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Infrared Image Segmentation using Hidden Markov Random Fields and Expectation-maximization Algorithm

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Abstract: Circuit board infrared image segmentation is an important procedure in the application of circuit board fault detection with infrared thermal imaging technology. A CNO-HMRF-EM algorithm combined with the advantage of HMRF, EM and CNO is designed to deal with the insufficiency of the traditional clustering methods in the circuit board infrared image segmentation. To get the best clustering segmentation results, HMRF-EM algorithm is used as the first step to estimate the tag of each image point so that each point of image can be clustered according to the tag estimation result. Then the HMRF-EM algorithm's optimal clustering number is determined in the use of CNO algorithm. The simulation results prove that, comparing with the methods of C-Mean clustering and OTSU clustering, bigger GS value as well as the better results of the clustering segmentation can be acquired in the use of CNO-HMRF-EM algorithm.

Key words: Infrared image segmentation, cluster analysis, HMRF, expectation maximization, CNO

INTRODUCTION

Infrared detection is used in many fields. Because of the characters of its non contact, non destructive, rapidity and so on, it can be well used in the printed circuit board fault detection (Guo *et al*., 2009). The infrared image segmentation of PCB is an important procedure of fault detection of PCB using infrared technology. Segmentation quality of infrared image directly influence the analysis result of the PCB electronic component. The method of PCB infrared image segmentation studied in this paper aim to extract the electronic component core heating area and to get the information of electronic component position. As a result, the electronic component performance can be well analyzed with the image segmentation.

Features of PCB infrared image:

- Infrared thermal image is the reflection of the scene temperature distribution. It is gray level image rather than color image. The gray scale of each point in the image represents the temperature, including the heat radiation of the surrounding environment and the distribution of thermal effects of this object. The contrast of the infrared image, which is closely related to the space location, is low. Moreover, infrared image has more noise factors, such as Johnson noise, salt and pepper noise, photon noise and so on (Chrysochoos and Louche, 2000). So, compared with the visible image, the SNR of infrared image is higher
- As the heat is continuous, it cannot change suddenly. The farther the distance, the smaller the heat radiation. So, infrared image, especially the near-infrared image, will not have clear edges as well as visible image.
- As the large amount of the information about the 2D image dealt by the infrared technology, the interested segments should be extracted then analyzed while the algorithm, which is fast and efficient, should be designed for different types of infrared images according to the features of related substance as well as the image processing purposes
- Infrared image records thermal information and has no reaction to the texture information of the object itself. Unless the object surface material changes and causes large temperature change, Infrared image will have no reaction to the texture information of object an all

Non spatial domain segmentation method consists of clustering and histogram threshold method. Among the current segmentation methods for infrared image, clustering methods, such as fuzzy entropy clustering (Jaffar *et al*., 2010), EM clustering (Kokkinos and Maragos, 2009), C-clustering method (Valvi *et al*., 2012), are widely used in infrared detection of electrical equipment and infrared extraction of military target.

CNO-HMRF-EM ALGORITHM

Algorithm introduction: A label is assigned to each cluster which is used to mark the object in the cluster.

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Label of each point is estimated in the image to determine which cluster the point belongs to. EM algorithm is used twice to estimate the label of each point. Finally the optimal number of clusters are get using the optimal number of clusters algorithm.

Given an image $y = (y_1,..., y_N)$, in which y_i is the intensity of the pixel i that represents the temperature in this paper. A label configuration that is $x = (x_1,..., x_N)$ in which $x_i \in L$, L is the set of all possible labels, is expected to get.

For example, a dual segmentation problem, $L\in\{0,1\}$, based on the standard of maximum posterior probability, a label x satisfying the following formula is needed to get:

$$x^* = \underset{x}{\arg\max}\{P(y \mid x_2\Theta)P(x)\} \tag{1}$$

The prior probability P(x) is a Gibbs distribution whose joint likelihood probability is:

$$P(y \mid x,\Theta) = \prod_i P(y_i \mid x,\Theta) = \prod_i P(y_i,\theta_{Z_i}) \tag{2}$$

In which $P(y_i|x_i,\theta_{x_i})$ is a Gaussian distribution, $\theta_{x_i} = (\mu_{x_i},\sigma_{x_i})$. The parameter list $\Theta = \{\theta_l|l\in L\}$ is get from EM algorithm. The steps of EM algorithm to estimate $\Theta = \{\theta_l|l\in L\}$ are as follows:

EM algorithm to estimate parameters:

- To begin with: we assume that the initial parameter list is $\Theta^{(0)}$
- Step E: in the t-th iteration, $\Theta^{(t)}$ is known and the conditional expectation should be calculated:

$$Q(\Theta \mid \Theta^{(t)}) = E[\ln P(x,y \mid \Theta) \mid y,\Theta^{(t)}] = \sum_{x\in\chi} P(x,y \mid \Theta^{(t)})\ln P(x,y \mid \Theta) \tag{3}$$

x is a set of possible label configuration.

- step M: getting the following estimation by maximizing the Q $(\Theta|\Theta^{(t)})$

$$\Theta^{(t=1)} = \underset{\Theta}{\arg\max}\, \underset{\sim}{O}(\Theta \mid \Theta(t)$$

Making the $\Theta^{(t+1)}$ close to the $\Theta^{(t)}$, then repeating it from the step E.

The hybrid algorithm of HMRF-EM: Assuming that G (z; θ_l) is a Gaussian distribution in which θ_l = (μ, σ_l) combined with the definition of HMRF:

$$G(z;\theta_l) = \frac{1}{\sqrt{2\pi\sigma_l^2}}\exp(-\frac{(z-\mu_l)^2}{2\sigma_l^2}) \tag{5}$$

Assuming that a prior probability can be expressed as:

$$P(x) = \frac{1}{Z}\exp(-U(x)) \tag{6}$$

U (x) is the function of the prior energy. It can also be get:

$$P(y \mid x,\Theta) = \prod_i P(y_i \mid x_i,\theta_{x_i}) = \prod_i G(y_i;\theta_{z_i}) = \frac{1}{Z}\exp(-U(y \mid x)) \tag{7}$$

Based on the assumptions above, the steps of HMRF-EM algorithm are as follows:

- Beginning from the starting parameters $\Theta^{(0)}$
- Calculating the likelihood probability $P^{(t)}(y_i \mid x_i,\theta_{x_i})$ distribution
- Estimating the label using maximum a posterior (MAP) estimation with the current parameter list $\Theta^{(t)}$t:

$$x^{(t)} = \underset{x\epsilon y}{\arg\max}\{P(y \mid x,\Theta^{(t)})P(x)\} = \underset{x\epsilon y}{\arg\max}\{U(y \mid x,\Theta^{(t)}) = U(x)\} \tag{8}$$

This maximum posterior estimation algorithm will be specifically described in later section.

- Calculating the posterior probability for all the $l\in L$ and all the pixels y_i:

$$P^{(t)}(l1y_t) = \frac{G(y_t;\theta_t)}{P(t)(y_t)}P(l \mid\mid x_{Mt}{}^{(t)}) \tag{9}$$

$$P(l \mid\mid x_{Nt}{}^{(t)}) = \frac{1}{Z}\exp(-U(l \mid\mid x_{Nt}{}^{(t)})) = \frac{1}{Z}\exp(-\sum_{t\in N} V_c(l,x_t{}^{(t)})) \tag{10}$$

Updating the parameters with the $P^{(t)}(l|y_i)$:

$$\mu_l{}^{(t+t)} = \frac{\sum p^{(t)}(l \mid\mid y_t)y_t}{\sum p^{(t)}(l \mid\mid y_t)y} \tag{11}$$

$$(\sigma_l{}^{(t+t)})^2 = \frac{\sum p^{(t)}}{\sum_t P^{(t)}(l \mid\mid y_t)}(l \mid\mid y_t)(y_t - \mu_l{}^{(t+t)})^2 \tag{12}$$

Maximum a posteriori (MAP) estimation: In the EM algorithm, X^* which makes the posterior energy maximum is needed to slove:

$$X^* = \mathrm{Arg}_{x\in\chi}\max\{U(y \mid x,\Theta) + U(x)\} \tag{13}$$

For a given y and Θ,the likelihood energy can be expressed as:

$$U(y\,||\,x,\Theta)=\sum U(y_t\,||\,x_2,\Theta)=\sum{}_t[\frac{(y_t-\mu_t)^2}{2\sigma^2{}_{zl}}+\text{in}\sigma_{zl}] \quad (14)$$

The prior energy function is expressed as:

$$U(\mathbf{x})=\sum{}_{c\in C}V_c(\mathbf{x}) \quad (15)$$

In which Vc (x) is the cluster potential function, C is the set of possible clustering.

In the field of image processing, this part assumes there are as many as four adjacent points around one pixel. That means four adjacent pixels are around one pixel. the cluster potential function is defined in the couple of adjacent pixels:

$$V_c(x_i,x_j)=\frac{1}{2}(1-I_{Zt,xj}) \quad (16)$$

This iterative algorithm can solve the Eq. 13:

- Beginning with the initial estimation x(0) which has been got from the previous cycle of EM algorithm
- As $x^{(k)}$ is known, $x^{(k+1)}$ can be updated by the the following formula for all variables in the condition that $1 \leq i \leq N$:

$$X_i^{(k+l)}=\text{Arg}\max\{U(y_i\,||\,l)+\sum{}_{j\in Ni}V_C(l,x_j^{(k)})\} \quad (17)$$

- Repeating the previous step until U (y | x, Θ) + U (x) converges or k reaches its maximum

Cluster number optimization(CNO) estimation: CNO of HMRF-EM clustering algorithm is needed to determine to get the best result of clustering segmentation. GS (Global Silhouette Index) (Gupta and Mukherjee, 2011) is used to determine C which is called method of Cluster Number Optimization of HMRF-EM. Each GS value can be calculated for different cluster number (n = 1,2,..., 10).The cluster number is considered as optimize as that C = n when GS value reached the maximum in n cluster numbers.

Global silhouette index: GS can be calculated by the following Eq.:

$$GS=\frac{1}{c}\sum{}^{c}{}_{m-1}S_m \quad (18)$$

$$S_m=\frac{1}{N}\sum{}_{iml}{}^{Nm}S(i) \quad (19)$$

$$S(i)=\frac{b(i)-\alpha(i)}{\max\{\alpha(i),b(i)\}} \quad (20)$$

Nm is the data point number of the m-th clustering, a(i) is the average distance from the i-th sample to all the samples of the m-th cluster ×m, b(i) is the minimum of the average distance from the i-th sample to all samples of the k-th cluster ×k (k = 1,...,c; k?m).That- = s(i) = 1 can be get by the above formula. For a good clustering, GS value should be close to 1. It means that the i-th sample is assigned to the appropriate clustering when s(i) is close to 1 while it means that the i-th sample can be assigned to the nearest cluster when s(i) is close to 0.

The flow chart of the whole algorithm is in Fig. 1.

CONCLUSION

That selecting C-Mean algorithm and OSTU algorithm to compared with CNO-HMRF-EM is done to analyze whether the CNO-HMRF-EM for circuit board infrared image clustering segmentation result is good or not. The original image were taken from laboratory 51 MCU development board. The PC configuration in the experiment are as follows: CPU is the type of Core2-i5-2410M while RAM's capability is 8G and software environment is under Matlab2009R.
Table 1 shows the results of three kinds of clustering GS values, Fig. 1 shows the infrared image clustering GS index values, Fig. 2 shows three kinds of clustering result image.

Analyzing the experimental results in Table 1, Fig. 3 and Fig. 4, the GS value acquired from the CNO-HMRF-EM method is bigger than that from the C-Mean clustering algorithm and OTSU (Chen *et al*., 2012) clustering method according to the results of clustering segmentation method. It illustrates that the points in the image are assigned to the correct cluster and clustering segmentation result is better. The visible segmentation results have little difference among different segmentation methods according to the segmentation results which can also prove that human beings can easily distinguish the high temperature components. Generally, each clustering which does not contain other clusters in geometry is an element or element group. The segmentation result improves the concept of electronic component temperature field The concept means the isotherm expands along the direction of temperature gradient as core heating region is considered as the center position. But the heat radiation area of low temperature and high temperature electronic component is divided into the same cluster. So, thermal radiation which is needed to be

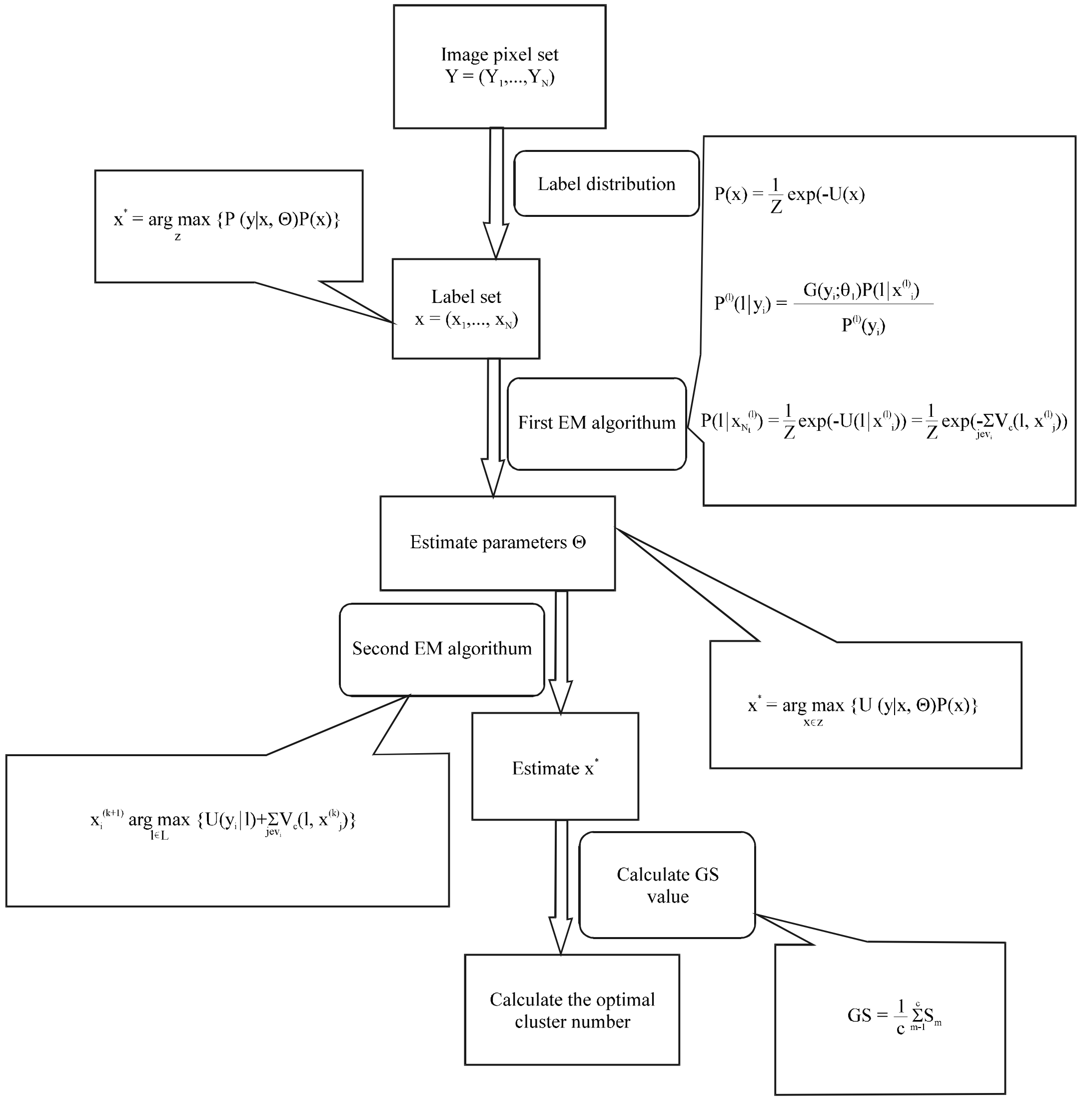

Fig. 1: Flow chart of the algorithm

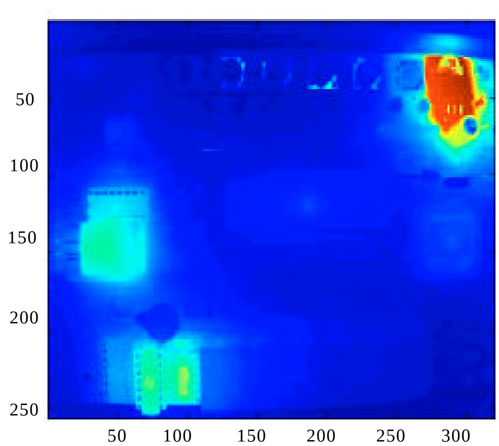

Fig. 2: PCB infrared image

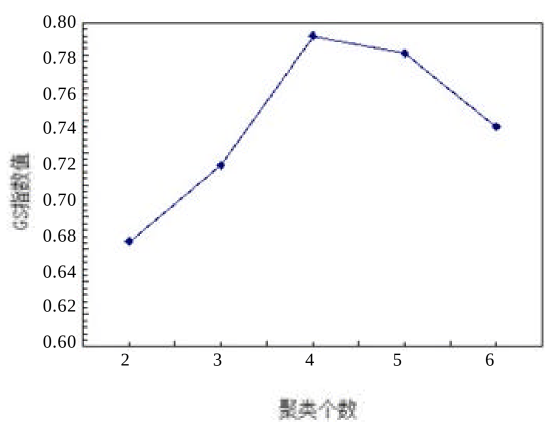

Fig. 3: CNO result

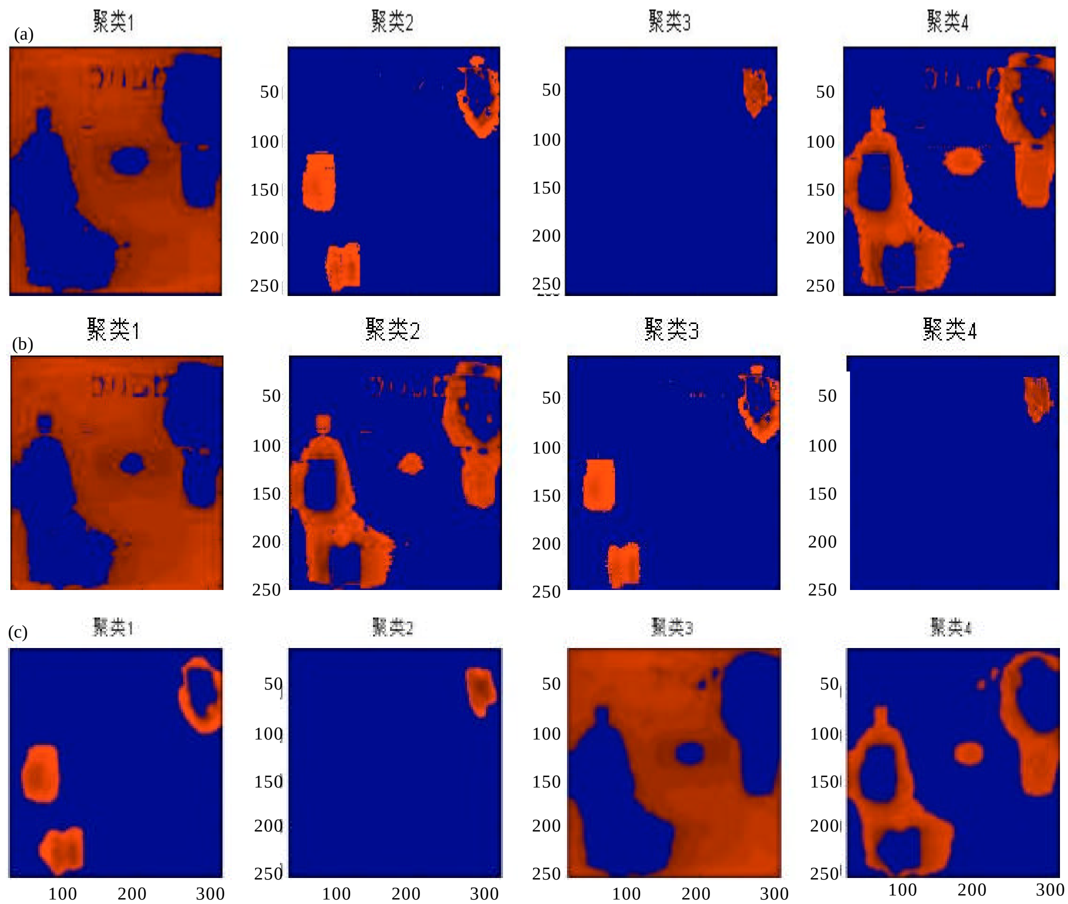

Fig. 4(a-c): (a): C-Mean clustering results, (b) OTSU clustering results and (c) CNO-HMRF-EM clustering results

Table 1: Infrared image clustering results adhesions

Clustering method	GS
C-Mean	0.7600
OTSU	0.6894
CNO-HMRF-EM	0.7905

removed, generated from the high temperature components is the important factors that affects the segmentation result of low temperature components. Another problem is the mixing of the component adhesions. The components cannot be separated when the distance of components is too short. This is what is needed to be further researched.

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