Markov Random Field Labeling of InfraRed Thermal Images: Applications in Industry and Veterinary Medicine

by N.Venkateswaran* , N.Padmapriya*, P.Sophia* and S.Upasana*

*SSN College of Engineering, Rajiv Gandhi Salai, Kalavakkam-603110, TamilNadu, India,

Abstract

In this paper, we propose an efficient approach for object segmentation in IR thermal images. Markov random field (MRF) is used for efficient segmentation that incorporates spatial information through priori information of the local structure present in the IR image. MRF is a conditional probability model that uses the statistical correlation of pixels among its neighborhood. The thermal parameters associated to each label in the IR image are derived based on K-means, unsupervised learning algorithm as initial label. Under the MRF segmentation framework, an energy function is formulated that comprises of a data driven term and a regularizing term involving the prior knowledge of the label associated. Upon minimization of the energy function results in the accurate labeling of different classes. To show the efficacy, the proposed approach is applied in the field of veterinary medicine to detect and segment the foot-and-mouth disease (FMD) of infected cattle. In another application, a non-invasive corrosion monitoring and assessment is demonstrated with the MRF labeling of IR images.

Keywords: IR Thermal Images, Thermography, Markov Random Field, Segmentation, Energy minimization, Nondestructive evaluation.

1. Introduction

Image segmentation play a vital role in recognition of objects. Many image segmentation algorithms have been developed to segment an image before identification and recognition. In computer vision, image segmentation is the process of partitioning an image into a number of different regions without any overlap based on certain properties of the image. Segmentation assigns a label to every pixel in an image such that pixels that are labeled under the same class have some similar characteristics such as color, intensity, etc. It is used to locate the objects, boundaries and other relevant information in images. It is an important process as it finds applications in many areas such as object detection, machine vision, medical imaging, video surveillance, traffic control systems, etc. Image segmentation process is done basically with two major goals. The first aim is to divide any digital image into several regions so that it can be used for further analysis. The second one is to change the representation of the image into another one. The existing image segmentation methods are based only on the different gray levels of the image pixel for classification. Most of these algorithms are very simple and easy to compute. But they are dependent on the gray scale value of the images and are not that much efficient.

Infrared thermography is used to find the areas of excess heat distribution in the images so that the problems can be corrected before a system starts malfunctioning, causing damage to the various components. Because increased heating is a sign of failure, infrared is the best diagnostic tool available for finding these excess heat distribution in the early stages of degeneration. IR wavelength responds to heat, it can indicate the locations of objects in an image taken during the day or at night. But, detecting objects in IR images is not trivial. Targets are often not as illuminated as one would expect in ideal case. To deteriorate the situation, luminous background regions also appear frequently in thermal images. Infrared imaging has become an important tool in the recent years particularly for predicting and preventing electrical equipment's failure. It can reveal various types of problems in electrical equipment by sensing the emission of infrared energy (i.e. temperature) of the equipment. It is well understood that the life of electrical equipment is drastically reduced as temperature increases. Condition monitoring using infrared images has the capability to detect and evaluate the presence of any anomalies in the equipment.

Infrared imaging inspection is well known as a noncontact measurement technique where the inspection can be done without interrupting or shutting down the operation of a system. It offers many advantages over conventional temperature measurement technique, including the capability of fast response times, wide temperature ranges, two-dimensional data acquisition, high spatial resolution, safe, reliable and very cost-effective approach for an electrical power system maintenance program. However, the nature of an infrared image is quite different from that of visual light image. The formation of a thermal image is purely based on the heat distribution of an object. Extracting the hot region within an infrared image is a challenging task, especially when the image contains a very complex background and low signal-to-noise ratio (SNR).

There are two main approaches to solve image segmentation problems such as the deterministic approach and the probabilistic based approach. The former one formulates the segmentation problem as a deterministic

optimization problem and can be classified as: 1) Edge based segmentation 2) Region-based segmentation and 3) Theory based segmentation. Deterministic approach includes the clustering method [1], "snakes" or active contours [2], etc. The latter approach formulates the segmentation problem as a stochastic optimization framework and can be further divided into two groups. One group models the probability distribution of the image entities directly either parametrically or non-parametrically, without using graphical models [3,4]. The other group uses various graphical model to model the joint probability distribution of the related image entities[5].There are two basic types of graphical models such as the undirected graphical model and the directed acyclic graphical model. The undirected graphical model can represent non-causal relationships among the random variables. The Markov Random Field [6] is a type of well-studied undirected graphical model. It incorporate the spatial relationships among neighboring pixels as a Markovian prior. This prior can encourage (or discourage) the adjacent pixels to be classified into the same group.

In this paper, the Markov random fields (MRF) are used for the efficient segmentation of thermal infrared images. It is based on the adaptive segmentation algorithm described by [7]. In the MRF based segmentation method, the local characteristics of an image is used as the priori information and is combined with the given data to segment the image. This improves the segmentation accuracy. The local characteristics of an image include nonparametric distribution of pixel intensities, neighborhood pixel correlations and signal in homogeneities modeled using a priori MRF.

This paper is structured as follows. Section 2 describes about the proposed methodology and the results and discussions are given in section 3. Section 4 gives the conclusion.

2. Proposed Method

The proposed framework makes use of the Markov Random Field modeling for the segmentation of images. In natural images, regions are often homogenous; neighboring pixels usually have similar properties such as intensity, color, texture, etc. Such contextual information can be expressed using probabilistic terms using MRF modeling which is associated with the Bayes's theorem. In this approach the observations and the labels are considered to be the random field variables. The observations are the information that can be directly observed and the labels denote the information which cannot be observed as it has to be extracted from the observations.
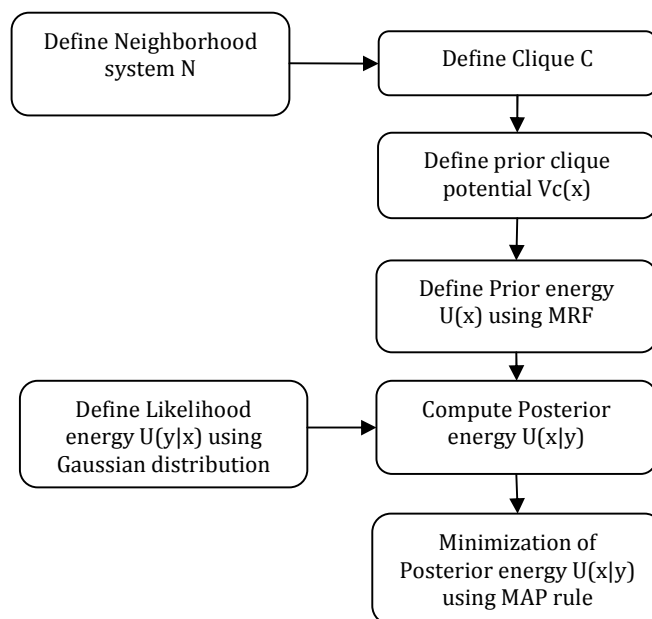

Figure.1   MRF-MAP based segmentation [8]

The MRF-MAP region labeling is used for segmenting the given input image. The goal is to find an optimal label x^* that maximizes the posterior probability $P(\ x\ /\ y\ )$ for a good segmentation of the image. This estimation is called as the maximum a posteriori (MAP) estimation. The MAP criterion is given by

$$x^* = arg\ \ max\ \ \{\ P(y/x)\ P(x)\ \} \tag{1}$$

By Markov-Gibbs equivalence which is defined using Hammersley - Clifford theorem, maximization of the posterior probability is equivalent to minimizing the posterior energy function $U(\ x\ ,\ y\ )$

$$x^* = arg\ min\ \{\ U(y/x)\ U(x)\ \} \tag{2}$$

As shown in Fig.1, the four major steps involved in MRF-MAP region labeling are

> **Step -1**: Finding the priori energy function $U(x)$ using Markov Random Fields
>
> **Step -2**: Finding the Likelihood energy function $U(y|x)$ using Gaussian distribution
>
> **Step -3**: Finding the posterior energy function $U(x|y)$
>
> **Step -4**: Minimization of posterior energy using MAP rule.

These steps results in exact labeling of regions.

2.1 Priori energy function using MRF:

Based on the Markov random field theory, any pixel in an image is correlated with its adjacent pixels and independent of the pixels outside. It is based on the fact that the neighboring pixels do not vary that much in their intensity values. Any digital image consists of discrete set of pixels which can be modeled as a random field. Every pixel in an image is a site and each site is assigned with a label which generally denotes the intensity value of a pixel.

Let $S = \left\{ (i,j)\ |\ 1 \leq i \leq m,\ 1 \leq j \leq n \right\}$ be the set of sites of a rectangular lattice for a 2D image of size $m\ X\ n$. These fields are observed on an image which can be taken as a rectangular grid S. The sites in S are related to one another via a neighborhood system defined as $N = \{\ N_i/\ i \in S\ \}$ where N_i is the set of sites neighboring i as shown in Figure 2. A set of sites in S is said to be a clique C if every pair of sites in C are neighbors to each other.
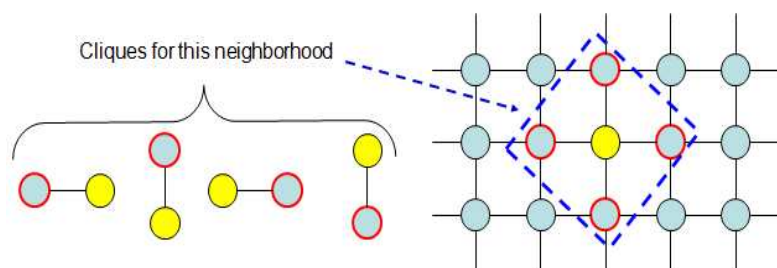

Fig.2.   A 4-Connectivity Neighborhood system and the associated Clique

There are two random fields namely the label random field $X = \{\ X_s,\ s \in S\ \}$ and the observable random field $Y = \{\ Y_s,\ s \in S\ \}$. A random field X is said to be a Markov random field on S with respect to a neighborhood system N and is given by

$$P(\ X_s = x_s/X_t = x_t,\ \forall t \neq s\ ) = P(X_s = x_s/X_t = x_t,\ \forall t \in N\{s\}\ ) \tag{3}$$

i.e. if the value of X at the site s depends only on its neighbors $N\{s\}$ rather on all the pixels in the image then it is said to be a Markov Random Field. According to the Hammersley - Clifford theorem [6], an MRF can equivalently be characterized by a Gibbs distribution. A Gibbs distribution is defined as

$$P(x) = Z^{-1} \, exp \, \{ \, -U(x) \, / \, T \, \} \tag{4}$$

where, Z is a normalizing constant called the partition function [6] , T is the temperature parameter and is assumed to take a value 1, and $U(x)$ is an energy function which is given by

$$U(x) = \sum_{c \in C} V_c(x) \tag{5}$$

where, $U(x)$ is the sum of clique potentials $V_c(x)$ over all possible cliques C. We assume that one pixel has at most 4 neighbors. Therefore the clique potential is defined on pairs of neighboring pixels which is given in

$$V_c(x_i, x_j) = (1 - I_{x_i, x_j}) / 2 \tag{6}$$

where

$$I_{x_i, x_j} = \begin{cases} 0 & if \quad x_i \neq x_j \\ 1 & if \quad x_i = x_j \end{cases} \tag{7}$$

The value of $V_c(x)$ depends on the local configuration of clique C. The optimal segmentation rule is given by the Baye's rule. And thus finally the priori energy function $U(x)$ is given by

$$U(x) = \sum_{c \in C} V_c(x) \tag{8}$$

2.2 Likelihood energy function using Gaussian distribution

The likelihood energy function is denoted as $U(y/x)$. It is determined using the Gaussian distribution. The likelihood energy $U(y/x)$ comes from the observation likelihood and is given by

$$U(y/x) = \sum_i ((y_i - \mu_{x_i})^2 / 2\sigma_{x_i}^2) + \ln \sigma_{x_i} \tag{9}$$

Where, μ is the mean and σ is the standard deviation of the Gaussian distribution.

2.3 Posterior energy function

Then the posterior energy $U(x/y)$ is given by the sum of two terms namely the likelihood energy function and the priori energy function.

$$U(x/y) = U(y/x) + U(x) \tag{10}$$

Where $U(y/x)$ is the likelihood energy function and $U(x)$ is the priori energy function.

2.4 Optimal MAP estimation

MAP estimation finds the value of x that maximizes the posterior probability $P(x/y)$. The MAP rule is given by

$$\hat{x}_{MAP} = arg \, \max_{x \in X} \{ P(x/y) \} \tag{11}$$

MAP estimation is also called as energy minimization. That is maximizing the posterior probability is also equal to the minimization of the posterior energy function. Hence instead of finding the value of x that maximizes the posterior probability $P(x/y)$, the value of x that minimizes the posterior energy function $U(x)$ is determined. This is denoted by the following equations.

$$\hat{x}_{MAP} = arg\ \min_{x\in X}\ \{\ U(x/y)\ \}\qquad(12)$$

As described above the posterior energy function is the sum of likelihood energy function and priori energy function, and hence the above equation can be written as

$$\hat{x}_{MAP} = arg\ \min_{x\in X}\ \{U(y/x)+U(x)\}\qquad(13)$$

Finally the value of x that minimizes the posterior energy function $U(x/y)$ is determined.

3. Results and discussions

The proposed algorithm is demonstrated by applying it in the field of veterinary medicine for the detection of foot-and-mouth disease in cattle. Foot-and-mouth disease (FMD) is one of the highly contagious diseases that affect cattle, swine and other domestic animals. About two years ago, Foot-and-Mouth disease of the cattle has reached epidemic proportions in the State of Tamil Nadu, India, leading to death of about 1200 buffalos. Effective control of this disease needs sensitive, specific, and quick diagnostic tools to avoid loss of economy. Presently FMD diagnosis is being carried out using techniques such as Virus Isolation (VI), Sandwich-ELISA (S-ELISA), Liquid-Phase Blocking ELISA (LPBE), Multiplex-PCR (m-PCR), and indirect ELISA (DIVA), and real time-PCR can be used for detection of antibody against nonstructural proteins [9].

For the purpose of Simulation, IR thermal images of the normal cattle and the cattle affected by foot-and-mouth disease are taken for the experimentation. Figure 3 (a) shows the thermal image of the normal cattle and Figure 4 (a) shows the thermal image of the diseased cattle. Initially the test image is converted into chroma component for better segmentation of the thermal image. The model parameters such as mean and standard deviation that is required for the developed image segmentation algorithm using Markov Random Fields are derived by using the K-means segmentation algorithm as initial label. In the MRF segmentation framework an energy function is formulated for which the data driven term is calculated using the Gaussian distribution and the regularizing term involving the prior knowledge of the label associated is determined using the MRF. Then, the obtained energy function is minimized for the accurate labeling of different classes in the test image. Figure 3 (b) shows the segmented normal cattle and Figure 4 (b) shows the segmented diseased cattle using the developed MRF segmentation algorithm. The results show that the number of pixels affected by disease is less in the normal cattle when compared with that of the cattle affected by foot-and-mouth disease.

Also, MRF is used for the monitoring and assessment of non-invasive corrosion in industries. The infrared thermal images show the excessive heat portions which is the indication of failure in the components and therefore the problems can be corrected before a component fails. The thermal infrared image of corroded fuse clip termination is shown in Figure. The corroded fuse clip termination overheats the fuse. This can be detected at the early stage by applying the developed labeling algorithm using MRF to the IR thermal image. Initially the test image shown in Figure 5 (a) is subjected to K-means segmentation algorithm for initial labeling and the model parameters such as mean and standard deviation for each class are derived. In the same manner the energy function is formulated and is minimized for the accurate labeling of the test image. Figure 5 (b) shows the segmented result obtained using MRF. It clearly segments the corroded portion in the test image.
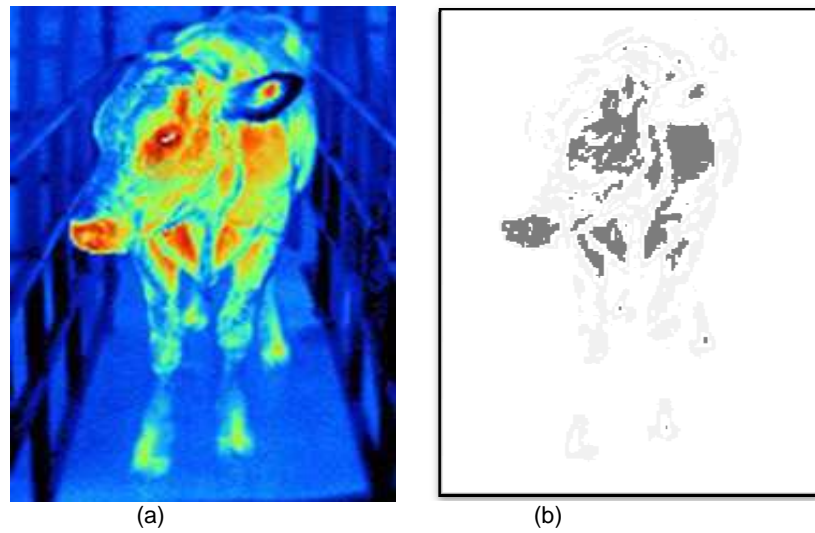
(a)   (b)

Fig. 3. *(a) Thermal image of normal cattle (b) Segmented image using MRF*

(a)   (b)
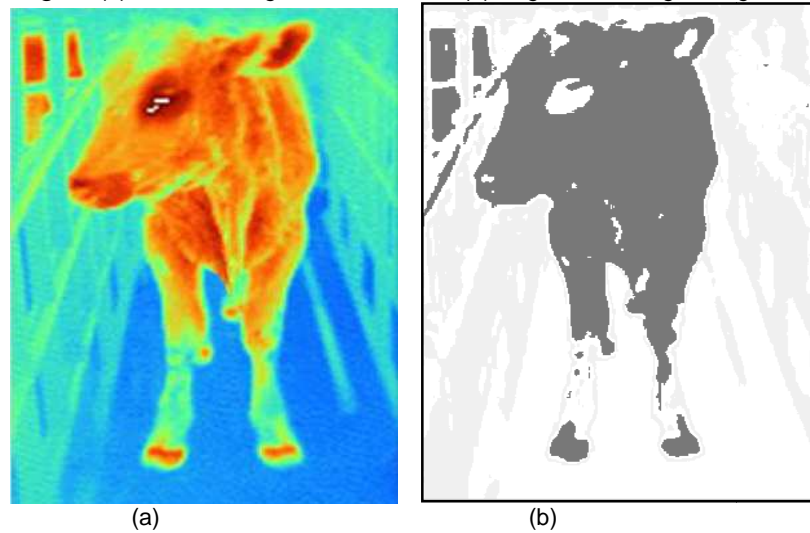
Fig. 4. *(a) Thermal image of cattle affected by foot-and-mouth disease (b) Segmented image using MRF*

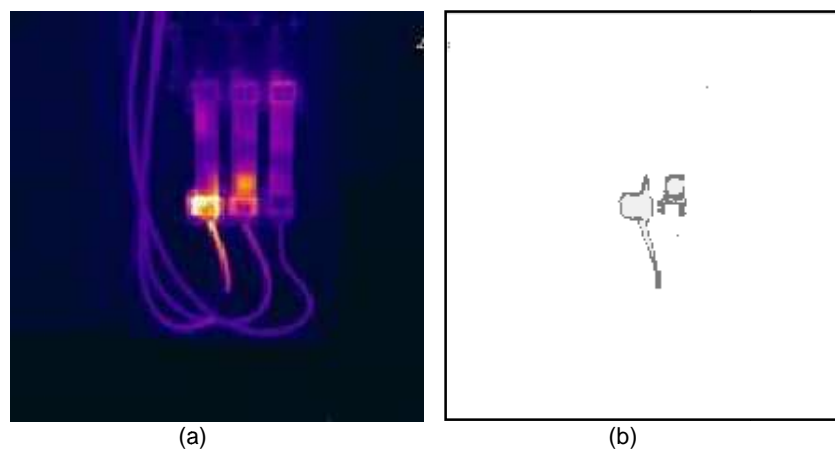(a)   (b)

Fig. 5. *(a) The thermal image of corroded fuse clip termination (b) Segmented image using MRF showing the corroded portion*

4. Conclusion

In this paper, we presented an image segmentation method that is based on the Markov Random Fields that can be used for the segmentation of thermal infrared images. The proposed method makes use of MRF-MAP framework which combines MRF model and the corresponding MRF-MAP estimation. It is applied to the thermal images of cattle and corroded electrical fuse in industry. The foot-and-mouth disease and the extent of the disease in the infected cattle are identified in the field of veterinary medicine. Also the presence of corrosion and the area of corrosion in the defected materials in the industry are detected. The simulation results show that the proposed algorithm using Markov random fields and Maximum a posteriori rule reduces the human interaction in medical diagnosis and also helps in the non-invasive corrosion monitoring and assessment.

REFERENCES

[1] Comaniciu D. and Meer P., "Mean Shift: A Robust Approach toward Feature Space analysis", IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 24, no. 5, pp. 603-619, May 2002.

[2] Kass M., Witkin A. and Terzopoulos D., "Snakes: Active Contour Models," Int'l J. Computer Vision, vol. 1, pp. 321-331, 1988.

[3] Tu Z., Narr C.,Dollar P., Dinov I., Thompson P. and Toga A., "Brain Anatomical Structure Segmentation by Hybrid Discriminative/Generative Models," IEEE Trans. Medical Imaging, vol. 27, no. 4, pp. 495-508,2008.

[4] Tu Z., Chen X., Yuille A.L. and Zhu S.C., "Image Parsing: Unifying Segmentation, Detection, and Recognition," Proc. IEEE Int'l Conf. Computer Vision, pp. 18-25, 2003.

[5] Geman S. and Geman D., "Stochastic Relaxation, Gibbs Distributions, and the Bayesian Restoration of Images," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 6, no. 6, pp. 721-741,1984.

[6] Li S.Z., Markov Random Field Modeling in Image Analysis. Springer, 2001.

[7] Wells W.M., Grimson W.E.L., Kikinis R. and Jolesz F.A., "Adaptive segmentation of MRI data," IEEE Trans. Med. Imag., vol. 15, pp. 429–442, 1996.

[8] Sophia P. and Venkateswaran N., "Segmentation of Medical Images Based on Probabilistic Markov Random Field Model". Adv. in Nat. Appl. Sci., vol.9, no.6, pp. 435-440, 2015.

[9] Neeta Longjam, et.al , "A Brief Review on Diagnosis of Foot-and-Mouth Disease of Livestock: Conventional to Molecular Tools", Veterinary Medicine International Volume 2011.