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The Effect of Using Histogram Equalization and Discrete Cosine Transform on Facial Keypoint Detection

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***Abstract*—This study aims to figure out the effect of using Histogram Equalization and Discrete Cosine Transform (DCT) in detecting facial keypoints, which can be applied for 3D facial reconstruction in face recognition. Four combinations of methods comprising of Histogram Equalization, removing low-frequency coefficients using Discrete Cosine Transform (DCT) and using five feature detectors, namely: SURF, Minimum Eigenvalue, Harris-Stephens, FAST, and BRISK were used for test. Data that were used for test were obtained from Head Pose Image and ORL Databases. The result from the test were evaluated using F-score. The highest F-score for Head Pose Image Dataset is 0.140 and achieved through the combination of DCT & Histogram Equalization with feature detector SURF. The highest F-score for ORL Database is 0.33 and achieved through the combination of DCT & Histogram Equalization with feature detector BRISK.**

Keywords—histogram equalization, DCT, facial keypoint

I. Introduction

There is an increasing trend in the use of face recognition application from USD 5.07 billion in 2019, with a predicted rise to USD 10.19 billion by 2025 [1]. The application with biometric system has various advantages on security compared to the use of conventional system. The face is more superior compared to other parts of the human body due to its ability to be checked from a distance depending on the capability of the camera [2].

After obtaining the facial image, it is compared with the database of images initially introduced [3]. The face detection has factors that capable of affecting the performance significantly, such as the illuminance variation, which occurs due to the reflection of illumination on the skin, camera setting, pose, the delay time due facial changes, and hindrance located at the upper section of face [4]. The effect of illuminance causes the ambiguity of someone's identity due to its ability to make an image of the same person appear like the image of two different people [5], [6]Therefore, the performance of the face recognition system is sensitive to illumination, and when poor, it causes the image to be classified as false positive or false negative [7] by the system.

Previous studies [8], [9] analyzed the effect of illumination on the success rate of face recognition using global features. The research carried out by [10] utilized local features and LD-SIFT algorithm for feature selection, without considering illumination. The study conducted by [11] only increased the performance of the SIFT algorithm for illumination generally, [12] studied the repeatability of keypoints using the epipolar geometry method on five feature detectors algorithm and the result was affected by noise and illumination. In the research carried out by [13], the accuracy rate of 3D face recognition was affected by the success rate of its reconstruction model, where it needed the accuracy of detecting facial keypoints. [14] researched the effect of illumination on the performance of face recognition and the result was using Histogram Equalization can yield a better result without no pre-processing and [15] studied that Discrete Cosine Transform (DCT) can be used to remove the illumination variation on the low-frequency component.

This research studies the effect of illumination in detecting the facial keypoints using the method of Histogram Equalization and DCT with five popular feature detectors namely SURF [16], Minimum Eigenvalue (Shi-Tomasi) [17], Harris-Stephens [18], FAST [19], and BRISK [20]. Histogram Equalization is used to increase the contrast of the image by distributing gray levels on the allowed limit [21] while DCT is used to normalize the illumination and create invariant images [22]. This is achieved because the illumination variation lies in the low-frequency band [15]. This study uses four combination of methods between DCT & Histogram Equalization for comparison. The evaluation uses F-score to determine the performance of each method.

From the research, the applied methods on the two data sets show an improvement in the detection of facial keypoints from testing two different datasets. Furthermore, it is important to detect keypoints in 3D face reconstruction [23]. This is because the higher the F-score achieved from detecting the facial keypoints, it will yield a better result.

The remaining section of this research is organized as follows: Part 2 discusses the related works, Part 3 provides further explanation on how the experiment was conducted and the variation of the method used, while Part 4 analyses the result. Part 5 provides an experimental conclusion.

II. Related Works

A. *Discrete Cosine Transform (DCT)*

There are four established types of Discrete Cosine Transform, namely DCT-I, DCT-II, DCT-III, and DCT-IV. DCT-II is more widely applied in signal coding and also JPEG image compression [15]. It is conceptually similar to Discrete Fourier Transform (DFT) due to its ability to transform a signal or an image from the spatial to the frequency domain [6]. DCT has been used for feature extraction in various studies of face recognition [24,25,6,26] and also used to remove the illumination effect [27,15,22]. The 2D DCT is defined in Equation 1 [15]:

$$C(u,v) = \alpha(u)\alpha(v)\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y) \times cos\left[\frac{\pi(2x+1)u}{2M}\right] cos\left[\frac{\pi(2y+1)v}{2N}\right] \quad (1)$$

And the inverse transform is defined at Equation 2 as [14]:

$$f(x,y) = \sum_{u=0}^{M-1}\sum_{v=0}^{N-1} \alpha(u)\alpha(v)C(u,v) \times cos\left[\frac{\pi(2x+1)u}{2M}\right] cos\left[\frac{\pi(2y+1)v}{2N}\right] \quad (2)$$

B. Histogram Equalization

The objective of Histogram Equalization is to spread gray levels over the entire allowable range, which is nonlinear and irreversible [21]. It has been mostly used to increase the contrast in face recognition studies [28], [29], [30], [15].

The occurrence probability of gray level r_k in an image is approximated by Equation 3 [31]:

$$p_r(r_k) = \frac{n_k}{n}\ k = 0,1,2,\ldots.,L-1 \quad (3)$$

The histogram equalization process is shown in the equation below by Equation 4 [31]:

$$s_k = T(r_k) = j = 0\text{kpr(rj)} = \text{j} = 0\text{knjn k} = 0,1,2,\ldots,\text{L}-1 \quad (4)$$

C. Facial Keypoints

The most fundamental task in 3D face reconstruction is to detect the keypoints which varies greatly from one image to another due to the difference of individuals' generic appearance and other physical factors as shown in Table 1 [32].

TABLE I. 15 FACIAL KEYPOINTS

Left eye center	**Right eye center**
Left eye inner corner	Right eye inner corner
Left eye outer corner	Right eye outer corner
Left eyebrow inner end	Right eyebrow inner end
Left eyebrow outer end	Right eyebrow outer end
Mouth left corner	Mouth right corner
Mouth center top lip	Mouth center bottom lip
Nose tip	

D. ORL Database

This data set contains ten different images taken between April 1992 and April 1994, which consists of 40 distinct subjects. For some subjects, the images were taken at different times, with varying illumination and facial expressions. All the images were taken against a dark homogenous background with the subjects in an upright, frontal position [33].

E. Head Pose Image Database

The database consists of 2790 monocular face images of 15 persons with variations of the pan and tilts angles from -90 to +90 degrees, with varying skin colors. The image background is willingly neutral and uncluttered to focus on face operations [34].

III. METHOD

This experiment used images from Head Pose Image and ORL Databases. The chosen images are the images of subjects that do not wear glasses and have no moustache or beard. Furthermore, the chosen images were cropped to eliminate areas without facial keypoints. Then, images will be converted into grayscale images. There are four combinations of methods used in this experiment:

1. Applying the feature detectors directly into the grayscale image (Original)
2. Applying only DCT to remove the low-frequency coefficient on the image (DCT)
3. Applying Histogram Equalization first then followed by applying DCT (Histogram Equalization & DCT)
4. Applying DCT first then followed by the Histogram Equalization (DCT & Histogram Equalization)

The mentioned combination of methods above will result in four different images. Those images then inputted to feature detector functions to determine the keypoints. The desired location of facial keypoints on the images of subjects is shown in Figure 1.

(a) (b)

Fig. 1. The location of facial keypoints: (a) ORL database (b) head pose image database.

After the images are fully detected by feature detectors, the obtained keypoints then get separated into three groups: True Positive (facial keypoints), False Positive (keypoints that are incorrectly detected as facial keypoints), and False Negative (undetected facial keypoints). With this information, F-score will be used to evaluate the performance of each method. Equations (5) and (6) show the equations used to calculate the Recall and Precision in this experiment:

$$Recall = \frac{True\ Positive}{(True\ Positive + False\ Negative)} \quad (5)$$

$$Precision = \frac{True\ Positive}{(True\ Positive + False\ Positive)} \quad (6)$$

Equation (7) is used to calculate the F-Score as follows:

$$F\ Score = 2 \times \frac{(Recall\ \times Precision)}{(Recall + Precision)} \quad (7)$$

IV. Experimental Results and Discussion

Figure 2 and 3 show the comparison of images resulted from the methods mentioned on the previous part.

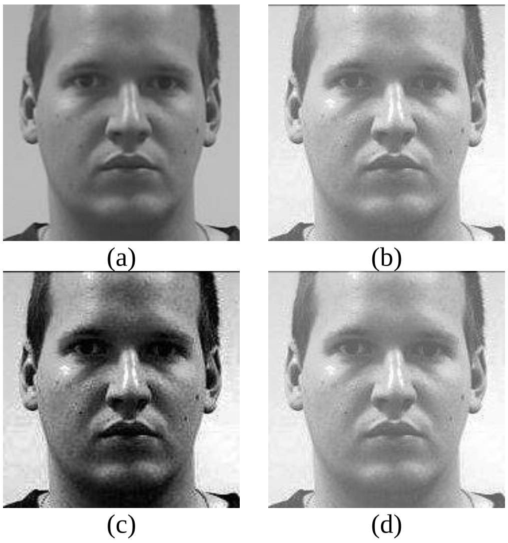


Fig. 2. Comparison of images from head pose dataset: (a) Original (b) DCT (c) DCT & histogram equalization (d) histogram equalization & DCT.

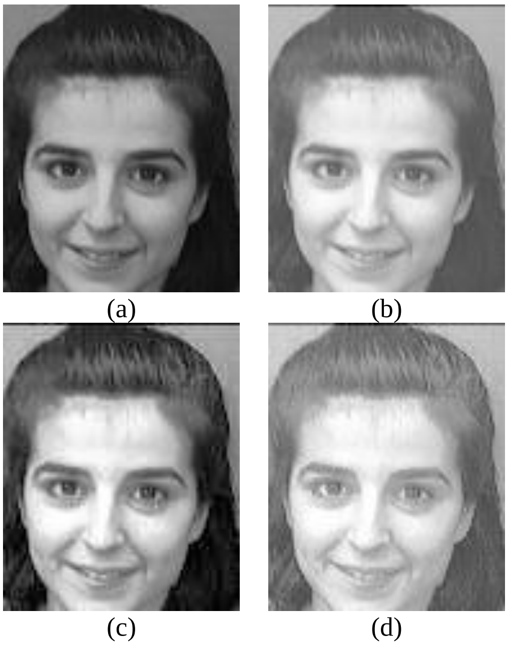


Fig. 3. Comparison of images from ORL database: (a) original (b) DCT (c) DCT & histogram equalization (d) histogram equalization & DCT.

By using the DCT, the low-frequency component is removed since the illumination variations mainly lie in the low-frequency band, and on the image of the face like shown in Figures 2 and 3, illumination tends to slowly change with the reflectance except for some casting shadows and secularities on the face [15]. Histogram Equalization is used to increase the contrast of the image.

The result (shown in Figure 4 to 8 and Figure 10 to 14) separated into two parts based on the data set. Tables 2 to 11 show the following data: Total Key Point (TK), True Positive (TP), False Positive (FP), False Negative (FN), Recall (Rc), Precision (Pr), and F-Score.

A. Experiment with Head Pose Image Dataset

1) FAST

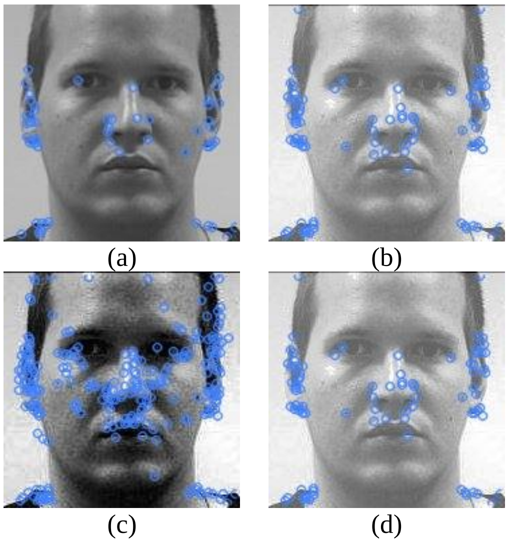


Fig. 4. FAST applied on the image: (a) original (b) DCT (c) DCT & histogram equalization (d) histogram equalization & DCT.

TABLE II. Results of Methods on FAST (Head Pose)

Method	TK	TP	FP	FN	Rc	Pr	F-Score
Original	54	2	13	52	0.04	0.13	0.06
DCT	85	3	12	82	0.04	0.20	0.06
DCT & HE	246	5	10	241	0.02	0.33	0.03
HE & DCT	85	3	12	82	0.04	0.20	0.06

2) Harris-Stephens

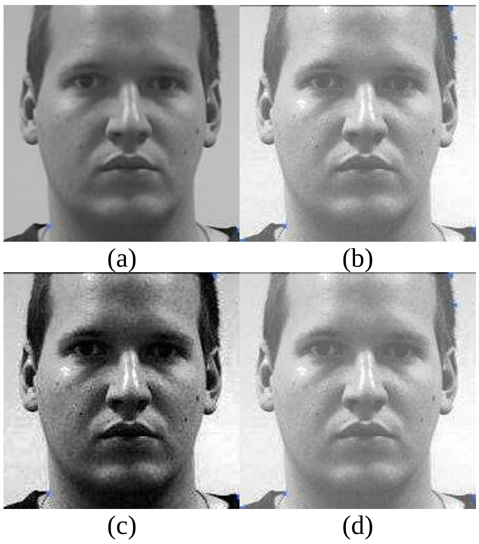


Fig. 5. Harris-Stephens applied on the image: (a) original (b) DCT (c) DCT & histogram equalization (d) histogram equalization & DCT.

TABLE III. Results of Methods on Harris-Stephens (Head Pose)

Method	TK	TP	FP	FN	Rc	Pr	F-Score
Original	15	0	15	15	0	0	0
DCT	44	0	15	44	0	0	0
DCT & HE	26	0	15	26	0	0	0
HE & DCT	44	0	15	44	0	0	0

3) Minimum Eigenvalue

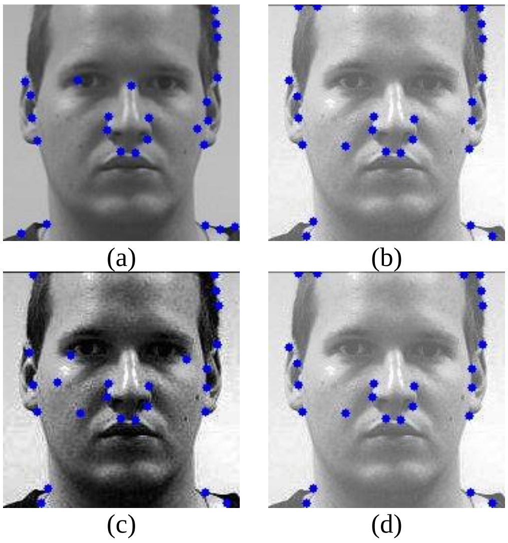


Fig. 6. Minimum-eigenvalue applied on the image: (a) original (b) DCT (c) DCT & histogram equalization (d) histogram equalization & DC

TABLE IV. RESULTS OF METHODS ON MINIMUM EIGENVALUE (HEAD POSE)

Method	TK	TP	FP	FN	Rc	Pr	F-Score
Original	25	0	15	25	0	0	0
DCT	25	0	15	25	0	0	0
DCT & HE	25	0	15	25	0	0	0
HE & DCT	25	0	15	25	0	0	0

4) BRISK

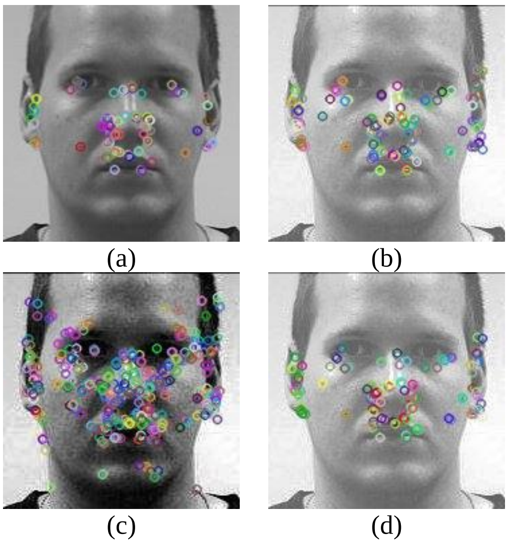


Fig. 7. BRISK applied on the image: (a) original (b) DCT (c) DCT & histogram equalization (d) histogram equalization & DCT.

TABLE V. RESULTS OF METHODS ON BRISK (HEAD POSE)

Method	TK	TP	FP	FN	Rc	Pr	F-Score
Original	88	1	14	87	0.01	0.07	0.01
DCT	119	4	11	115	0.03	0.27	0.054
DCT & HE	344	7	8	337	0.02	0.47	0.03
HE & DCT	119	4	11	115	0.03	0.27	0.054

5) SURF

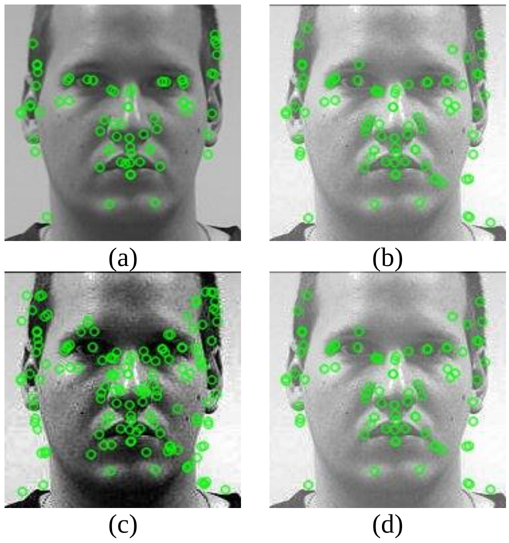


Fig. 8. BRISK applied on the image: (a) original (b) DCT (c) DCT & histogram equalization (d) histogram equalization & DCT.

TABLE VI. RESULTS OF METHODS ON SURF (HEAD POSE)

Method	TK	TP	FP	FN	Rc	Pr	F-Score
Original	69	5	10	64	0.07	0.33	0.115
DCT	81	9	6	72	0.11	0.60	0.185
DCT & HE	147	10	5	137	0.07	0.67	0.126
HE & DCT	81	9	6	72	0.11	0.60	0.185

Figure 9 shows the comparison of F-score of the methods applied through the dataset. SURF is the best performing feature detector and the most preferred method is the use of Histogram Equalization followed by DCT. There is an increase from the original method F-score value of 0.139 to 0.140.

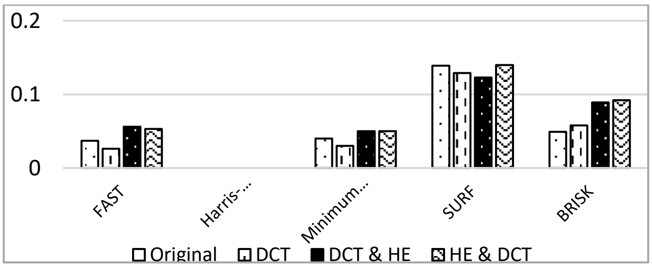


Fig. 9. F-Score result comparisons on head pose.

The preferred combination itself may cause the addition of noise due to the use of Histogram Equalization first, but it is then reduced by using DCT while still maintaining the defined corners that are achieved with Histogram Equalization.

In Head Pose Image Database, combining the preferred method with SURF does not detect as many keypoints as FAST or BRISK. The difference between the three method is the ratio of correctly detected facial keypoints to the number of detected keypoints that lead to a more balanced recall and precision in SURF. The characteristic of SURF is illumination invariant due to the wavelet responses in descriptor [16], while FAST and BRISK is strongly affected by contrast because BRISK works by detecting pixel intensities [19] and the descriptor is composed of a binary string by concatenating the results of simple brightness comparison tests [20]. From visual observation, Head Pose Image Dataset has lesser noise and more visible illumination around the face. Therefore, the illumination can affect both the method and the feature detector strongly.

B. *Experiment with ORL Database*

1) *FAST*

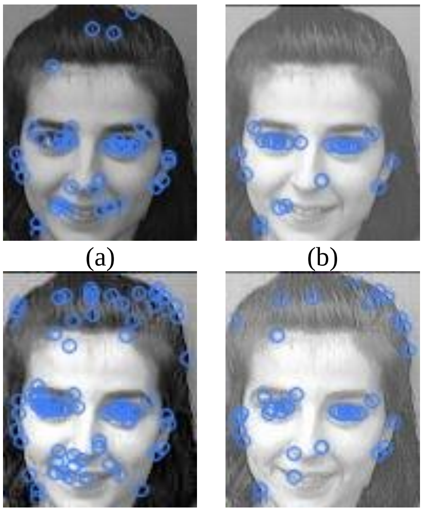


Fig. 10. FAST applied on the image: (a) Original (b) DCT (c) DCT & Histogram Equalization (d) Histogram Equalization & DCT.

TABLE VII. RESULT OF METHODS ON FAST (ORL)

Method	TK	TP	FP	FN	Rc	Pr	F-Score
Original	40	11	4	29	0.28	0.73	0.4
DCT	23	9	6	14	0.39	0.60	0.47
DCT & HE	76	11	4	65	0.14	0.73	0.23
HE & DCT	37	8	7	29	0.22	0.53	0.31

2) *Harris-Stephens*

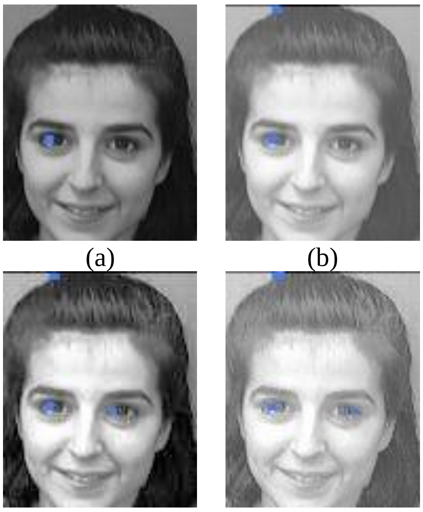


Fig. 11. Harris-Stephens applied on the image: (a) original (b) DCT (c) DCT & histogram equalization (d) histogram equalization & DCT.

TABLE VIII. RESULT OF METHODS ON HARRIS-STEPHENS (ORL)

Method	TK	TP	FP	FN	Rc	Pr	F-Score
Original	16	1	14	15	0.063	0.067	0.064
DCT	30	1	14	29	0.033	0.067	0.044
DCT & HE	39	2	13	37	0.051	0.133	0.073
HE & DCT	40	1	14	39	0.025	0.067	0.036

3) *Minimum Eigenvalue*

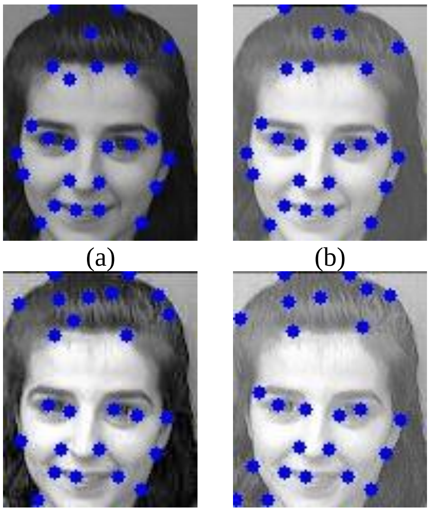


Fig. 12. Minimum-eigenvalue applied on the image: (a) original (b) DCT (c) DCT & histogram equalization (d) histogram equalization & DCT.

TABLE IX. RESULT OF METHODS ON MINIMUM EIGENVALUE (ORL)

Method	TK	TP	FP	FN	Rc	Pr	F-Score
Original	25	5	10	20	0.2	0.3	0.24
DCT	25	6	9	19	0.2	0.4	0.26
DCT & HE	25	4	11	21	0.2	0.3	0.24
HE & DCT	25	6	9	19	0.2	0.4	0.26

4) *BRISK*

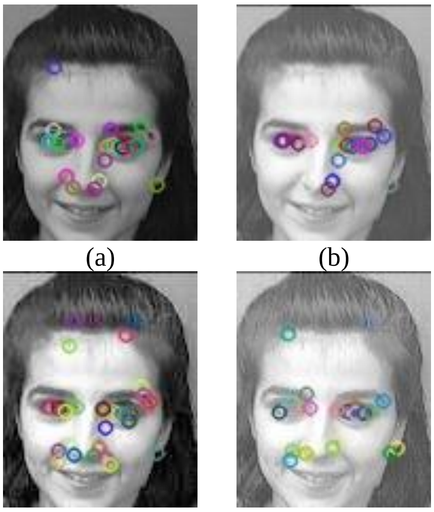
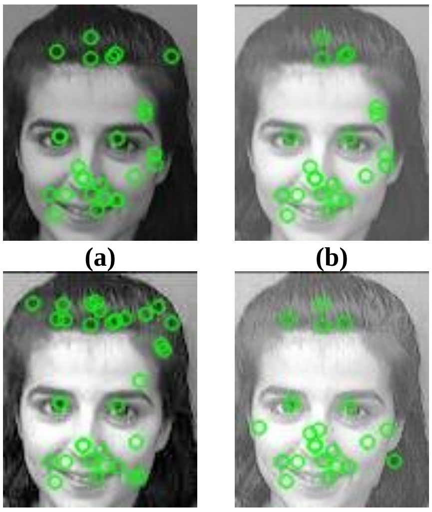


Fig. 13. BRISK applied on the image: (a) original (b) DCT (c) DCT & histogram equalization (d) histogram equalization & DCT.

TABLE X. RESULT OF METHODS ON BRISK (ORL)

Method	TK	TP	FP	FN	Rc	Pr	F-Score
Original	26	6	9	20	0.23	0.4	0.29
DCT	19	7	8	12	0.37	0.47	0.41
DCT & HE	38	7	8	31	0.18	0.47	0.26
HE & DCT	25	7	8	18	0.28	0.47	0.35

5) *SURF*



(a) (b)

(c) (d)

Fig. 14. SURF applied on the image: (a) Original (b) DCT (c) DCT & Histogram Equalization (d) Histogram Equalization & DCT.

TABLE XI. RESULT OF METHODS ON SURF (ORL)

Method	TK	TP	FP	FN	Rc	Pr	F-Score
Original	26	1	14	25	0.04	0.07	0.05
DCT	23	2	13	21	0.09	0.13	0.10
DCT & HE	33	4	11	29	0.12	0.27	0.16
HE & DCT	23	4	11	19	0.17	0.27	0.20

Figure 15 Shows the comparison of F-score of the methods applied through the dataset.

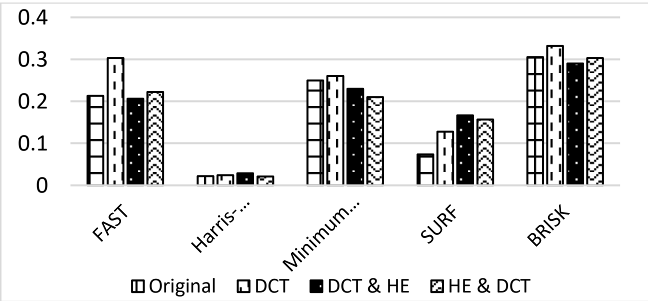


Fig. 15. F-Score result comparisons on database of faces

For ORL Database, the best performing method and detector are DCT and BRISK with F-score of 0.332. The original method (not applying any additional method) acquires F-score of 0.305.

Between the feature detectors used for ORL Database, FAST was able to detect the most keypoints, followed by BRISK. Both of the feature detectors have similar characteristics of being affected by the contrast and both have quite similar positive results in detecting the keypoints. What makes FAST do not perform well, is due to the ratio of detected keypoints to facial keypoints and additionally, the characteristic of ORL Database that has more noise than Head Pose's image. According to the research of [30], although FAST can detect more accurately, FAST is more sensitive to noise.

ORL Database has a significantly smaller size and produces a lesser number of detected keypoints compared to Head Pose's images. Therefore, the data set has a slightly bigger chance to score higher in recall and precision.

To prove this, a small test was conducted with an image from YALE [35] dataset, which was applied with the same combination of method. The result showed that the image scored lower F-score compared to ORL Database with the same combination of method because the number of detected keypoints was higher. The image size, even after the cropping was still bigger than Head Pose or ORL Database, therefore, it has the ability also to affect the F-score indirectly as shown in Figure 16.

(a) (b)

Fig. 16. Tested YALE image: (a) DCT with low-frequency removed (b) applying BRISK

DCT is the preferred method due to its ability to not adding more noise. From visual observation, image from the ORL Database also has less visible illumination variance and more visible artefact. Therefore, the use of DCT in this data set maintains a cleaner image and becomes invariant to illumination at the same time. With smaller size, images on this data set become more sensitive to noise

V. CONCLUSION

In conclusion, the proposed method by using the combination of DCT and Histogram Equalization can increase the detection rate of facial keypoints. The Head Pose Image Database shows an increase of 0.7% from the original by using the Histogram Equalization & DCT method with SURF, while the ORL Database shows an increase of 8.8% from the original by using DCT method and BRISK. The analysis showed that different datasets, methods, and feature detectors are needed to suit the character of the image. Although the research showed a positive result, further research that used synthetic images is needed to prove that the proposed method can be used in actual real life conditions.

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