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Defect Detection Image Processing Technology Based on Swarm Intelligence Optimization Algorithm

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Abstract. The swarm intelligence optimization algorithm has obtained good results in practical application in the field of image processing with defect detection, and it has become the focus and hot spot of attention and research in the field of image processing. In this paper, the application of ALO as the representative of the relevant swarm intelligence optimization algorithm is studied to address the problems and shortcomings of image processing technology in the field of object defect detection. By extracting typical defect detection image samples, the effect of the application of the algorithm in sample processing is systematically studied. In addition, the introduction of perturbation strategy and inertia weights in ALO effectively improves the search performance of the algorithm. Finally, this paper analyzes the performance comparison between the commonly used defect detection image processing techniques and the algorithm in this paper by establishing comparative verification experiments. The experimental results show that the image processing strategy constructed in this paper has significant application advantages in the dimensions of image enhancement and image processing applicability.

1. Introduction

At present, defect detection is widely and deeply used in various industries, and defect detection can effectively grasp the state data and characteristics of the inspected object [1]. The traditional method of object defect detection is to analyze and judge the defect data by using the characteristic types and properties of the object surface [2]. Generally speaking, defects on the surface of an object include cracks, holes, and miscellaneous spots, which can adversely affect the performance and functionality of the object [3]. Traditional methods of object defect detection mainly rely on manual methods, such as visual inspection and other ways. The advantage of these methods is simple, but the disadvantages are more prominent, such as subjectivity, low efficiency, poor accuracy, etc. For this reason, the automatic and intelligent means of detecting object defects are gradually receiving attention, research, and application [4].

Automated methods for object defect detection include infrared, laser scanning, eddy current, magnetic leakage, and visual images, among which eddy current detection is usually suitable for the detection of defects such as cracks and fissures because of the high requirements for conditions such as the object's own property frequency and temperature field. Infrared defect detection methods can detect defects in objects with the help of the induction current defect heating principle, but there are also many restrictions and limited detection range, and other shortcomings [5]. In addition, leakage detection is limited to the detection of metal defects, so the scope of application is narrow. Laser scanning detection has high applicability, but the principle is complex and the economy of large-scale applications is insufficient [6].

To address the shortcomings of manual inspection and traditional defect detection image processing techniques, this paper designs and builds a defect detection image processing method based on the swarm intelligence optimization algorithm [7]. Using the swarm intelligence optimization algorithm and image vision, the flexibility, applicability, and economy of the defect detection process are significantly improved [8]. The swarm intelligence optimization algorithm is able to target the defect images of the collected object surface, thus reducing the workload of the whole system data analysis and thus improving the efficiency and accuracy of detection [9]. This paper addresses the difficulties and challenges faced by defect detection image processing technology in terms of many types of object defects and subtle defect data not easily captured and carries out algorithm optimization, which brings significant improvements in the optimized retrieval, fusion, and recognition of images.

2. Swarm intelligence optimization algorithm

The swarm intelligence optimization algorithm is the bio-mimetic simulation and learning evolution based on the social behavior of group animals [10]. The application of swarm intelligence optimization algorithms in defect detection can guarantee the robustness and applicability of the detection process and can effectively deal with distributed problems. Representative swarm intelligence optimization algorithms include PSO, ACO, and several types, such as ALO, GOA, and IWO [11]. Among them, PSO and ACO algorithms have been studied and applied earlier, but they have the deficiency of easily falling into local optimality, so the latter algorithms have become the hotspot and focus of research and application.

2.1. Mechanism of swarm intelligence optimization algorithm

The optimal search performance of the ant-lion algorithm ALO is achieved by spatially feasible solution search, and its mathematical model is shown in Equation 1-2 below. Where L represents the cumulative sum of ant colony roving paths, *n* represents the current iteration number, n_{max} represents the maximum iteration number, and $s(n)$ represents the random function. R belongs to [0,1] and represents the generated random number. The implementation process of ALO is shown in Figure 1 below.

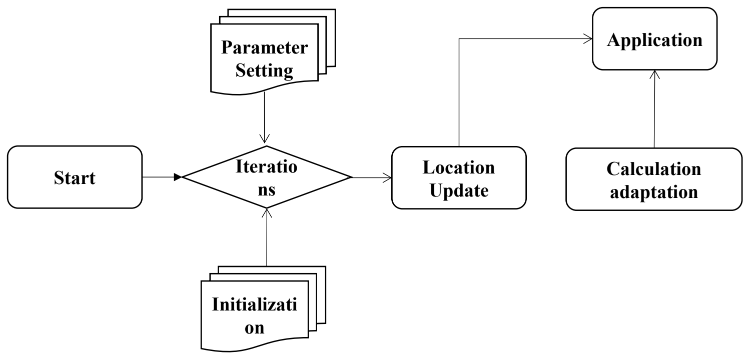

Figure 1. The process of ALO implementation

$$A(n) = [0, L(2s(n_1) - 1,\ L(2s(n_2) - 1), \dots, L(2s(n_{max}) - 1)] \tag{1}$$

$$s(n) = \begin{cases} 0,\ if\ R < \frac{1}{2} \\ 1,\ if\ R > \frac{1}{2} \end{cases} \tag{2}$$

The principle of IWO is that the number of feasible solutions is positively related to the fitness and the number of seeds, and the distribution and diffusion of seeds of feasible solutions are shown in Figure 2 below. From Figure 2, it can be seen that the seed diffusion and competition of feasible solutions can promote the iterative optimization of feasible solutions.

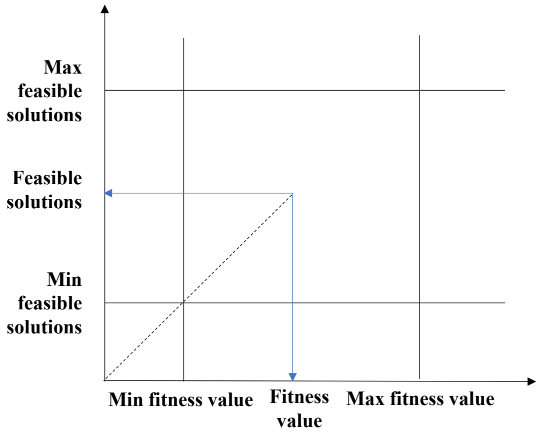

Figure 2. Distribution and diffusion patterns of viable solution seeds

The mathematical representation of IWO is shown in Equation 3 below, where B_i represents the initial value of the standard deviation, B_f represents the final value of the standard deviation, and δ represents the reconciliation factor.

$$I_n = \frac{(n_{max}-n)^{\delta}}{n_{max}}(B_i - B_f) + B_f \tag{3}$$

In addition, BA uses echolocation affine to achieve the search for the optimal solution. The algorithmic model of GOA is shown in Equation 4 below, where $H_i$represents the position of the *ith* locust, $y(x_{ij})$ represents the mutual influence between the *ith* locust and other individuals, Z_i represents the gravitational force on the *ith* locust, and F_i represents the wind force on the ith locust. dij represents the distance between the *ith* locust and the *jth* locust, and $\widehat{x_{ij}}$ represents the unit vector between the *i-th* locust and the *j-th* locust, *N* represents the population size, and *y* represents the action force function.

$$H_i = \sum_{j=1}^{N} y(x_{ij})\widehat{x_{ij}} + Z_i + F_i \tag{4}$$

2.2. Defect detection image data

Defect detection image data processing mainly includes several dimensions, such as defect image enhancement, image threshold segmentation, image texture feature extraction, optimal classification hyperplane, and image quality evaluation. Among them, the defect image is enhanced using LGE, and the quality of the image is analyzed after image conversion. The parameters of defect detection image quality evaluation mainly include several dimensions, such as pixel count, edge intensity, and entropy value, which are positively correlated with image quality. In addition, at the level of data samples of defect detection images, the defect images are compared and analyzed using publicly available data samples to establish effective prerequisites for conducting research on the characteristics of various types of defect images.

3. Defect detection image processing

3.1. Defect detection image enhancement

In the process of object defect detection, many internal and external factors can limit and interfere with the captured defect images, which can lead to low-quality conditions such as unclear boundaries, missing details, and poor contrast. In order to improve the detection accuracy and efficiency of the defect images, the captured low-quality images need to be optimized for data enhancement to reduce the difficulty and intensity of image post-processing.

The object defect images are enhanced by using the ALO algorithm, and several typical defects such as pockmarks, scratches and cracks are selected for image enhancement, and the results are shown in Figure 3 below. From the results, it can see that the processing effect of ALO on the defect images before improvement is not satisfactory, mainly in terms of incomplete detail processing. For example, there are several problems, such as data loss of image crack details, blurred image pockmarks data and incorrect image scratch data. For this reason, ALO needs to be improved and optimized to better realize the processing of defect images.

Figure 3. Typical defects for image enhancement effects

In the process of ALO image processing, the number of data iterations increases to gradually reduce the auxiliary effect of search accuracy, so the searchability, data mining ability, and convergence efficiency of the algorithm need to be further optimized so that the algorithm can achieve better image enhancement effect at a smaller cost.

3.2. *Swarm intelligence algorithm optimization*

To address the shortcomings of ALO in defect detection image processing applications, the inertia weight is introduced in the algorithm, and n_{max} is the maximum number of iterations.

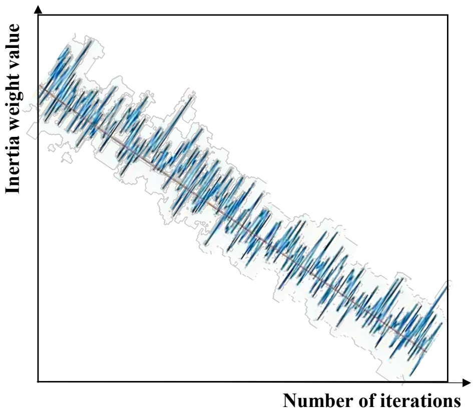

Figure 4. The inertia weight values versus the number of iterations of

The inertia weight is negatively correlated with the number of iterations, i.e., as the number of iterations of the algorithm increases, the inertia weight decreases continuously, and the correspondence between them is shown in Figure 4 above.

The introduction of inertia weights in ALO enables the algorithm to have stronger exploration and mining performance. IWO has the advantage of outstanding mining performance, and its fusion with ALO can significantly improve the efficiency performance of the algorithm's optimal solution search. IWO is applied to the process of defective image processing, and the searchability of the algorithm decreases with the increase of the number of iterations, so the search performance of the algorithm needs to be optimized. The application of the algorithm in populations with high applicability can reduce the demand for arithmetic power in the search process, thus improving search efficiency and quality. On the other hand, the introduction of the perturbation strategy shown in Figure 5 can further improve the convergence performance of the algorithm during the initial iterations. As can be seen from the results in the figure, the introduction of perturbation results in a larger range of optimal solutions, which leads to a significant improvement in the search performance without any reduction in the mining performance of the algorithm.

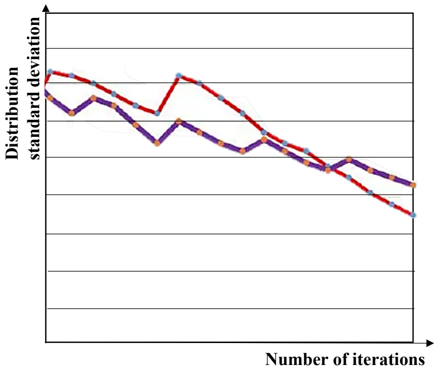

Figure 5. Perturbation strategy to improve the convergence performance

4. Result verification of defect detection image processing algorithm

In order to judge the performance of the defect detection image processing technique based on the swarm intelligence optimization algorithm designed in this paper, defect image samples from public databases are selected for processing, and the processing results are analyzed and compared with the results using traditional defect detection image processing methods, and then the effectiveness of the optimization algorithm in image processing is verified.

4.1. Application Scenarios

The Gamma, Gray Linear Transform, and HE methods are selected to enhance the defect image samples with the Group Intelligence Optimization Algorithm (GIOA) used in this paper. The selected defect image samples include three kinds of defects, such as cracks, pockmarks, and scratches, and the comparison results of different algorithms for processing the sample images are shown in Figure 6 below. From the results in Figure 6, it can be seen that the first three processing methods for cracks have the problem of missing details. Secondly, in the detection of pockmark defects, these three processing methods have problems such as excessive background image contrast, defect merging, and detail missing, respectively. In addition, in the scratch defect detection dimension, all three processing methods also have the problem of poor display of image enhancement details.

Gamma, Gray Linear Transform and HE methods

GIOA methods

Figure 6. Comparison results of different algorithms for processing sample images

In comparison, the defect detection image processing method based on the swarm intelligence optimization algorithm constructed in this paper has the best effect on the image enhancement method of the sample, whether pockmarks, cracks or scratches and other defect images have better enhancement processing effects.

In this paper, inertia weights and perturbation strategies are introduced in the ALO algorithm to improve the search and mining performance of the algorithm. The introduction of these strategies makes the algorithm significantly more effective in processing defective images such as pockmarks, cracks or scratches, and shows strong adaptability. In addition, the introduction of inertia weights and perturbation strategies enables the ALO algorithm to show higher adaptability earlier in the process of processing defective images, and the adaptability value shows a positive correlation with the number of iterations, which shows that the search performance of the algorithm has also been improved.

Through the above comparison and validation, it can be seen that the defect detection image processing method based on the swarm intelligence optimization algorithm shows greater advantages in terms of adaptability and image enhancement effect compared with other defect monitoring image processing techniques. The results of the comparison and validation show that the swarm intelligence optimization algorithm has high practicality and applicability in the field of defect detection image processing and is worthy of further in-depth application.

5. Conclusion

In summary, defect detection is being widely and deeply researched and applied in various industries. In view of the drawbacks and shortcomings of the traditional defect image detection processing methods, this paper significantly improves the flexibility, applicability and economy of the defect detection process by using the swarm intelligence optimization algorithm and image vision. By introducing inertia weights and perturbation strategies in the swarm intelligence optimization algorithm, we achieve targeted processing of defect images on the collected object surfaces, reduce the workload of data analysis of the defect image system, and improve the efficiency and accuracy of detection. Finally, this paper verifies the advantages and application value of the defect detection image processing method based on the swarm intelligence optimization algorithm compared with other defect monitoring image processing techniques in terms of adaptability, image enhancement effect, and other levels by selecting the image samples for comparison and verification analysis.

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