Research on Application of Ant Colony Algorithm Based on Multi-sensor Image Fuzzy Fusion in Image Recognition

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Abstract: In the current rapidly developing society, image recognition technology is currently an important means that can provide a full range of dynamic data. It plays an important role in economics, politics and other fields. Fuzzy image fusion algorithms have opened up to solve these problems in image recognition. Based on the current wide application of image recognition, this paper studies the research of multi-sensor image fuzzy fusion algorithm in the application of high-definition image recognition. Aiming at the characteristics of infrared and visible image fusion, an infrared-visible image fusion algorithm based on non-down sampling transformation and hybrid particle swarm algorithm is proposed. For low-frequency sub-images, an improved weighted average method based on area average is used for neighborhood fusion. For high-frequency sub-images, a hybrid particle swarm optimization algorithm is used to select the threshold, and the neighborhood algorithm based on average gradient selection is used for fusion. This algorithm can effectively improve the fusion effect of fused images. The experimental research results show that combining the characteristics of gradient intensity and phase consistence, the characteristic method of compressing the information while retaining important information, which is convenient for real-time processing, is used for related research on sensor image fusion.

1. Introduction

Object recognition mainly studies the classification of objects by computers, which is an important part of artificial intelligence. Commonly used object recognition methods include decision theory, grammar, artificial neural networks and word bag models. The target recognition method based on the bag-of-words model has attracted much attention due to its simple calculation and robustness to noise, illumination changes and local occlusion. For object recognition in the Internet of Things environment, it is necessary to further consider the problem of reducing the scope of identification objects [1-2]. For example, if a warehouse application only establishes an identification library for those object categories involved in the identification object, the warehouse Greatly reduce the space of the recognition library [3]. An ant colony algorithm structure is designed. Based on this structure, the gradient intensity and phase consistence of the image can be introduced into the ant colony search process as heuristic information, and the collaboration between ant colonies can be realized by sharing the pheromone matrix. Combining the advantages of ant colony algorithm, a more effective feature extraction method is formed [4].

The purpose of image fusion is to preserve important information in the two images to the greatest extent. Therefore, for multi-sensor images, it is necessary to retain the spectral information of the
original multi-spectral image and introduce the detailed texture information of the high-resolution image. Therefore, the extraction of feature information is directly related to the quality of the final fusion image [5]. As one of the technical means of optical information processing, optical image recognition has been successfully applied in many fields of science and technology, such as target tracking, pattern recognition, guidance. [6]. As far as optical feature recognition is concerned, the most meaningful work is to obtain the correlation signal between the target image and the reference image. Its intensity reflects the similarity of the two optical images, which provides a quantitative index for image recognition. The edge can outline the shape and contour of the target image and contains rich information. In image segmentation recognition and analysis, it has always been an important attribute of image feature extraction [7].

Multi-sensor image enhancement technology is one of the necessary foundations for the development of digital images. Image segmentation and image edge extraction segmentation of the target subject and background is a pre-requisite condition for achieving image responsiveness of human vision, and it is also a precursor of image processing [8]. How to segment the detected image and extract the edge feature value is the judging standard of the image processing. It is proposed to use different infrared images for the edge detection operator, but the literature does not discuss how to set the edge detection operator [9]. It is proposed to use edge continuity to evaluate the quality of edge extraction, which is only a threshold for judging edge continuity based on empirical experience. The edge detection operator is used to extract the edge of the image, calculate the local entropy of the image edge, implement weighted calculation on the gray information of the edge pixel, and calculate the weighted average edge local entropy of the edge point. The process is complicated and the calculation amount is very large. The ant colony algorithm is used to realize image analysis. Although the algorithm can obtain high-precision outer contours, the ant colony retrieval is random and the retrieval efficiency is not high [10].

2. The establishment of an algorithm incorporating fuzzy ant colony

2.1. Ant Colony Algorithm

The ant colony algorithm can accurately extract the features of multi-sensor images. It is divided into three parts: feature extraction, heuristic information acquisition and ant colony optimization. The algorithm calculates two heuristics based on the input image. The heuristic information is an image with high resolution, and the heuristic information of the gradient intensity is the phase consistency corresponding to the image I(x) with a relatively low resolution.

Optimization of ant colony:
First order: \[ \Delta T_{mt}=g_{x} \] (1)

Therefore, in the t time period, the ant colony is AC. The produced pheromone \( \lambda_{x}(t) \) becomes the pheromone produced by M ants:

\[ \lambda_{x}(t) = \sum_{m=1}^{M} \Delta \lambda_{x}^{m}(t) \] (2)

Similarly, \( \xi_{x}^{n}(t) \) is the pheromone left by the ant n contained in AC in the time period t at point x, then:

\[ \xi_{x}^{n}(t) = p_{c}(x) \] (3)

Then, in the t time period, AC produces pheromone \( k_{x}(t) \) here, that is, the pheromone produced by all N ants:

\[ k_{x}(t) = \sum_{n=1}^{N} \Delta \xi_{x}^{n}(t) \] (4)

Therefore, the pheromone \( \Delta T_{x}^{m}(t) \) at time t can be obtained by the update formula shown in equation (5):
\[
T_x(t) = (1 - \rho) \cdot [(1 - \rho) \cdot T_x(t - 1) + \rho \cdot \lambda_x(t)] + \rho \cdot T_x(t)
\] (5)

In the formula, \(\rho\) represents the pheromone volatilization coefficient. If \(t=0\), then at the beginning of starting the ant colony algorithm, \(T_x(0) = \varepsilon\) is always greater than 0 during processing. The initial set of \(T\) iterations will automatically stop. After completing the ant colony optimization, we enter the feature extraction work. In the algorithm, we use the pheromone matrix, and then through the corresponding processing, the image features can be obtained.

\[
L^F(i, j) = \frac{E^M_{ij}}{E^M_{ij} + E^N_{ij}} + \frac{E^N_{ij}}{E^M_{ij} + E^N_{ij}} L^F_{ij}(i, j)
\] (6)

In the formula, \(E^M_{ij}\) and \(E^N_{ij}\) are the energy of the local area of the high-frequency coefficient of image \(M\) and image \(J\) respectively. \((I, J)\) is the center. The fusion of high-frequency coefficients must comply with the corresponding principles. The high-frequency subband coefficients are correctly fused through the edge features of the source image. The relevant image processing measures are as follows: Use the ant colony algorithm to extract the edge features of the fused source image \(m\) and \(N\), and use Edge maps \(E^M_{ij}, E^N_{ij}\) with a single pixel width.

\[
S_{m,n}(i, j) = \begin{cases} 
1, & \text{if } |C^M_{ij}(i, j)| > |C^N_{ij}(i, j)| \\
0, & \text{otherwise}
\end{cases}
\] (7)

2.2. Ant colony algorithm fused with fuzzy clustering

In order to solve the problem of blindly moving ants in the traditional ant colony algorithm, the initial selection randomly forms a large number of invalid search problems. This paper proposes a concept: use fuzzy clustering to realize the designation of cluster centers to assist ants in orderly search. The fuzzy clustering process is divided into two stages: cluster center initialization and cluster center change.

Initialization of cluster centers:
According to the fuzzy matrix, select a limited number of representative pixels in the image as the clustering center for initialization. In the clustering process, once there are pixels that do not belong to the class, it means that the entire clustering process has not been completed, and the clustering center needs to be changed to perform the next clustering:

\[
\text{Center}_\alpha = \frac{1}{N_{\alpha}} \sum_{k=1}^{N_{\alpha}} X_k
\] (8)

This paper sets the heuristic function as the reciprocal of the Euclidean distance between the original pixels, calculates the path selection direction of the regional ant colony, and obtains the ratio of the distance \(d_{ij}\) between the current search pixel and the cluster center and the cluster radius \(r\):

\[
n_{ab} = \frac{r}{d_{ab}} = \frac{r}{\sqrt{\sum_{k=1}^{m} p_k (X_{ak} - \text{Center}_{bk})}}
\] (9)

2.3. The search strategy of boundary ant colony

For ants to choose a path, if the path is shorter, the probability of ant selection is greater, and the concentration of pheromone left is greater, and more ants will be attracted, but the border ant colony does not follow this path. In order to get rid of the path of maximum pheromone concentration, search for new paths and then search for the compensation boundary, the boundary ant colony search strategy is a solution proposed to solve the problem of repeated search. Different signs identify the area where the ant colony is located and reduce the search for repeated areas. Face to face and the next step to touch the non-local boundary ant colony in two different situations, two different strategies are adopted, which are specifically embodied as follows: (1) When two ants meet face-to-face, the two belong to different groups of boundary ants, and the next step is the same. One pixel, stop the next move. (2) When one ant touches the path taken by another ant, stop the next move. When all the ants are searching, this article establishes a taboo table for them to record the paths that the ants have walked to find new paths and avoid repeated searches until all the boundaries are searched.
3. Modeling method

3.1. Hybrid particle swarm algorithm model
Combining the sensor's running time, historical data, load size and other aspects to evaluate the life of the machine, a more scientific image recognition time can be obtained. The risk in the hybrid particle swarm algorithm model is the probability of no failure at a certain moment, but after this moment, the expression is as follows:

\[
h(t) = \lim_{\Delta t \to 0} \frac{\Delta t}{\Delta t} P\{t \leq T \leq t + \Delta t|T \geq t\}
\]

(10)

\[
\lambda_0(t) = \lim_{\Delta t \to 0} \frac{\Delta t}{\Delta t} P\{N(t + \Delta t) - N(t) \geq 1\}
\]

(11)

\[
h(t, z) = h_0(t)e^{\beta z(t)}
\]

(12)

The basic risk function hall \( h_0(t) \) is the failure rate, \( \beta \) is the regression coefficient, and \( z(t) \) is the covariate, which is the corresponding signal information of the observation object. Such as temperature, vibration, which reflect the characteristics of the proportional hazard model related factors affecting the life of the machine:

\[
f(t) = \beta \frac{t}{t_0}(1 - \varepsilon)^{\beta - 1}e^{-\frac{(1-\varepsilon)^\beta}{t_0}}
\]

(12)

\[
F(t) = 1 - e^{-\frac{(1-\varepsilon)^\beta}{t_0}}
\]

(13)

\[
\lambda(t) = \beta \frac{t}{t_0}(1 - \varepsilon)^{\beta - 1}
\]

(14)

\[
h(t, z) = \beta \frac{t}{t_0}(1 - \varepsilon)^{\beta - 1}e^{\beta z(t)}
\]

(15)

3.2. Hybrid particle swarm algorithm
Assuming that there are \( N \) particles in the particle swarm, and each particle has \( D \) feasible solutions, it shows that the particle swarm is in a \( D \)-dimensional space, and the speed and position of particle \( f \) at time \( f \), and the searched local optimum can be respectively determined by the formula (16), (17), (18)

\[
V_i(t) = (V_1, V_2, V_3, V_4, V_5, ..., V_D)
\]

(16)

\[
V_i(t) = (x_1, x_2, x_3, x_4, x_5, ..., x_D)
\]

(17)

\[
V_i(t) = (p_{b1}, p_{b2}, p_{b3}, p_{b4}, p_{b5}, ..., p_{bD})
\]

(18)

The intelligence of the intelligent algorithm is reflected in the memory and judgment of the algorithm, and the particle swarm algorithm as an intelligent algorithm also has these characteristics. Although particle swarm algorithm has many advantages, it still can not get rid of the dilemma of falling into local optimality. Therefore, particle swarm algorithm will be used in combination with other algorithms in use. Common particle swarm algorithm is combined with genetic algorithm, annealing algorithm and chaos algorithm. The combination and so on are all in order to improve the convergence speed of the algorithm to find the optimal value. This paper mainly uses the combination of particle swarm algorithm and genetic algorithm to design the objective function and optimize under the constraints of the state of the machine and the production qualification rate.

4. Data algorithm evaluation results and research Result

4.1. Experimental research results of multi-sensor fuzzy fusion algorithm
Table 1. Experimental results of the multi-sensor image fuzzy fusion ant colony algorithm data set

|        | DATA-1 | DATA-2 | DATA-4 | DATA-8 | DATA-16 |
|--------|--------|--------|--------|--------|--------|
| PSN-1  | 89     | 73     | 85     | 87     | 97     |
| PSN-2  | 91     | 82     | 93     | 99     | 91     |
As shown in the experimental results of the multi-sensor image fuzzy fusion ant colony algorithm data set experimentally in Table 1, this paper further studies the performance of other variants of the multi-sensor fuzzy fusion ant colony algorithm data set in order to explore the importance of the DATA network. This article adds DATA layer to different data sets in the PSN model. For the Office-51 data set, this article adds the DATA-16 layer after the different data sets according to the described settings. Table 1 shows the average classification accuracy of the Office dataset with DATA added. Where IBN-x means adding instance normalization and batch normalization blocks after the 16th data set, adding batch normalization blocks after other data sets, and IBN-xs means adding data sets at the xth and sth layers Then add instance normalization and batch normalization blocks, and so on. In view of the above-mentioned problems and shortcomings of deep learning algorithms, this paper combines sensor data fusion technology with deep learning methods, provides prior information through deep learning image processing, and proposes an image recognition method based on multi-sensor data fusion, and targets mixed particles. The swarm deep learning model is improved, and a new hybrid particle swarm model is designed for the data model of the multi-sensor image fuzzy fusion ant colony algorithm.

|     | PSN-3 | PSN-4 | AVERAGE |
|-----|-------|-------|---------|
|     | 93    | 94    | 91.75   |
|     | 95    | 89    | 84.75   |
|     | 71    | 87    | 84      |
|     | 69    | 73    | 82      |
|     | 83    | 87    | 89.5    |

As shown in Figure 1, the classification performance of three different choices is to compare the effects of different classifications. The three classifications of ELM, SVM and KNN are analyzed experimentally. ELM, SVM and KNN use 22, 27, and 19 features respectively. Figure 1 shows the classification performance obtained by the three classifications. It can be seen in the figure that the ELM classifier achieves the lowest performance, while the highest performance is KNN. Time efficiency is an important performance of real-time remote sensing image processing algorithms. At the same time, the time efficiency of the algorithm in the training phase and the test phase is considered. Figure 1 shows the experimental results of the training and testing time of the three classifiers. KNN classification does not require training processing, but its classification accuracy is far lower than SVM and ELM classifiers. In general, ELM with linear kernel achieves the lowest calculation time. Remote sensing images are rich in detail information and high in feature dimensions. Generally, remote sensing images extracted by traditional feature extraction schemes have weak feature expression and serious information loss, which has an adverse effect on the subsequent processing of remote sensing images.
5. Conclusion
Multi-sensor technology is indispensable in modern society, that is, the fusion of fuzzy sensing images of images is inseparable from the development of society. Using the strong organization, adaptability, discreteness and parallelism of the ant colony algorithm, combined with the characteristics of gradient strength and phase consistency, the effective information in the image can be extracted according to the sensitivity of the main features of the image, and it has important significance. When compressing information, you can keep the information for real-time processing. Compared with the traditional method, this method has made great progress in spectral preservation and spatial resolution improvement, and then compensates for the time difference between the image taken by the camera, and through inertial navigation, satellite navigation and positioning equipment, high-precision map, camera Based on multi-sensor data fusion, extraction of regions of interest, and improvement of target representation accuracy, the impact of non-target factors on the recognition algorithm is reduced.

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