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Research Article

Feature Extraction of Mold Defects on Fine Arts Painting using Derivative Oriented Thresholding

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ABSTRACT

Paintings can be damaged by natural causes or accidents. One of the crucial natural damages was frequently caused by mold defects. The mold discovery is an important step in the restoration of damaged paintings. The procedure is usually tedious and depends heavily on the qualitative visual judgement of an expert restorer. The aim of this work is to assist the restoration process via an automatic mold defect detection technique based on derivative and image analysis. This new method, designated as Derivative Level Thresholding (DLT), combines binarization and detection algorithms to detect mold rapidly and accurately from scanned high-resolution images of a painting. This work also benchmarks the performance of the proposed method to existing binarization techniques of Otsu's Thresholding Method, Minimum Error Thresholding (MET) and Contrast Adjusted Thresholding Method. Experimental results from the analysis of 20 samples from high-resolution scans of 2 mold-stained painting have shown that the DLT method is the most robust with the highest sensitivity rate of 84.73% and 68.40% accuracy.

1. Introduction

The physical damage on the artwork caused by several factors such as mishandling, high humidity, rapid fluctuations in temperatures and interactions with pollution-dust particles in the air. These factors cause growth of molds, craquelures and other types of wear on the materials especially for improperly stored artworks. If not detected and treated early, it will cause significant irreversible damage to the original painting. However, these defects can be evaluated and subsequently repaired by expert restorers. The flow of the restoration work consists of assessing the current conditions of the paintings, identifying defects and determining the suitable method of repair. Traditionally, restoration processes are conducted manually, relying heavily on the judgment and skills of the restorers. Using the traditional method, assessment and monitoring before restoration is costly, time consuming and depending too much on the skills of the restorers.

To counter this issue, with the advent of technology, computer-assisted scanning and image processing techniques are available to assist in the restoration process. Many researchers focus on nondestructive detection and assessment via vision-based technology as tool to improve productivity, cost and time management.

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These techniques use hi-tech detection methods and computer algorithms to objectively emulate the visual assessment and judgment of the restorers. Imaging technologies for the scanning of 2D artworks includes mass spectrometry[1], photoluminescence spectroscopy [2], x-ray fluorescence analysis[3], and shearography[4]. Imaging data obtained from the scanning of the 2D artworks can then be analysed to extract the required information using techniques such as heuristic graph searching[5], hyperspectral crack detection[6], colorimetry and watershed segmentation[7], and user intervention-based detection methods[8], [9].

Fig. 1 Painting 1 – Ink on Paper

Fig.2 Painting 2 – Ink on Paper

Non-destructive or non-invasive analytical imaging technique is preferable for painting monitoring and assessment. In this context, mesoscopy, enables the recording of details at very high resolutions. Images scanned at high resolution contains accurate colour information that may be discernible to the naked eye. Subsequent processing of the scanned data, such as image segmentations and thresholding, enables identification of features such as defects and inconsistencies. The combined technique of mesoscopy and image analysis have been demonstrated by Win et al [10] in the automatic detection of defects in coated metal specimens for the manufacturing industry. However, the technique has yet to be utilized in the restoration processes of artworks such as drawings and paintings.

This paper proposes a derivative oriented thresholding method for the automated detection of mold on paintings. This method combines two processes of binarization and detection. In the binarization process, the original image is converted into a binary image containing the defects while the detection process identifies the defects using a filtration approach. This newly proposed binarization process is benchmarked with existing thresholding based binarization methods of Contrast Adjusted Thresholding[10], Otsu's Method[11] and Minimum Error Thresholding (MET)[12]. The resulting binary images from these different methods are then filtered in the detection process, where the mold detection results are then compared to a ground truth image. The ground truth image is produced by manually labeling each pixel as either defects or non-defects, based on the feedback from an expert restorer. The accuracy and sensitivity of the detection results are then rated by comparison to this ground truth image.

2. Methodology and Testing

2.1. *Image Acquisition and Sampling*

Two paintings comprising of ink sketches on paper by a well-known Malaysian artist, the late Ibrahim Hussein (1936-2009), were selected as the subject of this study. A Niji-X High-Resolution Scanner (Kyoto University, Kyoto, Japan) was used to scan the paintings at a resolution of 600 dpi. Figure 1 and Figure 2 show the two paintings, designated as Painting 1 and Painting 2. These two paintings were chosen as they contained mold defects.

For mold detection process, the painting images are divided into smaller image samples. A 200 x 200 pixels capture area was assigned for the sample size, which corresponded to a scanned area of 8.4 mm x 8.4 mm on the actual artwork. Thus, each recorded pixel was approximately 42 µm x 42 µm in size. The sampling process has generated a total of 494 sample images from Painting 1 and 391 sample images from Painting 2. However, for the purpose of this study, only 20 image samples containing mold defects were selected, 14 from Painting 1 and 6 from Painting 2.

2.2. *Image Acquisition and Preparation*

The captured images were then converted into grayscale images for pre-processing. The grayscale image can be expressed in L gray levels $[1,2,\ldots,L]$. Each level consists of m points and the total number of points, M, is the sum of m_j where j are the individual levels by: $M = m_1 + m_2 + \ldots + m_L$. In the grayscale images, the mold defects are expected to have gray levels value, s, between 0 (black) and L (white). Figure 3 and Figure 4 shows the selected 20 samples of the originally scanned specimen images containing the mold defects.

Defects extraction from the grayscale images was performed by transforming them into their corresponding binary images. Binarization is carried out by determining the threshold value, t, which is a gray level that divides the images into two sets: C_0 (foreground) and C_1(background). The set C_0 consists of points with gray levels of $[1,2,\ldots,t]$ while C_1(have gray levels of $[t+1, t+2, \ldots, L]$.

As the mold defects are postulated to have gray levels values between 1 to L, determining the correct threshold value is essential for mold defect detection. In this paper, three established image thresholding methods were selected to determine the threshold gray value, t, and for binarization of the images. The image thresholding methods selected are Otsu's Method for Thresholding [11], Minimum Error Thresholding (MET) Method and Contrast Adjusted Otsu Thresholding. The three methods will be compared to the proposed Derivative Level Thresholding method.

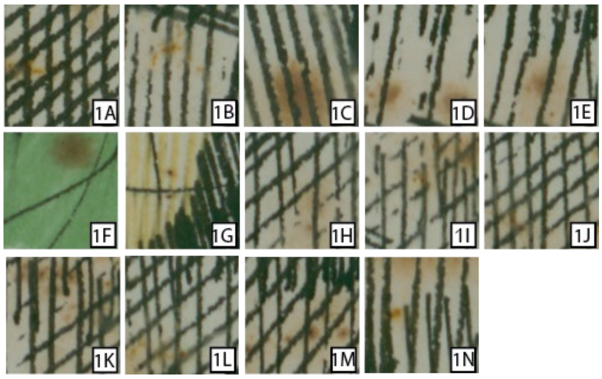

Fig. 3 Samples Selected from Painting 1

2.3. *Derivative Level Thresholding*

A new binarization method which does not produce a threshold level is proposed in this study. Instead, the method derives the final binary image from a combination of binary images that was binarized at different threshold levels. For simplicity, the maximum number of threshold images to be considered is set at 20, which would produce a set of 20 binary images I_j. The binary images are collected by setting the threshold value $t_j = j/20$, where $j = 1, 2, \ldots, 20$.

The resultant image consists of the background and foreground, and the mold defects would be identified in one or more images as black pixels against a white background. The percentage values of black pixels for each 20 images are calculated, and then plotted against the value of $j = 1, 2, \ldots, 20$. The gradient of the curve, y, is calculated by taking its first order derivative, dy/dx,

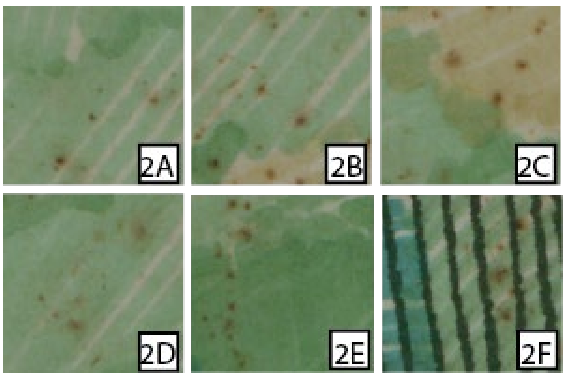

Fig. 4 Samples Selected from Painting 2

yielding a bimodal histogram. Both the curves y and its derivative, dy/dx, is shown in Figure 5 and Figure 6 respectively.

From Figure 5, we can see that the black pixel percentage values increase with the increase in the value of j increases. In the grayscale samples, the molds have grayscale values that are lighter than the artwork strokes but are darker than the background values. This results in the bimodal curve having two peaks that contains the artwork strokes and the background grayscale values, as indicated in Figure 6. The mold defects can be extracted by processing the images in between the two peaks.

Subsequently, the locations of the two peaks, $j_{peak\ 1}$ and $j_{peak\ 2}$, where $j_{peak\ 2} > j_{peak\ 1}$ are then located, from which the number of points, r, is determined. The number of points, r, is calculated by:

$$r = j_{peak\ 2} - j_{peak\ 1} \quad \text{for } j_{peak\ 2} - j_{peak\ 1} > 4 \qquad (1)$$

$$r = (j_{peak\ 2} - j_{peak\ 1}) + 4 \quad \text{for } j_{peak\ 2} - j_{peak\ 1} \leq 4 \qquad (2)$$

For the second case in (2), the value of $j_{peak\ 1}$ and $j_{peak\ 2}$ is modified to value of points $j_{peak\ 1}*$ and $j_{peak\ 2}*$:

$$j_{peak\ 1}* = j_{peak\ 1} - 2 \qquad (3)$$

$$j_{peak\ 2}* = j_{peak\ 2} + 2 \qquad (4)$$

where $j_{peak\ 2}* > j_{peak\ 1}*$ to supply two additional points for the case so that $r > 4$, while for the case in (1), the value $j_{peak\ 1}* = j_{peak\ 1}$ and $j_{peak\ 2}* = j_{peak\ 2}$.

The next step is to produce subtracted binary image, I_s, from every combination point pairs possible, from $j_{peak\ 1}*$ to $j_{peak\ 2}*$. The total number of point pairs, R, is calculated by:

$$R = \frac{r!}{2!(r-2)!} \qquad (5)$$

The process can be explained in a pseudocode form as follows:

ALGORITHM 1: PSEUDOCODE

BinaryImage $\boldsymbol{I_n}$;
SubtractedBinaryImage $(\boldsymbol{m})$;
NumberOfPoints **R**; //From Equation (1) and (2)
ModifiedFirstPoint $j_{peak\ 1}*$;
ModifiedSecondPoint $j_{peak\ 2}*$;

for $m = j_{peak\ 1}*: j_{peak\ 2}*$
  for $n = 1: \boldsymbol{R}$
  $S(m) = I_{n+1} - I_n$
  end
end
...

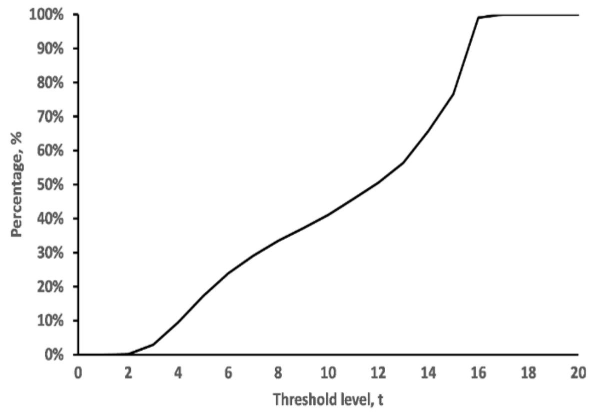

Fig. 5 Percentage of black pixel value, y

The percentage of black pixels of the resulting images

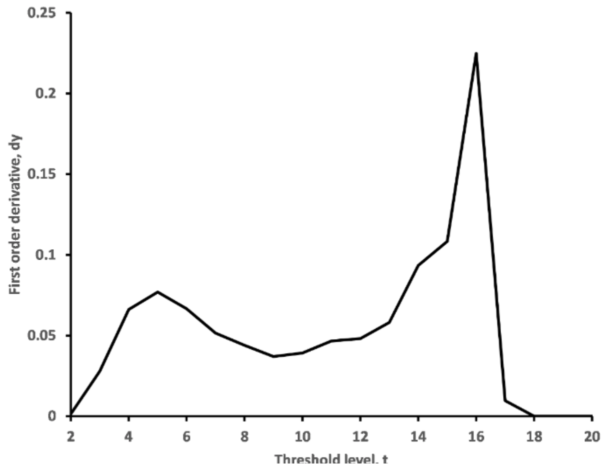

Fig. 6 The derivative of curve y, dy/dx

$S(m)$, where $m = 1, 2, \ldots, R$, is then plotted and analyzed. The resulting curve, designated as y_2, has multiple peaks and valleys culminated from different sets

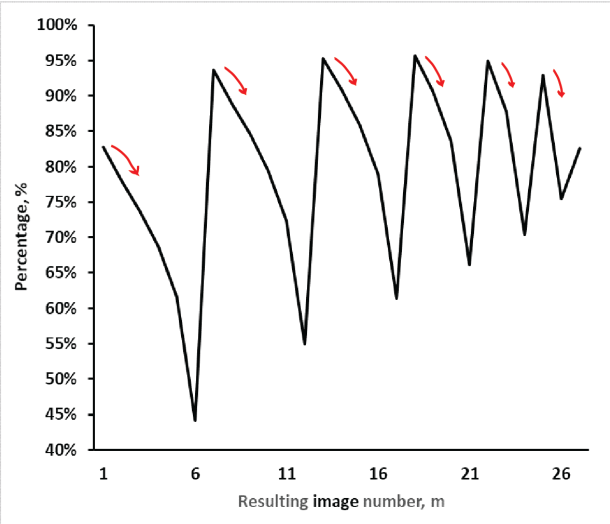

Fig. 7 Curve y_2 showing the peaks and valleys as a results of the image subtraction process.

of pairing between points. Curve y_2 is then plotted, as shown in Figure 7.

Curve y_2 is a 6 results series (indicated with arrows) can be identified where each series begins with a maximum value of black pixel to its minimum, and is separated with a straight line connecting the current series to the next. Ideally, some of the resulting images, $S(m)$, are adequate to be used in identifying the molds. The image that fit this criterion is called the optimized subtracted image, I_s. To obtain the optimized subtracted image, I_s, with visible mold defects image, the corresponding m values are determined. The m values for obtaining the optimized subtracted image, S, is designated as m_s. The average values for all the peaks, q_{ave}, and valleys, v_{ave}, in the y_2 curve are calculated as follow:

$$q_{ave} = \frac{q_1+q_2+\cdots+q_N}{N_{peaks}} \tag{6}$$

$$v_{ave} = \frac{v_1+v_2+\cdots+v_N}{N_{valleys}} \tag{7}$$

The two values derived from both equations cannot be used to determine the value of m directly, as the average value may not be positioned on the y_2 curve. The values of q_{ave} and v_{ave} would be used to calculate the closest value for m_s which is:

$$m_s = round\left(\frac{m_{UL}+m_{LL}}{2}\right) \tag{8}$$

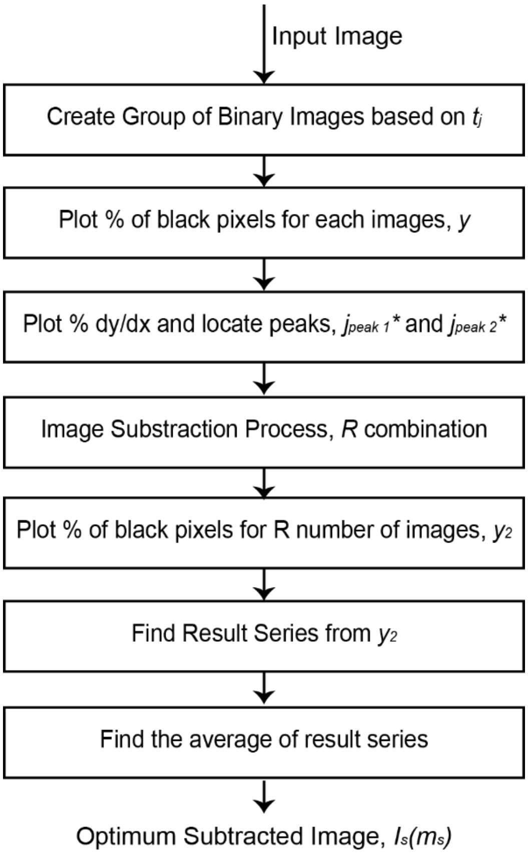

Fig. 8 Flow Diagram of the Derivative Level Method

where the lower limit, m_{LL}, is determined by finding the lowest m value that corresponds to the valleys, v, such that $y_2(m_{LL}) > v_{ave}$ and the upper limit, m_{UL}, is determined by finding the highest m value that corresponds to the peaks, q, such that $y_2(m_{UL}) < q_{ave}$. The obtained value is then rounded to the nearest integer to get m_S.

Finally, the binary subtracted image used for defect detection can be obtained from the labeled image $I_S(m_S)$. The flow diagram shown in Figure 8 summarizes the overall process of the Derivative Level Thresholding.

2.4. *Defect Detection and Analysis*

Filtering and defect analysis can also be conducted on the binary images to locate and characterize defects. In a black and white image, the defects are represented by the white pixels.

2.4.1. Connected Component Filtering for Noise

Figure 9 shows the overall image processing for the defect detection which comprises of the process after the Derivative Level Thresholding has been carried out, as well as after the other selected thresholding methods. Once the binarization is complete, the connected component filtering then be conducted. Prior to the filtering process, a connected component analysis using flood-fill algorithm is performed to locate groups of pixels. In this process, an unlabeled pixel is first located and a flood-fill algorithm is used to label adjacent pixels to be in the same group. In this study, 4-connected neighborhood component is used to determine pixel grouping. Each pixel group will be represented with a size, A_k, measured in unit pixel. The connected components are first filtered according to size, and the first filter will only store pixel groups that are larger than a_{min} and smaller than a_{max}:

$$a_{min} < A_k < a_{max} \quad (9)$$

Single pixels will not be stored, as well as group of pixels that are connected in diagonals. The value of a_{min} is set to 20 while a_{max} is set to 5000 pixels. Next, the selected group of pixels will be refined using a hole filter.

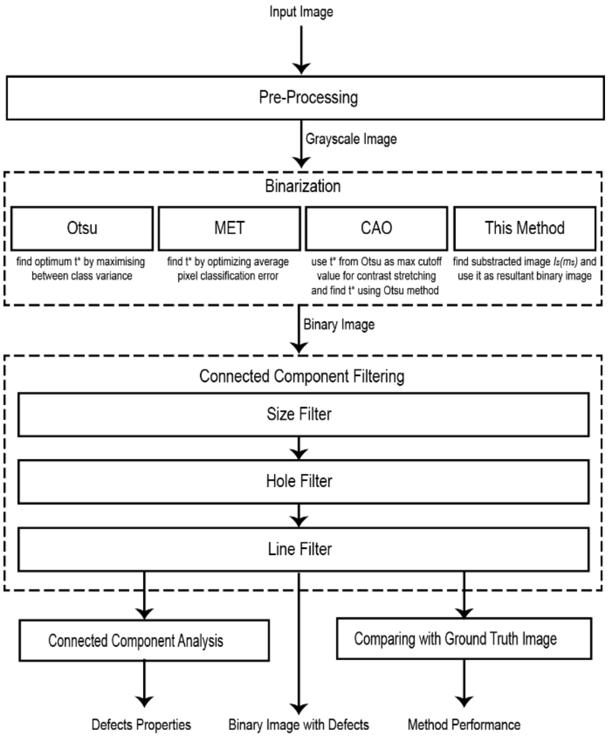

Fig. 9 Flow Diagram of the overall image processing for the defect detection.

The hole filter works by filtering group of pixels which have a difference of filled image area, A_{filled} to image area, A_k, that is larger than a preset scale threshold value. A filled image area is the total number of pixels in the same group of pixels with holes filled. By using this hole filter, group of pixels with holes will be filtered out. In this study, the hole filter threshold value is set at 0.1. This means that the group pixels with difference in size of

Table 1 Defect Detection Performance for Sample 5

No.	Binarization Method	Number of Defects Detected	Number of Defects Correctly Detected	Total Defect Surface Area (pixels)	Percentage of Defects (%)
1	Otsu's Method	9	1	13662	33.82
2	Minimum Error Thresholding (MET) Method	7	3	17099	42.32
3	Contrast Adjusted Thresholding Method (CA)	12	1	9614	23.80
4	Derivative Level Thresholding (DLT)	10	3	16614	41.12
5	Ground truth*	3	3	891	2.21

10% and more between A_k and A_{filled} will be filtered out, as they are confirmed to have holes.

The filter is calculated by:

$$\frac{(A_{filled}-A_k)}{A_k} \quad (10)$$

Subsequently, a line filter is also applied on the images. In this process, the pixel group is accepted when it has an area to perimeter ratio of more than 0.6. This filter will eliminate lines - which will usually have a low area to perimeter ratio, ranging from 0.1 to 0.5, especially for straight lines.

2.4.2. Connect Component Analysis for Mold Characterization

The selected group of pixels are then remapped into the final binary image and are subjected to another connected component analysis using a similar 4-connected neighborhood connected component analysis approach. Data on defect properties such as the area size (in pixels), centroid (location) and morphology are collected for comparison. The defect detection is carried out for the newly proposed Derivative Level Thresholding method and the three existing thresholding methods. The results obtained are then compared to determine their relative performance.

3. Results and Discussions

In this study, the proposed Derivative Level Thresholding is compared with three existing binarization by thresholding methods. These methods are implemented in MATLAB R2016a and computed on an Intel(R) Core™ i7-4500U 1.80GHz processor with 8GB RAM on a Windows 10 Pro platform. The images captured using mesoscopic technique are processed using the selected binarization methods in accordance to the flow diagram in Figure 8.

The comparative performance of all four methods were evaluated experimentally for detecting mold defects on the selected artworks. 20 samples were selected from different locations on the scanned image of the artwork with known mold locations from both the original painting image and the restored painting image. The respective ground truth images are also obtained to compare the performance of each thresholding and detection method. The results will be presented in two sections – the first section will focus on Sample 1E which originated from Painting 1. The second section is an overview of the results obtained from all 20 samples that consists of samples from Painting 1 and Painting 2.

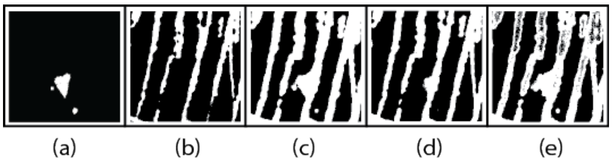

Fig. 10 Binary Images of Sample 1E from left: (a) Ground Truth Binary, and results of (b) Contrast Adjusted Thresholding, (c) MET, (d) Otsu and the (e) proposed Derivative Level Method.

3.1. *Sample 1E Results*

As the images are captured at a resolution of 650 dpi, the sizes of each pixel are approximately $1.6nm^2$. The variation in the size of defects of on Sample 1E ranges from 4.8 nm^2 to 705.6 nm^2. Figure 10 shows the comparison of the binarization results from the four methods. The results images visibly suggested that the results for the proposed method has included the defects in the resulting binary image, along with false positives.

The results are compared to a ground truth image indicated in Figure 10(a) to confirm the accuracy and sensitivity of the defect detection performance of the various binarization methods. The ground truth is represented as an image that is manually produced from the feedback of expertise on the actual amount of mold defects. This is used as the benchmark to compare the performance of each method using their resultant defect images. The sensitivity and accuracy of the binarization methods can be calculated by comparing the detection results with the data from the ground truth image. The sensitivity or true positive rate is determined as:

$$Sensitivity = \frac{TP}{TP+FN} \quad (11)$$

and the accuracy is determined as:

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (12)$$

where TP is True Positive, FP is False Positive, FN is False Negative and TN is True Negative.

As the binary images were processed with the Connected Component Filtering it can be said that while the Derivative Level Thresholding is robust with higher sensitivity (96.75%) and accuracy (60.94%) to MET method in the case of defect detection in Sample 1E.

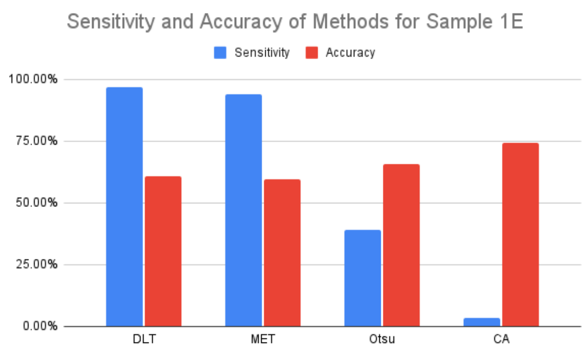

Fig. 11 Sensitivity and Accuracy level of Methods for Sample 1E

Table 1 summarizes the defect detection results from Sample 1E with Figure 11 presenting the comparison in graph.

Table 1 shows the detect detection performance of the newly proposed method with comparisons to Otsu's, MET and Contrast Adjusted Thresholding methods for the analysis of Sample 1E. The ground truth values, showing the actual size and number of defects, are also included for comparison. The results show that the Derivative Level Thresholding has managed to correctly identify all 3 defects with lesser false positive as compared to the MET method. This can be seen in Figure 10(e) when compared with the ground truth image in Figure 10(a).

3.2. *Thresholding Method Overall Performance*

To measure the overall performance of the methods, 20 samples were selected from Painting 1 and Painting 2. 14 samples from Painting 1, and 6 from Painting 2 were selected in this overall evaluation. As shown in Figure 3 and Figure 4, the samples selected depict different types of artwork details comprising of different stroke thicknesses and colors. This is purposely chosen as a fair indicator on the general performance of all four methods. The robustness of each method used in mold defect detection can be determined from the calculated values of the accuracy and the sensitivity.

The results showed that the newly proposed Derivative Level Thresholding method has performed better than the

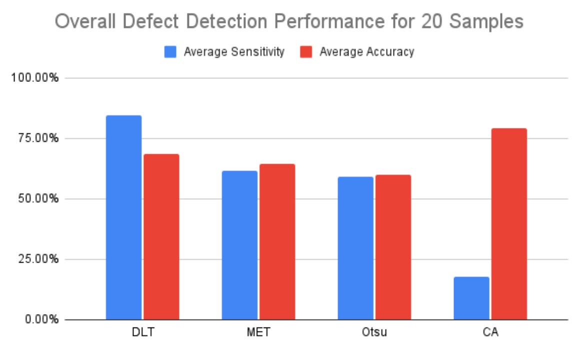

Fig. 12 Overall Defect Detection Performance for 20 Samples

three existing binarization methods. The DLT method has the highest average sensitivity at 84.73% as compared to the other methods having average sensitivity values ranging from 17 – 61%. DLT also has a high average accuracy 68.40%, second only to the Contrast Adjusted Thresholding Method with the latter having the lowest average sensitivity value. The average accuracy for DLT is also higher than the accuracy value discussed for Sample 1E. The study has also found that the value of accuracy for the DLT method is generally higher in samples that has less thick strokes.

From the results shown in Figure 12, it can be deduced that the Derivative Level Thresholding Method is efficient in detecting mold defects. The high sensitivity value means that the binary image produced by the DLT method was able to correctly detect the defects, while the lower accuracy value indicate it has successfully done so at a cost. The method has considered more pixels in the samples as defects, resulting in higher false positive values, thus lowering the accuracy.

This problem can be addressed by having a better filtering after the binary image has been produced, sufficient to reduce false positives while at the same time ensuring that actual defects do not get filtered out. In the future, a better way of classifying the binary images resulting from the methods is required, as it can be concluded that the rudimentary filtering suggested in this study is not fully capable of avoiding false positives in the mold defect detections. The accuracy can be increased by considering all the defects detected separately, rather than using a blanket filtering approach.

In addition, instead of treating the results from the methods suggested in this study as the final mold defects, they can be treated as features extracted that can be used in machine learning methods to correctly classify the mold defects and non-molds. This will improve the final mold detection results and reduce the error generated from the restored image samples.

4. Conclusions

An automatic mold defects detection method, the Derivative Level Thresholding (DLT) Method has been developed to locate mold-type defects on high resolution scanned images of artwork paintings. The performance of this newly proposed method was compared to three existing common binarization methods for the evaluation of the 20 samples. It was found that the DLT method is better in terms of average accuracy (up to 68%) and has the highest average sensitivity of 84.73%. In general, the DLT method is shown to be robust and effective in distinguish molds from various types of painting samples. The methods suggested in the study can be further developed with machine learning methods to optimize their performance.

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References

1. Kokkinaki, O., et al., Comparative study of laser induced breakdown spectroscopy and mass spectrometry for the analysis of cultural heritage materials. Journal of Molecular Structure, 2013. **1044**: p. 160-166.
2. Feng, Y.Q., N.N. Wang, and H.X. Ju, Highly Efficient Electrochemiluminescence of Cyanovinylene-Contained Polymer Dots in Aqueous Medium and Its Application in Imaging Analysis. Analytical Chemistry, 2018. **90**(2): p. 1202-1208.
3. Galli, A. and L. Bonizzoni, True versus forged in the cultural heritage materials: the role of PXRF analysis. X-Ray Spectrometry, 2014. **43**(1): p. 22-28.
4. Buchta, D., et al., Artwork Inspection by Shearography with Adapted Loading. Experimental Mechanics, 2015. **55**(9): p. 1691-1704.
5. Luo, Z.H., et al., Extraction of microcracks in rock images based on heuristic graph searching and application. Computers & Geosciences, 2015. **85**: p. 22-35.
6. Deborah, H., N. Richard, and J.Y. Hardeberg, Hyperspectral Crack Detection in Paintings. 2015 Colour and Visual Computing Symposium (Cvcs), 2015.
7. Guarneri, M., et al., 3D remote colorimetry and watershed segmentation techniques for fresco and artwork decay monitoring and preservation. Journal of Archaeological Science, 2014. **46**: p. 182-190.
8. Desai, S.D., et al., User Intervention Based Detection & Removal of Cracks from Digitized Paintings. 2014 Fifth International Conference on Signal and Image Processing (Icsip 2014), 2014: p. 15-19.
9. Desai, S.D., et al., Detection & Removal of Cracks from Digitized Paintings and Images by User Intervention. 2013 Second International Conference on Advanced Computing, Networking and Security (Adcons 2013), 2013: p. 51-55.
10. Win, M., et al., A Contrast Adjustment Thresholding Method for Surface Defect Detection Based on Mesoscopy. IEEE Transactions on Industrial Informatics, 2015. **11**(3): p. 642-649.
11. Otsu, N., A threshold selection method from gray-level histograms. Automatica, 1975. **11**(285-296): p. 23-27.
12. Kittler, J. and J. Illingworth, Minimum Error Thresholding. Pattern Recognition, 1986. **19**(1): p. 41-47.

Authors Introduction

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Hilman Nordin received the B.Eng degree in computer-aided design and manufacturing engineering and the M.Eng.Sc. degree in mechanical engineering (mechanical systems) from Universiti Malaya, Kuala Lumpur, Malaysia in 2009 and 2013, respectively. He is currently a Ph.D. candidate at Universiti Malaya. His research interest include image processing and analysis, high-resolution scanning and its industrial applications and mechanical systems.

Prof. Dr. Bushroa Abd Razak

Prof. Datin Ir. Dr. Bushroa Abd Razak received her B.Eng. in Electrical and Electronic Engineering from University of Manchester Institute Science and Technology, UK in 1997, which was merged to Manchester University. Consequently, she received her Master in Engineering Science and PhD from University of Malaya, Malaysia in 2004 and 2012, respectively. She started her career in 2004 at the Department of Engineering Design and Manufacture, UM, and later in 2013 at the Department of Mechanical Engineering in the same university when both departments were merged. Apart from teaching, she is actively involved in research, management and consultation works. In the late of 2020, she was appointed as a Head of Department of Mechanical Engineering, University Malaya. During her tenure, she has contributed impactful in securing the Engineering Accreditation Council (EAC) as well as revising new curriculum review for courses in Mechanical Engineering. She holds a few memberships including a board member of Advanced Manufacturing and Material Processing Centre, UM. She is awarded a Chartered Engineer of IET, UK. In July 2016, she was promoted to Associate Professor. In 2015-2016, she went to Univ of California, LA, USA for her post-doctoral research program sponsored by the Ministry of Higher Education, Malaysia. She was also awarded as a Professional Engineer by the Board of Engineers (BEM) in March 2017. Till now, she is the author and co-author of more than 100 publications in international journals and proceedings with H-index reaches above 25. Her research interest includes fundamental, application, technology and commercialization in Surface Engineering and its related field of study. She is passionate in research that contributes to society.

Dr. Norrima Mokhtar

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