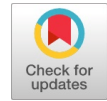


Metallic Surface Coating Defect Detection Using Firefly Based Adaptive Thresholding and Level Set Method



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

Abstract: An innovative approach is introduced to detect surface defects on titanium coated steel surfaces with varied size through the use of image processing techniques. This paper provides techniques which are useful to discover numerous kinds of surface defects present on coating surface. For defect detection, Firefly Algorithm (FA) based adaptive thresholding is proposed and is applied for the gray scale images. The FA ensuing nature inspired algorithm utilized expansively in support of determining various optimization problems and from the reconstructed image contours are extracted using level set method, the predictable images not including textures besides defects contours be compassed. The morphological post processing removes the noise in image and makes defects more distinguishable from the background. The speculative result persists in utilizing synchronous images of metal surface and shows that the proposed method can efficiently segment surface defects and obtain better performance than existing methods.

Keywords: Adaptive thresholding, Defect detection, Firefly Optimization, Level set method, Surface coating.

I. INTRODUCTION

Detection of surface defects in metal structures is an important issue in numerous industries. For these purposes the comprehensively practiced technique is automatic thresholding. In automatic thresholding [1] the value of best possible gray-level threshold is preferred on the way to take apart objects out of the background image according to their intensity distribution. In applications of identifying defects, possess dissimilar patterns and dimensions, which range in exceedingly minute to inordinate. Moreover, defect detection functions range from non-defective to minute in addition to outsized defects, which make range distributions of gray-level from unimodal toward bimodal distributions. Defect detection using the image processing depended methods allows rapid inquisition over huge part of structural expanse. Likewise, steady as well as precise inquisition is

realizable alongside an automated strategy. At present, the deliberations about image processing pay attention on identification of cracks [2] upon outsized structures in pavement, buildings and bridges. Thus automatic analysis and detection are crucial. Moreover, the detecting speed dispatch remains vital for real world purposes. The algorithms of clustering applied successfully as a digital image segmentation system in different fields and applications. The FCM algorithm is one of the prevailing clustering algorithms [3] in image segmentation for the reason that it has vigorous features for uncertainty and be able to maintain considerable insights than rigid segmentation techniques.

The ultrasonic reconstruction algorithm accompanied by the optimization methodologies degenerate the flaw description in ultrasonic outsized processing. The ultrasonic inspection [4] in synthetic aperture focusing technique, the reconstructed data is used to ascertain in addition to localizing small traces. The simulation model is established with this initial information and the optimal parameterization is recognized through iteratively regularized Gauss–Newton method. Image processing and machine learning acquainted to advance the crack assessment efficiency. The crack detection and identification develop into certainty on the basis of machine vision [5] approaches. Destructive testing procedures generally used to find unseen defects which can't be discovered with different process. Conversely the nondestructive testing (NDT) represents collection of analysis practices accustomed on way to analyze or recognize defects devoid of altering the cause of damage or original characteristics. Once being inspected the contrivances perform in general, the NDT is desirable process capable to accumulate time and capital both in detecting defects. Consequently, abides a necessity for rapid as well as regular algorithms turn out satisfactory effects on quite a few product types beyond tuning manually. The automatic image thresholding techniques like Otsu [6] and median based Otsu (MBOT) [7] are the existent thresholding approaches for image segmentation.

The image thresholding process separates the unusual image objects as of background. The perfect threshold selection is observed as a distinct unbiased optimization problem, wherein acquiring a solution becomes computably inordinate as well as consumes time, specifically in cases of increase in threshold number. Here, proposes a new distinctive evolutionary algorithm to select values of optimal threshold appropriate for an input gray level image.

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Optimization problems are very necessary in numerous branches of sciences and its main task is to discover the proper solution for an explicit problem. Consequently, the requisite in resolving optimization problems prompted the development of distinct search algorithms. The optimization algorithm is a procedure accomplished iteratively through the comparison over numerous solutions until the optimum solution is established. The optimization algorithms as such, particle swarm optimization (PSO) [8], artificial bee algorithm [9], gravitational search [10], Cuckoo search (CS) [11] ant colony algorithm [12], differential evolution [13], and Firefly (FF) algorithm [14] are the various optimization methods used. This paper proposes the adaptive thresholding with Firefly technique and level set method for identification and extraction of defects on the coated surface.

II. PROPOSED DEFECT DETECTION METHOD

In the proposed approach, in order to tackle the problems in identification and segmentation of defects in coated metal surface, introduced adaptive thresholding method with firefly optimization technique. This involves certain steps, which is depicted as in fig.1 follows. Initially the image input is preprocessed and subsequently the defected region in image is identified by segmentation based on the proposed adaptive thresholding with firefly method. Each of the steps involved in the proposed method is comprehensively explained in the following sub-sections.

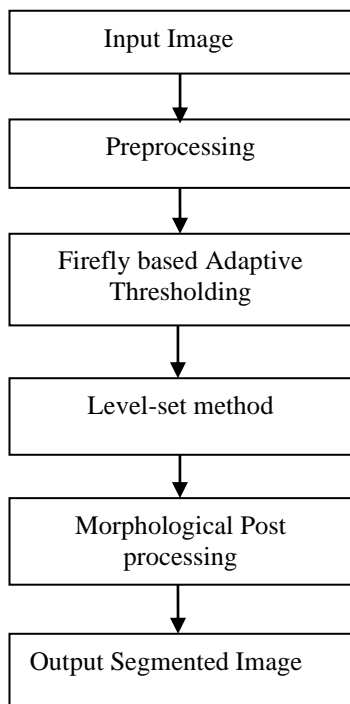


Fig.1: Processing steps

A. Image Preprocessing

The preprocessing method filters the image subsequent to make a coarse position in the image. The result of segmentation will be significantly enhanced following the preprocessing step. The sequence of combination of image preprocessing algorithms such as contrast stretching [15], median filtering [16] and grey level converter discover a improved segmentation method which be able to detect

defects from images accurately and automatically. To improve the image aspect or quality and filter out the noise to make certain the distinct contrast by contrast stretching method. The method attempts to improve image quality through stretching the intensity value range to a proper range of values. Each of the pixels in image is transformed as the correspondent pixels could have impact toward constructing high contrast than the original image. The color images usually need to be converted to gray scale images with the grey level converter. The median filters are edge retaining smoothing filters, wherein level set to the pixel values median within the neighborhood of pixel. With median of the pixels in the consequent filter region every image pixels interchanges and the median filter is a standard method since aimed at impulse noise such as salt and pepper noise it yields brilliant noise reduction capabilities.

B. Adaptive Thresholding

The adaptive thresholding [17] utilized to isolate the desirable image objects of foreground as of the background predicated about the intensity discrepancy in every region pixel. Global thresholding applies a fixed threshold in the image for all pixels, consequently can't accord by images encompassing an unreliable gradient of intensity. Conversely, local adaptive thresholding opts for each pixel an individual threshold derived on intensity values range within confined neighborhood. In general, adaptive thresholding deals with gray scale image as input along with the elementary implementation, binary image output characterizing edge facts. Adaptive threshold is a histogram based technique [18] employed to estimate the value of threshold devoid of any peripheral intrusion. In proportion to the range of values referred to the histogram, it can have numerous thresholds and only one value is obligatory to isolate two objects. It compacts with pixels and intensities, if the pixel intensity deceit under the threshold then consign back to it, else if higher then irregularity region is deliberated as crack. For every image pixels, estimated a threshold value. Besides if value of pixel beneath threshold is set to the background value, if not it the foreground value is speculated. The thresholding is precisely articulated as the equation follows.

$$f(c, t) = \begin{cases} 1, & I(c, t) > T(c, t) \\ 0, & otherwise \end{cases} \quad (1)$$

where, $f(c, t)$ is defined as binary for the input image pixel $I(c, t)$ and $T(c, t)$ is the threshold of image pixel distinct by the histogram techniques. As well, if the value of it is higher than $T(c, t)$ then the image pixel is enumerated as crack. In order to obtain a better optimal value for threshold, and is considered as problem in optimization. To achieve optimal threshold value, firefly optimization is applied in this problem, for better segmentation.

C. Firefly Algorithm (FA):

The FA based on brightness of fireflies, uses the process of attraction toward an objective function optimization. The FA implies possibly prevailing since it is constructive tool for optimization because of the consequence of function of attractiveness and that



is distinctive toward performance of fireflies. Firefly Algorithm uses, three idealized rules for development: (i) The participants are the fireflies which each of them are unisex; therefore enticed toward other fireflies. (ii) For any two fireflies attractiveness proportional with its brightness. As a result fireflies with less brightness move towards the one which is brighter due to attractiveness. The distance between fireflies increases with decrease in brightness and attractiveness. It moves randomly if it finds no other brighter one than a particular firefly. (iii) Each of the firefly brightness is found using the objective function. The parameter for firefly algorithm includes the light intensity divergence and attractiveness among fireflies. The aim is to find the precise distance or path that reaches target. The firefly algorithm involves the following steps:

(i) Population Initialization: At the beginning, the populations of fireflies are initialized; here *rand* refers within the range [0, 1] random number

$$Q = Q_{min} + (Q_{max} - Q_{min}) * rand() \quad (2)$$

(ii) Distance: At spatial coordinates q_i and q_j , the distance amongst the two fireflies i, j denotes cartesian distance and $q_{i,k}$ indicates the k^{th} spatial coordinate component q_i of i^{th} firefly with the number of d dimensions be represented as follows,

$$m_{ij} = \|q_i - q_j\| = \sqrt{\sum_{k=1}^d (q_{i,k} - q_{j,k})^2} \quad (3)$$

(iii) Attractiveness: The firefly attractiveness function can be calculated with the distance among any two fireflies be m . β denotes attractiveness degree of firefly at distance m . Initially attractiveness is β_0 at $m = 0$ and the light absorption coefficient γ that regulates light intensity constriction and $k \geq 1$.

$$\beta = \beta_0 e^{-\gamma m^k} \quad (4)$$

(iv) Movement: The firefly i move towards more attractive or a brighter firefly j . Each firefly changes itself to a better position from its current position. It is given by,

$$\begin{aligned} q_i(\text{new position}) &= q_i(\text{current position}) \\ &+ \beta (q_j - q_i(\text{current position})) \\ &+ \alpha (\text{rand}() - 0.5) \end{aligned} \quad (5)$$

where, q_i is the revised position in space of each firefly, $\alpha(\text{rand}() - 0.5)$ is the random disorder of which the step factor α and the random number generator *rand* distributed in [0,1]. To optimize an objective function, FA uses the method of attraction based on brightness of fireflies. The FA algorithm enhances the speed of convergence that could be used in iterative measures of algorithm [19]. Hence FA is regarded as much better for generating optimum in terms of time or near optimum value. Each of FA procedure detailed as follows. To recognize the intensity of light and attractiveness numerically, defined the intensity of light as I_x of FA, attractiveness $\beta_{xy}(d_{xy})$ in eq.(6) and (7)

$$I_x = (|f_{min}^n - f(a_x^n)| + 1)^{-1} \quad (6)$$

f_{min}^n is the majority among the evaluation values in the grouping of search point.

$$\begin{cases} \beta_{xy}(d_{xy}) = \beta_0 e^{-\gamma d_{xy}^2} \\ d_{xy} = \|b_y^n - a_x^n\| = \sqrt{\sum_{l=1}^z (b_{y,l}^n - a_{x,l}^n)^2} \end{cases} \quad (7)$$

where, β_0 is the greatest value of attraction furthermore, γ is a related to attenuation of light parameter. All fireflies persists attraction to another surrounded by prominent brightness strength to move [20]. The equation of firefly movement from x to y is defined by Eq.(8), d_{xy} is the Euclidean distance a_x of the search point with point of reference b_y .

$$a_x^n := a_x^n + \beta_{xy}(d_{xy})(b_y^n - a_x^n) + \alpha R \quad (8)$$

where, α corresponds parameter to the scale of random number and uniform random number vector R to be distorted in extent of $[-0.5, 0.5]^n$. According to the Eq. (9) the brightest firefly a_{min} moves randomly.

$$a_{min}^n = a_{min}^n + \alpha R \quad (9)$$

The objective function $f(a) = a \in R^z$ minimization problem of FA is shown below in the algorithm.

Algorithm of Firefly

- 1) Specify N_{max} the greatest quantity of iterations, the number of search points be m and α, β_0, γ be each parameter, the number of iterations set as $n=1$.
- 2) In the region $A(A \subseteq R^z)$, random search points is set to generate $a_i^1 (i = 1, 2, \dots, m)$, accumulate the solution as $b_i^1 = a_i^1 (i = 1, 2, \dots, m)$ and fix $i=1$.
- 3) Calculate I_x light intensity of each search point in accordance with the subsequent rule.

$$f_{min}^n = \min \{f(a_x^n) | i = 1, 2, \dots, m\} \quad (10)$$

$$I_x = (|f_{min}^n - f(a_x^n)| + 1)^{-1} \quad (11)$$

- 4) If $I_x < I_y$, move the search point a_x^n in accordance with the following formula.

$$a_x^n := a_x^n + \beta_0 e^{-\gamma} \|b_y^n - a_x^n\|^2 (b_y^n - a_x^n) + \alpha R \quad (12)$$

The uniform random vector is $R \in [-0.5, 0.5]^n$, above processes are repeated along with $y: y + 1$, till $y = m$ and the search point are moved a_x^n with the following formula.

$$a_x^n := a_x^n + \alpha R \quad (13)$$

- 5) If $x = m$, the search point are updated a_x^n and the solution set aside b_x^{n+1} ; if not, set $x := x + 1$ also return to Step 3.

$$a_x^{n+1} = a_x^n (i = 1, 2, \dots, m) \quad (14)$$

$$b_x^{n+1} = b_x^n (i = 1, 2, \dots, m) \quad (15)$$

- 6) If $n = N_{max}$, the algorithm is completed; or else, return to Step 3 and set $n := n + 1$ and $i = 1$.

D. Level set Segmentation

The Level-set method is an ideal framework for segmenting the area specified. The level set method can directly locate the region and border of images. This method is self- adapting model shifts the initial contour against the object boundaries based on energy function minimization. In general, the iterative algorithm is utilized to resolve the problem. The primary initiative of this method is to follow the curves or surfaces movement via impacting propagating interface seeing that the distinct level set of an elevated dimensional task or hyper surface. The active contours enforced by the use of level set methods [21] be able to be expressed as time dependent function ϕ of zero level set derives consistent with the equation of level set,

$$\frac{\partial \phi}{\partial v} + F|\nabla \phi| = 0 \quad (16)$$

The primary condition, $((y, z, v) = 0)$, F is speed function exemplified in support of association of the surface or curve, up to a range of arguments function, inclusive of the gradient curvature, normal direction and so forth. To the extent segmentation of image, F confides on image information along with level set function ϕ . Each time the propagating front is specified as a consequence of the zero level set.

$$\Gamma(v) = \{(y, z)\phi(y, z, v) = 0\} \quad (17)$$

In conventional level set approaches, re-initialized the function of level set seeing that a signed distance function constantly at some point in the evolution adequate on the way to retain stable curve evolution as well as make certain preferred effects. Though, in general the procedure of re-initialization formulates the calculation expensive and basis numerical error with the zero level set. The proposed new variational level set method absolutely reduces requisite for re-initialization as to retain stable level set function evolution and accelerate curve evolution. The variational formulation can be represented in the following equation:

$$\begin{aligned} \varepsilon(\phi) &= \tau Q(\phi) + \varepsilon_r(\phi) = \tau Q(\phi) + \alpha R(\phi) + \beta S(\phi) \\ &= \tau \int_{\omega} \frac{1}{2} (|\nabla \phi| - 1)^2 dydz \\ &\quad + \alpha \int_{\omega} g \delta(\phi) |\nabla \phi| dydz \\ &\quad + \beta \int_{\omega} g H(-\phi) dydz \end{aligned} \quad (18)$$

where, $\alpha > 0, \tau > 0$ and β be coefficients also, $Q(\phi)$ is the internal potency fines the variation of ϕ on or after a signed distance function next to various phase in its evolution and hence $\varepsilon_r(\phi)$ is the peripheral potency that turns to the boundary object of zero level set. The expression $R(\phi)$ indicates potency of zero level curves length, $S(\phi)$ indicate area energy influences evolution direction also expedites evolution in that order is Dirac function with one variable wherein the H denotes Heaviside function. The function edge indicator with the level set evolution is defined by

$$g = \frac{1}{1 + |\nabla G_{\sigma} * I(y, z)|^2} \quad (19)$$

Eq.(19) as the end constraint and the function $G_{\sigma} * I(y, z)$ convolution with standard deviation and the image intensity enclosed by the Gaussian smoothing filter.

E. Morphological Post processing

The post processing is necessary for vigorous solution of particles since there are quiet minute objects existent that can be erroneous as particle in the meanwhile counting. In this paper statistical morphology filtering is brought concerning to its benefits confiscating the unnecessary objects in the image. The one of the two basic operators of morphology [22] is erosion which erodes aside the region of interest in the midst of a set of coordinate points renowned as structuring element which is dependable for the specific consequence of erosion on the input image. Among the super pixels, there subsist boundaries by a distinct pixel width. Then, the recognized pixels defected has been abstracted by the ridge lines. In order to get absolute defect information, the abstracted super pixels characterizing defects must be associated in concert. For this task, closing is a proper morphologic operation. It comprehends dilation accompanied by erosion by means of the similar structuring element. Formerly exploiting closing operation, the image area merely in conjunction with super pixels defected ought to be distorted to a binary one since the periphery has barely one pixel width of which is preferred as the structure element. Sequentially to acquire added perfect defect information, subsequent to closing operation the noises must be evicted in the concluding detection result. As a result, following morphological operation the image is relieved from redundant objects and be able to be used in support of additional parameters analysis and enumerating of particles in the exploration.

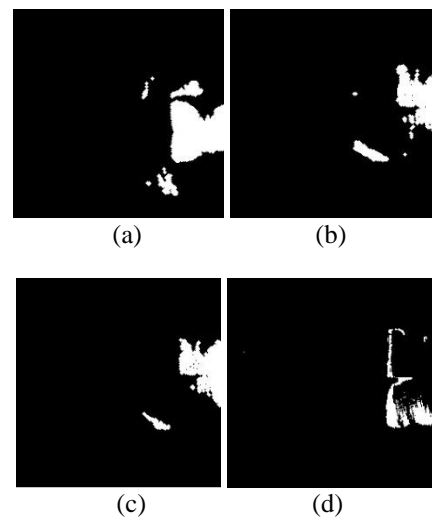


Fig.2: Defect detection result of sample 1 from, (a) ATFF, (b) ATCS, (c) ATPSO, (d) MBOT.

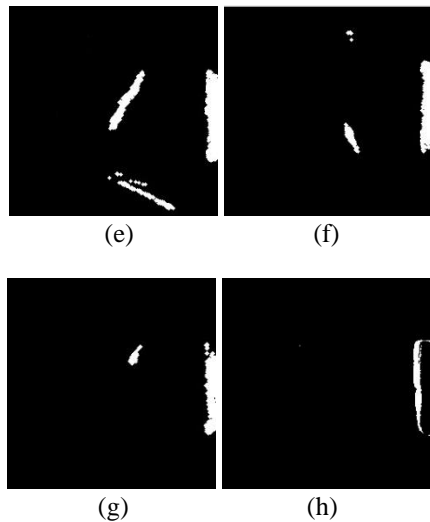


Fig.3: Defect detection result of sample 2 from, (e) ATFF (f) ATCS, (g) ATPSO, (h) MBOT.

The figures above illustrate the processed output images of two input samples adopting ATFF, ATCS, ATPSO, and MBOT. Fig.2 and Fig.3 shows the output images of both the sample 1 and sample 2, correspondingly. The defected or uncoated regions are denoted as the white portion in the image also the black portion denotes non defective or coated area. The output result shows that adaptive thresholding based on firefly optimization yields more appropriate segmentation result, in comparison with other three methods.

III. EXPERIMENTAL RESULTS AND DISCUSSION

The experimental result of proposed firefly based adaptive thresholding (ATFF) technique is analyzed and a comparison is made against cuckoo search based adaptive thresholding (ATCS), PSO based adaptive thresholding (ATPSO) and median based otsu thresholding (MBOT). The fig.2 and 3 shows the processed image of two sample input images. It can be seen that the more accurate segmentation result is obtained by the proposed method. The proposed algorithm detects defected pixels with reduced noise. The performances of the algorithms are measured using the following values of parameters:

Performance Evaluation:

a) Sensitivity:

It is the actual positives proportion renowned properly, also known as true positive rate.

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (20)$$

(b) Specificity:

It is the actual negatives proportion renowned properly, also known as true negative rate.

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (21)$$

(c) Accuracy:

It is the closeness of a value calculated with the standard value.

$$\text{Accuracy} = \frac{TN + TP}{(TN + TP + FN + FP)} \quad (22)$$

(d) Precision:

Precision is the fraction of appropriate occurrences among the retrieved occurrences.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (23)$$

The following table I shows the comparison between existing methods and proposed adaptive thresholding with Firefly method for the criterion sensitivity. The graphical representation for table I is illustrated in fig.4.

Table- I: Performance analysis of ATFF, ATCS, ATPSO and MBOT on the parameter sensitivity

Image No	ATFF	ATCS	ATPSO	MBOT
1	0.86508	0.80156	0.77951	0.737642
2	0.85905	0.79483	0.77461	0.739259
3	0.8662	0.80269	0.7394	0.726931
4	0.84827	0.79461	0.77319	0.737271
5	0.85875	0.82909	0.80573	0.755412

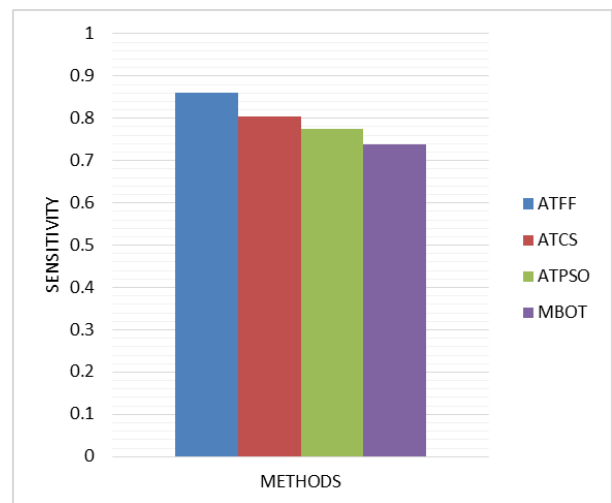


Fig.4: Performance comparison relative to sensitivity for the proposed and existing methods

The following table II shows the comparison between existing methods and proposed adaptive thresholding with firefly method for the specificity measures.

Table- II: Performance analysis of ATFF, ATCS, ATPSO and MBOT on the parameter specificity

Image No	ATFF	ATCS	ATPSO	MBOT
1	0.86096	0.84616	0.77326	0.71958
2	0.85217	0.79163	0.76796	0.70047

3	0.86184	0.81188	0.78531	0.70016
4	0.85869	0.82231	0.76642	0.70038
5	0.85326	0.81617	0.80177	0.71063

The following table III shows the comparison between existing methods and proposed adaptive thresholding with firefly method for the accuracy measures. The graphical representation for table III is illustrated in fig.5.

Table- III: Performance analysis of ATFF, ATCS, ATPSO and MBOT on the parameter accuracy

Image No.	ATFF	ATCS	ATPSO	MBOT
1	0.88788	0.84955	0.80179	0.72619
2	0.87432	0.81606	0.7984	0.71677
3	0.88316	0.80856	0.741	0.71657
4	0.86441	0.82895	0.79742	0.72671
5	0.88401	0.84133	0.81969	0.73324

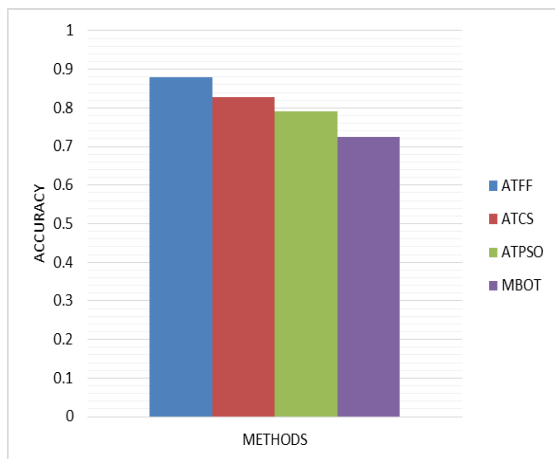


Fig.5: Performance comparison relative to accuracy for the proposed and existing methods

The following table IV shows the comparison between existing methods and proposed adaptive thresholding with firefly method for the precision measures.

Table- IV: Performance analysis of ATFF, ATCS, ATPSO and MBOT on the parameter precision

Image No	ATFF	ATCS	ATPSO	MBOT
1	0.91954	0.90722	0.8604	0.75221
2	0.89176	0.89441	0.8289	0.75244
3	0.88946	0.85472	0.83667	0.75236
4	0.89106	0.89941	0.84846	0.75242
5	0.89996	0.90032	0.83824	0.75508

The experimental results obtained with the proposed technique and existing algorithms of ATFF, ATCS and ATPSO, MBOT are represented through the tables and graphs. It is clear that the adaptive thresholding with firefly produces superior result while considering the evaluation parameters. The results obtained using the evaluation parameters shows the good performance of the proposed adaptive thresholding with Firefly algorithm for all set of

input images. Thus all of obtained results are close to optimal value as regard to the minimization problems. The obtained result indicates the proposed method effectiveness to automatically detect and segment defected region from the coated metal surface.

IV. CONCLUSION AND FUTURE SCOPE

The image surface defect detection utilizing the adaptive thresholding with firefly optimization has been initiated within this analysis. Our proposed method aims to modify the firefly algorithm’s parameters efficiently to attain the exploration and exploitation stability vigorously. The adaptive thresholding method is used for detection of defects. The defects are identified and segmented using the proposed method. Certainly, in adaptive thresholding method within each searching step the correct estimates is made toward the firefly parameters, the equivalence in knowledge of search space region accomplished effectively. The firefly algorithm shift successfully with direction of the optimum solution also, doesn’t fall in local optimum. The efficiency of proposed method is made comparison with different existing methods. The ATCS, ATPSO and ATOT algorithms are used for the experimental analysis and evaluation of the proposed method performance. From experimental results found, proposed method achieves superior effects than the existing algorithm. However, the lighting effects or shadows occurred in images were found to reduce detection accuracy. Thus, in future, this can be modified by fuzzy clustering algorithm or wavelet analysis based image processing to differentiate the metal surfaces as coated and uncoated.

REFERENCES

1. Mai Thanh Nhat Truong, and Sanghoon Kim, “Automatic image thresholding using Otsu’s method and entropy weighting scheme for surface defect detection”, *Soft Computing*, vol. 22, Issue 13, pp 4197–4203, July 2018.
2. Hwee Kwon Jung, Chang Won Lee, and Gyuhae Park, “Fast and non-invasive surface crack detection of press panels using image processing”, *Procedia Engineering*, 6th Asia Pacific Workshop on Structural Health Monitoring, vol.188, pp.72-79, 2017.
3. 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.
4. Karl T. Fendt, Hubert Mooshofer, Stefan J. Rupitsch, and Helmut Ermert, “Ultrasonic Defect Characterization in Heavy Rotor Forgings by Means of the Synthetic Aperture Focusing Technique and Optimization Methods”, *IEEE Transactions on Ultrasonics, Ferroelectrics and Frequency Control*, vol. 63, no.6, June 2016.
5. Gang Li, Xiaoxing Zhao, Kai Du, Feng Ru, and Yubo Zhang, “Recognition and evaluation of bridge cracks with modified active contour model and greedy search-based support vector machine”, *Automation in Construction*, vol.78,pp.51-61, June 2017.
6. N. Otsu, “A threshold selection method from gray-level histograms,” *Automatica*, vol. 11, no. 285–296, pp. 23–27, 1975.
7. J. H. Xue and D. M. Titterington, “Median-based image thresholding,” *Image Vis. Comput.*, vol. 29, no. 9, pp. 631–637, 2011.
8. 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.
9. Mustafa Servet Kiran, and Oguz Fındık, “A directed artificial bee colony algorithm”, *Applied Soft Computing*, vol.26, pp. 454-462, Jan 2015.



10. Yuan Chao, Min Dai, Kai Chen, Ping Chen, and Zhisheng Zhang, "A novel gravitational search algorithm for multilevel image segmentation and its application on semiconductor packages vision inspection", *Optik*, vol.127, Issue.14, pp.5770-5782, July 2016.
11. 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.
12. Lei Chen, Chuangbai Xiao, Xueliang Li, Zhenli Wang, and Shoudong Huo, "A seismic fault recognition method based on ant colony optimization", *Journal of Applied Geophysics*, vol.152, pp.1-8, Feb 2018.
13. UrošMlakar, Božidar Potocnik, and Janez Brest, "A hybrid differential evolution for optimal multilevel image thresholding", *Expert Systems with Applications*, vol.65, pp.221–232, Aug 2016.
14. Javad Rahebi, and Firat Hardalaç, "A new approach to optic disc detection in human retinal images using the firefly algorithm", *Medical & Biological Engineering & Computing*, vol.54, Issue.2–3, pp.453–461, March 2016.
15. 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 and Electrical Engineering*, vol.66, pp.569-582, Feb 2018.
16. Cecilia Pasquini, Giulia Boato, Naif Alajlan, and Francesco G.B. De Natale, "A Deterministic Approach to Detect Median Filtering in 1D Data", *IEEE Transactions on Information Forensics and Security*, vol.11, pp.1425–1437, Issue.7 , July 2016.
17. Kaveh Ahmadi, Ahmad Y. Javaid, and Ezzatollah Salari, "An efficient compression scheme based on adaptive thresholding in wavelet domain using particle swarm optimization", *Signal Processing: Image Communication*, vol.32, pp.33–39, March 2015.
18. Mustapha Ammiche, Abdelmalek Kouadri, Laith M.Halabi, Amar Guichi, and Saad Mekhilef, "Fault detection in a grid-connected photovoltaic system using adaptive thresholding method", vol.174, pp.762-769, Nov 2018.
19. Javad Rahebi, and Firat Hardalaç, "A new approach to optic disc detection in human retinal images using the firefly algorithm", *Medical & Biological Engineering & Computing*, vol. 54, Issue.2–3, pp.453–461, March 2016.
20. ArefYelghi, and CemalKose, "A modified firefly algorithm for global minimum optimization", *Applied Soft Computing*, vol.62, pp.29–44, Jan 2018.
21. Cheng Liu, Weibin Liu, and Weiwei Xing, "An improved edge based level set method combining local regional fitting information for noisy image segmentation", *Signal Processing*, vol.130, pp. 12–21, 2017.
22. Francesco G.B. De Natale, and Giulia Boato, "Detecting morphological filtering of binary images", *IEEE Transactions on Information Forensics and Security*, vol.12, Issue.5, pp.1207-1217 May 2017.

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