A Method for Segmentation of Transformer Oil Level Region Based on Infrared Image

Ying Chen¹, Songhai Fan², Yicen Liu², Xiaomin Ma² and Zhu Shi*¹

¹ State Grid Sichuan Integrated Energy Service Co., Ltd., chengdu, Sichuan, 610072, China
² State Grid Sichuan Electric Power Research Institute, chengdu, Sichuan, 610041, China
³ Automation and Information Engineering, Sichuan University of Science & Engineering, zigong, Sichuan, 643000, China

*Corresponding author email: shizhu973200@163.com

Abstract. With the rapid development of computer and artificial intelligence technology, infrared images are playing a higher and higher value in the state monitoring of electrical equipment in substations. Aiming at the detection of the oil level area of the oil conservator in the substation, in order to accurately obtain the oil level information, this paper proposes a transformer oil level detection method combining maximum entropy threshold segmentation algorithm and SLIC (simple linear iterative clustering) segmentation algorithm. First, the original infrared image is pre-processed by image cutting technology to obtain the infrared image of the oil pillow area; the green channel image is extracted, and then the infrared image is segmented by the maximum entropy threshold segmentation algorithm to remove the background interference and obtain the target area of the electrical equipment. Finally, SLIC is used to super the pixel segmentation algorithm performs segmentation to obtain the oil level area. Experiments show that the algorithm can clearly segment the oil level area of the oil pillow, and it has certain practical value.

Keywords: Infrared image; Maximum entropy threshold segmentation algorithm; SLIC super pixel segmentation algorithm.

1. Introduction

There are many types of transformers. They are important equipment for voltage rise, fall and power transmission. Once a failure occurs, the power supply will be interrupted. Transformer oil mainly plays the role of insulation, heat dissipation and arc suppression. The oil conservator is an important part of the oil-immersed transformer. It can absorb the excess insulating oil of the transformer body when the transformer is operating at high load; when operating at low load, Make up the excess insulating oil back to the transformer body[1]. The oil level is one of the important monitoring parameters of power transformers. Therefore, timely detection of the oil level is too low or too high and taking corresponding measures are of great significance to ensure the safe operation of power transformers.

At present, the detection of transformer oil level area mainly uses image segmentation technology to segment the oil level area, and then the specific oil level is judged according to the subsequent classification criteria. At present, infrared detection technology has been quite mature. With the maturity of information processing and other related technologies, infrared diagnosis technology is developing in the direction of digitization and intelligence, and it has been combined with digital
image processing technology to be applied to fault diagnosis of electrical equipment. Li Wenfang[2] uses image enhancement algorithms such as median filtering and histogram equalization to preprocess the infrared images of electrical equipment, and performs fault identification on electrical equipment based on hu invariant moments; Wang Qiyin[3] uses weighted Chebyshev distance The k-means algorithm is used to segment the infrared image of electrical equipment, and the algorithm can segment the target electrical equipment area better; On the basis of traditional FCM(Fuzzy C-means), Kang Long[4] proposes fuzzy image segmentation based on genetic algorithm and gray-scale histogram optimization. The algorithm, by separating the overheated area, the normal area and the background environment, extracts the temperature characteristics of the equipment, and realizes the fault detection of the substation equipment; Yu Chengbo[5] uses the OTSU algorithm to divide the faulty infrared image into the seed area and the background area to remove large areas Background interference; Then the region growth algorithm that automatically selects seed points is used to completely segment the fault area; Yu Yanliang[6] Aiming at the Faster RCNN defect recognition algorithm, through the optimization of the RPN network convolution kernel in the model, the calculation amount of the RPN(Region Proposal Network) network is reduced. , Realize the detection of defects in electrical equipment.

This paper takes the transformer oil conservator as the object and combines the characteristics of infrared images of electrical equipment. Aiming at the maximum entropy threshold segmentation algorithm that cannot adapt to low-quality infrared images with low contrast, low signal-to-noise ratio and blurred edges, a combined image cutting algorithm is proposed. The segmentation method of entropy threshold segmentation algorithm and SLIC super pixel segmentation algorithm. First, the original infrared image is pre-processed by image cutting technology to obtain the infrared image of the oil pillow area; the green channel image is extracted, and then the infrared image is segmented by the maximum entropy threshold segmentation algorithm to remove the background interference and obtain the target area of the electrical equipment. Finally, the SLIC super pixel segmentation algorithm is used for segmentation, and adjacent pixels with similar texture, colour, brightness and other characteristics are formed into irregular pixel blocks with a certain visual significance. The visual effect of the SLIC algorithm is used to eliminate the interference of the background and other impurities, so as to accurately get the oil level area.

2. Algorithm Theory

2.1. Maximum entropy threshold segmentation algorithm

The basic principle of the maximum entropy method is to maximize the entropy of the segmented image to select the optimal threshold[7][8][9]. The specific segmentation process of the maximum entropy multi-threshold method is as follows:

It is assumed that the image has N pixels, and the set of gray values of the image is represented by \{0,1,2,...,L-1\}. \(p_i\) is the probability of each gray level appearing in the image, therefore, \(p_i\) is:

\[ p_i = \frac{f_i}{N}, i = 0, 1, 2,..., L-1 \]  

(1)

After thresholding, the image is divided into two categories: target (A) and background (B):

\[ H_{(i)} = H_A + H_B = -\sum_{i=0}^{i=L} p_i \ln p_i - \sum_{i=L+1}^{i=L-1} p_i \ln p_i - \sum_{i=L+1}^{i=L-1} 1 - p_i \ln 1 - p_i \]  

(2)

If there are m thresholds, then there are \(m+1\) image segmentation regions, so the image is segmented into \(m+1\) categories: \(G_1, G_2, ..., G_m+1\), and the corresponding gray values are \{0,1,2,...,t_1\}, \{t_1 + 1,...,t_2\}, ..., \{t_{m+1},...,L-1\}.

Therefore, the gray-level probability distribution corresponding to each region is: \(C_1: p_1/w_1, ..., p_{t_1}/w_1, C_2: p_{t_1+1}/w_2, ..., p_{t_2}/w_2, ..., C_m+1: p_{t_{m+1}}/w_{m+1}, ..., P_{L-1}/w_{m+1}\), where \(w_k = \)
\[ \sum_{i \in C_k} p_i \ (k=1,2,\ldots,m+1). \] Then, the entropy of each category \( C_k \) (\( k=1,2,\ldots,m+1 \)) is:

\[ R_k = -\sum_{i \in w_k} p_i \ln \frac{p_i}{w_k}. \]

Therefore, the discriminant function of entropy is defined as:

\[ H_{(t_1, t_2, \ldots, t_m)} = \sum_{k=1}^{k+1} H_k \]

\[ = \sum_{i=0}^{b} p_i \ln \frac{p_i}{w_i} - \sum_{i=t_0+1}^{b} p_i \ln \frac{p_i}{w_2} - \ldots - \sum_{i=t_{m+1}+1}^{b} p_i \ln \frac{p_i}{w_{k+1}} \]

Where \( w_k = \sum_{i \in C_k} p_i \), (\( k=1,2,\ldots,m+1 \)). The optimal threshold \( t_1^*, t_2^*, \ldots, t_m^* \) can maximize the total entropy.

According to the principle of the maximum entropy algorithm, when the entropy value of each area has the maximum value, according to the additives of entropy, the amount of information of each target and background in the image can be maximized.

\[ t_1^*, t_2^*, \ldots, t_m^* = \text{Arg max} \ H(t_1, t_2, \ldots, t_m) \quad 0 \leq t_1 \leq t_2 \leq \ldots \leq t_m \]

The process of image multi-threshold segmentation is the process of optimizing the optimal thresholds \( t_1^*, t_2^*, \ldots, t_m^* \).

Although the maximum entropy multi-threshold segmentation method has certain advantages, it has the disadvantages of large amount of calculation and low segmentation accuracy.

2.2. SLIC super pixel segmentation algorithm

The emergence of the super pixel concept in 2003 provided a new direction for the development of image processing. In 2010, Achanta and Shaji proposed the SLIC super pixel algorithm\(^{[10]}\). The algorithm is low in complexity, simple to implement, fast and can well retain the boundary information of the target in the image, so it is widely used in image segmentation. The essence of the SLIC algorithm is a partial kmeans clustering method\(^{[11]}\). But it is different from the kmeans clustering algorithm: the SLIC algorithm only searches for similar pixels in the 2sx2 area around each cluster center, while the kmeans algorithm searches for similar pixels globally.

Second, the SLIC algorithm groups the pixels into a five-dimensional feature space and decomposes them into a five-dimensional feature vector \([l,a,b,x,y]\) where \([l, a, b]\) is the CIELAB colour space Component, \([x,y]\) is the spatial coordinate of the pixel. In SLIC, the similarity between two pixels is measured by the vector distance \(D\) between them (\(D\) is inversely proportional to the similarity). The calculation formula is as follows:

\[ d_{lab}(p_i, c_j) = \sqrt{(l_i - l_j)^2 + (a_i - a_j)^2 + (b_i - b_j)^2} \]

\[ d_{xy}(p_i, c_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \]

\[ D(p_i, c_j) = \sqrt{\left(\frac{d_{lab}(p_i,c_j)}{m}\right)^2 + \left(\frac{d_{xy}(p_i,c_j)}{s}\right)^2} \]

Among them, \( p_i = (l_i, a_i, b_i, x_i, y_i) \) is the coordinate of the i-th pixel in the image, and \( c_j = (l_j, a_j, b_j, x_j, y_j) \) is the coordinate of the j-th cluster center point in the image. \( d_{lab} \) and \( d_{xy} \) represent color distance and spatial distance, respectively. \( s = \sqrt{\frac{k}{N}} \) is the side length of the super pixel (that is, the sampling interval), \( N \) is the total number of pixels in the image, and \( k \) is the number of super pixels that are expected to be generated. \( m \) represents the weight of the colour distance, its value range is
between [1,40], usually 10, the smaller \( m \) is, the more the super pixel fits the edge of the image closely, the larger the \( m \) is, the more the super pixel is between compact.

3. Algorithm Flow
This paper takes the infrared image of the transformer oil pillow as the research object. Since the oil level of the oil pillow in the infrared image can be regarded as the contour of the oil, in order to obtain a more accurate oil level edge, we adopted a new detection method combined with image cutting. Algorithm, maximum entropy threshold segmentation algorithm and SLIC super pixel segmentation algorithm, so that the oil level can be clearly reflected. The specific algorithm flow of this article is as follows:

(1) Image pre-processing
   ① Use image cutting technology to cut the original infrared image to get the image of the oil pillow area
   ② Extract the green channel image that can highlight the oil part and the non-oil part of the oil pillow.
(2) Use the maximum entropy threshold segmentation algorithm to segment the green channel image of the oil pillow, so that the entropy of the segmented image reaches the maximum to select the optimal threshold, remove the background interference, and obtain the rough distribution area of the oil part.
(3) Use the SLIC super pixel segmentation algorithm to segment the image, and combine adjacent pixels with similar texture, colour, brightness and other characteristics to form irregular pixel blocks with a certain visual significance to obtain a clearer image of the oil level area.

The flow chart of transformer oil level area detection is shown in Figure 1:

![Flow chart of transformer oil level area detection](image)

**Figure 1.** Flow chart of transformer oil level area detection

4. Experimental Results and Analysis
In order to verify the superiority of the algorithm in this paper, the equipment under different scenarios is selected for experiment. The whole experiment process is divided into two parts. The first part verifies the rationality of the detection method in this paper, and carries out experiments according to the process; the second part is the comparative analysis of the oil level image processing performance of different algorithms.

(1) Results and analysis of the detection methods in this article
This section mainly takes transformer oil pillows as an example for verification. Figure 2 is the original infrared image of the transformer oil pillow, as shown in the figure below.

![Original infrared image of transformer oil pillow](image)

**Figure 2.** Original infrared image of transformer oil pillow

1) The influence of image pre-processing on the maximum entropy threshold segmentation algorithm
This article first uses image cutting technology to cut the original infrared image, extract the oil pillow area, and remove the interference of the edge parts, as shown in Figure 3(a). Since the target area obtained by the direct use of the maximum entropy threshold segmentation algorithm is prone to small dots around the target area due to noise, this article first extracts the green channel image before performing the maximum entropy threshold segmentation algorithm to highlight the oily and non-oily parts Part of the difference, reduce the interference of impurities, the effect diagram is shown in Figure 3(b).

![Image 3](image-url)

(a) Image cutting effect chart \hspace{1cm} (b) Maximum entropy threshold segmentation effect diagram

Figure 3. The effect of dividing the transformer oil pillow

2) The effect of the maximum entropy threshold segmentation algorithm on the SLIC algorithm
In the target area of the oil pillow oil level obtained after pre-segmentation, the interference of the background is removed, which is convenient for the SLIC to segment the emerging oil level more accurately. Figure 4(a) shows the segmentation result without pre-segmentation, and Figure 4(b) shows the segmentation result after pre-segmentation. It can be seen from the figure that the use of SLIC algorithm to segment without pre-segmentation has the influence of the background, and the parts above the oil level may be segmented together, resulting in the inability to observe the oil level; and after pre-segmentation, the SLIC algorithm is used to segment, which eliminates the interference of the background. Its visual effect, so as to accurately and clearly observe the oil level.

![Image 4](image-url)

(a) Effect picture without pre-segmentation \hspace{1cm} (b) Effect picture after pre-segmentation

Figure 4. SLIC segmentation effect diagram

(2) Contrastive analysis of oil pillow oil level image processing performance of different algorithms
In order to test the segmentation effect of different algorithms on the oil level, this section uses the watershed algorithm, the maximum threshold segmentation algorithm and the algorithm used in this article to test three typical transformer oil confinement images. The results are shown in Figure 5.

![Image 5](image-url)

(a) Three typical images of transformer oil pillows \hspace{1cm} (b) Watershed algorithm test results
Figure 5. Comparison of the segmentation effect of different algorithms on the oil level area

From the above segmentation results, it can be seen that due to the interference of noise points or other factors, the watershed algorithm may get densely packed small areas, that is, the image is over-segmented; segmentation using the maximum threshold segmentation algorithm can only segment the oil level area, but cannot highlight the oil. In addition, the target area image obtained after segmentation is greatly affected by noise, the edges are not smooth enough, and there are spots in the segmented target area. It can be seen that the maximum threshold segmentation algorithm cannot be used to detect the oil level area alone; finally, Observing the segmentation results of the algorithm in this paper, the detection method can accurately segment the oil level area, narrow the search range, can suppress the over segmentation phenomenon to a certain extent and clearly show the oil level, so the algorithm can be used for transformer oil level segmentation.

5. Summary

This article proposes a transformer oil level segmentation method based on infrared images, which reduces the detection range of the oil level area and highlights the location of the oil level, which is conducive to more accurate maintenance of the transformer oil pillow, reducing social costs and human resources. Waste. This method combines image cutting algorithm, maximum entropy threshold segmentation algorithm and SLIC super pixel segmentation algorithm, so that the oil level can be clearly reflected. This algorithm solves the problem that the maximum entropy threshold segmentation algorithm alone cannot adapt to low-quality infrared images with low contrast, low signal-to-noise ratio and blurred edges. It can clearly highlight the oil level area, but there is still a certain error, especially when using the maximum entropy After the threshold segmentation algorithm, there is too much interference in the edge area. The algorithm still has a lot of room for improvement, such as using a suitable oil level line fitting algorithm to highlight the oil level area for easy observation; and using the K-means algorithm to replace the maximum entropy threshold segmentation for pre-segmentation.

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