

# Genetic algorithm with ant colony optimization (GA-ACO) for multiple sequence alignment<sup>☆</sup>

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## Abstract

Multiple sequence alignment, known as NP-complete problem, is among the most important and challenging tasks in computational biology. For multiple sequence alignment, it is difficult to solve this type of problems directly and always results in exponential complexity. In this paper, we present a novel algorithm of genetic algorithm with ant colony optimization for multiple sequence alignment. The proposed GA-ACO algorithm is to enhance the performance of genetic algorithm (GA) by incorporating local search, ant colony optimization (ACO), for multiple sequence alignment. In the proposed GA-ACO algorithm, genetic algorithm is conducted to provide the diversity of alignments. Thereafter, ant colony optimization is performed to move out of local optima. From simulation results, it is shown that the proposed GA-ACO algorithm has superior performance when compared to other existing algorithms.

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**Keywords:** Multiple sequence alignment; Genetic algorithm; Ant colony optimization; Hybrid search; Local search

## 1. Introduction

Multiple sequence alignment (MSA) is an essential tool for analyzing biological sequences. It is one of the most important and challenging tasks in computational biology because the time complexity for solving MSA grows exponentially with the size of the considered problem [1–3]. In general, heuristics offer more practical solutions but usually produce quasi-optimal alignment [4,5]. The progressive approach is the most commonly used heuristic method by gradually aligning the closest pair to build MSA [6–8]. Its main disadvantage is the found alignments that may be trapped in local optima, which stems from the greedy nature of this algorithm. This means that if mistakes are made in intermediate alignments, they cannot be corrected later when more sequences are added into the alignment process. Furthermore, there is no objective function to evaluate the performance for multiple sequence alignment.

Another approach is to use an extension of dynamic programming for simultaneously aligning multiple sequences, such as Carrillo-Lipman algorithm [9], MSA [10], DCA [11,12], etc. In general, these algorithms often have higher quality solutions than that of progressive approach. However, the drawbacks of these algorithms are the complexity in running time and memory requirements. Thus, they can only be applied to problems with limited number of sequences [8].

There are also iterative, stochastic approaches for multiple sequence alignment. These approaches include simulated annealing (SA) [13], genetic algorithms (GAs) [14–18] and evolutionary programming (EP) [19–21]. SA is the first stochastic iterative method for simultaneously aligning a set of sequences, but its found alignments could be trapped in local optima [26]. Isokawa et al. applied a simple genetic algorithm with bit matrices to MSA [14]. Notredame et al. also used GAs to solve MSA and align two homologous RNA sequences [15,16]. However, GAs may cause certain degeneracy in search performance if their operators are not carefully designed [18,34,38,40]. Fogel proposed to use the evolutionary programming algorithm for multiple sequence alignment, and an extension version was proposed in the literature [21–23]. These algorithms work well for containing a large number of

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fully matched blocks, but few fully matched blocks will be found for sequences with low similarity [20]. Another method based on the iteration idea is the Gibbs sampling [24]. Gibbs sampling has been successfully applied to the problem of multiple alignment block without gaps. These above algorithms provided the versatile and effective alignments for multiple sequence alignment. Nevertheless, they do not incorporate local search as an add-on extra to conduct fine tuning for the found alignments. Recently, genetic algorithms with local search have been considered as good alternatives for solving optimization problems [17,18,25–27]. The concept of local search is to find a better candidate nearby the current one before move to the next stage of search [26]. In the literature [28–34], the genetic algorithm equipped with local search is also referred to as the memetic algorithm, the genetic local search, the hybrid genetic algorithm, or the cultural algorithm. In this paper, we present the genetic algorithm with ant colony optimization (GA-ACO) to explore and exploit search spaces for multiple sequence alignment. It has both the advantage of GA, the ability to find feasible solutions and to avoid premature convergence, and that of ACO, the ability to search over the subspace and then to move out of local optima.

This paper is organized as follows. Because the proposed algorithm is based on genetic algorithm and ant colony optimization, we describe both approaches in Section 2. In Section 3, we present the proposed GA-ACO algorithm for multiple sequence alignment. Next, Section 4 shows the simulation results. The results are also compared to other existing algorithms to demonstrate the superiority of the proposed GA-ACO algorithm. Conclusions are given in Section 5.

## 2. Genetic algorithm and ant colony optimization

GA and ACO are population-based search algorithms by maintaining a population of structures as key elements in design and implementation of problem solving algorithms. These algorithms are sufficiently complex to provide powerful adaptive search approaches, and usually can be embedded with other approaches to speed up the search performance. The basics of GA and ACO are described later.

### 2.1. Genetic algorithm

GA has been touted as a class of general-purpose search strategies for optimization problems. GA use a population of solutions, from which, using recombination and selection strategies, better and better solutions can be produced. GA can handle any kind of objective functions and any kind of constraints without much mathematical requirements about the optimization problems. When applying to optimization problems, genetic algorithm provides the advantages to perform global search and hybridize with domain-dependent heuristics for specific problems [35]. Genetic algorithm starts with a set of randomly selected chromosomes as the initial population that encodes a set of possible solutions. In GA, variables of a problem are represented as genes in a chromosome, and the chromosomes are evaluated according

to their fitness values using some measures of profit or utility that we want to optimize. Two genetic operators, crossover and mutation, alter the composition of genes to create new chromosomes called offspring. The selection operator is an artificial version of natural selection, a Darwinian survival of the fittest among populations, to create populations from generation to generation, and chromosomes with better fitness values have higher probabilities of being selected in the next generation. After several generations, GA can converge to the best solution.

### 2.2. Ant colony optimization

ACO algorithms have also widely used as a new cooperative search algorithm in optimization problems [36–38]. ACO algorithms are a class of algorithms inspired by the observation of real ants. Ants are capable of exploring and exploiting pheromone information, which have been left on the ground when they traversed. They then can choose routes based on the amount of pheromone. While building the solutions, each artificial ant collects pheromone information on the problem characteristics and uses this information to modify the representation of the problem, as seen by the other artificial ants [36]. The larger amount of pheromone is left on a route, the greater is the probability of selecting the route by artificial ants. In ACO, artificial ants find solutions starting from a start node and moving to feasible neighbor nodes in the process of ants\_generation\_and\_activity. During the process, information collected by artificial ants is stored in the so-called pheromone trails. In the process, artificial ants can release pheromone while building the solution (online step-by-step) or while the solution is built (online delayed). An ant-decision rule, made up of the pheromone and heuristic information, governs artificial ants to search towards neighbor nodes stochastically. Pheromone\_evaporation is a process of decreasing the intensities of pheromone trails over time. This process is used to avoid locally convergence and to explore more search space. Based on this property, we use ACO as local search in the proposed GA-ACO algorithm.

## 3. The proposed GA-ACO algorithm

The procedure of the proposed GA-ACO algorithm is to apply initialization, sexual reproduction operators, mutation operators, fitness evaluation, selection operator, and ACO for multiple sequence alignment. These above procedures are iterated until a pre-specified termination criterion is satisfied. The proposed algorithm is shown in Fig. 1. When the initial parent alignments are randomly generated, these alignment matrices are optimized by using the proposed algorithm. A population of parent alignments is maintained. Mutation and sexual reproduction operators are used to produce offspring alignments. The function of sexual reproduction operators is like the crossover operator in genetic algorithms. Sexual reproduction operators allow two alignments to exchange their information with each other and can produce one offspring alignment or two offspring alignments [20]. Mutation operators

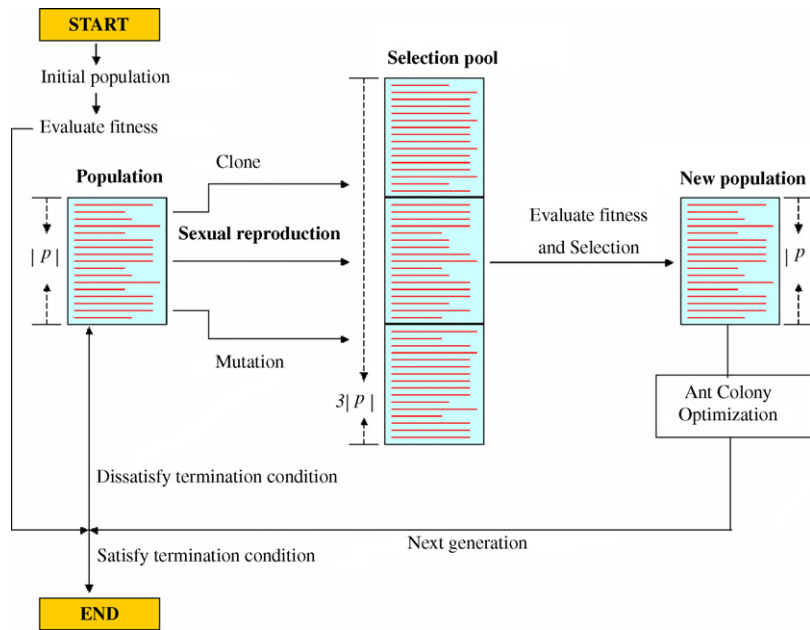


Fig. 1. The flowchart of the proposed algorithm.

provide possible variation on the alignments. After offspring alignments are generated via the mutation and sexual reproduction operators, the original parent alignments and all offspring alignments are put into a selection pool. The selection operator is employed to determine which alignments are suitable to survive and which alignments are culled in the next generation. Moreover, ACO is applied to the best alignment to escape from the local optima in each generation. In this section, we introduce all operators used in the proposed GA-ACO algorithm.

### 3.1. Representation

It is considered that there are  $k$  sequences to be aligned, and these sequences are generated with various lengths, say, from  $l_1$  to  $l_k$ . In our approach, parent alignments are presented as a matrix where each sequence is encoded as a row with the considered alphabet set. The maximum number of columns in the matrix is  $w = \lceil \alpha l_{\max} \rceil$ , where  $l_{\max} = \max\{l_1, l_2, \dots, l_k\}$ ,  $\lceil x \rceil$

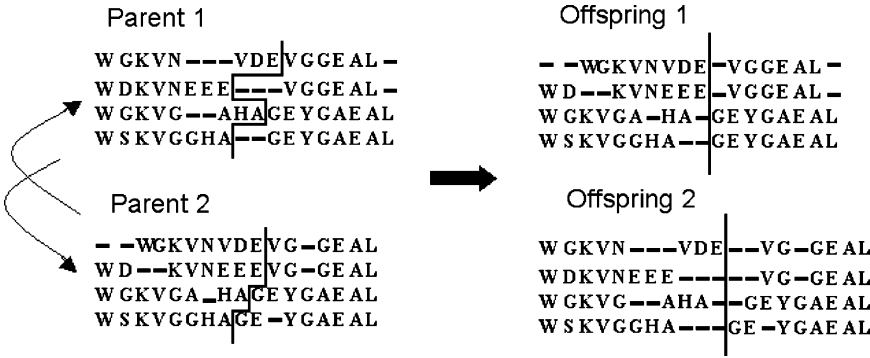
is the smallest integer greater than or equal to  $x$ , and the parameter  $\alpha$  a scaling factor [14,20]. In our study, each matrix may have variant number of columns. The value  $\alpha$  is chosen according to the probability distribution  $N(\mu, \sigma^2)$ , where  $\mu$  and  $\sigma^2$  denote the mean and variance of Gaussian distribution.

### 3.2. Population initialization

The initial population  $P$  is generated by randomly initializing their constituent rows in the following ways. First, for each sequence  $s_i$  with length  $l_i$ , a random permutation is generated from the set  $1, 2, \dots, w$ . Secondly, the first  $l_i$  numbers of the permutation are sorted in ascending order. Thirdly, those  $l_i$  numbers are used as the row indices in the matrix indicating where the corresponding base symbols taken from the original sequence  $s_i$  are placed. Finally, the positions for all rows in the matrix without associated base symbols are filled with the space symbols. Fig. 2 illustrates an example of

Sequence	Length	Permutation(1-9)	Positions	Sorted positions
ATCAA	(5)	3 5 2 6 9 1 7 4 8	3 5 2 6 9	2 3 5 6 9
TAATCAA	(7)	9 6 7 1 4 8 5 3 2	9 6 7 1 4 8 5	1 4 5 6 7 8 9
ATCA	(4)	6 2 5 1 4 8 3 7 9	6 2 5 1	1 2 5 6
TAATCAT	(7)	7 4 9 1 3 5 8 6 2	7 4 9 1 3 5 8	1 3 4 5 7 8 9
ATGATT	(6)	5 6 8 4 3 1 9 7 2	5 6 8 4 3 1	1 3 4 5 6 8
<b>Initial Alignment</b>		$\alpha = N(1.3, 0.2)$ , in this case $\alpha = 1.2$ $w = \lceil \alpha \times l_{\max} \rceil = \lceil 1.2 \times 7 \rceil = 9$		
-	A T - C A - - A			
T	- - A A T C A A			
A	T - - C A - - -			
T	- A A T - C A T			
A	- T G A T - T -			

Fig. 2. Example illustrating the initialization procedure.

Fig. 3. Example illustrating the procedure of *singlepoint* operator.

using the random initialization procedure to generate the initial population.

### 3.3. Fitness evaluation

Each alignment represented as a matrix has a corresponding fitness value. To determine which alignment will survive in the next generation is based on its fitness value. In the proposed GA-ACO algorithm, the optimization task is defined as a maximization problem for searching the alignment with the best fitness value. The fitness value for two sequences  $m_i$  and  $m_j$  of alignment  $M$  is defined as follows:

$$\text{Fitness}(m_i, m_j) = \sum_{1 \leq p \leq N} C(m_{ip}, m_{jp}). \quad (1)$$

Then, the fitness value of an alignment  $M$  is defined as:

$$\text{Fitness}(M) = \sum_{i=1}^{k-1} \sum_{j=i+1}^k \text{Fitness}(m_i, m_j). \quad (2)$$

where,  $N$  is the length of the alignment that must be greater than or equal to the length of the longest sequence, and  $C$  a scoring matrix.

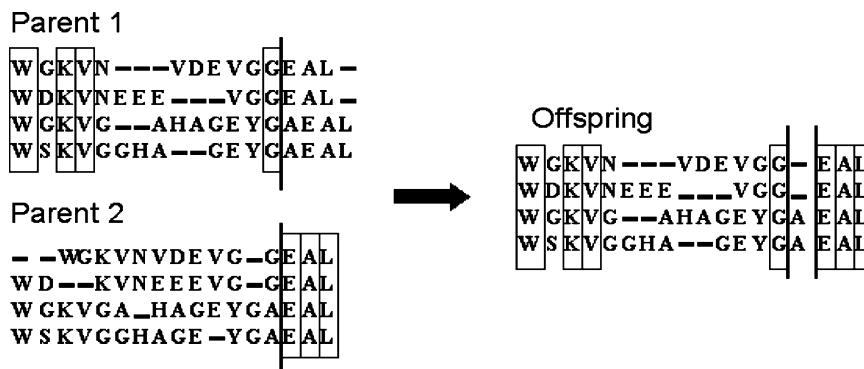
### 3.4. Selection and terminations

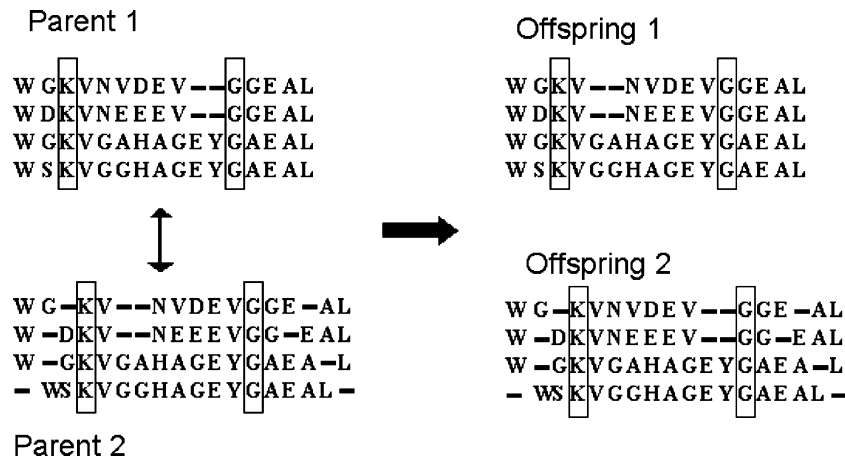
In this paper, tournament selection is implemented as the selection operator. This selection scheme is to determine which

alignments in the selection pool will become parent alignments in the next generation [25]. The termination condition is set as that the number of generation exceeds the permitted generation denoted as  $g_{\max}$ . When the termination condition is satisfied, the resultant alignment is obtained.

### 3.5. Sexual reproduction operators

The sexual reproduction operators include *singlepoint* operator, *recombinematchcolumn* operator [20], and *uniformexchangeblock* operator. The *singlepoint* operator produces two offspring alignments through exchanging information in parent alignments. The parent 1 alignment is cut at some randomly chosen positions, and parent 2 alignment is also tailored at the same ordered base position for each sequence. The left parts of both parent alignments are exchanged for keeping the original sequence base order, if there is a single cutting point in both parent alignments. To do above steps, extra spaces may be inserted into the junction points. Fig. 3 outlines this operator. The *recombinematchcolumns* operator tries to create an offspring alignment with match columns by swapping blocks and inserting spaces into the junction points [20]. Fig. 4 illustrates this operator. The *uniformexchangeblock* operator is to map the match columns that are consistent in parent alignments. Match columns are said to be consistent in parent alignments, if they contain the same ordered base. We randomly choose two consistent match columns as the two cutting points, and then blocks between two consistent match columns can be directly swapped [15]. This operator is outlined in Fig. 5.

Fig. 4. Example illustrating the procedure of *recombinematchcolumn* operator.

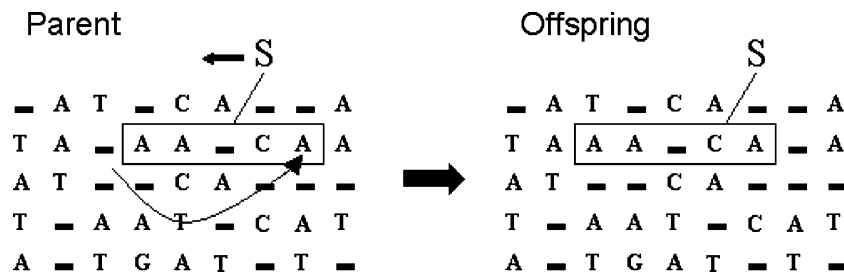
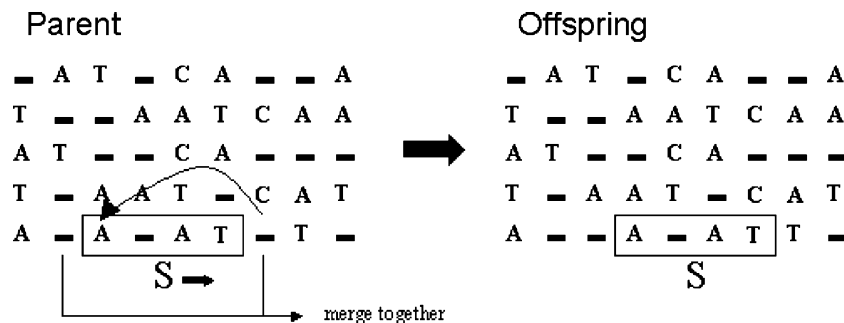
Fig. 5. Example illustrating the procedure of *uniformexchangeblock* operator.

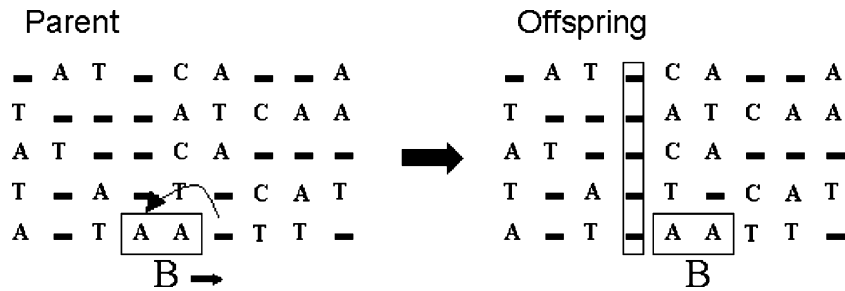
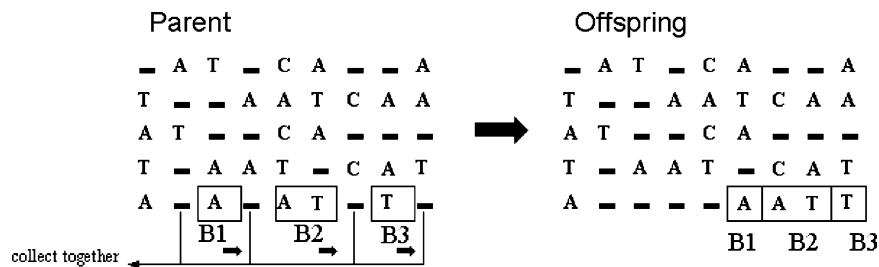
### 3.6. Mutation operators

The mutation operators perform modification to provide possible variation for the offspring alignments. The mutation operators are classified into three categories: the space block shuffle operators, the base symbol block shuffle operators, and the heuristic operators. The difference between the space block shuffle operators and the base symbol block shuffle operators is that the block to be shuffled is different. The former operators shuffle the space blocks and the later operators shuffle the symbol base block. Both types of mutation operators are used in providing variety for offspring alignments. The heuristic operators perform modifications in a rather smart and subtle manner, and have the power of searching higher fitness values.

#### 3.6.1. Space block shuffle operators

Space block shuffle operators include *changespace* operator and *mergespace* operator. The *changespace* operator randomly picks a space from a randomly chosen row in a parent alignment. Then, the randomly chosen space symbol is moved to a base symbol position selected randomly in the same row. There is an associated parameter with this operator denoted as  $\lambda$ , which is a self-adaptive parameter. It represents the number of rows to be selected for applying this operator,  $\lambda = [0.2k]$  ( $k$  is the number of sequences). Fig. 6 illustrates an example of this operator. The *mergespace* operator merges two separated spaces together. Both spaces are randomly chosen in a parent alignment. This operator is given in Fig. 7. This operator is to move the block  $S$  to the right hand side and move the randomly

Fig. 6. Example illustrating the procedure of *changespace* operator.Fig. 7. Example illustrating the procedure of *mergespace* operator.

Fig. 8. Example illustrating the procedure of *decrease search space* operator.Fig. 9. Example illustrating the procedure of *collect space* operator.

chosen space symbol to the destination position. In the *mergespace* operator, it also has the parameter  $\lambda$  representing the selected number of rows.

### 3.6.2. Base symbol block shuffle operators

Base symbol block shuffle operators include *decrease search space* operator and *collect space* operator. The *decrease search space* operator decreases the alignment length. This operator chooses a space column with poor performance to make a full space column by grabbing the neighborhood spaces, and then it deletes the full space columns. This operator

can delete the bad columns from the alignment and distribute the base symbols to another column. It is shown in Fig. 8. In Fig. 8, the ending symbol 'A' grabs a space symbol if the space column 4 is chosen. The space symbol is grabbed in the end of column 6 and then the base symbol block *B* is shuffled to the right hand side. The *collect space* operator collects separated spaces together. The *collect space* operator is given in Fig. 9. First, one space is randomly chosen from a parent alignment. Then, the separated spaces closed to the chosen space are collected together. This operation is to shuffle the base symbol blocks *B1*, *B2*, *B3* to the right hand side, hereafter the closed

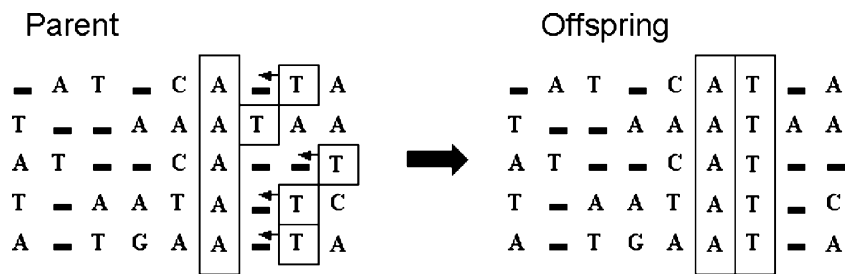
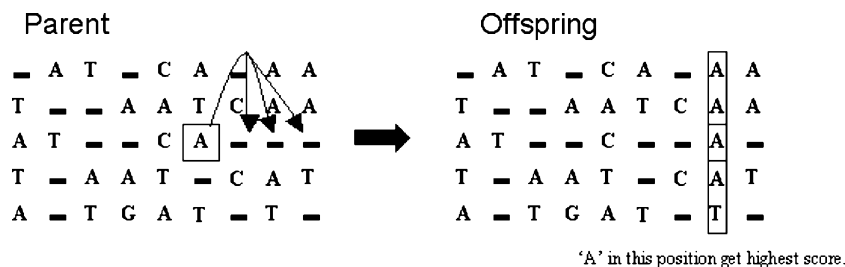
Fig. 10. Example illustrating the procedure of *catch match column* operator.Fig. 11. Example illustrating the procedure of *move to higher score position* operator.



Table 1  
List of data sets

ID	Number of sequences	Mean sequences length (min, max)	Similarity
D1	10	212 (211, 212)	0.9340
D2	8	457 (457, 457)	0.9825
D3	21	122 (122, 122)	0.8934
D4	21	334 (324, 348)	0.2969
PD1	4	199 (186, 208)	0.2931
PD2	6	493 (491, 498)	0.5691
PD3	10	348 (337, 352)	0.5057
PD4	15	151 (145, 163)	0.1726

three space symbols are collected together. In this operator, it also has a parameter  $\lambda$  representing the selected number of rows.

### 3.6.3. Heuristic operators

The Heuristic operators include *catchmatchcolumn* operator and *movetohigherscoreposition* operator. The *catchmatchcolumn* operator randomly selects a match column in a parent alignment. If possible, this operator tries to swap base symbol to space symbol, hereafter a new adjacent match column is generated either to the left or to the right of this selected match column [21]. Fig. 10 shows an example of this operator. In Fig. 10, the 6-th column is a match column with the base symbol 'A', and it is selected to generate adjacent match columns. For the 7-th column, the match column of 'T' can be found to generate a new match column. The *movetohigherscoreposition* operator randomly selects one row in a parent alignment, and then it scans through this row to find all base symbols that have one or more adjacent space symbols. Notice that the selected base symbol can be shifted to the left or right (or both) due to the presence of adjacent space symbols. The fitness value of this alignment is recomputed if the selected base symbol is shifted to neighboring space symbols. The position with the highest fitness value is selected for the selected base symbol. Fig. 11 shows this operator. The *movetohigherscoreposition* operator also has a parameter  $\lambda$  representing the selected number of rows.

### 3.7. Ant colony optimization as local search

In this paper, we use ACO embedded into GA as local search to enhance the search performance. It is noted that a sliding-window ( $N$ ) is used to detect mismatch blocks [8], and then ACO is used to ameliorate these poorly aligned regions. When the best alignment has been found in each generation, the pheromone trail update rule for sequence  $m_i$  ( $i = 1, \dots, k-1$ ) and  $m_j$  ( $j = i+1, \dots, k$ ) is performed as:

$$\tau_{ijl}(t+1) = (1-\rho)\tau_{ijl}(t) + \rho\Delta\tau_{ijl}(t) \quad 1 \leq l \leq N \quad (3)$$

where  $0 < \rho \leq 1$  is a parameter governing the pheromone decay process,  $l$  the position of residue,  $\Delta\tau_{ijl}(t) = \frac{\sum_{i=1}^{k-1} \sum_{j=i+1}^k W_{ij} \times \text{Score}(A_{ij})}{\sum_{i=1}^{k-1} \sum_{j=i+1}^k W_{ij} \times \text{Len}}$  then  $W_{ij}$  is the percent identity between two aligned sequences  $m_i$  and  $m_j$ ,  $A_{ij}$  is the pairwise projection of sequence  $m_i$  and  $m_j$  from the multiple sequence alignment,  $\text{Score}(A_{ij})$  is the number of aligned pairs of residues that are shared between  $A_{ij}$  and the library, and  $\text{Len}$  is the length of this alignment [39]. The global best alignment is defined as the alignment with best fitness value found from the beginning of generation and set as pairwise library [39]. In the ant's generation and activities of ACO, two sequences  $m_i$  and  $m_j$  with mismatch blocks are randomly selected. The ant-decision table for the ant  $s$  selecting the  $l$ -th residue in the mismatch blocks is governed by:

$$\pi(l) = \begin{cases} \arg \left\{ \max_{l=\text{allowed}_s(t)} \left[ \tau_{ijl}(t) \eta_{ijl}^\beta \right] \right\} & \text{when } (q \leq q_0) \\ L & \text{otherwise} \end{cases} \quad (4)$$

Table 2  
The comparison of the proposed algorithm, ClustalW, genetic algorithm without ACO, central-star algorithm, and Horng's genetic algorithm

ID	The proposed GA-ACO algorithm	ClustalW	Genetic algorithm without ACO as local search	Central-star	Horng's genetic algorithm [40]
D1	18627	18627	18627	18627	18627
D2	25343	25343	25343	25343	25343
D3	47889	47889	47889	47889	47889
D4	84394	81769	81769	81760	81769
PD1	12585	12418	12481	12273	12418
PD2	89775	89634	89693	89388	89634
PD3	193823	193632	193625	192969	193632
PD4	166982	161654	166135	160059	166573

where  $\eta_{ijl}$  is the heuristic information and is set as  $\eta_{ijl} = -\max[C(m_{il}, m_{jl})1]$ ,  $\beta$  a parameter representing the importance of heuristic information,  $q$  a random number uniformly distributed in  $[0, 1]$ ,  $q_0$  a pre-specified parameter ( $0 \leq q_0 \leq 0.1$ ),  $\text{allowed}_s(t)$  is the set of ordered and feasible residues for the ant  $s$  at time  $t$ . The probability distribution is given by:

$$P(t) = \begin{cases} \frac{\tau_{ijl}(t)\eta_{ijl}^\beta}{\sum_{u \in \text{allowed}_s(t)} \tau_{iju}(t)\eta_{iju}^\beta} & \text{if } l \in \text{allowed}_s(t) \\ 0, & \text{otherwise;} \end{cases} \quad (5)$$

In finding feasible solutions, ants perform online step-by-step pheromone update rule as:

$$\tau_{ijl}(t+1) \leftarrow (1 - \psi)\tau_{ijl}(t) + \psi\Delta\tau_s \quad (6)$$

where  $0 < \psi \leq 1$  is a constant, and  $\Delta\tau_s = 1/k|C(m_{il}, m_{jl})|$  is found by the ant  $s$ .

#### 4. Simulation and results

In simulation, we need to identify a set of parameters. We performed the simulation with various values, and the results are all similar. Experiments were conducted on PCs with P4 3 GHz processor. In the following simulations, we keep the following values as default:  $\rho = 0.1$ ,  $\psi = 0.1$ ,  $q_0 = 0.8$ ,  $\beta = 2$ , number of ant = 20, population size = 50, and  $g_{\max} = 5000$ . For genetic operators, the sexual reproduction probability ( $P_c$ ) is set as 0.5 and the mutation probability ( $P_m$ ) is 0.05. Thereafter, they are equi-probable for selecting corresponding operators in sexual reproduction operators and mutation operators. In simulation, the data sets used in the experiments are SWISS-PROT benchmark alignment database [22]. The data sets D1, D2, D3, and D4 are DNA or RNA types. The data sets from D1 to D3 are very similar but D4 data set has a poor similarity measure. The data sets PD1, PD2, PD3, and PD4 are protein types. The information for all data sets is shown in Table 1. For comparison, the fitness value is used to evaluate the search performance. The match, mismatch, and space scores are +2, -1, and -2, respectively, for DNA and RNA sequences. The scoring matrix and the space score are PAM250 and -1, respectively, for protein sequences [22]. In this experiment,

each test data is running for 10 -imes to average the results. These alignments were also constructed by using ClustalW [7], Gusfield's central-star algorithm [35], GA without ACO as local search, and the proposed GA-ACO algorithm. We also compare the simulation results with a genetic algorithm proposed by Horng et al. [40]. It is noted that the algorithm of GA without ACO uses the same genetic operators and the same CPU time requirements as in the proposed GA-ACO algorithm. The best results obtained by the proposed GA-ACO algorithm are shown from Figs. 12–19. Table 2 tabulates all simulation results. When the similarity of data set is high, all algorithms almost get the same performance. When the similarity of data set is low, the proposed GA-ACO algorithm has much better performance than other algorithms. It is clearly evident that the proposed GA-ACO algorithm indeed has the best results for all data sets.

#### 5. Conclusions

Most genetic algorithms have focused on genetic operators, crossover and mutation operators, for multiple sequence alignment. In this paper, we present a novel algorithm of genetic algorithm with ant colony optimization for multiple sequence alignment. In the proposed GA-ACO algorithm, ACO as local search is embedded into GA to escape from local optima and ameliorate the search performance. From simulation results, it is shown that the proposed algorithm can improve search performance and outperform other existing algorithms.

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#### Appendix

Figs. 12–19.



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HCV2L1A10  gtgtgacctggtacatcaaggcgaggctggtccctggggcggcgtacgctttctacggcg
HCV2L3A5    gtgtgacctggtacatcaaggcgaggctggtccctggggcggcgtatgctttctatggcg
HCV2L3A7    gtgtgacctggtacatcaaggcgaggctggtccctggggcggcgtacgctttctacggcg
HCV2L3A9    gtgtgacctggtacatcaaggcgaggctggtccctggggcggcgtacgctttctacggcg
HCV2L3B1    gtgtgacctggtacatcaaggcgaggctggtccctggggcggcgtacgctttctacggcg
HCV2L3B2    gtgtgacctggtacatcaaggcgaggctggtccctggggcggcgtacgctttctacggcg
HCV2L3C1    gtgtgacctggtacatcaaggcgaggctggtccctggggcggcgtacgctttctacggcg
HCV2L3C8    gtgtgacctggtacatcaaggcgaggctggtccctggggcggcgtacgctttctacggcg
HCV2L3D4    gtgtgacctggtacatcaaggcgaggctggtccctggggcggcgtacgctttctacggcg
HCV2L3E6    gtgtgacctggtacatcaaggcgaggctggtccctggggcggcgtacgctttctacggcg
*****.**.*****.***

HCV2L1A10  tatggccgctgctcctgctcctgttggcggtgccaccacgtgcatacgccatggaccggg
HCV2L3A5    tatggccgctgctcctgctcctgttggcggtgccaccacgtgcatacgccatggaccggg
HCV2L3A7    tatggccgctgctcctgctcctgttggcggtgccaccacgtgcatacgccatggaccggg
HCV2L3A9    tatggccgctgctcctgctcctgttggcggtgccaccacgtgcatacgccatggaccggg
HCV2L3B1    tatggccgctgctcctgctcctgttggcggtgccaccacgtgcatacgccatggaccggg
HCV2L3B2    tatggccgctgctcctgctcctgttggcggtgccaccacgtgcatacgccatggaccggg
HCV2L3C1    tatggccgctgctcctgctcctgttggcggtgccaccacgtgcatacgccatggaccggg
HCV2L3C8    tatggccgctgctcctgctcctgttggcggtgccaccacgtgcatacgccatggaccggg
HCV2L3D4    tatggccgctgctcctgctcctgttggcggtgccaccacgtgcatacgccatggaccggg
HCV2L3E6    tatggccgctgctcctgctcctgttggcggtgccaccacgtgcatacgccatggaccggg
*****.*****

HCV2L1A10  agatggctgcatcgctgcggaggcgcggtccttgtgggtctgatactcttgacctgtcac
HCV2L3A5    agatggc-gcatcgctgcggaggcgcggtccttgtgggtctgatactcttgacctgtcac
HCV2L3A7    agatggctgcatcgctgcggaggcgcggtccttgtgggtctgatactcttgacctgtcac
HCV2L3A9    agatggctgcatcgctgcggaggcgcggtccttgtgggtctgatactcttgacctgtcac
HCV2L3B1    agatggctgcatcgctgcggaggcgcggtccttgtgggtctgatactcttgacctgtcac
HCV2L3B2    agatggctgcatcgctgcggaggcgcggtccttgtgggtctgatactcttgacctgtcac
HCV2L3C1    agatggctgcatcgctgcggaggcgcggtccttgtgggtctgatactcttgacctgtcac
HCV2L3C8    agatggctgcatcgctgcggaggcgcggtccttgtgggttctgatactcttgacctgtcac
HCV2L3D4    aggtggctgcatcgctgcggaggcgcggtccttgtgggtctgatactcttgacctgttac
HCV2L3E6    agatggctgcatcgctgcggaggcgcggtccttatcggtctgatactcttgacctgtctc
**.*.***.*****.***.*.***.*****.***.*

HCV2L1A10  cacactataaagtgttcctcgctaagctcata
HCV2L3A5    cacactataaagtgttcctcgctaagctcata
HCV2L3A7    cacactataaagtgttcctcgctaagctcata
HCV2L3A9    cacactataaagtgttcctcgctaagctcata
HCV2L3B1    cacactataaagtgttcctcgctaagctcata
HCV2L3B2    cacactataaagtgttcctcgctaagctcata
HCV2L3C1    cacactataaagtgttcctcgctaagctcata
HCV2L3C8    cgcactataaagtgttcctcgctaagctcata
HCV2L3D4    cgcactataaagtgttcctcgccaagctcata
HCV2L3E6    cacactataaagtgttcctcgctaagctcata
*.*.*****.***.*****

```

Fig. 12. Alignment result of data set D1 by the proposed algorithm. An asterisk is used to indicate a match column.

```

AB023276      acttcaggacggggacaacagttggaaacgactgctaatacccgatgtgccgcaaggtga
AB023278      acttcaggacggggacaacagttggaaacgactgctaatacccgatgtgccgcaaggtga
AB023279      acttcaggacggggacaacagttggaaacgactgctaatacccgatgtgccgcaaggtga
AB023283      acttcaggacggggacaacagttggaaacgactgctaatacccgatgtgccgcaaggtga
B023284      acttcaggacggggacaacagttggaaacgactgctaatacccgatgtgccgcaaggtga
AB023285      acttcaggacggggacaacagttggaaacgactgctaatacccgatgtgccgcaaggtga
AB023286      acttcaggacggggacaacagttggaaacgactgctaatacccgatgtgccgcaaggtga
AB023287      acttcaggacggggacaacagttggaaacgactgctaatacccgatgtgccgcaaggtga
*****

AB023276      aacctaattggcctggagaagagcttgcgtctgattagctagtgtggtggggtaaaggcct
AB023278      aacctaattggcctgaagaagagcttgcgtctgattagctagtgtggtggggtaaaggcct
AB023279      aacctaattggcctggagaagagcttgcgtctgattagctagtgtggtggggtaaaggcct
AB023283      aacctaattggcctgaagaagagcttgcgtctgattagctagtgtggtggggtaaaggcct
B023284      aacctaattggcctgaagaagagcttgcgtctgattagctagtgtggtggggtaaaggcct
AB023285      aacctaattggcctgaagaagagcttgcgtctgattagctagtgtggtagggtaaaaggcct
AB023286      aacctaattggcctgaagaagagcttgcgtctgattagctagtgtggtagggtaaaaggcct
AB023287      aacctaattggcctgaagaagagcttgcgtctgattagctagtgtggtagggtaaaaggcct
*****

AB023276      accaaggcgacgatcagtagctggctctgagaggatgagcagccacactgggactgagaca
AB023278      accaaggcgacgatcagtagctggctctgagaggatgagcagccacactgggactgagaca
AB023279      accaaggcgacgatcagtagctggctctgagaggatgagcagccacactgggactgagaca
AB023283      accaaggcgacgatcagtagctggctctgagaggatgagcagccacactgggactgagaca
B023284      accaaggcgacgatcagtagctggctctgagaggatgagcagccacactgggactgagaca
AB023285      accaaggcgacgatcagtagctggctctgagaggatgagcagccacactgggactgagaca

```

Fig. 13. Alignment result of data set D2 by the proposed algorithm.

AB023286 accaaggcgacgatcagtagctgggtctgagaggatgagcagccacactgggactgagaca  
 AB023287 accaaggcgacgatcagtagctgggtctgagaggatgagcagccacactgggactgagaca  
 \*\*\*\*\*  
  
 AB023276 cggcccagactcctacgggaggcagcagtggggaattttccgcaatgggcgaaagcctga  
 AB023278 cggcccagactcctacgggaggcagcagtggggaattttccgcaatgggcgaaagcctga  
 AB023279 cggcccagactcctacgggaggcagcagtggggaattttccgcaatgggcgaaagcctga  
 AB023283 cggcccagactcctacgggaggcagcagtggggaattttccgcaatgggcgaaagcctga  
 B023284 cggcccagactcctacgggaggcagcagtggggaattttccgcaatgggcgaaagcctga  
 AB023285 cggcccagactcctacgggaggcagcagtggggaattttccgcaatgggcgaaagcctga  
 AB023286 cggcccagactcctacgggaggcagcagtggggaattttccgcaatgggcgaaagcctga  
 AB023287 cggcccagactcctacgggaggcagcagtggggaattttccgcaatgggcgaaagcctga  
 \*\*\*\*\*  
  
 AB023276 cggagcaacgcccgctgagggaggaaggcttttggattgtaaacctcttttctcaaggaa  
 AB023278 cggagcaacgcccgctgagggaggaaggcttttggattgtaaacctcttttctcaaggaa  
 AB023279 cggagcaacgcccgctgagggaggaaggcttttggattgtaaacctcttttctcaaggaa  
 AB023283 cggagcaacgcccgctgagggaggaaggcttttggattgtaaacctcttttctcaaggaa  
 B023284 cggagcaacgcccgctgagggaggaaggcttttggattgtaaacctcttttctcaaggaa  
 AB023285 cggagcaacgcccgctgagggaggaaggcttttggattgtaaacctcttttctcaaggaa  
 AB023286 cggagcaacgcccgctgagggaggaaggcttttggattgtaaacctcttttctcaaggaa  
 AB023287 cggagcaacgcccgctgagggaggaaggcttttggattgtaaacctcttttctcaaggaa  
 \*\*\*\*\*  
  
 AB023276 gaagtctgacggtacttgaggaatcagcctcggctaactccgtgccagcagccgcggtga  
 AB023278 gaagtctgacggtacttgaggaatcagcctcggctaactccgtgccagcagccgcggtga  
 AB023279 gaagtctgacggtacttgaggaatcagcctcggctaactccgtgccagcagccgcggtga  
 AB023283 gaagtctgacggtacttgaggaatcagcctcggctaactccgtgccagcagccgcggtga  
 B023284 gaagtctgacggtacttgaggaatcagcctcggctaactccgtgccagcagccgcggtga  
 AB023285 gaagtctgacggtacttgaggaatcagcctcggctaactccgtgccagcagccgcggtga  
 AB023286 gaagtctgacggtacttgaggaatcagcctcggctaactccgtgccagcagccgcggtga  
 AB023287 gaagtctgacggtacttgaggaatcagcctcggctaactccgtgccagcagccgcggtga  
 \*\*\*\*\*  
  
 AB023276 atacggggaggcaagtggttatccggaattattgggcgtaaaagcgtccgcaggtgggtcag  
 AB023278 atacggggaggcaagcgttatccggaattattgggcgtaaaagcgtccgcaggtgggtcag  
 AB023279 atacggggaggcaagcgttatccggaattattgggcgtaaaagcgtccgcaggtgggtcag  
 AB023283 atacggggaggcaagcgttatccggaattattgggcgtaaaagcgtccgcaggtgggtcag

Fig. 13. (Continued)

```

B023284   atacggggaggcaagcgttatccggaattattgggcgtaaagcgtccgcaggtggtcag
AB023285   atacggggaggcaagcgttatccggaattattgggcgtaaagcgtccgcaggtggtcag
AB023286   atacggggaggcaagcgttatccggaattattgggcgtaaagcgtccgcaggtggtcag
AB023287   atacggggaggcaagcgttatccggaattattgggcgtaaagcgtccgcaggtggtcag
          *****
          .

AB023276   ccaagtctgccgtcaaatacaggttgcttaacgacctta
AB023278   ccaagtctgctgtcaaatacaggttgcttaacgacctta
AB023279   ccaagtctgccgtcaaatacaggttgcttaacgacctta
AB023283   ccaagtctgccgtcaaatacaggttgcttaacgacctta
B023284   ccaagtctgccgtcaaatacaggttgcttaacgacctta
AB023285   ccaagtctgccgtcaaatacaggttgcttaacgacctta
AB023286   ccaagtctgccgtcaaatacaggttgcttaacgacctta
AB023287   ccaagtctgccgtcaaatacaggttgcttaacgacctta
          *****
          .

```

Fig. 13. (Continued).

```

1  aatctgtggggcttcttaataaccaccggtggcgggggcagactttctagcagccttggaa
2  aatctgtggggcttcttaataaccaccggtggcgggggcagactttcttgcagccttggaa
3  aatctgtggggcttcttaataaccaccggttagcgggggcggactttctggcggccttggaa
4  aatctgtggggcttcttaataaccaccggtggcgggggcagactttctagcagccttggaa
5  aatctgtggggcttcttaataaccaccggttagcgggggcggactttctggcggccttggaa
6  aatctgtggggcttcttaataaccaccggtggcgggggcggactttctggcggccttggaa
7  aatctgtggggcttcttgataccaccggttagcgggggcagactttctagcggccttggaa
8  aatctgtggggcttcttaataaccaccggtggcgggggcggactttctggcggccttggaa
9  aatctgtggggcttcttaataaccaccggtggcgggggcagactttctagcagccttggaa
10 aatctgtggggcttcttaataaccaccggtggcgggggcggactttctggcggccttggaa
11 aatctgtggggcttcttgataccaccggtggcgggggcagactttctggcggccttggaa
12 aatctgtggggcttcttaataaccaccggtggcgggggcggactttctggcggccttggaa
13 aatctgtggggcttcttaataaccaccggtggcgggggcagactttctagcagccttggaa
14 aatctgtggggcttcttaataaccaccggtggcgggggcagactttctagcagccttggaa
15 aatctgtggggcttcttaataaccaccggtggcgggggcagactttctagcagccttggaa
16 aatctgtggggcttcttaataaccaccggtggcgggggcagactttctggcggccttggaa
17 aatctgtggggcttcttaataaccaccggtggcgggggcagactttctagcagccttggaa
18 aatctgtggggcttcttaataaccaccggtggcgggggcggactttctggcggccttggaa
19 aatctgtggggcttcttaataaccaccggttagcgggggcggactttctggcggccttggaa
20 aatctgtggggcttcttaataaccaccggtggcgggggcagactttctagcagccttggaa
21 aatctgtggggcttcttaataaccaccggtggcgggggcggactttctggcggccttggaa

*****.*****.*****.***.*****.*****.***.*****

1  gcgagttgctttctgggggccttagcaccagttgattttctagcggttatttagttcta
2  gcgagttgctttctgggggccttagcaccagttgattttctagcggttatttagttcta
3  gcgagttgctttctgggggccttagcaccagtagactttctagcagttatttagttcta
4  gcgagttgctttctgggggccttagcaccagttgattttctagcggttatttagttcta
5  gcgagttgctttctgggggccttagcaccagtagactttctagcagttatttagttcta
6  gcgagttgctttctgggggccttagcaccagtagactttctagcggttatttagttcta
7  gcgagttattttctgggggccttagcaccagtagactttctagcagttatttagttcta
8  gcgagttgctttctgggggccttagcaccagtagactttctagcggttatttagttcta
9  gcgagttgctttctgggggccttagcaccagttgattttctagcggttatttagttctagc
10 gcgagttgctttctgggggccttagcaccagtagactttctagcggttatttagttctagc
11 gcgagttattttctgggggccttagcaccagtagactttctagcagttatttagttctagc
12 gcgagttgctttctgggggccttagcaccagtagactttctagcagttatttagttctagc
13 gcgagttgctttctgggggccttagcaccagttgattttctagcggttatttagttctagc
14 gcgagttgctttctgggggccttagcaccagttgattttctagcggttatttagttctagc
15 gcgagttgctttctgggggccttagcaccagttgattttctagcggttatttagttctagc
16 gcgagttattttctgggggccttagcaccagtagactttctagcggttatttagttctagc
17 gcgagttgctttctgggggccttagcaccagttgattttctagcggttatttagttctagc
18 gcgagttactttctgggggccttagcaccagtagactttctagcggttatttagttctagc
19 gcgagttgctttctgggggccttagcaccagtagactttctagcagttatttagttctagc
20 gcgagttgctttctgggggccttagcaccagttgattttctagcggttatttagttctagc
21 gcgagttgctttctgggggccttagcaccagtagactttctagcggttatttagttctagc

*****.*****.*****.*****.*****.*****.*****.*****

```

Fig. 14. Alignment result of data set D3 by the proposed GA-ACO algorithm.

```

1  c a t t t c t --- t t --- t t - a - g g g a t - t - - t - t a - a - a a g t t g t c - - t t - t t - - c t - - t - -
2  c a t t t c t --- t t --- t t - a a g g g - t - t - - t - t a - a - a a t t g t c - - t t - t t - - t - - t - -
3  c a t t t c t --- t t --- t t - a a g g g - t - t - - t - t a - a - a a t t g t c - - t t - t t - - c t - - t - -
4  c a t t t - t --- t t c - - t t - a a g t g - t - t - - t - t g - g - t a t t t a t c t - t t - t t - - c t - - t - -
5  c a t t t - t --- t g c - - t t - a t g t a - t - t - - t a t a g t - g g g t t g t c t - t t - t t g a c t - - t - -
6  c a t t t c t --- t t --- t g - a a g t g - a - t - - t - t g - a - g a t t t a t c t - t t - t t - - c t - - t - -
7  c a t t t c t --- t t --- t t - a a g g g - t - t - - t - t a - a - a a t t g t c - - t t - t t - - c t - - t - -
8  c a t t t c t --- t t --- t t - a t g - - t - t - - g - a g - a - t a t t t g t c t g t t - t t - - c t - - t - -
9  c a t t t - t --- t a - - - c t - a t g t g - t - t g a t - t g - t - g g a t t g t c t - t t - t t - - c t - - t - -
10 c a t t t c t t - - t t a - - t t - g a g t g - a - a - - g - a a g a g a t t t t g t c - - t t g t t - - t t g a t - -
11 c a t t t - t --- t c - - - t t - a - g t g - t - t - - t - t g - g - t a t t t a t c t - t t - t t - - c t - - t - -
12 c a t t t c t --- t t --- t - - a a g g g - t - t - - t - t a - a - a a t t g t c - - t t - t t - - c t - - t - -

```

Fig. 15. Alignment result of data set D4 by the proposed GA-ACO algorithm.



```

13  ctttt-t---ttc--tt-a-gtg-t-t--t-tg-g-tatttatct-tt-tt--ct--t--
14  catttct---tt---tg-a-gggat-t--t-ta-a-aagttgtc--tt-tt---t--t--
15  catttct---tt---tg-a-gggat-t--t-ta-a-aagttgtc--tt-tt--ct--t--
16  catttct---tt---tt-atg---t-t--g-ag-a-tatttgtctttt-tt--ct--t--
17  catttct---tt---tt-aaggg-t-t--t-ta-a-aaattgtc--tt-tt--ct--t--
18  ctttt-t---tc---tt-a-gtg-t-t--t-tg-g-tatttatct-tt-tt--ct--t--
19  catttct---ttggatg-aagag-a-t--t-tg-g-g-tttgtt--tt-tt--ct--t--
20  catttct---tt---t--aaggg-t-t--t-ta-a-aaattatc--tt-tt--ct--t--
21  ctttttagattg--ttgaagag-taggt-t-tg-a----ttgt---tt-tt--at--taa
    *****.*...*.....*.....**.*...**.*...*...*...

1   --tt-c-t-t-g--tg-tatt-g-attt-tt-tt-t-taataaaattctttatgagctag
2   --ct-t-----g--tg-tatt-g-attt-tt-tt-t-taataaaattctttatgagctat
3   --tt-tat-t-g--tg-tatt-g-attt-tt-tt-t-taataaaattctttatgagctat
4   --tt-gcc-g-g--ta--att---attt-tt-tt-t-taataaaattctttatgaacaac
5   --ttcttt-t-gaaggttatt---attt-tt-tt-t-taataaaattctttatcgacaac
6   --tt-gag---ga-t--tat--g-attt-tt-ttgt-taataaaattctttatggccaac
7   --tt-tat-t-g--tg-tatt-g-attt-tt-tt-t-taataaaattctttatgagctat
8   --tt-gaa-g-g--t--tatt---attt-tt-tt-t-taataaaattctttatggacaac
9   --tt-gaa-g-g--t--tatt---attt-tt-tt-t-taataaaattctttat-agaaaa
10  --tt-tttct-t--t--tgtt---attt-tt-tt-tgtataaaattctttatgctcaaa
11  --tt-gaa-g-g--t--tatt---attt-tt-tt-t-ttataaaattttttatgaagaac
12  --tt-tat-t-g--tg-tatt-g-attt-tt-tt-t-taataaaattctttatgagctat
13  --tt-gaa-g-g--t--tatt---attt-tt-tt-t-taataaaattttttatgaagaac
14  --ct-t-----g--tg-tatt-g-attt-tt-tt-t-taataaaattctttatgagctat
15  --tt-c-t-t-g--tg-tatt-g-attt-tt-tt-t-taataaaattctttatgagcttt
16  --tt-gaa-g-g--t--tatt---attt-tt-tt-t-taataaaattctttatggacaac
17  --tt-tat-t-g--tg-tatt-g-attt-tt-tt-t-taataaaattctttatgagctat
18  --tt-gaa-g-g--t--tatt---attt-tt-tt-t-taataaaattttttatgaagaac
19  --ttgta---ga-t--tat--g-atttgtt-tg-t-taataaaattctttatggccaac
20  --tt-tat-t-g--tg-tatt-g-attt-tt-tt-t-taataaaattctttatgagctat
21  agtt-ttt-tggact--tttaggaatttattatt-t-taataattttttatgaaggggatg
    ...*.....*.....*****.*.*.*.*.*.....*...*.....

1   caatcatgcga-tctcatttgaaat-gtttagaattatcc-tgcat-t-cgaagatatg
2   caatcatgcga-tctcatttgaaat-gtttggattatcc-tgtgat-t-cgaagatatg
3   caatcatgcga-tctcatttgaaat-gtttggattatcc-tgtgat-t-cgaagatatg
4   agttgaggata-gatcttttgaaat-gtttggagtatcc-ag-gat-tgagaagata--

```

Fig. 15. (Continued)



```

20 ccct--tttttgattggatactctcaacggaaatcagattttagagaaactatccaatca
21 cgcg--aatgcgattggatgattttttgaaattcggattaattaaatgctatccaatca
   .....*****.....**.**.***.....*...*.*****

1  gaatgcaaatctgaattgtatttggataagatgca-a-agat-t-tt-a-a-ataattaa
2  gaatgcatatctgaattgtatttggataacatgcg-a-agat-t-tt-a-a-ataattaa
3  gaatgcatatctgaattgtatttggataacatgcg-a-agat-t-tt-a-a-ataattaa
4  gaatcaaaatcttcacaaaatttggataat-tgggga-atat-t-tt-a-a-a-ag--aa
5  gatttgagatctccgatcaatttggataat-ta-g-a-t-at-tatt-a-a-aaaa--aa
6  gaagcgagatctaaattaaatgtggatt-gaagca-atacat-t-a--a-a-aaaa--aa
7  gaatgcatatctgaattgtatttggataacatgcg-a-agat-t-tt-a-a-ataattaa
8  gaatcaaaatcttaattaaatttaggataat-tg-g-ata-atat-tt-a-a-aaaa--aa
9  aatttggaaatctgtgagcaatttggataat-ta-g-a-t-at-tattca-a-a-aa--aa
10 gattgaatatctcaattaaattgaggataag-tgtgaa-agat-t-tt-a-aga-agcggga
11 gaatcaaaatcttaattaaatttggataggagg-gta-atat-t-tt-a-a-a-ag--aa
12 gaatgcatatctgaattgtatttggataacatgcg-a-agat-t-tt-a-a-ataattaa
13 gaatcaaaatcttaattaaatttggataggagg-gta-atat-t-tt-a-a-a-ag--aa
14 gattgcatatctaaattgtatttggataagataag-a-agat-t-tt-a-a-ataattaa
15 gaatgcaaatctgaaatgtatttggataagatgcg-a-agat-t-tt-a-a-ataattaa
16 gaatcaaaatcttaattaaatttaggataat-tg-g-ata-atat-tt-a-a-a-aa--aa
17 gaatgcatatctgaattgtatttggataacatgcg-a-agat-t-tt-a-a-ataattaa
18 gaatcaaaatcttaattaaatttggataggagg-gta-atat-t-tt-a-a-a-ag--aa
19 gaagcgagatctaaattaaatgtggatt-g--gcgca-atacat-ta-a-a-aaaa--aa
20 gaatgcatatctgaattgtatttggataacatgcg-a-agat-t-tt-a-a-ataattaa
21 gaatcgatatctggattaatttggataatatccc-aga-at-t-ta-aga-atgat-at
   .*.....***.....*..****.....*...*...*...*...*.....

1  ag--a-tctttgccccagtgaaatataa-tgattaaa-taaacaaata-aa-at-ta-aa
2  ag--a-tctttgcccccaatgaatataa-tgattaaa-caaacaaata-aa-aa-ta-aa
3  ag--a-tctttgcccccaatgaatataa-tgattaaa-caaacaaata-aa-aa-ta-aa
4  aggaa-tcttttcccaaaa-gactataa-tcattaaaacaaa-aaata-aaaaacta-a-
5  agaga-tctttt-ccccaaa-gactataa-tcattaaaacaaa-aa-ta-aataa-tctaa
6  agcaa-tcatt-ccccaaa-gccaataa-tcaaaaaa-caaa-aaata-aa-a--ta-ac
7  ag--a-tctttgcccccaatgaatataa-tgattaaa-canacaaata-aa-aa-ta-aa
8  aggaa-tctttaccta-aa-gcctataa-tcattaaaacaaa-aaataaaaaaacta-at
9  agaga-tctttt-ccccaaa-gactataa-tcattaaaacaaa-ata-a-aa-aa-tctaa
10 a---a-tcttccccccatccgatataa-tcaa-aaatcaaa-a--tc-aa-aa-ta-ac
11 aggaa-tctttt-ccccaaa-ggctataa-tcattaaaacaaa-aaata-aa-aa--a-ac

```

Fig. 15. (Continued).

P41048 MQARGTVKVQGDAAKVDGKMSTGOHSHHQHLNSTQANATTTALEYRAMNRPLYRGPISHNI  
P41049 MQARGTVKVQGDAENVGDKMSTGOHPHHQLHNSTQANATTTALEYRAMNRPLYRGPISHNI  
P25027 M--KD--K---AP-V-S--S--QQDHFSR--GGAVGGKPIS-DVRGTSRPFYRKPVSHNT  
P41045 M-SRS--K---E--V-S--P--NLSQQR--G-DVRSAGIS-GF-S-S-PIYGRGLNHSA  
\*.\*\*\*\*\*  
  
P41048 ISEMAEGFYVLSSGGYKKLFIPSKDVYALMQNVGMHLTEEEFHDLRVIGQSEPQNADELS  
P41049 ISEMAEGFYVLSSGGYKKLFIPSKDVYALMQNVGMHLTEEEFHDLRVIGQSEPQNADELS  
P25027 IAELAEGFRVLSNGQKTISI PMKEVSALMASVGLHLSDEEFHEVMRVFGQGEQTINTEELS  
P41045 SAELQEGYRIITGGQKANI ISDKDLFKA IHSCGLHTSEEVEVDLLRVVHQDERT-LG-LE  
..\*.\*.\*.\*.\*.\*.\*.\*.\*.\*.\*.\*.\*.\*.\*.  
  
P41048 FSDFLLLMTREVDDTMADELRSAFFHYDKYKTGYVTRKQFTL FATLGERSTPEELEELL  
P41049 FSDFLLLMTREVDDTMADELRSAFFHYDKHKTGYVTRKQFTL FATLAERSTPEELEELL  
P25027 FKDFLSLMMCEVDDTMLEEMRGAF LHYDKQKTGFVTCKQFTL FATGGECSTPEEVEELL  
P41045 FPFEFMLMTKGIDEASIAEMRRPFSVLDAKTGVITTKQFTL FVSSGEHSSAELEELM  
\*.  
  
P41048 AVAEVDETDDKIDYNRFVNELTSRVNCM  
P41049 AVAEVDETDDKIDYNRFVNELTSRVNCM  
P25027 TIAEQDETDDKIDYNRFINELIHRNFNM  
P41045 LLAEETSEELEVVDYNKLINELAILLNKM  
\*\*\*.\*.\*.\*.\*.\*.\*.\*.\*.\*.\*.

Fig. 16. Alignment result of data set PD1 by the proposed GA-ACO algorithm.

Fig. 17. Alignment result of data set PD2 by the proposed GA-ACO algorithm.





Fig. 18. Alignment result of data set PD3 by the proposed GA-ACO algorithm.



Fig. 19. Alignment result of data set PD4 by the proposed GA-ACO algorithm.

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P14822  ADEFGEIVGPLRQTLKARMG-NYFDEDTVSAWASLVAVVQASL-----
Q17156  ASEFGWIMKPIREVLMERMG-QFYDPSFVDAWGKLIGVVQASL-AREQ
P25165  AEEFGKIVGPFRAVLIRMG-DYFDEEIVAAWAALIAVVQAAL-----
P14821  GDAFGAIVEPMKETLKARMG-NYYSDDVAGAWAALVGVVQAAL-----
Q17155  PQVFGKINGPMDLLLKQRMG-KYYNRETANAWQLVGVVQAAL-TTPN
P14395  GDAFGSIIIEPMKETLKARMG-SYYSDDVAGAWAALIGVVQAAL-----
Q26269  SFEFQWALVPLLEVLRLRERLGRNRYRQETEEAWTKLVSVIQATLDDRKR
AAB24577 SFEFQWALVPLLEVLRLRERLGRNRYRQETEEAWTKLVSVIQATLDDRKR
Q17157  DDKFAWIKKPLEALLKNK-C-NC-KQDVVNAWCKLIDVICAVL--REG
...*.....*.....*.....*.....*.....*.....*.....*.....

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Fig. 19. (Continued).

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