novel method was applied to monitor watermelon production and global warming (GW), respiratory inorganics (RI), and non-renewable energy use (NRE). The results were promising. Das et al. (2008) introduced a DE algorithm for automatic clustering of a real-time dataset. Comparison of the proposed algorithm with evolutionary algorithms of PSO and GA showed that parameter tunning improves the performance of DE for dynamic clustering of completely unknown datasets. Gupta and Bhardwaj (2013) implemented an ACO algorithm to find the optimal rules that resolve binary classification problems. They investigated two public datasets found in the UCI database. The results showed that the swarm intelligence algorithm is competitive, compared with the conventional algorithms. Banerjee et al. (2012) implemented an artificial bee colony (ABC) metaheuristic algorithm for optimal classification of images in remote sensing data and demonstrated that it gives more effective results than the minimum distance classifier (MDC), maximum likelihood classifier (MLC), biogeography-based optimization (BBO), membrane computing (MC), and fuzzy classifier. Xu et al. (2015) introduced a harmony search algorithm to optimize the parameters in a least squares support vector machine (LSSVM) classifier to improve the efficiency of a brain CT image classification process. The simulation results showed that the proposed method increases both classification accuracy and speed, and it meets the real-time classification requirements of brain CT images.

A study of the literature reveals that nature-inspired computing paradigms have been used extensively to solve complicated problems and large-scale real-world applications in an effective manner. PSO and DE are the most popular learning algorithms for resolving nonlinear complex problems. Their learning behaviors are quite similar to those of SFO. The performance characteristics of the SFO algorithm are investigated in this study, and its competitiveness is evaluated against the most popular algorithms PSO and DE.

3 Synergistic fibroblast optimization (SFO) algorithm

SFO is a bio-inspired computing algorithm, which has been developed by the inspiration obtained from the intellectual behavior of fibroblast cellular organisms in the dermal wound-healing process (Dhivyaprabha et al., 2016; Krishnaveni et al., 2016; Subashini et al., 2016). Fig. 1 depicts the skeleton of the SFO algorithm. The SFO algorithm consists of a discrete unit of cells and a continuous unit of collagen deposition found in ECM. A cell has its own position and velocity. Each cell is searching continuously to find a global optimum in the n-dimensional problem space. For every iteration, the cells are allotted a random collagen. The cell fitness is evaluated using the objective function, and compared with the optimal solution cbest_{i-1} (previous collagen best). The cell with the best value is considered as the best solution cbest_i (current collagen best). It successively determines the next movement in the evolutionary region using the updating equations of position and velocity. Then, the remodeling of collagen is updated in ECM at every cycle. The cells evolve continuously to yield the global optimum (minimum or maximum) by a randomly chosen candidate solution found in ECM. In the given spatial coordinates, fibroblasts are distributed in a scattered way, and it converges slowly to find the best solution. This helps avoid cells being trapped in local optima. A summary of the SFO algorithm is given in this section. Cell speed s and diffusion coefficient ρ act as an external force that enforces cells to maintain the warm diversity in the problem space and converge slowly to the optimal solution. It is believed that a fibroblast has a memory-based approach, and uses knowledge of the previous search space to advance the search after a change. The collaborative and self-adaptive nature of a fibroblast to heal the wounds is associated greatly with the evolutionary algorithm strategy to discover the global optimum in the search space.

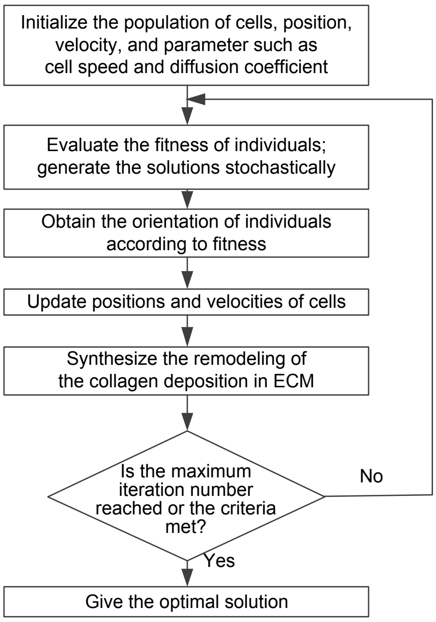

Fig. 1 Life cycle of the synergistic fibroblast optimization (SFO) algorithm

In the SFO algorithm, the numbers of fibroblasts and collagen particles are represented as discrete and continuous units, respectively. The survival of each cell is constant for its fitness evaluation at location, and then it determines the movement in the spatial coordinates, which depends on the members of the cell positioned towards the orientation in the evolutionary region and the remodeling of collagen deposition found in ECM with some random perturbations. This process is repeated until the pre-determined condition is met. Eventually, the swarm migrates collectively as a whole to find the optimum solution in the problem space. The original process for SFO implementation is given in Algorithm 1.

Algorithm 1 Synergistic fibroblast optimization (SFO)

Initialize the population of fibroblast cells $\boldsymbol{f}_i$ (i=1, 2, …, n), with randomly generated position $\boldsymbol{x}_i$, velocity $\boldsymbol{v}_i$, and collagen deposition **ecm** in an n-dimensional problem space. The parameters are defined as cell speed s and diffusion coefficient ρ.

1 **repeat**

2 Evaluate the individual fibroblast using fitness function $F(\boldsymbol{f}_i)$ in n variables for n times;

3 Perform reorientation of the cell to find the optimum (maximum or minimum) in the evolutionary space;

4 Update velocity $\boldsymbol{v}_i$ and position $\boldsymbol{x}_i$ of a cell using

$$\boldsymbol{v}_i^{(t+1)} = \boldsymbol{v}_i^{(t)} + (1-\rho)c(\boldsymbol{f}_i^{(t)}, t) + \rho\cdot\frac{\boldsymbol{f}_i(t-\tau)}{\left\|\boldsymbol{f}_i(t-\tau)\right\|}, \tag{1}$$

$$\boldsymbol{x}_i^{(t+1)} = \boldsymbol{x}_i^{(t)} + s\cdot\frac{\boldsymbol{v}_i^{(t+1)}}{\left\|\boldsymbol{v}_i^{(t+1)}\right\|}, \tag{2}$$

where t is the current time, τ is the time lag, $\boldsymbol{v}_i$ is the velocity of the i^{th} cell, function c denotes collagen deposition (candidate solution) present in the ECM matrix which is randomly chosen by the i^{th} fibroblast cell $\boldsymbol{f}_i$, ρ=0.5, and $s=s/(k_{\text{ro}}L)$ (s=15 μm/h, k_{ro}= 10^3 μ/min, cell length L=10);

5 Remodeling of collagen deposition c_i is synthesized in ECM **ecm**;

6 **until** the predetermined conditions are met or the maximum number of iterations has been performed.

Each individual in the cell population is composed of three D-dimensional vectors, where D is the dimensionality of the search space, $\boldsymbol{x}_i$ denotes the position, $\boldsymbol{v}_i$ represents the velocity, and **ecm** designates the matrix representation of collagen protein deposition. In every iteration of the algorithm, the group of cells collaboratively evaluates the particles with the remodeling of ECM. This is considered a problem solution. The best result obtained so far is stored in a variable cbest_{i-1} (previous best) for comparison with later iterations with cbest_i (current best). The cells are further moved to find a better position by updating $\boldsymbol{x}_i$. New positions of the migrating cells are updated using the velocity and position equations presented in the SFO algorithm. This can be effectively seen as a step size. The parameters include cell speed s and diffusion coefficient ρ, which act as an external force to maintain swarm diversity in the problem space, and converge slowly to the optimal solution. A fibroblast has the ability to sense relevant environmental chemical information, and then the cells migrate over the substrate of collagen protein to replace the fibrin present in the wounded region. It is believed that for fibroblasts, memory-based approaches have been proposed, using the knowledge of the previous search space to advance the search after a change. SFO movements for finding the optimal solution to solve non-linear complicated problems are described as follows: Step 1 indicates the discrete unit of fibroblast population with a randomly generated position and velocity. The SFO algorithm has two basic parameters, cell speed and diffusion coefficient, which need to be fixed. The cell speed is associated with the velocity of the cell to improve the positive gradient, and the diffusion coefficient enables fibroblast displacement in the domain space to follow a homogeneous distribution of collagen particles deposited in a coordinated way. In step 2, the fitness of individuals among the population cells is evaluated using the most popular benchmark functions. In step 3, the collaborative behavior of fibroblast towards the orientation of the solution space with the best success achieved so far is revealed. The cooperative behavior and interaction of fibroblast with collagen deposition force fibroblast to migrate to a new location. This can be achieved by updating the velocity and position of the cell (step 4). In the final step (step 5), the cells evolve continuously to yield the optimal (minimum or maximum) solutions with the reorganization of collagen found in ECM, which is problem specific. In the given spatial coordinates, fibroblasts are distributed in a scattered way. It converges slowly to find the best solution. This prevents the cells from being trapped in local optima.

Fig. 2 depicts the core idea underlying the SFO technique. Given a population of fibroblasts, each cell is chosen randomly as a collagen particle for fitness evaluation. Based on the results, the best candidate solutions are selected to seed the next generation population with the synthesis of encompass particles, found in ECM and orientation of the cell movement towards the problem space. This process can be repeated until the best solution is found or the predefined limit is reached.

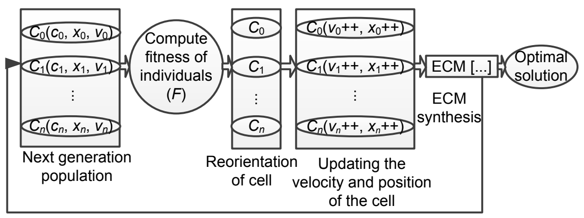

Fig. 2 Architecture of the synergistic fibroblast optimization (SFO) algorithm (ECM: extracellular matrix)

Initialization of population encompasses a discrete number of cells with a random generation of position and velocity, and the number of collagen particles deposited is included in the ECM repository. For every iteration, cells are stochastically chosen collagen particles for fitness evaluation. The cell with the finest collagen value is selected as the optimum in the current cycle, and the remaining cells are reorganized to track the path of the best performing cell. The velocity and position of cells are updated at each cycle to migrate towards the global optimum. The best collagen value is upgraded in ECM. The continuous evolution process has been repeated until the maximum number of executions is reached or the predetermined condition is met.

4 Analysis of synergistic fibroblast optimization

The SFO technique was implemented to find the global minimum in solving mathematical function $f(x)=x_1^2+x_2^2+\cdots+x_{10}^2$ using the mean-squared error (MSE). The results suggest that both collaborative- and self-adaptation characteristics are more critical factors in SFO accuracy than in PSO accuracy. It can be well suited for solving complex problems (Subashini et al., 2017). The SFO algorithm was applied to enhance the efficiency of the weighted median filter by optimizing the weight matrix using a Sphere test function as the objective function for degradation of impulse noise present in digital images. It was tested in the real-time Tamil sign language (TSL) dataset, especially vowel signs, which were generated manually from the signs of several people with the limitation of single hand pose and black background images. The quantized 16-bit-per-pixel grayscale image data represented by numerical values were fitted with the continuous, differentiable, separable, scalable, and multi-modal characteristics of the Sphere test function to find the optimal weights, and were applied to the weighted median filter. The experimental results showed that the optimal weight retrieved by SFO predominantly removes the impulse noise found in digital images without loss of information. Meanwhile, the quality of images is improved significantly (Krishnaveni et al., 2016).

The SFO algorithm was implemented for an optimal rule discovery mechanism. This enhances the generalization and comprehensibility of a robot classification system in classifying the objects from extracted attributes to effectively categorize its domain and evaluate the compatibility of SFO with various kinds of machine learning algorithms, namely, decision tree (DT), classification-based association

(CBA), and feed forward neural network (FFNN) (Dhivyaprabha et al., 2016). The characteristics (such as continuous, differentiable, non-separable, scalable, and multi-modal) of the Ackley function are well suited to the multivariate characteristics of Monk's dataset (Jamil and Yang, 2013; Liang et al., 2013). It was tested with Monk's problem with benchmark instances found in the UCI Repository (https://archive.ics.uci.edu/ml/datasets/MONK's+Problems). It signifies that SFO is highly sensitive to the changing environment, and the probability of finding an optimal solution is improved steadily in the problem space.

To examine the robustness, generalization, scalability, and comprehensibility of the proposed SFO algorithm, benchmark functions can be used to evaluate the performance of the optimization algorithm in diverse and complex situations. The goal of any objective function is to find the best possible solutions r^* (minimum or maximum) from set R according to a set of criteria $F=\{\boldsymbol{f}_1, \boldsymbol{f}_2, \ldots, \boldsymbol{f}_n\}$. An objective function is expressed as a mathematical function f: $\mathrm{DCR}_n \rightarrow R$ subject to additional constraints. Set D is referred to as the set of possible points in a search space. x denotes the solution and i signifies the current value. A general optimization problem to find the global optimum (minimum or maximum) is defined as

$$\begin{cases} \min f(x), & (3) \\ \max f(x). & (4) \end{cases}$$

A study on the collection of benchmark functions revealed that the properties of test functions are categorized generally into continuous or discontinuous, differentiable or non-differentiable, separable or non-separable, scalable or non-scalable, and uni-modal or multi-modal ones. The proposed SFO algorithm was tested with such fitness functions to evaluate the robustness, scalability, and comprehensibility. Ten benchmark functions, Sphere, Schwefel, Cosine Mixture, Alpine, Step 2, Ackley, Schumer Steiglitz, Griewank, Chung Reynolds, and Rastrigin, were selected, each of which has diverse properties such as continuous or discontinuous, differentiable or non-differentiable, separable or non-separable, scalable or non-scalable, and uni-modal or multi-modal ones (Colaco, 2009; Herrera et al., 2009; Jamil and Yang, 2013; Liang et al., 2013).

The continuous or discontinuous and scalable or non-scalable properties of benchmarks are used to test the adaptability and robustness of SFO, solving combinatorial optimization problems in dynamic environments. It is concerned with efficient allocation of limited resources, including decision variables, solution space, parameters, and constraints, to meet desired objective(s). The decision variables can either be continuous ($\boldsymbol{x} \in \mathbb{R}^n$) (all decision variables are real numbers), discrete ($\boldsymbol{x} \in \mathbb{Z}^n$) (all decision variables are finite), or mixed (some decision variables are real and some other variables are discrete).

The separable and non-separable characteristics of fitness functions are used to validate the convenience and flexibility of SFO specifically to resolve large-scale global optimization problems. A function is separable if the variable of a function is independent of other variables. Then, the parameters and variables can be optimized independently. On the other hand, a function containing variables with inter-relationships among them is referred to as a non-separable function. That is, the sub-components of the function overlap (interact) with other sub-components that share common decision variables to attain the same/different optimum value with respect to both sub-component functions. A function is called 'partially separable' if some sub-components of a function are coupled among themselves, while the others, the parameters and variables, can be optimized separately.

The range of the search space defines the dimensionality of the problem space. When the numbers of parameters, variables, and search spaces increase, the difficulty of finding the solution increases. The multi-modal test functions are used to investigate whether the SFO algorithm suffers from more than one local optimum. In some situations, a function with many local optima may deviate from the global optimal solution in the problem space. Therefore, it would not be able to find the optimal solution in the fitness landscape effectively and may be trapped in a local optimum which is surrounded by regions of steep descent in the hostile environment. It is known as a hard test problem. The uni-modal functions can be used to examine the convergence analysis of SFO. In certain cases, it may suffer from a slow convergence problem because of single global extremum. The differentiable or non-differentiable features are used to validate the comprehensibility of SFO. This is suitable for solving both continuous and discrete optimization problems.

The mathematical representation of the aforementioned test functions is defined in Eqs. (5)–(14), namely, Sphere, Schwefel, Cosine Mixture, Alpine, Step 2, Ackley, Schumer Steiglitz, Griewank, Chung Reynolds, and Rastrigin's. All these benchmark functions were examined with 10 cells, the number of iterations was set to 1000, 5000, or 10 000, and the domain of each target function was constrained to the size of the search space (Table 1). Among these functions, Ackley, Alpine, Chung Reynolds, Sphere, and Step 2, which include the varied properties of benchmark functions, were selected to evaluate the performance of SFO with evolutionary computation techniques such as PSO and DE (Poli, 2007; Das and Suganthan, 2011). The experimental settings and observations are shown in Table 2.

1. Sphere function (continuous, differentiable, separable, scalable, and multi-modal):

$$f(\boldsymbol{x})=\sum_{i=1}^{D}\boldsymbol{x}_i^2. \tag{5}$$

2. Schwefel function (continuous, differentiable, non-separable, scalable, and uni-modal):

$$f(\boldsymbol{x})=\sum_{i=1}^{D}\boldsymbol{x}_i^{10}. \tag{6}$$

3. Cosine Mixture function (discontinuous, non-differentiable, separable, scalable, and multi-modal):

$$f(\boldsymbol{x})=\sum_{i=1}^{D}\left|\boldsymbol{x}_i\sin\boldsymbol{x}_i+0.1\boldsymbol{x}_i\right|. \tag{7}$$

4. Alpine function (continuous, non-differentiable, separable, non-scalable, and multi-modal):

$$f(\boldsymbol{x})=\sum_{i=1}^{D}\left|\boldsymbol{x}_i\sin\boldsymbol{x}_i+0.1\boldsymbol{x}_i\right|. \tag{8}$$

5. Step 2 function (discontinuous, non-differentiable, separable, scalable, and uni-modal):

$$f(\boldsymbol{x})=\sum_{i=1}^{D}\left(\left\lfloor\boldsymbol{x}_i+0.5\right\rfloor\right)^2. \tag{9}$$

6. Ackley function (continuous, differentiable, non-separable, scalable, and multi-modal):

$$\begin{aligned}f(\boldsymbol{x})=&-20\mathrm{e}^{-0.02}\sqrt{D^{-1}\sum_{i=1}^{D}\boldsymbol{x}_i^2}\\&-\mathrm{e}^{D^{-1}}\sum_{i=1}^{D}\cos(2\pi\boldsymbol{x}_i)+20+\mathrm{e}.\end{aligned} \tag{10}$$

7. Schumer Steiglitz function (continuous, differentiable, separable, scalable, and uni-modal):

$$f(\boldsymbol{x})=\sum_{i=1}^{D}\boldsymbol{x}_i^4. \tag{11}$$

8. Griewank function (continuous, differentiable, non-separable, scalable, and multi-modal):

Table 1 Global optimum solution of the synergistic fibroblast optimization (SFO) algorithm

Benchmark function	$\boldsymbol{x}^*$	$f(\boldsymbol{x}^*)$	Search range	Initialization range	Mean-squared error (MSE)		
					1000 iterations	5000 iterations	10 000 iterations
Sphere	[0, 0, …, 0]	0	$[0, 10]^D$	$[0, 10]^D$	0.08	0.17	0.27
Schwefel	[0, 0, …, 0]	0	$[-10, 10]^D$	$[-10, 10]^D$	0.50	0.80	3.10
Cosine Mixture	[0, 0, …, 0]	(0.2 or 0.4)	$[-1, 1]^D$	$[-1, 1]^D$	0.99	−0.96	−0.90
Alpine	[0, 0, …, 0]	0	$[-10, 10]^D$	$[-10, 10]^D$	7.30	0.20	0.10
Step 2	[0.5, 0.5, …, 0.5]	0	$[-100, 100]^D$	$[-100, 100]^D$	0.30	0	0
Ackley	[0, 0, …, 0]	0	$[-35, 35]^D$	$[-35, 35]^D$	0	0.80	0.20
Schumer Steiglitz	[0, 0, …, 0]	0	$[-100, 100]^D$	$[-100, 100]^D$	13.20	14.90	9.00
Griewank	[0, 0, …, 0]	0	$[-100, 100]^D$	$[-100, 100]^D$	−4.10	−5.70	8.30
Chung Reynolds	[0, 0, …, 0]	0	$[-100, 100]^D$	$[-100, 100]^D$	−0.80	0	0
Rastrigin's	[0, 0, …, 0]	0	$[-5.12, 5.12]^D$	$[-5.12, 5.12]^D$	0	0.10	−0.30

Grey-shaded areas indicate the multi-modal functions with the best results. White areas indicate the uni-modal functions

Table 2 Mean-squared error (MSE) comparison of the synergistic fibroblast optimization (SFO) algorithm

Benchmark function	Problem size	MSE		
		1000 iterations	5000 iterations	10 000 iterations
Sphere	$[0, 10]^D$	0.0064	0.0289	0.0729
Schwefel	$[-10, 10]^D$	0.2500	0.6400	9.6100
Cosine Mixture	$[-1, 1]^D$	0.9801	0.9216	0.8100
Alpine	$[-10, 10]^D$	53.2900	0.0400	0.0100
Step 2	$[-100, 100]^D$	0.0900	0	0
Ackley	$[-35, 35]^D$	0	0.6400	0.0400
Schumer Steiglitz	$[-100, 100]^D$	174.2400	222.0100	81.0000
Griewank	$[-100, 100]^D$	16.8100	32.4900	68.8900
Chung Reynolds	$[-100, 100]^D$	0.6400	0	0
Rastrigin's	$[-5.12, 5.12]^D$	0	0.01	1.5129

Grey-shaded areas indicate the multi-modal functions with the best results. White areas indicate the uni-modal functions

$$f(\boldsymbol{x}) = \sum_{i=1}^{n} \frac{\boldsymbol{x}_i^2}{4000} - \prod_{i=1}^{n} \cos\left(\frac{\boldsymbol{x}_i}{\sqrt{i}}\right) + 1. \tag{12}$$

9. Chung Reynolds function (continuous, differentiable, partially separable, scalable, and uni-modal):

$$f(\boldsymbol{x}) = \left(\sum_{i=1}^{D} \boldsymbol{x}_i^2\right)^2. \tag{13}$$

10. Rastrigin's function (continuous, differentiable, partially separable, scalable, and multi-modal):

$$f(\boldsymbol{x}) = 10n\sum_{i=0}^{n}\left[\boldsymbol{x}_i^2 - 10\cos(2\pi\boldsymbol{x}_i)\right]. \tag{14}$$

In this study, the effectiveness of the SFO algorithm in solving the numeric minimization problem was evaluated, with the mean-squared error (MSE) with respect to unknown parameter $\widehat{\theta}$ (McCaffrey, 2012; Snásel et al., 2013). The results (Table 1) illustrate that each entry is the MSE between the best solution found and the optimal solution of {0, 0, 0, 0, 0} in the fitness evaluation of 1000, 5000, and 10 000 runs. The amount of collagen deposited in ECM (N) and the maximum number of iterations (t) are the two primary independent variables that represent the population size, which is used to compute the better fitness value to find candidate solutions in the problem space over time. The results show that the SFO algorithm gives the best results in the minimum number of iterations, demonstrating the high efficiency of the SFO algorithm in gaining the optimal solution. It may decrease the complexity of algorithmic execution in solving problems in dynamic and uncertain environments. The outcomes of the study suggest that the SFO algorithm is effective on test functions, and can be solved using simple gradient descent.

The multi-modal functions with the best results among the 10 benchmark functions are grey-shaded modal, while other uni-modal functions are white. SFO was examined in an exploratory search space where better results were achieved on both uni-modal and multi-modal functions. By analyzing the experimental results (Table 2), it is found that the SFO algorithm performs better than Schwefel, Ackley, and Rastrigin's functions in all the three fitness executions (1000, 5000, and 10 000 iterations). However, a decrease of performance is identified in Schumer Steiglitz and Griewank functions. It is inferred that the SFO algorithm follows the principle of 'no-free-lunch theorem', which states that "a general strategy is impossible to solve problems with similar characteristics at all the times".

The fitness landscape analysis of SFO towards an optimum solution is depicted in Fig. 3. It explains the collaborative behavior of cells that maintain an equilibrium state of convergence and divergence to obtain the global optimal solution in the problem space with dimensionality D=3 involving the domain space. It can be inferred from Fig. 3 that the SFO algorithm is well-suited with the diverse characteristics of benchmark functions for finding the global optimum.

Performance metrics such as MSE, average convergence rate, and statistical measures were applied to validate the efficiency of the SFO algorithm in different perspectives. MSE was examined to show how well SFO solves the error minimization problem. The convergence rate was used to analyze the divergence and convergence characteristics of SFO to find the optimum solution. Statistical measure tests were carried out on convergence performance (of the search process) of the SFO. Furthermore, SFO needs to be compared with the state-of-the-art algorithms to demonstrate its effectiveness.

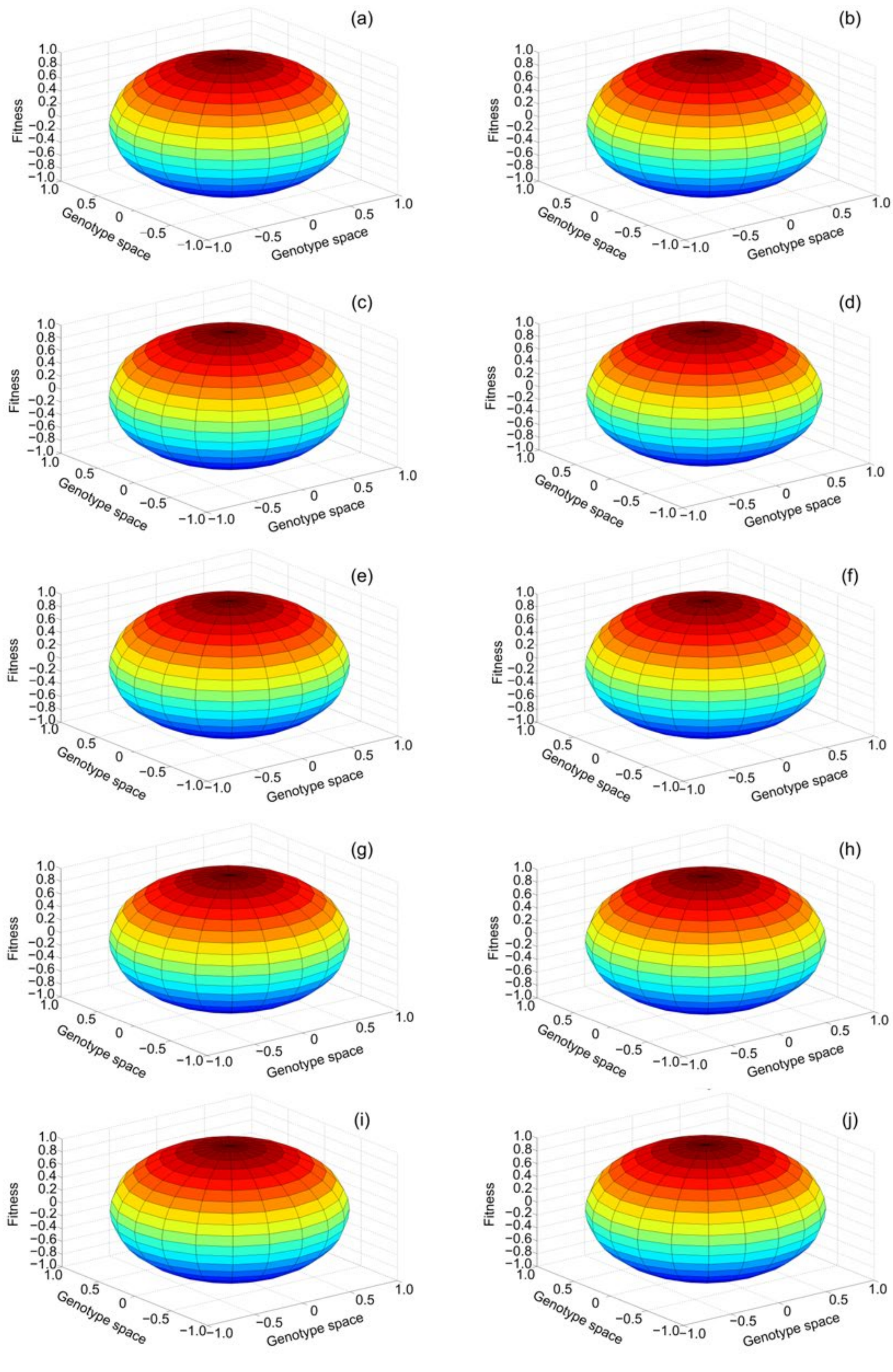

Fig. 3 Fitness landscape analysis of the synergistic fibroblast optimization (SFO) algorithm towards optimum functions: (a) Sphere; (b) Schwefel; (c) Cosine Mixture; (d) Alpine; (e) Step 2; (f) Ackley; (g) Schumer Steiglitz; (h) Griewank; (i) Chung Reynolds; (j) Rastrigin's (References to color refer to the online version of this figure)

The final solutions of the SFO algorithm were compared with those of the most popular optimization algorithms PSO and DE. The results are explored here. Various characteristics of SFO such as evolution, interaction, migration, and the search process were well suited for performance analysis with PSO and DE (Eberhart and Shi, 2001; Qin et al., 2009), which have similar characteristics.

In evolutionary optimization, it is important to investigate the convergence speed of the optimization algorithms to find the optimum solution per generation or their convergence rates. When solving complex combinatorial problems, many stochastic algorithms have often been subjected to local optima; i.e., they have the premature convergence problem. The optimal solution occurred in the lower bounds of the evolutionary region over the population generation in convex optimization problems. Optimization algorithms have to be adapted to increase the exploration ability to track the global optimum in a dynamic environment and to maintain high levels of swarm diversity (Zhao and Feng, 2014). A new measure of the convergence rate, called the 'average convergence rate', is defined as a normalized geometric mean of the reduction ratio of the fitness value, which differs from each other in every generation (George et al., 1997; Zhao, 2009; Derrac et al., 2013; He and Lin, 2016). Let Φ_t be the best fitness value of the population defined by Φ. Since $f(\Phi_t)$ is a random variable, its mean value is defined as $f_t \equiv E[\Phi_t]$. Let f_{opt} denote the optimal fitness value. The fitness difference between f_{opt} (optimal value) and f_t (best value at iteration t) is $|f_{\text{opt}}-f_t|$. The convergence rate for one generation is represented by

$$\left|\frac{f_{\text{opt}}-f_t}{f_{\text{opt}}-f_{t-1}}\right|. \tag{15}$$

The mathematical representation of the average (geometric) convergence rate of an evolutionary algorithm for t generations with the given initial population Φ_0 is defined as

$$\begin{aligned} R(t\,|\,\Phi_0) &:= 1-\left(\left|\frac{f_{\text{opt}}-f_1}{f_{\text{opt}}-f_0}\right|\left|\frac{f_{\text{opt}}-f_2}{f_{\text{opt}}-f_1}\right|\cdots\left|\frac{f_{\text{opt}}-f_t}{f_{\text{opt}}-f_{t-1}}\right|\right)^{1/t} \\ &\equiv 1-\left(\left|\frac{f_{\text{opt}}-f_t}{f_{\text{opt}}-f_0}\right|\right)^{1/t}. \end{aligned} \tag{16}$$

When there is a larger convergence rate, the optimization algorithm is able to attain a faster convergence to find the optimum per generation. The rate takes the maximum value of 1 at $f_t=f_{\text{opt}}$. In solving the continuous optimization problem, when R=1, the rate of convergence is linear; when R=2, the rate of convergence is quadratic; when 1<R<2, the rate is super-linear (He and Lin, 2016).

The convergence analysis of the SFO algorithm is depicted in Fig. 4. The performance of SFO in finding the optimum per generation is improved progressively in the initialization stage, and then it is reduced slightly to give a lower rate when the number of candidate solutions increases.

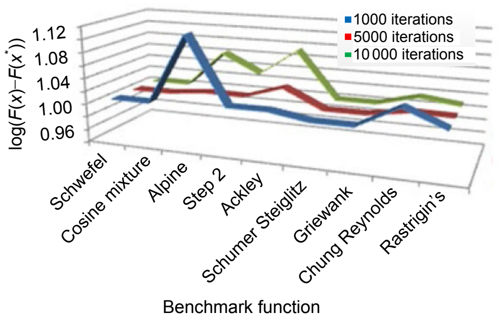

Fig. 4 Average convergence rate of the synergistic fibroblast optimization (SFO) algorithm (References to color refer to the online version of this figure)

However, the self-adaptation characteristic of the SFO optimization technique enforces the cells to improve the degree of convergence at later stages in 1000, 5000, and 10 000 fitness evaluations, where the progress achieved is remarkable. The cell speed and diffusion coefficient reinforce the diversified swarm movement in the search space and converge slowly to the global optimal solution. In comparison of the fitness solution among 10 benchmark test suites, only the results obtained at the end of the search process are obtained. However, the convergence rate was used to measure the search behavior of the evolutionary algorithm to find the optimum solution. Therefore, SFO exhibits equivalent convergence performance with all the 10 benchmark functions.

The performance of the SFO algorithm has been tested using various statistical measures including mean, median, and standard deviations (Wan et al., 2014). The results are depicted in Table 3 and Fig. 5. It is observed that the SFO algorithm generated better

Table 3 Statistical measures of the synergistic fibroblast optimization (SFO) algorithm

(a) 1000 iterations

Benchmark function	Best	Worst	Mean	Median	Standard deviation
Sphere	0	0.39	0.14	0.60	0.09
Schwefel	0	9.90	0.99	0.90	1.18
Cosine Mixture	0	1.00	0.48	0.94	0.80
Alpine	0	56.80	8.34	7.10	10.62
Step 2	1.0	42.30	3.44	46.55	20.49
Ackley	0	34.80	14.60	11.60	16.39
Schumer Steiglitz	−2.5	40.00	5.57	3.60	9.31
Griewank	0.5	98.70	10.78	11.90	14.41
Chung Reynolds	1.0	52.30	7.45	6.55	10.49
Rastrigin's	−2.1	4.00	0.86	0.95	1.12

(b) 5000 iterations

Benchmark function	Best	Worst	Mean	Median	Standard deviation
Sphere	0	0.51	0.14	0.25	0.10
Schwefel	0.2	4.70	1.09	1.00	1.19
Cosine Mixture	0.4	0.80	0.46	0.93	0.79
Alpine	0	44.30	6.72	5.60	10.01
Step 2	0	−90.40	16.13	4.50	30.60
Ackley	0	32.00	10.05	15.95	17.12
Schumer Steiglitz	0.2	22.50	6.60	5.85	10.02
Griewank	−0.3	44.30	10.15	11.80	15.24
Chung Reynolds	0	50.40	6.13	5.00	10.41
Rastrigin's	0.7	3.30	0.84	1.00	1.12

(c) 10 000 iterations

Benchmark function	Best	Worst	Mean	Median	Standard deviation
Sphere	0	0.58	0.12	0.11	0.09
Schwefel	−3.0	4.10	0.87	0.90	1.12
Cosine Mixture	0.2	0.40	0.47	0.92	0.79
Alpine	0.1	32.80	5.89	4.40	9.51
Step 2	0	35.50	5.29	5.80	33.12
Ackley	0	33.00	16.42	12.42	16.14
Schumer Steiglitz	0	9.10	6.10	5.10	10.05
Griewank	0.1	10.00	12.24	11.70	16.87
Chung Reynolds	0	35.50	7.28	5.80	10.13
Rastrigin's	0.1	2.00	0.72	0.90	1.24

results in terms of all the characteristics of objective functions, since it is constructed using the uni-modal Sphere basic function. Good regions are easier to identify. When the global area has been found, the global optimal solution is not difficult to attain. Since Alpine and Griewank are constructed with more complicated multi-modal functions, they have many local optima, thereby increasing their complexities. Then, the global area is not easy to identify and even when the global region has been found, it is a complex task to achieve the real optimum solution.

The results presented in Tables 4 and 5 indicate that the chosen PSO and DE can offer progressive results when the survival period of swarm increases gradually in the search space. However, SFO outperforms PSO and DE algorithms in all the examined benchmark functions in the given optimal values during 1000, 5000, and 10 000 iterations. Worse results given by SFO for an Alpine fitness evaluation in 1000 runs show that the algorithm finds a solution which is far away from the optimum (minimum), leading to a steep decline in the evolutionary region called 'basin'. Furthermore, SFO is able to provide better results than PSO and DE in 5000 and 10 000 fitness executions. It is evident that the collaborative nature of the fibroblast moves towards the global extremum, and it avoids the stagnation problem while the performance in the evolutionary period has been improved in the problem space.

SFO exploration to solve the error minimization problem has been compared with PSO and DE heuristics for performance evaluation. It is observed that Alpine and Chung Reynolds suffer in the fitness evaluation of PSO and DE algorithms during 1000 runs, but when the duration of the evolutionary increases in the problem space, the performance of particles is improved. However, SFO provides a better solution than PSO and DE algorithms in 1000, 5000, and 10 000 executions. It indicates that the self-adaptive characteristic of SFO enforces the cells to progress gradually towards the optimum, irrespective of the number of iterations and the population size.

Fig. 6 shows that PSO, DE, and SFO exhibit super-linear convergence rates in obtaining fittest solutions. When the number of fitness evaluations increases, SFO attains the best convergence rate. It is evident that SFO does not get trapped in local optima for both uni-modal and multi-modal functions. Individuals that are mapped into the behavioral space consequently demonstrate a divergent search. The search process is like natural evolution, and it may

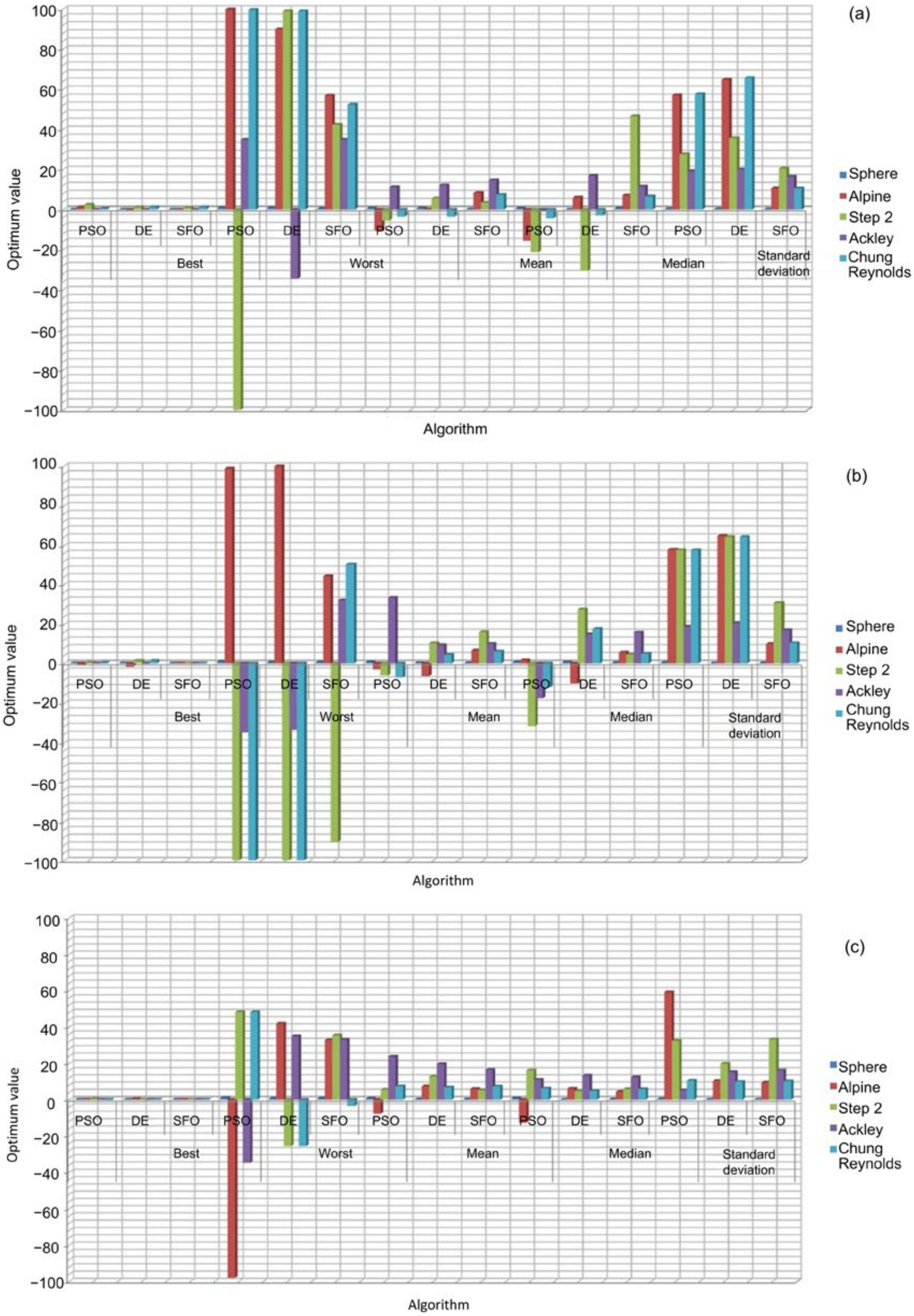

Fig. 5 Statistical measures of SFO, DE, and PSO in 1000 (a), 5000 (b), and 10 000 (c) iterations
SFO: synergistic fibroblast optimization; DE: differential evolution; PSO: particle swarm optimization. References to color refer to the online version of this figure

Table 4 Global optimum solutions of PSO and DE

Benchmark function	Problem size	Mean-squared error (MSE)					
		1000 iterations		5000 iterations		10 000 iterations	
		PSO	DE	PSO	DE	PSO	DE
Sphere	$[0, 10]^D$	0.01	0.25	0.48	0.50	0.28	0.76
Cosine Mixture	$[-10, 10]^D$	82.20	58.20	−30.80	−56.00	82.70	13.00
Schumer Steiglitz	$[-100, 100]^D$	1.60	1.90	−1.50	9.70	3.10	0.80
Griewank	$[-35, 35]^D$	25.90	24.40	25.00	−16.70	−20.50	−3.00
Rastrigin's	$[-100, 100]^D$	28.60	51.90	−29.50	69.70	37.10	30.80

PSO: particle swarm optimization; DE: differential evolution

Table 5 Mean-squared error (MSE) comparison of SFO with PSO and DE

Benchmark function	Problem size	Mean-squared error (MSE)								
		1000 iterations			5000 iterations			10 000 iterations		
		PSO	DE	SFO	PSO	DE	SFO	PSO	DE	SFO
Sphere	$[0, 10]^D$	0.0001	0.0625	0.0064	0.2304	0.2500	0.0289	0.0784	0.5776	0.0729
Alpine	$[-10, 10]^D$	6756.8400	3387.2400	53.2900	948.6400	3136.0000	0.0400	6839.2800	169.0000	0.0100
Step 2	$[-100, 100]^D$	2.5600	3.6100	0.0900	2.2500	94.0900	0	9.6100	0.6400	0
Ackley	$[-35, 35]^D$	670.8100	595.3600	0	625.0000	278.8900	0.6400	420.2500	9.0000	0.0400
Chung Reynolds	$[-100, 100]^D$	817.9600	2693.6100	0.6400	870.2500	4858.0800	0	1376.4100	948.6400	0

PSO: particle swarm optimization; DE: differential evolution; SFO: synergistic fibroblast optimization

implicitly reward lineages better at the divergent process. The evolutionary computation techniques eventually converge to a point in the search space that locally maximizes the fitness function. SFO exhibiting a faster convergence for Ackley and Alpine functions reveals that the SFO algorithm can be suited well for solving continuous optimization problems.

The convergence rate of the SFO algorithm is significantly better than those of PSO and DE algorithms as the number of generations increases. It reveals that SFO does not get trapped in local optima (stagnation) when the iteration number increases for the diverse characteristics of benchmark functions. It illustrates that the group of cells has been explored in a collaborative way for their survival and that it converges steadily to find the optimal solution in the problem space. This implies that SFO gives a better convergence performance than PSO and DE. It is confirmed that the SFO algorithm is more appropriate to the fitness evaluation of varied characteristics of test functions, and it is able to solve non-linear complex problems efficiently.

Exploratory analysis of statistical measures obtained by PSO, DE, and SFO algorithms (Fig. 5) shows that the performance of the above mentioned algorithms is good in finding optimal or near-optimal solutions. PSO and DE suffer slightly in finding optima in the fitness evaluation of Step 2 and Chung Reynolds, which have a large population. However, when the number of iterations increases, PSO and DE can find a near-optimal solution. It reveals that when the number of population generations increases, the convergence speeds of PSO and DE are improved. However, the optimal solution found by SFO is significantly better than those of PSO and DE in terms of both the minimum number of fitness evaluations and the smallest population set. This exemplifies that SFO will not get stuck in local optima and that it is able to converge to the optimal point in the evolutionary space. In most cases, the modality of Step 2 encounters a relatively steep decline in the surrounding region (basin), which leads to a certainly worst solution in PSO, DE, and SFO. When these regions get maximized, the optimization algorithms will be trapped in one peak value, which suffers from moving towards global optima in the search space. The comprehensive statistical measures, including mean, median, and standard deviation values found by PSO, DE, and SFO, illustrate that the overall performance of the algorithms in finding the global optimum is acceptable. The statistical outcome of SFO shows that SFO produces more promising results than PSO and

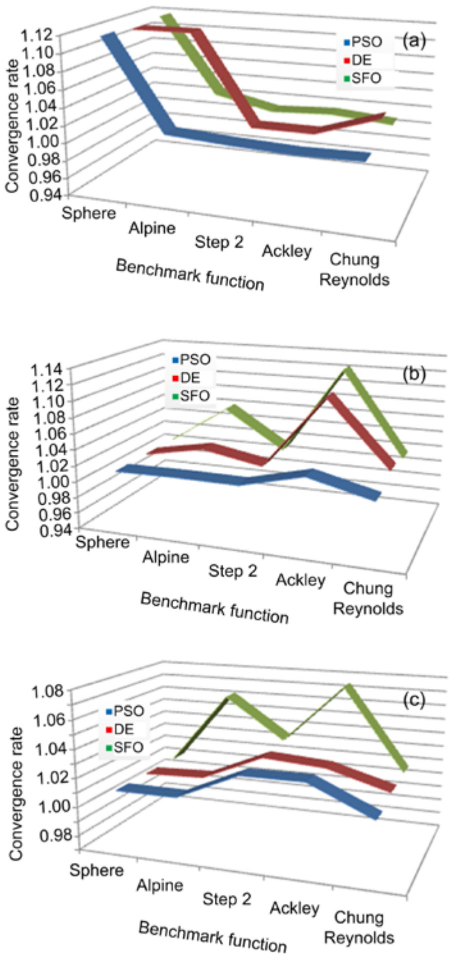

Fig. 6 Average convergence rates of SFO with PSO and differential evolution in 1000 (a), 5000 (b), and 10 000 (c) iterations

SFO: synergistic fibroblast optimization; PSO: particle swarm optimization; DE: differential evolution. References to color refer to the online version of this figure

DE. It reveals that SFO can solve complex problems, and it is competitive with other metaheuristics.

5 Experiments and observation

The proposed technique was tested on Intel® Core™ i7-4790 3.60 GHz CPU with a 4 GB RAM. The operating system platform was 64-bit Windows 7 Professional. The programming languages were C language (MATLAB (R2013a)), JAVA, and Visual Basic (Microsoft Excel 2016). The performance of SFO was investigated by the implementation of the SFO algorithm in solving the binary classification problem of Monk's benchmark instances available in the UCI Repository (https://archive.ics.uci.edu/ml/machine-learning-databases/monks-problems/) and the edge detection method for manually generated real-time TSL digital images (Rajam and Balakrishnan, 2012). The results were compared with those of PSO and DE based techniques for exploratory analysis. The results emphasized that the cooperative behavior of the fibroblast has synchronized the collagen particles to attain the best solution in an evolutionary problem space.

The newly developed SFO algorithm was validated using various performance metrics under different scenarios. From the investigation, it was confirmed that the natural source of inspiration or metaphor exhibited by SFO is able to achieve its optimum when the candidate solutions evolve in the search space. The results (Table 6) showed that the diverse characteristics of SFO are compatible with those of

Table 6 Performance evaluation of PSO, DE, and SFO optimized classifiers for Monk's problem

Classifier	Accuracy (%)			Sensitivity (%)			Specificity (%)		
	Monk's 1	Monk's 2	Monk's 3	Monk's 1	Monk's 2	Monk's 3	Monk's 1	Monk's 2	Monk's 3
PSO+DT	96.26	90.63	91.68	95.77	88.30	82.40	89.12	91.25	88.96
DE+DT	98.33	85.40	83.44	94.89	87.66	81.39	93.01	93.19	89.08
SFO+DT	99.54	99.79	92.13	99.67	99.69	85.06	99.20	99.50	96.28
PSO+CBA	86.11	91.20	81.40	91.36	84.78	76.40	88.39	89.55	84.90
DE+CBA	89.53	88.36	76.67	94.28	82.90	78.11	80.12	78.30	82.79
SFO+CBA	90.27	95.60	89.81	92.28	95.63	82.43	85.82	95.56	94.74
PSO+FFNN	97.29	93.22	88.90	94.50	97.80	81.72	93.46	90.24	90.93
DE+FFNN	96.10	91.30	81.86	90.00	92.96	95.01	98.90	86.08	84.80
SFO+FFNN	100.00	100.00	97.22	100.00	100.00	98.51	100.00	100.00	98.15

PSO: particle swarm optimization; DT: decision tree; DE: differential evolution; SFO: synergistic fibroblast optimization; CBA: classification-based association; FFNN: feed forward neural network other machine learning algorithms. The intellectual behavior of the SFO algorithm improves the performance of classification techniques in terms of accuracy for solving Monk's problem. SFO was implemented to find optimal thresholds using a Canny technique for detection of continuous, smooth, and thin edges of the TSL hand-pose images and for reducing the broken edges. The results (Table 7) suggested that SFO optimizes a Canny method to detect edges more accurately, compared with other analyzed algorithms. Indeed, the varied characteristics of benchmark suites, benchmark test instances, and real-time problems were tested to better represent that SFO can solve real-world optimization problems.

SFO was applied to develop the predictive model for solving the binary classification problem of chronic kidney disease. It was evaluated in the dataset procured from the UCI Repository (http://archive.ics.uci.edu/ml/datasets/Chronic_Kidney_Disease) and compared with the PSO and DE techniques (Levey et al., 2005). The aforementioned metaheuristic algorithms were implemented to choose optimal rules for the construction of the knowledge base in the predictive model. The results (Table 8) illustrated that the SFO-based approach ultimately improves the learning mechanism of DT and FFNN.

6 Conclusions and future work

Benchmark functions were used to validate the reliability and efficiency of SFO under various perspectives. It was proved that SFO delivers better results than competitive algorithms in fitness function evaluation and convergence analysis, to find an optimum solution in solving the minimization problem. It also offers an enhanced outcome for most of the test functions, specifically, Sphere, Cosine Mixture,

Table 7 Objective evaluation of edge detection methods on the Tamil sign language dataset

Index	Similarity index			Pearson correlation coefficient		
	PSO optimized canny	DE optimized canny	SFO optimized canny	PSO optimized canny	DE optimized canny	SFO optimized canny
1	0.03328	0.03327	0.10170	−0.0166	−0.0055	0.0050
2	0.06900	0.03900	0.17413	0.0235	0.0254	0.0704
3	0.24195	0.24193	0.24202	0.0236	0.0254	0.0695
4	0.13153	0.13148	0.13158	−0.0080	0.0012	0.0110
5	0.27947	0.27940	0.27961	0.0144	0.0203	0.0893
6	0.19202	0.19201	0.19207	0.0677	0.0719	0.1233
7	0.11463	0.11461	0.11469	0.0197	0.0185	0.0974
8	0.12899	0.12896	0.12905	0.0071	0.0088	0.0616
9	0.11729	0.11726	0.11734	0.0096	0.0094	0.0547
10	0.29847	0.29844	0.29852	0.0276	0.0229	0.1110
11	0.11625	0.28808	0.11629	0.0254	0.0240	0.1058
12	0.10953	0.06102	0.10957	0.0204	0.0235	0.0888

PSO: particle swarm optimization; DE: differential evolution; SFO: synergistic fibroblast optimization

Table 8 Performance evaluation of PSO, DE, and SFO optimized classifiers for the chronic kidney disease problem

Algorithm	Accuracy (%)	True positive rate (%)	False positive rate (%)	True negative rate (%)	False negative rate (%)	Precision	Geometric mean 1	Geometric mean 2	*F*-measure
DT	81.61	86.77	24.53	75.47	13.23	168.21	120.81	80.93	114.49
PSO+DT	83.62	87.63	21.43	78.57	12.37	175.15	123.89	82.98	116.81
DE+DT	78.74	79.72	22.90	77.10	20.28	178.77	119.38	78.40	110.27
SFO+DT	85.63	88.06	17.69	82.31	11.94	183.81	127.22	85.14	119.07
FFNN	88.51	90.95	14.77	85.23	9.05	189.23	131.19	88.05	122.86
PSO+FFNN	89.94	91.18	11.81	88.19	8.82	196.94	134.00	89.67	124.65
DE+FFNN	83.91	86.57	19.73	80.27	13.43	180.00	124.83	83.36	116.91
SFO+FFNN	90.23	92.46	12.75	87.25	7.54	193.68	133.82	89.82	125.17

PSO: particle swarm optimization; DT: decision tree; DE: differential evolution; SFO: synergistic fibroblast optimization; CBA: classification-based association; FFNN: feed forward neural network

Rastrigin's, Step 2, Ackley, and Chung Reynolds. There was an indication that the efficiency of the SFO algorithm is reduced with a few benchmark functions (such as Griewank, Schumer Steiglitz, and Alpine), which have many local optima. It is stated that the significant characteristic of the SFO algorithm is subject to the 'no free lunch' theorem. Moreover, the SFO algorithm was tested on both the benchmark and a real-time dataset. The results illustrated that SFO gives a better solution than existing methods and that it can be a suitable method for solving complicated and uncertainty problems. The proposed method, which models the collaborative and adaptation behavior of fibroblast in the dermal wound-healing process, improves the optimization strategies to suite the concept of finding the optimal solution. Future work may focus on the investigation of the performance of the SFO algorithm in real-time applications like travelling salesman, graph coloring, optimized routing, combinatorial and assignment problem, scheduling, and resource constraint problems (Goldbarg et al., 2006; Zou et al., 2011; Zhang et al., 2015).

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