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Research article

Multi-population cooperative evolution-based image segmentation algorithm for complex helical surface image

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Abstract: Accurate image segmentation results would show a great significance to computer vision-based manufacturing for complex helical surface. However, the image segmentation for complex helical surface is always a difficult problem because of the uneven gray distribution and non-homogeneous feature patterns of its images. Therefore, a multi-direction evolutionary segmentation model is constructed and a multi-population cooperative evolution algorithm is proposed to solve the new model. According to the characteristics of gray distribution and feature patterns of complex helical surface image, an eigenvector extraction and description strategy is researched by combining gray level co-occurrence matrix algorithm with fractal algorithm, and the complex helical surface image can be described succinctly by gray feature and shape feature. Based on the description algorithm of image features, an image segmentation strategy using cooperative evolution from different eigenvector is discussed, and the helical surface image segmentation is decomposed from a single objective optimization problem to a multi-objective optimization problem to improve the accuracy of segmentation. Meanwhile, a multi-objective particle swarm optimization algorithm based on multi-directional evolution and shared archives is presented. Due to the fact that each eigenvector segmentation corresponds to one evolution direction, the collaboration of local and global segmentation can be realized by information sharing and interaction between evolution directions and the archive set. The comprehensive quality of non-dominated solution can be improved by the selection strategy of local and global optimal solution as well as the archive set maintenance. The practical numerical experiments for complex helical surface image segmentation are carried out to prove the validity of the proposed model and algorithm.

Keywords: image segmentation; evolutionary computation; helical surface; multi-objective optimization

1. Introduction

As one of the most widely used mechanical components in industrial engineering, the automatic and accurate detection and measurement for complex helical surface is of great significance to its manufacturing [1,2]. In recent years, the application of laser, electromagnetic and ultrasonic in mechanical measurement has provided a new idea for non-contact measurement of complex helical surface, but the high cost has severely restricted their development. In recent decades, with the rapid development of digital image processing and computer vision techniques, image-based non-contact detection and measurement method is becoming a hot research direction in manufacturing of high-performance helical surface, and its image segmentation is the basis of subsequent understanding and analysis of image features. Therefore, it is urgent to research an effective image segmentation strategy for complex helical surface.

Accurate segmentation effect for complex helical surface image is difficult to be achieved by using conventional image segmentation algorithms; this is principally because the uneven gray distribution and the non-homogeneous feature patterns of its image, which increase the possibility of characteristic confusion. On the one hand, spiral lines moving according to different rules usually form helical surface, hence the physical structure of itself is very complex. When image acquisition is performed, the angle of the surface is variable comparing with the fixed collection equipment, and the reflection of light from different angles of the surface will cause uneven gray level of the captured image. At the same time, dust and vibration in the industrial production scene are easy to cause image offset, which affects the gray distribution of the measurement images. The segmentation features of the helical surface image, which includes the defects formed in the production process or the marks formed by the measurement factors, and the irregular edges of the local area in image, are usually difficult to distinguish by common algorithm. In addition, all kinds of similar features are diverse in the helical surface image, and the internal mode of the same kind of target is very complex. Therefore, image segmentation of complex helical surface is an essential and challenging problem for accurate vision measurement. Considering its important effects in the whole image measurement and detection works, it is necessary to study the effective algorithm for complex helical surface image segmentation.

Due to the complexity of image features and the specialty of domain knowledge for complex helical surface, the research works on its image segmentation are lack of progress, and the effective segmentation algorithm based on new technology and new method is far from enough. Intelligent computing technique based on evolutionary optimization theory is mainly focus on how to solve multi-objective problems by using evolutionary computing method, which is one of the research hotspots in the application of industry production. By simulating the evolution process of biological system, the modern evolutionary theory constructs an evolutionary computing model to solve complex scientific problems in engineering [3,4]. This paper considers that the image segmentation problem of complex helical surface image is mechanism consistency to multi-objective optimization approach essentially, and results that are more attractive can be obtained by implicating a novel evolutionary computation strategy to image segmentation. Therefore, a multi-directional evolution optimization algorithm is researched for the segmentation challenge. The work in this paper has important innovation value and application significance for the image measurement and detection of complex helical surface by computer vision method.

The major work of this paper are as follows:

(1) A multi-direction evolutionary based image segmentation model for complex helical surface image is proposed. First, the segmentation model extracts different image eigenvectors that can represent the critical characteristics of complex helical surface image, and then, the segmentation problem of helical surface image can be transformed into a problem of multiple eigenvectors segmentation. Therefore, the segmentation of helical surface image can be described as a multi-directional objective optimization problem with the optimal segmentation of each eigenvector.

(2) A multi-population cooperative evolution algorithm is proposed. Each eigenvector segmentation maintains one evolution direction. Through the information sharing of evolution and interaction between each direction and the archive set, the local and global cooperation in multi-directional co-evolutionary segmentation of complex helical surface image is realized. The comprehensive quality of non-dominated solution is improved by the introduction of archive set maintenance as well as the novel selection strategy for global and local optimal solution.

(3) Meanwhile, the multi-directional object cooperative evolution optimization algorithm is used to segment the complex helical surface image, and the segmentation effect of new algorithm is obviously superior to conventional algorithm. By calculating the omission segmentation rate and error segmentation rate of the segmented helical surface images, the index quantitative evaluation model is constructed by combining the two rates, and numerical experiments results show that the presented algorithm and segmentation model is accuracy and efficient.

It contains five sections as fellows in this paper. Section 1 is a general introduction to research background and significance of image segmentation for complex helical surface. Section 2 discusses the related work about this theme at home and abroad in summary. Section 3 presents a novel multi-objective optimization algorithm and constructs an image segmentation model for complex helical surface in details. Numerical experiments are carried out to validation of the proposed algorithm and model in section 4. Conclusions are finally addressed in section 5.

2. Related works

The purpose of the segmentation for complex helical surface image is to distinguish different objects in image while keeping feature details as far as possible, which will make a good foundation for further vision measurement and detection. By segmenting complex helical surface image into different sub regions or sub objects, such as background, general surface, production process measurement point object, defect and defect abnormal object, etc., the accurate understanding and analysis for complex helical surface image will become efficient and convenient. To achieve a satisfactory segmentation results, it is necessary to introduce new techniques constantly to innovate research approaches. As a classic problem in the field of image processing, image segmentation has always been a research hotspot. In recent years, with the wide application of computer vision technology in modern industry, segmentation object in image is becoming more and more complex, new segmentation technologies are emerging quickly [5,6]. Nowadays, in order to solve the problem of complex image segmentation, it has already become an important research direction for image segmentation by constructing multi-objective optimization calculation model based on evolutionary computation and other related theories [7,8], especially for complex image segmentation.

The multi-objective optimization problem widely exists in practical engineering applications, and the evolutionary calculation method of multi-objective optimization has been widely concerned by researchers. In the 1980s and 1990s, many researchers concerned evolutionary multi-objective optimization algorithm, and it obtained a great development in less than 20 years. Of all these research works, Schaffer and horn have made great contributions to the research on the first generation evolutionary multi-objective optimization algorithm. Their research work characterized by the individual selection method based on Pareto level as well as the population diversity maintenance algorithm based on fitness sharing mechanism, and the algorithm has been widely used in engineering, such as the small cell allocation optimization [9] as well as privacy protection problem [10], and so on. While scholars have made innovative achievements in the research of the second-generation evolutionary multi-objective optimization algorithm characterized by elite retention mechanism [11]. With the increasing complexity of engineering application problems, researchers proposed new Pareto dominance mechanisms for uncertain environments and high-dimensional complex problems. Multi-objective algorithm was applied to solve the image classification problem [12], video-coding problems [13], and also applied to solve problems in the situation of uncertain environment [14]. Some other scholars at home or abroad, have studied the evolutionary multi-objective optimization algorithm to the enhancement of algorithm performance. The classical multi-objective optimization algorithms are usually combined with intelligent computing strategy [15]. The application of the improved algorithm in some fields has also been studied, such as population classification in fire evacuation [16], image classification [17] and personalized recommendation and filtering [18]. Particle swarm optimization, artificial immune, co-evolution, cultural evolution, distribution estimation are constantly used to solve multi-objective optimization problems, and various calculation models are gradually proposed and researched [19]. These works has greatly promoted the development of internal and external evolution multi-objective optimization technology and its application.

Image measurement and detection for complex helical surface is one of the most important application of image processing technology in national production. As the basis of the application of image technology, image segmentation is also a process of finding the optimal partition under the constraints of various image related conditions [20]. Evolutionary multi-objective optimization can provide greater selection space for image segmentation [21]. Therefore, the application of evolutionary multi-objective computing model to solve image segmentation problem has become a hot issue for scholars [22,23]. In recent years, scholars at home and abroad are gradually carrying out relevant research works. In these studies, the application of multi-objective optimization based on particle swarm optimization in image segmentation [24,25] has become the potential solution due to its simple process [26], multiple solutions can be obtained by a single run, and the algorithm has the ability to approach the non-convex and discontinuous optimal front-end [27,28]. The multi-objective particle swarm optimization algorithm is also researched to improve the adaptability of the algorithm [29]. Dynamic multi-objective particle swarm optimization algorithm for solving the problem of uncertainty change [30] and the multi-objective particle swarm optimization algorithm based on Pareto entropy for the purpose of improving the convergence and diversity have been successively studied and proposed, and research ideas of the multi-objective particle swarm optimization algorithm for image segmentation is extended widely. At the same time, the image segmentation solution model which is always combining multi-objective particle swarm optimization with classical segmentation algorithm, clustering analysis algorithm, distribution estimation and difference algorithm, co-evolution, grey theory and so on, a variety of algorithms have been proposed and applied continuously. These researches not only show the feasibility of multi-objective optimization algorithm for image segmentation, but also provides a useful idea for image segmentation in the case of uneven gray distribution for complex helical surface image and different segmentation targets.

In the process of complex helical surface image segmentation, the purpose of applying multi-objective optimization algorithm is to reveal the characteristics of complex features in the image as far as possible. To achieve this goal, it is necessary to solve the file maintenance, global optimal solution selection, local optimal solution selection and increasing population diversity in many objective optimization algorithms, which are also the key issues in the research of multi-objective optimization algorithm. In order to achieve better application effect, scholars have proposed a variety of improvement strategies for multi-objective optimization algorithm. For the application problem of multi-objective optimization with constraints, the diversity and distribution of Pareto frontier improved by adaptive evolutionary learning strategy and other related constraints. Competition and cooperation mode are introduced to multi-objective and optimized particle swarm optimization algorithm, and the equilibrium problem of the development and exploitation for multi-objective and optimized particle swarm optimization algorithm is always researched [31]. Reducing the size of non-inferior solution set and improving the efficiency of problem solving by establishing a preference Pareto dominant relationship. By integrating the theory of cellular automata, a multi-objective particle swarm optimization algorithm based on differential evolution idea is studied to increase the diversity of Pareto solutions and balance the ability of global search and local optimization [32,33]. By introducing intelligent algorithms such as quantum behavior into multi-objective PSO evolutionary algorithm, the efficiency of the algorithm in solving collaborative task allocation is improved [34,35]. The selection strategy of global optimal solution of PSO multi-objective optimization optimized by constructing weight value function [36]. The development of multi-objective optimization algorithm is improved by studying the congestion distance calculation strategy of objective and solution space equilibrium of mining [37]. Researches usually focus on the convergence and diversity of Pareto front-end. Generally speaking, how to achieve the optimal solution, how to find the global optimal solution and individual optimal solution with high quality and fast speed, and how to balance the development and mining operations, so that the algorithm can keep fast convergence without falling into the local Pareto front end, and so on.

Due to the complexity and diversity of engineering applications and scientific problems, the research work related to multi-objective optimization algorithm is full of challenges. In view of certain engineering application problems, it is an important problem for current scientific researchers to carry out work from various aspects and research the multi-objective, optimization algorithm is suitable for the solution, which is also the key research content of this project for complex helical surface image segmentation.

3. Image segmentation algorithm for complex helical surface image

3.1. Multi-population cooperative evolution based segmentation model

The image segmentation purpose for complex helical surface is to divide the image into different regions by image processing strategy according to its own characteristics. The segmented image can be more convenient for classification and recognition of different features and it will provide accurate and reliable data basis for the measurement and detection of complex helical surface image. Based on the previous analysis of the complex helical surface image features, if all the features of the complex helical surface image are taken as a whole to construct its segmentation objective function, then the image segmentation of the image is described as a single objective optimization problem. However, the grey distribution of pixels in complex helical surface image does not have a certain regular pattern. Therefore, this paper will research the method of searching threshold solutions for image segmentation from multiple feature directions at the same time, and construct the multi-directional co-evolution based segmentation model for complex helical surface image. The overall research ideas of this strategy are shown in Figure 1.

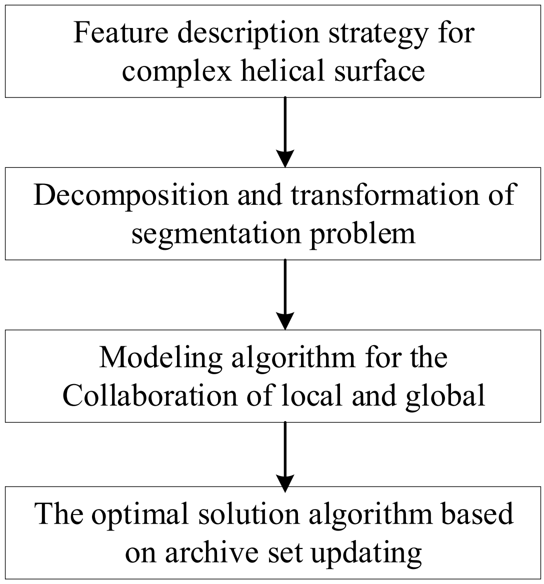

Figure 1. Flowchart of construction for image segmentation model.

To realize the new segmentation model, we will study the feature description algorithm of complex helical surface image at first. By analyzing the characteristics of complex helical surface image, the algorithm combining gray level co-occurrence matrix with fractal strategy, which is mature and in line with its own image characteristics, is researched to extract and describe different for image. According to the uneven gray distribution characteristics of the image, an image extraction method based on the image gray level co-occurrence matrix is studied, and the algorithm achieves an accurate discrimination rate of complex helical surface image features in terms of the gray distribution. At the same time, because the pattern of segmentation features in one class is complex, and the features between different classes are easy to be confused. This paper researches an extraction algorithm of image feature based on fractal theory, and the established image features model by this method can achieve a discrimination rate in terms of shape feature level for complex helical surface image. The work about the multi-feature description of complex helical surface image focuses on the key features that are satisfactory to represent the image, is beneficial to the construction of a more concise and efficient segmentation model for complex helical surface image. The image is described exactly by the eigenvector extraction and representation methods based on the above two descriptions.

The feature extraction of complex helical surface image researched in this paper is based on the gray level co-occurrence matrix of image. The extracted feature parameters can include energy, entropy, contrast, etc. Supposed that the gray level co-occurrence matrix of helical surface image is G, *M* and *N* are the number of pixels in the horizontal and vertical directions of the helical surface image, *(x, y)* is the coordinates of the current pixel, and then the calculation formula of energy extraction is as follows:

$$ENG = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} G(x, y)^2 \tag{1}$$

The calculation formula of entropy is:

$$ENPY = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} G(x, y) Log G(x, y) \tag{2}$$

The extraction formula of contrast is as follows:

$$CNTRST = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} G(x, y) * (x, y)^2 \tag{3}$$

Based on the feature extraction of complex helical surface image, it is described in the form of eigenvector. In essence, the segmentation problem of complex helical surface image can be decomposed and transformed as follows:

$$G(x,y) \Rightarrow \begin{matrix} f_1(x,y) \\ f_2(x,y) \\ \cdots\cdots\cdots \\ f_n(x,y) \end{matrix} \tag{4}$$

where, *G(x,y)* means the image segmentation of complex helical surface, *f(x,y)* represents the image segmentation based on the description of eigenvector. Considering the efficient and concise of image segmentation, two key eigenvectors are selected to describe the complex helical surface image.

Based on the transformation above, the research of complex helical surface image segmentation can be transformed into a research of multi-eigenvector image segmentation. The optimal image segmentation for complex helical surface will be the combination optimization result of each eigenvector segmentation, in which each eigenvector is independent and equal for image segmentation. However, as the eigenvector extraction is based on the single feature of the image, each eigenvector only focuses on one aspect of the complex helical surface image. The further optimization of one eigenvector segmentation often leads to the weakening of the segmentation result of the other eigenvector. Therefore, the segmentation problem of complex helical surface image is essentially a multi-objective optimization problem, and the ultimate purpose of the optimization is to obtain the comprehensive optimal segmentation of each eigenvector. According to the principle of multi-objective optimization, the segmentation problem can be described as follows:

$$\begin{aligned} &\min Y = f(X) = (f_1(X), f_2(X), \ldots, f_r(X)) \\ &g_i(X) \geq 0, (i = 1,2,\ldots,k) \\ &h_i(X) = 0, (i = 1,2,\ldots,l) \end{aligned} \tag{5}$$

By the formula above, decision vector $X \in R^n$; objective vector $Y \in R^r$; $g_i(X) \geq 0$ and $h_i(X) = 0$

means constraint conditions; $f_i(X), i = 1, 2, \ldots, r$ Represents objective function. In the multi-objective optimization description for complex helical surface image, the objective function is defined as several functions mapping from decision space to objective space.

Because of the property of itself, there are usually conflict relationship between the eigenvectors, which leads the search of optimal threshold to different directions and regions during the segmentation of helical surface image. In order to achieve the optimal segmentation result, it is necessary to make full use of the cooperative relationship between the different targets.

In the process of helical surface image segmentation, there are many eigenvectors that occupying the equal status. During the each optimization process, the archive set will face two different eigenvector segmentation results. Supposed that, one optimization value can improve the segmentation result of some other eigenvectors, but makes the segmentation result of another eigenvector worse, then the archive set will not select this new optimization value. On the other hand, when the segmentation of two eigenvectors is invariant, the segmentation value will be retained in archive set to lead the optimization to a better direction.

The concept of relative segmentation rate of complex helical surface image will be introduced in the model to evaluate the effect of image segmentation.

Suppose *F(x)* is the segmentation degree of complex helical surface image when the optimal segmentation value is *X*. The unsupervised image evaluation function proposed by pichel is used to calculate segmentation degree in our model [33]. x'_j represents the current optimal value of the *j-th* eigenvector, and x_j is the previous optimization value of the *j-th* eigenvector, v_i means the *i-th* threshold value in the archive set, *k* is the capacity of the archive set during evolution. The relative segmentation rate of complex helical surface image can be calculated out as follows:

$$\partial = \sum_{i=1}^{k} \frac{|F(v_i) - F(x_j')|}{F(v_i)} \qquad s.t. F(x_j') - F(x_j) >= 0 \tag{6}$$

The relative segmentation rate reflects the relevance between the optimal segmentation of the current vector and all the solutions in the archive set. The comprehensive of all the solutions in the archive set reflects the current optimal segmentation of the complex helical surface image. The relative segmentation rate indicates whether the segmentation solution of the current vector is close to the comprehensive optimal segmentation of the complex helical surface image. Therefore, based on the relative segmentation rate of complex helical surface image, the model proposed in this paper can construct the cooperation relationship between eigenvector segmentation and archive set, so as to achieve the purpose of global and local unified cooperation.

In the multi-objective optimization of complex helical surface image segmentation, a set of non-dominated solutions is obtained by optimization. Therefore, the model will also study the determination of segmentation value of complex helical surface image based on archive set. Due to the existence of local and global cooperation in this model, each non-dominated solution in the archive set reflects the comprehensive characteristics of a certain feature in the complex helical surface image segmentation to a certain extent. Therefore, according to the principle of maximum distance between classes and minimum distance within classes, the model will focus on the non-dominated solution, and take the gray distance between each pixel and each center point in the complex helical surface image as the similarity evaluation basis, which is also a relatively mature and stable image segmentation strategy in the field of image processing. By the adaptive image segmentation, the optimal segmentation of complex helical surface based on multi-objective optimization algorithm can be obtained.

Generally, the novel model discussed in this paper will decompose and transform the image segmentation problem of complex helical surface to a new form, which is described by different eigenvectors. When the images described by each eigenvector are segmented, they are interrelated and mutually restricted, and the image segmentation problem isconsistency with the multi-objective particle swarm optimization algorithm in ideology. Therefore, our research is able to establish a multi-objective optimization segmentation model suitable for complex helical surface image segmentation.

3.2. Multi-population cooperative evolution particle swarm optimization algorithm

Based on multi-directional evolution and archives collaboration, a multi-objective optimization algorithm, which is satisfied to the image segmentation of complex helical surface image segmentation, is presented in this paper. Each eigenvector of complex helical surface image maintains a population for evolution. Each eigenvector has the independence of itself, but other eigenvectors can be combined with the archive set. In this process, we use the eigenvector segmentation represents the local segmentation of the complex helical surface image, the non-dominated solution of the archive set reflects the global segmentation of the complex helical surface image, and the cooperation in the eigenvector segmentation represents the segmentation of each eigenvector cooperating with other features while performing self-segmentation. Following these analysis and design, specific strategies based on local optimal solution selection, global optimal solution selection and archive update in multi-objective optimization algorithm is researched.

The general process of algorithm researched in this paper is shown in Figure 2.

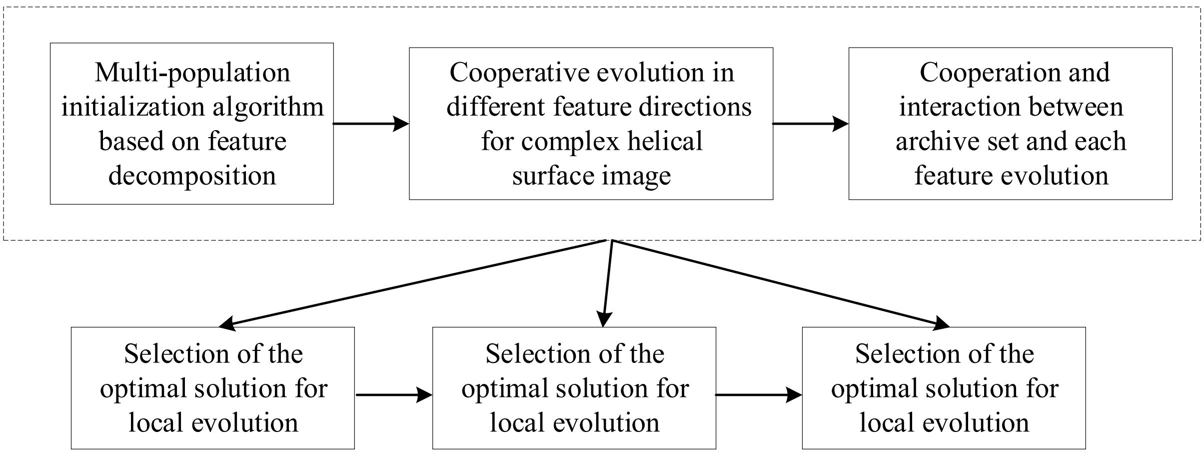

Figure 2. Flowchart of multi-population cooperative evolution algorithm.

Particle swarm optimization is an evolutionary computing model based on velocity and position update iteration. The position of each particle in the swarm represents the candidate solution of the problem in the search space, and the quality of each solution is determined by the fitness function of the particle. Its position and speed are updated as follows.

$$v_i^{(k+1)} = wv_i^k + c_1 r_1 (Pb_i^k - x_i^k) + c_2 r_2 (Gb^k - x_i^k) \tag{7}$$

$$x_i^{(k+1)} = x_i^k + v_i^{(k+1)} \tag{8}$$

where r_1 and r_2 are random numbers on an interval (0,1), c_1 and c_2 are learning factors, w is an inertia weight coefficient, v represents velocity, x is the position of particle, i means the *i-th* particle, k means the *k-th* iteration. *Pb* represents the best position of the current particle (local optimum), and *Gb* represents the best position of the entire population (global optimum).

During the evolution of multi-objective optimization, supposed that p and q are the two different individuals in the population pop. If p dominates q, then we must satisfy the following conditions: for all sub objectives, p is not worse than q, that is, $fi(p) \leq fi(q),\ i=1,2,\ldots k$; There is at least one sub object that makes p better than q, that is $\exists l \in \{1,2,...,k\}, f_l(p) < f_l(q)$. Where k is the number of sub object, and p is non-dominated, while q is dominated, the relationship can be defined as $p \succ q$, where "$\succ$" means denotes dominance.

Based on the above theory and related concepts, the selection strategy of local optimal solution in multi-objective particle swarm optimization algorithm is improved in this paper. The segmentation of each eigenvector maintains an independent population, which is composed of randomly generated eigenvectors. By optimizing the population, the solution generated is the segmentation of a certain feature for the complex helical surface image, and the fitness function of segmentation optimization is the relative segmentation rate of complex helical surface image. According to this improvement, the assessment of evolution for a single population is different from the traditional algorithm, the evaluation of the optimal solution of a certain eigenvector segmentation is not only limited to the current feature segmentation range, but is also based on the global segmentation effect of the image. In the meantime, the relative segmentation rate of the complex helical surface image is taken as the optimization objective function, which increases the global factor disturbance for the evolution of the current local particle swarm optimization. These disturbances also enhance the diversity of multi-objective optimization algorithm. Therefore, the local optimal selection algorithm in this paper makes the local solution obtained stronger global contribution ability during the single population evolution process.

The selection strategy of global optimal solution in multi-objective optimization algorithm is also studied in this paper. During the image segmentation that using multi-objective optimization algorithm for complex helical surface, the archive set maintains a global non-dominated solution set. These solutions are global and they are selected from local optimal solutions. The complex helical surface image segmentation problem is decomposed into segmentation of multiple eigenvectors, each of which produces the optimal local solution for its own segmentation, and it also has obvious bias. Therefore, the research work study the global optimal solution generation algorithm combined with achieve set partition solution distribution. Suppose that the *i-th* local cut is valid after each iteration, and the corresponding relative segmentation rate is (refer to the formula calculation in the multi-objective optimization segmentation model of complex helical surface image), and there are N eigenvectors in the complex helical surface image, then the global optimal calculation formula is as follows:

$$G_{val} = \sum_{i=1}^{N} \left(\frac{\partial_i}{\partial_1 + \ldots + \partial_i + \ldots + \partial_n} * val_i \right) \tag{9}$$

The result of the above formula is a comprehensive local optimal solution, which reflects the relationship between the local cut of eigenvector and the local segmentation of other eigenvectors, as well as the relationship between the local partial cut of eigenvector and the global solution set of the non-dominated optimal solution set. The cooperative relationship between local and global is used. In the multi-objective optimization of complex helical surface image, the eigenvectors can be taken as two, so the algorithm of this paper is less likely to be limited by the amount of calculation.

Updating and maintaining for the optimal solution archive set in multi-direction co- evolutionary optimization algorithm. The non-dominated solution of the archive set is obtained by integrating the local solutions and the solutions of the current archive set. To a certain extent, it has reflected the comprehensive needs of the local and global. The strategy of updating and maintaining archives will adopt the method of updating every time a global optimal solution is generated. The capacity of archives is generally set according to the characteristics of images, and the optimal capacity of archive can be determined by experiments. When updating the archives, the number of solutions in the non-dominated solution set is less than the collection capacity, it is added directly; if the number of solutions in the set is greater than the collection capacity, the method of evaluating individual density is used for replacement. The method based on the evaluation of individual density is relatively stable, for only two characteristics

In our research work, segmentation information between different eigenvectors is shared, and the information between the segmentation of each eigenvector and the archive set is exchanged. Based on these, the local and global cooperation in multi-directional co-evolutionary segmentation of complex helical surface image is realized. By the research on the maintenance strategy of archive set and the selection strategy of global and local optimal solution, the comprehensive quality of non-dominated solutions in Archives is improved.

3.3. Evaluation of the image segmentation model

It is one of the most important research tasks to verify and evaluate the effectiveness of the proposed multi-population cooperative evolution model. Quantitative analysis is mainly used to carry out experiments in two aspects: the first is to apply the model presented in this paper to segment the complex helical surface image, and then, the advantages and disadvantages of the novel algorithm and traditional algorithm are compared; on the other hand, the proposed multi-population cooperative evolution algorithm is applied to the classical test function sequence to verify the advantages and disadvantages of the proposed algorithm. The flowchart of research work is shown in Figure 3.

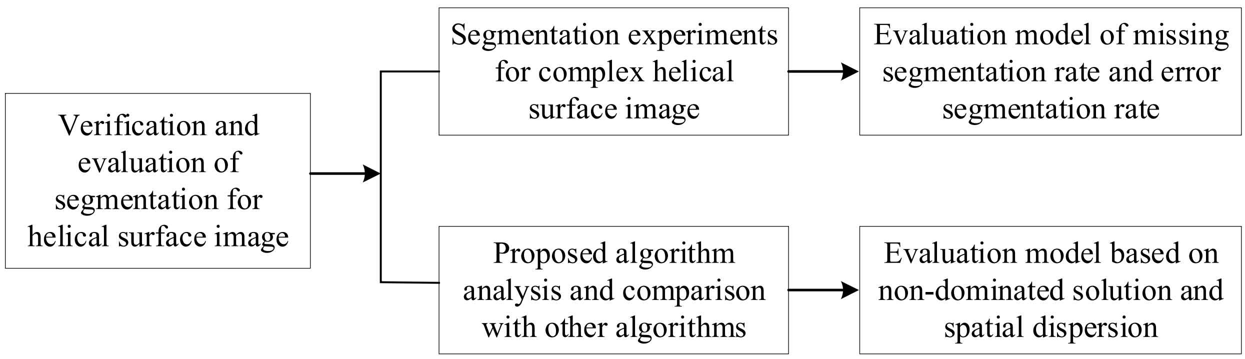

Figure 3. Flowchart of evaluation of the image segmentation.

On the one hand, the performance of the classical multi-objective optimization algorithm and the multi-population cooperative evolution algorithm is analyzed. The index reflecting the performance of multi-objective optimization algorithm is the size of the dominant solution on the target value and the dominance degree of the non-dominated solution in the solution space. On the other hand, the project will select a variety of typical complex helical surface images and apply the multi-directional co-evolutionary algorithm model for segmentation. For the segmentation of complex helical surface image, the evaluation model of error segmentation rate and missing segmentation rate for features will be introduced in the research. Among them, the error segmentation rate is the ratio of the number of non-features to the number of all features; the omission segmentation rate is the ratio of the number of omission features to the number of features that should be segmented. The joint evaluation function can be expressed as follows:

$$\delta = \frac{1}{K}\sum_{i=1}^{K}(p_i * \frac{TF_i}{TC_i} + q_i * \frac{LC_i}{RC_i}) \tag{10}$$

$$p_i + q_i = 1 \tag{11}$$

where, K means the number of helical surface images for experiment; i represents the *i-th* image; p and q are adjustment coefficient, means the weight of the two segmentation rates, and the default value is 0.5; TF_i represents the number of non-eigenvectors in the *i-th* image; TC_i means the total number of feature vectors; LC_i represents the number of omission features; RC_i represents the total number of features.

As shown in the joint evaluation function, generally speaking, if the histogram of complex helical surface image is relatively smooth, it reflects that the feature division is relatively difficult, and the possibility of error segmentation is relatively larger. Therefore, the average gray distribution rate of the complex helical surface image is constructed, and the method of adjusting the segmentation rate coefficient based on the image gray histogram information is studied, which is the basis for adjustment of coefficients.

Due to the uneven gray distribution of complex helical surface image, we will take the artificially labeled complex helical surface image as the evaluation sample, and take the marked feature segmentation effect as the data source of effect evaluation for image segmentation. The smaller the joint evaluation function, the better the performance of the algorithm. A further study about the relationship between the adjustment coefficient and the global gray distribution of the complex helical surface image is carried out to determine the weight of the two segmentation rates adaptively.

Considering that the more even the gray distribution of complex helical surface image is, the greater the probability of error segmentation occurs. Therefore, the gray standard deviation reflecting the gray dispersion of helical surface image is usually calculated as the error segmentation adjustment coefficient. The gray standard deviation is calculated out as follows:

$$STD = \sum_{i=0}^{255}(r_i - AvgG) * P(r_i) \tag{12}$$

where STD is the gray standard deviation of the helical surface image; $AvgG$ is the gray mean value of the helical surface image; r_i is the i-level gray value in the helical surface image; $P(r_i)$ is the probability of r_i appearing in the helical surface image. The calculation formula of $P(r_i)$ is shown as follows:

$$P(r_i) = \frac{N_i}{N} \tag{13}$$

where N_i is the number of pixels in r_i and N is the total number of pixels in the image.

The calculation formula of AvgG is as follows:

$$AvgG = \sum_{i=0}^{255} r_i * P(r_i) \tag{13}$$

4. Numerical experiments

In this section, we implement the image segmentation model and the multi-population cooperative evolution algorithm, and the numerical experiments have been done to verify the effectiveness of the model and algorithm. The complex helical surface images used in experiments are all collected by our laboratory for vision measurement. We use the standard test functions to test the performance of the algorithm, and use the standard optimization algorithm and the proposed algorithm in this paper for comparative experiments.

4.1. Experimental conditions

As a key component for vision measurement of complex helical surface, the main function of industrial camera is to convert the optical signal reflected by the object surface into orderly electrical signal, which directly determines the resolution, image quality and noise of the collected image. In this experimental system, HiVision Dcam 100M is used as the acquisition device, and its parameters are shown in Table 1.

Table 1. Parameters of Hivision Dcam 100M.

Parameter Item	Parameters of industrial camera
image resolution	1280*1024
pixel depth (Bit)	8
maximum frame rate (Frames/sec)	20
exposure mode	field exposure mode
pixel size (μm)	8
Lens interface type	CS

The optical lens used in this experiment is Computar M1214. In the process of image acquisition, when the light from the surface of the complex spiral surface is reflected to the optical lens, it gathers on the camera chip through the focusing effect of the lens to form an electrical signal and output the image. The parameters of Computar M1214 are shown in Table 2.

Table 2. Parameters of optical lens in measurement.

Parameter Item	Parameters of optical lens
lens size (inch)	1/3
aperture	1.4
focal length	12
field of view (angle)	wide-angle
Lens interface type	CS

In order to verify and analyze the algorithm conveniently, we use manual method to mark the surface of complex helical surface model with black dots. The marking diagram is shown below as in Figure 4.

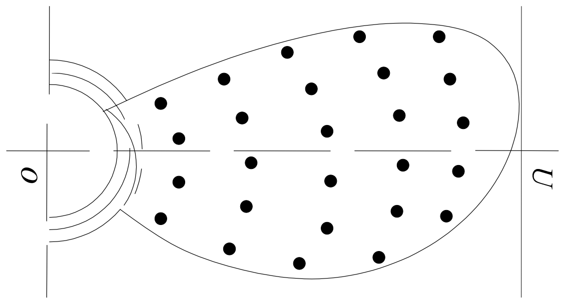

Figure 4. Mark points made by manual operation on helical surface.

4.2. Segmentation results and comparative analysis

In order to verify the performance of the proposed multi-population cooperative evolution algorithm, six classical basic test functions are used to test the algorithm. In the actual experiment, the standard optimization algorithm and the algorithm proposed in this paper were run 600 times under the same conditions, and the optimal value and average value obtained were used as the evaluation basis. The maximum number of iterations was set to 200 times, the dimension was set to 5, the inertia coefficient was set to 0.5, the acceleration factor was set to 2, and the population size was set to 8. The running results are shown in Table 3.

Table 3. Performance of the proposed algorithm.

Test function	Algorithms	Iterations	Optimal value	Average value
1	Stand algorithm	26	0.98752	0.96793
Schaffer	Proposed algorithm	16	0.97336	0.95477
2	Stand algorithm	44	0.00272	0.00283
Griewank	Proposed algorithm	52	0.00059	0.00042
3	Stand algorithm	37	0.00122	0.00119
Sphere	Proposed algorithm	21	0.00071	0.00035
4	Stand algorithm	63	8.22601	9.63764
Rastrigin	Proposed algorithm	30	1.77532	1.79695
5	Stand algorithm	43	0.02768	0.01987
Ackley	Proposed algorithm	19	0.00039	0.00022
6	Stand algorithm	41	4.01337	3.64796
Rosenbrock	Proposed algorithm	25	0.00182	0.00203

As it can be seen from Table 3, in general, the performance of the proposed evolution algorithm studied in this paper plays better, and all of them have obtained better optimal values. Except for the test function Griewank, the algorithm in this paper uses less iterations but to find a better optimal value.

At the same time, the proposed algorithm is applied to the segmentation of complex helical surface image, and the result of image feature segmentation is shown as below in Figure 5. From the experimental results, it can be seen that the image segmented by the new model maintains better feature details and obtains better image segmentation results.

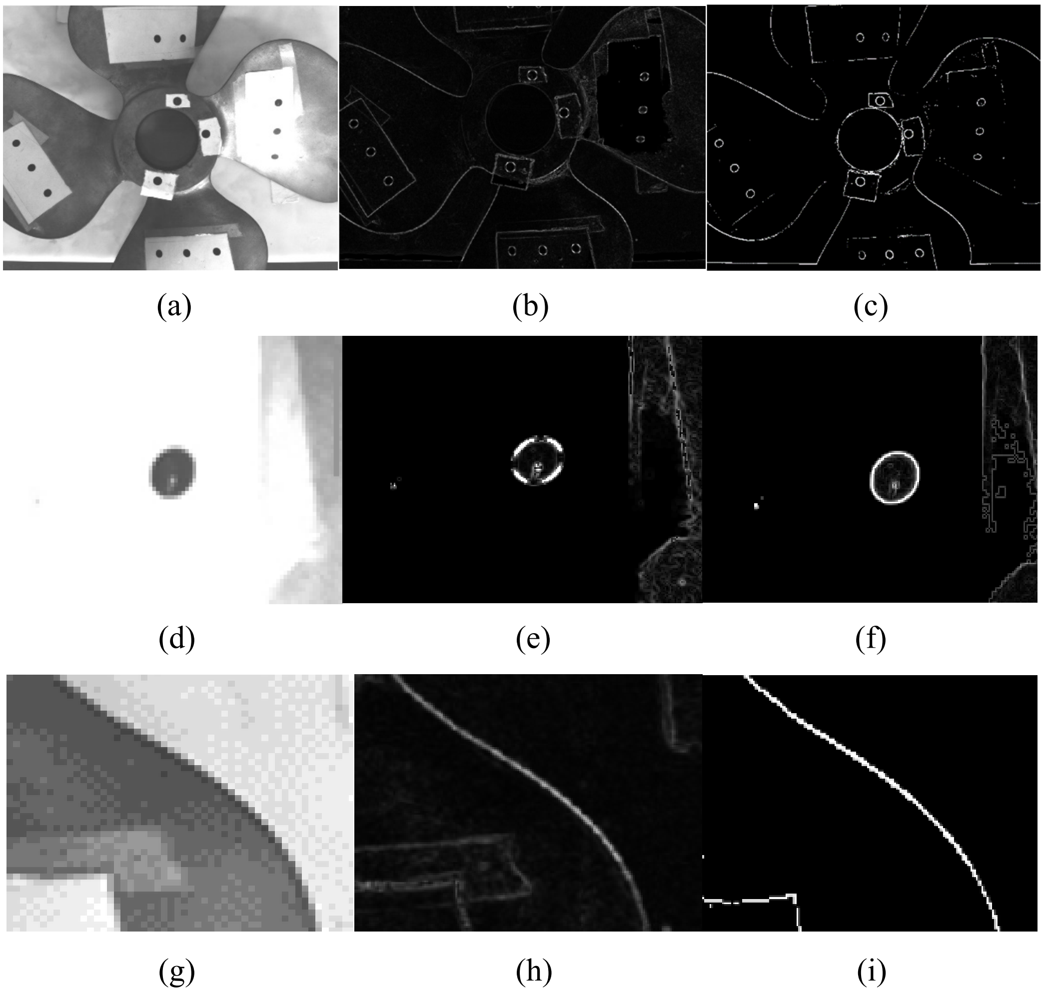

Figure 5. Comparison of segmentation results for helical surface image. (a) Original image, (b) Image segmented by stand, (c) Image segmented by algorithm proposed algorithm, (d) Local magnification of image (a), (e) Local magnification of image (b), (f) Local magnification of image (c), (g) Local edge magnification of image (a), (h) Local edge magnification of image (b), (i) Local edge magnification of image (c).

Table 4. Segmentation rate results for helical surface image.

Algorithms	Omission segmentation rate	Error segmentation rate	Comprehensive segmentation rate
Stand algorithm	0.0403	0.0392	0.9602
Proposed algorithm	0.0287	0.0261	0.9726

Based on the segmentation results of complex helical surface image, the calculation method of feature omission segmentation rate and error segmentation rate proposed in this paper is used for calculation and analysis. Among them, the weight ratio of omission segmentation rate and error segmentation rate is calculated adaptively. The comparative analysis results of standard algorithm and the novel algorithm in this paper are shown in Table 4. The result segmented by multi-population cooperative evolution algorithm achieves a more satisfactory result.

5. Conclusions

This paper presents a multi-population cooperative evolution-based image segmentation algorithm to solve the accurate segmentation problem of complex helical surface image. According to the characteristics that the gray distribution is uneven and the feature patterns are easily to be confused in helical image, we researched the internal mechanism of segmentation problem for complex helical surface image solving by multi-population cooperative evolution algorithm firstly, and then brought insight into the consistency and applicability of the segmentation problem and the novel algorithm. Following that, we discussed a feature description strategy by combining gray level co-occurrence matrix and fractal algorithm, which ensured a correct distinguishing rate from the aspects of image gray level and feature structure. Based on these, the segmentation for complex helical surface problem was transformed into a multi-feature evolution problem. A multi-directional evolution model for image segmentation was proposed, and the construction details was discussed. Meanwhile, a multi-population cooperative evolution algorithm based on shared archive set was presented. By the information sharing and interaction of different directions and archives, the local and global cooperation in multi-directional cooperative evolutionary segmentation of helical surface image was realized. Finally, it was verified by numerical experiments that the novel segmentation model is effective for segmentation of helical surface image, and the performance of the optimization algorithm is superior to traditional optimization algorithm. The research work in this paper is of great significance to vison-based manufacturing of complex helical surface, and it can be used for reference to improve the production level of modern industry.

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Conflict of interest

The author declares no conflict interest.

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