InfraRed Thermal Image Segmentation using Expectation-Maximization-based Clustering

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***Abstract*—Category 2. In infrared (IR) based non-destructive and evaluation tests (NDT&E) for automated fault detection and identification processes, the segmentation task is a crucial stage. In fact, thermal imaging gives vital condition information of equipment and structures. So, pattern recognition algorithms can perform an accurate diagnosis, through an adequate segmentation. In this paper the Expectation Maximization Clustering (EM-Clustering) segmentation is evaluated for IR images, using as reference watershed transform-based segmentation. IR images were acquired from a test rig of an operating motor at Vibrations Laboratory. Proposed Clustering based segmentation performance is assessed by Dice's coefficient metric, obtaining an average 0.87 Dice's coefficient value. Demonstrating that EM-Clustering Segmentation is a valid choice for IR image processing.**

***Keywords*— Clustering, Dice's coefficient, EM-Algorithm, IR image, Segmentation.**

I. INTRODUCTION

IMAGE segmentation consist in the partitioning of an image into regions by using some pre-established criteria. In human perception the segmentation is an important feature, being therefore one of the most important task in image analysis and processing [1]. In fact, feature extraction and object recognition depend on the quality of the segmentation, since a not adequate segmentation brings the region of interest (ROI) to be often difficult to be recognized for unsupervised classification purposes.

However, when processing IR images, this task is often difficult to achieve, since IR images present low-contrast issues. IR image processing has become in recent years a primary area of concern [2], specially for fault diagnosis of equipment or structures using Non-Destructive and Evaluation Tests (NDT&E) [3] in which IR thermography plays a key role. In this case, joint evaluation [4], surface cracks, size and depth of defects in structures [5] may be observed due the non uniform heat pattern propagation. Moreover, mass unbalance, misalignment of operating motors can be noticeable due to the heating of its component parts [6].

This paper presents a segmentation technique using the expectation maximization algorithm (EM-Algorithm) [7]. To improve the segmentation accuracy, the IR image is processed in Y intensity plane from YUV color space [8] and it was considered the spatial pixel location to create a robust image representation. Clustering of pixels [9] by EM-Algorithm is achieved according to pixel distribution of probability density function (PDF) and exhibit advantages such as image scaling and rotating insensitivity and lack of contrast. This method is compared against watershed transform segmentation based on markers, with the aim of evaluate the segmentation it was used Dice's coefficient as metric.

This paper is composed by the following sections: Section II illustrates the proposed method, the Section III describes the steps of experimental setup, whose results are illustrated in Section IV. Finally, these results are discussed and concluded in Section V.

II. PROPOSED SEGMENTATION METHOD

Proposed segmentation method uses the expectation maximization algorithm (EM-Algorithm), which is an iterative process that estimates maximal likelihood when missing or hidden data is present, to know the model parameter set that fits the data.

The EM-Algorithm consist of two steps, repeating until a criterion of convergence is reached; the first step is called expectation step (E-step) consists of a missing data estimation given the observed data and current estimated parameters; the second step, called maximization step (M-step) consists of maximizing the likelihood function, by assuming the knowledge of missing data as the estimated data found in previous step. The convergence is carried out when the maximal difference between estimated parameter values of E-step and M-step is achieved.

So, let $\mathbf{X}$ be the data vector. We want to know the parameter θ such that the maximal likelihood of estimate θ, $\mathcal{P}(\mathbf{X}|\theta)$ is achieved. In order to estimate θ we use the log likelihood function defined as:

$$L(\theta) = \ln \mathcal{P}(\mathbf{X}|\theta) \tag{1}$$

Where $L(\theta)$ is the likelihood function defined as a function of parameter of θ. Since $\ln \mathcal{P}(\mathbf{X}|\theta)$ is a strictly increasing function, the value of θ that maximizes $\mathcal{P}(\mathbf{X}|\theta)$ also maximize $L(\theta)$.

Since EM-Algorithm is an iterative process for maximizing $L(\theta)$, after n^{th} iteration the current estimate of θ is given by θ_n. Consequently, we want to compute an updated estimate of θ such that $L(\theta) > L(\theta_n)$. Likewise, we want to maximize the difference.

$$L(\theta) - L(\theta_n) = \ln \mathcal{P}(\mathbf{X}|\theta) - \ln \mathcal{P}(\mathbf{X}|\theta_n) \quad (2)$$

Considering the missing data as the random vector $\mathbf{Z}$ and a given realization by $\mathbf{z}$ the Eq. 2 can be rearranged as:

$$L(\theta) - L(\theta_n) = \ln \left(\sum_{\mathbf{z}} \mathcal{P}(\mathbf{X}|\mathbf{z}, \theta)\mathcal{P}(\mathbf{z}|\theta) \right) - \ln \mathcal{P}(\mathbf{X}|\theta_n) \quad (3)$$

So, the EM-Algorithm uses arguments of Equation 3 as follows:

1) **E-step:** Determining the conditional estimation of: $\mathrm{E}_{\mathbf{Z}|\mathbf{X},\theta_\mathbf{n}} \{\ln \mathcal{P}(\mathbf{X}, \mathbf{z}|\theta)\}$
2) **M-step:** Maximize this expression respect to θ

Likewise, EM-Clustering has the same principle of EM-Algorithm, using image elements (pixels) as processed data, and the clustering of pixels are given by the initialization of the original data. This initialization consists of an untrained classifier mapping, used to update the labels of the initially dataset iterating the following steps:

1) **Trained Mapping:** The classifier is trained with the training dataset obtaining a trained map.
2) **Relabel Dataset:** Dataset is relabeled accordingly the trained map obtained in Trained Mapping step.

The convergence criterion is reached when labels keep unchanged for the next iteration.

III. EXPERIMENTAL SETUP

To evaluate the segmentation performance, Fig 1 illustrates the methodology, applied to IR thermal images, comprised by the following stages: i) Data Base, ii) Resizing and Parameter Extraction, iii) Representation, iv) Clustering, v) Region Selection, vi) ROI Artifact Cleaning, vii) Segmented Image and viii) Image segmentation assessment.

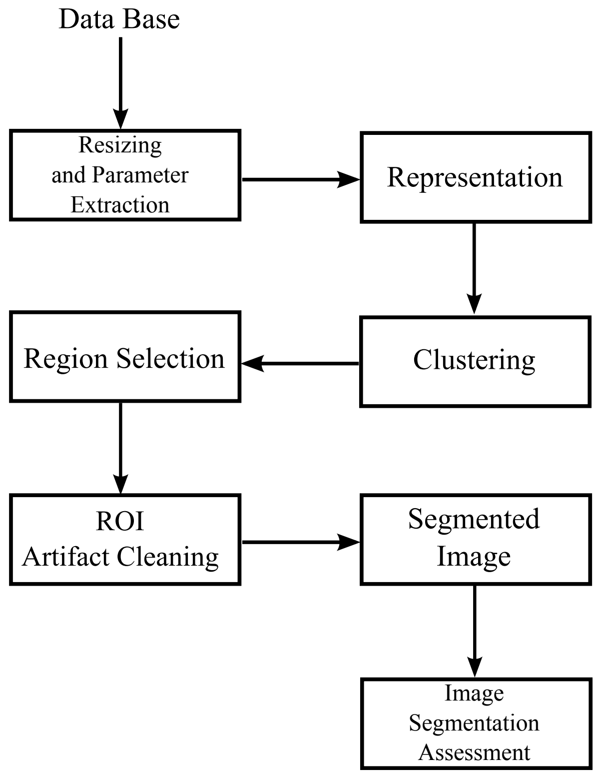

Fig. 1. Developed methodology for segmentation of intensities images.

A. Data Base

The Data Base consist of thermal images as a result of the decomposition of recorded video frames acquired with a thermal IR camera. Table I shows IR camera specifications used for the acquisition. YUV color space was established by default to record the video and used images. For this experiment, only intensity (Y) were used from image.

B. Resizing and Parameter Extraction

To alleviate the computational cost of clustering process, the intensity images were resized to 185×355 pixels focused in the ROI, also it was considered the spatial location of pixels in the resized image, with the aim of have a good set of features for the representation stage.

C. Representation

In this step, the intensity image is represented as a $(p \times q)$ dataset, where p is the total number of pixels in the image and q is the number of features. In this scenario we have the Y color plane intensities and the respective spatial location of pixels (x, y) as a dataset.

D. EM-Clustering

At this point the dataset is ready to be processed; in order to start the clustering process, a trained map for the initialization of the first set of labels is obtained. A 70% of the dataset is randomly taken to train the EM-Clustering with an LDC untrained classifier. EM-Clustering relabels the dataset on each iteration until the labels of the dataset does not change anymore. Number of cluster is set to 2, LDC classifier selection was made after seeing the results of apply EM-Clustering Segmentation to images with different classifiers; LDC shows the best performance. After conclude the iteration of the EM-Clustering, pixels of the IR image are labeled.

E. Region Selection

EM-Cluster returns the labels of the grouped regions, with randomized ROI labels. In this case an expert is required to point the correct pixel location in image, e.g., pixel $(8, 113)$. The label selection was made taking the label of that pixel.

F. ROI Artifact Cleaning

As a result of the clustering; segmented areas has same labels for the region of interest and surrounding objects in background; to obtain a clean image a morphological operations were used removing the extra elements in the image that does not belong to the ROI.
In order to be able of apply morphological operations to the images a binarization is required, assigning 1 to the pixel having the same value of the label selected in the region selection step and the rest of labels were assigned with the

TABLE I
FLIR A-320 IR CAMERA SPECIFICATIONS

FLIR A320 IR Camera		
Camera parameters (FLIR A320)	Emissivity	0.82
	Reflected temperature	20°C
	Distance between camera and test rig	1.5m
	Relative humidity	50,00%
	Ambient temperature	20°C
	Thermal scale	$10 - 50$°C
	Frame size	640×480 pixels
Video acquisition Parameters	Video format	MPEG-2

0 value.
First morphological operation applied was *Closing* procedure used with a structural element of type *disk* and size 1; defining better the regions. Finally, a *fill-holes* process were applied next to the images to avoid ambiguous regions, and by last a remotion of the background objects with an area less than 50 pixels.

The segmentation task is achieved when the image is cleaned. Fig. 2 shows some results obtained in this process.

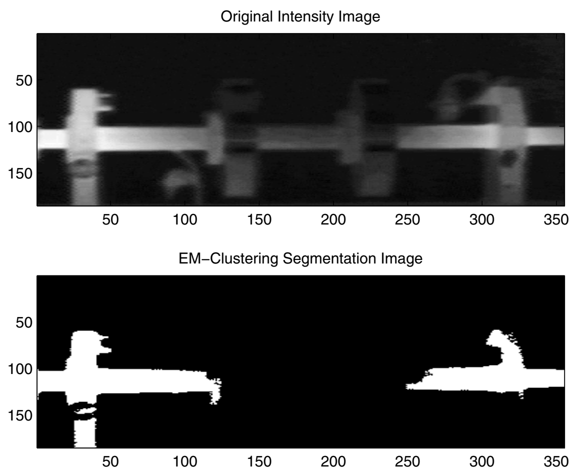

Fig. 2. Original Y images and EM-Clustering Segmentation

G. Image segmentation assessment

To assess the EM-Clustering segmentation performance, it is compared against Watershed Transform based in markers [10] as a ground truth, Watershed transform was applied to same database composed of intensity images.
The Dice's Coefficient measure [11] is used to achieve the comparison . This measure is used frequently in literature [12], [13], [14] as a special case for appropriate image segmentation assessment. Dice's coefficient is defined as:

$$k(S_1, S_2) = \frac{2\,|S_1 \cap S_2|}{|S_1| + |S_2|} \tag{4}$$

Where S_1 and S_2 are the segmented area obtained with EM-Clustering and segmented area obtained with Watershed Transform respectively. A value near to 1 means the segmented area is almost the same segmented area of the ground truth; while a 0 value means the segmented area is completely different to the ground truth.

IV. RESULTS

Fig 3 shows the results of EM-Clustering segmentation against watershed segmentation.

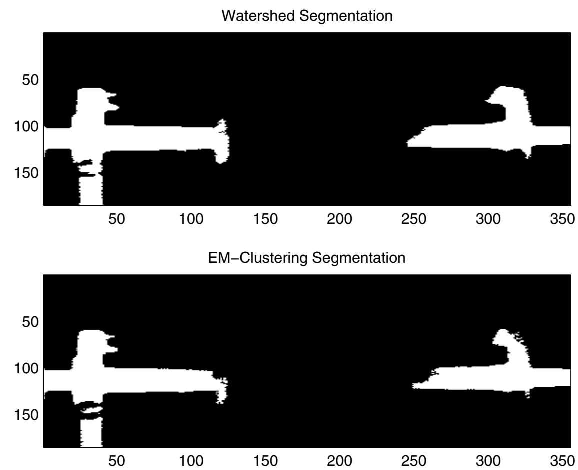

Fig. 3. Watershed Transform Segmentation Vs EM-Clustering Segmentation

An overall of 10 iterations are achieved to evaluate the variability of EM-Clustering segmentation in the 56 samples; Dice's Coefficient was computed for all the iterations, with an average value of 0.87. Fig 4 shows the outcomes of this procedure. Also it is noticeable that proposed segmentation method does not achieve an adequate performance for some images (17, 21, 24, 25, 29, 30, 31, 33, 34, 36 , 37, 38, 40, 56), due the training set selection; this is, when randomly EM-clustering process takes the training set pixels, non of this belong to the ROI.

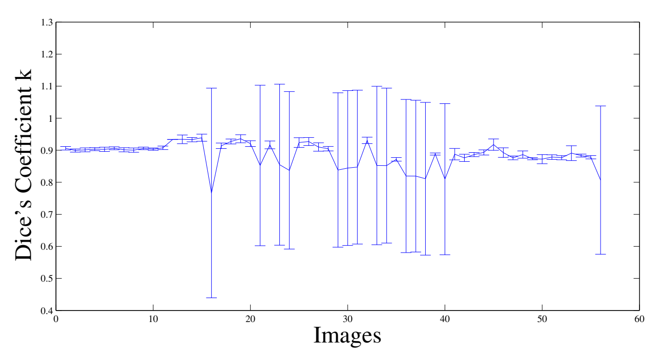

Fig. 4. Variability of EM-Clustering segmentation

V. DISCUSSION AND CONCLUSIONS

Thermal IR image segmentation is an important task that takes place in several NDT&E analysis. Fault diagnosis can be achieved from a proper segmentation using pattern recognition algorithms, since the thermal image of a machine can give us a very important information about machine's condition.
In this paper it was assessed the performance of EM-Clustering segmentation of IR images acquired from a test rig of an operating motor, with a FLIR A320 IR camera. The thermograms frames were processed in Y color plane of YUV color space. The EM-Clustering segmentation was compared against watershed transform segmentation based on markers, the obtained results show an average Dice's coefficient of 0.87, indicating an acceptable segmentation performance, evidencing advantages such insensibility to lack of contrast, scaling and rotating; as a result of clustering criterion which is based in pixels distribution.

However, the results exhibit a high variability of EM-Clustering segmentation, this can be attributed to the random nature of the involved process, when a training set is selected to train EM-Clustering with the aim to found the sub-optimum PDF to fit the pixel distribution data.

For a future work, the proper initialization on EM-Clustering Algorithm would arrange the pixels inside ROI in order to enhance the robustness of EM-Clustering Segmentation, leading to an improvement of Dice's coefficient. Also it can be considered an accurate label selection without expert supervision, making the segmentation a completely unsupervised process.

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