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# Infrared Electric Image Thresholding Using Two-Dimensional Fuzzy Renyi Entropy

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**Abstract**

Infrared thermograph is of great significance in electric equipment monitoring, but due to both the limitation in thermograph technology and surrounding interferences, infrared electric images are always fuzzy by nature, and thus the segmentation of infrared electric image is a challenging task. To handle this ambiguity, we first calculate the two-dimensional histogram of image to make full use of spatial information, and then transform the two-dimensional histogram into fuzzy domain employing fuzzy membership. A new kind of two-dimensional fuzzy entropy, namely two-dimensional fuzzy Renyi entropy, is defined and employed to compute the fuzzy entropy of object and background respectively, and thus the image is segmented following maximum entropy principle. Compared with other typical methods by experiments, the presented method is verified to be more effective and robust.



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*Keywords: Infrared electric image, image segmentation, two-dimensional histogram, fuzzy Renyi entropy;maximum entropy principle Introduction*

## 1. Introduction

Infrared thermograph for equipment fault detection has been widely used in power systems for the reasons that general fault of power equipment such as discharge and overheating always involves the variation of temperature [1]. Typical steps of online automatic monitoring based on infrared thermograph include capturing the infrared image of electric equipment and then analyzing the image by computer. In this process, image segmentation is an indispensable step to recognize the overheated equipments or parts. However, on one hand, as the infrared thermograph is extremely sensitive to the change of temperature, the heat exchange between the object and surrounding environment, combined with the scattering and

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absorption effect of air on thermal radiation, leads to low contrast, blur edge and almost invisible texture of infrared thermograph image. On the other hand, duo to the limitations in camera technology, infrared image sensor have lower spatial resolution and less sensitivity than visible images sensor which also lead to low image quality, such as blurring and great noise, low target-to-background contrast, low luminance[2]. Therefore, it is a complex challenge to make precise segmentation of thermal infrared imagery.

Among all the segmentation methods, image thresholding has attracted much attention for its simplicity and effectiveness. Excellent reviews on early thresholding methods can be found in [3], and the latest development in this topic is summarized in [4]. Of all the thresholding methods, entropy-based method is widely studied and is considered effective. Recently, Renyi entropy is applied in image thresholding[5]. Later, this work in one-dimensional histogram is extended into two-dimension with much better effects by Sahoo *et al*. [6] Fuzzy sets play a significant role in many deployed systems because of their capability to model nonstatistical imprecision[7]. The notion of entropy, in the theory of fuzzy sets, was first introduced by Luca and Termini [8]. There have been lots of applications of fuzzy entropies in image segmentation. Cheng et al.[9] proposed fuzzy homogeneity vectors to handle the grayness and spatial uncertainties among pixels, and to perform thresholding. Tao et al. [10] presented a approach for object segmentation using ant colony optimization algorithm and fuzzy entropy. Cheng et al. [11] presented a thresholding approach by performing fuzzy partition on a two-dimensional histogram based on the fuzzy relation and the maximum fuzzy entropy principle. Zhao et al.[12] presented an entropy function by the fuzzy *C*-partition (FP) and the probability partition (PP) which was used to measure the compatibility between the PP and the FP.

Sahoo et al.[6] presented an image thresholding method based on two-dimensional Renyi entropy, taking into account the fuzzy nature of infrared image, this paper extended Sahoo's method into fuzzy domain. The performance of the presented method is compared with the existing entropy-based object segmentation methods.

This paper is organized as follows: In Section 2, we present a brief description of image thresholding based on two-dimensional Renyi entropy. In Section 3, we describe the definition of two-dimensional fuzzy Renyi entropy and the newly proposed thresholding method. In Section 4, we report the effectiveness of our thresholding method when compared with other famous methods. In Section 5, we present some concluding remarks about our method.

## 2. Image Thresholding Based on Two-dimensional Renyi Entropy

### *2.1. Two-dimensional histogram of image*

The two-dimensional histogram of a given image can be computed as follows[11]. Calculate the average gray value of the neighborhood of each pixel. Let $g(x,y)$ be the average of the neighborhood of the pixel located at the point $(x,y)$. The average gray value for the neighborhood of each pixel is calculated as

$$g(x,y) = \lfloor \frac{1}{4}[f(x,y+1) + f(x,y-1) + f(x+1,y) + f(x-1,y)] + 0.5 \rfloor \tag{1}$$

where $\lfloor r \rfloor$ denotes the integer part of the number $r$. While computing the average gray value, disregard the two rows from the top and bottom and two columns from the sides. The pixel's gray value, $f(x,y)$, and the average of its neighborhood, $g(x,y)$, are used to construct a two-dimensional histogram using,

$$h(m,n) = \Pr\mathrm{ob}(f(x,y) = m \text{ and } g(x,y) = n) \tag{2}$$

where $m, n \in G$, and $G$ is the set of all gray levels of the image. For a given image, there are several methods to estimate this density function. One of the most frequently used methods is the method of relative frequency. By this method, the normalized histogram is approximated by using the formula

$$p_{ij} = \frac{n_{ij}}{N \times M} \tag{3}$$

where $N \times M$ denotes the image size, and $n_{ij}$ denotes the number of pixels whose gray value equals *i* and local average value equals *j*. The two-dimensional histogram plane can be described as Fig.1

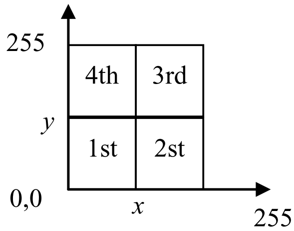


Fig. 1. Two-dimensional histogram plane

where Area 1 and Area 3 denote back-ground and objects respectively, while Area 2 and Area 4 denote edges and noise. So a threshold vector $(t, s)$, where $t$ is a threshold for pixel intensity and $s$ is another threshold for the local average of pixels, should be determined to divide them. According to the maximum entropy principle, the determined threshold vector should make area 1st and area 3rd have the maximum information.

Suppose the Area 1 and Area 3 have different probability distributions. According to the threshold vector $(t, s)$, we denote $P_O$ (object) and $P_B$ (background) as:

$$\begin{cases} p_B = \sum_{i=0}^{s-1} \sum_{j=0}^{t-1} p_{ij} \\ p_O = \sum_{i=s}^{L-1} \sum_{j=t}^{L-1} p_{ij} \end{cases} \tag{4}$$

*2.2. Two-dimensional RENYI entropy*

According to the definition of Renyi entropy[5], the a priori Renyi entropy for each distribution as

$$\begin{cases} H_O^q(t) = \dfrac{\log \sum_{i=0}^{t-1} \sum_{j=0}^{s-1} (\frac{p_{ij}}{p_o})^q}{1-q} \\ H_B^q(t) = \dfrac{\log \sum_{i=s}^{L-1} \sum_{j=t}^{L-1} (\frac{p_{ij}}{p_B})^q}{1-q} \end{cases} \tag{5}$$

where the parameter $q$ is a real number not equal to one associated with the extensitivity of the system, and it is system dependent. With the additivity rule, the corresponding Renyi entropy $H_q$ is formulated as the following sum of each entropy:

$$H_q = H_q^O + H_q^B \tag{6}$$

By maximizing $H_q$ , i.e.,

$$t_{opt} = \arg\max_{(t,s)}[H_O^q + H_B^q] \tag{7}$$

the luminance lever $t_{opt}$ is considered to be the optimal threshold value in Renyi entropy based thresholding approach[6].

## 3. Image Thresholding Based on Two-Dimensional Fuzzy Renyi Entropy

### *3.1. Fuzzy set of image*

There are many kinds of functions available for mapping an image into a fuzzy field, such as S-function, Z-function, π -function, trigonometric function, etc. For the reason that S-function and Z-function are smoother than others, and they can express the fuzziness of image much better, we selected S-function and Z-function as the membership function in the paper, which is defined as following,

$$\mu_O(l) = S(l \mid a,b,c) = \begin{cases} 0, & l \le a \\ \dfrac{(l-a)^2}{(c-a)(b-a)}, & a < l \le b \\ 1 - \dfrac{(l-c)^2}{(c-a)(c-b)}, & b < l \le c \\ 1, & l \ge c \end{cases} \tag{8}$$
$$\mu_B(l) = Z(l \mid a,b,c) = 1 - S(l \mid a,b,c)$$

where $l$ is an independent variable, (i.e., the gray level of a certain pixel in the image), and $(a,b,c)$ are the parameters which determine the shape of the trigonometric function, they are limited by the condition that $0 \le a \le b \le c \le L-1$ , in which $L$ means the gray levels of the image. When a set of optimal parameters $(a,b,c)$ obtained, the optimal threshold can be expressed as[10]:

$$t^* = \begin{cases} a + \sqrt{(c-a)(b-a)/2}; & (a+c)/2 \le b \le c \\ c - \sqrt{(c-a)(c-b)/2}; & a \le b \le (a+c)/2 \end{cases} \tag{9}$$

### *3.2. Fuzzy RENYI entropy of image*

Mapping an image into a fuzzy field employing the function defined above, we got

$$\begin{cases} P_O^l : \dfrac{\mu_O(0)h(0)}{p_O}, \dfrac{\mu_O(1)h(1)}{p_O}, \ldots, \dfrac{\mu_O(L-1)h(L-1)}{p_O} \\ P_B^l : \dfrac{\mu_B(0)h(0)}{p_B}, \dfrac{\mu_B(1)h(1)}{p_B}, \ldots, \dfrac{\mu_B(L-1)h(L-1)}{p_B} \end{cases} \tag{10}$$

where $P_O = \sum_{l=0}^{L-1} \mu_O(l)h(l)$ , $p_B = \sum_{l=0}^{L-1} \mu_B(l)h(l)$ .

According to the definition of Renyi entropy[5], we define the Fuzzy Renyi Entropy (FRE) of Object $O$ and Background $B$ as:

$$\begin{cases} H_O^q(t) = \dfrac{1}{1-q}\log\sum_{l=0}^{L-1}\left(\dfrac{\mu_O(l)h(l)}{p_O}\right)^q \\ H_B^q(t) = \dfrac{1}{1-q}\log\sum_{l=0}^{L-1}\left(\dfrac{\mu_B(l)h(l)}{p_B}\right)^q \end{cases} \tag{11}$$

### *3.3. Two- dimensional Fuzzy Renyi entropy（2DFRE） of Image*

When defining the two-dimensional fuzzy Renyi Entropy(2DFRE) of image, we first calculate the two-dimensional histogram of image as Fig.1, and then transform the each axis of the two-dimensional histogram into fuzzy domain employing the S-function and Z-function defined above, i.e.

$$\begin{cases} \mu_{OX} = S(x,a,b,c) \\ \mu_{OY} = S(y,l,m,n) \end{cases} \quad \begin{cases} \mu_{BX} = Z(x,a,b,c) \\ \mu_{BY} = Z(y,l,m,n) \end{cases} \tag{12}$$

where the parameters $x$ and $y$ are independent variables denote the gray level of the pixel itself and the average gray level of the neighborhood, respectively. Parameters $(a,b,c)$ and $(l,m,n)$ determine the shape of the membership function along $X$ axis and $Y$ axis respectively. The fuzzy-transform of two-dimensional histogram is illustrated in Fig.2.

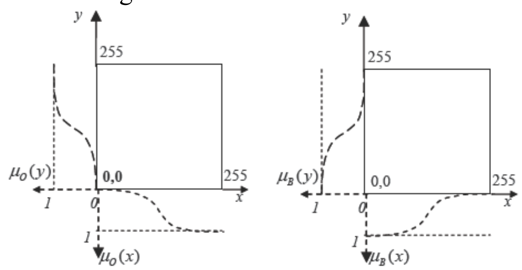


Fig. 2. Fuzzy transform of two-dimensional histogram

And thus four fuzzy sets is defined as follows[11]:

$$\begin{cases} ObjectX = \sum_{x\in X}\dfrac{u_{OX}}{x} = \sum_{x\in X}\dfrac{S(x,a,b,c)}{x} \\ ObjectY = \sum_{y\in Y}\dfrac{u_{OY}}{y} = \sum_{y\in Y}\dfrac{S(y,l,m,n)}{y} \\ BackgroundX = \sum_{x\in X}\dfrac{u_B(x)}{x} = \sum_{x\in X}\dfrac{Z(x,a,b,c)}{x} \\ BackgroundY = \sum_{y\in Y}\dfrac{u_B(y)}{y} = \sum_{y\in Y}\dfrac{Z(y,a,b,c)}{y} \end{cases} \tag{13}$$

where $Z(\cdot) = 1 - S(\cdot)$ .

The fuzzy relation *Object* and *Background* are subsets of the full Cartesian product space $X \times Y$ respectively, i.e.

$$Object = ObjectX \times ObjectY \subset X \times Y \tag{14}$$

$$Background = BackgroundX \times BackgroundY \subset X \times Y \tag{15}$$

the membership function $\mu_O(x,y)$ and $\mu_B(x,y)$ can be obtained as follows[11, 13],

$$\mu_O(x,y) = \mu_{OX\times OY}(x,y) = \min(\mu_{OX}, \mu_{OY}) \tag{16}$$

$$\mu_B(x,y) = \mu_{BX\times BY}(x,y) = \min(\mu_{BX}, \mu_{BY}) \tag{17}$$

Then we can mapping the two-dimensional histogram into fuzzy domain employing the member function $\mu_O(x,y)$, $\mu_B(x,y)$ obtained above, we got

$$P_O^{(x,y)} : \frac{\mu_O(x,y)h(x,y)}{p_O}, (x,y) \in \{0,1,...L-1\} \tag{18}$$

$$P_B^{(x,y)} : \frac{\mu_B(x,y)h(x,y)}{p_B}, (x,y) \in \{0,1,...L-1\} \tag{19}$$

where $h(x,y)$ denotes value of element located at (*x,y*) in the two-dimensional histogram, and

$$P_O = \sum_{x=0}^{L-1}\sum_{y=0}^{L-1} \mu_O(x,y)h(x,y) \tag{20}$$

$$P_B = \sum_{x=0}^{L-1}\sum_{y=0}^{L-1} \mu_B(x,y)h(x,y) \tag{21}$$

According to the definition of Renyi entropy[5], we define the two-dimensional fuzzy entropy of Object *O* and Background *B* as:

$$H_O^q(t,s) = \frac{1}{1-q}\log\sum_{x=0}^{L-1}\sum_{y=0}^{L-1}\left(\frac{\mu_O(x,y)h(x,y)}{p_O}\right)^q \tag{22}$$

$$H_B^q(t,s) = \frac{1}{1-q}\log\sum_{x=0}^{L-1}\sum_{y=0}^{L-1}\left(\frac{\mu_B(x,y)h(x,y)}{p_B}\right)^q \tag{23}$$

With the pseudo additivity rule, the corresponding Renyi entropy $H_q$ is formulated as the following sum of each entropy:

$$H^q = H_O^q + H_B^q \tag{24}$$

We followed the maximum entropy principle[6] to search for the optimal threshold, i.e.

$$t_{opt} = \underset{(a,b,c,l,m,n)}{\arg\max}\,[H_O^q + H_B^q] \tag{25}$$

### *3.4. Thresholding based on 2DFRE*

To obtain the optimal threshold it is required to obtain the optimal combination of all the fuzzy parameters. Therefore, the segmentation problem can be formulated as an optimization problem. We use the particle swarm optimization (PSO)[14] method to effectively obtain the optimal combination of the fuzzy parameters. The proposed method consists of the following major steps:

1) Find the 2D histogram of the input image;
2) find the optimal combination of fuzzy parameters;
3) Compute the fuzzy entropy.

Step 1) needs to be executed only once while steps 2) and 3) are performed iteratively for each set of fuzzy parameters. Once the optimal threshold vector ($t, s$) is obtained, the imaged is segmented into object and background as showed in Fig.1.

## 4. Experiment and Discussion

In order to verify the validity and robustness of the presented method, we segment a large number of images of different gray level distributions by the proposed method and compared the results with those of other famous methods including Ostu's method[15]( method based on the variance between classes), Tao's method[10](method based on one dimension fuzzy entropy), Sahoo's method[6]( method based on two-dimensional Renyi entropy) and Cheng's method[11](method based on two-dimensional fuzzy entropy).

The parameters in the experiments are set as follows, the size of the population PSO is set to be 30, the iteration of generation is set to be 20. Parameter $q$ is selected by the method introduced in [16]. The resulted binary images are illustrated in Fig.4~8.

From Fig.4 we can find out that as a one-dimension method based on the variance between classes, Ostu's method don't considerate both the fuziness of infrared image and the spatial information, so its effect is not so good when apply to infrared electric image.

From Fig.5 we can find out that, as a method based on one-dimensional fuzzy entropy, Tao's method don't considerate the information of local neighborhood. It failed when applied to segment Fig.3(c). In addition, Tao's method expressed certain extent of over-segmentation in Fig.3(a) .

As a method based two-dimensional Renyi entropy, Sahoo's method considerate not only the gray level of the pixel itself, but also the neighbor pixels around it, so its result is much better than those of Tao's method. However, it does not take in account the fuzziness of image, it expressed some kind of over-segmentation when applied to Fig.3(a). and some kind of under-segmentation when applied to Fig.3(b).

(a) (b) (c)

Fig. 3. The original infrared electric images

Fig. 4. The results of Ostu's method

Fig. 5. The results of Tao's method

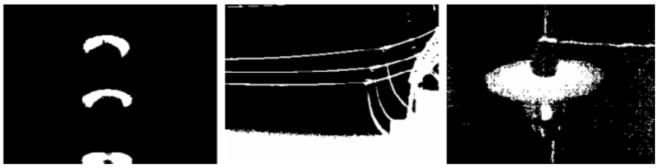

Fig. 6. The results of Sahoo's method

Fig. 7. The results of Cheng's method

Fig. 8. The results of Our method

As a method based on two-dimensional fuzzy Shannon entropy, Cheng's method got almost the same result with the presented method at a first glance. However, Shannon entropy is not well suitable for the discription of nonadditive information content which exists in the field of image segmentation[5]. The results of Cheng's method on Fig.3(a) and Fig.3(c) expressed certain extend of over-segmentation as that of Tao's method, which is also based on Shannon entropy.

Based on two-dimensional fuzzy Renyi entropy, the presented method considerate not only the spatial information, but also the fuziness nature of infrared image, in addition, as a generalization of Shannon entropy, Renyi entropy is more suitable for the description of nonadditive information than the former[5]. Therefore, we can found out that the results of the presented method are much more desirable than others as illustrated in Fig.(8).

## 5. Conclusion

Based on the concept of Renyi entropy, a new kind of two-dimensional fuzzy Renyi Entropy is put forward and applied in the field of image segmentation with rather good effects. Therefore, the application of two-dimensional Renyi entropy is generalized into fuzzy fields. When non-fuzzy approaches are extended into fuzzy domain, it results in much better segmentation at the cost of the exponential increment of computational time, therefore, the use of fast optimization algorithm is absolutely necessary. For its excellent convergence speed and stablility, PSO is selected in this paper to accelerate the search of fuzzy parameters in this paper. The presented method costs about ten seconds when segmenting a 320×240 image of 256 gray levels on our computer(Core(TM)2 Duo CPU T7100 1.80GHz, 2G memory, Matlab(R2007a). If coded with C or C++, this cost may be reduced further. However, when used in real-time situation, it is still not fast enough, therefore, our future work will focus on decreasing the computational complexity of the algorithm .

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