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Negatively Correlated Search Based on Multi-neighborhood Generation Strategy and Its Application in Exit Layout for Crowd Evacuation

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Abstract

The performance of negatively correlated search algorithm is directly related to its population diversity and local search capability. To improve the searching ability of negatively correlated search algorithm, this paper put forward a negatively correlated search based on multi-neighborhood generation strategy (NCS-MGS). In this algorithm, each individual generates three individuals, and then only the individual with the best fitness is selected as the offspring population. Thus, this algorithm can not only maintain the global search capability of the original algorithm, but also enhance its local search capability. Compared with the other nine algorithms on 20 test functions of CEC2005, the simulation results show that the overall performance of NCS-MGS is the best. In addition, the proposed algorithm is apply to solve the building exit layout optimization problem to shorten the crowd evacuation time. The experimental results show that the proposed algorithm can provide a better scheme and a reliable solution for the actual crowd evacuation problem.

Keywords

Negatively correlated search; Local search; Crowd evacuation; Exit layout optimization.

1. INTRODUCTION

With the development of data analysis rapidly, the challenge of complex optimization problems have become harder than ever. In the field of complex system modeling, how to select the optimal parameters to obtain higher accuracy can be regarded as a kind of optimization problem with the characteristics of discontinuity, indiscernibility, multi-modality, multi-region, etc. The traditional optimization methods, such as gradient descent method [1] and Lagrange relaxation method [2], have been greatly challenged in solving such challenging optimization problems. To solve complex optimization problems, many intelligent optimization algorithms are constantly being proposed, such as genetic algorithm (GA) [3], particle swarm algorithm (PSO)[4], differential evolution (DE) [5]and artificial bee colony algorithm (ABS)[6]. These intelligent optimization algorithms have simple principle, strong robustness and no special requirements for objective function and constraint conditions. Therefore, this kind of optimization algorithm is considered as an important methods to solve complex optimization problems.

Negatively Correlated Search (NCS) is a meta-heuristic algorithm proposed by Tang et al [7] in 2016, which enhances the search performance with information sharing and collaboration mechanisms. The algorithm has strong global search ability and strong robustness. Niu et al. [8]

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proposed an improved negatively correlated search algorithm inspired by particle swarm optimization (PSO-NCS). Each individual in the PSO-NCS does not need to calculate the Bhattacharyya distance (BD) with all other individuals and only needs to calculate the distance between the mean of the current global best solution and the personal best solution. By doing this, not only the computation time is reduced greatly, but also the performance of the algorithm is optimized. Wang et al. [9] proposed an improved firefly algorithm enhanced by negatively correlated search mechanism (NCFA). NCFA associates fitness with brightness, and fitness is inversely proportional to brightness, resulting in better population diversity. The NCFA has alleviated the problem of premature convergence of FA. As a result, a balance between development and exploration was achieved and the search performance was further improved. Lin et al. [10] applied NCS in deep learning to decide the sizes of the deep belief network (DBN) and the learning rates during the training processes, and it exhibits excellent performance. NCS is also widely used in the field of communication. Focusing on the capacity allocation optimization problem of energy harvesting wireless sensor networks (EH-WSNs) with interfering channels, Jiao et al. [11] adopted negatively correlated search algorithm to optimize the capacity allocation and obtained a good solution. The study verified the potential advantages of the negatively correlated search algorithm in solving the non-convex capacity allocation problem.

However, during selecting individuals, BD was considered as the second criterion. Consequently, the algorithm may discard individual with better fitness, which might result in low accuracy and slow convergence. In order to improve the performance of the algorithm, a negatively correlated search based on multi-neighborhood generation strategy (NCS-MGS) is proposed. In the stage of individual variation, each individual generates three individuals to strengthen the search of its neighborhood, and then only the individual with the best fitness is selected as the offspring individual, which avoids the reduction of population diversity. In order to verify the effectiveness of the algorithm, NCS-MGS is used on 20 test function experiments and compare with other classical optimization algorithms. Finally, the proposed algorithm is applied to the problem of exit layout optimization for crowd evacuation, which shortens the evacuation completion time.

2. NCSMTV

2.1. Standard NCS

The core idea of NCS is a model for implementing the cooperation among individuals in a population. NCS comprises multiple search processes. The search processes are run in parallel to find better solutions, while information is shared to encourage each search process to emphasize the regions that are not covered by others. Bhattacharyya distance [12] is used to determine the difference and correlation between the probability distributions of two search processes. Eq. (1) and Eq. (2) gives the BD for two continuous and discrete probability distributions, respectively:

$$D_B(p_i, p_j) = -\ln\left(\int \sqrt{p_i(\mathbf{x})p_j(\mathbf{x})}\, d\mathbf{x}\right) \tag{1}$$

$$D_B(p_i, p_j) = -\ln\left(\sum_{\mathbf{x}\epsilon\mathbf{X}} \sqrt{p_i(\mathbf{x})p_j(\mathbf{x})}\right) \tag{2}$$

Where p_i and p_j denote the probability density functions of two distribution. In case that the probability density function is not explicitly known, a group of candidate solutions of both distributions can be generated randomly, and the BD can be estimated by using the Bhattacharyya coefficient.

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In addition, the distance between each individual and the association group $Corr_{(p_i)}$ is given by Eq. (3):

$$Corr(p_i) = \min_{j}\{D_B(P_i, P_j) | j \neq i\} \tag{3}$$

Given an existing solution $\mathbf{x}_i$, a new solution $\mathbf{x}_i'$ is generated by Gaussian mutation operator by Eq. (4):

$$x_{id}' = x_{id} + \mathcal{N}(0, \sigma_i) \tag{4}$$

Where x_{id} denotes the dth element of $\mathbf{x}_i$ and $\mathcal{N}(0, \sigma_i)$ denotes a Guassian random variable with zero mean and standard deviation σ_i.

Then, each σ_i is adapted for every epoch iterations according to the 1/5 successful rule suggested in [13], as given in Eq. (5):

$$\sigma_i = \begin{cases} \frac{\sigma_i}{R} & \textbf{if} \quad \frac{c}{epoch} > 0.2 \\ \sigma_i * R & \textbf{if} \quad \frac{c}{epoch} < 0.2 \\ \sigma_i & \textbf{if} \quad \frac{c}{epoch} = 0.2 \end{cases} \tag{5}$$

Where R is a parameter that is suggest to be set beneath 1, and c is the times that a replacement happens during the past epoch iterations.

In NCS, the criteria for individual selection are the small objective function valua $f(\mathbf{x}_i')$ and the large $Corr(p_i')$. NCS integrates the solution quality and correlation between the search processes into one heuristic rules as Eq. (6):

$$\begin{cases} discard \ \mathbf{x}_i, & \textbf{if} \ \frac{f(\mathbf{x}_i')}{Coor(p_i')} < \lambda \\ discard \ \mathbf{x}_i', & \textbf{otherwise} \end{cases} \tag{6}$$

Where $\lambda \epsilon (0, +\infty)$ is a parameter. According Eq. (6), different λ can influence the decision-making and the solution is accepted or dropped. As a result, the search process and the performance of NCS are affected.

The different λ value might be suitable for different search stages as Eq. (7):

$$\lambda_{iter} = \aleph\left(1, 0.1 - 0.1 * \frac{G}{G_{max}}\right) \tag{7}$$

Where the G_{max} is the user-defined total number of iterations for an execution of NCS, and G is the current iterations.

According to Eq. (4) each $\mathbf{x}_i$ uses Gaussian mutation operator to generate a new solution based on normal distribution. The expectation of the distribution expectation is $\mathbf{x}_i$ and the covariance matrix $\mathbf{\Sigma}_i$ is $\sigma_i^2\mathbf{I}$, where I is the identity matrix of size dimensional. Hence, given two solutions $\mathbf{x}_i$ and $\mathbf{x}_j$, the BD given by Eq. (1), (2) can be written as Eq. (8):

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$$D_B(p_i, p_j) = \frac{1}{8}(\mathbf{x}_i - \mathbf{x}_j)^T \mathbf{\Sigma}^{-1}(\mathbf{x}_i - \mathbf{x}_j) + \frac{1}{2} ln\left(\frac{det\mathbf{\Sigma}}{\sqrt{det\mathbf{\Sigma}_i det\mathbf{\Sigma}_j}}\right) \tag{8}$$

Where $\mathbf{\Sigma} = \frac{\mathbf{\Sigma}_i + \mathbf{\Sigma}_j}{2}$.

2.2. NCS-MGS

In the standard NCS, the mutation stage is mainly conducted by the current indiviual combined with its step-size to search its neghborhood. Each individual generates a trial vector by Gaussian mutation operator and calculates its fitness and correlation, and then uses Eq. (6) to select better individuals to enter the next generation, thus guiding population evolution.

In order to improve the ability of negatively correlated search to solve complex optimization problems, this paper proposes a negatively correlated search based on multi-neighborhood generation strategy (NCS-MGS). Based on the Gaussian mutation operator in Eq. (4), each individual $\mathbf{x}_i$ generates three trial vectors $\mathbf{x}'_{i1}$, $\mathbf{x}'_{i2}$, and $\mathbf{x}'_{i3}$ in each iteration, and selects the trial vectors with the best fitness among the three trial vectors. The individual $\mathbf{x}'_i$ is the progeny population of $\mathbf{x}_i$. The proposed algorithm maintains the global search ability of the algorithm while enhancing the local search ability and solution accuracy.

The pesudo-code of NVS-MGS is show in Algorithm 1.

Algorithm 1. Procedures of NCSMTV

Randomly generate an initial population of N individuals.
Evaluate the N individual with respect to the objective function f.
Identify the best individual $\mathbf{x}^*$ in the initial population and store it in BestFound.
Set G $\leftarrow$ 0
While (G<G_{max}) do
  Set $\lambda_t \leftarrow \mathcal{N}\left(1, 0.1 - 0.1 * \frac{G}{G_{max}}\right)$.
  For i = 1 to N do
    Generate three different trial vectors $\mathbf{x}'_{i1}$, $\mathbf{x}'_{i2}$, $\mathbf{x}'_{i3}$ by applying Gaussian mutation operator with σ_i to $\mathbf{x}_i$, from among them, choose the one with the best fitness as the final trial vector $\mathbf{x}'_i$.
    Compute $Corr(p_i)$ and $Corr(p'_i)$
  EndFor
  For i = 1 to N
    If $f(\mathbf{x}'_i) < f(\mathbf{x}^*)$
      Update BestFound with $\mathbf{x}'_i$.
    EndIf
    If $\frac{f(\mathbf{x}'_i)}{Corr(p'_i)} < \lambda_t$
      Update $\mathbf{x}_i$ with $\mathbf{x}'_i$.
    EndIf
  EndFor
  G $\leftarrow$ G +1
  If mod(t, epoch) = 0
    For i = 1 to N
      Update σ_i for each Randomized Local Search according to 1/5 successful rule.

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```
        EndFor
      EndIf
    EndWhile
  Output BestFound
```

The general procedures of NCS-MGS can be summarized as in the following:

Step 1: Initialize N individuals in a population randomly.

Step 2: Evaluate all individuals in the initial population.

Repeat the following steps until a preset termination condition is reached.

Step 3: According to Eq. (4), each individual in the population is subjected to mutation operations to generate three trial vectors and perform fitnesss calculations. Select the individual with the best fitness function values among the three trial vectors as its offspring;

Step 4: Calculate the difference and correlation between individuals by Eqs. (3) and (8);

Step 5: Update the individual enter the next generation by Eq. (6).

3. EXPERIMENTAL RESULT AND ANALYSIS

To verify the performance of the NCS-MGS algorithm, NCS-MGS is compared with nine other algorithms, including GL-25[14], CLPSO[15], CMA-ES[16], SaDE[17], SS[18], Simulated Annealing (SA)[19], Tabu Search (TS)[20], Parallel Hill-Climbing (PHC) and standard Negatively Correlated Search (NCS)[7]. To ensure the reliability of the experimental results, Bonferroni-Dunn [21], Holm, Hochberg[22] and Friedman[23] tests were used to make a statistical analysis for the results, with the significance level set at 5%. The best results obtained in the experiment are indicated in bold type.

3.1. Experimental Parameter Setting

All experimental parameters of this experiment are the same as those in the literature [7], specifically the population size of NCS-MGS is set to 10. The population size of CLPSO and SaDE are set to 40 and 50, respectively. The population size of PHC is set to 10. SA and TS were implemented with the same Gaussian mutation operator, and a deterministic cooling schedule was used to control the Temperature of SA. The TS in [20] was used and the 5 most recently generated solutions were kept in the Tabu list. In this experimental study, the standard CMA-ES was compared. The GL-25 first performs a global search within 25% of the computational budget, and then performs a local search. The global search has a population size of 400, while the local search selects the best 100 solutions. The PHC copied all the NCS, except for the calculation of negative correlations.

This study focuses on multimodal optimization problems. Therefore, 20 test functions numbered F6-F25 in CEC2005 were used in the experimental study [24]. The dimension of each question is set to 30. All algorithms were performed with the same number of fitness function evaluation times, and each algorithm was evaluated 300 thousand times. Each algorithm in this experiment runs independently 25 times on each problem.

3.2. Experimental Results Analysis

Table 1 lists the average results of the 10 algorithms on 20 benchmark multi-modal problems in the form of "mean ± standard deviation". All results are presented in the terms of a function error.

As can be seen from Table 1, none of the 10 algorithms achieved the best results on 20 test functions (in terms of function error). NCS-MGS algorithm has achieved better optimization results than other algorithms on F12 and F14. In the test functions F6, F7, F8, F10, F11, F12,

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F13, F14, F15, F16, F17, F18, F19, F20, F21 and F24, the results of NCS-MGS optimization are in the forefront. Among them, F6, F11, F12, F16, F17, F18, F19, F20, F21 and F24 have the same structural characteristics: they are composed of multiple local optima and in the search space, the local optima and the global optima are far apart. The search algorithm may well fall into the local optima of these test functions. Compared with other algorithms, NCS-MGS shows better performance on these test functions. The optimization performance of CLPSO in F9, F13, F15, F23 and F25 is better than NCS-MGS algorithm. The main reason is that particle swarm optimization algorithm has better local search ability and can search individual neighborhoods accurately, so the accuracy of the solution is higher.

In addition, non-parametric statistical analysis was performed on the experimental results, which were shown in Table 2 and Table 3. The results of Friedman statistical analysis of the 10 algorithms are shown in Table 2. The experimental ranking results show that NCS-MGS ranks first, which indicate that the NCS-MGS algorithm has better overall performance than other algorithms. As can be seen from Table 3, the overall performance of the proposed NCS-MGS algorithm is significantly better than the TS, SA, SS, GL-25, PFC and CLPSO algorithms. In the statistical sense, the optimization performance of NCS-MGS is not significantly better than CMA-ES, NCS and SaDE. The main reason is that the multi-neighborhood generation strategy is used in the algorithm to strengthen the local search ability, but to a certain extent, the global search capability of the algorithm is reduced.

It can be seen from the above analysis that among 20 multi-modal test functions the overall performance of NCS-MGS is better than the other 9 optimization algorithms. Introducing the multi-neighborhood generation strategy into the mutation strategy enhances the local search ability of the algorithm and the ability to solve complex multimodal problems.

4. APPLICATION IN EXIT LAYOUT OPTIMIZATION PROBLEM

With the development of society and the acceleration of urbanization, the number of urban population has been rising. Large-scale crowd gathering has become a common phenomenon in today's society. However, in recent years, the lack of effective management and control of dense crowds results in frequent pedestrian accidents, which not only causes huge losses to people's lives and property, but also poses a serious threat to urban public safety. When a fire or other emergency occurs, people in the building or in a particular area need to escape from the danger zone as quickly as possible.

How to ensure the safety of personnel and the efficiency of evacuation is a core goal in the field of public safety. It is a core goal to ensure the safety of personnel and the efficiency of evacuation in the field of public safety. To improve the efficiency of crowd evacuation, reasonable building design is of great significance. As the key facility for evacuation, the rational layout of building exit is particularly critical. Through research, it is found that there are many factors affecting crowd evacuation efficiency, including exit width[25][26], exit number [27], initial distribution of evacuees [28][29], obstacles[30][31][32] , ect. Studying the factors affecting the evacuation efficiency can achieve the purpose of shortening the evacuation time of pedestrians.

According to literature [33], a macroscopic and microscopic two-layer optimization framework was constructed. At the macro level, the optimal spatial layout is generated by continuous optimization. While at the micro level, the dynamic process of crowd evacuation is simulated by the pedestrian motion simulation model. The fitness function in the traditional heuristic algorithm is replaced by the simulation results of the crowd evacuation dynamics process. Hence, the fitness values under different exit layouts are evaluated to guide the random search direction. Compared with the traditional heuristic optimization, it is proposed to use the

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evacuation simulation result instead of the fitness function. As a result, the evaluation of the feasible solution is more accurate, and more reasonable optimization results can be obtained.

Table 1. Experimental results on 30D

	PHC	SA	TS	SS	GL-25	SaDE	CMA-ES	CLPSO	NCS	NCS-MGS
F6	2.61E+01 ±2.35E+01	3.90E+02 ±4.09E+01	7.00E+03 ±1.01E+04	2.17E+05 ±6.41E+04	2.13E+01 ±1.02E+01	4.76E+01 ±3.35E+01	0.00E+00 ±0.00E+00	4.80E+00 ±3.55E+00	2.08E+01 ±3.61E+00	2.02E+01 ±2.03E+00
F7	9.86E-04 ±2.76E-03	2.21E+00 ±1.84E+00	1.64E-02 ±1.59E-02	1.40E+00 ±7.37E-02	2.78E-02 ±3.76E-02	1.95E-02 ±1.37E-02	1.84E-03 ±4.59E-03	4.63E-01 ±7.31E-02	1.69E-02 ±1.38E-02	1.37E-02 ±1.06E-02
F8	2.00E+01 ±1.29E-02	2.10E+01 ±7.13E-02	2.01E=01 ±3.60E-02	2.09E+01 ±3.60E-02	2.10E+01 ±5.12E-02	2.09E+01 ±4.76E-02	2.03E+01 ±5.62E-02	2.10E+01 ±5.60E-02	2.00E+01 ±1.22E-02	2.00E+01 ±3.99E-02
F9	1.07E+02 ±2.13E+01	2.41E+02 ±8.62E+01	4.83E+02 ±9.60E+01	2.57E+02 ±3.85E+01	2.63E+01 ±5.64E+00	1.99E-01 ±4.06E-01	4.12E+02 ±1.38E+02	0.00E+00 ±0.00E+00	9.36E+01 ±1.38E+01	6.99E+01 ±6.18E+00
F10	9.64E+01 ±1.84E+01	2.17E+02 ±8.69E+01	7.92E+02 ±1.43E+02	3.48E+02 ±9.51E+01	1.35E+02 ±6.67E+02	5.08E+01 ±1.32E+01	4.97E+01 ±1.12E+01	1.06E+02 ±1.31E+01	9.03E+01 ±1.79E+01	6.67E+01 ±1.12E+01
F11	1.57E+01 ±1.89E+00	2.70E+01 ±2.18E+00	1.89E+01 ±4.44E+00	2.58E+01 ±4.55E+00	3.15E+01 ±8.45E+00	1.68E+01 ±2.82E+00	6.23E+00 ±1.47E+00	2.53E+01 ±1.65E+00	1.37E+01 ±1.27E+00	9.22E+00 ±1.21E+00
F12	7.53E+03 ±6.72E+03	6.06E+03 ±5.30E+03	2.28E+03 ±3.39E+03	1.18E+04 ±7.82E+03	6.83E+03 ±4.34E+03	3.11E+03 ±2.15E+03	1.28E+04 ±1.53E+04	1.96E+04 ±4.44E+03	1.57E+03 ±1.52E+03	1.30E+03 ±1.34E+03
F13	4.32E+00 ±9.03E-01	1.33E+01 ±1.04E+01	1.19E+01 ±3.36E+00	2.80E+01 ±4.44E+00	7.88E+00 ±5.79E+00	3.72E+00 ±5.89E-01	3.35E+00 ±8.52E-01	2.14E+00 ±2.09E-01	4.54E+00 ±8.04E-01	2.43E+00 ±5.51E-01
F14	1.34E+01 ±2.11E-01	1.47E+01 ±1.07E-01	1.42E+01 ±3.11E+01	1.35E+01 ±3.92E-01	1.29E+01 ±3.72E-01	1.26E+01 ±2.71E-01	1.47E+01 ±1.95E-01	1.27E+01 ±2.64E-02	1.24E+01 ±3.31E-01	1.21E+01 ±3.31E-01
F15	3.79E+02 ±5.35E+01	5.72E+02 ±1.18E+02	8.42E+02 ±3.19E+02	4.33E+02 ±4.75E+01	3.00E+02 ±7.62E-02	3.60E+02 ±6.51E+01	5.13E+02 ±2.69E+02	6.33E+01 ±4.87E+01	3.15E+02 ±5.68E+01	2.46E+02 ±5.68E+01
F16	1.42E+02 ±4.36E+01	3.77E+02 ±1.93E+02	5.96E+02 ±3.35E+02	4.21E+02 ±1.89E+00	1.44E+02 ±7.76E+01	8.16E+01 ±6.90E+01	3.39E+02 ±2.99E+02	1.76E+02 ±3.25E+01	1.21E+02 ±1.53E+01	1.03E+02 ±1.18E+01
F17	1.90E+02 ±3.94E+01	6.46E+02 ±3.12E+02	8.75E+02 ±3.34E+02	3.28E+02 ±1.29E+02	1.58E+02 ±7.17E+01	7.31E+01 ±2.79E+01	4.15E+02 ±3.07E+02	2.36E+02 ±4.37E+01	1.55E+02 ±2.40E+01	1.11E+02 ±2.09E+01
F18	9.10E+02 ±1.98E+00	8.23E+02 ±1.60E+01	9.29E+02 ±1.60E+02	8.32E+02 ±4.00E+01	9.06E+02 ±1.49E+00	8.75E+02 ±6.32E+01	9.04E+02 ±1.86E-01	9.10E+02 ±2.15E+01	8.79E+02 ±8.68E+01	8.53E+02 ±1.11E+02
F19	9.09E+02 ±1.74E+00	8.23E+02 ±1.40E+01	9.54E+02 ±1.92E+02	8.45E+02 ±7.77E+01	9.07E+02 ±1.71E+01	9.07E+02 ±4.08E+01	9.25E+02 ±1.07E+02	9.14E+02 ±1.79E+00	8.93E+02 ±4.12E+01	8.59E+02 ±2.08E+00
F20	9.09E+02 ±1.92E+00	8.29E+02 ±3.46E+01	1.01E+03 ±1.95E+02	8.24E+02 ±8.86E-01	9.07E+02 ±1.54E+00	8.83E+02 ±5.84E+01	9.04E+02 ±2.32E-01	9.14E+02 ±1.19E+00	8.81E+02 ±1.23E+02	8.51E+02 ±8.91E+01
F21	4.96E+02 ±1.81E+01	8.47E+02 ±1.03E+02	9.08E+02 ±3.43E+02	8.22E+02 ±2.60E+02	5.00E+02 ±4.83E-13	5.00E+02 ±2.09E-13	5.12E+02 ±6.00E+01	5.00E+02 ±2.38E-13	5.00E+02 ±2.32E-13	5.00E+02 ±1.41E-13
F22	9.41E+02 ±2.11E+01	7.45E+02 ±2.25E+02	1.34E+03 ±1.60E+02	5.74E+02 ±1.27E+02	9.28E+02 ±1.07E+01	9.33E+02 ±2.00E+01	8.24E+02 ±1.59E+01	9.70E+02 ±1.04E+01	9.06E+02 ±1.31E+01	8.31E+02 ±1.17E+01
F23	5.43E+02 ±1.57E-12	8.36E+02 ±1.13E+02	1.31E+03 ±1.10E+02	9.62E+02 ±3.27E+02	5.34E+02 ±4.24E-02	5.34E+02 ±2.26E-03	5.35E+02 ±1.88E+00	5.34E+02 ±1.57E-04	5.71E+02 ±2.99E+01	5.38E+02 ±1.43E+01
F24	2.00E+02 ±3.59E+02	3.69E+02 ±2.79E+02	1.57E+03 ±1.04E+02	2.35E+02 ±8.36E+01	2.00E+02 ±2.96E-09	2.00E+02 ±0.00E+00	2.00E+02 ±6.39E-13	2.00E+02 ±2.67E-12	2.00E+02 ±2.72E-12	2.00E+02 ±2.53E-06
F25	1.35E+03 ±3.29E+03	1.43E+03 ±6.85E+03	2.00E+03 ±7.30E+01	1.32E+03 ±3.66E+01	2.17E+02 ±1.59E-01	2.13E+02 ±1.15E+00	2.07E+02 ±6.30E+00	2.00E+02 ±1.96E+00	2.22E+02 ±1.37E+01	2.15E+02 ±2.73E+00

Table 2. Ranking obtained by Friedman's test on 30D

Algorithm	Ranking
TS	8.600
SA	7.075
SS	6.875
GL-25	5.625
PHC	5.425
CLPSO	5.375
CMA-ES	4.875
NCS	4.150
SaDE	4.100
NCSMTV	2.900

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Table 3. p-Values obtained by Bonferroni- Dunn's, Holm's, and Hochberg's procedure on experimental results with 30D

Algorithm	z	Unadjusted p	Bonferroni- Dunn p	Holm p	Hochberg p
TS	5.9534	2.63E-09	2.36E-08	2.36E-08	2.36E-08
SA	4.3606	1.30E-05	0.0001	0.0001	0.0001
SS	4.1517	3.30E-05	0.0002	0.0002	0.0002
GL-25	2.8461	0.0044	0.0398	0.0265	0.0265
PHC	2.6372	0.0083	0.0752	0.0418	0.0389
CLPSO	2.5850	0.0097	0.0876	0.0418	0.0389
CMA-ES	2.0628	0.0391	0.3521	0.1173	0.1174
NCS	1.3055	0.1916	1.0000	0.3834	0.2101
SaDE	1.2533	0.2100	1.0000	0.3834	0.2101

4.1. Pedestrian Motion Simulation Model

The pedestrian motion simulation model is established based on the social force model [34][35]. The target driving force is calculated as Eq. (9):

$$f_i^0 = m_i \frac{v_i^0(t)e_i^0(t) - v_i(t)}{\tau} \tag{9}$$

Where m_i represents the quality of pedestrians; v_i^0 represents the expected speed of pedestrians; e_i^0 indicates the target direction of pedestrians; v_i is the actual speed of pedestrians.

The change of velocity in time t is shown in Eq. (10):

$$m_i \frac{dv_i}{dt} = f_i^0 + \sum_{j(\neq i)} f_{ij} + \sum_w f_{iw} \tag{10}$$

Where f_{ij} denotes the safe distance between pedestrian i and other pedestrians; f_{iw} denotes the safe distance between the pedestrian i and the obstacle.

In general, pedestrians will keep a certain distance from others in their movements, and the interaction force f_{ij} between pedestrians can be expressed by Eq. (11):

$$f_{ij} = A_i e^{(r_{ij}-d_{ij})/B_i} n_{ij} + kg(r_{ij} - d_{ij})n_{ij} + kg(r_{ij} - d_{ij})\Delta v_{ji}^t t_{ij} \tag{11}$$

Where $A_i e^{(r_{ij}-d_{ij})/B_i} n_{ij}$ denotes psychological repulsive force; $r_{ij} = (r_i + r_j)$ denotes the sum of the radius of pedestrian i and pedestrian j; $d_{ij} = \|S_i - S_j\|$ denotes the distance between pedestrian i and pedestrian j. $n_{ij} = (n_{ij}^1,\ n_{ij}^2) = (S_i - S_j)/d_{ij}$ denotes the unit vector pointing from pedestrian j to pedestrian i; $k\left((r_{ij} - d_{ij})\right)n_{ij}$ denotes the repulsive force of the body; $k\left((r_{ij} - d_{ij})\right)\Delta v_{ji}^t t_{ij}$ denotes the sliding friction fotce; $t_{ij} = (-n_{ij}^2, n_{ij}^1)$ denotes the unit vector perpendicular to n_{ij}; $\Delta v_{ji}^t = (v_j - v_i)t_{ij}$ denotes the rate difference in the tangent direction between pedestrians.

The expression of the interaction force f_{iw} between people and obstacles is shown in Eq. (12):

$$f_{iw} = A_i e^{(r_i-d_{iw})/B_i} n_{iw} + kg(r_{ij} - d_{iw})n_i + kg(r_{ij} - d_{iw})(-v_i t_{iw})t_{iw} \tag{12}$$

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Where d_{iw} denotes the distance from the pedestrian i to the obstacle w; n_{iw} denotes the direction perpendicular to the obstacle; t_{iw} denotes the direction tangent to the obstacle.

According to literature [34] [35], parameters of pedestrian motion simulation model are shown in Table 4.

Table 4. Social force model parameters

Symbol	Mean	Value
M	Pedestrian quality	80kg
A	Strength of repulsive force	2000N
B	Exclusion force range	0.08m
k	Body compressibility	100000kg/s^2
κ	coefficient of sliding friction	30000kg/s^2
τ	Pedestrian response time	0.2s
$\boldsymbol{v_i^0}$	Expected pedestrian speed	1.5m

The optimization goal of this experiment is the pedestrian evacuation completion time T, and the experimental variable is the coordinate X (exit1, exit2) of the two exits in the two-dimensional coordinates. Therefore, the objective function is established in order to find the shortest evacuation completion time:

$$T = min\big(f(\mathbf{X})\big) \tag{13}$$

Where min (.) is the minimum function.

4.2. Experiment Settings

According to the literature [33], the exit width and pedestrian body radius are factors that affect pedestrian evacuation time. This experiment is set up as a 12m*12m room with two exits. Considering the different density conditions, the number of personnel is 100 and the distribution density of personnel is 1 person/m2. Suppose that the crowd starts evacuating at the same time, ans can see all exits, and choose the exit that is closer to the individual's current location. The evacuation exit layout has two exits on the same side wall, and the two exits have the same width. Morever, the width valua ranges from 0.8m to 1.6m. The pedestrian body radius r is 0.2m, 0.25m, 0.3m, respectively. The algorithm runs independently 25 times under different conditions, and the final result takes the mean.

4.3. Expreimental Result Analysis

Based on the above conditions, NCSMTV algorithm is adopted to optimize the exit position. The introduced variable ΔS denotes the distance between the two exit. Under the conditions of different exit widths and pedestrian body radius, the distance between the optimal positions of the two exits and the corresponding evacuation completion time are shown in Table 5.

It can be seen from Table 5 that under the same pedestrian body radius condition, the distance between the two exits is decreasing and the evacuation completion time is shorting as the exit width increases. Under the same exit width condition, the smaller the pedestrian body radius, the shorter the evacuation completion time. Based on the above conclusions, under the condition that the exit width is 1.6m and the pedestrian body radius is 0.2m, the evacuation completion time is the shortest, which we call the “best condition”.

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Under the "best conditions", the evacuation completion time of NCS-MGS is compared with that of NCS, as shown in Table 6. It can be seen from Table 6 that the evacuation completion time of the NCS-MGS algorithm is shorter than that of the NCS algorithm. The results show that the NCS-MGS algorithm is better than the NCS algorithm in the problem of the building exit layout optimization of the crowd evacuation.

Table 5. Optimal distribution spacing of two exits and corresponding evacuation completion time under different evacuation conditions

Exit widths (m)	pedestrian body radius r=0.2m	pedestrian body radius r=0.25m	pedestrian body radius r=0.3m
	Optimal distribution spacing (Evacuation completion time)		
0.8	10.21 (9.39)	9.65 (11.76)	9.50 (12.29)
1.0	9.20 (9.22)	9.18 (10.57)	8.83 (11.49)
1.2	7.21 (9.01)	5.43 (10.11)	6.93 (10.78)
1.4	5.23 (8.56)	3.46 (9.72)	5.74 (10.22)
1.6	3.75 (8.49)	1.47 (9.20)	5.05 (9.92)

Table 6. Evacuation completion time obtained by NCS and NCS-MGS

Evacuation completion time (s)	NCS	NCSMTV
Optimizing time mean (standard deviation)	8.62(2.74)	8.49(2.42)

5. CONCLUSION

To improve the ability of negatively correlated search to solve multimodal optimization problems, this paper proposes a negatively correlated search based on multi-neighbourhood generation strategy algorithm (NCS-MGS). In this algorithm, each individual of the population uses the Gaussian mutation operator to generate three individuals and then only the individual with the best fitness is selected as offspring individual. NCS-MGS not only maintains the global search capability of the original algorithm, but also enhances the local search capability of the algorithm. Compared with other algorithms, the results show that the proposed algorithm has better optimization ability than other compared algorithms. Finally, NCS-MGS was applied to the problem of building exit layout optimization. Compared with NCS, NCS-MGS obtains a shorter evacuation completion time. The results show that the proposed algorithm is better than the negatively correlated search algorithm.

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