Speciation based firefly algorithm for optimization in dynamic environments

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ABSTRACT

In many optimization problems in real world, objective function, design variable or constraints can be changed during time, so optimal value of these problems also can be changed. These kinds of problems are called dynamic. Algorithms which are designed for optimizing in these environments have some principles that distinguish them from algorithms designed in static environment. In this paper, for the first time, an algorithm based on firefly algorithm is proposed for optimization in dynamic environment. Firefly algorithm is a new meta-heuristic algorithm with a great potential for discovering multiple optima simultaneously. Mentioned ability of this algorithm has been used to propose a novel approach for multi-modal optimization in dynamic environments. The proposed approach evaluated on Moving peaks benchmark problem, which is the most famous benchmark for assessment in dynamic environments. The obtained results show the proper accuracy and convergence rate for the proposed approach in comparison with other well-known approaches.

Keywords: Dynamic optimization problem, local search, Firefly Algorithm, Moving peaks benchmark.

1 Introduction

In real world, many optimization problems are non-stationary and dynamic. These optimization problems alter when the environment changes over time. Solving this type of problems by algorithms designed specifically for static environment is almost disappointing. Finding global optimal value is not sufficient for optimizing in dynamic environments and tracking optimum during the changes in the environment is also important. During recent years, different groups of methods have been proposed for solving optimization problems in dynamic environment. Among them, evolutionary computing and swarm intelligence methods have received significant attention during last decade. In order to design swarm intelligence algorithms for dynamic environments, two important points have to be taken into consideration: outdated memory and losing diversity.

Outdated memory refers to condition in which memory of the components of the algorithm may no longer be valid after a change in the environment. It can be solved by re-evaluating the memory or forgetting it. Furthermore, losing Diversity happens due to nature of evolutionary algorithms and swarm intelligence ones in converging to a point during executing the algorithm. At this point, if a change happens in environment, converging to a new optimal point is impossible or time consuming due to diversity loss. There are various methods for generating or maintaining diversity in environment that will be discussed in following.

The simplest way to react against environment change is to considering any changes as an input of a new optimization problem which has to be resolved. In case of having enough time, this solution is a proper option, but this time is often rather short for re-optimization. An attempt to improve the optimization process and convergence rate is moving information of search space from current environment to the next environment. If the change is extensive and there is a little similarity before and after a change in the environment, restarting the optimization algorithm can be the only proper option and any new use of collected information based on problem space before the change will be misleading. In most of real world problems, intensity of changes is not too much and new environment is closely related to the old environment.

There are two approaches to deal with losing diversity. In the first approach, a diversity maintenance mechanism runs during executing the algorithm (Hu and Eberhart, 2002). In the second approach, diversity is always monitored, and as soon as it falls below a threshold, the swarm will be re-diversified. Reported mechanisms in the literatures for either diversity maintenance or re-diversification have been classified into four groups (Blackwell, 2007): randomization (Hu and Eberhart, 2002), repulsion (Blackwell, 2003) (Blackwell and Branke, 2004), dynamic topology (Janson and Middendorf, 2004) and multi-populations (Blackwell and Branke, 2004) (Blackwell and Branke, 2006) (Li, Branke and Blackwell, 2006) (Parrott and Li, 2006) (Lung and Dumitrescu, 2007) (Blackwell, Branke and Li, 2008) (Du and Li, 2008) (Li and Yang, 2009) (Liu, Yang and Wang, 2010). Hu and Eberhart proposed randomization to randomize various proportions of the swarm to maintain some degree of diversity in order to track better the optimum after a change. However, this approach may suffer from losing some useful information due to randomization. Repulsion is used to repel the particles from each other. Blackwell and Bentley proposed a repulsion mechanism by using the concept of atom in nature and concluded that some charged particles which repel each other and orbit a neutral particle. Dynamic topology prevents the convergence of particles to the global best position by changing the topology of sharing information, thereby enhancing population diversity. Li and Dam proposed grid-like neighborhood structure (Kennedy and Mendes, 2002). Janson and Middendorf proposed HPSO, a tree-like structure hierarchical PSO (Janson and Middendorf, 2004), and Hashemi and Meybodi Proposed CellularPSO, a hybrid model of particle swarm optimization and cellular automata (Hashemi and Meybodi, 2009). In cellular PSO, a cellular automaton is embedded into the search space and partitions the search space into some cells. In each cell, a group of particles present and search for an optimum. Multi-population group is the most used and promising group for optimizing in dynamic environment. Multi-population approach divides the particles into some sub-swarms which each sub-swarm is responsible for searching in a different area. Therefore, in multi-swarm approaches, each swarm searches for a local optimum and at the same time avoids overlapping with other swarms. This is specifically helpful if the environment changes in a way that makes the previous local optimum as the new global optimum. If one of the swarms tracks the local optimum or a neighbor region, the new global optimum is quickly found. Several algorithms that use multi-swarm approaches for dynamic environments have been recently reported. Blackwell et al. proposed mQSO (Blackwell and Branke, 2004) (Blackwell and Branke, 2006) and adaptive mQSO (Blackwell et al., 2008) in which the entire population is divided into several sub-swarms, including three diversity operators, called quantum particles, exclusion and anti-convergence operators. Quantum particles appear at random positions to maintain the diversity of each sub-swarm and help to follow the changes in the environment. Exclusion operator reinitializes worse swarm in environment when two sub-swarms overlap with each other. Anti-convergence operator keeps at least one sub-swarm patrolling, which helps to find new and probably better local optima when there are more local optima than sub-swarms. By means of these operators, each sub-swarm in mQSO and adaptive mQSO aims to track a peak.

With a similar goal to locate and track multiple peaks in a dynamic environment, Parrott and Li(Parrott and Li, 2004) proposed a species-based PSO (SPSO) containing a speciation algorithm proposed by Petrowski (Petrowski, 1996). The SPSO uses a local species seed which provides the local optimum with particles whose positions in the search space are within a user-specified radius of the seed. It encourages swarms to converge toward multiple local optima instead of converging to a single global optimum; hence multiple sub-populations develop in parallel.

In this paper, an optimization algorithm based on firefly algorithm is proposed for acting in dynamic environments, which satisfy all requirements for designing an algorithm for dynamic environments. The proposed algorithm uses the potential capability of firefly algorithm well in converging to multiple optima and creates the sub-swarm the same as speciation based approach dynamically. The proposed algorithm is applied on different settings of moving peak benchmarks (MPB) (Branke, 1999) which are of the most famous benchmarks of dynamic environments and its efficiency is compared with ten known algorithms. Comparison measure is offline error which is one of the main standard measures for comparing designed algorithms in dynamic environments (Branke and Schmeck, 2003) . Moreover, beside offline error as a criterion for assessing and comparing algorithms reliability, standard error is used too (Branke and Schmeck, 2003). Experimental results show that the proposed algorithm has an acceptable efficacy.

The rest of this paper organized as follows: section 2 briefly introduces Firefly Algorithm and section 3 presents the proposed algorithm. Section 4 gives the results of the proposed algorithm on moving peaks benchmark problem and compares it with alternative approaches from the literature. The last section concludes the paper.

2 Firefly Algorithm

Firefly algorithm is a new meta-heuristic algorithm which is inspired from flashing light behavior of fireflies in nature. This algorithm was proposed by Yang in 2008(Yang, 2008). It uses three idealized rules for simplifying the algorithm: All fireflies are unisex and can be attracted by other fireflies; attractiveness of each firefly is proportional to their brightness and brightness of each firefly is determined by evaluating objective function.

In this algorithm, each firefly has a location $X = (x_1, x_2, x_3, ..., x_d)^T$ in a d-dimensional space and a light intensity $I(x)$ or attractiveness $\beta(x)$ which are proportional to objective function $f(x)$. Attractiveness $\beta(x)$ and light intensity $I(x)$ are relative and these should be judged by the other fireflies. Thus, it will vary with the distance r_{ij} between firefly i and firefly j. So attractiveness β of a firefly can be defined by equation (2.1).

$$\beta = \beta_0 e^{-\gamma r^2} \tag{2.1}$$

Where r is the distance between any two firefly i and j at x_i and x_j, respectively is the Cartesian distance, β_0 is attractiveness at $r = 0$ and γ is light absorption coefficient in the environment.

Algorithm 1: Firefly Algorithm

begin
    Define light absorption coefficient γ , Initial attractiveness β_0 ,
    Randomization parameter α.
    Objective function f(x), $x = (x_1, ..., x_d)^T$
    Generate initial population of fireflies x_i $(i = 1, 2, ..., n)$
    Light intensity I_i at x_i is determined by $f(x_i)$
    while *(t < MaxGeneration)* **do**
        for *i = 1 : n all n fireflies* **do**
            for *j = 1 : n all n fireflies* **do**
                if $I_i > I_j$ **then**
                    Move firefly i towards j based equation (2.2)
                end
                Attractiveness varies with distance r via exp[$-\gamma r^2$]
                Evaluate new solutions and update light intensity
            end
        end
        Rank the fireflies and find the current best
    end
    Postprocess results and visualization
end

Also, each firefly i can move toward another more attractive (brighter) firefly j by equation (2.2).

$$x_i = x_i + \beta_0 e^{-\gamma r_{ij}^2}(X_j - X_i) + \alpha(Rand - \frac{1}{2}) \tag{2.2}$$

Where α is a significance factor of randomization parameter and Rand with uniform distribution U(0,1) is a random number obtained from uniform distribution.

Recently, some studies reveal efficiency of this algorithm(Yang, 2009) by outperforming other meta-heuristic algorithms including some variation of particle swarm optimization(Łukasik and Żak, 2009) and also, in dealing with stochastic test functions and noisy environments(Aungkulanon, Chai-ead and Luangpaiboon, 2011). A more comprehensive description of this algorithm is given in (Yang, 2008) . Also, a pseudo code of firefly algorithm is presented in Algorithm 1.

3 Proposed Algorithm

In this section, a novel speciation based on firefly algorithm named SFA is presented for optimization in a dynamic environment. In the proposed algorithm, some modifications are done on firefly algorithm for better performance in dynamic environment. First, the best personal location of each firefly (Pbest) is added to the algorithm by inspiration from particle swarm optimization. The best personal location of each firefly can only help algorithm to move toward the best position. By holding Pbest of each firefly before fitness evaluation, algorithm can move to a better position if fitness value decreases. Second, randomization parameter of the firefly (α) is changed in an adaptive manner. The value of α increases if new location of firefly has better fitness value than previous fitness value of the best personal location of that firefly, otherwise it decreases.

Also, in the proposed algorithm, there is only one swarm of fireflies which acts on the environment. This is one of the most important differences between our proposed algorithm and many other multi-population approaches. When the algorithm starts working, fireflies scatter around the environment randomly. After a while of executing the firefly algorithm, speciation of fireflies happens and fireflies swarm is divided into some species which each species moves toward one local optimum. This is due to potential capability of firefly algorithm in converging toward more than one local optimum if parameters have been set properly. But because many local optima may exist in the environment, convergence to all of them requires a large population of fireflies and a chance for good initialization. To solve this issue, an exploring swarm is added which is responsible to explore the entire environment to find better solutions. If exploring swarm can find any better solution, the best point of exploring swarm will be added to population. Therefore, firefly algorithm can converge to some local optimum which population hasnt found them yet.

Furthermore, to improve local search ability of the algorithm, the idea of quantum particles has been used (Blackwell and Branke, 2006). Quantum particles used in this paper are completely different from prior application. They are used only to improve the convergence of global best firefly in the population.

The pseudo code of proposed algorithm is presented in Algorithm 2 and applied routines are shown in Algorithm. 3 to 6.

Algorithm 2: Proposed Algorithm (SFA)

```
begin
    Initialize Parameters
    Initialize fireflies swarm and discoverer swarm Randomly
    while stop criteria is not satisfied do
        call Test_for_change()
        Initialize test_point
        if Discovery is true then
            Call Discovery()
        end
        if mod(iteration, discovery_period) == 0 then
            if number of fireflies in swarm is less than max_firefly_in_swarm then
                Add best discoverer to firefly swarm
            else
                Replace best discoverer with a firefly in swarm which has most fitness value
                and at least a neighbor firefly is in radios of r_neighborhood
            end
        end
        call Move_firefly()
        call Update_best_swarm()
    end
end
```

In proposed algorithm, $discovery\_period$ indicates how much iteration must be run until the discoverer point is ready for adding to population. $r_{neighborhood}$ is neighborhood radios for each firefly. If two fireflies has Euclidian distance less than rneighborhood , we say these fireflies are very close to each other. When we want to add a new discoverer point to the swarm, we try to add a point, which is not a neighborhood for other fireflies. $Max\_firelfly\_in\_swarm$ indicate maximum number of fireflies which can be contributed in optimization process. Also, we suppose best firefly as a test point for determining change in the environment.

Algorithm 3: $Test\_for\_change()$

begin
  Evaluate $test\_point$
  if *new value of* $test\_point$ *is different from previous fitness value* **then**
    Reinitialize r_{cloud} and α
    re-evaluate all fireflies in swarm
  end
end

Algorithm 3 shows pseudo code of $test\_for\_change()$ routine. In this routine, r_{cloud} is the radios of quantum. With respect to (Blackwell and Branke, 2006) and (Blackwell et al., 2008) , quantum cloud value has to be determined based on peaks shift length.

Algorithm 4: $Discovery()$

begin
  t=0
  while *t is less than* $discovery\_iteration$ **do**
    Set a new point based on best firefly in discovery swarm by adding a random vector number between -r_{cloud} and r_{cloud} to best firefly in discovery swarm
    Evaluate new $test\_point$
    if *fitness of new point is better than best firefly in discovery swarm* **then**
      Set best firefly to this new point
      Set r_{cloud} by equation (3.1)
    end
    t = t + 1
  end
end

$$r_{cloud}(t) = r_{cloud}(t-1) \times (L_{Low} + (Rand \times (L_{High} - L_{Low}))) \tag{3.1}$$

Also, Algorithm 4 shows pseudo code of Discovery() routine. In equation (3.1), r_{cloud} in each iteration is obtained randomly based on its value at previous iteration. L_{Low} and L_{High} are lower limit and upper limit of rcloud change percentage in compare with previous iteration. Rand is the random number generator function with uniform distribution in $[0, 1]$. Hence, r_{cloud} value in each iteration randomly is in [$r_{cloud}(t-1) \times L_{Low}$, r_{cloud}(t-1) $\times$ L_{High}]. For this reason, L_{High} value should be considered less than one and $L_{Low} \leq L_{High}$. It should be mentioned that r_{cloud} value is initialized after every environment change to adapt itself with problem space conditions.

Algorithm 5: $Move\_firefly()$

```
begin
    for i = 1 : n all n fireflies do
        for j = 1 : n all n fireflies do
            if I_i > I_j then
                Move firefly i towards j based equation (2.2)
                Evaluate new solution
                if new fitness value is better than personal best fitness value then
                    Set personal best position to new firefly position
                else
                    Set firefly position to previous personal best position
                end
            end
            Attractiveness varies with distance r via exp[-γr^2]
        end
    end
end
```

Algorithm 5 shows Pseudo Code of $Move\_firefly()$ routine. It shows some difference with standard firefly algorithm which described yet.

Algorithm 6: $Update\_best\_swarm()$

```
begin
    for counter =1 to try_number do
        Update Quantum based on equation (3.2)
        if f(Quantum) > f(Global_best) then
            Global_best = Quantum
        end
    end
    update r_cloud based on equation (3.1)
end
```

$$x_{Quantum,j} = Global\_best + (r_{cloud} \times R_j) \tag{3.2}$$

Algorithm 6 show pseudo code of $update\_best\_swarm()$ routine. In equation (3.2), R_j is a random number with uniform distribution in [-1, 1]. So component jth of quantum firefly locates at [$-r_{cloud}$,r_{cloud}] around the same component in global best of the firefly swarm. Therefore, quantum firefly position would place in a d-dimensional ball around global best of the firefly swarm. Also, try_number specify number of try to improve global best firefly of swarm.

4 Experimental Study

To evaluate correctness and efficiency of the proposed algorithm, this algorithm was compared with some well-known algorithms on Moving Peaks benchmark (MPB) which is one of the most famous benchmarks for dynamic environments. In this section, first MPB introduced and then needed experimental setting is given. After that, we study effect of shift severity, number of peaks and environmental change frequency on proposed algorithm.

4.1 Moving Peaks Benchmark (MPB) problem

Moving Peaks Benchmark(Branke, 1999) is widely used for evaluating the performance of opimization algorithms in dynamic environments. In this benchmark, there are some peaks in a multi-dimensional space, where height, width and position of peaks alter when a change occur in the environment. For the D-dimensional landscape, the problem is defined as equation (4.1):

$$F(\overrightarrow{x},t) = max(B(\overrightarrow{x}), maxP(\overrightarrow{x}, h_i(t), w_i(t), \overrightarrow{p}_i(t))) \tag{4.1}$$

Where $h_i(t)$ and $w_i(t)$ are the height and width of peak i at time t, respectively, and $p_i(t)$ is the position of peak i at time t. The p independently specified peaks are blended together by the max function. The position of each peak is shifted in a random direction by a vector $\overrightarrow{v}_i$ of a distance s (s is also called the shift length, which determines the severity of the problem dynamics), and the move of a single peak can be described as equation (4.2):

$$\overrightarrow{v_i}(t) = \frac{S}{|\overrightarrow{r} + \overrightarrow{v_i}(t-1)|}((1-\lambda)\overrightarrow{r} + \lambda\overrightarrow{v_i}(t-1)) \tag{4.2}$$

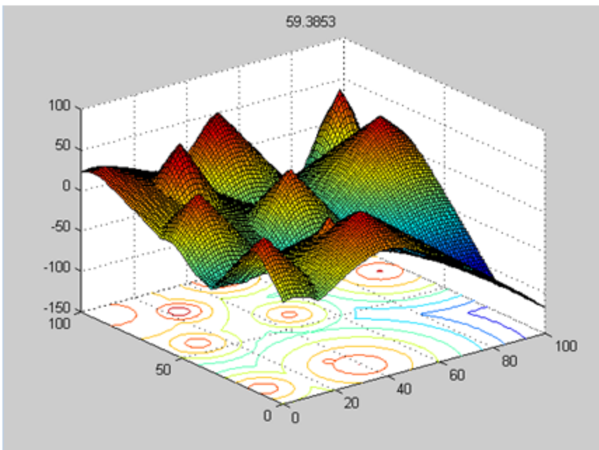
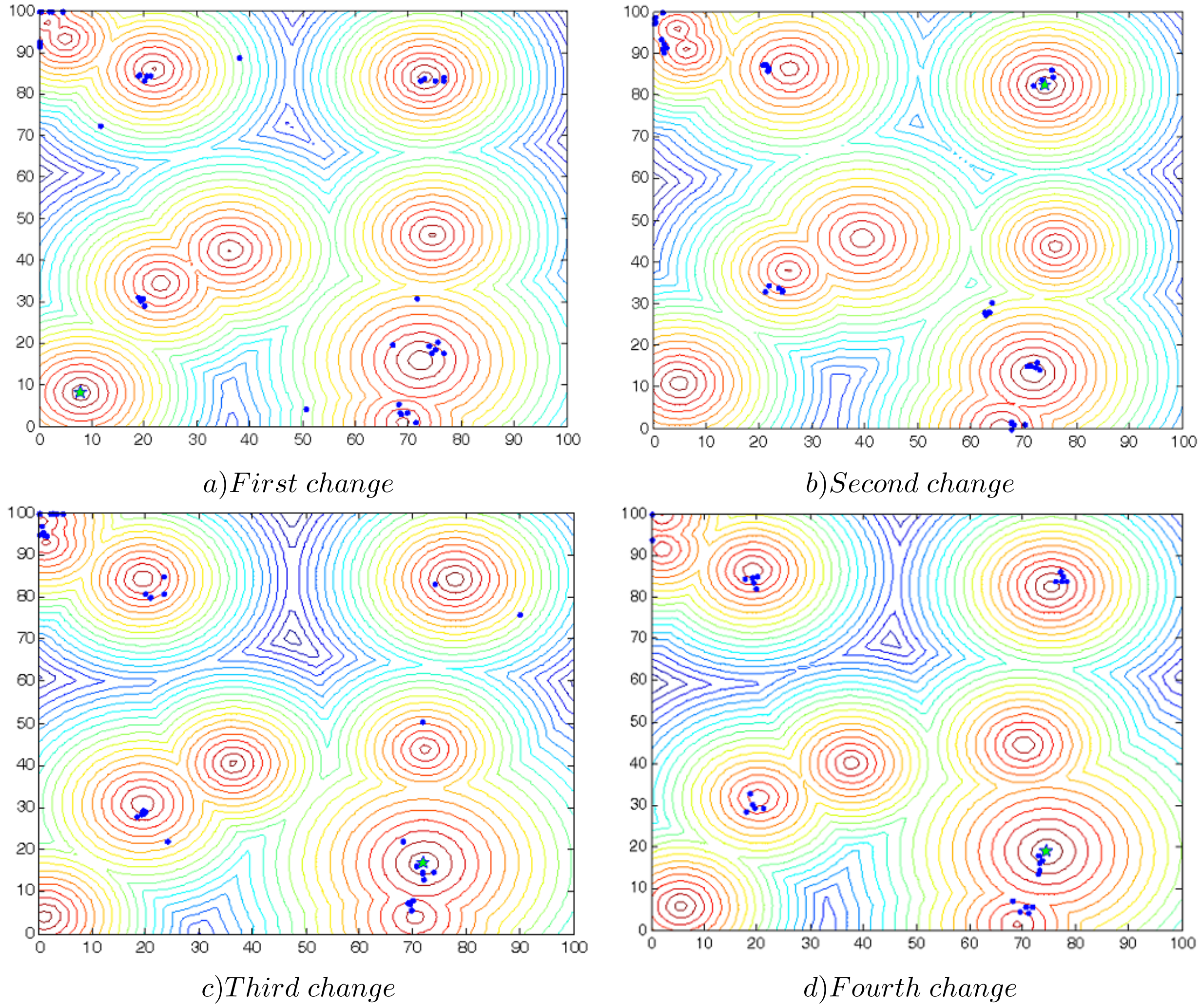


Figure 1: Shape of Moving Peaks Benchmark Problem.

Where the shift vector $\overrightarrow{v_i}(t)$ is a linear combination of a random vector $\overrightarrow{r}$ and the previous shift vector $\overrightarrow{v_i}(t-1)$ and is normalized to the shift length s. the correlated parameter λ is set to 0, which implies that the peak movements are uncorrelated. More formally, a change of a single peak can be described as equation (4.3):

$$
\begin{aligned}
&\sigma \in N(0,1) \\
&h_i(t) = h_i(t-1) + height_{severity} * \sigma \\
&w_i(t) = w_i(t-1) + width_{severity} * \sigma \\
&\overrightarrow{p_i}(t) = \overrightarrow{p_i}(t-1) + \overrightarrow{v_i}(t)
\end{aligned}
\tag{4.3}
$$

Also, for the shape of function P, Cone and Hilly shape function can be selected. Shape of MPB and movement of the peaks in the landscape for four changes in environment showed in figure. 1 and 2.



$a)First\ change$ $b)Second\ change$

$c)Third\ change$ $d)Fourth\ change$

Figure 2: Movement of the peaks in the landscape for four changes in the environment.

Experiments were done with respect to MPB parameters setting which are given in table (1).

Table 1: MPB parameters setting.

Parameter	Value
Number of peaks, M	Variable between 1 to 200
Change frequency	5000
Height change	7.0
Width change	1.0
Peaks shape	Cone
Basic function	No
Shift length, s	1.0
Number of dimensions,D	5
Correlation Coefficinet,	0
peaks location range	[0 100]
Peak height	[30.0 70.0]
Peak width	[1 12]
Initial value of peaks	50.0

4.2 Experimental setting

Adjustment of parameters values in the proposed algorithm are as follows:
At the beginning of execution, algorithm starts with 5 fireflies in population, and maximum number of fireflies which can contribute in execution limited to 100 fireflies. It was proved (Blackwell et al., 2008) that this number of particles has the best efficiency in solving MPB problem. It was shown (Blackwell et al., 2008) that adjusting r_{cloud} value equal to half of shift length would give proper results, so we consider this as initialized value of r_{cloud} too. According to various experiments have been done it concluded that adjusting try_number equal to 50 and also L_{Low} and L_{high} equal to 0.6 and 1 would give appropriate results. The primary performance measure is the offline error (Branke and Schmeck, 2003) which is the average over, at every point in time, the error of the best solution found since the last change of the environment. This measure is always greater or equal to zero and would be zero for perfect tracking. Experiments were repeated independently 50 times and each time they were performed by different random seeds. Every experiment continued until environment changes 100 times. For example when change frequency was 5000, experiments performed 5×10^5 fitness evaluations and during this time the environment changes 100 times.

4.3 Experimental investigation of SFA

In this section, we study effect of varying shift severity, number of peaks on proposed algorithm.

4.3.1 Effect of varying shift severity

In this section, the performance of proposed algorithm is compared with six other algorithms which are mQSO (Blackwell and Branke, 2006), AmQSO (Blackwell et al., 2008), mCPSO

(Blackwell and Branke, 2006), SPSO (Du and Li, 2008), rSPSO (Bird and Li, n.d.) and PSO-CP (Liu et al., 2010) on the MPB problems with 10 peaks, change frequency 5000 and different settings of the shift length (vlenght). The experimental results regarding the offline error and standard error are shown in Table 2.

Table 2: Effect of varying shift severity.

	Shift Severity			
Algorithm	**1.0**	**2.0**	**3.0**	**5.0**
mQSO	1.75(0.06)	2.40(0.06)	3.00(0.06)	4.24(0.10)
AmQSO	1.51(0.10)	2.09(0.08)	2.72(0.09)	3.71(0.11)
mCPSO	2.05(0.07)	2.80(0.07)	3.57(0.08)	4.89(0.11)
SPSO	2.51(0.09)	3.78(0.09)	4.96(0.12)	6.76(0.15)
rSPSO	1.50(0.08)	1.87(0.05)	2.40(0.04)	3.25(0.09)
PSO-CP	1.31(0.06)	1.98(0.06)	2.21(0.06)	3.20(0.13)
SFA	**1.05(0.08)**	**1.44(0.06)**	**2.06(0.07)**	**2.89(0.13)**

4.3.2 Effect of varying number of peaks

In table 3, efficiency of proposed algorithm are compared with ten other algorithms include mQSO, mCPSO, AmQSO, CellularPSO(Hashemi and Meybodi, 2009), FMSO(Li and Yang, 2008), RPSO(Hu and Eberhart, 2002), SPSO, rSPSO, mPSO(Kamosi, Hashemi and Meybodi, 2010) and PSO-CP on the MPB problems with various number of peaks, change frequency 5000 and shift length 1. The results of some algorithms obtained from their papers. As can be seen in this table, the proposed algorithm has much better performance than other algorithms. In fact, the results show the proposed algorithm is robust with number of peaks and when the number of peaks is low or when the number of peaks is high can achieve acceptable results.

Table 3: comparison of offline error (standard error) of 11 algorithms on MPB problem with different number of peaks

	Number Of Peaks							
Algorithm	**1**	**5**	**10**	**20**	**30**	**50**	**100**	**200**
mQSO	4.92(0.21)	1.82(0.08)	1.85(0.08)	2.48(0.09)	2.51(0.10)	2.53(0.08)	2.35(0.06)	2.24(0.05)
AmQSO	0.51(0.04)	1.01(0.09)	1.51(0.10)	2.00(0.15)	2.19(0.17)	2.43(0.13)	2.68(0.12)	2.62(0.10)
CLPSO	2.55(0.12)	1.68(0.11)	1.78(0.05)	2.61(0.07)	2.93(0.08)	3.26(0.08)	3.41(0.07)	3.40(0.06)
FMSO	3.44(0.11)	2.94(0.07)	3.11(0.06)	3.36(0.06)	3.28(0.05)	3.22(0.05)	3.06(0.04)	2.84(0.03)
RPSO	0.56(0.04)	12.22(0.76)	12.98(0.48)	12.79(0.54)	12.35(0.62)	11.34(0.29)	9.73(0.28)	8.90(0.19)
mCPSO	4.93(0.17)	2.07(0.08)	2.08(0.07)	2.64(0.07)	2.63(0.08)	2.65(0.06)	2.49(0.04)	2.44(0.04)
SPSO	2.64(0.10)	2.15(0.07)	2.51(0.09)	3.21(0.07)	3.64(0.07)	3.86(0.08)	4.01(0.07)	3.82(0.05)
rSPSO	1.42(0.06)	1.04(0.03)	1.50(0.08)	2.20(0.07)	2.62(0.07)	2.72(0.08)	2.93(0.06)	2.79(0.05)
mPSO	0.90(0.05)	1.21(0.12)	1.61(0.12)	2.05(0.08)	2.18(0.06)	2.34(0.06)	2.32(0.04)	2.34(0.03)
PSO-CP	3.41(0.06)	-	1.31(0.06)	-	2.02(0.07)	-	2.14(0.08)	2.04(0.07)
SFA	**0.42(0.07)**	**0.89(0.09)**	**1.05(0.04)**	**1.48(0.05)**	**1.56(0.06)**	**1.87(0.05)**	**2.01(0.04)**	**1.99(0.06)**

5 Conclusion

In this paper, a new method for optimization in dynamic environments was proposed based on speciation based firefly algorithm. Results on various configuration of moving peak benchmark problem were compared with several well-known methods. The proposed algorithm used new mechanisms to divide population into some swarms. Totally, in this algorithm, it attempted to satisfy all dynamic environments requirements. Experimental results showed that the proposed algorithm has an acceptable performance than other algorithms.

Also, there are some relevant works to pursue in the future. First, some work can be done to set a good initialization before the algorithm start. Second, some adaptation can be done on fireflies parameters such as β and γ to improve efficiency of the algorithm. Third, some works can be done to improve local search ability of algorithm by using prior knowledge of the problem space.

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