

Segmentation of Thermographic Sequences in Frequency Modulated Thermal Wave Imaging for NDE of GFRP

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Abstract: Image processing techniques have become highly essential to improve the data usefulness of the raw images obtained for infrared non-destructive evaluation (NDE). The identification of defective regions from a thermogram has been a common problem in the field of NDE. Image segmentation is one of the promising approaches to identify defective regions from thermogram. In the present work, segmentation approach based on clustering is employed. In this image patterns are organized into clusters or groups considering the relationship among these. The method involves finding the centroids of the regions and formation of clusters around each centroid. Thresholding is applied to improve accuracy in formation of clusters. Double thresholding method is adapted to retrieve the shape of defect and to improve the possible diagnosis capabilities of system for NDE applications. The proposed method is investigated with frequency modulated thermal wave imaging (FMTWI) over glass fiber reinforced polymers (GFRP). The GFRP sample consists of square shaped Teflon inserts of different dimensions placed at various depths. A comparative study of the proposed novel segmentation scheme and existing segmentation methods is conducted.

Key words: non-destructive evaluation (NDE); image processing; segmentation; pulse compression

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0 Introduction

Glass fiber reinforced polymers (GFRPs) are attractive materials for aircraft, automotive, electronics and infrastructure applications. In recent times, GFRP composites are becoming more acceptable alternative for carbon fiber reinforced polymers (CFRPs) due to their high resistance to corrosion, high strength to weight ratio, and relatively low cost^[1]. The basic principle of NDE involves import of energy into the structure to assess (identification of defects, voids, inclusion, etc.) the condition of the material. A wide variety of non-destructive evaluation (NDE) techniques are found in the literature for damage/defect identification in composite materials. These include radiographic testing^[2], ultrasonic testing^[3,4], acoustic emission testing^[4], infrared thermogra-

phy testing^[5], electromagnetic testing^[6], magnetic particle testing^[7], step phase thermography^[8] etc. However, among these, infrared thermography has become a more preferred nondestructive inspection method to evaluate subsurface defects in different types of materials. The preference is due to its fast inspection rate, noncontact procedure, portability, and easy to interpret features^[9]. Several infrared thermography methods have been proposed in the literature to detect delamination defects in composite materials, but only three of them are predominantly used: Pulse Thermography (PT), lock in thermography (LT) and pulse phase thermography (PPT)^[10-13]. However all these suffer from certain limitations. PT requires high peak power heat sources, and suffers from nonuniform heating and is sensitive

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to surface emissivity variations. LT suffers from limited depth resolution and long processing time^[14,15]. PPT requires heat sources with high peak power to effectively detect deeper subsurface defects. Due to this precaution has to be taken to avoid damage of the test sample because of high power. In this work, to overcome the mentioned limitations, frequency modulated thermal wave imaging (FMTWI)^[16] is employed for identification of the defects in solid material.

Data processing is an essential step in NDE to visualize the subsurface defects in the sample and to determine the shapes and sizes of the defects. The data processing intends to analyze temporal variations in the contrast of each pixel, relative to defect-free reference point on the sample. For this, several post processing algorithms are applied to the recorded thermograms. In this paper, GFRP sample with 25 square shaped Teflon inserts of different dimensions placed at various depths is used. These inserts are examined by means of frequency modulated thermal wave imaging^[16]. Pulse compression^[17, 18] is applied overmean removed profiles to ensure better defect detection. Subsequently, the proposed segmentation algorithm is investigated over GFRP sample and results are compared and contrasted with the existing segmentation methods.

1 Frequency Modulated Thermal Wave Imaging

The principle of frequency modulated thermal wave imaging consists of introducing frequency modulated heat flux, containing different frequencies, into the object to be tested. Then the resulting temperature field in the transient regime is recorded remotely by capturing its thermal emission (infrared range) using infrared (IR) camera^[15]. When frequency modulated heat flux is excited into the specimen, the infrared camera controlled by the computer monitors the surface temperature profile of the heated sample. The expression for propagation of thermal wave incident on the solid sample at surface [$x = 0$] is given

by^[15]

$$T(x, t) = T_0 e^{-x\sqrt{\frac{\pi}{\alpha}(f + \frac{Bt}{\tau})}} \cdot e^{j[2\pi(f + \frac{Bt}{\tau}) - x\sqrt{\frac{\pi}{\alpha}(f + \frac{Bt}{\tau})}]} = T_0 e^{-x\sqrt{\frac{\pi}{\alpha}(f + \frac{Bt}{\tau})}} [\cos k + J \sin k] \quad (1)$$

where $k = 2\pi\left(ft + \frac{Bt^2}{2\tau}\right) - x\sqrt{\frac{\pi}{\alpha}\left(f + \frac{Bt}{\tau}\right)}$, where B is band width, τ the duration, x the space coordinate, t the time, f the frequency, α the thermal diffusivity, B/τ the frequency sweep rate of the chirp, and T_0 the surface temperature at the sample surface ($x=0$).

From Eq. (1) the diffusion length (μ_{f_m}) can be computed as

$$\mu_{f_m} = \sqrt{\frac{\alpha}{\pi\left(f + \frac{Bt}{\tau}\right)}} \quad (2)$$

Eq. (2) indicates that the thermal diffusion length is a function of bandwidth (B) of the heat flux. The complete depth of the sample can be scanned in one (f_m) cycle as it contains multiple frequencies instead of single frequency. And for the frequency modulated thermal wave imaging, thermal wave length (λ) is given by

$$\lambda = 2\pi\mu_{f_m} = 2\pi\sqrt{\frac{\alpha}{\pi\left(f + \frac{Bt}{\tau}\right)}} \quad (3)$$

It can be noted from Eq. (3), that λ is varying with time. This implies that resolution for detection of defects varies with depth.

2 Materials and Experiment

The experiment is carried on a GFRP sample having 25 square Teflon inserts. The Teflons are of various dimensions and situated at different depths (Fig. 1). A synchronized IR camera (Model: FLIR IR CAMERA SC6200) having a maximum frame rate of 450 Hz, and 0.001 K temperature resolution with a pixel resolution of 320×256 pixels is used to record the image sequences. A frequency modulated chirped thermal wave stimulation of frequencies ranging from 0.01 to 0.1 Hz in 100 s, has been applied to the sample using two halogen lamps of power 1 kW each (Fig. 2). With the help of mid band infrared camera, Temporal thermal response is captured at

a frame rate of 20 Hz.

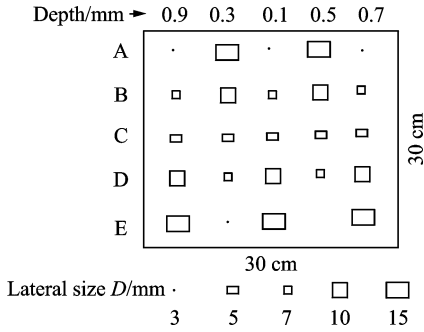


Fig. 1 Layout of the experimental GFRP sample

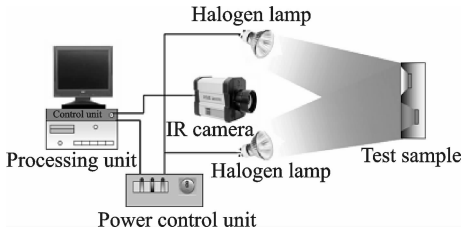


Fig. 2 Experimental set up

3 Image Segmentation and Quantitative Identification of Defect from Thermogram

The identification of defective regions from a thermogram has been a common problem in the field of NDE. Image segmentation is a highly promising method that helps to effectively analyze thermogram quantitatively and qualitatively. This helps in finding sizes and depths of defects. Image segmentation involves assignment of each pixel to regions of an image relative to interest. That is, it separates regions of deviant temperature from the image. Several segmentation methods have been proposed in the past, and are broadly classified into three categories: thresholding, clustering and edge detection. However, from the literature it is observed that image segmentation techniques are strongly application dependent. Sezgin and Sankur^[20] presented an extensive survey on automated image thresholding techniques and quantitative performance evaluation. They classified thresholding techniques into six categories: (1) Histogram shape-based methods, (2) local methods, (3) object attributed-based methods, (4) entropy-based methods, (5) spatial methods, and (6) clustering-based methods. Among these

methods clustering and entropy based threshold methods are preferred for NDE images. Thresholding based segmentation is not only simple but also appropriate, because it separates objects from the background, making it appropriate for NDE purposes^[19]. The performance of thresholding algorithms is strongly influenced by image content and method of thresholding. However, thresholding approach for NDE applications is complex due to the following reasons: High noise, insufficient illumination, variance of gray levels inside the object, inadequate contrast in the background. Also the object shape and size are not commensurate with the scene. Various thresholding based segmentation algorithms have been proposed in literature namely, Otsu's method^[21], Contrast Otsu method^[22], adaptive threshold^[23], K-means clustering^[24], and Fuzzy C-means clustering^[19,25].

4 The Proposed Segmentation Method

In the present work, clustering based segmentation approach is employed. The approach begins with considering dominant component in FMTWI, where frequency modulations are used as segmentation features. In this, the regions/defects in the image are organized into clusters based on relationship between them. The flow chart of the proposed segmentation method is shown in Figs. 3,4. The segmentation method involves three stages.

(1) Finding the centroids of the regions

Step 1 Apply adaptive thresholding method for the fused image.

Here the fused image is having non-uniform texture as shown in Fig. 5(a). Adaptive thresholding is capable of segmenting segments into two types of regions, i. e, white region in the dark background and dark region in the white background.

Step 2 The centroid for each and every region is identified using "regionprops" function of MATLAB (shown in Fig. 5(b)).

Step 3 The false centroids (white regions in

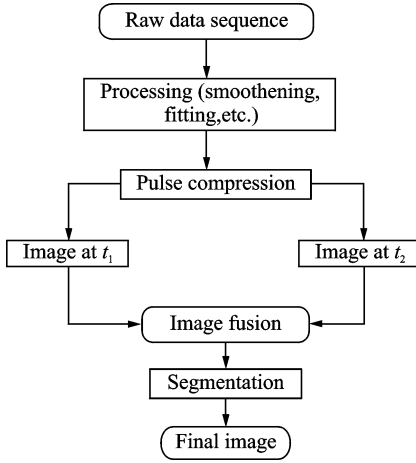


Fig. 3 Flow chart of thermal image processing

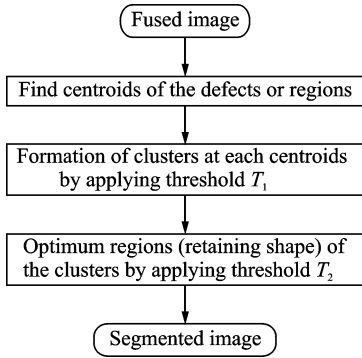


Fig. 4 Proposed segmentation approach

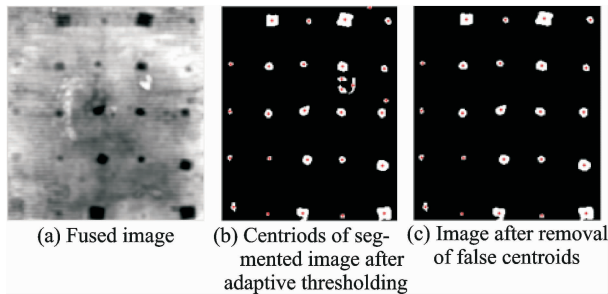


Fig. 5 Fused image and corresponding centroids

the dark back ground) is removed by using connectivity with the pixels as shown in Fig. 5(c).

(2) Formation of clusters around each centroid

Each pixel including the centroid pixel is assigned to one of the centroids depending on the euclidean distance between the pixel and the centroid. For example if the pixel $I(i, j)$ making the shortest distance with centroid 2 then this pixel $I(i, j)$ is assigned to the centroid 2. Algorithm is used for clustering as shown in Fig. 6.

(3) Application of thresholds

The line intensity profiles at each defect is il-

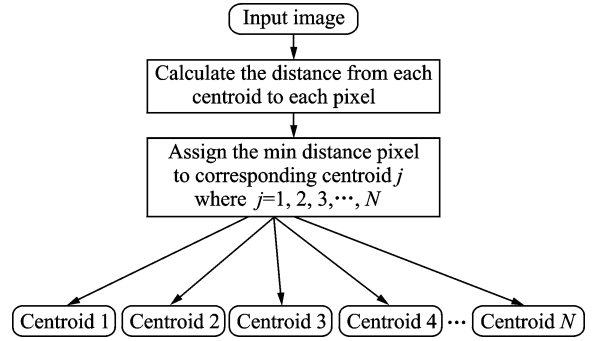


Fig. 6 Algorithm for clustering

lustrated in Fig. 7. To improve the accuracy of segmentation, it is proposed to adapt dual threshold method instead of single local adaptive threshold for segmentation. The procedure for finding the dual thresholds (T_1 & T_2) for the second defect in first row is illustrated in Fig. 8. The threshold T_2 value is calculated using

$$\frac{1}{N} \int_1^N f(X) dX = T_2$$

where N is the number of pixels considered around each centroid.

The mean value of the pixels below the threshold line T_2 is considered as a line and it intersects the intensity profile at X_1 and X_2 . The threshold T_1 value is calculated as

$$X_2 - X_1 = T_1$$

However, T_1 and T_2 values for all defects are tabulated in Table 1. The threshold value T_1 is applied to the cluster corresponding to the centroid for first level segmentation. The segmented cluster is subject to second level segmentation with T_2 , resulting in final segmented output. The segmented image after application of T_1 and T_2 is shown in Fig. 9 and Fig. 10(h), respectively.

Table 1 Threshold values (T_1 and T_2) of each defect

Depth/ mm	D/mm									
	15		10		7		5		3	
	T_1	T_2	T_1	T_2	T_1	T_2	T_1	T_2	T_1	T_2
0.9	8	0.55	6	0.68	5	0.78	6	0.7	—	—
0.7	10	0.35	8	0.4	8	0.45	6	0.8	6	0.55
0.5	10	0.28	8	0.55	7	0.3	5	0.38	5	0.64
0.3	11	0.4	6	0.52	6	0.4	6	0.43	5	0.38
0.1	10	0.25	8	0.25	10	0.25	6	0.6	5	0.6

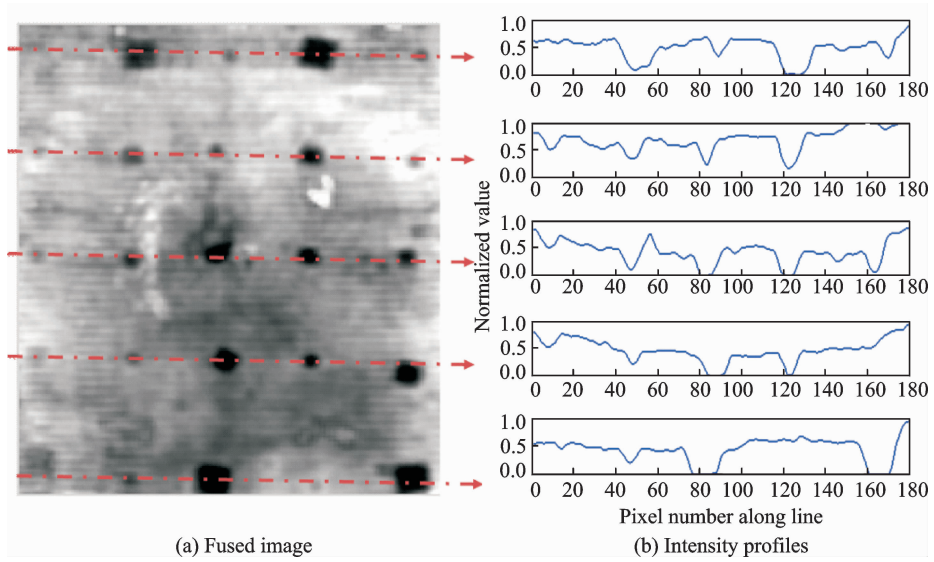
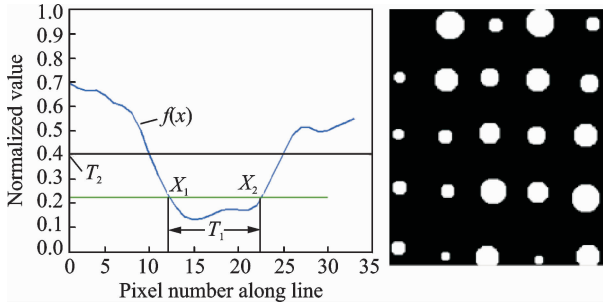
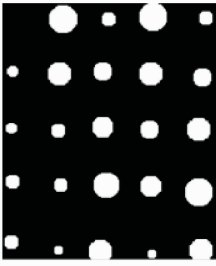


Fig. 7 Line intensity profiles at each defect

Fig. 8 The computation thresholds T_1 and T_2 Fig. 9 Segmented image after application of T_1 

tion. In correlation based pulse compression, mean removed thermal profiles of each pixel are cross correlated with a reference profile. The correlation coefficient contrast due to depth dependent delay is used for detection^[9]. In order to further improve SNR, discrete wavelet transform (DWT) based image fusion algorithm is applied to pulse compressed images at different time instances. More details of image fusion of GFRP sample can be referred in Ref. [26]. The discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations obeying some defined rules. In other words, this transform decomposes the signal into mutually orthogonal set of wavelets. By using DWT, the image is first divided into sub-bands under different resolutions. The resulting two-dimensional array of coefficients contains four bands of data, each labelled as LL (low-low), HL (high-low), LH (low-high) and HH (high-high) as shown in Fig. 11. The LL band can be decomposed once again in the same manner, thereby producing even more sub-bands. This can be done upto any level, thereby resulting in a pyramidal decomposition as shown in Fig. 11. Each and every sub-bands of the Image-I and Image-II are going to be fused with different fusing algorithms. The basic idea of image fusion using DWT shown in Fig. 12.

5 Pre-processing of Raw Image

In general, thermal responses from deeper subsurface anomalies are more contaminated with noise. The result is low signal to noise ratio (SNR), which makes it necessary to preprocess the raw image. The overview of preprocessing flow is shown in Fig. 3. In order to reveal subsurface features, the offset in temporal thermal profiles of each pixel is removed by a linear fit. Further processing is carried over these mean removed profiles of each pixel in view. Processing methods are applied over these profiles to reduce noise influence thereby improving SNR. This results in enhanced detection performance in revealing deeper subsurface features pulse compression applied over these noise contaminated profiles enhances the SNR and provides better defect detec-

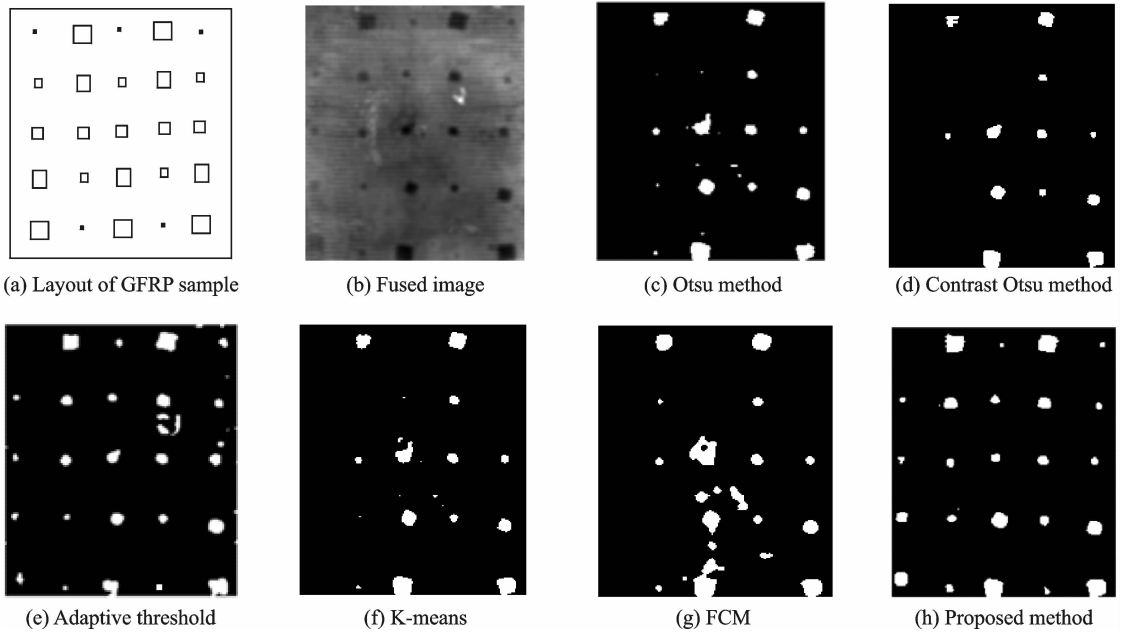


Fig. 10 Pulse compressed image after segmentation

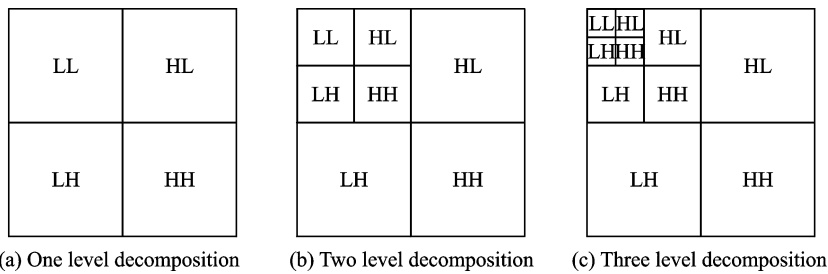


Fig. 11 Wavelet decompositions

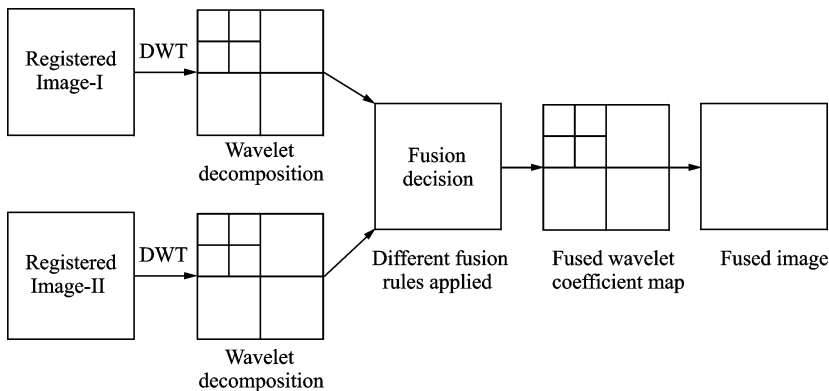


Fig. 12 Image fusion using DWT

Image-I is having the focus at one area and Image-II is having the focus at another area. When we combine these two images then we get an image having both focused areas in single scene.

The procedure for fusion is as follows:

- (1) Apply DWT for Image-I;
- (2) Apply DWT for Image-II;

- (3) Combine LL components of Image-I and Image-II;
- (4) Combine LH components of Image-I and Image-II;
- (5) Combine HL components of Image-I and Image-II;
- (6) Apply IDWT and obtain the output image.

6 Results and Discussion

The proposed segmentation algorithm is investigated over fused image (31) of on a GFRP specimen including 25 Teflon inserts of different dimensions placed at various depths. The results indicate that the proposed method showed better performance in both qualitative and quantitative aspects. Compared with thermal image, the segmented image provides visualized information about true defects and false alarms. Analyzing the binary images after segmentation would be obviously easier for the inspector. A segmentation procedure based on the use of the clustering based instead of the conventional, this allows removing the fluctuation in values of pixels corresponding to defect. It is compared with state of the art segmentation methods based on thresholding and clustering including Otsu's method^[21], Contrast Otsu method^[22], adaptive threshold^[23], K-means clustering^[24] and Fuzzy C-means clustering^[19,27] as shown in Fig. 10. In this context it is felt necessary to apply and performance evaluate the NDE problem using proven methods in literature. The results clearly brought out the uniqueness of the proposed method over other thresholding methods (global and local). It is observed from the literature, also as emphasized by Wang Zhenzhou^[28], that the global thresholding methods are more suitable for processing of uniform image(30). In the present research, the image is non uniform, hence it is pertinent to consider local thresholding methods. However, the overall comparison is made for both local and global methods considering the end application involved in the research. The results emphasize that the proposed method could segment almost all the defective regions from the background, whereas the other segmentation methods are able to segment the brighter objects only. The quantitative quantification of different sizes of defects is also compared by counting number of defects segmented.

The number of defects observed is 24 out of 25 with 96% accuracy rate by the proposed method. The accuracy rate of state of the art segmentation methods is 56%, 92% and 52% with K-means, adaptive thresholding and FCM methods, respectively. It is clearly found that the segmentation accuracy is better in the proposed method.

7 Quantitative Analysis

The performance of proposed method is evaluated quantitatively, using relative foreground area error(RAE)^[20,29]. RAE parameter is pertinent since area and shape of an object are essential parameters for quantitative analysis in the case of NDE applications. RAE can be expressed in terms of feature area^[20]. The value of RAE measures the quantity of segmentation. That is zero value indicates an optimal segmentation, where as zero overlap of object areas gives maximum one

$$RAE = \begin{cases} \frac{A_T - A_M}{A_T} & A_M < A_T \\ \frac{A_M - A_T}{A_M} & A_T \leq A_M \end{cases}$$

where A_T is the true value, and A_M the measured value.

The results obtained after applying various thresholding methods to NDE images in terms of threshold value, number of defects detected and RAE are tabulated in Table 2. The results are also displayed through bar charts in Fig. 13. RAE is equal to zero for an optimal segmentation i. e. a perfect match of the segmented regions, while it is one, if there is zero overlap of the object areas. The results are evaluated by measuring RAE for various segmentation techniques viz: Otsu's method, contrast Otsu method, adaptive threshold, K-means clustering and Fuzzy C-means clustering. It is concluded that using the proposed method a better performance observed in both qualitative and quantitative aspects in terms of area/shape and density of defects. However, it is observed that image segmentation techniques are strongly application dependent. The proposed tech-

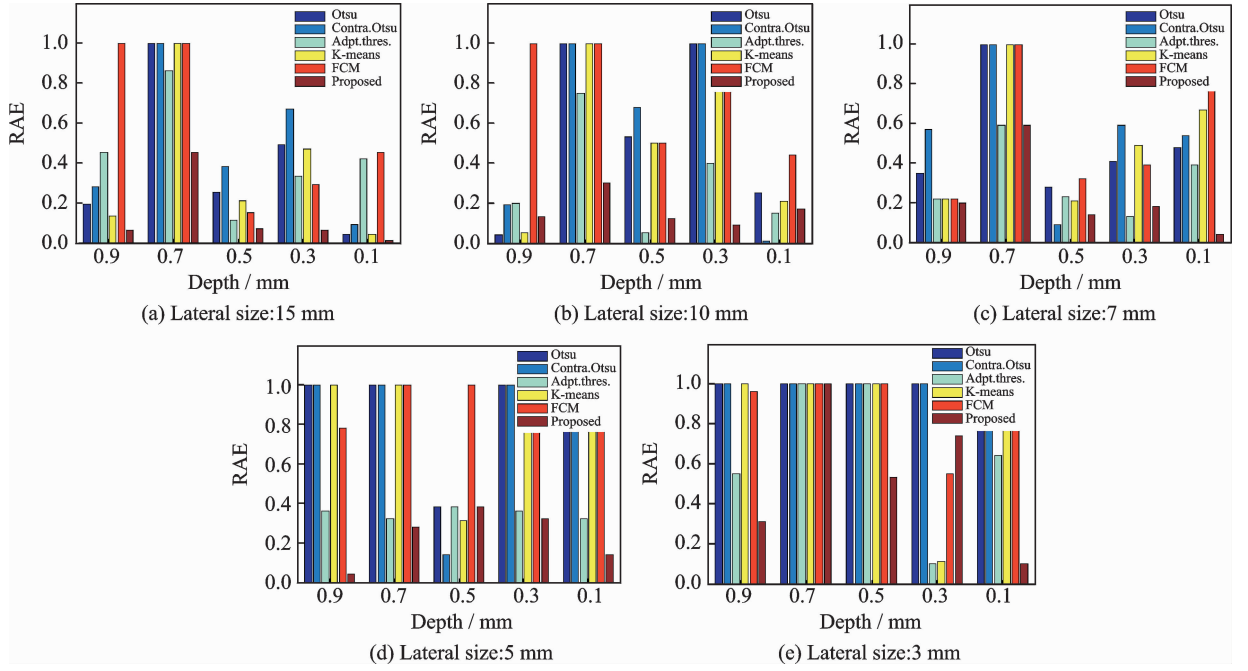


Fig. 13 RAE v. s. segmentation methods

Table 2 Comparison of area and RAE value of each defect

Depth/ mm	Method	(15 mm, 2.15 cm ²)		(10 mm, 1.00 cm ²)		(7 mm, 0.49 cm ²)		(5 mm, 0.25 cm ²)		(3 mm, 0.09 cm ²)	
		Measured/ cm ²	RAE	Measured/ cm ²	RAE	Measured/ cm ²	RAE	Measured/ cm ²	RAE	Measured/ cm ²	RAE
0.9	Otsu	1.74	0.19	0.96	0.04	0.32	0.35	—	1	—	1
	Contra. Otsu	1.54	0.28	0.81	0.19	0.21	0.57	—	1	—	1
	Adpt. thresh	1.19	0.45	0.8	0.2	0.63	0.22	0.39	0.36	0.2	0.55
	K-means	1.86	0.13	0.95	0.05	0.38	0.22	—	1	—	1
	FCM	—	1	—	1	0.38	0.22	1.13	0.78	2.03	0.96
	Proposed	2.03	0.06	1.15	0.13	0.39	0.2	0.26	0.04	0.13	0.31
0.7	Otsu	—	1	—	1	—	1	—	1	—	1
	Contra. Otsu	—	1	—	1	—	1	—	1	—	1
	Adpt. thresh	0.31	0.86	0.25	0.75	0.2	0.59	0.17	0.32	—	1
	K-means	—	1	—	1	—	1	—	1	—	1
	FCM	—	1	—	1	—	1	—	1	—	1
	Proposed	1.19	0.45	0.7	0.3	0.2	0.59	0.18	0.28	—	1
0.5	Otsu	1.61	0.25	0.47	0.53	0.68	0.28	0.4	0.38	—	1
	Contra. Otsu	1.34	0.38	0.32	0.68	0.54	0.09	0.29	0.14	—	1
	Adpt. thresh	1.92	0.11	0.95	0.05	0.64	0.23	0.4	0.38	—	1
	K-means	1.7	0.21	0.5	0.5	0.62	0.21	0.36	0.31	—	1
	FCM	1.82	0.15	0.5	0.5	0.72	0.32	—	1	—	1
	Proposed	1.99	0.07	0.88	0.12	0.57	0.14	0.4	0.38	0.19	0.53
0.3	Otsu	1.1	0.49	—	1	0.29	0.41	—	1	—	1
	Contra. Otsu	0.71	0.67	—	1	0.2	0.59	—	1	—	1
	Adpt. thresh	1.44	0.33	0.6	0.4	0.56	0.13	0.16	0.36	0.1	0.1
	K-means	1.14	0.47	—	1	0.25	0.49	—	1	0.08	0.11
	FCM	1.52	0.29	0.13	0.87	0.3	0.39	—	1	0.2	0.55
	Proposed	2.03	0.06	0.91	0.09	0.4	0.18	0.37	0.32	0.34	0.74
0.1	Otsu	2.25	0.04	1.34	0.25	0.95	0.48	—	1	—	1
	Contra. Otsu	1.96	0.09	1.01	0.01	1.06	0.54	—	1	—	1
	Adpt. thresh	1.24	0.42	0.85	0.15	0.8	0.39	0.37	0.32	0.25	0.64
	K-means	2.23	0.04	1.26	0.21	1.48	0.67	—	1	—	1
	FCM	3.93	0.45	1.77	0.44	3.34	0.85	—	1	—	1
	Proposed	2.13	0.01	1.2	0.17	0.47	0.04	0.29	0.14	0.1	0.1

nique is well-suited for scenes with strong spatial changes in illumination. Temporal variations in illumination are also handled automatically, which is not the case with other thresholding methods. It is observed that the proposed method has higher value for number of defects detected and lower value for RAE. That means the proposed method showed better performance in both qualitative and quantitative aspects as compared to other methods.

8 Conclusions

Segmentation is one of the promising methods to extract defective regions from thermographic sequence. Traditional clustering algorithms could not correctly classify defects with respect to shape, size and number. In this paper a novel approach is proposed and evaluated for segmentation of NDE images. The method involved clustering based segmentation in which patterns are organized into clusters or groups considering the relationship between these. The double thresholding is used to retrieve the shape of defect; it improves the possible diagnosis capabilities of system for NDE applications. The results are evaluated by measuring RAE for various segmentation techniques viz: Otsu's method, contrast Otsu method, adaptive threshold, K-means clustering and Fuzzy C-means clustering. It is concluded that using the proposed method a better performance is observed in both qualitative and quantitative aspects in terms of defect shape, size and number. However, it is observed that image segmentation techniques are strongly application dependent.

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