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Morphological Edge Detection Algorithms on the Noisy Car Image Database

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***Abstract*— Development of edge detector using mathematical morphology can provide remarkably more precise edge detection. This system mainly focuses on edge detection of cars. This paper uses car database for the early detection in automatic traffic law enforcement. The methodology for accurate edge detector includes grayscale image conversion, median filter, element structures formation, mathematical morphology, synthetic weighted and segmentation using Otsu method. The morphological operation that was used in this study is basic operation such as dilation and erosion. The use of morphological operation was to find the limits and the image terminals by selecting different size and extensions converted to images of grey levels and the results were compared to determine the most suitable and better methods. In this study, 371 car databases and 100 objects from the publicly available Berkeley and Greek car databases were used as data. This methodology is proved highly accurate 0.7-1.58% higher than Canny edge detector. The accuracy of the results from Mathematical Morphlogy Edge Detection were 83.23%; 83.27%; 82.66%; 79.78% while the results from Canny Edge Detection were 81.90%; 82.08%; 81.08%; 79.71%. In comparison with the results from Canny edge detector. It shows that mathematical morphology renders better overall performance. It was also tested with salt and pepper noises and still shows better results. Z-test was used for comparing the means of two populations while F-test was used to test if two population variances are equal. Both tests were done because in this study two populations were used as main datasets. The effectiveness and robustness make this mathematical morphology method a suitable tool to be integrated into complete pre-screening systems for the early detection in automatic traffic law enforcement.**

***Kata kunci*— Canny, Edge detection, Mathematics morphology, Structure elements**

I. PENDAHULUAN

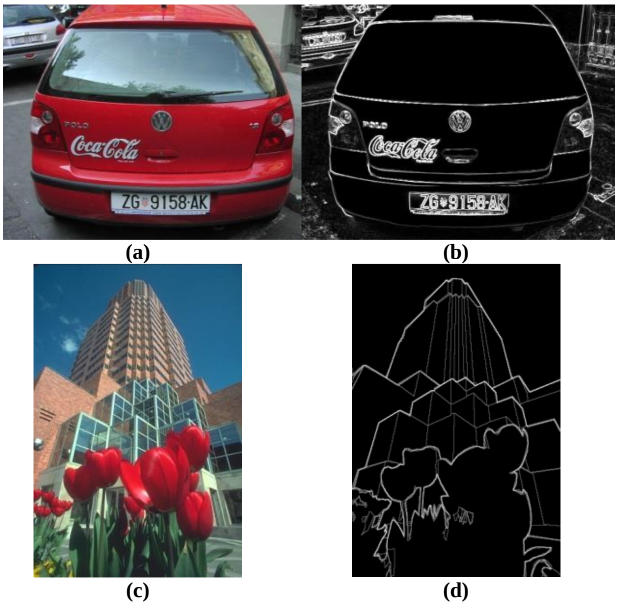
Edges in a digital image mean that there is information about boundaries of the object in the image. The edge detection of an image should erase useless information such as noise while retaining important information in the image. Edge detection has a substantial role in image analysis. Based on image analysis needs, edge detection is an important step in pre-processing image analysis. Dina et al [1] and Mousa et al [2] used edge detection as a preliminary process before performing an image segmentation to identify each character in the vehicle license plate, the edges caught played an important role in getting the segmentation result. Some other researchers used dental images to classify dental problems based on the edge-detected images [3], the other researchers like [4] used the edge-detected-car-images to calculate the number of vehicles on road. If the edge detection result is not accurate enough, then the further process will not produce the best result. Therefore, edge detection becomes one of the most substantial task in image processing.

Conventionally, mathematical morphological edge detection method uses a single element structure and symmetric element structure. But it is a tough job to detect complicated edge features of images, as those features are not sensitive to the image edges if they do not have similar direction of element structure. Rani et al [5] implemented various morphological operators in examining medical images. She used erosion, dilation, opening and closing. The result is better than traditional operators. The output has continued edges. Na'am et al used Multiple Morphological Gradient Method to identify the caries in dental images [6]. They also used erosion and dilation to enhance the intensity of the edges. In this paper, many kinds of image processing problems are handled by the implementation of mathematical morphology. An arithmetic set is used to define mathematical morphology's operation. Some basic morphological operations for example erosion, dilation, opening, closing are used to detect, modify, and manipulate features present in images. In this paper, to detect the edge of the image using morphology algorithm of multi structure elements.

The classic method of edge detection uses different operators such as Prewitt operator, Sobel operator, Robert Cross edge operator, Robinson, and FreiChen. Then another Gaussian-based method which are some optimal Edge Detection methods for example Laplacian, Canny and the ISEF algorithm [7]. Among those Gaussian based method algorithms, Canny is the most well-known even though this method is not perfect as it also has shortcomings just like in every other method. Yingke feng [8] stated that the disadvantage of Canny algorithm are a poor self-adaptability threshold, and more sensitive to noise. Because of those reasons, Yingke Feng et al [8] modified Canny algorithm into new edge detection method. Cao et al [9] stated that the Canny operator is widely used to detect edges in images. Kanika [3] used Laplacian edge detection technique to sharpen the edges of the dental image. Also, there are many researchers who have improved edge detection methods.

In this article, we propose a method that can detect edges using mathematical morphology on specific images. Afterwards, the accuracy will be calculated and tested to measure the performance of the method on noisy images. The Canny method was used to compare the mathematical morphology method. Salt and pepper noise is added to the images. Since there are several levels in the salt and pepper noise, we used three different levels, such as 0.2;0.4;0.4. Then, images will be tested using mathematical morphology and Canny methods. More details of material and methodology will be explained in Section 2. Statistic test is used to test the performance and significance.

This paper is structured as follows: Section 2 explains the overall material and methods of the proposed system. It also presents the steps by which images are processed. In Section 3, we present results of our experiments in each different scene and compare our results with an existing method. All the experimental process is completed using Matlab version R2016a. The conclusion and possible future work are explained in Section 4.



(a) (b) (c) (d)

Fig. 1 Example of database used (a) Car database (b) Ground truth Car database (c) Berkeley database (d) Ground truth Berkeley database

II. METHODS

To evaluate the edge detection algorithm using mathematical morphology described in next subsection, we present two groups of publicly available car images from Greek, which can be accessed in http://www.medialab.ntua.gr/research/LPRdatabase.html and object images from The Berkeley Segmentation Dataset and Benchmark, which is accessible in the following address http://www.eecs.berkeley.edu/Research/Projects/CS/vision /bsds/BSDS300/html/dataset/images.html. These databases contain 371 and 100 images respectively. The ground truth of car images was obtained by the authors manually using image processing tools, but the ground truth of object image database from The Berkeley Segmentation Dataset and Benchmark is also provided. Both databases contain colour images. The total number of images processed in the article was 471. The example of colour images and each ground truth from the Greek car and Berkeley databases are shown in Fig. 1.

This work is aimed at introducing a methodology for better results of object edge detection processed in segmentation phase. The segmentation phase will not be discussed in this work. Further work to discuss it more details is yet to be done. The performance of the methodology was tested under particular conditions: Salt and Pepper Noise level 0.2; 0.4; 0.4. The noises had been added to the images. The general process may be identified as follows: (1) Conversion from color images to grayscale images; (2) Pre-process using median filter; (3) Formation of eight directions of the element structure; (4) Mathematical morphology; (5) Synthetic weighted; (6) Segmentation using the threshold Otsu method. The illustration which is used to simplify the stages is shown in Fig. 2. In general, the method of edge detection of Multi Structured Elements has several steps as shown in Fig. 2.

A. *Convertion color images to grayscale images*

The original image which used as an input is color images but the algorithm requires grayscale images. So, the imaged was pre-processed before undergoing the main proses. Grayscale image is easy to be simplified by algorithm and also it reduces the steps in order to fulfill computational requirements [10].

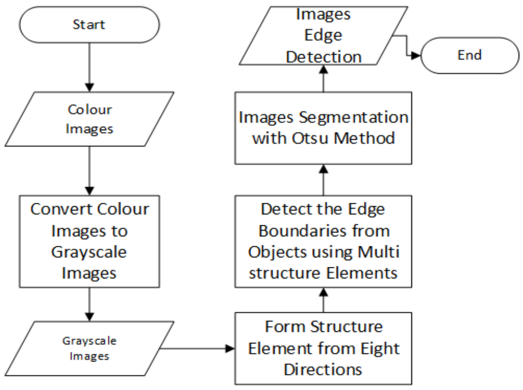


Fig. 2 System flowchart

B. Pre-process median filter

The first step of the system is the pre-processing of the input image using the Median Filter, so that no error occurs in the classification of regions in the input image. To reduce noise, Median Filter is used because of its effectivity in reducing noise. In the experimental scenario is presented in chapter 5

A trial scenario is conducted on the database image with Salt and Pepper noise with a level of 0.2, 0.4, 0.6. Therefore, Median Filter is used as the pre-process of input image. To remove Salt and Pepper noise then Standard median filter is used [11].

C. The formation of eight directions of the element structure

The process of formation of eight-way element structure is one of the main stages of this system. Each structure of the elements to be used is formed from eight types of line element structures, whose degree of direction in each line element structure is = 0^0, 22.5^0, 45^0, 67.5^0, 90^0, 112.5^0, 135^0, 157.5^0. The first step in the formation of the structure of the elements, eight-way element is to form each element structure in each degree of direction to obtain eight elemental structures [12][13]. Eight types of elements structure of the eight directions can be seen in Fig. 3.

1	1	1	1	1

(a)

0	0	0	1	1
0	0	1	0	0
1	1	0	0	0

(b)

	0	0	0	
0	0	0	1	0
0	0	1	0	0
0	1	0	0	0
1	0	0	0	0

(c)

0	0	1
0	0	1
0	1	0
1	0	0
1	0	0

(d)

1
1
1
1

(e)

	0	0
1	0	0
0	1	0
0	0	1
0	0	1

(f)

1	0	0	0	0
0	1	0	0	0
0	0	1	0	0
0	0	0	1	0
0	0	0	0	1

(g)

1	1	0	0	0
0	0	1	0	0
0	0	0	1	1

(h)

Fig. 3 Structure Elements Eight Direction (a) Strell line 0^0 (b) Strell line 22.5^0 (c) Strell line 45^0 (d) Strell line 67.5^0 (e) Strell line 90^0 (f) Strell line 112.5^0 (g) Strell line 135^0 (h) Strell line 157.5^0

D. Mathematical morphology

In this process, the image edge detection process uses eight elemental structures that have been formed in the previous process. We used mathematical morphological methods to detect the edges of images [12][13]. The stages of mathematical morphology are described in (1) and (2).

$$M = (G \bullet S) \circ S \quad (1)$$

$$MGED = (M \bullet S) \oplus S - M \bullet S \quad (2)$$

At (1) the closing operation of the grayscale image to generate the first elemental structure is followed by an opening operation to the same element structure. After Equation (1) is completed then we proceed to (2). The resulted image in the closing process is then undergone a dilation. The result is deducted with the closing results. Indra et al used dilation as a morphological process to expand the area or size of an object [14]. At this stage the structure of the elements used is still the same. This process is repeated over the structure of the eight-way element. The total number of the mathematical morphology stages was eight because there are eight types of structural elements based on the degree of direction. The final results are eight mathematical morphological images.

E. Synthetic Weighted

In this process, after the eight mathematical morphological results are obtained, the next step is to obtain the end result of image edge detection, one of which is using the method of Synthetic Weighted. Each resulted image of edge detection from a mathematical morphological method correlates with the number of elemental structures used. The equations of the Synthetic Weighted method are shown in (3) and (4).

$$E(F) = \sum_{i=0}^{M} W_i E_i(F) \quad (3)$$

$$W_i = 1/ M \quad (4)$$

where:

$E_i(F)$ = the result images after mathematical morphology edge detection has been applied.

M = the number of structured elements.

F. Segmentation with threshold Otsu method

The final process of the system is to distinguish objects and background objects. Otsu method used to segment the gray digital image into black (foreground) and white (background) digital images to generate black and white images [15].

G. Pseudocode for testing the accuracy

Comparison of the predictive image and the ground truth image is made to calculate the accuracy. The predictive images are binary image consisting of 0 and 1. It is same as the ground truth images which is also a binary image. There are four criteria: true positive, false positive, true negative, false negative. The term of each criteria as follows:

```
Testing Accuracy
Input: himage(i,j); img(i,j)
Output: accuracy
tp = 0;
fn = 0;
tn = 0;
fp = 0;
for i=1:xImg
    for j=1:yImg
        if himage(i,j) == 1 && img(i,j) == 1
            tp = tp + 1;
        End
    End
End
for i=1:xImg
    for j=1:yImg
        if himage(i,j) == 0 && img(i,j) == 1
            fp = fp + 1;
        End
    End
End
for i=1:xImg
    for j=1:yImg
        if himage(i,j) == 1 && img(i,j) == 0
            fn = fn + 1;
        End
    End
End
for i=1:xImg
    for j=1:yImg
        if himage(i,j) == 0 && img(i,j) == 0
            tn = tn + 1;
        End
    End
End

accuracy= (tp+tn)/(tp+tn+fp+fn)*100;
```

III. RESULT AND DISCUSSION

A series of experiments have been done to verify the algorithm used in this paper. In order to verify the mathematical morphology edge detection algorithm, eight groups of comparative experiments are carried out. Two algorithms are used to detect edges: mathematical morphology edge detection and Canny edge detection. Also, there are two different groups of images, the first group were 371 images from Greek car repository and the other one were 100 images from Berkeley. To validate the mathematical morphology edge detection as the main edge detection method , we compared it with a Canny edge detection algorithm. We added four conditions to the group, images without noise and other three images with level 0,2;0,4;0,6 salt and pepper noises. To evaluate the different algorithms the the result are compared with the ground truth quantitively. All the edge detection's works are done using Matlab R2016a.

A. Experiments on edge detection

Two groups of experiments are conducted for the edge detection using mathematical morphology. The first group is a Greek car image group as shown in Fig. 4, 6, 10, 11. The second group of experiments is Berkeley images as shown in Fig. 5, 7, 9, 12. Some examples of these images have been discussed in Section 3. However, for the convenience of comparing, we put them here again. Fig. 6(a) is the color image figures downloaded from Greek car images (http://www.medialab.ntua.gr/research/LPRdata-base.html). While the second group is Berkeley images which were downloaded from The Berkeley Segmentation Dataset and Benchmark (http://www.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/BSDS300/html/data-set/images.html). One of the color images from the second group is in Fig. 7(a).

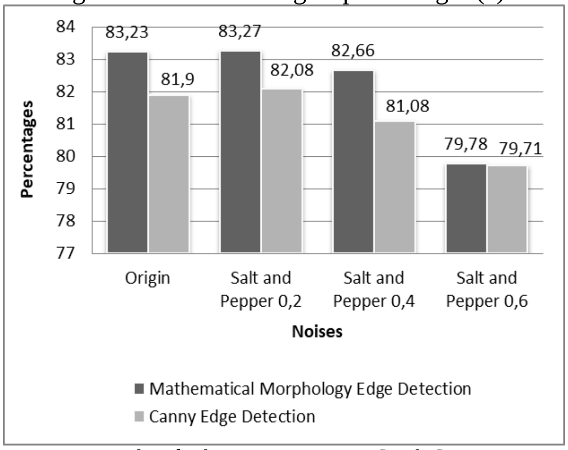


Fig. 4 Results of Edge Detection using Greek Car Images

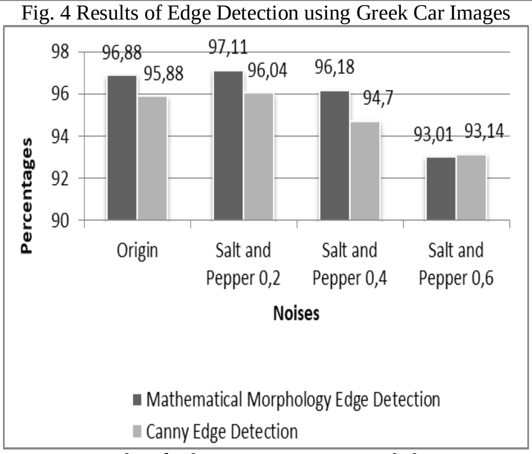


Fig. 5 Results of Edge Detection using Berkeley Images

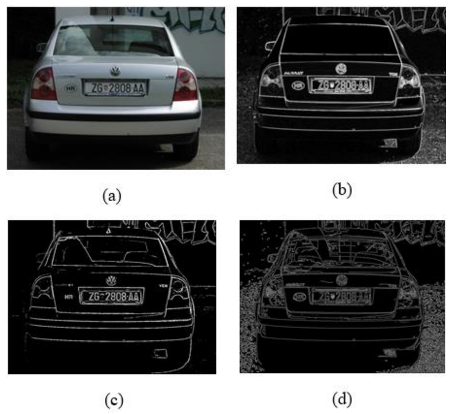


Fig. 6 First group from Greek car images of edge detection experiments with different algorithms (a) Color image (b) Ground truth image (c) Result by using Mathematical Morphology (d) Results by using Canny operator

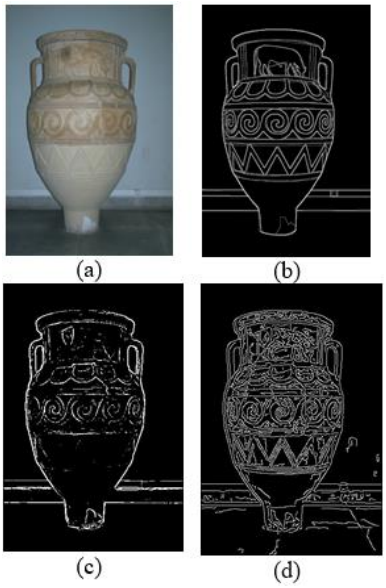


Fig. 7 Second group from Berkeley images of edge detection experiments with different algorithms (a) Color image (b) Ground truth image (c) Result by using Mathematical Morphology (d) Results by using Canny operator

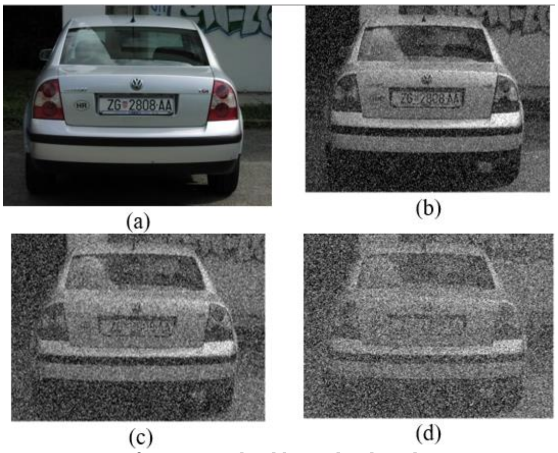


Fig. 8 First group of images with additional Salt and Pepper Noises with different levels using Greek car images (a) Grayscale image without Salt and pepper noise (b) Salt and pepper noise level 0.2 (c) Salt and pepper noise level 0.4 (d) Salt and pepper noise level 0.6.

To evaluate the morphological edge detection in Greek car images and Berkeley images quantitatively, experiments on 471 images with ground truth are conducted. The mathematical morphology edge detection results are shown in Table 1. The results are also illustrated in Fig. 4 and 5. Mean square errors (MSEs) are also calculated from the result of mathematical morphology edge detection. The MSEs' value of mathematical morphology from Greek car images is 531.95. Each different level of Salt and pepper noises yields different MSEs value. The higher the level of noise, the bigger value is. At the same time, the MSEs value of Berkeley images is also calculated. The values is 12.21. Similar to Greek car images, the higher the level noises the bigger the MSEs' value is. Overall, the number of MSEs from Greek car images are much bigger than Berkeley images. The MSEs measures the average of the squares of the errors. The lesser the MSEs the smaller the error is, the better the estimator will be.

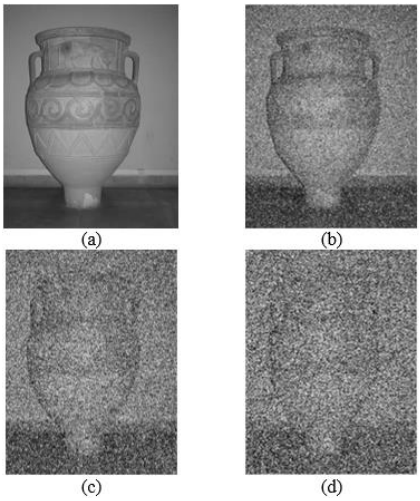


Fig. 9 Second group of images with additional Salt and Pepper Noises with different levels using Berkeley images (a) Grayscale image without Salt and pepper noise (b) Salt and pepper noise level 0.2 (c) Salt and pepper noise level 0.4 (d) Salt and pepper noise level 0.6

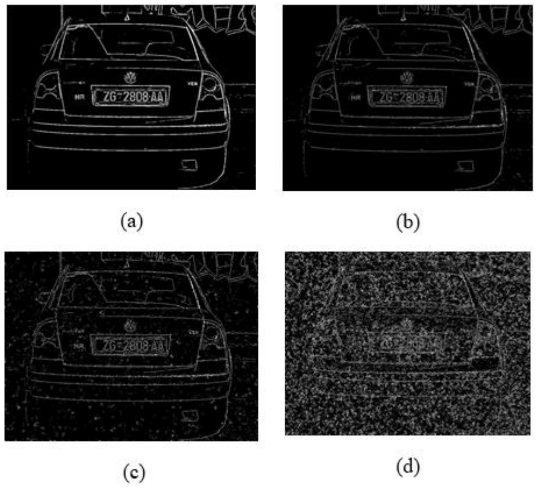


Fig. 10 First group of images resulted Mathematical Morphology edge detection from Greek car images with different levels (a) Without Salt and pepper noise (b) Salt and pepper noise level 0.2 (c) Salt and pepper noise level 0.4 (d) Salt and pepper noise level 0.6

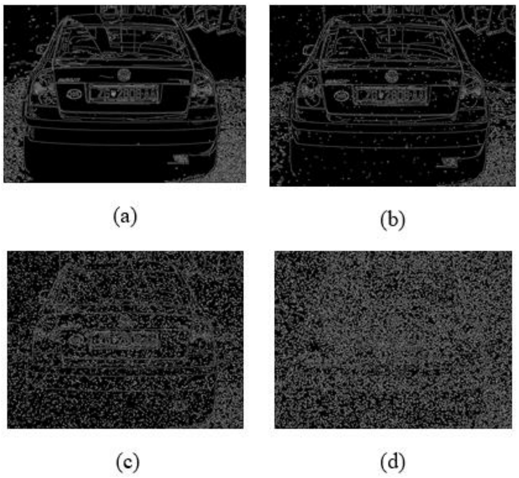


Fig. 11 First group of images resulted from Canny edge detection using Greek car images with different levels (a) Without Salt and pepper noise (b) Salt and pepper noise level 0.2 (c) Salt and pepper noise level 0.4 (d) Salt and pepper noise level 0.6.

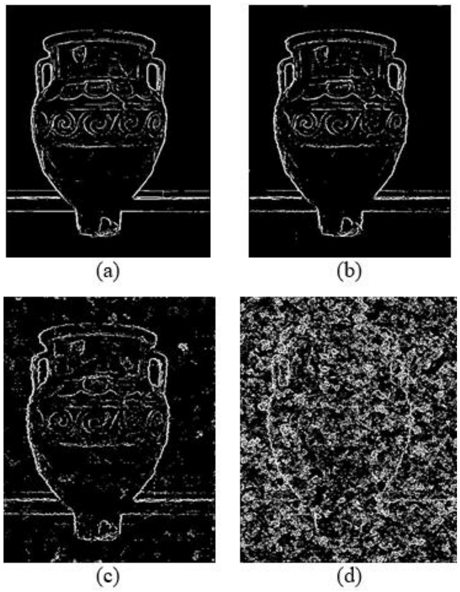


Fig. 12 Second group of images resulted from Mathematical Morphology edge detection using Berkeley images with different levels (a) Without Salt and pepper noise (b) Salt and pepper noise level 0.2 (c) Salt and pepper noise level 0.4 (d) Salt and pepper noise level 0.6

B. Proposed method evaluation and comparison with Canny method

The methodology was tested on 371 Greek car images and 100 Berkeley images using previously defined performance measure in Section 2-G towards ground truth images provided. These measurements are performed using a comparative study. Canny method is used in the comparison because Canny is widely used to detect edges in images [9] and the most well-known and among Gaussian based method algorithms. The experiments are done to compare the mathematical morphology edge detection algorithm with the Canny edge detection.

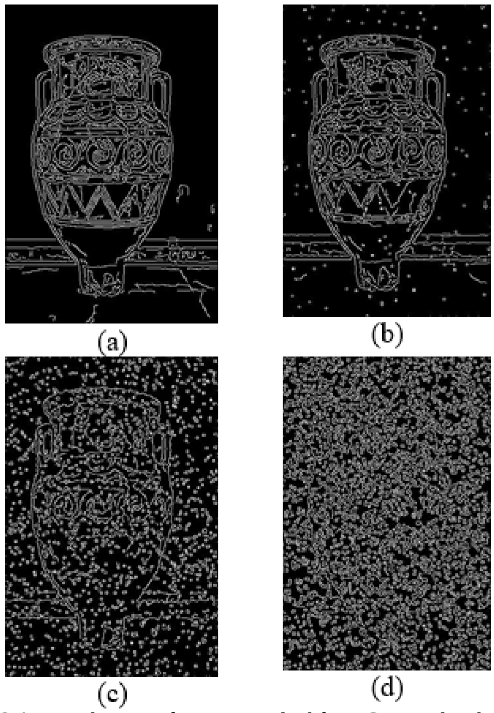


Fig. 13 A second group of images resulted from Canny edge detection using Berkeley images with different levels (a) Without Salt and pepper noise (b) Salt and pepper noise level 0.2 (c) Salt and pepper noise level 0.4 (d) Salt and pepper noise level 0.6

The mathematical morphology edge detection and Canny edge detection results from both groups are shown in Table 1 and 2. The results are also illustrated in Fig. 12 and 13. As shown in these tables and bar diagrams, the mathematical morphology edge detection is more accurate in detecting edge especially in car object boundaries. Most of the results from mathematical morphology method in each level noises from both groups are about 0.07–1.58% higher than Canny method, except for the images from Berkeley in Salt and pepper noise level 0.6 which is shown in the Table 2. The accuracy of Canny method is slightly higher than mathematical morphology at about 0.13%. One of the things that is out of the ordinary is the accuracy of both images and both methods in the level 0.2 of Salt and pepper noise which is higher in both groups of images than the accuracy of edge detection without Salt and pepper noise. It is safe to say that this area needs a more depth exploration.

Similar to the MSEs' value of mathematical morphology, MSEs' value of Canny is also calculated. As shown in Table 3, it is suggested that the MSEs value of mathematical morphology edge detection is closer to zero, if compared to the MSEs value of Canny edge detection except in the level 0.6 Salt and pepper noise. Canny's MSEs are smaller than mathematical morphology's MSEs. The MSEs values from both images are calculated, too. The number of MSEs from Greek car images are much bigger than Berkeley images. More details about Means Square Error has been provided in Table 3.

TABLE I
MATHEMATICAL MORPHOLOGY EDGE DETECTION

No.	Level of Noises	Greek car images	Berkeley images
1	Without Noise	83.23 %	96.88 %
2	Noise Salt and Pepper 0.2	83.27 %	97.11 %
3	Noise Salt and Pepper 0.4	82.66 %	96.18 %
4	Noise Salt and Pepper 0.6	79.78 %	93.01 %

TABLE II
CANNY EDGE DETECTION

No.	Level of Noises	Greek car images	Berkeley images
1	Without Noise	81.90 %	95.88 %
2	Noise Salt and Pepper 0.2	82.08 %	96.04 %
3	Noise Salt and Pepper 0.4	81.08 %	94.70 %
4	Noise Salt and Pepper 0.6	79.71 %	93.14 %

C. F-test two samples of variances

F-test to test the equality of variance is used to test the hypothesis of the equality of two population variances. F-test is done to obtain the ratio of variance of two samples. In this case, it is used to check if there is any variability among the accuracy produced by two different methods for each group of images.

C.1 F-test for Berkeley images

In this case, the independent variables which are measured are the accuracy of methods and noises. First, we test the significance between methods and accuracy of Berkeley images. So, the accuracy of both methods in Berkeley images are checked. The data which used are from Table 1 and 2. The test is used to measure the strength and the weaknesses of the correlation and whether the direction is directly proportional or inverse proportional. Therefore a correlation analysis is performed.

Second, null hypothesis and an alternative hypothesis are determined. The null hypothesis (H_0) in this case is that there is no statistical significance between methods and accuracy of Berkeley images, in other hand the alternative hypothesis (H_1) is that there is statistical significance between methods and accuracy of Berkeley images. From Table 4, it can be seen that the number of F-critical value of methods variable is smaller than F-stat (5.53 < 6.24) and also the number of p-value is smaller than α used in this research (0.08 < 0.1). Because F-stat > F-critical value, then the null hypothesis (H_0) is rejected. The F-stat exceeds the F-critical value of 5.53 so the null hypothesis (H_0) is rejected and the alternative hypothesis (H_1) is accepted. Therefore, it can be concluded that there is statistical significance between methods and accuracy of Berkeley images.

TABLE III
MEANS SQUARE ERROR (MSES)

No.	Edge detection method	MSEs			
		Without Salt and pepper noise	Salt and pepper noise level 0.2	Salt and pepper noise level 0.4	Salt and pepper noise level 0.6
Greek car images					
1	Mathematical Morphology	531.95	532.36	542.83	597.57
2	Canny	559.97	553.78	568.66	596.77
Berkeley images					
1	Mathematical Morphology	12.21	10.47	16.30	49.07
2	Canny	18.52	16.94	28.53	47.15
Greek car images and Berkeley images					
1	Mathematical Morphology	421,60	421,56	431,04	481,12
2	Canny	445,01	439,81	453,98	480,07

TABLE IV
RESULT OF F-TEST TEST IN BERKELEY IMAGES

	F-stat	*P-value*	*F-critical value*
Methods	6.242939	0.087816	5.538319
Noises	21.82374	0.015363	5.390773

Using the same F-test, the significance test between noises variable and accuracy is also calculated, too. The null hypothesis (H_0) in this case is there is no statistical significance between noises and accuracy of Berkeley images, whereas the alternative hypothesis (H_1) is there is statistical significance between noises and accuracy of Berkeley images. The F-stat exceeds the F-critical value of 5.39 so the null hypothesis (H_0) is rejected and the alternative hypothesis (H_1) is accepted. Therefore, it can be concluded that there is statistical significance between noises and accuracy of Berkeley images.

C.2 F-test for Greek car images

The accuracy of Greek car images was tested into the same independent variables as the one used in Berkeley images. F-test was performed to test the significance between the two variables. All the F-test was exactly the same as the Berkeley images. The null hypothesis (H_0) in this case is that there is no statistical significance between methods and accuracy of Greek car images, whereas the alternative hypothesis (H_1) is that there is statistical significance between methods and accuracy of Greek car images. From Table 4, the null hypothesis (H_0) is rejected and the alternative hypothesis (H_1) is accepted. Therefore, it can be concluded that there is statistical significance between methods and accuracy of Greek car images.

The null hypothesis (H_0) for variable noises and accuracy is that there is no statistical significance between noises and accuracy of Greek car images, whereas the alternative hypothesis (H_1) is that there is statistical significance between noises and accuracy of Greek car images. The number of p-value is smaller than α used in this research (0.02 < 0.1) and the F-stat > F-critical value, then the null hypothesis (H_0) is rejected. The F-stat exceeds the F-critical value of 5.39 so the null hypothesis (H0) is rejected and the alternative hypothesis (H_1) is accepted. So, it can be concluded that there is statistical significance between noises and accuracy of Greek car images.

TABLE V
RESULT OF F-TEST IN GREEK CAR IMAGES

	F-stat	*P-value*	*F-critical value*
Methods	9.738218	0.052447	5.538319
Noises	16.50694	0.022774	5.390773

C.3 F-test for both groups of images

The accuracy of all the images from both dataset was also tested into the same independent variables. From Table 6, it can be seen that the number of F-critical value of methods variable is smaller than F-stat (7.92 < 5.53) and also the number of p-value is smaller than α used in this research (0.06 < 0.1). The null hypothesis (H_0) is rejected and the alternative hypothesis (H_1) is accepted. There is statistical significance between methods and accuracy in all images.

Table 6 shows that the number of F-critical value of noises variable is smaller than F-stat (5.39 < 19.22). The F-stat exceeds the F-critical value of 5.39 so the null hypothesis (H_0) is rejected and the alternative hypothesis (H_1) is accepted. So, there is statistical significance between noises and accuracy in all images.

TABLE VI
RESULT OF F-TEST IN ALL IMAGES

	F-stat	*P-value*	*F-critical value*
Methods	7.920502	0.067052	5.538319
Noises	19.2225	0.018389	5.390773

D. Z-test two samples for means

Z-test compares two population means and checks if they are equal or unequal. The number of populations which are tested using z-test should be more than 30. If the number of population is less than 30, then the t-test is used. In this research, the number of populations are 100 and 371 from Berkeley images and Greek car images. Because the number of populations is more than 30, it also means that the populations are approximately normally distributed.

Table 7 showed the result of z-test for Berkeley images and Greek car images which has the result that the value of z-test are all greater than z-critical value. The α value which was used is 0,1. The Hypothesized Mean Difference is 0 which lead to use two-tailed. Also, the result of all p-value are 0 so it is not written in the Table 7. If the z-critical value is lesser than the z-stat and also the α value is greater than p-value, then it rejects the null hypothesis. It could be concluded that the population means for each group of images with the same level of Salt and pepper noises are not the same.

TABLE VII
Z-TEST RESULT FOR BERKELEY AND GREEK CAR GROUPS OF IMAGES

Method	**Level of Salt and Pepper Noises**	**Z-stat**	**Z-critical value**
Mathematical Morphology	Without Noises	16.26	1.64
	0.2	16.48	1.64
	0.4	16.49	1.64
	0.6	18.45	1.64
Canny	Without Noises	17.42	1.64
	0.2	17.4	1.64
	0.4	17.97	1.64

IV. CONCLUSION

A mathematical morphology edge detection is used to obtain better results in object boundaries from two different groups of images. The Canny method is applied to color image to extract edges. Mathematical morphology is also applied to optimize the edges detected from the color images. Finally the Canny method and mathematical morphology are compared to obtain best results. Several conditions such as Salt and pepper noises with different level are also tested into images. Experimental results demonstrate that the mathematical morphology can extract object boundaries better than Canny method except the images from Berkeley in Salt and pepper noise level 0.6 which is shown in the Table 2. The accuracy of the Canny method is slightly higher than mathematical morphology method by about 0.13%. One of the things that is out of the ordinary is the accuracy of both images in the level 0.2 of Salt and pepper noise which is higher in both groups of images than the accuracy of edge detection without Salt and pepper noise.

Using statistic F-test, it was found that there is statistical significance between methods and accuracy and also there is statistical significance between noises and accuracy. Along with the F-test result which are rejecting the null hypothesis, the Z-test result is also rejecting the null hypothesis that proves if the population means for Berkeley images group and Greek car images group with the same level of Salt and pepper noises are not the same.

The population means of Berkeley images' accuracy are higher than Greek car images. This can be caused by the ground truth of Berkeley images, which is produced by The Berkeley Segmentation and Benchmark. Meanwhile, the ground truth of Greek car images is produced by the authors. There might be a different way to produce the ground truth.

The future work includes the implementation of the above process on a larger population and the comparison of ground truth made from the same source. Also in-depth research about the oddity of the accuracy of both images in the level 0.2 of Salt and pepper noise which is higher in both groups of images than the accuracy of edge detection without Salt and pepper noise.

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