Performance Analysis of various filters for noise removal in EDM electrode surface crack images

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Abstract

The aim of this paper is to discuss the development of Computer Aided Detection (CAD) system for the detection of surface cracks present in the electro discharge machined Inconel X750, when it is machined with copper electrodes by using Heuristic Algorithms. It is not possible to detect the cracks and flaws accurately in the metal surface by using human vision technology. So there is a need for automated solution to detect the cracks in the metal surface using CAD system. The detection of flaws in metals is performed in four phases namely Image Enhancement, Segmentation, Feature Extraction and Classification. This paper describes the first phase - various non-linear filters such as mean, median, wiener, Gaussian filters and improved hybrid median are used for effectively removing noise from an image and their performance are analyzed.

Keywords: *Electric Discharge Machining (EDM), Image Processing, CAD system.*

1. Introduction

Auditing the quality of products is more critical task in the modern industrial manufacturing. With the global developments in the manufacturing industry and particularly in aerospace manufacturing mainly because of the speedy growth in the amount of people journeying across the world is fast and prospering using the air route, the stuffs that are applied in that industry and its economical machining operations develops need for their prominence. Before making them usable for industries and factories, they should be examined for flaws. The early detection is the most effective way to reduce serious hazards in the finished products [1]. But it is not possible to detect the cracks and flaws accurately in the metal surface by using human vision technology. So there is a need for automated solution to detect the cracks in the metal surface using CAD system. The evolution of CAD system has made a giant leap in the effective detection. Furthermore, it can help to get better sensitivity, cost effectiveness and less time-consumption. The detection of flaws in metals is performed in four phases namely Image Enhancement, Segmentation, Feature Extraction and Classification.

In this work, metal surface images have been taken by using metallurgical microscope with 200X magnification. This microscope gives an output image in .jpg format with 2048x1536 resolutions.

2. Image Enhancement and Noise Removal

In image processing, filters are mainly used to suppress the high frequencies in the image and enhancing or detecting edges in the image. An image can be filtered either in the frequency or in the spatial domain. The first involves transforming [2] the image into the frequency domain, multiplying it with the frequency filter function and re-transforming the result into the spatial domain. The filter function is shaped so as to attenuate some frequencies and enhance others. Filters are broadly classified into two types such as, linear and non-linear filters. Linear filters tend to blur edges and other image details and perform poorly with non-Gaussian noise. Whereas, Nonlinear filters can preserve edges and is very effective at removing impulsive noise. And hence, non-linear filters are most widely used. In this work, various non-linear filters such as mean, median, wiener, Gaussian filters and improved hybrid median are used for effectively removing noise from an image and their performance are analyzed.

2.1. Mean filter

Mean filtering is a simple [3] intuitive and easy to implement method. The idea of mean filtering is simply to replace each pixel value in an image with the mean (`average') value of its neighbors, including itself. This has the effect of eliminating pixel values which are unrepresentative of their surroundings. Mean filtering is usually thought of as a convolution filter. Like other convolutions it is based around a kernel, which represents the shape and size of the neighborhood to be sampled when calculating the mean.

The two main problems with mean filtering are:

A single pixel with a very unrepresentative value can significantly affect the mean value of all the pixels in its neighborhood.

When the filter neighborhood straddles an edge, the filter will interpolate new values for pixels on the edge and so will blur that edge. This may be a problem if sharp edges are required in the output.

2.2 Median filter

The median filter considers each pixel in the image in turn and looks at its nearby neighbors to decide whether it is a representative of its surroundings or not. Instead of simply replacing the pixel value with the mean of neighboring pixel values, it replaces it with the median of those values. The median is calculated by first sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value. One of the major problems with the median filter is that it is relatively expensive and complex to compute.

2.3. Wiener Filter

The most important technique [4] for removal of blur in images due to linear motion or unfocussed optics is the Wiener filter. Blurring due to linear motion in a photograph is the result of poor sampling. Wiener filter performs denoising by means of linear time invariant filter operation. Instead of low pass filtering operations wiener filter determines the upper bound and lower boundary points for the filtering model. Once these boundary points are identified then the pixel values are compared with the boundary limits and the values lies outside the boundary points are marked as noise pixel points and hence filtered out from the image.

2.4 Gaussian Filter

Gaussian filter performs low pass filtering operations and it is achieved by identifying the relationship between the pixel values of the image. It takes impulse response by means of

Gaussian function. It estimates the relationship parameters named as standard deviation of the pixel points to perform the denoising operation. After computing this relationship value the pixel value is compared and greater values are eliminated.

2.5 Proposed Improved Hybrid Median Filter

Improved hybrid median filter (IHMF) preserves edges better than a square kernel median filter because it is a three-step ranking operation where data from different spatial directions are ranked separately. Three median values are then calculated and they are MR is the median of horizontal and vertical R pixels, and MD is the median of diagonal D pixels. The filtered value is the median of the two median values and the central pixel C: median ([MR, MD, C]).

The three step ranking operation does not impose a serious computational penalty as in the case of median filter. Each of the ranking operations is for much smaller number of values than used in a square region of the same size. Even with the additional logic and manipulation of values, the hybrid method is faster than the conventional median. This median filter overcomes the tendency of median and truncated median filters to erase lines which are narrower than the half width of the neighborhood and to round corners.

$$\begin{bmatrix} D & * & R & * & D \\ * & D & R & D & * \\ R & R & DCR & R & R \\ * & D & R & D & * \\ D & * & R & * & D \end{bmatrix}$$

Fig. 1 Matrix showing the elements of IHMF

Spot is a granular commotion that innately exists in and debases the nature of ultrasound pictures. It by and large has a tendency to lessen the determination and difference, subsequently, to debase the demonstrative exactness of this methodology. Spot lessening is a standout amongst the most imperative procedures to improve the nature of ultrasound pictures. Cross breed Median Filter for pixel lessening, which processes the middle of the inclining components and most extreme of the flat and vertical components in a moving window lastly the two qualities are contrasted and the focal pixel and the middle estimation of the three qualities will be the new pixel esteem. The maximum value of the 45 degree neighbors forming an “X” and the median value of the 90 degree neighbors forming a “+” are compared with the central pixel and the median value of that set is then saved as the new pixel value.

The extent of the window of the IHMF is chosen in light of the picture locale. Since the relationship amongst the pixels is high in the homogeneous area, a bigger window size of 5x5 is selected. On the other hand a littler window size of 3x3 is utilized for the pixel that fits in with an edge district since it has got less number of corresponded pixel in its neighborhood. To separate between the edge and smooth edge location administrator is utilized. The edge recognition of picture is got by thresholding the slope picture.

3. Performance Evaluation

The various performance evaluations are discussed for the copper electrode surface.

3.1 Mean Square Error (MSE)

In analysis MSE of an estimator and the predictor calculates the normalized value of the squared value of errors. It produces the error value by summing up the squared pixel value of all the pixel images and it is divided by the total pixel count. For a good filtering output the MSE value must be minimum [5]. It is evaluated by the following formula: MSE is defined as:

$$MSE \ \frac{1}{mn} \sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left[I(i,j)-K(i,j)\right]^2 \quad (1.1)$$

Where, m=Number of rows; n=Number of columns; I=Input image; K= Reconstructed image.

3.2 Mean Absolute Error (MAE)

MAE is used to measure the average magnitude of the error. It outcomes as the accuracy of the observation. Instead of squaring, the value in MSE absolute summation of error is calculated and is divided by the total pixel points. MAE has to be minimum for the better filter output [6].

$$MAE \ \frac{1}{mn} \sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left[\left|I(i,j)-K(i,j)\right|\right] \quad (1.2)$$

Where, m=Number of rows; n=Number of columns; I=Input image; K=Reconstructed image.

3.3 Peak Signal to Noise Ratio (PSNR)

Peak Signal to-Noise Ratio outcomes the relationship between the signal and noise pixels of the image. It is inversely proportional to the MSE value and directly proportional to the logarithm of data pixel value. For the optimum filtering output the PSNR value needs to be higher. The PSNR (in dB) is characterized as: [7]

$$PSNR=20log10\ (MAX)\text{-}10log10\ (MSE) \quad (1.3)$$

Where MAX = Maximum value of % density.

3.4 Entropy

It is the expected value of the data which is used to measure the disorder of the system. Entropy outcomes the characteristics of the systems 'state. It is the negative summation of the product of pixel points and the logarithm with the second base of the pixel points. Lower the entropy value better the filtering process. It is calculated using the following formula:

$$Entropy = \sum_{i=0}^{n-1}\left[p(i)\log 2\left(p(i)\right)\right] \quad (1.4)$$

3.5 Entropy 2

It is the absolute expected value of the data which is calculated by second order product values.

$$Entropy-2=\sum_{i=0}^{n-1}\left[p(i)^2.log2\left(p(i)^2\right)\right] \tag{1.5}$$

Where, p = histogram of the image; n = number of element in the histogram.

3.6 Structural Similarity Index (SSIM)

Structural similarity index is used to calculate the similarity between the images. This referential metrics considers image degradation which is perceived changes in the form of structural information of the inter dependence points. It is done by considering the average, variance, co variance of the pixel values. For the better filtering methods this metric SSIM should be higher.

The SSIM metric is calculated on various windows of an image. The measure between two windows x and y of common size N×N is:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y+c_1)\,(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \tag{1.6}$$

μ_x the average of x; μ_y the average of y; σ_x^2 the variance of x; σ_y^2 the variance of y; $c_1=(k_1L)^2$,$c_2=(k_2L)^2$ two variables to stabilize the division with weak denominator; L, the dynamic range of the pixel-values; $k_1=0.01$ and $k_2=0.03$ by default.

3.7 Image Enhancement Factor (IEF)

Image enhancement factor validates the enhanced factor of the images by comparing each and every pixel points which are modified after denoising [8]. It is calculated by taking the ratio between sum of square of difference of original with the noise image and sum of square of difference of denoised image with the noisy image. For better filters the IEF factor should be maximum. IEF is calculated using the following formula.

$$IEF=\frac{\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[N(i,j)-O(i,j)]^2}{\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[D(i,j)-O(i,j)]^2} \tag{1.7}$$

m=Number of rows, n=Number of columns, O=Original image, N=Noisy image, D= Denoisy image

4. Results and Discussion

The Performance of the filtering algorithm is analyzed and the results are displayed in the following tables.

Table 1.1 MSE Evaluation

Filters\Noise density (%)	10	20	30	40	50	60	70	80	90
Mean-Copper	3.09	4.41	5.73	7.09	8.42	9.72	11.04	12.36	13.65
Median-Copper	25.19	26.22	27.24	28.28	29.26	30.3	31.37	32.37	33.41
Wiener-Copper	9.18	12.59	15.62	18.66	21.62	24.76	27.79	30.59	33.45
Gaussian-Copper	14.98	17.88	20.9	23.91	26.55	29.34	32.1	34.51	36.98
IHMF-Copper	2.99	4.27	5.5	6.83	8.06	9.31	10.56	11.82	13.08

Table 1.2 MAE Evaluation

Filters\ Noise density (%)	**10**	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**
Mean-Copper	1.11	1.75	2.39	3.04	3.68	4.31	4.94	5.57	6.21
Median-Copper	3.59	4.2	4.81	5.44	6.02	6.64	7.28	7.88	8.51
Wiener-Copper	1.6	2.33	3.00	3.65	4.34	5.01	5.69	6.33	6.99
Gaussian-Copper	2.42	3.22	4.00	4.77	5.51	6.26	6.97	7.68	8.38
IHMF-Copper	1.01	1.64	2.24	2.89	3.5	4.12	4.74	5.36	5.99

Table 1.3 PSNR Evaluation

Filters\Noise density (%)	**10**	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**
Mean-Copper	60.08	58.53	57.39	56.47	55.72	55.10	54.55	54.06	53.63
Median-Copper	50.97	50.79	50.63	50.46	50.31	50.16	50.01	49.88	49.74
Wiener-Copper	55.35	53.98	53.04	52.27	51.63	51.04	50.54	50.12	49.73
Gaussian-Copper	53.22	52.45	51.77	51.19	50.74	50.30	49.91	49.60	49.30
IHMF-Copper	60.23	58.67	57.57	56.64	55.91	55.29	54.74	54.25	53.81

Table 1.4 Entropy Evaluation

Filters\Noise Density (%)	**10**	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**
Mean-Copper	6.35	6.35	6.35	6.35	6.35	6.35	6.35	6.35	6.35
Median-Copper	6.26	6.26	6.26	6.26	6.26	6.26	6.26	6.26	6.26
Wiener-Copper	6.42	6.44	6.47	6.48	6.50	6.51	6.52	6.53	6.54
Gaussian-Copper	6.38	6.38	6.38	6.38	6.38	6.38	6.38	6.38	6.38
IHMF-Copper	6.35	6.35	6.35	6.35	6.35	6.35	6.35	6.35	6.35

Table 1.5 Entropy-2 Evaluation

Filters\Noise density (%)	10	20	30	40	50	60	70	80	90
Mean-Copper	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19
Median-Copper	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20
Wiener-Copper	0.18	0.18	0.18	0.18	0.18	0.18	0.17	0.17	0.17
Gaussian-Copper	0.19	0.19	0.19	0.19	0.18	0.18	0.18	0.18	0.18
IHMF-Copper	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19

Table 1.6 SSIM Evaluation

Filters\Noise density (%)	10	20	30	40	50	60	70	80	90
Mean-Copper	0.72	0.54	0.42	0.33	0.27	0.22	0.19	0.16	0.15
Median-Copper	0.61	0.45	0.34	0.26	0.21	0.17	0.14	0.12	0.10
Wiener-Copper	0.87	0.73	0.63	0.56	0.50	0.46	0.42	0.39	0.37
Gaussian-Copper	0.68	0.52	0.41	0.33	0.28	0.24	0.21	0.19	0.17
IHMF-Copper	0.73	0.55	0.43	0.34	0.28	0.24	0.21	0.18	0.17

Table 1.7 IEF Evaluation

Filters\Noise density (%)	10	20	30	40	50	60	70	80	90
Mean-Copper	1.49	2.75	3.81	4.70	5.45	6.11	6.51	6.88	7.25
Median-Copper	0.19	0.37	0.55	0.74	0.91	1.09	1.27	1.44	1.62
Wiener-Copper	0.17	0.23	0.28	0.31	0.34	0.36	0.38	0.39	0.40
Gaussian-Copper	0.13	0.21	0.26	0.30	0.33	0.35	0.38	0.39	0.41
IHMF-Copper	1.71	3.10	4.16	5.05	5.76	6.34	6.82	7.16	7.54

Fig. 2 depicts the Average performance of filters in terms of MSE. The average MSE levels of filters are from 1.73 to 15.12 for brass electrodes and 1.79 to 17.97 for copper electrodes. In this comparison the proposed IHMF generates the lowest MSE value of 1.73 and 1.7973. Lowest MSE ensures the better filtering noise. Mean filter produces next better level of MSE value with the average of 1.81 and 1.83.

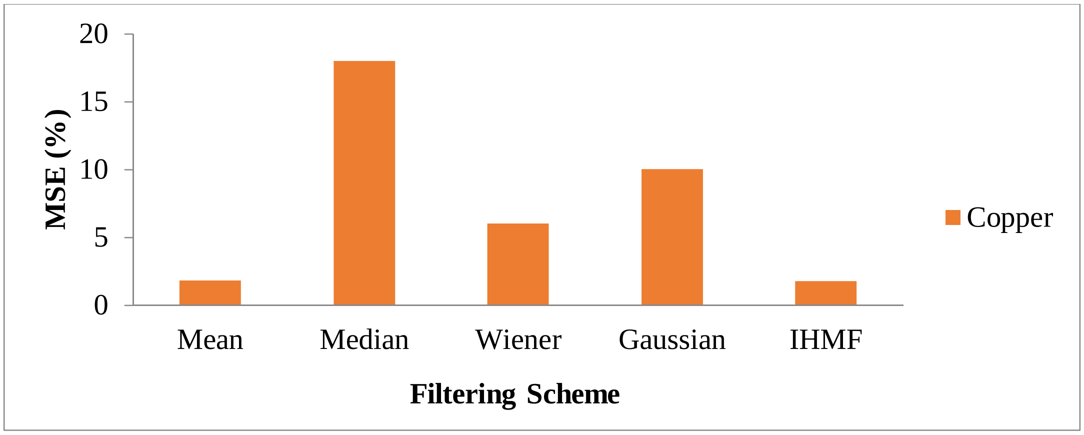

Fig. 2 Average level Mean Squared Error of various filters for brass and copper images

Fig 3 depicts the average performance of filters in terms of MAE. The average MAE levels of filters are from 0.548 to 2.22 for brass electrodes and 0.60 to 2.50 for copper electrodes. In this comparison, the proposed IHMF consequences the lowest level of MAE value and that is 0.54 and 0.60 for brass and copper electrodes respectively. Lowest MAE indicates the better filtering noise. Mean filter produces next better level of MAE value with the average of 0.63 and 0.68.

Fig. 3 Average level Mean Absolute Error of various filters for brass and copper images

In fig. 4, the average performance of filters is depicted in terms of PSNR. These average levels of filters are from 53.71dB to 62.84 dB for brass electrodes and 52.65dB to 62.59 for copper electrodes. In this comparison, the proposed IHMF ensures the highest level of PSNR value and that is 62.84dB and 62.59dB for brass and copper electrodes respectively. The higher the PSNR value authenticates the better noise filtering.

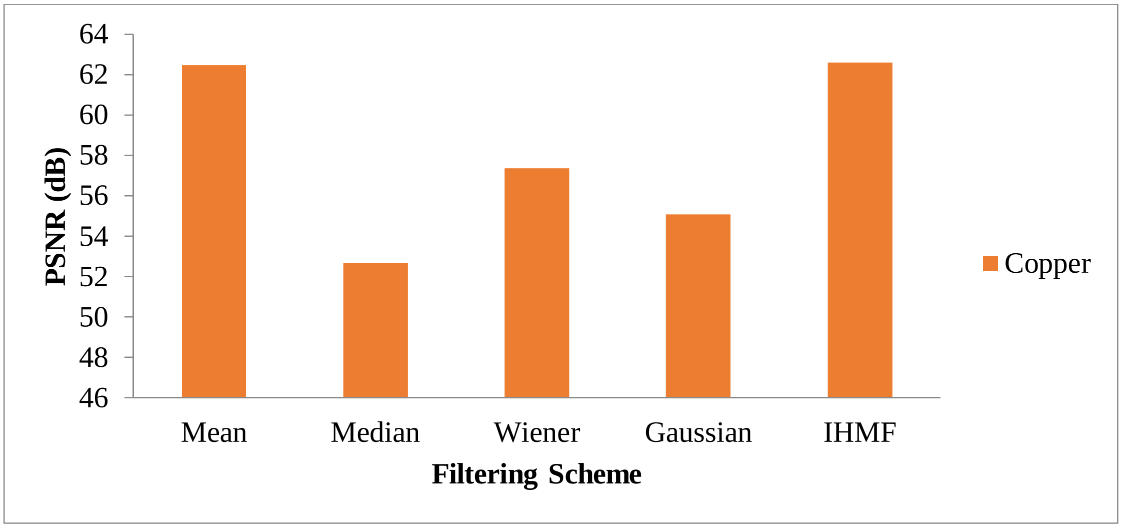

Fig. 4 Average PSNR of various filters for brass and copper images

Fig 5 shows the Entropy of various filters for brass and copper images. These average values of filters lie between 6.673 to 6.77 for brass electrodes and 6.26 to 6.37 for brass electrodes. In this comparison, IHMF consequences the average level of entropy value and that is 6.70 and 6.34 for brass and copper electrodes respectively.

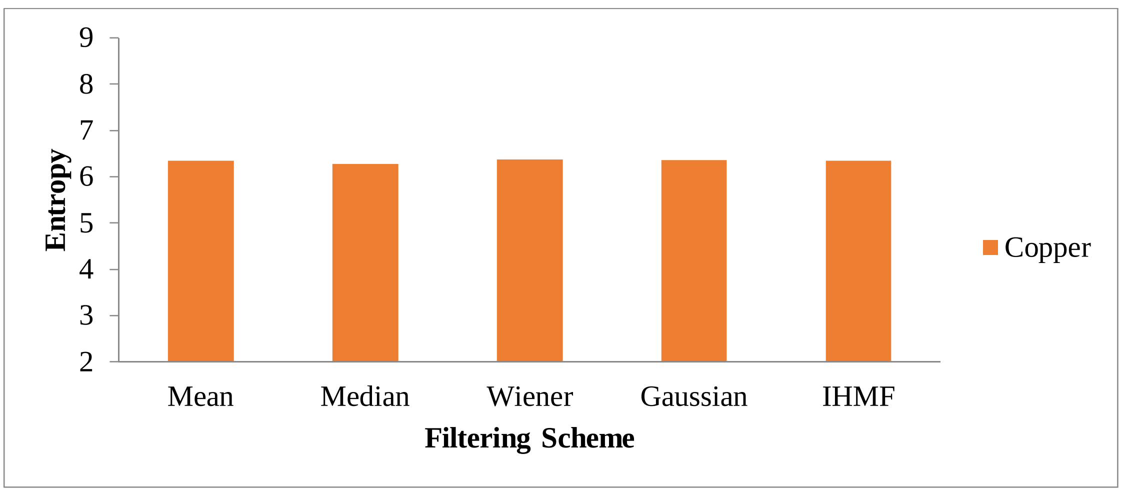

Fig. 5 Average Entropy of various filters for brass and copper images

Fig 6 shows the Entropy-2 of various filters for brass and copper images. It depicts the Average performance of filters in terms of entropy. These average values of filters are lies from 0.14 to 0.15 for brass electrode and 0.18 to 0.109 for copper electrode. In this comparison, IHMF achieves the average level of entropy value as 6.70 & 0.18 for brass and copper electrode respectively.

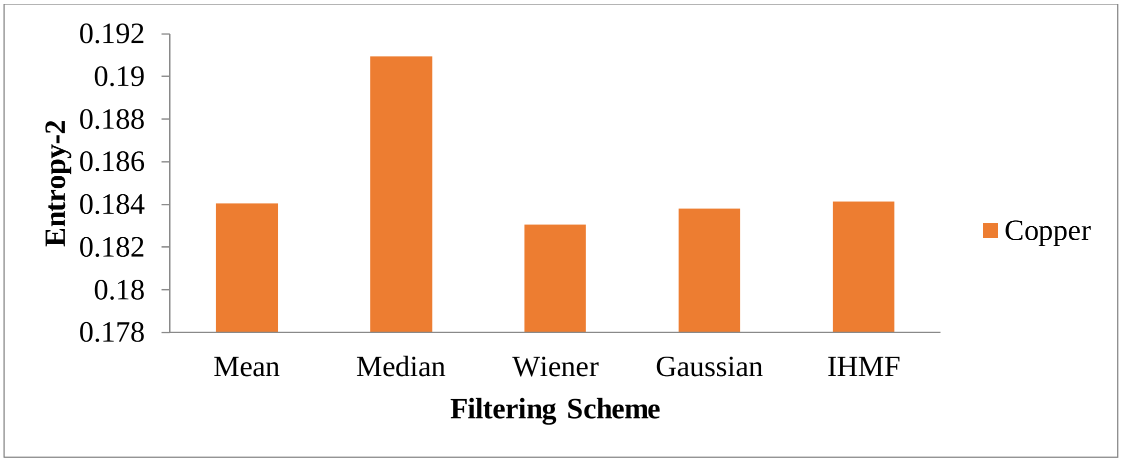

Fig. 6 Average Entropy-2 of various filters for brass and copper images

Fig. 7 demonstrates the SSIM index of IHMF with other filtering approach. The proposed approach achieves better results compared to Mean, Median and Gaussian filters. The average level SSIM value of IHMF approach is estimated as 0.84.

Fig. 7 Average level SSIM of various filters for brass and copper images

In Fig 8 average level IEF for various copper and brass images is demonstrated for all existing filter approach and Improved Hybrid Median Filter. The Estimated IEF values are lies between 0.12 and 1.48 for brass electrode and 0.11 to 1.53 for copper electrode. Among these filters, IHMF produces average IEF value as 1.48 & 1.53 for brass and copper electrode respectively.

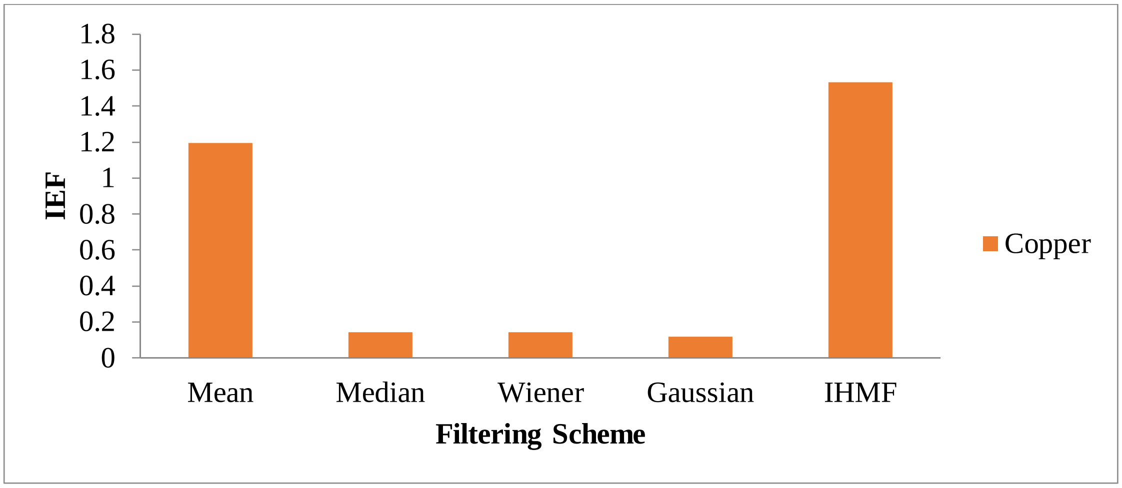

Fig. 8 Average IEF of various filters for copper and brass images

8. Conclusions

The computer aided detection system is designed to identify the cracks present in the electric discharged machined Inconel X750 metal surface images when machined by using copper electrode. In this work, an intelligent scheme is proposed to perform the filtering process in the pre-processing stage by using Improved Hybrid Median Filter (IHMF. In this phase, metal image is acquired and noises from those images are removed using Improved hybrid median Filter (IHMF) which performs the three-step ranking operation from different spatial directions on the image data that offers higher PSNR value of 62.8496dB and the MSE value of 1.73.The performance results show that the proposed IHMF filter outcomes better results compared to Mean filter, Median filter, Wiener filter and Gaussian filter, in terms of Mean Square Error(MSE),Mean Absolute Error(MAE), Image Enhancement Factor(IEF), Entropy, Structural Similarity Index(SSIM) and Peak Signal to Noise Ratio (PSNR).

Among mean, median, wiener, gaussian and proposed improved hybrid median filters, IHMF produces the better results as shown below.

Evaluation Parameter	Copper electrode	Desirable Value
MSE	1.73	LOW
MAE	0.633333	LOW
PSNR	62.8496dB	HIGH
SSIM	0.840567	HIGH
IEF	1.483767	HIGH
ENTROPY	6.34	AVERAGE
ENTROPY-2	0.18	AVERAGE

From the above results, the output of proposed IHMS filter will be used in the next phase i.e segmentation. The results of segmentation and other phases will be presented in future publications.

9. References

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