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Fuzzy C-Means Clustering Based Anomalies Detection in Quadratic Frequency Modulated Thermal Wave Imaging

A. Vijaya Lakshmi, V. S. Ghali, Muzammil Parvez M, G. V. P. Chandra Sekhar Yadav, V. Gopi Tilak

Abstract*: Defect characterization from its non-defective counterpart from the raw thermal response plays a vital role in Quadratic frequency modulated thermal wave imaging (QFMTWI). The strength of the bone reduces due to the skeletal disorder as the age of the person grows, Early diagnosis corresponding to disease is necessary to provide good bone strength. By detecting bone density variations the disease can be managed effectively. A non-stationary thermal wave imaging method, Quadratic frequency modulated thermal wave imaging (QFMTWI) is used to characterize strictness of the human bone, as well as experimentation also carried on Carbon fiber reinforced polymers (CFRP) sample and are extended to unsupervised machine learning algorithms like k-means clustering and fuzzy c-means clustering algorithms. In case of an observer with less expertise, a perfect unsupervised clustering approach is necessary to fulfill this requirement. In present article, we applied k-means and fuzzy c-means based unsupervised clustering techniques for subsurface defect detection in QFMTWI. The applicability of these algorithms is tested on a numerical simulated biomedical bone sample having various density variations and an experimental Carbon fiber reinforced polymers (CFRP) sample with flat bottom holes of different depths with same size. Signal to noise ratio (SNR) is taken as performance merit and on comparison, we conclude Fuzzy c-means provides better detection and characterization of defects compared to K-means clustering for QFMTWI.

Keywords*: Infrared thermography, clustering and Quadratic frequency modulated thermal wave imaging.

I. INTRODUCTION

To provide high quality and defect free materials various non-destructive methods are available. Among them, the infrared non-destructive testing (IRNDT) is a non-destructive and non-contact method for testing the integrity of test specimen and is able to inspect large areas with less time [1]. IRNDT can be performing by mapping the temperature contrast on the surface, caused by thermal in-homogeneity of test specimen. This temperature map is used for further analysis. Passive and active thermography are two varieties of Infrared thermography.

Specimen observed at adiabatic temperature conditions in passive thermography, whereas, a known and controlled external optical stimulus is applied to break the thermal equilibrium of the specimen in active thermography, corresponding temporal thermal response of surface of material has been observed using an infrared imager. Further different processing approaches have been employed over the collected data from infrared camera. From recent decades IRNDT introduced various non-stationary thermal wave methods with some conventional methods.

Ahead to non-stationary excitation, conventional Pulse (PT) [2-3] and lock-in thermography (LT) [4-5] are widely used thermal wave imaging (TWI) techniques. In PT, a high peak power stimulus spanning very short duration is imposed on the testing specimen and corresponding temporal thermal response collected from the surface and further processed. This high peak power results non uniform emissivity and non-uniform radiation of thermal response. Whereas, a moderate peak power continuous modulated stimulus is imposed over the testing specimen corresponding temporal thermal response is captured. The property i.e., less sensitive to non-uniform radiation and non-uniform emissivity makes the advantage of using phase based analysis in LT. In thermography, defect at a particular depth can be assessed by a particular frequency of excitation, which needs the repetition of experimentation to assess all the defects at different depths in LT. Introducing the phase based analysis in PT, pulse phased thermography (PPT) [6-7] is proposed. Still the application of PPT is limited by its high peak power excitation.

To achieve the advantages over conventional PT and LT, a moderate peak power stimulus imposed on testing object with a band of modulating frequencies, named Frequency modulated thermal wave imaging (FMTWI) is introduced [8-10]. The band of frequencies overcomes the repetitive experimentation limitation in LT. Further, to improve the contrast and reduces the non-uniform backgrounds QFMTWI [11] has been proposed, which can provide sufficient energy for low frequencies and provides better depth detection even for deeper anomalies.

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* Correspondence Author

A. Vijaya Lakshmi*, Research Scholar, Department of ECE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, A.P, India.

V. S. Ghali*, Professor, Department of ECE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, A.P, India.

Muzammil Parvez M, Assistant Professor, Department of ECE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, A.P, India.

G. V. P. Chandra Sekhar Yadav, Research Scholar, Department of ECE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, A.P, India.

V. Gopi Tilak, Research Scholar, Department of ECE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, A.P, India.

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In present work, we applied unsupervised fuzzy c-means clustering based analysis is used for detection of anomalies in bone and CFRP samples for QFMTWI. Osteoporosis, a skeletal disease of decreased bone density is modeled and analyzed through phase based FMTWI [12]. In this paper, we try to distinguish the density variations of bone and subsurface defects of CFRP specimen excited by QFM heat flux from their non-defective counterparts using K-means and Fuzzy C-means clustering analysis [13-14]. Finally, a comparison is made among them in accordance with defect visualization and SNR and concluded that Fuzzy C-means potentially characterizes the defects.

Paper organized as, section II discusses about the theory of QFMTWI followed by k-means and Fuzzy C-means clustering in section III. The subsequent observations and their discussions given in section IV and finally article concluded in section V.

II. THEORY FOR QFMTWI

In this section a theoretical development for surface evaluation corresponding to QFMTWI as stimulation by solving one-dimensional heat equation. A QFMTWI stimulus is applied to surface of test specimen and is represented by [11]:

$$H(t) = H_0 \sin (a\,t + b\,t^3) \tag{1}$$

The initial frequency represented by 'a' bandwidth of chirped excitation is represented as 'b' in the above with peak value of stimulation 'H_0'. With this stimulation thermal perturbation creates on the surface of the test specimen and moves in depth. Depending on thermal properties of the surface temperature contributes over the surface of test specimen. By solving heat equation, the thermal wave temperature variations at the surface of specimen can be represented by:

$$\frac{\partial^2 T\ (x,t)}{\partial T^2} = \frac{1}{\alpha}\frac{\partial T(x,t)}{\partial t} \tag{2}$$

Here, 'α' denoted by material thermal diffusivity and thickness of the material is represented by 'L'. By solving Equation 2 under boundary conditions is represented as:

$$-k\frac{\partial T}{\partial Z}\bigg|_{x=L}=0 \tag{3}$$

At initial temperature of applied stimulus is attenuated with thin layer of material surface and provides heat flux over the surface of the material is represented by:

$$-k\frac{\partial T}{\partial Z}\bigg|_{x=0}=Q_0 e^{j2\pi\left(a+bt^2\right)t} \tag{4}$$

Here, 'k' is the thermal conductivity; 'Q_0' is intensity of heat flux. With the utilization of boundary conditions, by solving Eqn. 2 in Laplace domain, the surface temperature is expressed as:

$$T(x,s)=\frac{Q(s)}{k\sigma(1-e^{-2\sigma L})}[e^{-\sigma x}+e^{\sigma(x-2L)}]-\frac{T_0}{s} \tag{5}$$

Where $\sigma=\sqrt{s/\alpha}$ the resulting diffusion length as:

$$\delta \propto \sqrt{\frac{\alpha}{1.77(a+bt^2)}} \tag{6}$$

By the Equation 6, so Quadratic frequency modulated stimulation gives best depth resolution.

III. METHODOLOGY

The clustering algorithm can be used to create grouping the data by partitioning data points into groups using similarity in the data object.

A. K-means based clustering

In an un-supervised clustering method, K-means clustering is used to categorize the data into specified clusters. In this era, we need to represent a centroid for every cluster then allocate every data point to the nearby centroids. Corresponding data sets are categorized by minimizing the sum of squares in between centroids. If the number of centroids (K) is changes then their location for every cycle will changed until there is no further changes are done. In this algorithm the equation (7) is used to minimize the objective function P, Where P is sum of squared error [14].

$$P=\sum_{i=1}^{k}\ \sum_{j=1}^{n}\left\|X_j-C_i\right\|^2 \tag{7}$$

Where X_j is a vector points in cluster, j and C_i is mean of cluster. This K-means clustering algorithm follows these steps.

1. Initially choose the number of clusters represented as k.
2. Initial cluster centers are selected randomly depending on k number of clusters.
3. Based on Euclidean distance between cluster center and distance between each points allocate each point nearby cluster.
4. Again calculate mean of each cluster.
5. Replicate the above two steps until the no data points change in the groups and function 'P' reaches the minimum value.

B. Fuzzy c-means based clustering

Fuzzy c-means (FCM) is another unsupervised machine learning method used to create the clusters depending on similarity in the data objects [13-14]. There are various types of clustering methods based on partition, density and model related to the data. In this partition based clustering fuzzy c-means are used in present work. In this method, the allocation of data belonging to more than one clusters. FCM algorithm widely used in segmentations, and is sensitive because of spectral information not considered into account. Let P= {p_1, p_2… p_n} as set of data containing n samples p_n has p features. Then divide the data set into q clusters. Assume set of clusters as Q= {q_1, q_2… q_t} and set of t cluster centers represented by W= {w_1, w2… w_t}. FCM algorithm represents with membership degree of every sample to [0, 1] for every group. So Fuzzy c-means provides each sample belong to more than one group. The objective function of FCM is represented as:

$$J_m(U,W)=\sum_{k=1}^{t}\ \sum_{i=1}^{n}(u_{ik})^m(d_{ik})^2 \tag{8}$$

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Where U= (u_{ik}) is an (n x t) matrix with membership and u_{ik} value of membership function of i^{th} sample with k^{th} cluster, d_{ik} is Euclidean distance between i^{th} sample and k^{th} cluster, m is fuzziness index. The defaulting value of 'm' as 2, in general m ϵ [1, ∞). This method works depending on member ship value of every data corresponding to each group center depending on distance between data value and cluster center. The data corresponding to cluster center have most cluster value. By the updated values of U and W iteratively, the FCM algorithm is minimizing objective function J_m and depending on membership value able to achieve classification of defective and non-defective regions.

IV. RESULTS AND DISCUSSION

In this paper, a general skeletal disorder arises in human bones of reduced bone density named osteoporosis is numerically simulated with various layers such as skin of 0.5mm, muscle of 0.5mm, fat of 0.5mm and bone with 2.5mm thickness as shown in Figure 1. a. and the respective thermal properties in table 1. The bone region is embedded with seven holes are comprised with 2cm size and 0.25cm depth with various thermal properties. The Experimentation also carried on CFRP Sample having nine flat bottom holes of 1cm size each with different depths represented in Layout. Figure.1.a. represents the Layout of bone sample with bone deficiencies as simulated defectives with same size 2cm each. Figure.1.b. represents the Layout of CFRP specimen with different depths and same size. The thermal properties of experimental CFRP specimen are represented in Table 1. Bone is numerically simulated and CFRP is excited by QFMTWI.

Table1. Thermal properties of experimental CFRP and simulated bone sample [7, 12]

Region/ Specimen	Density (ρ) (Kg m^{-3})	Thermal Conductivity (k) (W m^{-1} K^{-1})	Specific Heat (c) (J Kg^{-1} K^{-1})
CFRP	1600	0.8	1200
Skin	1109	0.37	3391
Fat	911	0.21	2348
Muscle	1090	0.49	3421
Bone	2420	0.616	1430
A1	1480	0.25	1200
A2	1908	0.32	1313
A3	1200	0.34	2000
A4	1980	0.504	1170
A5	2090	0.532	1235
A6	2200	0.560	1300
A7	2310	0.588	1365

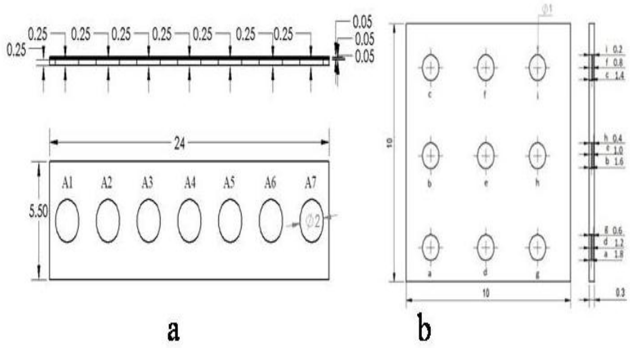

Fig.1.a. Layout of modeled bone sample b. Layout of CFRP sample.

The experimental setup /of active infrared thermography is shown in Figure. 2. The test sample was energized using QFMTWI with a frequency sweep of 0.01 to 0.1 Hz within time duration of 100s. Two halogen lamps with 1KW each focused onto the test specimen. Corresponding temporal thermal response from surface of testing specimen was captured by IR camera placed 1m from the test specimen at a sampling rate of 25Hz. The collected temporal thermal response of test specimen can be pre-processed by employing linear fitting process and further applied to afore mentioned unsupervised clustering method to extract fine subsurface details.

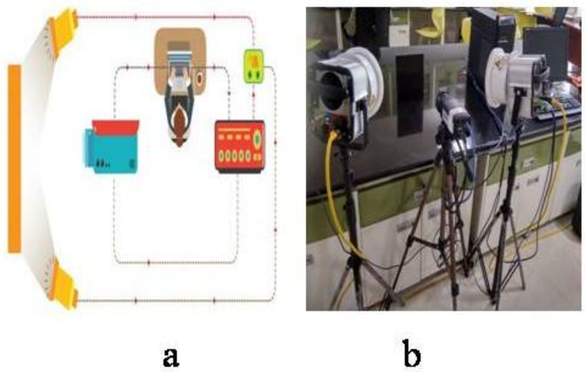

Fig.2.a. Schematic view b. experimental setup of active thermography

Linear fitting removes the mean and extracts the dynamic response from the temporal thermal response of each pixel. Further the proposed methods are applied over the preprocessed data to visualize the anomalies placed in the material as shown in Figure.3 and Figure.4 corresponding to Bone and CFRP specimens respectively. As k-means clusters the thermal response with nearest mean through expectation maximization given in equation (7). This leads to uneven cluster shapes further said to be defects, due to the non-uniform distribution of heat over a defective region. This can be observed in micro level for numerical simulated bone sample and in perfectly visible for experimental CFRP sample in left figures of Figure 3a and Figure 4a respectively.

Since, fuzzy c-means clusters the thermal response based on the closest similarity of elements in the same cluster and the dissimilarity of elements in different clusters.

This is achieved by similarity measures. Here we choose the measure as partition, such that each partition is related to each defect and the clustering carried out by closeness of the profiles in the partition. Since a defect at a particular depth has similar thermal responses which further makes the suitability of fuzzy c-means classifier to cluster each defect from other defects and from its non-defective counterpart as well. From Figure 3b and 4b, the defect characterization of fuzzy c-means clustering for simulated bone and experimental CFRP gives good results compared to k-means based clustering.

The signal to noise ratio is used to quantify the efficiency of clustering method, with equation. 9 SNR values can be calculated for different processing methods of Bone sample and CFRP samples. The SNR values of specimens are illustrates in Table 2 and Table 3 respectively. By the SNR values, it is clear that SNR's of proposed method are high compared to k-means clustering method which is due to its perfect distinguishing capability between defective and non-defective counterparts. So Fuzzy-c clustering algorithm provides better detectability compared to k-means clustering for QFMTWI.

$$\text{SNR(dB)} = \frac{\mu_{\text{Defective area}} - \mu_{\text{Non-Defective area}}}{\sigma_{\text{non defective area}}} \qquad (9)$$

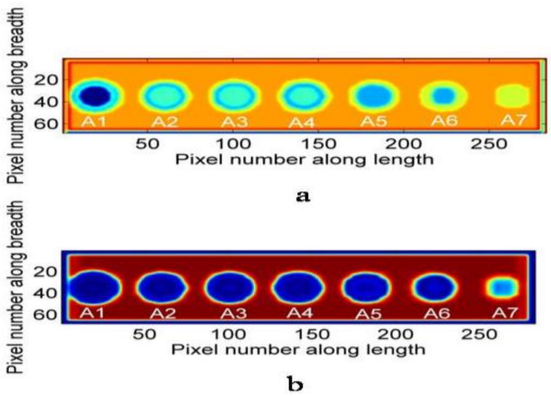

Fig.3. a. k-means clustering b. Fuzzy c-means clustering for bone sample

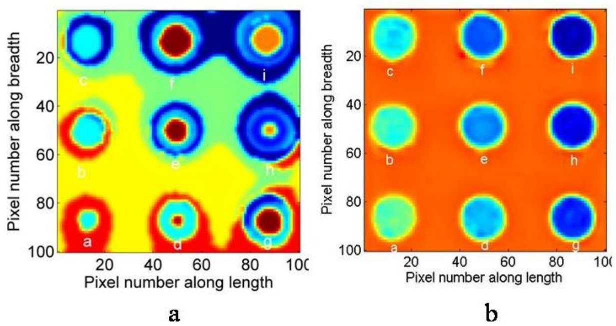

Fig. 4 a. k-means clustering b. Fuzzy c-means clustering for CFRP sample

Table 2 SNR of defects for bone sample

Defect	SNR of defects	
	k-means clustering	Fuzzy c-means clustering
A1	27.56	70.57
A2	18.82	93.41
A3	22.41	92.93
A4	19.52	93.14
A5	18.12	84.25
A6	13.88	41.27
A7	-5.37	22.72

Table 3 SNR of defects for CFRP sample

Defect	SNR of defects	
	k-means clustering	Fuzzy c-means clustering
a	21.62	67.52
b	14.78	63.47
c	16.67	58.50
d	12.12	58.98
e	5.21	63.42
f	5.25	46.93
g	4.32	59.34
h	2.31	48.22
i	8.59	48.97

V. CONCLUSION

Fuzzy c-means based clustering algorithm is employed on QFMTWI to characterize subsurface defects over simulated bone sample and experimental CFRP specimens. The ability of fuzzy c means approach verified and compared with k-means clustering algorithm. The proposed Fuzzy c-means clustering provides better detectability has been validated by taking defect signal to noise ratio into consideration. We conclude that, proposed Fuzzy c-means based clustering machine learning algorithm provides better anomalies detection in QFMTWI.

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AUTHORS PROFILE

A. Vijaya Lakshmi received her M. Sc degree in Electronics from Acharya Nagarjuna University, Guntur, India, in 2003 and the M.E degree in Applied Electronics from Satyabama University, Chennai, India in 2010. Her area of interest includes Infrared thermography, Non-Destructive Testing & Evaluation, Thermography. Currently she is pursuing her Ph. D from Infrared Imaging Center, ECE, College of Engineering, K L University, Andhra Pradesh, India.

Dr. V. S. Ghali (M94255510) received his M. Sc degree in Electronics from Acharya Nagarjuna University, Guntur, India, in 1998 and the M.E degree in Applied Electronics from Satyabama University, Chennai, India in 2008. He received his Ph. D degree in ECE from IIITDM, Jabalpur India in 2013. He is a recipient of research award from University grant commission, India in 2014. Currently he belonged to Infrared Imaging Center and also Professor in ECE, College of Engineering, K L University, Vaddeswaram, Andhra Pradesh, India.

Muzammil Parvez M received his B.E degree in Electronics and Communication Engineering from Anna University in 2009 and M. Tech in Communication Systems from B S Abdur Rahman University in 2011. Currently he is working as an assistant professor in ECE, College of Engineering, K L University, Vaddeswaram, Andhra Pradesh, India.

G.V.P Chandra Sekhar Yadav received his B. Tech degree in Electronics and Communication Engineering from JNTU Kakinada in 2012, M. Tech degree in Digital Electronics & Communication Systems from JNTU Kakinada in 2015 and his area of interest includes Infrared Thermography, Non Destructive Testing & Evaluation, Thermal wave Imaging and Signal processing. Presently he is working as a Research scholar at Infrared Imaging Center, Department of ECE, College of Engineering, K L University, Vaddeswaram, Andhra Pradesh, India.

V. Gopi Tilak received his B. Tech degree in Electronics and communication engineering from JNTU Kakinada in 2016 and M. Tech in communication and radar systems from KL University in 2018. Currently he is pursuing his Ph. D from Infrared Imaging Center, ECE, College of Engineering, K L University, Andhra Pradesh, India.