

Differential Evolution – A diversity approach

Joel Chacón Castillo · Carlos Segura

Received: date / Accepted: date

Abstract Differential evolution is a popular evolutionary algorithm widely used in optimization problems. However, it is well known that the performance of differential evolution is affected by the premature convergence. An alternative to alliviate this drawback is to explicitly try to maintain proper diversity. In this paper is proposed a replacement strategy that preserves useful diversity. The novelty of our method is that it induces a balance between exploration and exploitation to various optimization stages. Specifically, in the initial phases, larger amounts of diversity are accepted. The concept is oriented in the speciation concept, which is based on calculate distances to the closest surviving individual. The experimental validation is carry out with several benchmark tests and the top-rank algorithms of the competitions organized in the Congress on Evolutionary Computation. The results illustrate the usefulness of the proposal. The new method significantly improves on the best results of the state-of-the-art.

Keywords Diversity · Differential Evolution · Evolutionary

1 Introduction

Evolutionary Algorithms (EAs) are built to deal with optimization problems, which are designed from many scientific and application fields, such as science, economic and engineering [1,2]. Principally, EAs can be classified into following categories, such as Genetic Algorithms (GAs) [3,4], Evolutionary Strategies (ESs) [5], Genetic Programming (GP) [6], Evolutionary Programming (EP) [7],

Joel Chacón
Guanajuato, Gto.
E-mail: joel.chacon@cimat.mx

Carlos Segura
Guanajuato Gto.
E-mail: carlos.segura@cimat.mx

Differential Evolution (DE) [8] and other natural-inspired algorithms [9]. DE was introduced by Storn and Price [8], also is considered as one of the most effective EAs used to deal with real-world optimization problems, mainly for its convergency properties. Similarly than with other EAs, DE follows the natural evolution process which involves mutation, recombination and selection to evolve a population through an iterative progress until the criteria stop is reached. However, the peculiarity of DE resides in considering difference of vectors parameters to explore the search space, being very similar than its precursor algorithms namely the Nelder-Mead [10] and the Controlled Random Search (CRS) [11]. In spite of the popularity and effectiveness of DE, there exists several weakness that had been partially solved through learning techniques. One of the first weakness and possibly the most important, is the performance of DE which is very sensitive to choice of the strategy parameters depending in the objective function [12]. Several strategies as adaptive and self-adaptive have been proposed to alliviate this drawback [13, 14]. However, none of them has shown superior results than the rest.

A second weakness of DE algorithms resides in the reproduction phase. In DE this phase involves the vector differences, therefore it depends on the content of the population affecting the search process, therefore a limited number of solutions are produced. In fact, this issue can lead to the converge into a local optima or the lost of diverse solutions better known as premature convergence [15]. On the other hand, there exist situations where the search process could not progress and the population remains diverse, this phenomena is known as stagnation [16]. Its well known that stagnation occurs with small populations size. Although that large populations are not prone to stagnate, it involves more evaluation functions and in some scenarios might not converge, also in certain situations is not available a large population e.g. expensive optimization problems [17].

The last one drawback is highly related with the diversity of the population. Generally speaking, the search process of all the EAs involves two process: exploration and intensification. A desirable behavior of an algorithm is to produce a proper balance between these two process. So that first it induces an exploration in the search space and after that an exploitation of the knowledge gathered during the search process [18]. Both exploration as exploitation are equally important, since that with a excessive exploitation, the population loses its diversity and the populations members can be located in a reduced sub-optimal region of the search space. On the other hand, if the exploration is dominant, the algorithm waste resources on uninteresting regions, resulting in too slow convergence and in poor quality-solutions. Principally, DE algorithms are very likely to prematurely converge, since that introduce a high selection pressure [15]. Several strategies have been proposed in DE to deal with premature convergence, as parameter adaptation based on the idea of controlling the population diversity [18], auto-enhanced population diversity mechanism [19], alternative selection strategy [15].

A recent and novel approach to deal with these diversity issues, is through a sophisticated replacement strategy that explicitly preserves the diversity [20].

This method transforms a single-objective problem into a multi-objective one, by considering diversity as an explicit objective, with the idea of adapting the balance induced between exploration and exploitation to various optimization stages. Thus, the ideal balance is reached considering the criteria stop of the algorithm.

Our proposal follows a similar guideline, where it aims an ideal balance between exploration and exploitation considering the criteria stop. However, we keep the single-objective context and focus in DE algorithms.

The rest of the paper is organized as follows. The basic concepts of the classic DE and a review of the related work of diversity with DE is described in the section 2. In the section 3 is showed the tendency of algorithms of the Congress on Evolutionary Computation among the last years. Our proposal based in diversity is described in the section 4. In the section 5 are showed the experimental results including some of the most popular EAs. Finally, our conclusions and some lines of future work are given in section 6.

2 Literature Review

2.1 Differential Evolution: Basic Concepts

In the literature are present several variants of DE [1, 8]. For simplicity, in this work is used the classic DE scheme [24]. Originally DE was proposed as direct search method for single-objective continuous optimization problems [24] (improving). Usually, the parameters governing the system performance are presented in a vector like $\mathbf{X} = [x_1, x_2, \dots, x_D]^T$, which is identified as an individual. Particularly, for real parameter optimization each parameter x_i is a real number.

In single-objective optimization, the aim is to obtain the vector \mathbf{X}^* which minimizes (or maximizes) a defined objective function, mathematically denoted by $f(\mathbf{X})$ ($f : \Omega \subseteq \mathbb{R}^D \rightarrow \mathbb{R}$), i.e., $f(\mathbf{X}^*) < f(\mathbf{X})$ for all $\mathbf{X} \in \Omega$, where Ω is a non-empty large finite set identified as the domain of the search.

The basic scheme of DE consists that given the target parameter vectors (each vector of the population), a new mutant (or donant) vector is created using a vector generation strategy. After that, the mutant vector is combined with the target vector to generate the trial vector. In the same vein, each one of the trial vectors is compared with the corresponding target vector, and the vector with the best fitness is selected to survive as trial vector of the next generation. In case of tie, the new generated trial vector survives.

2.1.1 Initialization

The DE algorithms as is usual begins with a randomly initiated population of NP parameter vectors. Subsequent generations in DE are denoted by $G = 0, 1, \dots, G_{max}$. The i th vector of the population at the current generation is

denoted as:

$$\mathbf{X}_{i,G} = [x_{1,i,G}, x_{2,i,G}, \dots, x_{D,i,G}]. \quad (1)$$

The initial population should cover a bounded range and is reached by uniformly randomizing individuals within the search space constrained by the prescribed minimum and maximum bounds. Hence, each j th component of the i th vector is initialized as follow:

$$X_{j,i,0} = x_{j,min} + rand_{i,j}[0, 1](x_{j,max} - x_{j,min}) \quad (2)$$

where $rand_{i,j}[0, 1]$ is a uniformly distributed random number lying between 0 and 1.

2.1.2 Mutation

The mutation can be seen as a change or perturbation with a random element. Particularly, in DE a parent vector called *target* vector is combined through a defined strategy to form the *donor* vector. In one simple form, a mutant vector $V_{i,G}$ is created from the i th target vector and is established as follows:

$$\mathbf{V}_{i,G} = \mathbf{X}_{r1,G} + F(\mathbf{X}_{r2,G} - \mathbf{X}_{r3,G}) \quad r1 \neq r2 \neq r3 \quad (3)$$

The indices $r1, r2, r3 \in [1, NP]$ are mutually exclusive integers randomly chosen from the range $[1, NP]$. It is important take into account that the difference of any two vectors is scaled by a scalar number F and usually is defined in the interval $[0.4, 1]$, also the scale difference is added to the third one.

2.1.3 Crossover

In order to increase the diversity of the perturbed parameter vectors, a crossover operation is applied to the generated donor vector. Accordingly this, the target vector is mixed with the mutated vector to form the trial vector $\mathbf{U}_{i,G} = [u_{1,i,G}, u_{2,i,G}, \dots, u_{D,i,G}]$. In the DE-context are present two kinds of crossover methods –*exponential* and *binomial* (or uniform), however in this paper only is considered the binomial crossover. In the binomial crossover strategy, the trial vector $\mathbf{U}_{i,G}$ is generated as follows:

$$\mathbf{U}_{j,i,G} = \begin{cases} \mathbf{V}_{j,i,G}, & \text{if}(rand_{i,j}[0, 1] \leq CR \quad \text{or} \quad j = j_{rand}) \\ \mathbf{X}_{j,i,G}, & \text{otherwise} \end{cases} \quad (4)$$

where $rand_{i,j}[0, 1]$ is a uniformly distributed random number, which is generated for each j th component of the i th vector parameter. j_{rand} is a randomly chosen index, which ensures that $\mathbf{U}_{i,G}$ has at least one component from $\mathbf{V}_{i,G}$. CR is the crossover constant $\in [0, 1]$, which has to be determined by the user.

2.1.4 Selection

Once generated the trial vectors, is performed a greedy selection scheme. This selection determine wheter the target or the trial vector survives to the next generation, and is described as follows:

$$\mathbf{X}_{j,i,G+1} = \begin{cases} \mathbf{U}_{i,G}, & \text{if } f(\mathbf{U}_{i,G}) \leq f(\mathbf{X}_{i,G}) \\ \mathbf{X}_{i,G}, & \text{otherwise} \end{cases} \quad (5)$$

where $f(\mathbf{X})$ is the objective function to be minimized. Hence, the population eigher gets better or remains the same fitness status, but never deteriorates.

The mutation scheme deccribed with the crossover proposed is refered as DE/rand/1/bin. The general convention is DE/ $x/y/z$, where DE indicates “differential evolution”, x denotes the base vector to be perturbed, y is the number of difference vectors considered for perturbation and z is the type of crossover to use.

2.2 Differential Evolution and Diversity techniques

DE is highly susceptible to the diversity drawbacks generally seen in EAs. This fact is since the selection pressure is very aggressive, well known as a greedy strategy. However through the last decade has developed several analyses and strategies to deal with these drawbacks. One of them is proposed in 2003 by Zaharie et al. [18] estimated the theorical variance and proposes a parameter adaptation through two critical equations based on the idea of controlling the population diversity. In 2009 James Montgomery [21] analyses the effect of the difference vectors showing that small differences vectors applied to solutions in one cluster can produce improvements, thus movements produced by large difference vectors are wasted. After that in 2010 Montgomery shows a study where are analyzed the DE parameters, principally is empirically demonstrated the effect of the crossover probability. In 2012 Montgomery et al. [22] proposed a strategy that prevents the movements vectors that could provoke premature convergence, specifically it prevents the movements that are below a threshold and it decreases over the algorithm’s run, however this strategy only slow down the convergency since that only is considered the distance bewteen the base vector and the trial vector but the distance between the trial vector and the target vector is not considered. Also in 2013 derived of this strategy is proposed an adaptive threshold convergence mechanism by Antonio et al. [23].

A similar work is proposed by Angela et al. [15], which suggests a modification of the selection operator of the classical DE. Particularly, the seleciton pressure is relaxed through a probabilistic selection to maintain the population diversity and consequently to allow scape from basin of attraction of local optima, however to compute the probabilistic selection is considered the fitness therefore it depends in the cost function.

Ming Yang et al. (2013) [19] proposed a mechanism named *Auto-Enhanced Population Diversity* (AEPD) where are identified the moments when a population becomes converging or stagnating by measuring the distribution of the population in each dimension and diversifying at the dimensional level. Similar strategies has been proposed as the one by Zhao Li et al. in 2016 [24] where are varied the assembling positions of the premature individuals by mutation operation.

Our proposal is based in several ideas of the previously mentioned works, specifically the following:

- Is considered a threshold to control explicitly the convergency of the solutions.
- This threshold decreases over the algorithm's run.
- The selection operator should be relaxed.

3 Differential Evolution Through Years

In the last decade, DE has been recognized as one of the most promising EAs, likely for its efficient and simple approach to solve optimization problems. Specifically, the DE variants have been highly present in several optimization competitions, principally in the Congress on Evolutionary Computation (CEC). In fact DE occupied the top places in several optimization scenarios as are single-objective, multi-objective, constrained problems, large scale problems, dynamic problems, multi-niche landscape problems and learned based problems. In this work we are interested in the design tendency of DE algorithms and CEC competitions problems through the last years.

In CEC 2005 competition on real parameter optimization [25], on 10-D problems classical DE secured 2nd rank and a self-adaptive DE variant called SaDE secured third rank although they performed poorly over 30-D problems. Later in CEC 2006 on constrained problems [26] DE algorithms obtained first place with ϵ constrained Rank-based Differential Evolution (ϵ RDE) and third place with SaDE.

Multi-objective optimization problems were proposed in CEC 2007 [27] competition, where DE obtained the second place with the based Generalized Differential Evolution 3 (GDE3), it is important take into account that later in CEC 2009 the first place was reached by the Multi-Objective Evolutionary Algorithm Based in Decomposition (MOEA/D) which applies the DE operators instead of its old version that used genetic operators (Simulated Binary Crossover).

However, in the large scale global optimization (CEC 2008) [28] a Self-adaptive DE (jDEdynNP-F) reached the third place, unfortunately in later competitions (CEC 2010) DE algorithms did not reach the top rank, this could be an indicator of the weakness of DE in large scale problems [29].

In CEC 2010 competition on constrained real-parameter optimization [30] the first place was reached by the ϵ Constrained DE with gradient based

mutation (ϵ Deg) and the third place by the Self-adaptive DE for solving constrained optimization (jDEsoco).

In CEC 2011 competition with real world optimization problems [31], the second and third places were reached by Hybrid DE (DE- λ_{CR}) and Self-adaptive Multi-Operator DE (SAMODE) respectively. Later in CEC 2014 [32], the first place was reached by the Linear Population Size Reduction Success-History Based Adaptive DE with Linear Population Size Reduction (L-SHAE) in the single objective real parameter optimization scenario. In CEC 2015 with the scenario of learned based single-objective [33] DE obtained the first three places, Successful-Parent Selecting L-SHADE with Eigenvector-Based Crossover (SPS-L-SHADE-EIG), DE with success Parameter Adaptation (DesPA), Mean Variance Mapping Optimization (MVMO) and Neurodynamic L-SHADE (L-SHADE-ND), being the last two in third place. DE was also present in the scenario of multi-niche single objective optimization in the third place with Neighborhood based Speciation Differential Evolution (NSDE). In CEC 2016 competition in single objective optimization [33] the first place was reached with the United Multi-Operator Evolutionary Algorithm (UMOEAs-II), the second place was reached by Ensemble Sinusoidal Differential Covariance Matrix Adaptation with Euclidean Neighborhood (L-SHADE-EpSin) and in the third place Improved L-SHADE (iL-SHADE), all of them apply DE operators. In the scenario of learned based single objective optimization [34], the second and third places were reached by Cooperative Co-evolution L-SHADE with restarts (CCL-SHADE) and L-SHADE with four strategies (L-SHADE44) respectively.

In CEC 2017 single objective optimization competition [35] the first three places were obtained by DE variants which are Effective Butterfly Optimizer with Covariance Matrix Adapted Retreat Phase (EBOWwithCMAR) considered as an improvement of UMOEAs-II, jSO (improvement of iL-SHADE) and L-SHADE-EpSin, being the first, second and third places respectively.

It is important to take into account two dominant approaches in the described competitions: Multi-operator EAs (EBOWwithCMAR) and adaptive (family of SHADE). Also it seems that in the last algorithms the criteria stop is considered to control the convergence level either explicitly or implicitly, such as Linear Population Size Reduction (LPSR), decreasing $pBest$ mutation strategy, local search in the last stages, among others.

In the competitions of the last years SHADE's family algorithms seems to be more participative, however based in that the ability exploration of DE is highly affected by the population size, usually the search is complemented with a Covariance Matrix Adaptation variant as is showed in the UMOEAs-II and L-SHADE-EpSin algorithms.

4 Proposal

Principally, our proposal is based in the following two works. The first one that is delimited for DE algorithms, it is shown by Montgomery et al. [22] where

is suggested a strategy to prevented the premature caused by the displacement of the mutation. The second one that is a generalization of EAs, it is proposed by Carlos Segura et al. [20] and it transforms the single objective optimization problem to multiple objectives where one of them is the fitness and the other one is a diversity measurement, similarly is used a threshold which is decreased as the criteria stop is reached.

Particularly, our proposal induces a balance between exploration and exploitation that is automatically adjusted on the given stopping criterion. Thus, the stopping criterion, as well as the elapsed time or the evaluations already executed, are used as inputs to the replacement strategy. In this way, for shorter stopping criteria the method induces a faster reduction in diversity than for longer stopping criteria. To achieve such balance are considered three populations, parent vectors, offspring vectors and elite vectors, being one of the novelties of the new design.

One of the basic principles behind the development of the replacement strategy devised in this paper is that individuals that contribute too little to diversity –the contribution is measured with the Distance to Closest Neighbour (DCN) value– should not be accepted as be part of the parent vectors, instead it could replace one of the elite vectors.

In our approach, vector that contribute too little are penalized. The value D represent the minimum DCN required to avoid being penalized. Any vector whose DCN value is lower than this threshold value is penalized. The key principle resides in how to evaluate wheter an vector contributes enough or not, i.e., how to set the value D . The value of D should depend on the optimization stage. Specifically, this value should be reduced as the stopping criterion is approached. In our scheme, an initial D_I value must be set. Then, a linear reduction of D is done. Particularly, in this work, the stopping criterion is set by function evaluations (nfes). The reduction is calculated in such way that by the 95% of maximum number of evaluations the resulting D value is 0, and the rest is present a similar behaviour of the classical DE. Thus, if max_nfes is the maximum number of evaluations and $nfes$ the elapsed number of evaluations, D can be calculated as $D = D_I - D_I * (nfes / (0.95 * max_nfes))$. According to Segura et al. [20] updating D is more appropriate through a linear reduction.

Specifically, the previously strategy is implemented in the replacement phase (algorithm 1) where is used a popular niche-strategy known as *Speciation* [36]. Initially, based in a niche-radius (D) and a defined distance¹ (6), in an iterative process the seeds (or survivors) are identified, these are the vectors with best fitness and whose minimal DCN is not lower than the one determined by the D value.

$$d(x_{seed}, x_j) = \sqrt{\sum_{d=1}^D (x_{seed}^d - x_j^d)^2} \quad (6)$$

¹ For simplicity we use euclidean distance, however can be user other distance as the mahalanobis distance.

Therefore, the vectors that have a lowest distance to any seed than D are moved to the penalized set. In this way are preserved the best fitness vectors and simultaneously the diversity is maintained in some level. It is important to take into account that if the niche-radius is too high, just one seed or survivor will be selected. In this scenario the rest of parent vectors are selected from the penalized vectors. Thus, are selected the penalize vectors that considering the selected seeds vectors have the maximum contribution to diversity. Although that in the literature exist several diversity measures, we consider the DCN. According this, in an iterative process is selected as survivor the penalized vector that has the maximum DCN.

Algorithm 1 Replacement Phase

```

1: Survivors = Penalized =  $\emptyset$ .
2: Current = Population  $\cup$  Offspring  $\cup$  Elite.
3: Sort Current according to fitness.
4: while Survivors < pop_size do
5:   Select the best individual Currentbest of Current as a new seed.
6:   Find the other individuals nearest according to Eq. (6) and move to Penalized.
7:   Move the best individual Currentbest to Survivors.
8: while Survivors < pop_size do
9:   Select the individual Penalized with maximum distance to closest Survivor.
10:  Move individual Penalized to Survivors.
11: return Current

```

On the other hand, since that the diversity in the parent vectors should be kept, the selection operator indicated in the equation (5) is modified. Thus, instead of made a comparison between the target or parent vectors and the trial or offspring vectors, is applied a comparison between the offspring vectors with the elite vectors. Hence, the elite vectors record the best individuals obtained among the optimization process.

Algorithm 2 General scheme of DE considering diversity

```

1: Randomly initialize the population of  $NP$  individuals, where each one is uniformly distir-
   buted.
2: while stopping criterion is nor satisfied do
3:   for  $i = 1$  to  $NP$  do
4:     Mutation: Generate the donor vector according Eq. (3)
5:     Crossover: Recombine the mutate vector according Eq. (4)
6:     Selection: Update the parent vector according Eq. (5)
7:     Replacement: Select the parent vectors according to algorithm 1

```

5 Experimental Study

In this section the experimental validation of our proposal is showed that controlling the diversity in a classic DE, is a way to improve further some of the results obtained by the state-of-the-art algorithms. Particularly, the benchmarks of CEC 2016 and CEC 2017 are considered, each ome of them is composed of thirty different problems. As the state-of-the-art are used the

Table 1 Summary results - CEC 2016

Algorithm	Always Solved	At least one time solved	Score	Statistical tests		
				↑	↓	↔
UMOEAsII	9	14	41.65	5	31	24
L-SHADE-Epsilon	7	13	45.84	18	14	28
Proposal	13	21	100.00	31	9	20

Table 2 Summary results - CEC 2017

Algorithm	Always Solved	At least one time solved	Score	Statistical tests		
				↑	↓	↔
EBOwithCMAR	11	15	30.6792	11	23	26
JSO	8	19	41.8322	8	29	23
Proposal	21	28	100.0000	36	3	21

algorithms that belong to the first two places. Thus, the algorithms considered from the CEC 2016 are UMOEAs-II [37] and L-SHADE-EpSin [38] that are the first and second place respectively. Also the top algorithms from CEC 2017 are EBOwithCMAR [39] and jSO [40]. It is interesting to take into account that EBOwithCMAR is an improvement of the UMOEAs-II. Also, jSO and L-SHADE-EpSin are from SHADE's family.

Given that all of them are stochastic algorithms, each execution was repeated 51 times with different seeds. The stopping criterion was set to 25,000,000 functions evaluations. Also a problem is considered as solved (error zero) if its difference with the true optimal is below of $1e-8$. The parametrization specific of each of the tested algorithms is as follows:

- **EBOwithCMAR:**
- **UMOEAs-II:**
- **jSO:**
- **L-SHADE-EpSin:**

Our experimental analyzes has been performed in base of the error between the true optimal and the optimal obtained. In order to statistically compare the results, a similar guideline than the one proposed in [41] was used. First a Shapiro-Wilk test was performed to check whatever or not the values of the results followed a Gaussian distribution. If, so, the Levene test was used to check for the homogeneity of the variances. If samples had equal variance, an ANOVA test was done; if not, a Welch test was performed. For non-Gaussian distributions, the nonparametric Kruskal-Wallis test was used to test whether samples are drawn from the same distribution. An algorithm X is said to win algorithm Y when the differences between them are statistically significant, if the mean and median obtained by X are higher than the mean and median achieved by Y .

In the tables 1 and 2 are showed the summary of CEC 2016 and CEC 2017 respectively. The statistical tests indicate that the diversity DE algorithm provides significantly better results than the state-of-the-art algorithms.

Table 3 Results for DE based diversity CEC 2016 problems

	Best	Worst	Median	Mean	Std	Succ. Ratio
f_1	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_2	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_3	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_4	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_5	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_6	0.00E+00	3.60E-02	4.00E-03	7.39E-03	1.15E-02	3.92E-01
f_7	2.00E-02	1.02E-01	5.90E-02	5.77E-02	4.93E-02	0.00E+00
f_8	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_9	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_{10}	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_{11}	0.00E+00	6.00E-02	0.00E+00	5.88E-03	1.90E-02	9.02E-01
f_{12}	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_{13}	1.00E-02	8.00E-02	5.00E-02	4.67E-02	2.60E-02	0.00E+00
f_{14}	1.00E-02	5.00E-02	3.00E-02	2.82E-02	2.13E-02	0.00E+00
f_{15}	0.00E+00	4.70E-01	2.20E-01	1.99E-01	1.55E-01	1.96E-02
f_{16}	4.00E-02	1.50E-01	8.00E-02	8.47E-02	4.96E-02	0.00E+00
f_{17}	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_{18}	0.00E+00	2.00E-02	1.00E-02	7.65E-03	6.32E-03	3.14E-01
f_{19}	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_{20}	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_{21}	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_{22}	0.00E+00	3.00E-02	0.00E+00	3.73E-03	2.76E-02	7.65E-01
f_{23}	0.00E+00	1.00E+02	0.00E+00	2.55E+01	5.10E+01	7.45E-01
f_{24}	0.00E+00	6.90E-01	0.00E+00	2.61E-02	1.33E-01	9.61E-01
f_{25}	1.00E+02	1.00E+02	1.00E+02	1.00E+02	0.00E+00	0.00E+00
f_{26}	8.00E-02	1.00E+02	5.29E+01	5.20E+01	3.19E+01	0.00E+00
f_{27}	2.50E-01	9.10E-01	5.40E-01	5.60E-01	2.92E-01	0.00E+00
f_{28}	0.00E+00	3.57E+02	3.43E+02	2.76E+02	1.60E+02	1.96E-01
f_{29}	1.00E+02	1.00E+02	1.00E+02	1.00E+02	0.00E+00	0.00E+00
f_{30}	1.84E+02	1.84E+02	1.84E+02	1.84E+02	3.25E-02	0.00E+00

5.1 Sensitive analyses of the radius niche

6 Conclusion

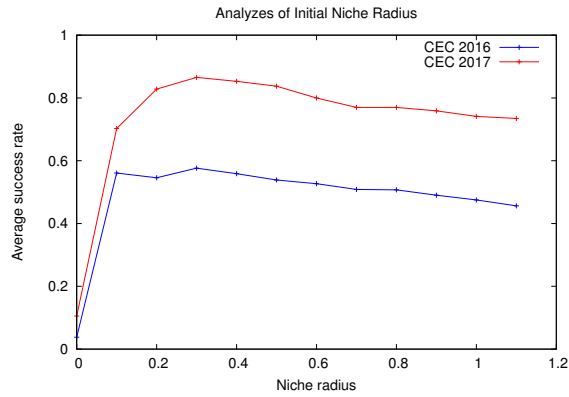
From the experimental results in this paper, several conclusions can be drawn.

Firstly, from experimental investigation on the working mechanism, it can be seen that our proposal is able to relieve the premature convergency to several optimization levels. Secondly, our proposal is able to enhance the performance of DE algorithms, in particular when the search space is large. Third, it is also less sensitive to the parameter of population size, so our proposal can also be competitive even if the population size is small.

For future work of this paper, two interesting issues should be addressed for our proposal. The first one is that explored areas in the search space should be avoided to save computing resources. Applying our proposal to real-world problems is also an interesting topic. Development a strategy of adaptive dis-

Table 4 Results for DE based diversity CEC 2017 problems

	Best	Worst	Median	Mean	Std	Succ. Ratio
f_1	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_2	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_3	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_4	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_5	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_6	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_7	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_8	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_9	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_{10}	0.00E+00	1.20E-01	0.00E+00	1.65E-02	3.39E-02	7.45E-01
f_{11}	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_{12}	0.00E+00	2.20E-01	0.00E+00	6.37E-02	1.76E-01	6.67E-01
f_{13}	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_{14}	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_{15}	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_{16}	0.00E+00	2.10E-01	0.00E+00	2.47E-02	7.27E-02	8.82E-01
f_{17}	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_{18}	0.00E+00	1.00E-02	0.00E+00	1.96E-03	4.47E-03	8.04E-01
f_{19}	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_{20}	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_{21}	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_{22}	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_{23}	0.00E+00	3.00E+02	0.00E+00	3.49E+01	1.03E+02	8.82E-01
f_{24}	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_{25}	0.00E+00	1.00E+02	0.00E+00	3.92E+00	2.00E+01	9.61E-01
f_{26}	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_{27}	0.00E+00	3.87E+02	3.87E+02	2.05E+02	2.68E+02	1.96E-02
f_{28}	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.00E+00
f_{29}	1.45E+02	2.26E+02	2.18E+02	1.99E+02	4.21E+01	0.00E+00
f_{30}	3.95E+02	3.95E+02	3.95E+02	3.95E+02	2.10E-01	0.00E+00

**Fig. 1** Average success rate with different initial distance factors in the benchmark of CEC 2016 and CEC 2017, is considered a population size of 250 and 25000000 funtion evaluations.

tance factor. Based in several analyzes the mutation factor could be selected inside the distance factor.

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