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Retraction

Retracted: Research on the Spread Path and Evolution Causes of Oral Language in the Digital Era

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] Z. Li, "Research on the Spread Path and Evolution Causes of Oral Language in the Digital Era," *Journal of Mathematics*, vol. 2022, Article ID 2325711, 9 pages, 2022.

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Research Article

Research on the Spread Path and Evolution Causes of Oral Language in the Digital Era

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Visual orientation seems to indicate the decline of oral communication, but oral communication has its own living space under the new media ecology. Research has found that in the digital media era, voice communication is manifested as a single-level feature that simulates current interaction and information communication. Although voice communication is a lie constructed by individuals, the interaction between the subject's discourse and the actual field of interaction separate the emotional distance, but the situation is harmonious and inclusive. The following voice communication and new media technologies are still trustworthy. Aiming at multifactor evolutionary algorithm (MFEA), the most classical multifactor evolutionary algorithm in multitask computation, we theoretically analyze the inherent defects of MFEA in dealing with multitask optimization problems with different subfunction dimensions and propose an improved version of the multifactor evolutionary algorithm, called HD-MFEA. In HD-MFEA, we proposed heterodimensional selection crossover and adaptive elite replacement strategies, enabling HD-MFEA to better carry out gene migration in the heterodimensional multitask environment. At the same time, we propose a benchmark test problem of multitask optimization with different dimensions, and HD-MFEA is superior to MFEA and other improved algorithms in the test problem. Secondly, we extend the application scope of multitask evolutionary computation, and for the first time, the training problem of neural networks with different structures is equivalent to the multitask optimization problem with different dimensions. At the same time, according to the hierarchical characteristics of neural networks, a heterodimensional multifactor neural evolution algorithm HD-MFEA neuro-evolution is proposed to train multiple neural networks simultaneously. Through experiments on chaotic time series data sets, we find that HD-MFEA neuro-evolution algorithm is far superior to other evolutionary algorithms, and its convergence speed and accuracy are better than the gradient algorithm commonly used in neural network training.

1. Introduction

`Spoken language has changed from the stage of mimicry to the formation of conventional language symbols, from the vagueness of information to the clarity of consensus, and from the narrow tribal communication to the social communication with both depth and breadth. Oral communication plays a key role in the interactive communication between individuals and society. Oral communication can not only cultivate individual consciousness but also participate in the shaping process of social development. The effectiveness of spoken language is not only in simple information interaction but also in knowledge transmission, cultural production, and emotional maintenance. Socrates' sitting and discussing the Dao sowed the seeds of wisdom to the audience in the form of oral communication, and knowledge inheritance depended on the listener's self-realization. The recitation and poetry culture generated by spoken language makes up for the impoverishment of individual spiritual culture. The oral language integrates with visual symbols in the form of presence to realize the experience of emotional integration.

1.1. The Balance Theory Crisis of Oral Communication under the Mapping of Internet. The emergence of written language makes language shift from oral tradition to secular power, resulting in the emphasis on spatial relations over temporal relations [1]. The interactive communication of spoken language between individuals could not be preserved in the past. The recording of human voice originated from the development of modern science and technology. The invention of the phonograph made the recording of voice no longer a myth. Recording sound has been a very popular behavior, and individuals also enjoy the sensory experience of hearing. Oral communication can be preserved under the construction of Internet technology, and the vertical communication of oral language can be realized in the dimension of time. McLuhan put forward the concept of a global village, and the distance of oral communication is no longer a problem. With the help of Internet technology, oral communication has broken through the bondage of distance and realized the horizontal leap of the spatial dimension of oral communication. Oral communication has broken through the limitations of time and space dimensions. Under the dominant discourse system of information and knowledge sharing, the monopolistic behavior of knowledge inheritance caused by oral communication tends to solidify. The popularization of knowledge is a normalized behavior. The Internet aggregates all kinds of knowledge, and individuals' search for information on demand is a daily presentation. The monopoly of knowledge inheritance constructed by oral communication has been questioned in the new context. Similarly, the effect of oral communication in space diffusion is no less than that of paper, which plays a key role in the process of civilization because of its portability.

1.2. The Real and Virtual Distinction in the Field of Oral Interactive Communication. Traditionally, relying on written means (rather than eyes and ears), and visual art, architecture, sculpture, painting and other means (rather than relying on time and space) to express [2] under the influence of the media, the reality of oral decay seems to be impossible to verify, especially facing the visual era in the era of printed text and images. But in fact, oral communication has not died out. Oral communication and other media on which information transmission depends have created the same space of discourse expression. The existence of new media is not based on the premise of sacrificing the existence of spoken language but enables them to combine and form a harmonious situation. Spoken language is one of the modes of multi-information expression, and its practical utility still plays an important role in the daily life of individuals. The perceived happiness of communication is not limited to the acquisition of the latest information but to the emotional comfort of communicating with each other. The ways of information interaction and dissemination are diversified, and the ideographic nature of visual standard is highlighted in the presentation of diversified information. Real spoken interaction is actually quite different from virtual spoken interaction. The characteristics of present and nonpresent are as follows: in real oral interaction, people participate in the same field of communication mode, and the subjects and objects of communication can perceive each other's subtle details and psychological changes. The spoken language interaction in the virtual space presents the surreal simulation of the communication field. In the local framing of the horizon, the individual cannot perceive the changes of objects outside the horizon. However, in the real oral communication environment, the oral communication environment is flexible, and the intervention of information transmission can be flexible in the face of unexpected situations. From the perspective of relationship composition, it is not difficult to construct the relationship between subject and object in real field communication, while the relationship construction of oral communication in a virtual environment has distinct directivity.

1.3. The Synergy and Information Heterogeneity of Nonverbal Symbols Are Reduced. "Nonverbal communication" refers to the process in which people exchange information with "nonverbal" behavior consciously or thought to be consciously in a specific environment [3]. As a medium, oral communication is not a single ideographic process but a clear description of the same object together with nonverbal symbols. These nonverbal signs include individual actions and expressions, and their main function is to facilitate the clarification of meaning. The coordination of oral communication and nonverbal signs builds a complete system together. The main body of information transmission is often different in explaining something or even blurring the fact itself, which affects the effect of interactive oral communication. Individual differences are shown on the basis of familiar semantic code, and their own grasp of semantic code cannot explain the fact itself, familiar semantics! When code blocks are in heterogeneous areas, nonverbal symbols play a key role with their unique advantages. Under the Internet media ecology, nonverbal symbols show the characteristics of richness. In the past, information circulation was transmitted through multiple levels. In the process of circulation, different levels of audiences interpreted information in various self-interpretation processes. In the process of interpretation, there are a lot of misinterpretations and misinterpretations. This phenomenon is the key factor that causes the deviation between oral communication and actual intention.

At present, a large number of literature works have promoted, improved, applied to multitask evolutionary computing, and achieved good results. The research on multitask evolutionary computing can be divided into four categories: extending multitask framework to a wider range of evolutionary algorithms, applying multitask evolutionary computing to multiobjective problems, applying multitask evolutionary computing to practical optimization problems, and proposing improved multitask evolutionary algorithms based on MFEA. For the study of the first type of problem, Wen and Ting [4] extended the concept of multitasking evolutionary computation to genetic programming (GP) and proposed multifactorial genetic programming (MFGP). Feng et al. [5] proposed multifactorial particle swarm optimization (MFPSO) and multifactorial difference algorithm (MFDE) algorithms based on PSO and DE. Yokoya et al. [6] proposed the multifactorial artificial bee colony algorithm (MFABC) and applied it to the optimization of automobile structure design. In view of the research of multitasking evolutionary computation in multiobjective problems, Fogel et al. [7] first proposed the multiobjective and multitask evolutionary algorithm (MO-MFEA) and verified the effectiveness of the algorithm in multiobjective optimization problems in reality. Gupta et al. [8] modeled the operation index optimization problem in the beneficiation process as a multiobjective and multitask problem and solved this problem by using improved MO-MFEA. For the third type of problems, multitask evolutionary computation has obtained good results in symbolic regression problem [9], biological network module identification problem [10], shortest path tree problem [11], and combinatorial optimization problem [12]. The fourth type of research is defect improvement of MFEA, mainly focusing on two major problems in MFEA: (i) how to adjust gene migration adaptively according to the similarity between tasks. Denoising autoencoders proposed [13] should be used to automatically construct mappings between tasks and complete gene migration through mapping. MFEA is based on the decomposition method [14] and resource allocation mechanism, which can dynamically adjust gene migration according to the similarity between tasks. (ii) How to make gene migration in MFEA play a role when the optimal solutions between tasks differ greatly. Bali et al. [15] proposed an adaptive strategy to solve this problem. Assuming that the algorithm simultaneously processes two optimization tasks of different difficulties, the strategy maps the optimization space of the low difficulty task to the optimization space of the high difficulty task, and the mapping and the similarity of the latter two tasks become higher, which can amplify the effect of gene migration. Gustafson and Burke [16] proposed the strategy of decision variable transformation, whose basic idea is to map individuals in different tasks to the same position in the normalized search interval before gene transfer.

This paper systematically introduces the multifactor evolutionary algorithm (MFEA), in 2 sections, gives the basic properties of MFEA in the multitask environment, and systematically analyzes the entire algorithm flow of MFEA. In Section 3, the benchmarking problems used in multitasking optimization are introduced in detail, and the performance of MEFA is analyzed by comparing MFEA with SOMA in benchmarking problems. Through the analysis, we found that MFEA could not solve the test problems with different subfunction dimensions well. In Section 3, we proposed an improved version of MFEA for such dimensional multitask optimization problems and applied it to the prediction problem of chaotic time series.

2. Multifactor Evolutionary Algorithm

This section focuses on multitask evolutionary computing. Multitask evolutionary computing is a new direction of evolutionary computing that has attracted much attention in recent years. When there is a similarity between tasks, evolutionary algorithms can be used to simultaneously optimize multiple tasks and achieve better results than single-task algorithms by sharing information between tasks through gene transfer. This section mainly introduces the first multitask evolutionary algorithm and multifactorial evolutionary algorithm. In Section 2, firstly, the mathematical definition of multitask optimization and the special properties of the evolutionary algorithm in multitask environment are given. Then, the whole algorithm flow of MFEA is analyzed in detail, and the selective intersection algorithm (assortative) in MFEA introduces mating and selective imitation in detail. In Section 2, MFEA is verified experimentally. Firstly, the benchmark test in multitask optimization is introduced, and then, the results of MFEA on the benchmark function are analyzed. Section 2 summarizes the content of Section 2.

2.1. Algorithm Analysis. The multifactor evolutionary algorithm (MFEA) is the first multitask evolutionary algorithm that can simultaneously optimize multiple problems through a single population. In this section, we first introduced the basic definition of MFEA and then analyzed the whole process of MFEA in detail.

2.1.1. Basic Definition. Here, we first define multitask optimization: consider K optimization tasks, denoted by $T_1, T_2, \ldots, T_k$, the objective function of the jth task T_j is $f_j\colon X_j \longrightarrow \mathfrak{R}$, where $X_j \in \mathfrak{R}^{D_j}$ is the domain after the function. The purpose of multitask optimization can be expressed as $\{x_1, x_2, \ldots, x_k\} = \arg\min\{f_1(x), f_2(x), \ldots, f_K(x)\}$, wherein $x_i \in X_i$. MFEA regards each task as a factor and defines the population P scale as N. In order to make the algorithm apply to multitask problems, MFEA defines three basic properties for individual p_i and $i \in \{1, 2, \ldots, N\}$ in population P.

Definition 1 (factorial rank). The adaptive values of all individuals in population P on task T_j form an adaptive array $[f_j^1(x), f_j^2(x), \ldots, f_j^N(x)]$, where N represents the population number and f represents the adaptive values of individual p_i on task T_j. The array of adaptive values is sorted in ascending order. The factor level of individual p_i on task T_j is the subscript value of F in the sorted array, denoted as r_{ij}.

According to the definition, we can know $r_{ij} \in N^+$ and $1 < r_{ij} < N$, and factor grade r_{ij} represents the quality of individual p_i on task T_j. The smaller the factor grade r_{ij} is, the better the individual p_i performs on task T_j. When $r_{ij} = 1$, it means that individual p_i is optimal on task T_j. The factor levels of all individuals in the population on all tasks constitute the factor level matrix R of the population.

Definition 2 (standard adaptive value, scalar fitness). The standard adaptive value is the evaluation standard for the quality of an individual in a multitask environment. The standard adaptive value of individual p_i is denoted as φ_i, which can be obtained from the following equation:

$$\varphi_i = \frac{1}{\min_{j\in\{1,2,\ldots,k\}} r_{ij}}. \tag{1}$$

From the definition, we can see that $\varphi_i \in (0, 1]$, the larger the φ_i, the better the individual. In a single-task environment, the value of an individual on the objective function can be directly taken as the adaptive value, but in a multitask environment, there are K objective functions, and a single individual will have K adaptive values. How to evaluate the merits and disadvantages of an individual in a multitask environment becomes a problem? It can be seen from Formula (1) that as long as the individual is optimal in a task (factor level is equal to 1), the individual's standard fitness value will be the largest.

Definition 3 (optimal factor, skill factor). The optimal factor of individual p_i is denoted as φ_i. Task T_j is the task in which p_i performs best out of all K tasks.

$$\tau_i = \arg\min_{j\in\{1,2,\ldots,k\}} r_{ij}. \tag{2}$$

Standard fitness can help us measure the merits and disadvantages of individual p_i in multitask environment, but we still need to know the standard fitness φ_i of p_i is generated by the task of p_i. Therefore, MFEA introduces the concept of individual optimal factor, which is used to represent the task in which an individual is optimal.

From the above three definitions, we can know that, different from a single-objective optimization problem, multitask optimization does not require an individual to obtain the optimal solution on all tasks. As long as an individual obtains the optimal solution on one task, the individual will achieve the optimal solution in the multitask environment. Multifactor evolutionary algorithm introduces the concept of multitask optimization to describe the above situation.

Definition 4 (multitask optimal). The adaptive value of individual p on K tasks is $\left\{f_j^*(x), f_j^*(x), \ldots, f_K^*(x)\right\}$. If $j \in \{1,2,\ldots,K\}$ makes $f_j^*(x) \le f_j(x_j)$ valid for all feasible $x_i \in X_i$, p is said to be multitask optimally.

To test and verify the effectiveness of the above improvements, choose Sphere, Rosenbrock, Griewank, Ackley, and Rastrigin experiment the five classical test functions, and the function definition and variable scope are as follows:

(i) Sphere:

$$\begin{gathered}\min f(x) = \sum_{i=1}^{n} x_i^2, \\ x_i \in [-20, 20], \quad i = 1, 2, \ldots, n.\end{gathered} \tag{3}$$

(ii) Rosenbrock:

$$\begin{gathered}\min f(x) = \sum_{i=1}^{n-1}\left[100\left(x_{i+1} - x_i^2\right)^2 + \left(x_i - 1\right)^2\right], \\ x_i \in [-10, 10], \quad i = 1, 2, \ldots, n.\end{gathered} \tag{4}$$

(iii) Griewank:

$$\begin{gathered}\min f(x) = \frac{1}{4000} S(x) - U(x) + 1, \\ S(x) = \sum_{i=1}^{n} \left(x_i - 100\right), \\ U(x) = \prod_{i=1}^{n} \cos\left(\frac{x_i - 100}{\sqrt{i}}\right), \\ x_i \in [-300, 300], \quad i = 1, 2, \ldots, n.\end{gathered} \tag{5}$$

(iv) Ackley:

$$\begin{gathered}\min f(x) = -20\, \exp[U(x)] - \exp[V(x)] + 20 + e, \\ U(x) = -0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}, \\ V(x) = \frac{1}{n}\sum_{i=1}^{n} \cos 2\, \pi x_i^2, \\ x_i \in [-32, 32], \quad i = 1, 2, \ldots, n.\end{gathered} \tag{6}$$

(v) Rastrigin:

$$\begin{gathered}\min f(x) = \sum_{i=1}^{n}\left[x_i^2 - 10\cos\left(2\pi x_i\right) + 10\right] \\ x_i \in [-5.12, 5.12], \quad i = 1, 2, \ldots, n.\end{gathered} \tag{7}$$

2.1.2. Algorithm Flow. The traditional single-objective evolutionary algorithm (SOEA) uses real or binary encoding. The main process of the algorithm is to generate offspring through crossover and mutation and then select excellent individuals for the next generation through selection operation. MFEA takes the traditional genetic algorithm as the prototype algorithm and extends the encoding mode and generation mode of offspring.

(1) Encoding-Decoding Method. Evolutionary algorithm is used in the vector to represent the individual in the population, and individual elements of vector are called "gene," and in the same way, we will be a single vector called "chromosome." MFEA uses single species and optimizes all tasks at the same time, but for different tasks, the search space of different dimensions may be different, and new coding methods need to be designed to map individuals to multiple tasks. Multifactor evolutionary algorithm adopts a new code-decoding method to solve this problem. In the coding stage, the search space of different tasks is linearly

mapped to the uniform interval Y. It means that, in each dimension, the search space of different tasks is linearly compressed to the range of $[0, 1]$; if the dimensions between tasks are different, the highest dimension in all tasks is taken as a dimension D_m of the unified interval Y. The decoding phase refers to the decoding of the individual encoded in the unified interval Y into the value in the actual search space corresponding to the task when the individual is evaluated for its adaptation value. For example, suppose that the real variable y on the ith dimension of the task corresponds to the real search space $[L, U]$, and the corresponding variable on the unified interval Y is X. The decoding process refers to the process of obtaining Y from X so that the decoding of a single variable can be completed. For task T, its dimension is D, so we only need to decode the first D variables of the vector on the unified interval Y. The reason why the multifactor evolutionary algorithm adopts this coding-decoding method is that the search space of different tasks is compressed into a unified interval, and then, the gene transfer between tasks can be carried out well through crossover operation.

(2) Traditional Single-Objective Genetic Algorithm. It generates offspring through crossover mutation operator, but the generation mode of offspring is different in the multifactor evolutionary algorithm. The core of the multifactor evolutionary algorithm is to make use of the similarity between tasks and carry out implicit gene transfer between different tasks through crossover operators to speed up the convergence of tasks. Assortative mating is used to generate offspring in the multifactor evolutionary algorithm. The pseudocodes of the assortative mating algorithm are shown in Table 1.

Selective crossover algorithm is the core of multitask evolutionary computing, which uses crossover operators to transfer genes between different tasks. Let the optimal factor of an individual P be t, indicating that P is optimal on task T. All individuals in population P whose optimal factor is 1 together constitute the candidate solution of task T. The purpose of selecting a crossover algorithm is to communicate with other tasks on the premise that the distribution of the candidate solution of task T will not change too much. In the selection crossover algorithm, if the two parent optimal factors are the same or rand$(0, 1)$ & gt, in RMP, the offspring generation is directly generated through crossover or mutation operator, and the distribution of the offspring will be basically consistent with that of the parent generation. Only if the rand$(0, 1)$ & lt, in RMP, the parents with different optimal factors were crossed to complete implicit gene transfer. RMP stands for random mating probability, which is used to control the size of gene migration. As can be seen from the pseudocode of the selection crossover algorithm, if the RMP is too small, the migration between tasks will be less, and the multitask evolutionary algorithm will degenerate into the traditional single-task evolutionary algorithm. If RMP is too large, the distribution of candidate solutions for a single task will change greatly, and the algorithm will over explore, and convergence will slow down. After the generation of the offspring, it is necessary to determine the optimal factor attribute of the offspring. The adaptation value of the offspring can be evaluated on all K tasks, and then, the optimal factor of the offspring can be determined according to formula (2). However, such an operation is time-consuming when the value of K is very large. Selective imitation is used in multifactor evolutionary algorithms to solve this problem. Selective imitation means that the offspring directly inherit the optimal factor from the parent and only perform decoding and fitness evaluation on the task corresponding to the optimal factor. When the optimal factors of two parent generations are different, the offspring randomly choose one parent to inherit its optimal factor. The specific flow of the selective imitation algorithm is shown in Table 2.

Other operations of the multifactor evolutionary algorithm are the same as those of the traditional genetic algorithm, and the pseudocodes of the overall algorithm are shown in Table 3. Firstly, the population is randomly generated, and the adaptive value is evaluated on all tasks to obtain the individual factor grade and optimal factor attribute. The above steps are the initialization steps. After initialization, the algorithm iteration begins. Firstly, children are generated according to the selective crossover algorithm. In RMP, two parents with different optimal factors complete gene transfer between different tasks through crossover operators. Then, selective imitation operation was carried out on the generated progeny in order to determine the optimal factor of the progeny individual according to the parent. After determining the optimal factor of the offspring, only the adaptive value of the offspring is calculated on the optimal factor task, and then, the parent and offspring are combined to form the intermediate generation. At this point, the adaptive value of the individuals in the intermediate generation is known, and the factor grade, optimal factor, and standard adaptive value attribute of the individuals in the intermediate generation are updated. The standard adaptive value is taken as the measurement, and the optimal individuals are selected from the intermediate generation to enter the next cycle. Finally, the algorithm is iterated until the end of the algorithm.

3. Experimental Results

In this section, the performance of multifactor evolutionary algorithm is verified by experiments. Firstly, the benchmark test problem used in the experiment is introduced, and then, the performance of multifactor evolutionary algorithm on the test problem is analyzed.

3.1. Benchmarking Issues. Different from the existing single-task optimization and multiobjective optimization problems, multitask optimization needs to design a new test problem. Reference [13] pointed out that the degree of overlap of global optimal values between tasks and the correlation between tasks had the greatest influence on the multitask problem. Multitask optimization problems can be divided into the complete intersection (CI), partial intersection (PI), and no intersection (ND) according to the degree of overlap of global optimal values between tasks.

Table 1: Selecting the cross algorithm pseudocodes.

```
Algorithm 1: select the crossover algorithm
Input: two parents $p_a$ and $p_b$ randomly selected from the current population; random cross probability RMP.
(1) if $\tau_a = \tau_b$ or $\text{rand}(0, 1) < \text{rmp}$ then
    Parent $p_a$ and $p_b$ produce two children C1 and C2 by crossing operators
(2) else
    Parent $p_a$ directly produces a child C1 through the mutation operator
    Parent $p_b$ directly produces a child C2 by the mutation operator
(3) end if
    Output: children C1 and C2
```

Table 2: Pseudocodes of selective imitation algorithms.

```
Algorithm 2: selective imitation algorithm
Input: child individual $C$ generated by two parents $p_a$ and $p_b$ or single parent $p$
(1) if $C$ is generated by two parents then
    (i) if $\text{rand}(0, 1) > 0.5$ then
        $C$ directly inherits the optimal factor of parent $p_a$
    (ii) else
        $C$ directly inherits the optimal factor of parent $p_b$
    (iii) end if
        $C$ directly inherits the optimal factor of its parent $p$
(2) else
    $C$ directly inherits the optimal factor of its parent $p$
(3) end if
Output: child $C$ with the optimal factor attribute
```

Table 3: Pseudocode of multifactor evolutionary algorithm.

```
Algorithm 3: multifactor evolutionary algorithm (MFEA)
(1) Initialize population P and calculate individual fitness on all tasks
(2) Calculate individual factor grade ($R$) and optimal factor ($T$)
(3) While (termination condition not met) do
    (i) Selecting cross-generation progeny population $C$ (Algorithm 1)
    (ii) Run selective imitation algorithm in progeny population $C$ (Algorithm 2)
    (iii) Only on task $T$, the adaptation value of offspring population $C$ is calculated
    (iv) Generate intermediate generation population $R$, where $R = PUC$
    (v) Update factor grade ($R$), optimal factor ($T$), and standard fitness ($P$) of individuals in intermediate population $R$
    (vi) According to the standard adaptive values, the optimal individuals in the intermediate population $R$ were selected to form the next
    generation population $P$
```

According to the correlation between tasks, it can be divided into three types: high similarity (HS), middle similarity (MS), and low similarity (LS). Single-objective multitask benchmarking problems are shown in Table 4.

Spearman's rank correlation coefficient was used as a measure of similarity between tasks. It was assumed that individual X was decoded as y_1 and y_2 on task T_1 and T_2 on the uniform interval y. $R(y_1)$ and $R(y_1)$, respectively, represent individual factor grades on the two tasks. We randomly generate 1×10^6 individuals on the unified interval y to form the sequence x, decode the sequence on task T_1 and T_2, respectively, and generate new sequences y_1 and y_2. Then, the similarity between T_1 and T_2 can be expressed by R:

$$R_s = \frac{\text{cov}(r(y_1), r(y_2))}{\text{std}(r(y_1)) \times \text{std}(r(y_1))}. \tag{8}$$

According to the overlap degree and R_s value of global optimal values between tasks, several common single-objective test functions were rotated and shifted, and then combined into three types of 9 benchmark test problems [13], as shown in Table 3. More detailed information on benchmarking issues is available in the original paper [13].

3.2. Result Analysis. In this section, the results of multifactor evolutionary algorithm (MFEA) and single-objective genetic algorithm (SOMA) are compared. The population size of MFEA is equal to 100, the final number of cycles is equal to 1000, and the random crossover probability is RMP-0.3. The crossover operation is selected to simulate a simulated binary crossover operator (SBX), and polynomial mutation operator is selected for mutation operation. Since MFEA optimizes two tasks simultaneously while SOMA optimizes

Table 4: Single-objective multitask benchmarking problems.

Problem category	Function	dim	Global optimal degree of overlap	R_s
CI + HS	T = Griewank T = Rastrigin_	50 50	Coincide	1
CI + MS	T = Ackley T = Rastrigin	50 50	Coincide	0.2261
CI + LS	T = Ackley T = Schwefei	50 50	Coincide	0.0002
PI + HS	T = Rastrigin T = Sphere	50 50	Part of the overlap	0.867
PI + MS	T = Ackley T = Rosenbrock	50 50	Part of the overlap	0.2154
PI + LS	T = Ackley T = Weierstrass	50 25	Part of the overlap	0.0725
NI + HS	T = Rosenbrock T = Rastrigin	50 50	No overlap at all	0.9434
NI + MS	T = Griewank T = Weierstrass	50 50	No overlap at all	0.3669
NI + LS	T = Rastrigin T = Schwefel	50 50	No overlap at all	0.0016

Table 5: Results of MFEA and SOMA on the multitask benchmark problem.

Problem category	MFEA		SOMA	
	T_n	T_2	T_n	T_2
CI + HS	0.3493 (0.0480)	189.5901 (39.2992)	0.9014 (0.05675)	419.7629 (61.8293)
CI + MS	4.6468 (0.5185)	229.8366 (49.5841)	5.4119 (1.7629)	424.9846 (56.8671)
CI + LS	20.1471 (0.0528)	3884.6405 (427.5915)	21.1944 (0.0934)	4240.0025 (517.8067)
PI + HS	557.7668 (73.8933)	8.7799 (1.4670)	425.6852 (51.1415)	86.7612 (21.0913)
PI + MS	3.5587 (0.4635)	704.5293 (261.5528)	5.0311 (0.6787)	29158.8343 (14301.4714)
PI + LS	20.0767 (0.0646)	20.5621 (3.0864)	5.0346 (0.8623)	12.2019 (2.3042)
NI + HS	755.7619 (316.9677)	233.2365 (70.0560)	25339.6592 (11111.8147)	434.1805 (54.4270)
NI + MS	0.4018 (0.0452)	25.9959 (3.2959)	0.9162 (0.0521)	38.2774 (3.6352)
NI + LS	670.0172 (169.6736)	3858.2066 (470.5808)	435.0968 (51.5959)	4364.407 (611.3337)

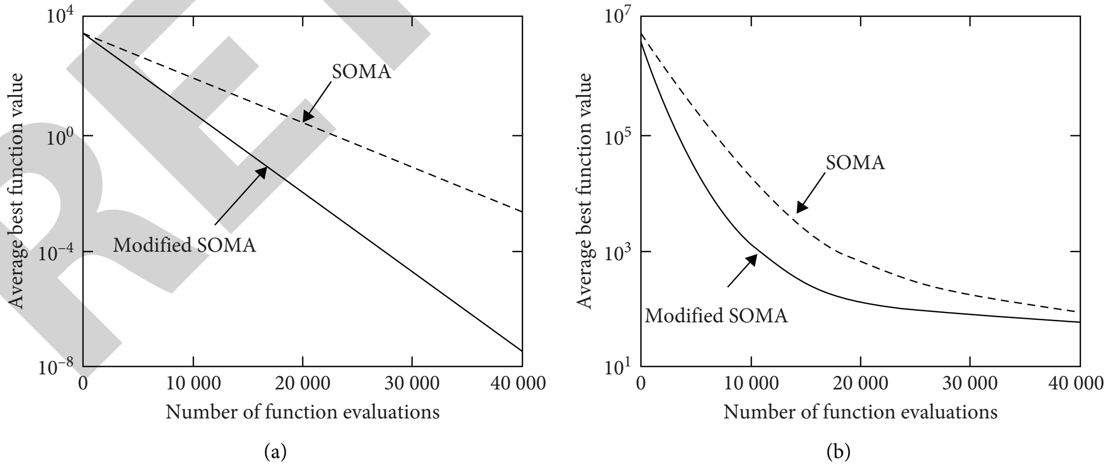
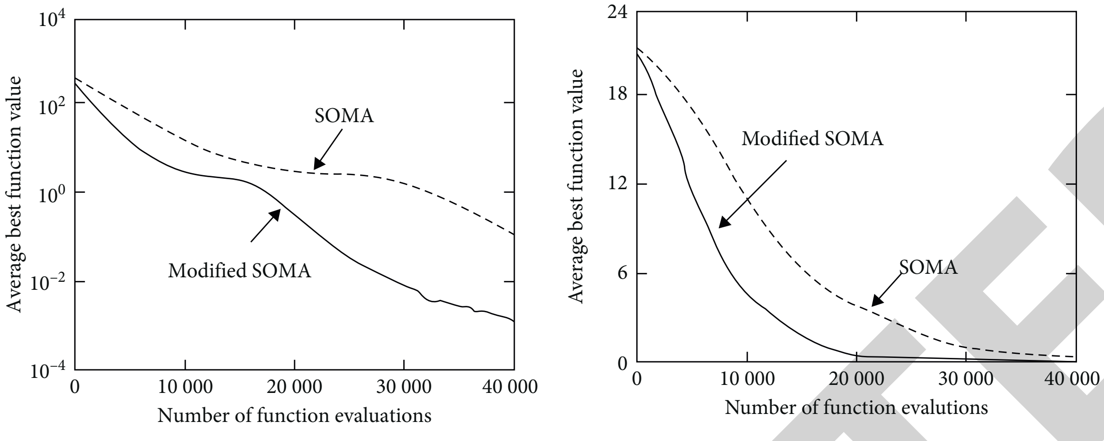


Figure 1: Convergence curves of modified SOMA and SOMA on the problem of full coincidence of global optimal values (CI).

only one task, the maximum number of iterations of SOMA is set to 500 to ensure the fairness of comparison, and other parameters are consistent with MFEA. Each algorithm is independently run for 50 times to eliminate the randomness of the results, and the final results are shown in Table 5. Convergence curves of modified SOMA and SOMA on the problem of full coincidence of global optimal values (CI) are shown in Figure 1.

As can be seen from Table 5 and the convergence diagram, MFEA has an excellent performance in 6 questions



(a) (b)

Figure 2: Convergence curves of modified SOMA and SOMA on global optimal partial coincidence (PI).

(CI + HS, CI + MS, CI + LS, PI + MS, NI + HS, and NI + MS) and is superior to SOMA in terms of accuracy and convergence speed. In terms of PI + LS and NI + LS, MFEA does not perform well. Reference [13] certainly states that when the similarity between tasks becomes low, the effect of MFEA will become worse. As can be seen from Figure 1, modified SOMA is slightly worse than SOMA in NI + LS problem, and MFEA is far worse than SOMA in PI + LS problem. However, the *R* of Pi-LS problem is greater than that of NI + LS problem, so the performance of MFEA is not only affected by the similarity between tasks. It can be seen from Table 5 that the dimensions of the two tasks in PI + LS problem are different, and MFEA performs poorly in the multitask optimization problem with different dimensions. Convergence curves of modified SOMA and SOMA on global optimal partial coincidence (PI) are shown in Figure 2.

The improved ant colony algorithm (IVRS + 20PT), ant colony algorithm combined with 20PT (AC0 + 20PT), and ant colony algorithm combined with artificial bee colony algorithm (ACO + ABC) with excellent results in recent years were selected as the comparison to verify the effectiveness of discrete lion colony algorithm. Table 4 shows the comparison results on six TSP problems. "__" indicates that there are no data in the original literature, and the boldface number indicates the best performance among the four algorithms. As can be seen from Table 4, the discrete lion colony algorithm is superior to the other three algorithms in both optimal and average solutions. For ACO + ABC algorithm, the discrete lion colony algorithm can improve the quality of solution within the range of [1%, 5%]. For ACO + 20PT algorithm, discrete lion group algorithm can improve the quality of Eil51, KroA100, and D198 problems, and especially for KroA100 problem, discrete lion group algorithm can improve the accuracy of about 10%. For IVRS + 20PT algorithm, discrete lion swarm algorithm can improve the solution accuracy by about 0.5% for Ei151, KroA100, and D198 problems.

4. Conclusion

This paper focused on the multifactor evolutionary algorithm (MFEA) and introduced the improved version of MEFA that is HD-MFEA. In the process, the basic properties of MFEA in the multitask environment were given. Meanwhile, a systematic analysis was carried out for the entire algorithm flow of MFEA. Moreover, the detailed introduction of benchmarking problems used in multitasking optimization was given. In addition, the comparison between MFEA and SOMA was carried out to evaluate their performances in benchmarking problems. As a result, MFEA was found to be unable to efficiently solve the test problems with different subfunction dimensions. To this end, i.e., for such dimensional multitask optimization problems, the improved version of MFEA was proposed. Finally, it was applied for the prediction problem of chaotic time series.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that he has no conflicts of interest.

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