

Artificial Neural Network and Gray Level Co-Occurrence Matrix Based Automated Corrosion Detection



V.Thanikachalam , M.G.Kavitha, V.Bharathi

Abstract: In this paper, we show an image processing algorithm with its capabilities in detecting the corrosion. This algorithm is programmed and requires no parameter modification and no previous knowledge of image acquisition process because function evaluates their parameters. Digital image processing technique proposed to avoid such incident occurrences. Combining Poisson-Gaussian- Mixture distribution with a Fuzzy segmentation framework an algorithm is developed to clutch image information. Artificial neural network and gray level co-occurrence matrix (GLCM) utilized to recognize the corrosion. The developed algorithm can be used in the ROV to detect the corrosion spots. The algorithm results exhibit the sufficiency in perceives corroded spots. Using image processing the corrosion detection process can be automated with a monitoring software setup which can generate an alert based on corrosion severity. Using image processing the infrastructure's corrosion evaluation effort will be minimized, and presenting the result statistics is easier. In application point of view, we can extend the algorithm capabilities to the fatigue crack detection.

Keywords: Image Processing, Corrosion Detection, Image denoising.

I. INTRODUCTION

Object classification is a fundamental mode in image processing; it demands to recognize objects of a particular class in images. In [1], the author introduced a multi-step processing method to identify underwater fish localization. The picture analyzed initial, then the picture statistically assessed element by element and joins with the original picture utilizing Poisson - Gauss theory. In [2] wavelet based noise reduction is proposed. To remove the backscattering noise author, combine High-pass Filter and Wavelet method. Wavelet based thresholding; anisotropic filtering and homomorphism filtering are applied [3] to reduce noises. Nevertheless, these wavelets based thresholding methods cause loss of spatial resolution in the resulting image.

Revised Manuscript Received on October 30, 2019.

* Correspondence Author

Dr.V.Thanikachalam*, Associate Professor Department of IT , SSN College of Engineering , Chennai.

Dr.M.G.Kavitha, Assistant Professor, Department of CSE, University College of Engineering , Paddukottai.

V.Bharathi , Assistant Professor , Department of ECE , Kongunadu College of Engineering and Technology , Thottiyam, Trichy.

© The Authors. Published by Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP). This is an [open access](http://creativecommons.org/licenses/by-nc-nd/4.0/) article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>)

To remove the noise, authors utilize a median filter and RGB Color Level Stretching to enhance a picture.

This strategy can only help on pictures with minor noise [4].The underwater picture quality relies on the turbidity of fluid. Author [5]

anticipated and proposed a data set comparing both nature of the image and turbidity of the fluid using the segmentation process. Reestablished picture quality relies onsegment precision. Author [6] intended a methodology for efficient segmentation dependent on Fuzzy clustering and the morphological component analysis. The intention of this analysis is broadening the scope. Corrosion process usually creates rough surface structures on many materials GLCM qualities of cutting edge pictures convey proper information for an area or pixel discrimination purposes. Along these lines, they apply to show corroded surfaces [7]. The neural network (Self-Organizing map [SOM]) envelops an unsupervised learning algorithm in view to discovering models which better represent patterns.SOM is a clustering algorithm which gathers fragmentary objects into a group as per their features [8]. This paper presents a computational non-destructive examination to recognize corrosion on metallic facades by utilizing surface characteristics and SOM algorithm utilized for underwater structure. Our proposed approach will be useful for machine inspectors. Using the simulation results, Corrosion on the metal facades can be efficiently verified to ensure safety[9]. Automatically Identifying corrosion on metallic facades in submerged infrastructure is a challenging task, which needs a multi-step methodology. In pre-processing phase is to reestablish the data in the photograph by tweaking the contrast and eliminating the noise. Then the characteristic extraction method is used to create a Model class. The extricated details will serve as an initial data to neural network, which exhibits the archetype evaluation by grouping the corroded and non-corroded areas in the underwater pictures. The article endeavors at generating a composite algorithm which automatically detecting corrosion[10].

II. PROPOSED METHOD

In this research, a hybrid algorithm is proposed using prior investigations with the ability to distinguish corroded areas in underwater infrastructure Proposed methodology to detect corrosion using SOM technique.

In this technique, NDE method uses GLCM for detecting the surface texture of the metal. The GLCM technique incorporates more 14 surface features. Although for

effortlessness purpose, we adopt an optimized subset of contrast, correlation, energy, homogeneity proposed.

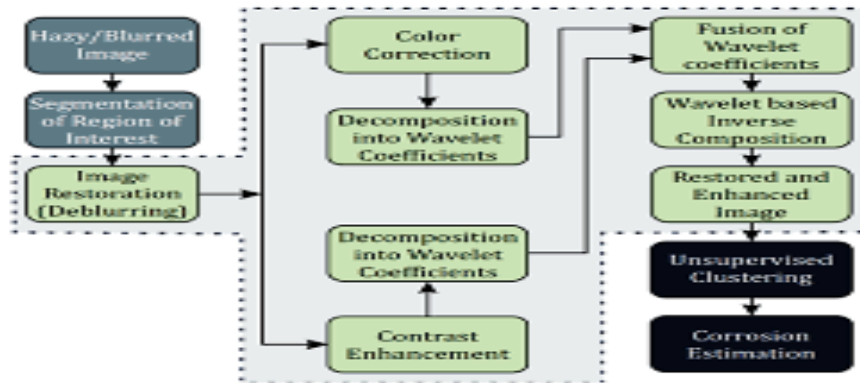


Figure.1:Proposed Methodology

Intensity difference between pixel and its neighbor in the complete image is measured by the contrast.

$$\sum k^2 [\sum (\sum S(i, j))]$$

Where S represents the GLCM .k is sum index denoted by the GLCM which is less than one. Correlation

function describes how interrelated pixels in the image are correlated. shows the proposed method logy block diagram. To Changing RGB to Gray scale image which permit us to work with the surface textures the tests incorporate 5 pictures of metallic surfaces from different oil plants with different levels of corrosion. We physically connected GLCM and extracted data to construct highlight vectors. Those properties were used for SOM training and models estimation.

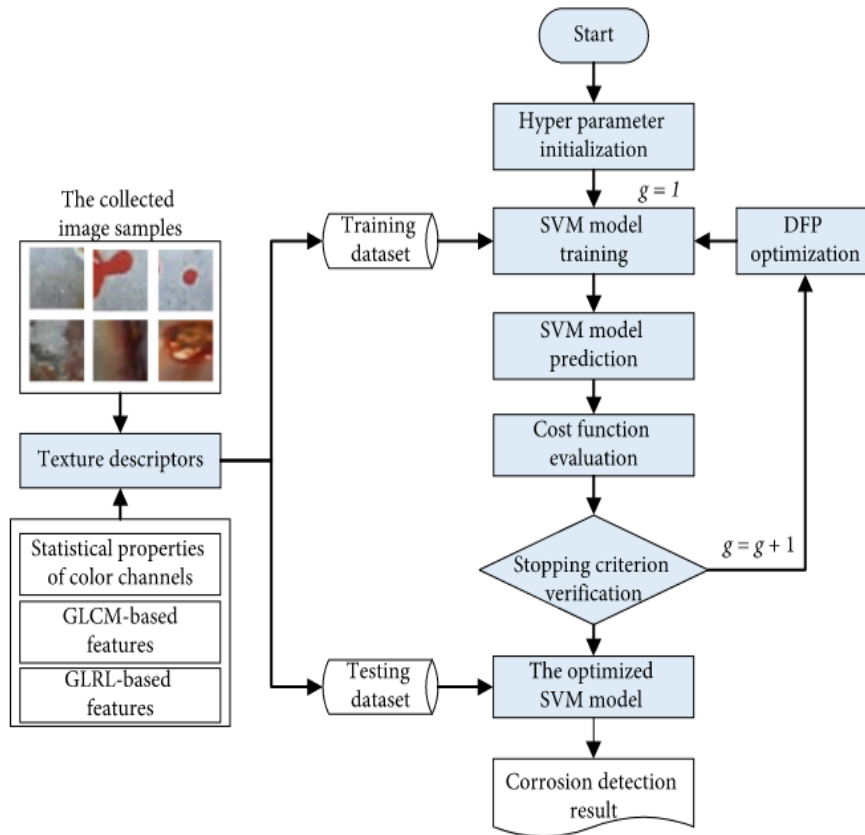


Figure.2: ANN Detection Unit

The validation process is carried by comparing actual and expected corroded and non-corroded areas on the image shown in figure.2.

III. RESULTS AND DISCUSSION

Accordingly, the overall model performance is reliably evaluated by averaging prediction results obtained from the repeated data sampling. Correlation with a correlation factor of 0.9932, with the processed data little over predicting the corroded area in the images. This minor discrepancy between the actual and processed result is caused due to figs on the images, figs covered over the infrastructures is also treated as corroded zone, Which is slightly over-predicting the processed area in pixels. In this experiment, 93% of validation data set were correctly classification.

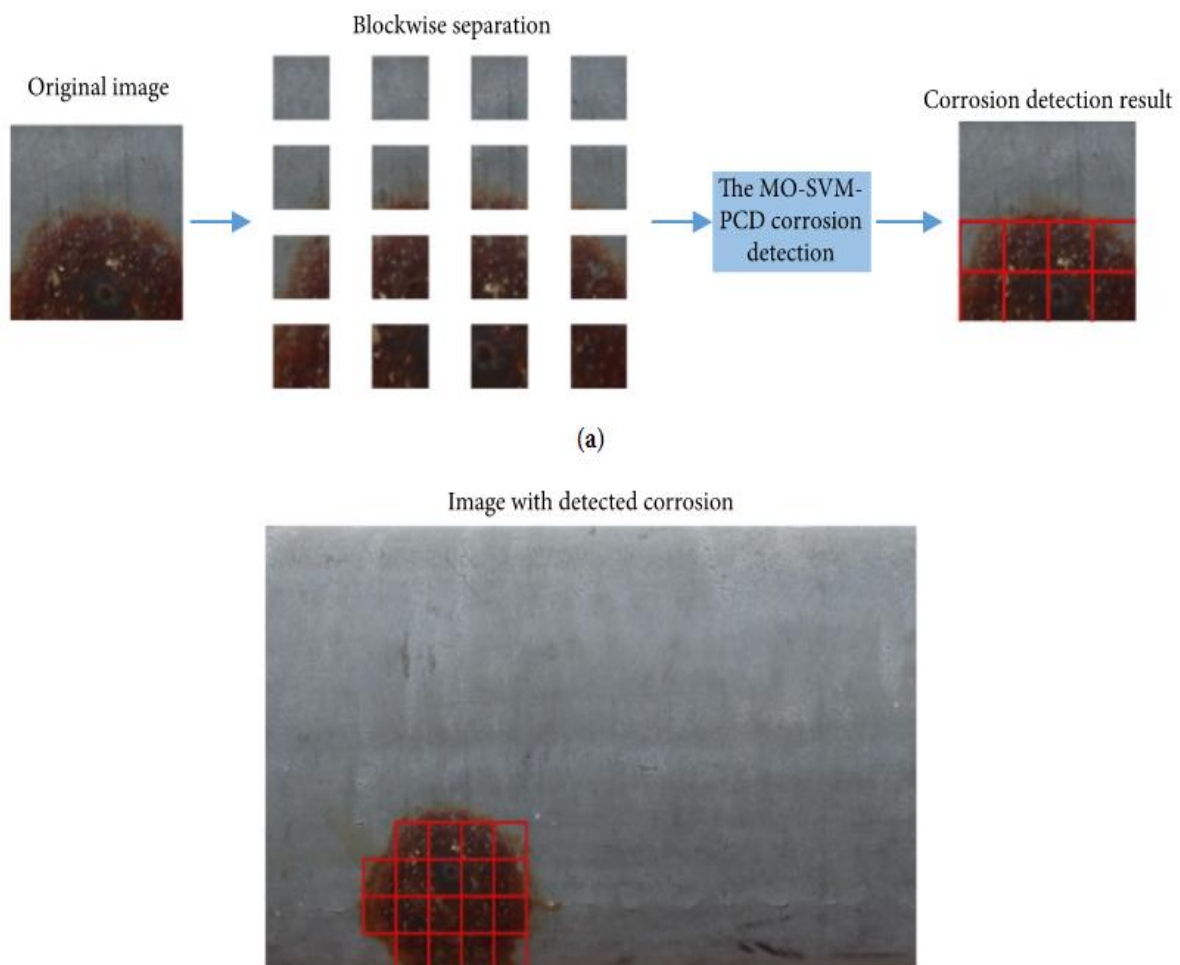


Figure.3: Sampled and correlated output

Phase	Indices	MO-SVM-PCD		LSSVM		CTree		BPANN		CNN	
		Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Train	CAR (%)	98.382	0.236	96.432	0.435	97.018	0.532	94.593	1.674	90.890	1.649
	PPV	0.982	0.004	0.937	0.008	0.970	0.006	0.937	0.020	0.891	0.024
	Recall	0.986	0.004	0.996	0.002	0.971	0.008	0.956	0.016	0.933	0.020
	NPV	0.986	0.004	0.995	0.002	0.971	0.007	0.956	0.016	0.930	0.019
	F1	0.984	0.002	0.965	0.004	0.970	0.005	0.947	0.016	0.911	0.016
Test	CAR (%)	92.808	1.094	87.467	1.121	85.825	1.467	88.733	1.721	87.258	1.571
	PPV	0.922	0.015	0.886	0.016	0.854	0.016	0.877	0.022	0.855	0.028
	Recall	0.936	0.017	0.860	0.016	0.864	0.021	0.902	0.026	0.899	0.022
	NPV	0.935	0.016	0.864	0.014	0.863	0.019	0.899	0.024	0.894	0.018
	F1	0.929	0.011	0.873	0.011	0.859	0.015	0.889	0.017	0.876	0.014

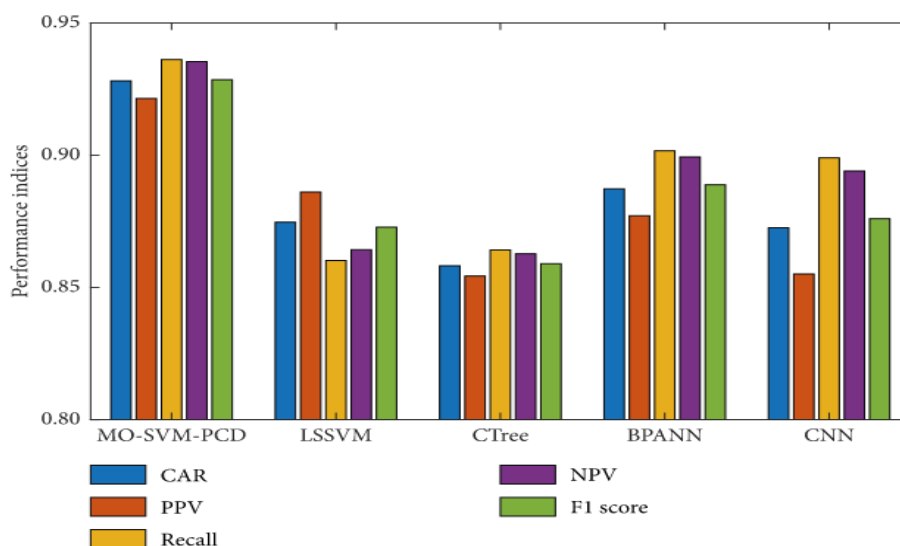


Figure.4: Performance Analysis

REFERENCES

- Nath A.: Image Denoising Algorithms; A Comparative study of Different Filtration approaches used in image restoration. In Communication Systems and Network Technologies (CSNT), 2013 International Conference on 2013 (pp. 157- 163). IEEE, April 6.
- Schettini R, Corchs S.: Underwater image processing: state of the art of restoration and image enhancement methods; . EURASIP Journal on Advances in Signal Processing. 2010; 2010(1):746052, April 21.
- .Prabhakar CJ, Kumar PP.: Underwater image denoising using adaptive wavelet sub band thresholding; . InSignal and Image Processing (ICSIP), 2010 International Conference on 2010 (pp. 322-327). IEEE, December 15.
- Feifei S, Xuemeng Z, Guoyu W.: An approach for underwater image denoising via wavelet decomposition and high-pass filter; . In Intelligent Computation Technology and Automation (ICICTA), 2011 International Conference on 2011 (Vol. 2, pp. 417-420). IEEE, March 28.
- Zhang M, Gunturk BK.: Multiresolution bilateral filtering for image denoising;. IEEE Transactions on image processing. 2008; 17(12):2324-33, December 17.
- Yang S, Peng F.: Laser underwater target detection based on Gabor transform; . In Computer Science & Education, 2009. ICCSE09. 4th International Conference on 2009 (pp. 95-97). IEEE, July 25.
- Ouyang B, Dalgleish F, Vuorenkoski A, Britton W, Ramos B, Metzger B: Visualization and image enhancement for multistate underwater laser line scan system using image-based rendering; . IEEE Journal of Oceanic Engineering. 2013; 38(3):566-80, July 7.
- Li Y, Wang S.: Underwater polarization imaging technology; In Conference on Lasers and Electro- Optics/Pacific Rim 2009 Aug 30. Optical Society of America.
- Boudhane M, Nsiri B.: Underwater image processing method for fish localization and detection in submarine environment; .Journal of Visual Communication and Image Representation. 2016 Aug 31; 39: 226-38.
- Rabbani H, Vafadoost M, Selesnick I.: Wavelet based image denoising with a mixture of Gaussian distributions with local parameters;. In Multimedia Signal Processing and Communications, 48th International Symposium ELMAR- 2006 focused on 2006 (pp. 85-88). IEEE, June 15.