Detection of Surface Coating Defects using Fuzzy C-Means Clustering with Firefly Optimization

Yasir Aslam, Santhi N, Ramasamy N, K. Ramar

***Abstract*:** *Defect detection in metallic surface images is a challenging task in the image analysis process. The data clustering and optimization techniques have been widely used for image segmentation and the combination of these two approaches improves the output stability as well as convergence speed. In this work developed an automatic, efficient method for the detection and segmentation of coating defects in metal surfaces. The Fuzzy c-means (FCM) and Firefly algorithm (FA) are well-known and popular methods to discover the image information comprising indiscriminate objects and solves many complex problems involved in image segmentation. In this paper, proposed a new technique for the coated metal surface defect detection using the hybridization of two methods, FCM with FA (FCM-FA). The results from experiments verified the efficiency of the developed FCM with FA over comparison with three existing methods in terms of evaluation parameters of defect detection for scanned high resolution images. It can be seen from the experimental results that the incorporated algorithm has the potential to segment and identify the defected regions from the coated surface.*

***Keywords*:** *Clustering, Firefly algorithm, Fuzzy C-mean, Optimization, Surface defect detection.*

I. INTRODUCTION

The stainless steel surfaces are coated with titanium nitride to strengthen the corrosion resistance and material lifespan. The TiN plated films generally contain several intrinsic defects and pin holes resulting corrosion of protection film [1]. Inspecting the surface defects is extremely significant in preserving the material quality standards. Several types of algorithms introduced to identify and classify the surface defects. A distinct and competent algorithm development is considerably important for machine vision system [2]. Previously, scholars used many algorithms based on machine vision for image defect inspection. The algorithms used generally are mainly classified as spatial domain, statistical, morphological, joint spatial domain and frequency domain analysis. Amongst these algorithms, the spatial domain, frequency domain and joint spatial domain are comprehensively practicable with each kind of surfaces. S. Kowieski and J.Mezyk [3] utilized thermal imaging for finding defects such as discontinuities, burrs and uneven edges in Friction Stir Welding (FSW) surface.

* Correspondence Author
Yasir Aslam*, Research Scholar, Department of Electronics and Communication Engineering, Noorul Islam Centre for Higher Education, Kumaracoil, India. E-mail: yasiaslam@gmail.com
Santhi N, Associate Professor, Department of Electronics and Communication Engineering, Noorul Islam Centre for Higher Education, Kumaracoil, India.
Ramasamy N, Associate Professor, Department of Mechanical Engineering, Noorul Islam Centre for Higher Education, Kumaracoil, India.
K. Ramar, Professor & Dean, in Computing Science, Muthayammal Engineering College (autonomous), Rasipuram, India.

The weld sub surface defects were determined using temperature plots chosen amongst the weld cross section as of thermally recorded image sequence. Li et al. [4] introduced the incorporated lighting transform and the image ratio techniques for detecting the surface defects found on oranges. Various studies examined the surface bugholes detection which specifically determined the proportion along with the bugholes area ratio, however the optimum diameter as well as aspect grading system of bugholes had been ignored. Besides, the surface descriptions to discover the concrete surface bugholes are indefinite and utilization of specialized software or equipment [5] is quite complex for the users. Image segmentation approaches based on clustering are generally adapted by many researchers. The segmentation with clustering approach finds difficulties during the computation of the number of clusters present within the feature space. The clustering approach gathers substantial and regular clusters within the datasets. FCM clustering algorithm [6] is the predominant class of partitional clustering which builds upon the initial seed points with convergence to local optima. It is practicable towards extensive range of geostatistical data analysis obstruction. Cannon [7] presented an effective realization of FCM clustering algorithm. A cohesive structure for implementing the clustering with density weighted FCM [8] developed in order to optimize and deal with the problems of FCM algorithm. K-Means is specific clustering method [9] to find out the pixels groupings in an image and the method used generally, since it is uncomplicated and very fast. It subdivides the dataset input into k clusters, also each individual cluster is described through variable cluster center, evolving from a range of initial values recognized as seed points. The K-Means method measures distances amongst the cluster centers and inputs data points also provides inputs to the adjacent cluster center. The researchers make efforts in improvising optimization methods to prevail over problems in FCM clustering approach besides improve clusters characteristics. The combination of the adaptive thresholding with cuckoo search (ATCS) [10] and adaptive thresholding with particle swarm optimization methods (ATPSO) [11] are found to be efficient methods for defect detection techniques, but the lighting effects or shadows formed in images were found to decrease detection accuracy. The procedure of optimization is determining the appropriate solutions to the problems defined. Many researchers pay attention in the bio-inspired optimization algorithms on the way to resolve the drawbacks of different fields. The most important purpose of these methods is to obtain the near optimal solution in support of defined problem statement.

Detection of Surface Coating Defects using Fuzzy C-Means Clustering with Firefly Optimization

The FA is one of the subsequent swarm intelligence strategies; furthermore, a type of meta-heuristic, nature inspired algorithm meant for interpreting difficult problems. Senthilnath et al. [12] suggested an improved firefly algorithm to resolve the problems in clustering. A wide ranging analysis of firefly algorithm with its relevance in engineering practice being generally studied and recommended contrivances to build up hybridized or modified FA algorithm [13] to solve different drawbacks. Adaptive thresholding with firefly method [14] for defect detection is one among them. Recently, numerous competent optimization algorithms such as hybrid clustering algorithms being specific on the way to accomplish clustering to acquire better output other than the algorithms for traditional data clustering. The traditional clustering algorithms difficulty could overcome with hybrid algorithm and moreover converges rapidly to absolute optimal solution. The optimization method hybridized with traditional algorithms thereby upgrades to efficient as well as faster method. It is observed from the literature that the hybrid algorithm certainly strengthen the clustering process performance. In this paper, proposes a hybridized FCM with Firefly algorithm (FCM-FA) for segmentation and recognition of the defected areas in coated surfaces. The proposed method identifies and segments defected and defect free regions using the image processing methods.

II. METHODOLOGY AND TESTING

1. Image Acquisition and Preparation

In this work the stainless steel is used as the material which is coated with Titanium Nitride (TiN). The material is polished before coating and the thickness of the stainless steel material is 12mm. The Physical vapour deposition method (PVD) is used for coating the material. The PVD interprets a diversity method of vacuum deposition which is capable to make coatings and thin films. This is specified by the procedure into which the object goes to vapour phase from condensed phase and subsequently reverse to a thin film reduced phase. The widespread Physical vapour deposition procedures are evaporation and sputtering. The thickness of the coating is $4\mu m$. The high resolution images is used for processing, which is obtained using high resolution scanning, which provides superior scanning capability to capture the finest details.

III. PROPOSED METHOD

An efficient surface defect detection technique is proposed to determine the coated surface defects. The images with high resolution are utilized for processing. The phases associated with detection of defects are illustrated in the fig.1 block diagram. Primarily, input images are subject to pre-processing through the contrast stretching and median filtering methods. A hybridized FCM with Firefly Algorithm is the proposed method for segmentation and recognition of the defected areas of coated surfaces. The firefly optimization process is applied for the evaluation of each specific group fitness function and morphological operation is the final stage in segmentation process.
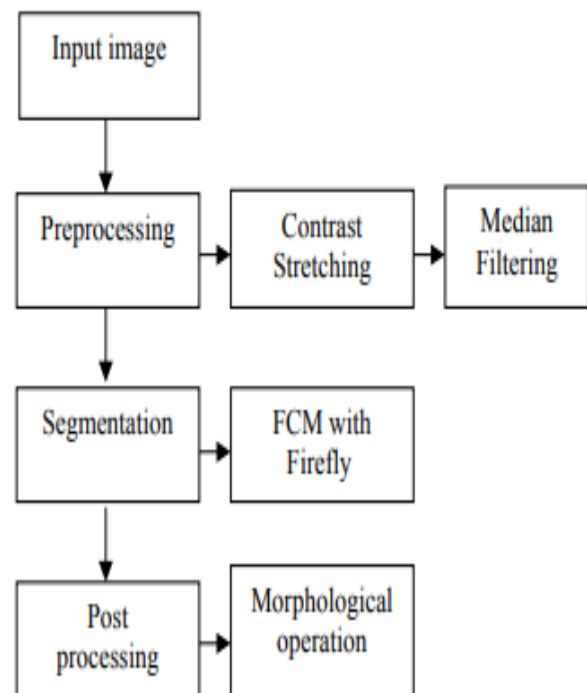

Fig.1 Image processing and analysis flow diagram.

A. Preprocessing

The primary step in image processing technique is preprocessing for enhancing the image quality. In image acquisition procedure, specific noise as well as other excessive discrepancies may occur. For this reason in most of the image analysis and classification operations preprocessing [15] is mandatory. It mainly smoothen the input image suitable for further analysis. The main intend of pre-processing phase is to remove redundant noise as well as improves the image intensity.

(a) Contrast Stretching

The image enhancement method is contrast stretching which attempts by stretching intensity grade range of values to get better contrast in an image. The image contrast is the separation factor between the darkest and brightest spot in the image. The contrast stretching method [16] involves calculation of numerical information involved with every pixel of an image. The process of contrast stretching is an essential pre-processing phase in maintaining the contrast and quality of images.

(b) Median Filtering

The standard median filter is a ranking filter in which the pixels in neighborhood filtering space are prearranged depending on its grade or ranking. The median filter method is expansively utilized for removing the impulse noise which are indiscriminately spread all over the degraded image. Though, while carrying out filtering in the image, impulse noise occurs, for that reason each one pixel is to be processed. The neighborhood filtering interface or window pixels is prearranged, furthermore the median value is calculated for each corresponding pixel neighborhood. Finally, the resultant pixel obtained from processing is initialized with value of median.

The procedure repeated till each one pixel formerly converted same as the pixel at center within filtering window. The median filter method [17] well suited method toward filtering salt and pepper noise. In view of fact that the median value substitution doesn't remove any inappropriate pixel. Therefore median filtering method is suitable for image smoothing.

B. Segmentation Method

Modified FCM: Firefly Algorithm (FA) based Fuzzy-C-Means Clustering (FCM-FA)

(a) Fuzzy C Means

The clustering process [18] involves grouping of a set of objects into groups in order that the grouped objects must be similar to each other than the other cluster or group. Every group inside a separate cluster set could be compared with other cluster groups. The dissimilar groups consisting of data points are distinct as of one another. The FCM method [19] distributes the data set U toward D clusters throughout the distance subjective to all data point u_i to every centroid v_d of clusters D which is as follows.

$$MinK_{FCM}$$
$$= \sum_{d=1}^{D} \sum_{i=1}^{S} m_{id}^q \|u_i - v_d\|^2 \quad (1)$$

$$\sum_{d=1}^{D} m_{id} = 1, i$$
$$= 1,2, \dots S \quad (2)$$

where, q represents exponent and m_{id} refers the standardized distance from sample instance i toward the cluster d which is value membership point of the cluster. The centroid v_d and the weight m_{id} can be represented with the expectation–maximization (EM) algorithm [20]:

$$E_{step}: m_{id} = \frac{1}{\sum_{j=1}^{D} \left(\frac{a_{id}^2}{a_{ij}^2}\right)^{\frac{1}{q-1}}} for \ i$$
$$= 1,2, \dots, S \ and \ d$$
$$= 1,2, \dots, D \quad (3)$$

$$whereas, a_{id}^2$$
$$= \|u_i - v_d\|^2 \quad (4)$$

$$M_{step}: v_d = \frac{\sum_{j=1}^{S} m_{jd}^q . u_j}{\sum_{j=1}^{S} m_{jd}^q} for \ d$$
$$= 1, 2, \dots, D \quad (5)$$

(b) FCM with Firefly

The clustering algorithm based on the genetic firefly is capable to get the optimum point of function instantaneously. In genetic firefly method [21] the first step is that all fireflies are generated arbitrarily. From the input data to each firefly, takes two data as initial population and two centroids are formed for the corresponding fireflies. Subsequently, the distance between the entire data in the dataset and data in the firefly are computed. Similarly, distance among the centroid and data in the dataset is estimated for each data in the firefly. Then the fitness for each firefly which is the minimum distance between the centroids for every firefly is calculated. Certainly, fitness of

each firefly is calculated in terms of Davies Bouldin Index (DBI). After, taken two solutions to perform mutation in addition to cross over procedure and the stopping criteria is met, these steps are repeated.

The firefly population initially, $R = R_1, R_2, R_3, \dots, R_N$. The two input data a_1, a_2 are taken for each firefly and has two centroids of each $D_1^1 and D_2^1$. The DBI is then calculated for the chosen data to identify minimum distance that is obtained new solution. Firstly, for every single firefly in the population minimum distance is found on the basis of procedure as follows. Initially, distance among the whole data within dataset and data in the firefly are computed. The centroid data taken at random forms the data in the firefly which is represented as D_i^j, wherein $0 < i \leq 2 \ and \ 0 < j \leq N$. Consider, two centroids for the first firefly denoted as $D_1^1 and D_2^1$. The whole dataset is described by a_i wherein $0 < i \leq K$ and K represents total number of data within dataset. The expression $D_i^1 - a_j$ describes the distance between the ith centroid and jth data within the dataset. The distance calculation is made through the formula as follows:

$$dis = \sum_{n=1}^{K} \left(w_{in} - w_{jn}\right)^2 \quad (6)$$

where, w_{in} is the nth element of the ith data and w_{jn} is the nth element of the jth data. Once the distance calculations is performed, determine the value of minimum distance with each single row, that is to find minimum distance amongst centroids in firefly [22] corresponding the data from the dataset. As, value of least distance among centroids of first firefly along with initial data from dataset established through as follows:

$$Amin_1^1 = \{D_1^1 - a_1; if \ [(D_1^1 - a_1) < (D_2^1 - a_1)] \ D_2^1 - a_1; if \ [(D_2^1 - a_1) < (D_1^1 - a_1)] \ D_3^1 - a_1; if \ [(D_3^1 - a_1) < (D_1^1 - a_1)] \quad (7)$$

Generalizing, value of minimum distances among centroids in first firefly, also jth data from dataset is discovered with the following:

$$Amin_j^1 = \{D_1^1 - a_j; if \ [(D_1^1 - a_j) < (D_2^1 - a_j)] \ D_2^1 - a_j; if \ [(D_2^1 - a_j) < (D_1^1 - a_j)] \ D_3^1 - a_j; if \ [(D_3^1 - a_j) < (D_1^1 - a_j)] \quad (8)$$

Then for each firefly considered DB Index for minimum distance $A \ min$. The DBI is given below for N number of clusters represented by,

$$DB \equiv \frac{1}{N} \sum_{i=1}^{N} A_i \quad (9)$$

The DBI is absolutely based on both the data as well as the algorithm. Select the worst case scenario from the above equation A_i and this value is equivalent to M_{ij} for alike cluster i. The symmetry condition for A_i is as shown below,

$$A_i \equiv M_{ij} \ where, M_{ij} = \frac{C_i + C_j}{S_{i,j}} \quad (10)$$

Here, M_{ij} be separation between i^{th} and j^{th} clusters which must be as large as possible ideally, C_i the within cluster scatter for i^{th} cluster which is as low as possible. Let D_i be a cluster of vectors and V_j be an n dimensional feature vector given to cluster D_i. The within cluster scatter C_i for i^{th} cluster is denoted as

$$C_i = \left(\frac{1}{T_i}\sum_{j=1}^{T_i} \left|V_j - B_i\right|^p\right)^{\frac{1}{p}} \quad (11)$$

Here, B_i is the centroid of D_i and T_i is the size of cluster i. The movement calculation is given by:

$$w_i = w_i + \beta_0 e^{-\gamma r_{ij}^2} + \alpha\left(random - \frac{1}{2}\right) \quad (12)$$

where, w_i is firefly attribute data value consisting higher DB index, the β_0, γ and α were the constants, random denotes a value that hold in range 0 to 1, r_{ij} is the difference among w_i and w_j. The comparison is made for every firefly and the movement calculation and substitution is implemented appropriately.

C. Morphological operation

The methods of morphological operation [23] involve erosion and dilation processes, the simple extension of the two processes is opening and closing. Using this technique, the noise can be reduced thereby increased the quality of the images. The opening procedure will possibly smooths image edges, also eliminate small overlaps and disrupt narrow block connectors from a processed image. The closing operation could not only smooth image edges but also combine narrow blocks as well as fill in holes. The objects in binary form which are connected together are dissociated all through opening operation besides the closing operation can fill in thin holes. Both of these operations causes a definite extent of smoothing on a given object contour with the use of smooth structuring element. The process of opening smooths from inside of the object contour and process of closing smooths from outside of the object contour.
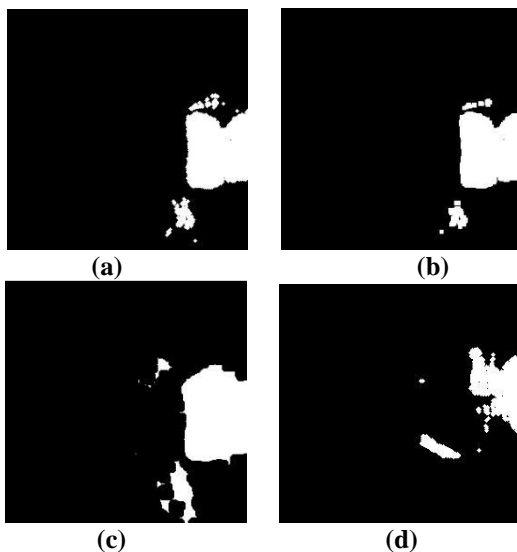

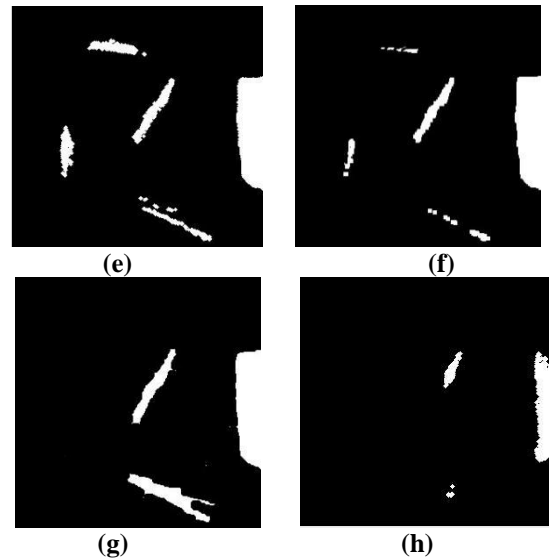**Fig.2 Processed images of sample 1 using, (a) FCM-FA, (b) FCM, (c) K-Means, (d) ATCS.**

Fig.3 Processed images of sample 2 using, (e) FCM-FA, (f) FCM, (g) K-Means, (h) ATCS.

In fig.2 and fig.3 the output images obtained with two different sample inputs using four different methods are shown. The white portion points out the defective part and black portion points out the defect-free part.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

For solving local optima and low convergence rate existing in the standard FCM, a new modified FCM which is FA based FCM algorithm is proposed for coating defect detection. We have examined the efficiency of the method proposed with other existing methods. It gives better result compared to existing titanium coated surface defect detection based on FCM, K-Means and ATCS method. Also we have evaluated the experimental results in terms of several parameters and the method proposed determines the coated surface defects with greater accuracy. The comparison table shows the performance of the methods with regard to evaluation parameters .Thus the proposed FCM-FA proves to be robust and capable of processing image data sets and produce better segmentation results.

1. Parameter Calculation

The parameter estimation of the defect detection approach is evaluated with the following parameters:

(a) Sensitivity: This is the percentage of positives that can be effectively recognized by measure for affectability, determines by means of test measure for identifying optimistic results.

$$Sensitivity = \frac{TP}{TP + FN} \times 100 \quad (13)$$

(b) Specificity: The proportion of negatives that efficiently recognized indicates specificity measure, ascertains by way of test measurements for identifying negative results.

$$Specificity = \frac{TN}{TN + FP} \times 100 \quad (14)$$

(c) Accuracy: The percentage among the number of TP, TN and total number of data, it can be express in the following equation,

$$Accuracy = \frac{TN + TP}{(TN + TP + FN + FP)} \quad (15)$$

(d) Precision: The fraction of relevant instances among the found instances.

$$Precision = \frac{|(relevant match) \cap (derived match)|}{|(relevant match)|} \quad (16)$$

The comparison between existing methods, FCM, K-Means, ATCS and proposed FCM-FA method for the certain parameter measures are illustrated with the following table 1, 2, 3 and 4. The graphical representation for the table 1 with four different methods with respect to parameter sensitivity is shown in fig 4 and for table 3 the corresponding graphical representation with respect to parameter accuracy is shown in fig.5.

Table 1: Comparison table of Firefly based FCM method with existing FCM, K-Means, and ATCS methods in terms of sensitivity.

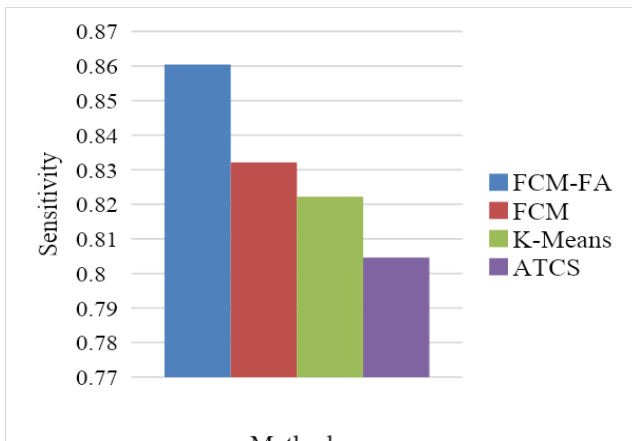| Image No.	FCM-FA	FCM	K-Means	ATCS
1	0.87056	0.83239	0.8137	0.80156
2	0.86149	0.82867	0.80556	0.79483
3	0.86118	0.8429	0.83074	0.80269
4	0.85361	0.82817	0.80933	0.79461
5	0.85523	0.82863	0.85177	0.82909

Fig 4: Graphical representation for comparison of sensitivity measures for proposed and existing methods

Table 2: Comparison table of Firefly based FCM method with existing FCM, K-Means, and ATCS methods in terms of specificity.

Image No.	FCM-FA	FCM	K-Means	ATCS
1	0.90553	0.86548	0.85148	0.84616
2	0.89499	0.87769	0.81973	0.79163
3	0.91983	0.86243	0.83528	0.81188
4	0.88996	0.89113	0.84186	0.82231
5	0.92621	0.86817	0.82987	0.81617

Table 3: Comparison table of Firefly based FCM method with existing FCM, K-Means, and ATCS methods in terms of accuracy.

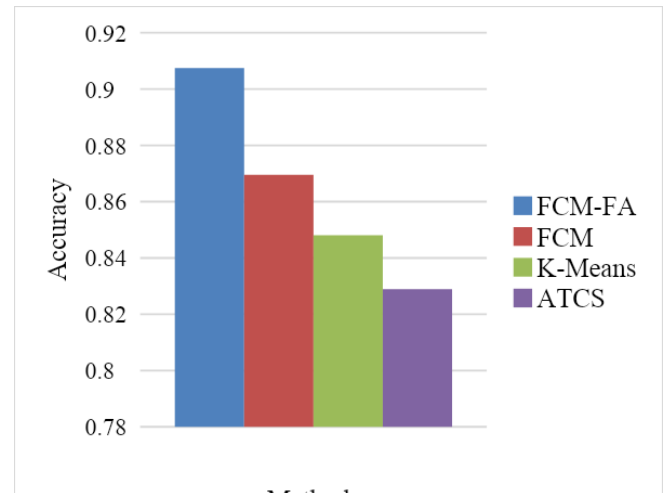| Image No.	FCM-FA	FCM	K-Means	ATCS
1	0.92032	0.87583	0.85648	0.84955
2	0.89953	0.86576	0.83959	0.81606
3	0.90069	0.86654	0.84074	0.80856
4	0.90518	0.86958	0.84257	0.82895
5	0.91164	0.87005	0.86118	0.84133

Fig 5: Graphical representation of accuracy measures for proposed and existing methods

Table 4: Comparison table of Firefly based FCM method with existing FCM, K-Means, and ATCS methods in terms of precision.

Image No.	FCM-FA	FCM	K-Means	ATCS
1	0.91592	0.88957	0.86735	0.90722
2	0.90998	0.89572	0.86784	0.89441
3	0.86441	0.85472	0.83541	0.85472
4	0.90459	0.88951	0.8676	0.89941
5	0.91977	0.89023	0.86977	0.90032

It can be seen from the above graphical representation, the results obtained from various techniques for defect identification and segmentation. The FCM-FA is proposed to yield more prominent result while measured the assessment parameters in comparison with the other existing techniques. Comparing the measures of all methods, the FCM with Firefly method yield much greater outputs in terms of sensitivity, accuracy and precision. While analyzing the graph, proposed FCM with firefly method shows better results.

V. CONCLUSION AND FUTURE SCOPE

The Firefly optimization algorithm is combined with the standard Fuzzy C-Mean clustering technique, called FCM-FA, in the proposed work.

Retrieval Number: A1847109119/2019©BEIESP
DOI: 10.35940/ijeat.A1847.109119
Journal Website: www.ijeat.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

4342

Detection of Surface Coating Defects using Fuzzy C-Means Clustering with Firefly Optimization

The experimental results verified that FCM-FA outperformed the standard FCM and firefly methods. Thus our proposed algorithm has the capability to automatically distinguish the defected image region with greater accuracy than the existing methods of defect detection. Moreover, the proposed FCM-FA overcomes the problems such as lower rate of convergence, being fixed in local minima as well as initialization sensitivity. FCM-FA performs better result for separating the defected and non-defected portions of titanium nitride coated surface images. The limitation of this method is difficulty in finding defects in images having high intensity invariability and noise. Thus, in future, convolutional neural network based image segmentation can be used to distinguish defected and defect free regions in coating surfaces.

REFERENCES

1. Nur Fawwaz Asri, Teuku Husaini, Abu Bakar Sulong, Edy Herianto Majlan, Wan Ramli Wan Daud, "Coating of stainless steel and titanium bipolar plates for anticorrosion in PEMFC: A review", International Journal of Hydrogen Energy, vol.42, Issue.14, pp.9135-9148, April 2017.
2. Hao Shen, Shuxiao Li, Duoyu Gu, Hongxing Chang, "Bearing defect inspection based on machine vision", Measurement, vol.45, pp. 719–733, Jan 2012.
3. Jordan Mezyk, Szymon Kowieski, "The application of thermal imaging method for monitoring the FSW processes", In: Proceedings of the 11th international symposium on measurement and quality control, Sept 2013.
4. Jiangbo Li, Xiuqin Rao, Fujie Wang, Wei Wu, Yibin Ying, "Automatic detection of common surface defects on oranges using combined lighting transform and image ratio methods", Postharvest Biology and Technology, vol. 82, pp. 59-69, Aug 2013.
5. Baoju Liu, Tengyu Yang, "Image analysis for detection of bugholes on concrete surface", Construction and Building Materials, vol.137, pp. 432–440, April 2017.
6. Yasir Aslam , Santhi N , Ramasamy N , K. Ramar, "A Heuristic Fuzzy Clustering Approach for Defect Detection on Titanium Coated Metal Surface", Journal of Advanced Research in Dynamical & Control Systems, Vol. 10, No. 4, 2018.
7. Robert L. Cannon, Jitendra V. Dave, and James C. Bezdek, "Efficient Implementation of the Fuzzy C-Means Clustering Algorithms", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol.8, Issue.2, pp.248-255, March 1986.
8. Richard J. Hathaway, and Yingkang Hu, "Density-Weighted Fuzzy C-Means Clustering", IEEE Transactions on Fuzzy Systems, vol.17, Issue.1, pp.243-252, Feb 2009.
9. Shiv Ram Dubey, Pushkar Dixit, Nishant Singh, Jay Prakash Gupta, "Infected Fruit Part Detection using K-Means Clustering Segmentation Technique", International Journal of Artificial Intelligence and Interactive Multimedia, vol. 2, June 2013.
10. Yasir Aslam , Santhi N , Ramasamy N , K. Ramar, "A Modified Adaptive Thresholding Method using Cuckoo Search Algorithm for Detecting Surface Defects", International Journal of Advanced Computer Science and Applications, Vol. 10, No. 5, 2019.
11. Yasir Aslam , Santhi N , Ramasamy N , K. Ramar, "An Effective Surface Defect Detection Method Using Adaptive Thresholding Fused With PSO Algorithm", International Journal of. Simulation. Systems, Science & Technology,Volume 19, Number 6, Page 1, December 2018.
12. J. Senthilnath, S.N. Omkar, and V. Mani, "Clustering Using Firefly Algorithm: Performance Study", Swarm and Evolutionary Computation, vol.1, Issue.3, pp.164-171, Sept 2011.
13. Iztok Fister, Iztok Fister Jr, Xin-She Yang, and Janez Brest, "A Comprehensive Review of Firefly Algorithms", Swarm and Evolutionary Computation, vol. 13, pp. 34-46, Dec 2013.
14. Yasir Aslam, Santhi N, Ramasamy N, K. Ramar, "Metallic Surface Coating Defect Detection Using Firefly Based Adaptive Thresholding and Level Set Method", International Journal of Innovative Technology and Exploring Engineering , Volume-8 Issue-10 (2019)
15. Hu Han, Shiguang Shan, Xilin Chen and Wen Gao, "A comparative study on illumination preprocessing in face recognition", Pattern Recognition, vol.46, Issue.6, pp.1691-1699, June 2013.
16. Gang Cao, Lihui Huang, Huawei Tian , Xianglin Huang, Yongbin Wang and Ruicong Zhi, "Contrast enhancement of brightness-distorted images by improved adaptive gamma correction", Computers & Electrical Engineering, vol.66, pp.569-582, Feb 2018.
17. Ashwani Kumar Yadav, "Algorithm for De-noising of Color Images based on Median Filter", Third International Conference on Image Information Processing, pp.428–432, Dec 2015.
18. Du-Ming Tsai, Guan-Nan Li, Wei-Chen Li, Wei-Yao Chiu, "Defect detection in multi-crystal solar cells using clustering with uniformity measures", Advanced Engineering Informatics, vol. 29, Issue 3, pp. 419-430, Aug 2015.
19. Hua Zhang, Qunming Wang, Wenzhong Shi, and Ming Hao, "A Novel Adaptive Fuzzy Local Information C-Means Clustering Algorithm for Remotely Sensed Imagery Classification", IEEE Transactions on Geoscience and Remote sensing, vol.55, Issue.9, pp.5057-5068, Sept 2017.
20. Mutasem K. Alsmadi, "A hybrid Fuzzy C-Means and Neutrosophic for jaw lesions segmentation", Ain Shams Engineering Journal, vol.9, Issue.4, pp.697-706, Dec 2018.
21. Chengye Zhang, Qiming Qin, Tianyuan Zhang, Yuanheng Sun and Chao Chen, "End member extraction from hyperspectral image based on discrete firefly algorithm (EE-DFA)", ISPRS Journal of Photogrammetry and Remote Sensing, vol.126, pp. 108–119, Feb 2017.
22. Daniela Sánchez, Patricia Melin and Oscar Castillo, "Optimization of modular granular neural networks using a firefly algorithm for human recognition", Engineering Applications of Artificial Intelligence, vol.64, pp. 172–186, Oct 2017.
23. Syed Mohammad Abid Hasan, Kwanghee Ko, "Depth Edge Detection by image-based Smoothing and Morphological Operations", Journal of Computational Design and Engineering, vol.3, Issue.3, pp.191-197, July 2016.

AUTHORS PROFILE

Yasir Aslam received B.E degree in Electronics and Communication Engineering from Anna University, Tirunelveli, Tamil Nadu, India in 2011, and M.E in Communication Systems from Noorul Islam Centre for Higher Education, Tamil Nadu, India in 2013. Currently pursuing PhD degree in the department of Electronics and Communication Engineering at Noorul Islam Centre for Higher Education,in the field of Digital Image Processing.

Santhi N received B.E degree in Electronics and Communication Engineering from Madurai Kamaraj University in 1989, M.E in Microwave and Optical Engineering from Madurai Kamaraj University in 1995 and PhD in the area of Image retrieval from Dr.M.G.R.Educational & Research Institute University, in 2013. She has 25 years of teaching experience and is working as Associate Professor in the department of Electronics and Communication Engineering, Noorul Islam Centre for Higher Education, Kumaracoil, India. Her research interest includes Image Processing, Pattern Recognition, Image Retrieval and Soft Computing.

Ramasamy N received B.E degree in Mechanical Engineering from Anna University, Chennai in 1984, M.E in Engineering Design from Bharathiar University in 1993 and PhD from Noorul Islam Centre for Higher Education, Kumaracoil in 2016. He has 31 years of teaching experience and is working as Associate Professor, Department of Mechanical Engineering, Noorul Islam Centre for Higher Education, Kumaracoil, India.

K.Ramar received B.E degree in Computer Science and Engineering from Govt. College of Engineering.,Tirunelveli in 1986, M.E in Computer Science and Engineering from PSG College of Technology, Coimbatore in 1991 and PhD in the area of image processing from Manonmaniam Sundaranar University, Tirunelveli in 2001. He has 30 years of teaching and research experience. He is working as Professor and Dean in Computing Science, Muthayammal Engineering College (autonomous), Rasipuram, India.