Adaptive Clustering SOFC Image Segmentation Based on Particle Swarm Optimization

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Abstract: Microstructural parameters are important for analyzing the chemistry and performance of solid oxide fuel cells (SOFCs). Aiming at the YSZ / Ni anode optical microscopy (OM) image of SOFC, in this paper, particle swarm intelligent optimization algorithm is used to improve the fuzzy C-means clustering algorithm for image segmentation. Particle swarm optimization is used to adaptively search the initial clustering center, helping to avoid local optimization and preserve more image detail. The experimental results show that the proposed method can improve the segmentation accuracy of images. At the same time, it can accurately segment the SOFC three-phase and provide effective image segmentation results for the microstructure parameters.

1. Introduction
Solid oxide fuel cell (SOFC) [1] is a new type of renewable energy that uses chemical reactions to convert chemical energy from fossil fuels directly into electrical energy. It is known for its efficiency and environmental protection. The SOFC mainly passes through the oxidation reaction of the fuel gas in the anode [2]. As a fuel gas oxidation reaction site, the Ni-YSZ anode can provide gas diffusion paths and conductivity to prevent diffusion polarization and ohmic polarization of the battery. Related studies have shown that the electrochemical properties such as conductivity of Ni-YSZ anode are directly related to its microstructure [3]. Relevant scientists have proposed some microstructural analysis techniques such as nano-X-ray tomography [4], microscopic analysis [5], focused ion beam scanning electron microscopy (FIB SEM) [6] and image analysis [7] method. However, complicated operations and time consuming cannot meet the requirements of daily testing. Paper [7] proposed a feasible image analysis method and developed an image analysis method to distinguish each constituent phase of Ni / YSZ cermet. Therefore, in order to accurately and effectively realize the microstructure segmentation of SOFC, a special image segmentation method should be proposed for YSZ / Ni anode OM images.

Fuzzy C-means clustering method (FCM) [8] is a widely used image segmentation method and successfully applied to SOFC image segmentation [9]. Because the FCM method is sensitive to noise and illumination, and, in the image is not consider the spatial domain information, the segmentation
result is determined only by the intensity of a single pixel, which has a certain influence on the segmentation result. Considering the spatial neighborhood relationship, rich changes in the FCM objective function have emerged. And FCM is highly dependent on the initialization parameter setting in the segmentation process, therefore, it is easy to fall into the local optimal solution in the continuous iterative process. In 2013, Gong proposed to weigh the weighted fuzzy factor and kernel metric to enhance the robustness of the algorithm, however, this method has a high computational density, which is not only sensitive to the initial clustering center, but also needs to manually set the initial clustering center. Recently, more and more evolutionary algorithms have been used by researchers to optimize FCM parameters, such as genetic algorithm (GA), particle swarm optimization (PSO) and so on.

In order to avoid falling into local optimum, the proposed method uses PSO to adaptively search the initial cluster center, and then uses the combined spatial domain information clustering algorithm to segment the image. The effectiveness and applicability of the algorithm are verified by segmentation tests of natural images and real SOFC images.

The arrangement of this article is as follows: the next section provides the proposed method in detail. In section 3, give the applications segmentation result. Finally, Section 4 gives the conclusions.

2. Proposed algorithm

This paper proposes an adaptive optimization clustering center method to improve the fuzzy C-means. PSO is an evolutionary computational technique based on swarm intelligence theory, inspired by bird foraging behaviour. Let the population size be S and the solution space dimension be N. Then in the k-th iteration, the velocity and position of the particle i are updated as follows,

\[ v_{ij}^{k+1} = \omega \times v_{ij}^k + c_1 \times r_1 \times (pbest_{ij} - x_{ij}^k) + c_2 \times r_2 \times (gbest - x_{ij}^k) \]

\[ x_{ij}^{k+1} = x_{ij}^k + v_{ij}^{k+1} \quad i = 1,2,\ldots,S \quad and \quad j = 1,2,\ldots,N \]

where \( \omega \) is the inertia weight value, \( c_1 \) and \( c_2 \) are the learning factors, use \( r_1 \) and \( r_2 \) to represent random number in the interval (0,1).

KWFLICM improved the FCM algorithm by introducing trade-off weighted fuzzy factors and kernel distance metrics.

The objective KWFLICM objective function is defined as:

\[ J_{KWFLICM} = \sum_{i=1}^{N} \sum_{k=1}^{C} u_{ik}^m (1 - K(x_i, v_k)) + G_{bi} \]

\[ G_{bi} = \sum_{i=1}^{N} \sum_{k=1}^{C} u_{ik}^m \sum_{j \in N_i} w_{ij} (1 - u_{ij})^m (1 - K(x_i, v_j)) \]

Where \( N_i \) is the set of neighbors in a window around \( x_i \), \( w_{ij} \) is the trade-off weighted fuzzy factor of jth, \( 1 - K(x_i, v_j) \) represents a non-Euclidean distance metric, \( (1 - u_{ij})^m \) is a penalty which can accelerate the iterative convergence to some extent. \( v_1, v_2, \ldots \) is the centers of the clusters.

The follows are show the updated membership values and cluster centers:

\[ u_{bi} = \frac{1}{\sum_{j \in N_i} \left(\frac{1}{1 - K(x_i, v_j)} \sum_{j \in N_i} w_{ij} (1 - u_{ij})^m (1 - K(x_i, v_j))\right)^{1/(m-1)}} \]

\[ \sum_{j \in N_i} \left(\frac{1}{1 - K(x_i, v_j)} \sum_{j \in N_i} w_{ij} (1 - u_{ij})^m (1 - K(x_i, v_j))\right) \]
\[ V_k = \frac{\sum_{i=1}^{N} (u_{ik} K((x_i, v_j), x_i))}{\sum_{i=1}^{N} (u_{ik} K((x_i, v_j)))} \]  

(6)

Lastly, de-fuzzification process calculated by the maximum membership degree is adopted to assign the pixel \( x_i \) to the \( \eta_j \) class with the largest \( u_{ij} \), which is defined as follows:

\[ \eta_j = \max(u_{ij})(j = 1, 2, \ldots, C) \]  

(7)

2.1. Algorithm description

The results of the PSO algorithm are influenced by the fitness function of the guided search function, therefore the fitness function is defined as:

\[ \text{Fitness} = \frac{k}{1 + J} \]  

(8)

where \( k \) is a normal number, \( J \) is the value of the objective function.

The flow chart of the method is shown in Figure 1.

Figure 1. Method flow chart.

The algorithm flow of this paper is as follows:

1. Initialize the final cluster number \( C \) and the stop condition \( e \); initialize the particle swarm, which contains the population size \( N \), initial position \( x_i \) and velocity \( v_i \).
2. According to formula (8), calculate the fitness value \( F \) of each particle and compare it to the individual extreme value \( p_{new} \) and the population extreme value \( g_{new} \).
3. The particle’s velocity \( v_i \) and position \( x_i \) are updated according to equations (1) and (2).
4. If the end condition \( e \) is satisfied, exit and record the optimal cluster center \( v^*_{new} \); otherwise, return to step 3.
5. According to the optimal clustering center of step 4, the membership degree is updated according to formula (5);
6. Update the cluster center \( v_i \) according to formula (6);
7. Repeat steps 5-6 until successive iterations converge
8. The final segmentation result is obtained by defuzzifying the maximum membership degree of equation (7).

3. Experimental results and analysis

The experimental hardware is 2.8 GHz, 8GB PC, test platform win10 operating system, and the test environment is Matlab2016. FLICM [11], FFCM [12], FRGMM [13] and KWFLICM [14] algorithms were used as comparison methods. The parameter \( \beta \) in FRGMM is set to 5, and the parameter of FFCM is set to 0.4 in the natural image and 0.2 in the real SOFC image according to the empirical value. In the FFCM and the proposed algorithm, the window size is set to 3×3 and the constraint parameter \( e \) is set to \( 10^{-3} \). The parameters of the PSO algorithm are: acceleration factor \( c_1 = 2.0, c_2 = 2.0 \), minimum inertia weight \( \omega = 0.4 \), maximum inertia weight \( \omega = 0.9 \). The size of the selected particle group is 50, the maximum number of iterations of the algorithm is 100, and the particle velocity is limited to [-1, 1].
3.1. Natural images

A quantitative evaluation of segmentation criteria based on the entropy-based evaluation function

\[ E = H_r(X) + H_l(X) \]  

[14] to evaluate the segmentation performance of natural images and SOFC images.

The smaller the E value, the better the segmentation result of the algorithm.

In this section, natural images are used to compare the proposed algorithm with other algorithms. Figure 2 shows a comparison of the segmentation effect of a representative natural image, where the red box in the upper right corner is a partial enlargement. In Figure 2, the accuracy of the (b) and (c) methods is poor, and the three categories are not clearly distinguished. These methods have a large misclassification between the "moon" area, the "forest" area, and the background area. (d) and (e) performed a substantially correct segmentation of the "forest" area, but the trunk on the left side of the image was imaged as a discontinuous trunk. They ignore the outlines of the branches and leaves of the "forest" area and lose some details. In the method (f), the outline of the tree is very clear and is basically close to the original image. Table 1 shows the objective evaluation index. The proposed method obtains the minimum value E, which is superior to other algorithms. In terms of entropy-based performance and visual effects, only the proposed method successfully divides the image into three regions while retaining the details of the image, and has a satisfactory segmentation effect and evaluation index.

![Figure 2](image)

**Figure 2.** (a) original natural image. (b)–(f) results by FLICM, FRGMM, FFCM(0.4), KWFLICM, the proposed method respectively.

|          | FLICM | FRGMM | FFCM(0.4) | KWFLICM | Proposed |
|----------|-------|-------|-----------|---------|----------|
| \(H_r(L)\) | 1.0471 | 1.0838 | 1.1872    | 1.1882  | 1.1767   |
| \(H_l(L)\) | 0.4264 | 0.3826 | 0.2569    | 0.2556  | 0.2551   |
| \(E\)     | 1.4734 | 1.4664 | 1.4441    | 1.4439  | **1.4318** |

3.2. Real SOFC images

In this section, the actual cross-sectional microscopic images of the SOFC anodes obtained using optical microscopy instruments at different magnifications are used to verify the application value of the algorithm. There are three different magnifications (200, 400, 1000) for experimental testing.

Figure 3 is an experimental result of 400 magnification amplification. b–f uses the algorithms FLICM, FFCM (0.2), FRGMM, KWFLICM and the methods proposed in this paper. In order to accurately compare the details of the segmentation, the red borders correspond to the corresponding position markers of the various segmentation results in Figure 3. Figure 4 is a partial enlarged view of the red box of Figure 3. As shown in the figure, (d) is mis-segmented in the rightmost YSZ phase and the void phase. Although (b), (c), (e) and the methods herein can substantially separate the pore phase, Ni phase, and YSZ phase, in(b), some of the pores of (c) and (e) are misclassified into YSZ phase. It
can be seen that the algorithm proposed in (f) has better segmentation results, which can separate different three phases more accurately and retain a lot of details.

In Table 2 given the E value results at 200 and 1000 magnifications images. As shown in the table, the method in this paper obtains the smallest E value. By comparing the above methods, the best segmentation result is the method proposed in this paper. Table 3 lists the average running times of the methods and comparison algorithms. Among them, different anode microscope images with a sample of 10 were run 10 times with different algorithms, and obtain the average time. Among them, the average running time of FFCM is the shortest, and KWFLICM has the longest running time due to iteration of algorithm parameter values. Considering that SOFC image segmentation has no real-time requirements, this method can meet the actual needs. The proposed algorithm can obtain better segmentation effect with relatively short computation time and has certain application value.

![Figure 3.](image1)

![Figure 4.](image2)

Table 2 The entropy-based evaluation of all algorithms on different magnification SOFC images

|          | FLICM    | FFCM(0.2) | FRGMM   | KWFLICM  | Proposed |
|----------|----------|-----------|---------|----------|----------|
| 200      |          |           |         |          |          |
| $H_r(L)$ | 1.9488   | 1.9376    | 1.9593  | 1.9551   | 1.9207   |
| $H_p(L)$ | 0.4679   | 0.4744    | 0.4615  | 0.4657   | 0.4702   |
| E        | 2.4167   | 2.4121    | 2.4208  | 2.4208   | **2.3909** |
| 1000     |          |           |         |          |          |
| $H_r(L)$ | 1.7532   | 1.7468    | 1.7559  | 1.7591   | 1.7428   |
| $H_p(L)$ | 0.4638   | 0.4673    | 0.4614  | 0.4620   | 0.4638   |
| E        | 2.2170   | 2.2141    | 2.2174  | 2.2211   | **2.2066** |

Table 3 Comparison of average running time of different algorithms

|          | FLICM    | FRGMM   | FFCM(0.2) | KWFLICM  | Proposed |
|----------|----------|---------|-----------|----------|----------|
| Average running time(s) | 115.6063 | 39.73823 | **28.47187** | 654.5686 | 620.6953 |
4. Conclusions
In this paper, the PSO intelligent algorithm is introduced in the fuzzy clustering of SOFC anode OM image segmentation. The algorithm can effectively find the global optimal clustering center, enhance the global search ability and accuracy, reduce the error classification, and effectively improve the defects that are easy to fall into the local optimum. It can be seen from the experimental results of natural images and real images that the proposed algorithm is superior to the traditional FCM image segmentation algorithm in segmentation accuracy. The algorithm has strong robustness, stability and practicability. It helps to study the microstructure parameters and distribution of SOFC anodes.

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