Evolutionary Manytasking Optimization Based on Symbiosis in Biocoenosis

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Abstract

Evolutionary multitasking is a significant emerging search paradigm that utilizes evolutionary algorithms to concurrently optimize multiple tasks. The multi-factorial evolutionary algorithm renders an effectual realization of evolutionary multitasking on two or three tasks. However, there remains room for improvement on the performance and capability of evolutionary multitasking. Beyond three tasks, this paper proposes a novel framework, called the symbiosis in biocoenosis optimization (SBO), to address evolutionary many-tasking optimization. The SBO leverages the notion of symbiosis in biocoenosis for transferring information and knowledge among different tasks through three major components: 1) transferring information through inter-task individual replacement, 2) measuring symbiosis through inter-task paired evaluations, and 3) coordinating the frequency and quantity of transfer based on symbiosis in biocoenosis. The inter-task individual replacement with paired evaluations caters for estimation of symbiosis, while the symbiosis in biocoenosis provides a good estimator of transfer. This study examines the effectiveness and efficiency of the SBO on a suite of many-tasking benchmark problems, designed to deal with 30 tasks simultaneously. The experimental results show that SBO leads to better solutions and faster convergence than the state-of-the-art evolutionary multitasking algorithms. Moreover, the results indicate that SBO is highly capable of identifying the similarity between problems and transferring information appropriately.

1 Introduction

Evolutionary algorithms (EAs) (Holland 1975; Goldberg 1989; Schwefel 1995) have shown their great capability of tackling search and optimization problems. Inspired from Darwinian evolution theory (Darwin 1859), EAs mimic natural evolution to search for the optimal solutions by manipulating a population of candidate solutions. There have been various EAs proposed for different problems (Eiben and Smith 2003; Gen and Cheng 1997). In EA, a population of individuals evolves for searching the optimal solution, where a solution is encoded as chromosome, and the fitness implies the quality of a solution. The principle of "survival of the fittest" drives the population towards better and optimal solutions.

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Evolutionary multitasking introduces the new concept of simultaneously solving *multiple* problems through a single run of EA (Gupta, Ong, and Feng 2016). The multi-factorial evolutionary algorithm (MFEA) has proved effective at realizing evolutionary multitasking by leveraging the synergy of fitness landscapes among different problems. By regarding each problem as a task, MFEA seeks the optima for all tasks in a unified decision space, where the search space of multiple problems are unified by a transformation function. The solution information of different tasks is exchanged through skill factor and mating. MFEA has achieved several promising results in dealing with two or three tasks. However, there exists room for improving EAs in multitasking.

This paper aims to address three issues at evolutionary multitasking. First, information transfer plays a crucial role in solving multiple tasks concurrently. In MFEA, information is transferred through recombination of individuals that are good at some specific tasks under the user-defined random mating probability (rmp). Nevertheless, MFEA does not control the rmp during evolution; that is, it lacks a mechanism for controlling the quantity and frequency of information transfer. Second, MFEA is inapplicable to the model-based EAs, such as estimation of distribution algorithm (Hauschild and Pelikan 2011) and ant colony optimization (Dorigo, Maniezzo, and Colorni 1996), in that these EAs seldom adopt recombination of individuals. The information transfer among tasks is therefore disabled. Third, evolutionary multitasking is focused on two or three tasks, whereas concurrently solving more tasks is highly desirable but has not been investigated yet. In particular, appropriate transfer becomes even harder as the number of tasks increases due to the squared number $\binom{m}{2}$ of possible transfers. Therefore, the increase of tasks intensifies the importance of balancing the exploitation within a task and the exploration among multiple tasks.

This paper proposes a novel framework for evolutionary multitasking, called the symbiosis in biocoenosis optimization (SBO), which manipulates multiple EAs and each one is responsible for a task. In SBO, the collection of EA populations constitutes the *biocoenosis*, while the transfer of information between populations caters to the *symbiosis*. Specifically, the inter-task individual replacement is proposed for information transfer; hence, SBO enables the use of EAs without recombination for evolutionary multitasking. For measuring the symbiosis, we combine the inter-task individual replacement with paired evaluations. Furthermore, SBO controls the quantity and frequency of information transfer through symbiosis to balance exploitation within single task and exploration between different tasks. The effectiveness of SBO is verified on the suite of many-tasking problems (MaTPs), in which each problem comprises 30 test functions of CEC 2017 competition. A series of experiments is conducted on the MaTPs to investigate the effects and advantages of SBO in evolutionary many-tasking.

The main contributions of this study are summarized as follows:

- A novel framework SBO for evolutionary multitasking.
- Three features of SBO: transferring information through inter-task individual replacement, measuring symbiosis through inter-task paired evaluations, and coordinating the frequency and quantity of transfer based on symbiosis in biocoenosis.
- Empirical study on the effectiveness and efficiency of SBO, in comparison with single-task optimization and multitask optimization methods.
- Comprehensive analysis of transfer behavior for SBO and MFEA.

The remainder of this paper is organized as follows. Section 2 reviews the related work about evolutionary multitasking. Section 3 elucidates the proposed SBO framework and its components. Section 4 presents the experimental results. Finally, we draw conclusions in Section 5.

2 Related Work

Evolutionary multitasking establishes a new class of EAs capable of solving multiple problems simultaneously. MFEA is a renowned EA for evolutionary multitasking (Gupta et al. 2017; Gupta, Ong, and Feng 2018; Ong and Gupta 2016; Strasser et al. 2016). MFEA utilizes a single population for optimizing multiple tasks. The main ideas behind MFEA are the designs of scalar fitness serving as a unified fitness function for survival selection and the assortative mating operator for information transfer. The skill factor of an individual represents the task index with the best rank over all tasks, while the scalar fitness is the reciprocal of the rank of the most talented task. The assortative mating operator performs crossover in two cases: the two parents have the same skill factor or the predefined random mating probability (rmp) is met. The offspring generated by crossover operator randomly imitates the skill factor from either parent, whereas the offspring perturbed only by mutation operator inherits the skill factor. A newly generated offspring is evaluated only on the task of the skill factor. It is worth noting that assortative mating supports transfer of information between different tasks. When the number of tasks m increases, the frequency of information transfer will gradually change to the predefined rmp owing to the decreasing probability $1/m$ of selecting individuals with the same skill factor.

MFEA has been applied to a variety of applications. Wen and Ting (2016) adopted the concept of MFEA on genetic programming for building ensemble of decision trees. Gupta et al. (2015) incorporated a nested bi-level EA into MFEA for tackling bi-level optimization problems. Sagarna and Ong (2016) used MFEA to solve the software testing problems. Chandra et al. (2016) utilized MFEA to optimize the architecture and parameters of feed forward neural network. Zhou et al. (2016) adopted MFEA on a combinatorial optimization problem, i.e., the capacitated vehicle routing problem. In (Gupta et al. 2016b), MFEA tackled multi-objective optimization problem by treating two performance metrics for multi-objective optimization problem, i.e., the nondominated front and crowding distance, as different tasks.

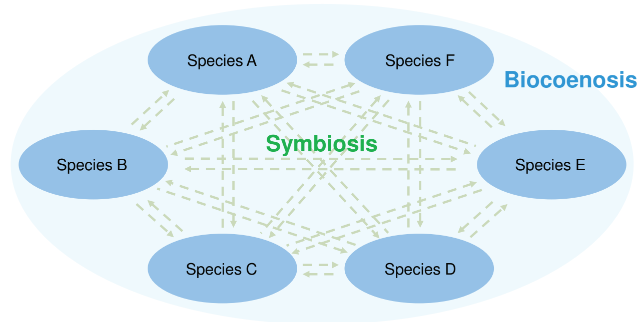


Figure 1: An illustration of SBO framework

Some studies focus on improving or analyzing the effect of transfer. The synergy of fitness landscapes affects the effectiveness and efficiency of MFEA. That is, a better movement in decision space for one task can be good for the other task. Gupta et al. (2016a) analyzed the synergy of fitness landscapes on some test functions. Wen and Ting (2017) designed a parting ways strategy based on the survival rate of transferred individuals; such strategy aims at terminating information transfer between tasks if transfer is useless. Li et al. (2018) enabled multiple rmp to determine the frequency of transfer, where each rmp is adapted according to the survival rate after genetic transfer. Cheng et al. (2017) applied the scheme of co-evolution to evolutionary multitasking, yet the performance is similar to MFEA in bi-tasking test problems. Ding et al. (2017) improved the transfer mechanism in MFEA by learning the decision space transformation, including the location and permutation of decision vector. Feng et al. (2018) proposed transferring knowledge through task mapping, where the mapping is learnt by a denoising autoencoder. Some studies utilize the transfer from past experience or knowledge. In (Feng et al. 2015), a memetic search paradigm was proposed by incorporating EA with transfer learning. Specifically, the knowledge is learnt as memes from past solved problems and then used to guide the search of EA. Feng et al. (2017) incorporated EA with knowledge from past experiences, namely, the solutions from the other tasks for improving the search efficacy.

Recent studies suggest using island model or multiple populations for evolutionary multitasking. Hashimoto et al. (2018) presented an island model with two populations for evolutionary multitasking. Liaw and Ting (2017) proposed a multi-population based method, called the evolution

Algorithm 1 Symbiosis in biocoenosis optimization

EA_i: EA for i^{th} task
τ_i: i^{th} task
λ_i: Offspring size of i^{th} task
m: number of tasks

for $i \leftarrow 1$ to m **do**
  Initialize EA_i for τ_i
end for
$\{\mathcal{M}, \mathcal{N}, \mathcal{C}, \mathcal{O}, \mathcal{P}, \mathcal{A}\} \leftarrow 1$ ▷ Initialize symbiosis
Update transfer rates $\mathcal{R}_{i,j}$ ▷ Algorithm 3
while Not terminated **do**
  for $i \leftarrow 1$ to m **do**
    $Ofsp_i \leftarrow$Variation (EA_i) ▷ Generate offspring
  end for
  for $i \leftarrow 1$ to m **do**
    $j \leftarrow \underset{k \in \{1,\ldots,m|k \neq i\}}{\arg\max} \mathcal{R}_{i,k}$ ▷ Transferred task
    $\mathcal{R}_i \leftarrow \mathcal{R}_{i,j}$ ▷ Transfer rate
    if Rand (0,1) $< \mathcal{R}_i$ **then**
      $S_i \leftarrow \lfloor \mathcal{R}_i \cdot \lambda_i \rfloor$ ▷ Transfer quantity
      for $k \leftarrow 1$ to S_i **do**
        $Ofsp_{i,\lambda_i - S_i + k} \leftarrow Ofsp_{j,k}$
      end for
      Evaluate $(Ofsp_i,\tau_i)$
      Survive (EA_i)
    end if
  end for
  Update symbiosis ▷ Algorithm 2
  Update transfer rates ▷ Algorithm 3
end while

Algorithm 2 Update of symbiosis

m: number of tasks

for $i \leftarrow 1$ to m **do**
  for each $c \in Ofsp_i$ **do**
    $j \leftarrow \text{task}(c)$ ▷ Belonging task
    if $i \neq j$ **then** ▷ Transfer occurs
      Update $\mathcal{M}$, $\mathcal{N}$, $\mathcal{C}$, $\mathcal{O}$, $\mathcal{P}$, and $\mathcal{A}$ by (10).
    end if
  end for
end for

Algorithm 3 Update of transfer rates

m: number of tasks
$\mathcal{R}_{i,j}$: transfer rate from task τ_j to task τ_i

for $i \leftarrow 1$ to m **do**
  for $j \leftarrow 1$ to m and $j \neq i$ **do**
    $\mathcal{T}^{\text{pos}}_{i,j} \leftarrow \mathcal{M}_{i,j} + \mathcal{O}_{i,j} + \mathcal{P}_{i,j}$
    $\mathcal{T}^{\text{neg}}_{i,j} \leftarrow \mathcal{A}_{i,j} + \mathcal{C}_{i,j}$
    $\mathcal{T}^{\text{neu}}_{i,j} \leftarrow \mathcal{N}_{i,j}$
    $\mathcal{R}_{i,j} \leftarrow \mathcal{T}^{\text{pos}}_{i,j} \,/\, (\mathcal{T}^{\text{pos}}_{i,j} + \mathcal{T}^{\text{neg}}_{i,j} + \mathcal{T}^{\text{neu}}_{i,j})$
  end for
end for

of biocoenosis through symbiosis (EBS), in which the transferees are randomly selected from all offspring.

3 Symbiosis in Biocoenosis Optimization

This study proposes a novel framework SBO for evolutionary many-tasking. Inspired from the symbiosis in the biocoenosis, SBO enables multiple populations, each of which is associated with an EA (see Fig. 1). The transfer of information among all tasks constitutes symbiosis. Restated, SBO considers the pairwise correlation between tasks when selecting transferees, and further enables adaptive control over the transfer frequency and the number of transferees. The SBO holds three main features: 1) information transfer through inter-task individual replacement, 2) symbiosis estimation via paired evaluations, and 3) adaptive control of transfer frequency and quantity based on the measure of symbiosis.

The proposed SBO framework is presented in Alg. 1. Given m tasks to be solved concurrently, SBO manipulates m EAs for the m tasks. In each iteration, the m EAs transfer information according to the transfer rates, determined by the degree of symbiosis among them. In SBO, the unit of information to transfer is individual, more precisely, the offspring. The information transfer in SBO relies on offspring replacement and paired evaluations. After survival selection, the update of symbiosis (Alg. 2) and transfer rates (Alg. 3) are alternately performed as per transferred individuals. SBO can be viewed as an island-model EA because it manipulates several EAs in the course of evolution. In particular, SBO features adaptive control over the transfer (migration) rate, transfer frequency, and selection of transferees. Moreover, SBO does not require to predetermine the migration topology (ring, grid, etc.)—the topology is formed automatically and adaptively in the SBO.

3.1 Analogues of Symbiosis and Biocoenosis

In a biocoenosis, the symbiosis defines the effects of interaction between two species. Table 1 lists the six main types of symbiosis in a biocoenosis. These six types of symbiosis are determined according to two unidirectional influences of two species with three cases, i.e., beneficial, neutral, and harmful. A species is defined to be beneficial / neutral / harmful to the other species if such species has positive / no / negative effect to the other species. Two species are in mutualism ($\mathcal{M}$), neutralism ($\mathcal{N}$), or competition ($\mathcal{C}$) if they are beneficial, neutral, or harmful to each other, respectively. On the other hand, if a species A is beneficial to the other species B, the facts that the species B is neutral or harmful to the species A result in different symbiosis. The relation of species A to species B forms commensalism ($\mathcal{O}$) for the former case, and parasitism ($\mathcal{P}$) for the latter case. In the last type of symbiosis, the amensalism ($\mathcal{A}$) comes from the situation that a species A is neutral to the other species B, while the species B is harmful to the species A.

The symbiosis in biocoenosis can be a good analogue of information transfer in evolutionary multitasking. As aforementioned, SBO comprises multiple EAs, each of which is responsible for a task. The populations of different tasks form species, and the information transfers among EAs re-

Table 1: Six types of symbiosis in biocoenosis, including mutualism ($\mathcal{M}$), commensalism ($\mathcal{O}$), parasitism ($\mathcal{P}$), neutralism ($\mathcal{N}$), amensalism ($\mathcal{A}$), and competition ($\mathcal{C}$)

Interaction		Species A		
		Benefit	Neutral	Harm
Species B	Benefit	$\mathcal{M}$	$\mathcal{O}$	$\mathcal{P}$
	Neutral	$\mathcal{O}$	$\mathcal{N}$	$\mathcal{A}$
	Harm	$\mathcal{P}$	$\mathcal{A}$	$\mathcal{C}$

flect symbiosis. In addition, this study uses implicit measure of symbiosis through individuals because explicit measure requires landscapes analysis, which is computationally expensive. Hence, this study defines the meaning of beneficial, neutral, and harmful from an individual to a task.

Definition 1 (Beneficial)**.** *An individual c is said to be* beneficial *to a task τ if c's fitness is at task τ's top $\mathcal{B}N$ ranking, denoted by*

$$c \succ \tau, \tag{1}$$

where N represents the population size, and $\mathcal{B}$ is the beneficial factor.

Definition 2 (Harmful)**.** *An individual c is defined to be* harmful *to a task τ if c's fitness is at task τ's bottom $\mathcal{H}N$ ranking, expressed by*

$$c \prec \tau, \tag{2}$$

where $\mathcal{H}$ stands for the harmful factor.

Definition 3 (Neutral)**.** *An individual c is defined to be* neutral *to a task τ if c is neither beneficial nor harmful to task τ, denoted as:*

$$c \approx \tau. \tag{3}$$

According to the above three relations between a solution to a task, we can define the six types of symbiosis, i.e., mutualism, neutralism, competition, commensalism, parasitism, and amensalism.

Definition 4 (Mutualism)**.** *Any two tasks $\tau_i \neq \tau_j$ are regarded as having mutualism with respect to an individual c if such individual is beneficial to both of the tasks,*

$$c \succ \tau_i \quad \text{and} \quad c \succ \tau_j. \tag{4}$$

Similar concept can be extended to symbiosis of neutralism and competition.

Definition 5 (Neutralism)**.** *Any two tasks $\tau_i \neq \tau_j$ are regarded as having neutralism with respect to an individual c if such individual is neutral to both of the tasks,*

$$c \approx \tau_i \quad \text{and} \quad c \approx \tau_j. \tag{5}$$

Definition 6 (Competition)**.** *Any two tasks $\tau_i \neq \tau_j$ are regarded as having competition with respect to an individual c if such individual is harmful to both of the tasks,*

$$c \prec \tau_i \quad \text{and} \quad c \prec \tau_j. \tag{6}$$

Aside from the above symmetric relations, the other three types of symbiosis are asymmetric; that is, an individual has different effects to two tasks.

Definition 7 (Commensalism)**.** *A task τ_i to the other task τ_j forms commensalism if there is an individual c which is beneficial to τ_i, and neutral to τ_j,*

$$c \succ \tau_i \quad \text{and} \quad c \approx \tau_j. \tag{7}$$

Definition 8 (Parasitism)**.** *A task τ_i to the other task τ_j forms parasitism if there is an individual c which is beneficial to τ_i, but harmful to τ_j,*

$$c \succ \tau_i \quad \text{and} \quad c \prec \tau_j. \tag{8}$$

Definition 9 (Amensalism)**.** *A task τ_i to the other task τ_j forms amensalism if there is an individual c which is harmful to τ_i, but neutral to τ_j,*

$$c \prec \tau_i \quad \text{and} \quad c \approx \tau_j. \tag{9}$$

As per the above six types of symbiosis, this study approximates the degree of symbiosis (Alg. 2) by counting the number of times these conditions are satisfied:

$$\begin{cases} \mathcal{M}_{i,j} \leftarrow \mathcal{M}_{i,j} + 1 & c \succ \tau_i, c \succ \tau_j, \\ \mathcal{N}_{i,j} \leftarrow \mathcal{N}_{i,j} + 1 & c \approx \tau_i, c \approx \tau_j, \\ \mathcal{C}_{i,j} \leftarrow \mathcal{C}_{i,j} + 1 & c \prec \tau_i, c \prec \tau_j, \\ \mathcal{O}_{i,j} \leftarrow \mathcal{O}_{i,j} + 1 & c \succ \tau_i, c \approx \tau_j, \\ \mathcal{P}_{i,j} \leftarrow \mathcal{P}_{i,j} + 1 & c \succ \tau_i, c \prec \tau_j, \\ \mathcal{A}_{i,j} \leftarrow \mathcal{A}_{i,j} + 1 & c \approx \tau_i, c \prec \tau_j, \end{cases} \tag{10}$$

where $\mathcal{M}$, $\mathcal{N}$, $\mathcal{C}$, $\mathcal{O}$, $\mathcal{P}$, and $\mathcal{A}$ maintain the degrees of mutualism, neutralism, competition, commensalism, parasitism, and amensalism, respectively. Through the degree of symbiosis, transfers between different tasks can be measured as having positive, neutral, or negative effect.

3.2 Transfer Strategy

Rather than directly measuring the symbiosis between two tasks, this study leverages individuals to estimate the degree of symbiosis. The unit of transfer in SBO framework is an individual. Given two tasks τ_i , and τ_j, and assume that τ_i accepts the transfer from τ_j. When the inter-task individual replacement occurs, a portion S_i of offspring of τ_i is replaced by the offspring of τ_j:

$$Ofsp_{i,\lambda_i - S_i + k} \leftarrow Ofsp_{j,k} \quad k \in \{1, ..., S_i\}, \tag{11}$$

where λ_i denotes the offspring size of task τ_i. Paired evaluations of the two tasks are applied on these transferees, and the paired evaluations will serve as the basis for measuring the degree of symbiosis (10). Note that offspring are transferred before they are evaluated; in addition, the transferred offspring will replace the same amount of offspring in the target population. Therefore, the total number of fitness evaluations remains the same, and SBO does not require additional evaluations. Based on the degree of symbiosis, SBO controls the information transfer adaptively.

3.3 Coordinating Information Transfer

Algorithm 3 is the procedure of updating the transfer rates. Given the i^{th} task τ_i, transfers with positive effect ($\mathcal{T}^{\text{pos}}_{i,j}$) from the other tasks τ_j include mutualism $\mathcal{M}_{i,j}$, commensalism $\mathcal{O}_{i,j}$ and parasitism $\mathcal{P}_{i,j}$, while transfers with negative effect ($\mathcal{T}^{\text{neg}}_{i,j}$) are composed of amensalism $\mathcal{A}_{i,j}$ and

Table 2: Parameter setting

Parameter	Value
Problem size (d)	100
#Evaluations	$10^4 d$
Pop. and ofsp. sizes (GA)	$(50m,\, 50m)$
Pop. and ofsp. sizes (CMAES)	$(17m,\, 34m)$
Beneficial factor ($\mathcal{B}$)	0.25
Harmful factor ($\mathcal{H}$)	0.50

competition $\mathcal{C}_{i,j}$. The transfers with neutral effect ($\mathcal{T}^{\mathrm{neu}}_{i,j}$) are from neutralism $\mathcal{N}_{i,j}$. The transfer rate ought to be proportional to the transfers with positive effect; therefore, the transfer rate $\mathcal{R}_{i,j}$ from τ_j to τ_i is defined by

$$\mathcal{R}_{i,j} \leftarrow \mathcal{T}^{\mathrm{pos}}_{i,j} \,/\, (\mathcal{T}^{\mathrm{pos}}_{i,j} + \mathcal{T}^{\mathrm{neg}}_{i,j} + \mathcal{T}^{\mathrm{neu}}_{i,j}). \tag{12}$$

The transfer rate plays an important role in the control of transferring information. It determines 1) the task of individuals to be transferred, 2) the transfer frequency, and 3) the transfer quantity. First, each task τ_i selects transferees from the task that has the highest transfer rate, denoted by $\mathcal{R}_i$. The transfer frequency for task τ_i is determined by $\mathcal{R}_i$. If transfer occurs, the transfer quantity S_i for τ_i is then calculated by

$$S_i \leftarrow \lfloor \mathcal{R}_i \cdot \lambda_i \rfloor \,. \tag{13}$$

In this way, SBO is capable of adaptively controlling the transfer frequency and quantity.

4 Experimental Results

This study investigates the performance of the proposed SBO using GA (SBGA) and CMAES (Hansen 2006) (SBCMAES), in comparison with MFEA (Gupta, Ong, and Feng 2016) and EBS (Liaw and Ting 2017) on four MaTPs (cf. Sec. 4.1). The experiments examine the solution quality and convergence speed of the proposed method. This study further looks into the behaviors of MFEA and SBO methods in the course of evolution through the analysis of transfer among tasks.

Table 2 lists the parameter setting used in the following experiments. The beneficial and harmful factors are set to 0.25 and 0.50, respectively. The setting of MFEA follows the use of simulated binary crossover, polynomial mutation, and rmp set to 0.3 in (Gupta, Ong, and Feng 2016). The population size is set to $50m$ to better handling the many-tasking benchmarks. All experiments run over 30 trials due to the stochastic nature of EAs. Significant analysis is done by using Wilcoxon-Mann-Whitney U-test with level of significance $\alpha = 0.05$.

4.1 Many-tasking Benchmark Problems

This study presents a test suite based on the benchmark functions of CEC 2017 competition (Awad et al. 2016; Liaw and Ting 2017). A many-tasking problem (MaTP) is composed of 30 benchmark functions, including 3 unimodal, 7 simple multi-modal, 10 hybrid, and 10 composite functions, and each function is regarded as a task. By adjusting the positions of optimal solutions of all tasks, there are four MaTPs labeled as $\mathrm{MaTP_Z}$ for zero shift, $\mathrm{MaTP_S}$ for small shift, $\mathrm{MaTP_M}$ for medium shift, and $\mathrm{MaTP_L}$ for large shift of the positions of optimal solutions, and the four MaTPs correspond to four shift ranges: 1) zero (no) shift, 2) small shift $U(-1, 1)$, 3) medium shift $U(-5, 5)$, and 4) large shift $U(-10, 10)$ at each dimension between any two test functions, where U denotes uniform distribution. The similarity among tasks decreases from $\mathrm{MaTP_Z}$ to $\mathrm{MaTP_L}$.

4.2 Solution Quality and Convergence

This study examines the significance of difference in solution quality through non-parametric significance analysis. Table 3 lists results of Wilcoxon-Mann-Whitney U-test with level of significance $\alpha = 0.05$ for GA, CMAES, MFEA, EBSGA, EBSCMAES, SBGA, and SBCMAES on the four MaTP benchmarks. The SBGA outperforms GA on most test functions, validating that the SBO framework can improve the solution quality of GA. As for CMAES, SBCMAES acquires significantly better results than CMAES on 27, 24, 19, and 12 test functions in $\mathrm{MaTP_Z}$, $\mathrm{MaTP_S}$, $\mathrm{MaTP_M}$, and $\mathrm{MaTP_L}$, respectively. Note that the decrease in the number of better results respond to the increase in the shift of optimal solutions. Comparing the performance of MFEA and SBGA, SBGA achieves better solution quality than MFEA does on 29, 21, 15, and 11 test functions in $\mathrm{MaTP_Z}$, $\mathrm{MaTP_S}$, $\mathrm{MaTP_M}$, and $\mathrm{MaTP_L}$, respectively. Additionally, SBCMAES excels MFEA on all test functions in all four MaTPs. In comparison of SBO and EBS, SBGA performs better than EBSGA does on $\mathrm{MaTP_s}$, $\mathrm{MaTP_M}$, and $\mathrm{MaTP_L}$; moreover, SBCMAES outperforms EBSCMAES on the four MaTPs except two functions in $\mathrm{MaTP_L}$. These results indicate that the proposed SBO framework can effectively improve single-task methods (GA and CMAES) and prevail multitask optimization methods (MFEA and EBS) on many-tasking problems with varied similarities among tasks.

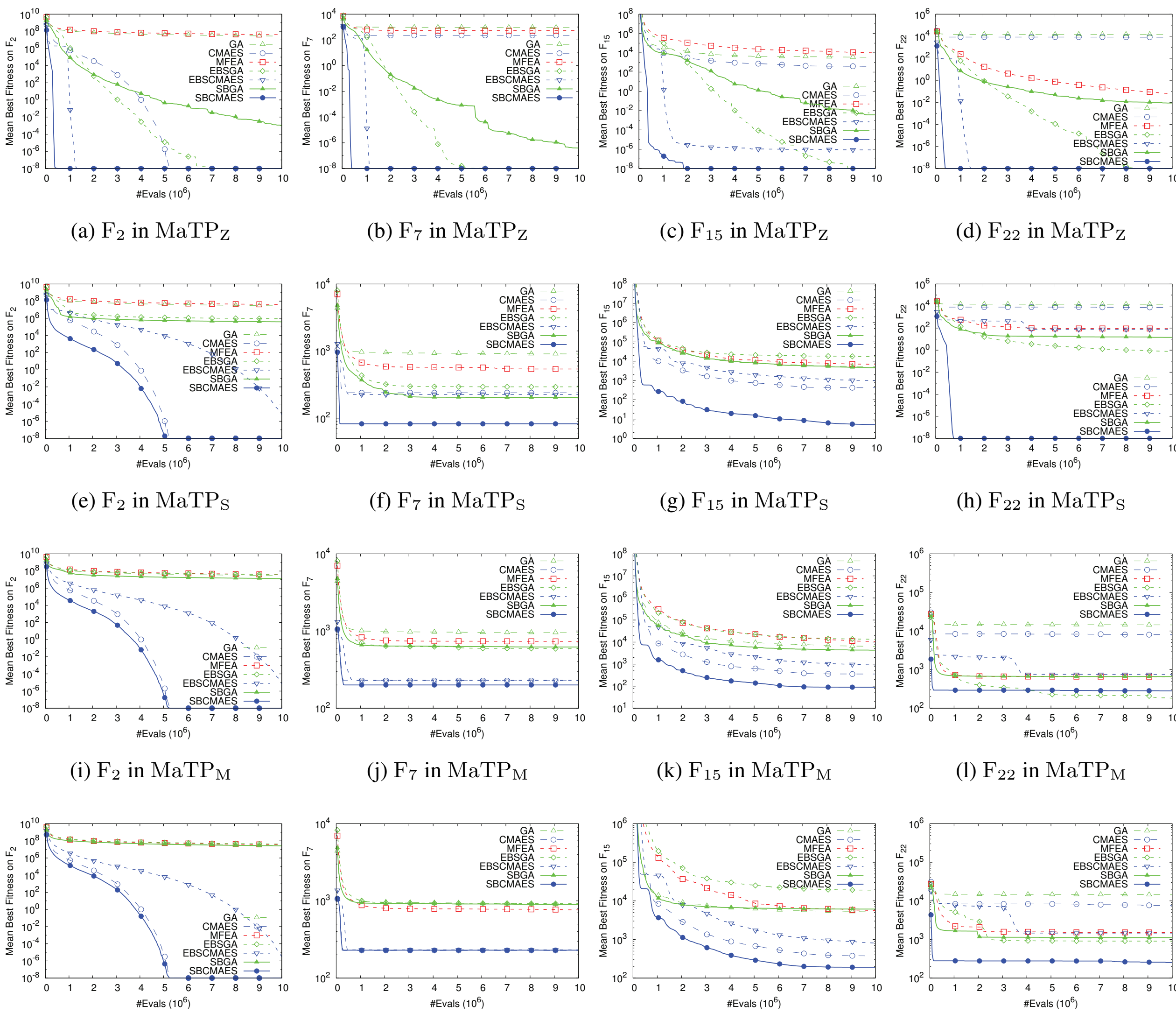
Figure 2 compares the variation of fitness values during evolution for GA, CMAES, MFEA, EBSGA, EBSCMAES, SBGA and SBCMAES on the four MaTP benchmarks. Due to the space limitation we illustrate only one function for each type. The SBCMAES achieves fastest convergence on all four MaTPs, and the SBGA gains faster convergence speed than GA and MFEA on $\mathrm{MaTP_Z}$, $\mathrm{MaTP_S}$, $\mathrm{MaTP_M}$, and composite function in $\mathrm{MaTP_L}$. Likewise, SBGA converges faster than EBSGA does on unimodal, multi-modal, and hybrid functions in $\mathrm{MaTP_S}$, $\mathrm{MaTP_M}$, and $\mathrm{MaTP_L}$. These results validate the nice convergence of the proposed SBO framework.

4.3 Effect on Transfers

In this study, we use survival rates to examine the utility of information transfer. Figure 3 compares the variation of survival rates of transferred and non-transferred individuals during evolution in MFEA, SBGA, and SBCMAES on the four MaTP benchmarks. The SBGA and SBCMAES both have higher survival rates of transferred individuals than MFEA does. The survival rate of transferred individuals in

Table 3: The numbers of functions that the former is superior / equal / inferior to the latter with significance

	SBGA GA	SBGA MFEA	SBGA EBSGA	SBCMAES CMAES	SBCMAES MFEA	SBCMAES EBSCMAES
$\mathrm{MaTP_Z}$	30 / 0 / 0	29 / 1 / 0	0 / 1 / 29	27 / 3 / 0	30 / 0 / 0	11 / 19 / 0
$\mathrm{MaTP_S}$	22 / 8 / 0	21 / 7 / 2	15 / 12 / 3	24 / 0 / 6	30 / 0 / 0	25 / 5 / 0
$\mathrm{MaTP_M}$	17 / 10 / 3	15 / 14 / 1	16 / 7 / 7	19 / 10 / 1	30 / 0 / 0	20 / 10 / 0
$\mathrm{MaTP_L}$	8 / 21 / 1	11 / 16 / 3	16 / 11 / 3	12 / 16 / 2	30 / 0 / 0	17 / 11 / 2



(a) $\mathrm{F_2}$ in $\mathrm{MaTP_Z}$ (b) $\mathrm{F_7}$ in $\mathrm{MaTP_Z}$ (c) $\mathrm{F_{15}}$ in $\mathrm{MaTP_Z}$ (d) $\mathrm{F_{22}}$ in $\mathrm{MaTP_Z}$

(e) $\mathrm{F_2}$ in $\mathrm{MaTP_S}$ (f) $\mathrm{F_7}$ in $\mathrm{MaTP_S}$ (g) $\mathrm{F_{15}}$ in $\mathrm{MaTP_S}$ (h) $\mathrm{F_{22}}$ in $\mathrm{MaTP_S}$

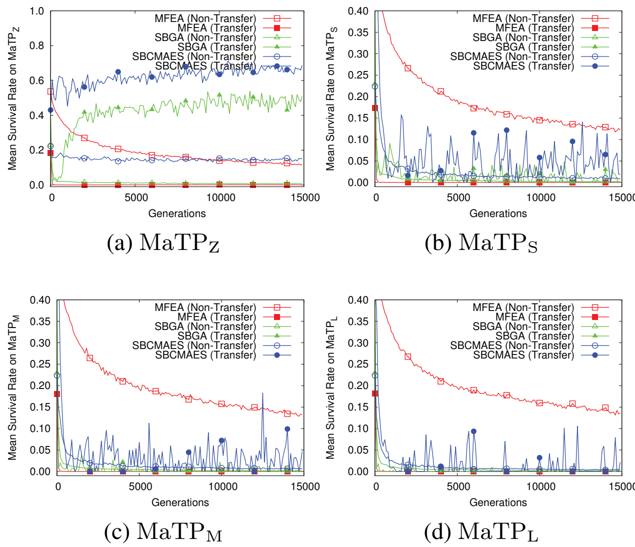
(i) $\mathrm{F_2}$ in $\mathrm{MaTP_M}$ (j) $\mathrm{F_7}$ in $\mathrm{MaTP_M}$ (k) $\mathrm{F_{15}}$ in $\mathrm{MaTP_M}$ (l) $\mathrm{F_{22}}$ in $\mathrm{MaTP_M}$

(m) $\mathrm{F_2}$ in $\mathrm{MaTP_L}$ (n) $\mathrm{F_7}$ in $\mathrm{MaTP_L}$ (o) $\mathrm{F_{15}}$ in $\mathrm{MaTP_L}$ (p) $\mathrm{F_{22}}$ in $\mathrm{MaTP_L}$

Figure 2: Variation of fitness values in the course of evolution for GA, CMAES, MFEA, SBGA, and SBCMAES on the four MaTP benchmarks

SBCMAES is higher than that of non-transferred individuals during most of the evolution on $\mathrm{MaTP_Z}$, $\mathrm{MaTP_S}$, and $\mathrm{MaTP_M}$. On $\mathrm{MaTP_L}$, the survival rate of transferred individuals in SBCMAES is lower than that of non-transferred individuals. Such phenomenon is caused by the adaptation mechanism of transfer rates (cf. Sec. 4.4). By contrast, the survival rate of transferred individuals in MFEA is smaller than that of non-transferred individuals on the four MaTP benchmarks.

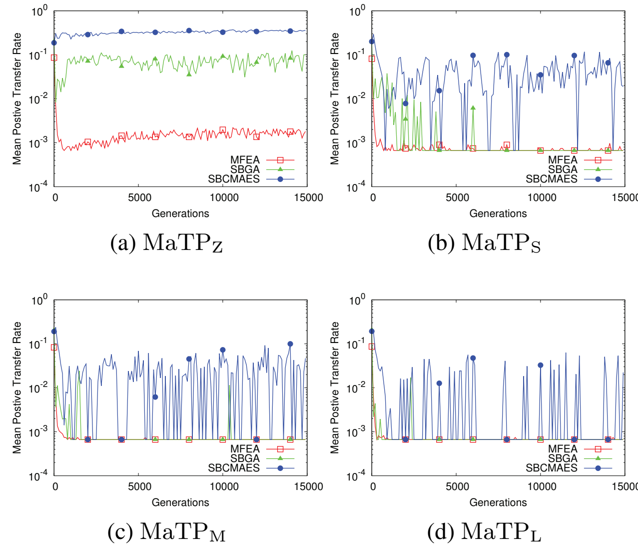
Furthermore, Figs. 4 and 5 plot the variation of positive



(a) $\mathrm{MaTP_Z}$ (b) $\mathrm{MaTP_S}$

(c) $\mathrm{MaTP_M}$ (d) $\mathrm{MaTP_L}$

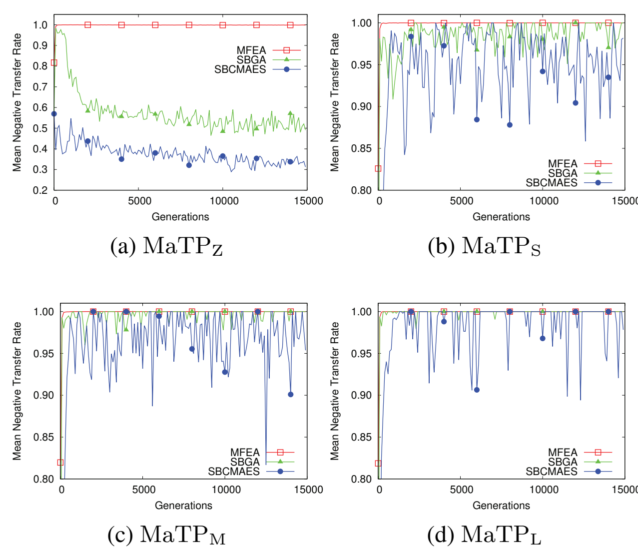
Figure 3: Variation of survival rates of transferred and non-transferred individuals during evolution



(a) $\mathrm{MaTP_Z}$ (b) $\mathrm{MaTP_S}$

(c) $\mathrm{MaTP_M}$ (d) $\mathrm{MaTP_L}$

Figure 4: Variation of positive transfer rates for transferees during evolution



(a) $\mathrm{MaTP_Z}$ (b) $\mathrm{MaTP_S}$

(c) $\mathrm{MaTP_M}$ (d) $\mathrm{MaTP_L}$

Figure 5: Variation of negative transfer rates for transferees during evolution

and negative transfer rates for transferees in MFEA, SBGA, and SBCMAES, respectively. SBCMAES achieves highest positive transfer rate and lowest negative transfer rate. SBCMAES and SBGA both gain higher positive transfer rates and lower negative transfer rates than MFEA does on the four MaTPs. These results validate that SBO framework has better mechanism for transfer than MFEA.

4.4 Adaptation of Transfers

Figure 6 further shows the variation of total transfer rate, i.e., the sum of positive, negative, and neutral transfer rates, in the course of evolution. The total transfer rate in SBGA decreases during evolution owing to the decrease of positive transfer. Similar trend can be found in SBCMAES; moreover, SBCMAES endures the total transfer rate in a high level in the $\mathrm{MaTP_Z}$ due to its high rate of positive transfer in high similarity many-tasking problem. On the other hand, the total transfer rate in MFEA stays at relatively high level in the course of evolution on the four MaTPs, reflecting that MFEA fails to respond to environmental changes for different problems.

5 Conclusions

Evolutionary multitasking is an emerging topic. Previous research concentrated on resolving problems with a small number of tasks concurrently. Enlarging the number of tasks intensifies the importance and need for appropriately transferring information among tasks. This study proposes a novel framework SBO for evolutionary many-tasking. From the inspiration of symbiosis in the biocoenosis, SBO considers the interaction of multiple populations. In SBO, each EA is responsible for a task, and the transfer of information among tasks brings about symbiosis. SBO has three main components: transferring information through inter-task individual replacement, measuring symbiosis through inter-task paired evaluations, and coordinating the transfer frequency and quantity based on symbiosis in biocoenosis.

The efficacy of the proposed SBO is validated on a set of many-tasking problems (MaTPs) with four different shifts of optima, i.e., the $\mathrm{MaTP_Z}$, $\mathrm{MaTP_S}$, $\mathrm{MaTP_M}$, and $\mathrm{MaTP_L}$. The results have shown that the proposed SBO achieves the best solution quality and convergence speed, in comparison with conventional single-task optimization methods and state-of-the-art multitask optimization methods. Analysis on the effect of transfer demonstrates the advantages of SBO

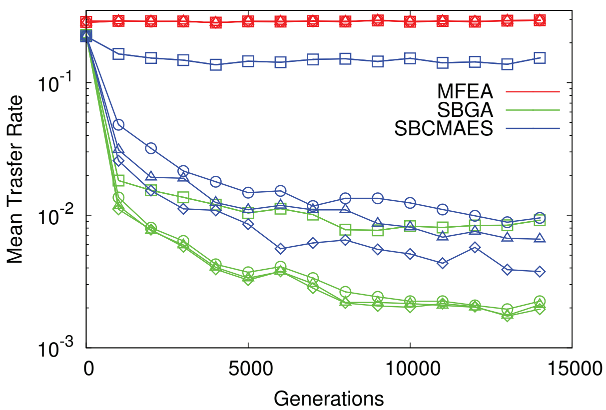


Figure 6: Variation of total transfer rate during evolution. The square, circle, triangle, and diamond symbols represent the rates on $\mathrm{MaTP_Z}$, $\mathrm{MaTP_S}$, $\mathrm{MaTP_M}$, and $\mathrm{MaTP_L}$, respectively.

framework over MFEA. More specifically, the SBO can appropriately manipulate the transfer frequency and quantity.

Some directions remain for future work. For example, concurrent optimization of homogeneous and even heterogeneous problems can be considered. Incorporating different EAs into SBO is also promising.

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