Accelerating Vegetation Evolution with Mutation Strategy and Gbased Growth Strategy

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Accelerating Vegetation Evolution with Mutation Strategy and Gbased Growth Strategy

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***Abstract*—We propose two strategies, mutation strategy and Gbased growth strategy, to enhance the performance of standard vegetation evolution (VEGE) that simulates the growth and reproduction of vegetation repeatedly to find the global optimum. We introduce two different mutation methods into the growth period and the maturity period individually to increase the diversity of population by simulating different types of mutations in real plants. Inspired by various growth patterns of real plants, the Gbased growth strategy is proposed to replace a completely random growth operation of original VEGE and bias all non-optimal individuals to grow towards the current best area. We design a series of controlled experiments to evaluate the performance of our proposed strategies using 28 benchmark functions from CEC2013 suite with three different dimensions. The experimental results confirmed the mutation strategy can increase the diversity and the Gbased growth strategy plays an important role in accelerating convergence. Besides, the combination of both strategies can further improve the VEGE performance.**

***Index Terms*—evolutionary computation, vegetation evolution, optimization, mutation strategy, Gbased growth**

I. Introduction

Evolutionary computation (EC) algorithms as a powerful optimization technique have attracted lots of attention from practitioners thanks to their various characteristics, such as easy-using, robustness, intelligence and others. Besides, they have been used in industry widely and solved many complex real-world applications successfully [1], [2], e.g. image processing, speech recognition, engineering design, robotics, games, etc. Due to the vast demand from academia and industry, many efficient EC algorithms inspired by survival of the fittest and group behavior of animals, have sprung up like mushrooms in recent decades, e.g. differential evolution [3], particle swarm optimization [4], fireworks algorithm [5] and others [6], [7]. Moreover, many researchers are enthusiastic about introducing novel strategies into these existing EC algorithms to further improve their performance [8]–[11]. Thus, how to improve the performance of EC algorithms has become a hot topic in the EC community.

Vegetation evolution (VEGE) [12] is a new member of EC algorithms and simulates the growth and reproduction of vegetation repeatedly to find the global optimum. Each individual of VEGE experiences the growth period and the maturity period to undertake exploitation and exploration, respectively. Then, these two periods are performed alternately to balance two different search capabilities until a termination condition is reached. Subsequently, we investigated the impact of each component of VEGE on performance and gave several experience settings when applying VEGE to optimize problems. As a rising star, there is still a lot of room to further improve the performance of VEGE.

The main objective of this paper is to integrate two proposed strategies into VEGE to enhance its performance based on our previous analysis results. The random mutation and Gaussian mutation are used in the growth period and the maturity period individually to increase the diversity of population. The Gbased strategy promotes all non-optimal individuals bias to grow towards the current best area rather than completely random growth. The second objective is to analyze the effect of our proposed two strategies as well as their applicability. Finally, we point out a few open topics to discuss.

After this introduction section, we summarize the optimization framework of VEGE in the Section II. Then, the proposed two strategies are presented in detail in the Section III. A series of controlled experiments are designed to evaluate the performance of our proposed strategies in the Section IV. Finally, we analyze issues coming from the experimental results and discuss some potential directions, and conclude our work in the Section V and VI, respectively.

II. Vegetation Evolution

Many real plants grow up from the seeds and use various complex mechanisms to ensure their survival. Once these surviving individuals mature, they generate a large number of next-generation seeds and disperse these seeds widely to thrive population with diverse methods, e.g. water dispersal, animal carrying and others [13]. Then, some seeds rooted in the suitable environment start a new round of growth and generate their seeds when they become mature. Inspired by these processes, a new optimization framework is spawned, and the growth and maturity of plants can be viewed as local search and wide search in VEGE. The Fig. 1 demonstrates growth pattern of plants abstractly, which may help understand the core ideas of our proposed VEGE easily.

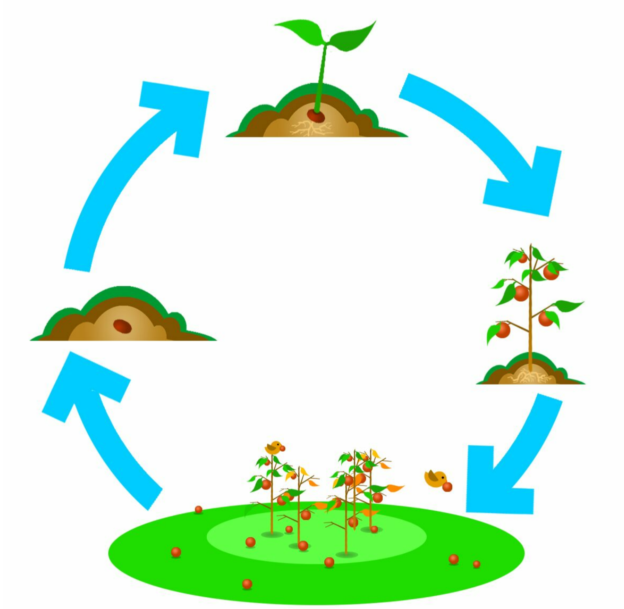


Fig. 1: The abstract growth state of plants. We divide it into two different periods subjectively, the growth period and the maturity period.

As same as all other EC algorithms, VEGE is also a population-based optimization method. It randomly generates a fixed number of individuals as the initial population, and these individuals grow independently each other to undertake local search (reference the upper left part of the Fig. 1). After the local search reaches to the predetermined maximum number of growth, each individual becomes mature and generates multiple seed individuals to achieve wide search (reference the lower right part of the Fig. 1). Then, the top PS individuals with better fitness are selected into the next generation from a mixed pool consisting of current population and all generated seed individuals. These selected individuals repeat the growth process as the same as their parent until a termination condition is reached. The Fig 2 demonstrates the general framework of the VEGE. Because the focus of this paper is not to introduce VEGE, see the implementation details of the VEGE in the original literature [12].

III. Mutation Strategy and Gbased Growth Strategy

We observe the growth pattern of vegetation, abstract their survival mechanisms simply, and simulated them as VEGE to find the global optimum. Although our previous studies have shown that VEGE was effective and promising, it can still be further improved by introducing new strategies inspired by various real plants, that use more sophisticated strategies to adapt to different environments. For example, different plants have different growth patterns, such as phototropism, aggregate, and they reproduce both sexually and asexually. Inspired by these real and effective mechanisms, we propose two strategies to enhance the performance of standard VEGE. The

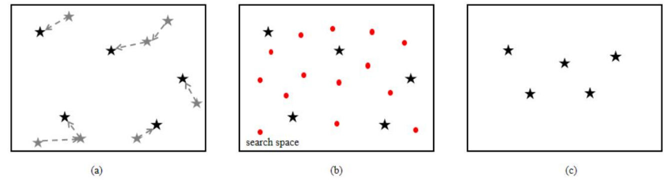


Fig. 2: The search process of our proposed VEGE algorithm. (a) Initial population is randomly generated, dotted arrows indicate the growth directions of individuals within a local area. (b) Multiple seed individuals are generated by each individual. Red circles indicate seeds individuals and all of them form a temporary seed population. (c) Individuals in the new generation are selected from all individuals in the step (b). Steps (b) and (c) are iterated until a termination condition is satisfied.

Algorithm 1 Two different mutation methods are used in the growth period and the maturity period, respectively. D: dimension; MR: mutation probability; x^j_{min}: lower of the j-th dimension; x^j_{max}: upper of the j-th dimension.

for $j = 0; j < D; j++$ **do**
  if $rand(0,1) < MR$ **then**
    if An individual, x, is in the growth period **then**
      $x^j = rand(x^j_{min}, x^j_{max})$
    else
      $x^j = x^j + Gaussian(0,1)$
    end if
  end if
end for

first mutation strategy introduces different mutation methods to increase diversity and avoid falling into local optima. The Gbased growth strategy is expected to accelerate the growth of non-optimal individuals to more potential areas rather than completely random growth. Here, two proposed strategies are described in detail.

A. Mutation Strategy

Mutation is an important means to increase diversity of plants to face various unknown environments. Plant mutations can be roughly divided into two categories, caused by external factors and internal factors. External factors, e.g. surroundings and radiation may make individuals change dramatically or even lose some of their functions, while internal factors, e.g. gene mutation make a large change in individuals with a small probability, usually mutated individuals belong to the same race and can mate with others individuals. Inspired by these observations, a random mutation method is used in the growth period to simulate uncertain external factors, and the Gaussian mutation is used in the maturity period to simulate mutations at the gene level. The Algorithm 1 outlines these two kinds of mutation pseudo-codes. Note that a standard Gauss mutation is employed in following evaluation experiments, and MR is set to a constant 0.05.

B. Gbased Growth Strategy

The growth period is originally designed to further improve the convergence accuracy of individuals by motivating them to evolve into promising areas. Based on our previous findings, random growth strategy used in standard VEGE does not achieve the desired effects [14]. Thus, a new growth strategy with higher efficiency is needed to replace the original strategy to achieve the above objectives.

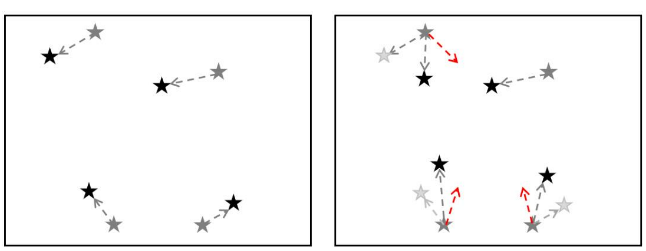
Through observations of the growth patterns of real plants, there are many different growth strategies to ensure their survival after a long period of natural selection and evolution. For example, many plants show a tendency towards the sun to receive more light. Additionally, they also tend to be develop in aggregate rather than independent, which is a good defense against unknown risks.

Inspired by these observations, we roughly extract the characteristics of their growth and propose a Gbased growth strategy. Corresponding to our proposed VEGE, we set the current best individual as the sun, i.e. the source of attraction, which causes other individuals to converge toward it to achieve accelerated convergence. Thus, the new growth strategy uses the Eq. (1) instead of the Eq. (2) used in standard VEGE for controlling the local growth of individuals. The Fig. 3 demonstrates the difference between these two growth strategies. So far, both proposed strategies have been described in detail, and the Algorithm 2 shows a generic framework of standard VEGE combined with our proposed two strategies.

$$\hat{\boldsymbol{x_i}} = \boldsymbol{x_i} + rand(-1,1) \times GR + \omega \times (\boldsymbol{x_{best}} - \boldsymbol{x_i}) \qquad (1)$$

$$\hat{\boldsymbol{x_i}} = \boldsymbol{x_i} + rand(-1,1) \times GR \qquad (2)$$

Where, $\boldsymbol{x_i}$ and $\boldsymbol{x_{best}}$ are the i-th and the best individual of current population, respectively. The GR is a constant to control the maximum radius of a growth. The ω is a weight for tuning the influence of the optimal individual, and we set it as 0.5 in our following evaluation experiments.



(a) (b)

Fig. 3: (a) Random growth strategy used in standard VEGE, where offspring is randomly generated within GR. (b) Our proposed growth strategy, where the red dashed lines indicate the effect of the current best individual on the attraction of other individuals to achieve aggregation.

Algorithm 2 General framework of the VEGE with our two proposed strategies. The steps 6, 7 and 13 describes our proposal.

1: Initialize population randomly.
2: Evaluate the population.
3: **while** A termination condition is not reached **do**
4:   **if** individuals are still in the growth period **then**
5:     **for** $i = 0; i < PS; i++$ **do**
6:       The i-th individual performs proposed Gbased growth.
7:       Perform a random mutation described in the Algorithm 2.
8:       The better offspring replaces its parent, otherwise keep the i-th individual.
9:     **end for**
10:   **else**
11:     **for** $i = 0; i < PS; i++$ **do**
12:       The i-th individual performs a maturity operation.
13:       Perform the Gaussian mutation described in the Algorithm 2.
14:     **end for**
15:     Select the next generation from a mixed pool consisting of current population and all generated seed individuals.
16:   **end if**
17: **end while**
18: Output the found optima.

IV. Experimental Evaluations

We evaluate two proposed strategies for VEGE by changing their combination as shown in the Table I and analyze their performance. The evaluation is conducted using 28 CEC2013 benchmark functions [15] with 3 different dimensions of 2-D, 10-D, and 30-D. They contain a series of competitions for solving single-objective optimizations. We run these four VEGE variants with the same set of 30 different initial individuals, i.e. 30 trial runs, for each benchmark function. The Table II shows the experimental parameter settings.

TABLE I: Four VEGE variants.

1	original VEGE [12]
2	original VEGE + mutation strategy
3	original VEGE + Gbased growth strategy
4	original VEGE + both strategies

TABLE II: VEGE algorithm parameter settings.

population size for 2-D, 10-D, and 30-D search	20
growth cycle GC	5
growth radius GR	a random number in [-1,1]
total seed individuals SI for 2-D, 10-D, and 30-D search	100
moving scaling MS	a random number in [-2,2]
stop condition; max. # of fitness evaluations, MAX_{NFC}, for for 2-D, 10-D, and 30-D search	1000, 10,000, 40,000

We evaluate convergence along the number of fitness calls rather than generations for fair evaluations, and apply the

Friedman test and Holm's multiple comparison test at the stop condition, i.e., the maximum number of fitness evaluations, to check significant difference among four variants. The results of statistical tests are shown in the Table III. The Fig. 4 shows the average convergence curve of four variants with 30 trial runs on 30-D benchmark functions.

TABLE III: Statistical test results of the Friedman test and Holm's multiple comparison test for average fitness of 30 trial runs among four variants at the stop condition. $A \gg B$ and $A > B$ mean that A is significant better than B with significant levels of 1% and 5%, respectively. $A \approx B$ means that although A is better than B, there is no significant difference between them. Symbols 1-4 are defined in the Table I.

	2D	10D	30D
F_1	$4 \approx 3 \gg 1 \approx 2$	$3 \approx 4 \gg 1 \approx 2$	$3 \gg 4 \gg 1 \gg 2$
F_2	$2 \approx 3 \approx 1 \approx 2$	$3 \approx 4 \gg 2 > 1$	$3 \gg 4 \gg 1 \gg 2$
F_3	$3 \approx 4 \approx 1 \approx 2$	$2 > 4 \approx 3 > 1$	$3 \approx 4 \gg 1 \gg 2$
F_4	$2 \approx 1 \approx 4 \approx 3$	$4 \approx 3 \approx 1 \approx 2$	$4 \approx 3 \gg 1 \approx 2$
F_5	$3 \approx 4 \gg 2 \approx 1$	$4 \approx 3 \gg 1 > 2$	$3 \gg 4 \gg 1 \gg 2$
F_6	$3 \approx 4 \gg 2 \approx 1$	$1 \approx 2 \approx 3 \approx 4$	$1 \approx 3 \approx 4 \gg 2$
F_7	$4 \approx 3 \gg 2 \approx 1$	$4 \approx 3 \gg 2 \approx 1$	$4 \gg 3 > 1 \approx 2$
F_8	$3 \approx 4 \gg 1 \approx 2$	$1 \approx 4 \approx 3 \approx 2$	$1 \approx 3 \approx 2 \approx 4$
F_9	$4 \approx 3 \gg 2 \approx 1$	$4 \approx 3 \gg 2 > 1$	$4 \gg 3 \approx 2 > 1$
F_{10}	$3 \approx 4 \gg 2 \approx 1$	$3 \approx 4 \gg 1 \approx 2$	$3 \gg 4 \gg 1 \gg 2$
F_{11}	$4 \approx 3 \gg 2 \approx 1$	$4 \approx 3 \approx 2 \gg 1$	$4 \gg 2 \gg 1 \approx 3$
F_{12}	$4 \approx 3 \gg 2 \approx 1$	$4 > 2 \approx 3 \approx 1$	$4 \gg 3 \approx 1 \approx 2$
F_{13}	$3 \approx 4 > 1 \approx 2$	$2 \approx 1 \gg 4 \approx 3$	$4 \gg 3 \gg 2 \approx 1$
F_{14}	$3 \approx 4 \approx 2 \approx 1$	$2 \gg 4 \approx 1 > 3$	$2 \gg 4 \gg 1 > 3$
F_{15}	$4 \approx 3 \approx 2 \approx 1$	$1 \approx 2 \approx 3 > 4$	$1 \gg 2 > 3 \approx 4$
F_{16}	$2 \approx 1 \approx 4 \approx 3$	$1 \approx 2 \approx 4 \approx 3$	$1 \gg 3 \approx 2 \approx 4$
F_{17}	$2 \approx 4 \approx 3 \approx 1$	$3 \approx 4 \gg 2 \approx 1$	$4 \approx 3 \gg 2 \approx 1$
F_{18}	$2 \approx 3 \approx 4 \approx 1$	$4 \approx 3 \gg 2 \approx 1$	$4 \approx 3 \gg 2 \approx 1$
F_{19}	$3 \approx 4 \gg 2 \approx 1$	$4 \approx 3 \gg 1 \approx 2$	$4 > 3 \gg 1 \approx 2$
F_{20}	$4 \approx 3 \gg 2 \approx 1$	$3 \approx 4 \approx 2 \approx 1$	$3 \approx 4 \gg 2 \approx 1$
F_{21}	$3 \approx 4 \gg 2 \approx 1$	$1 \approx 2 \approx 3 > 4$	$3 \approx 4 \approx 1 \gg 2$
F_{22}	$3 \approx 4 \approx 2 \approx 1$	$2 \gg 4 > 1 \approx 3$	$2 \gg 4 \gg 1 \approx 3$
F_{23}	$3 \approx 4 \gg 2 \approx 1$	$1 \approx 2 \approx 4 \approx 3$	$1 > 2 \gg 3 \approx 4$
F_{24}	$3 \approx 4 \gg 1 \approx 2$	$4 \gg 3 \gg 2 \approx 1$	$4 \gg 3 \approx 2 \approx 1$
F_{25}	$4 \approx 3 > 2 \approx 1$	$3 \approx 4 \gg 2 \approx 1$	$4 \gg 3 \approx 2 \approx 1$
F_{26}	$3 \approx 4 > 2 \approx 1$	$2 \approx 1 \approx 4 \approx 3$	$2 \approx 1 \approx 4 \approx 3$
F_{27}	$4 \approx 3 \approx 2 \approx 1$	$4 \approx 3 \gg 2 \approx 1$	$4 \gg 3 \gg 2 \gg 1$
F_{28}	$3 \approx 4 \gg 2 \approx 1$	$2 \approx 1 \approx 4 \approx 3$	$4 \gg 1 \approx 2 \gg 3$

V. Discussions

A. Discussion on Mutation Strategy

Gene mutations are randomness and uncertainty into evaluation, and can generate diverse individuals to overcome complex and changeable environments. Although mutant individuals become better or poor, some of these mutant individuals that adapt to new natural selection and then survive. Because of the rapid development of technology, humans have been able to intervene and guide mutations, even integrate genes among different species. We can say that mutation is one of the important means for plants to survive the population.

However, original VEGE uses no mutation operation. We introduce two different mutation methods into the VEGE to simulate the mutation characteristics of natural plants in different periods to increase risk resistance. The random mutation is used in the growth period and does not have any regularity to alter genetic information randomly. We expect that this will prevent it from falling into local optimum areas. Gaussian mutation is used in the maturity period, and the greater the difference, the smaller the probability of individual occurrence, which we expect to increase the diversity of population. A new parameter, MR, is introduced to control the frequency of mutations in our proposal. Although the mutational probability is equal on each dimension, the mutational probability of individuals increases as the dimension increases. The experimental results confirmed our hypothesis, and the convergence curve indicates that the mutation strategy can jump out of local arears in some cases. However, acceleration effect is not stable and obvious.

One of potential topics is how to use mutations to accelerate convergence efficiently. Actually, mutations in real plants are affected by many factors, and even different individuals belonging to the same species have different mutational probabilities. We have assigned the same mutation probability to each dimension without considering their fitness and the characteristics of the optimization problems. Perhaps an adaptive mutation probability could be more powerful and intelligent according to the optimization process; we will pay our attention to this aspect.

B. Discussion on Gbased Growth Strategy

We proposed the Gbest growth strategy because excellent mechanisms of natural plants in their growth period. Even after extensive research of plants, humans have discovered that plants have many almost-magical mechanisms and unknowns methods of ensuring their growth. We did not extract these effective mechanisms or simulate them in the original VEGE, but only use random growth strategy to simulate plant growth.

The new growth strategy consists of two parts as our first attempt: random search and Gbased attraction. The latter uses the current best individual to attract others and favor it. We introduce a new weighting parameter, ω, to control the influence of the optimal individual. When ω is set to 0, the proposed growth strategy degenerates to random growth strategy used in the original VEGE. As the ω increases, so too does the strength of the effect of the optimal individual on the others, i.e., the aggregation speed becomes faster. The experimental results (Fig. 4) conformed that the Gbased growth strategy does accelerate the convergence speed, especially in the early stages.

Although the proposed growth strategy shows a powerful acceleration effect, it still needs further improvements. Here, several open topics are given. (1) The current best individual still grow randomly because the Gbased attraction is 0, and it affects the convergence of other non-optimal individuals. Thus, how to accelerate the growth of the optimal individual reasonably becomes one of our future work. Perhaps using historical information is a good choice to guide the growth of the current best individual. (2) ω is the key factors affecting performance of our proposal. We used a constant ω in our evaluation experiments, but, its results fell into local optimum areas in some case, e.g. F_{24} to F_{28} on 30-D, because the Gbased attraction was too strong. To overcome these limitations, we are going to propose an adaptive version to tune the ω according to optimized processes and evolution information of individuals.

C. Analysis of Additional Cost

We would like to discuss the advantages of the two strategies confirmed through our experimental evaluation. Both strategies are inspired by the behaviour of real plants and their characteristics for plant evolution. Although both strategies need new parameters, they do not need additional fitness calculations. We observed that the mutation strategy jumps out of local area by increasing diversity, but its acceleration effect was not obvious. Conversely, the Gbased growth strategy could accelerate the convergence speed of the population significantly, but it may lead to fall in local areas as mentioned above. The combination of both strategies, however, can balance their shortcomings and achieve better performance. Anyway, we can say that our proposal is *low cost, high return* strategies.

We apply the Friedman test and the Holm multiple comparison test to check significant difference among four VEGE variants. From the results of statistical tests, the Gbased growth strategy has better acceleration than the mutation strategy on the low dimension. However, the mutation strategy shows stronger effects in some cases of higher dimensional tasks. It is because the probability of a high-dimensional individual mutation becomes higher, thus the higher the dimension, the more obvious the effect is. Our proposals did not work at all for F_{15} and F_{16}, and even worsened the performance. It may be because there are too many local optima, and they make our proposal fall into local optima and hindered evolution. This indicates that increasing randomness may be beneficial for such problems because it allows the population to jump out of the local optima. We need further analysis that may give us hints to develop more suitable strategies for VEGE.

VI. Conclusion

We proposed two strategies to improve the performance of the VEGE. The controlled experiments confirmed that the mutation strategy increased the diversity of population and avoid falling into premature. The Gbased growth strategy can accelerate the convergence speed of non-optimal individuals. Besides, the combination of both strategies may further enhance performance of VEGE in some cases.

We continuously introduce novel mechanisms inspired by real plants as our future work, e.g. dynamic population mechanism and adaptive parameter tuning to improving the performance of the VEGE.

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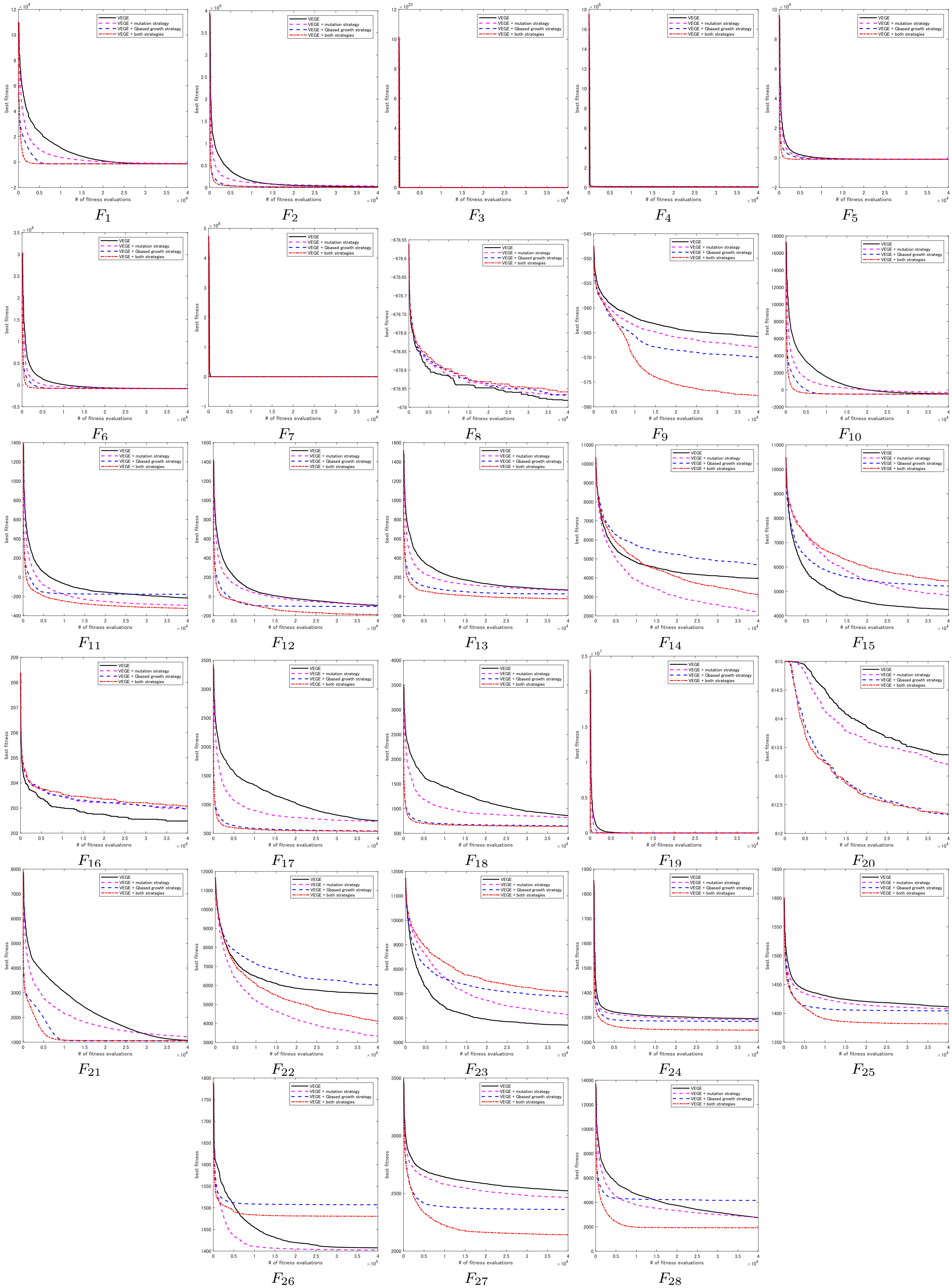

Fig. 4: Average convergence curves of 30-D F_1–F_{28} benchmark functions. We can observe that VEGE with our proposal can its accelerate search.