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# A Robust Illumination-Invariant Face Recognition Based on Fusion of Thermal IR, Maximum Filter and Visible Image

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## Abstract

Face recognition has many challenges especially in real life detection, whereby to maintain consistency in getting an accurate recognition is almost impossible. Even for well-established state-of-the-art algorithms or methods will produce low accuracy in recognition if it was conducted under poor or bad lighting. To create a more robust face recognition with illumination invariant, this paper proposed an algorithm using a triple fusion approach. We are also implementing a hybrid method that combines the active approach by implementing thermal infrared imaging and also the passive approach of Maximum Filter and visual image. These approaches allow us to improve the image pre-processing as well as feature extraction and face detection, even if we capture a person's face image in total darkness. In our experiment, Extended Yale B database are tested with Maximum Filter and compared against other state-of-the-filters. We have conduct-ed several experiments on mid-wave and long-wave thermal Infrared performance during pre-processing and saw that it is capable to improve recognition beyond what meets the eye. In our experiment, we found out that PCA eigenface cannot be produced in a poor or bad illumination. Mid-wave thermal creates the heat signature in the body and the Maximum Filter maintains the fine edges that are easily used by any classifiers such as SVM, OpenCV or even kNN together with Euclidian distance to perform face recognition. These configurations have been assembled for a face recognition portable robust system and the result showed that creating fusion between these processed image illumination invariants during preprocessing show far better results than just using visible image, thermal image or maximum filtered image separately.

**Index Terms;** *Thermal face detection, Fusion, Biometrics, Face recognition, Maximum Filter, SVM, Illumination.*

## I. INTRODUCTION

Illumination condition changes varies from time to time, throughout the day whether you are indoor or outdoor as long as the source of lighting changes, like from dawn to dusk, illumination condition will not only change its illuminated/ lighting quality but also the position of the illumination where no one is able to get the exact illumination position (azimuth and elevation light position) and able to produce the same picture again. Due to human faces are in 3D form, uncontrolled illumination which produces reflection and shadows on the face, altered face's illumination position, that create different face format throughout time. Too bright or too dark of lights quality may brighten up the face and unable to capture some of the face features that all we see is bright light or may result in total dark image that make us unable to identify any face images in the picture. These inconsistencies create huge variations in face weight calculation. As a result, we are unable to create any discriminant as well as classification among faces hence yield a lower recognition rate.

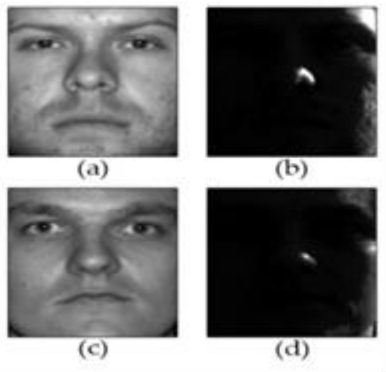


**Fig. 1. (a) and (c) Good photo vs (b) and (d) Photo with bad illumination.**

Fig. 1. Illustrates that with bad illumination, no classes of images can be categorized sometimes even between classes can be in the same classes. Images (a) and (b) belong to the same subject as well as (c) and (d) however only with the common visible different illumination.

Illumination invariant face recognition methods are generally defined either passive or active methods [1]. Solving problem using spectrum images methods, which include filtering, morphological processing and logarithm are consider passive. On the other hand, by implementing thermal and near infrared imaging, using cameras with 3D sensors for the purpose of improving illumination for better face recognition are known as passive approaches. A more common passive method and usually grouped in three main categories are, normalization, illumination modeling and illumination invariant feature ex-traction of face image.

In this paper, a hybrid method is proposed which combines these passive and active approaches to create a more robust face recognition against lighting condition or occlusion and even spoofing. The reflection-illumination model is the passive approach that we are based on[2]. This approach does not need training data prior processing it's filtering processes. This method able to extract dark visual image using maximum filter. This method remove noise, retain and increases the size edges, and create a smooth that shows a clear face feature. Maximum filter is a computationally efficient where there is no need in geometry process and parameter adjustment that usually are done manually. Maximum filter is a method that it uses its own noise and redundant segmentation to subtract its own original image This method makes it simple to be executed and less usage of computer resources.[2].

To incorporate our hybrid method by incorporating passive method such as maximum filter and with the implementation of thermography spectrum in capturing human face image which is categorized as active approach in illumination invariant. The acceptance of face image captured using thermal sensor cameras, which is the active approaches. Infrared (IR) spectrums are rapid, relatively easy to implement and secure because it is a non-contact, non-intrusive only capturing heat that emits from the subject's body and face image are taken and identified without the subject knowing it.

One of the main advantage of infrared especially thermal whereby regardless under any illumination or lighting condition, where we can categorize illumination under natural, artificial and under infrared environment, and under good, poor and bad lighting, thermal specifically low wave infrared (LWIR) and mid wave infrared (MWIR) are consistent in its images intensity, quality and texture. Unlike visual and near infrared (NIR) images that are dependent on illumination or lighting condition. With this quality of being consistent, LWIR able to be use as thermal signature of every person, in order words infrared identification. The reason of LWIR being consistent as compare to other image capturing method mainly because human's temperature varied from 35°to 37°celsius and anything above it is a sign of sickness or due to certain condition in a person's body. Therefore, apart from able to give us a consistent face features, thermal also able to give us detail anatomical details of a person, which include vein or



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tissue injuries or fever or other physical injuries. Apart from that thermal maintain the anatomical details of a person regardless of medical condition. IR basically captures the pattern images of superficial blood vessels that are laying 4 cm underneath the skin surface. Thermal will show that our body including our face are built symmetrically. [5].

## II. RELATED WORKS

IR imaging has opened a new chapter ever since it has been discovered to be an essential tool for face recognition. [6] Francine et al presented a study about the IR imaging analysis as a technique for identification of faces classification and recognition. He discussed the compassion of the visual face recognition performance to the variations in the illumination. Socolinsky et al. presented a performance study of face recognition methodologies on visible and thermal IR imagery [7]. He examined the invariance of LWIR images under different lightning quality and level of illumination. Farokhi, et al. [8] proposed a Zernike moments method for Near IR (NIR) face recognition. Wu et al. [9] presented a blood perfusion model of human faces based on thermal physiology.SeWoon Cho et al.[10] suggested face detection in night-time Images using visible -light camera sensor with two-step faster region -based convolutional neural network (CNN) designed a device including GPU cuda tensor flow, a visual camera, an active NIR lighting, and an optical sensor. They compared the effect of varying the environmental conditions over IR and visible images.

## III. INFRARED TECHNOLOGY

In this paper, prior to our proposed embedded process, image that was captured by IR thermal camera must be preprocessed in order to detect skin area, as thermal camera will capture our face that emits heat.

(a) (b) (c) (d) (e) (f)

**Fig. 1.(a) Image captured using IR camera, (b) Image improved with Histogram Equalization (c) Binary Threshold (d) Morphological Processing (e) Ellipse Fitting for face detection (f) Face Cropping**

### A. Ellipse Fitting for Face Detection

In total darkness no visual camera can be used to detect face image, not even the state-of-the-art face detector, like opencvhaar cascade can assist in face detection since no face image can be seen. At first, we will use Histogram equalization (HE) as one of the most popular in image enhancement which improves the recognition results by equalizing the pixel intensities of the imagesin the histogram of [4].In our proposed methodology we use IR camera to capture in a poor illuminated environment or total darkness. Since IR captures the heat that emit from our body, our face and our body will be glowing that are almost ellipse-like objects glowing among the dark background [11]. In our method, we use ellipsefitting technique to track not just face or head but also other facial components. The use of an ellipse can be a powerful representationof certain features around the faces. We use the ellipse fitting algorithm for facedetection to segment the face region out of the facial images.An ellipse is a special case of the general conic, which can be representedas [11]:

$$F(A,T) = AT = ax^2 + bxy + cy^2 + dx + ey + f = 0 \quad (1)$$

$F(A,T)$ is called the geometric distance of the point (x, y) to the given conic with an ellipse-specific constraint [11]

$$b^2 - 4ac < 0 \quad (2)$$

where **A** = [a,b,c,d,e,f] known as the vector containing the coefficients of the ellipse and **T** =



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[$x^2$, xy, $y^2$,x,y,1] the vector containing the coordinates of the points lying on the ellipse.Researchers suggested different methods to fit conics, while applying constraints such as [11]

$$a + c = 1,\ f=1,\ \text{and}\ a^2 + \frac{1}{2}b^2 + c^2 = 1 \quad (3)$$

By applying the following quadratic constraint on the parameters [12]

$$A^T CA = I \qquad (4)$$

where C is A constraint matrix that enforce the fitting to an ellipse given as:

$$C = \begin{bmatrix} 0 & 0 & 2 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 & 0 & 0 \\ 2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \qquad (5)$$

By using a general Eigen-value system, which can be denoted as below for the purpose of minimizing the irrelevant pixels[13]:

$$D^T DA = SA = \lambda CA \qquad (6)$$

where D is the design matrix, S is the scatter matrix defined as:

$$D = \begin{bmatrix} x_1^2 & x_1y_1 & y_1^2 & x_1 & y_1 & 1 \\ x_2^2 & x_2y_2 & y_2^2 & x_2 & y_2 & 1 \\ x_3^2 & x_3y_3 & y_3^2 & x_3 & y_3 & 1 \\ x_4^2 & x_4y_4 & y_4^2 & x_4 & y_4 & 1 \\ \dots & \dots & \dots & \dots & \dots & \dots \\ x_N^2 & x_Ny_N & y_N^2 & x_N & y_N & 1 \end{bmatrix} S = \begin{bmatrix} S_{x^4} & S_{yx^3} & S_{x^2y^2} & S_{x^3} & S_{yx^2} & S_{x^2} \\ S_{x_y^3} & S_{x^2y^2} & S_{xy^3} & S_{yx^2} & S_{xy^2} & S_{xy} \\ S_{x^2y^2} & S_{xy^3} & S_{y^4} & S_{xy^2} & S_{y^3} & S_{y^2} \\ S_{x^3} & S_{yx^2} & S_{xy^2} & S_{x^2} & S_{xy} & S_x \\ S_{x_y^2} & S_{xy^2} & S_{y^3} & S_{xy} & S_{y^2} & S_y \\ S_{x^2} & S_{xy} & S_{y^2} & S_x & S_y & S_1 \end{bmatrix} \quad (7)$$

The solution of Eq. 7 gives six pairs eigenvalues and eigenvectors. The eigenvector corresponding to the minimum positive eigenvalue gives the coefficients of the ellipse the best fit the data points [13].

### B. Maximum Filter

Face skin is isotropic, means regardless whether it is measured from any different directions, a physical property will give the same value. Lambertian object, is an isotropic, such as our skin, will provide consistent weight calculation in pixels measurements both lighting and reflectance. From here we know that $I$ illumination are the reconstruction of reflectance and illumination representation. Therefore, illumination can be presented as illumination-reflection model, [14].

$$I(x, y) = L(x, y).R(x, y) \qquad (8)$$

where $R(x, y)$ represents the reflectance point of (x, y) and $L(x, y)$covers the illuminance sectors of the illumination point of (x,y). Our main objective here is to find the image's illumination invariant part which is the reflection points R (x, y). It is expected that reflectance placed or lies on the high frequency part of the image while in the low frequency part of the image lies the illumination [15]. In several recent biological test result showed that the outcome of image intensity reflecting to the inner back surface of our eyeball cells, which is the retina, able to be measured by a nonlinear function. This function that reduces illumination invariant is the increasing intensity of each pixel by applying logarithm to them. Logarithm application on an image will amplify the dark pixels values and suppress the lighter or bright pixels values. By taking the logarithm of I, we have:

$$\grave{I} = log(I) = log(L) + log(R) = \grave{L} + \grave{R} \qquad (9)$$

L' and R are logarithms of reflectance and illumination, respectively. Since the low frequency (LF) part of the image I, lies illumination, therefore, we can obtain the illumination invariant information and details of the image by applying a 2D High-Pass Filter (HPF) on I'. The outcome of the 2D HPF is illumination invariant and can be used for the recognition process. Fig 2 shows the flowchart of this system.



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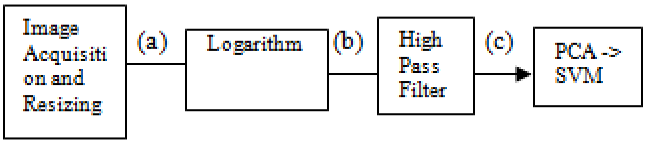


(a) Image $(I)$ $I = L.R$ (b) $\grave{I} = log(I)$, $\grave{I} = \grave{L} + \grave{R}$ (c) $J \cong \grave{R}$

**Fig. 2. By applying a 2D High Pass Filter on the I' logarithm of an image, enable to extract the illumination invariants.**

R'=*I'-L'*. As shown in Fig.2(c), once the illumination has been subtracted and produced R'.

Fig 3 shows that a 2D Low-Pass Filter (LPF) on the logarithm of the input image and then subtracting the output, L', from I' The resultimage, J, will approximate R'.

(a) Image $(I)$ $I = L.R$
(b) $\grave{I} = log(I)$, $\grave{I} = \grave{L} + \grave{R}$
(c) $K \cong L$ (d) $J \cong \grave{R}$

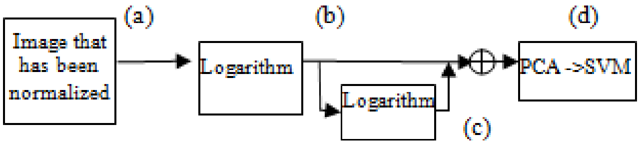


**Fig. 3. Extracting the illumination invariants by using 2D low passed filter (LPFs)**

Used to be known as dilation filters [16], Maximum filters are morphological filters, (dilation and erosion) that work by considering a neighborhood around each pixel. As usual the norms in image processing, that is to remove negative outlier noise we adopt the concept which is using nonlinear 2D low-pass filters [2].Among the neighbor pixels list of, before we store as the corresponding resulting value, first the maximum value must be found. In the end of the process, each pixel in the image is going to be replaced with the resulting value generated for its associated neighborhood. The Maximum filter main objective is to enhance the bright pixel values in the image by expanding or increasing its area. In the output image, *B* every pixel, the intensity value is the maximum value in an $m \times n$neighborhood in the input *A* [2].

$$B(x,y) = maxA(i,j)and(i,j) \in \{mxnneighbourhoodof\ (x,y)\}$$

(10)


**Fig. 4.The changes of Lena image when applying 3×3 and 5×5 maximum filters**

Further to confirm on comparison among filters as to find which among these filters is illumination invariant. To achieve this, state of the art filter has been used for comparison. These filters are Median, Gaussian, Maximum filters, Sobel and Canny edge detectors. In this experiment, we have conducted the classification using several different classifiers such as *k*NN and SVM and fuzzy *k*NN applied on CMU-PIE, ExtendedYale B and Yale B databases[2].

Fig.5 shows the illumination invariants achieved by using, Maximum, Median andGaussian filters and Canny and Sobel edge detectors. Here we can clearly see that Maximum filter has maintained the textures details of the face and at the same time improved the and remove all the illumination effect and the noise.[2].

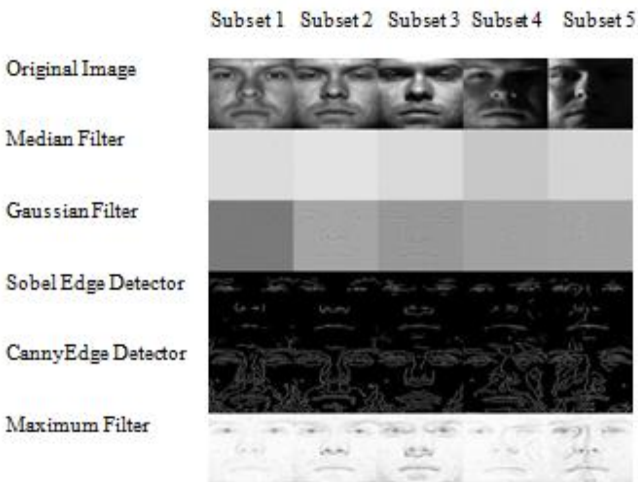


**Fig. 5.Illumination invariants achieved by different lowpass and high-pass filters.**



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**Table 1.Comparison of distances between Filters**

| | Subset 1 | Subset 2 | Subset 3 | Subset 4 | Subset 5 |
|---|---|---|---|---|---|
| Sobel Edge Detector | 35.11 | 34.32 | 35.12 | 36.32 | 37.23 |
| Median Filter | 10.22 | 12.78 | 14.12 | 16.32 | 19.32 |
| Gaussian Filter | 13.53 | 18.32 | 19.12 | 25.21 | 21.32 |
| Maximum Filter | **9.24** | **9.12** | **12.43** | **15.43** | **16.23** |
| Canny Edge Detector | 59.22 | 49.12 | 58.23 | 65.23 | 59.93 |

Table 1 shows the average of the euclidian distance between the illumination invariants of Yale Extended B Subset 1 until Subset 5 with good frontal illumination, and to the ones with good illumination variations. Among other filters, maximum filter shows results with less distance in Euclidian calculation meaning better accurate when used for feature extraction.

## IV. PROPOSED APPROACH

The flowchart below shows the methodology on how to reduce the illumination challenges in face recognition. In our proposed methodology, we implement the fusion at the 2nd round of preprocessing with*output 2*, the raw image captured by IR thermal camera,that has been normalized with Histogram Equalization (HE), binary threshold and morphological process, and *output 1*, whereby it was an image captured using visual camera, an image full of illuminations challenges but since it was captured at the same time as the infrared camera, maybe we can align the bad illuminated face image eyes, nose, mouth and edges to the one that is glowing with thermal heat, and finally with *output 3*, an improved image after filtered with maximum filter (also known as max 3x3).

### A. Fusion Algorithm

The following is the algorithm fused for the purpose of achieving the aim of this paper.

1. **Step 1**: Output Images must be in the same size, aligned and in grayscale. *Output1, Output 2* and *Output 3* must have the same size and must be in grayscale. Here Output1, visual image labeled as $vi$ , Output 2, infrared image labeled as $ir$and Output 3, Maximum filter image will be labeled as $mi$and as for our Fusion image labeled as $fi$.Here all these 3 outputs and $fi$ will have the same size as $m \ x \ n$.

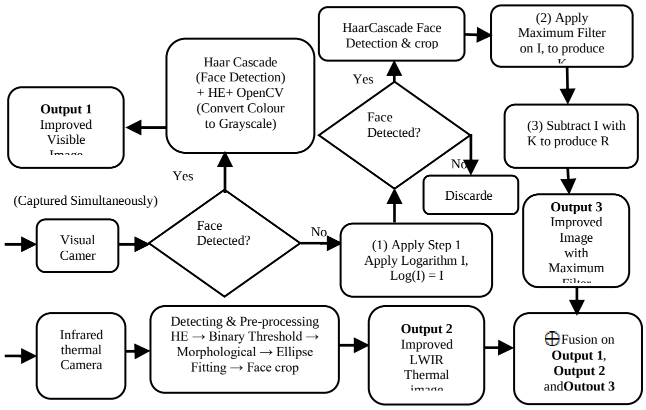


**Fig. 6. Flowchart of getting 3 Outputs invariant against illumination**

**Step 2**: Infrared background similar pixel intensity. Since infrared images will always create a glowing area on the face due to the blood vessels under the skin and this creates more pixel intensity differences. Here we are forcing similar pixel intensity in the same pixel location with the given thermal image. This can be achieved by reducing the empirical error. $l^r$ , usually (r ≥1)

$$\varepsilon_1(fi) = \frac{1}{r} \|fi - \quad ir\|_r^r \tag{11}$$

2. **Step 3**: Preserving the characteristic of maximum filter image and visual image. Usually on a bad illuminated lighting condition or no presence of light visual image will be able to show any picture but only maximum filter image able to provide the face edges. Nevertheless, the infrared and visual images represent different result which leads to different pixel intensities in the same pixel location making it unsuitable to generate $fi$ by simultaneously minimizing

$$\frac{1}{r} \|\nabla fi - \quad \nabla ir\|_r^r, \qquad \frac{1}{s} \|\nabla fi - \quad \nabla vi\|_s^s$$
and$\frac{1}{s} \|\nabla fi - \quad \nabla mi\|_s^s$ (12)



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In order to characterize the detailed appearance information, we need to consider the gradients of the image. Thus, we propose to constrain the fused image to have mixture pixel gradients of $vi$ and $mi$ , visual image (if $vi > 0$) and rather than similar pixel intensities only with the $mi$.

$$\varepsilon_2(fi) = \frac{1}{s} \|\nabla fi - (\nabla mi - \nabla vi)\|_s^s \qquad (13)$$

In these equation $\nabla$ is the gradient operator. In the case of s = 0, Eq.13 is defined as $\varepsilon_2(fi) = \|\nabla fi - (\nabla mi - \nabla vi)\|_0^0$, which equals the number of non-zero entries of $\nabla fi - (\nabla mi - \nabla vi)$ .Therefore, Eq.11 and Eq.13, the fusion problem is formulated as reducing of the following objective function.

$$\varepsilon(fi) = \varepsilon_1(fi) + \lambda\varepsilon_2(fi)$$

$$\varepsilon(fi) = \frac{1}{r} \|fi - ir\|_r^r + \lambda \frac{1}{s} \|\nabla fi - (\nabla mi - \nabla vi)\|_s^s \qquad (14)$$

where from the fuse formula above, we can see that at fusing process is nothing but grouping or developing a constraint by comparing fuse image $fi$ pixels to that of similar pixel intensities with the infrared image before fusing them together in the first stage and ,in the second stage, fuse image $fi$ by having the maximum filter image $mi$ minus visual image $vi$ and it pixels are to be to be evaluated to the one that has similar intensities at the correspondent position. At the same time $\lambda$ is threshold, a positive parameter that control the trade-off between these two main fusions. The main objective of the above additional function is to compare between maximum filtered edges with the dark pixels of visual image before this refined edges and textures being export to the corresponding positions in the infrared image. This concept not only increases the reliability and quality of infrared image by importing important features from maximum filter image and visual image. [17].

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

**Fig. 7.(a) Visual Image (b)Thermal Image, (c) Maximum Filter Image, (d)Fusion result (Parameters: $\lambda$=7)**

**Fig. 7 shows the respective example pictures of Output 1 in (a), Output 2 in (b), Output 3 in (c) and Fusion Output in (d).**

## V. EXPERIMENTS AND RESULTS

These experiments were conducted in a room with 600 square feet of size and for various level of illumination. For good illuminated indoor we need 12,000 lumens, which is equivalent to about 12 of 100-watt incandescent light or 12 of 23 watt CFLs, or 9 of 10 watt LED light bulbs [3].

a) Good illuminated indoor, 12K Lumens (12 bulbs of 100 watt) [3]

b) Poor illuminated indoor, 8K Lumens (8 bulbs of 100 watt)

c) Bad illuminated indoor, 4K Lumens (4 bulbs of 100 watt)

**Table 2. Table below is the average result of face recognition under different imaging methods, varies pre-processing output(s) combination and varies illumination quality**.

| Imaging Methods | Pre-processing Dataset | Successful Recognition Rate Illumination Quality | | |
|---|---|---|---|---|
| | | Good | Poor | Bad |
| Visual imaging | Output 1 | 87.3% | 62.5% | 45.2% |
| Thermal Imaging | Output 2 | 78.5% | 73.7% | 70.5% |
| Visual /Thermal | Fusion Output 1, 2 | 90.2% | 75.8% | 72.8% |
| Visual imaging | Fusion Output 1, 3 | 94.7% | 68% | 59.4% |
| Visual /Thermal | Fusion Output 2, 3 | 92.5% | 85% | 80% |
| Visual/ Thermal | Fusion Output 1, 2, 3 | **96.8%** | **92.2%** | **88.7%** |



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Basically, we have collected 6 types of datasets that are classified under their Imaging methods; 1) visual-*output1*, 2) thermal-*output2*, 3) visual/thermal- fusion *output1& output2* 4) visual-fusion *output1& output3* 5) visual/thermal- fusion *output2 & output3* 6) visual/thermal- *output1, output2 & output3*. For each dataset we will have 10 subjects/ persons and each subject's pictures are taken 3 times on each environment. Since there are 3 different environments; Good, Poor & Bad, so each subject will have 9 pictures. 6 pictures go into training and 3 pictures goes to testing. So, if we have 10 subjects in a dataset means that there are 90 pictures taken on every dataset. 30 pictures for testing and 60 pictures training. Same goes with all the datasets with fusions. For every 2-imaging method that produce either 2 output or 3 output will be ended with 1 fusion output. We applied principle component analysis (PCA) for data extraction and later we applied Support Vector Machine (SVM) for classification. Table 2 shows the percentages successful recognition rate of each dataset with the respective illuminated conditions. From Table 2 shown above, it is clearly seen that the fusion of illuminated visual, thermal and maximum filter images can produce better image quality that is not only able to show face features and all its textures and edges but also its unique printed thermal signature of the person's face.*Output 1* that was produced from visual imaging and *output 2* which was produced from thermal imaging are not good when there are on their own. 1) *Output 1,* images captured using visual camera unable to capture face image fully once lighting condition becomes badly illuminated. 2) *Output 2,* thermal images that only displaying face thermal heat excluding the edges and face texture. PCA feature extraction does not do well in accumulating discriminant features from thermal image, o*utput 2*, especially when face detail features are missing. Therefore, PCA had to use only the heat signature of the subject, but at least, recognition rate result does not change as illumination changes. 3)Visual and thermal imaging fusion - o*utput 1* and *output 2* has good 90% under good illumination. Under poor and bad illumination with the help of thermal image-*output 2,* enable to brighten and improved visual image, *output 1,* from 62.5% before fusion, under poor illumination to 75.8% accuracy rate and from 45.2% before fusion to 72.8% under bad illumination after the fusion. Under poor and bad illumination visual image lost some of its edges and textures even though how much thermal images trying to help in brightening *output 1* from the fusion process. 4) Fusion o*utput 1,* visual image, and *output 3,* max filter image, produces better result because maximum filter is helping in sharpening the face edges and textures even under poor and bad illumination. Unfortunately, under poor and bad illumination, max filter must do most of the job. It seems that PCA doesn't work well with max filter images cause PCA's nature of reducing dimensionality reduce the features of max filter until too little left to discriminate a subject. 5) Fusion output 2 and 3 produced good result as thermal produce glowing face structures and maximum filter provides the clean textures and edges. 6) Fusion *output 1*,*2* and *3* is where thermal image able to enrich and brighten the visual images and at the same time maximum filter re-establish not just all the edges and textures of the face but also enhance the distinctiveness among face components.

## VI. CONCLUSION

In this paper, we have proposed a novel methodology for thermal face recognition fusion with another method of less computational expense which are maximum filter (max filter) process and for an additional option visual images when there is a good illumination. From the conducted experiments, the results showed a superior performance of our approach by evaluating the performance of recognition on the fused images, a merged representation of face.

## VII. ACKNOWLEDGMENT

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## REFERENCES

[1]. Z. Xuan, J. Kittler, K. Messer, Illumination Invariant Face Recognition: Proceedings of IEEE Conference on Biometrics: Theory, Applications, and Systems, BTAS (2007) 1-8

[2]. AmirhoseinNabatchian, “Human Face Recognition” University of WindsorWindsor, Ontario, Canada pp.71-75, 2011

[3]. https://www.archdaily.com/897277/how-to-determine-how-many-led-lumens-youll-need-to-properly-light-your-space, 2016, page 4-6

[4]. R.C. Gonzalez, R.E. Woods, Digital Image Processing, second ed., Prentice Hall, 1992

[5]. F. J. Prokoski and R. Riedel, Infrared Identification of Faces and Body Parts; chapter 9 in BIOMETRICS: Personal Identification in Networked Society", 1998.

[6]. J. Dowdall, I. Pavlidis, I., and G. Bebis.: Face detection in the near-ir spectrum, Image and Vision Computing Vol. 21 , PP. 565–578, 2001.

[7]. D. A. Socolinsky and A. Selinger, "Thermal face recognition in an operational scenario," Conference of Computer Vision and Pattern Recognition, 2004.

[8]. SajadFarokhia, Jan Flussera , UsmanUllah Sheikh ”Near infrared face recognition: A literature survey “, 2016.

[9]. Shi-Qian Wu et al, "Infrared face recognition by Using Blood PerfusionData," AVBPA, LNCS 3546, pp. 320-328, 2010.

[10]. Se Woon Cho, Na Rae Baek, MinCheol Kim, JaHyung Koo, Joong Hyun Kim and Kang Ryoung Park “Face DetectioninNighttime Images Using Visible-Light Camera Sensor with two steps faster region-based CNN” 31 July 2018.

[11]. A. W. Fitzgibbon, M. Pilu, & R. B. Fisher,"Direct Least Square Fitting of Ellipses," 1999.

[12]. F. L. Bookstein, "Fitting conic sections to scattered data," Computer Graphics and Image Processing, Vol. 9, PP. 56-71, 2017.

[13]. A. W. Fitzgibbon, R. B. Fisher, "A Buyer’s Guide to Conic Fitting," Proc.5th British Machine Vision Conference, Birmingham, pp. 513-522, 1995.

[14]. B.K.P. Horn, Robot Vision, MIT Press, Cambridge, 2006)

[15]. J. Ruiz-del Solar, J. Quinteros, “Illumination compensation and normalization in eigenspace-based face recognition: a comparative study of different pre-processing approaches, Pattern Recognition Letters, 29 (2008) 1966-1979.

[16]. B. Saether, H. Rueslatten, A. Gronlie, Application of the Hough transform for automatedinterpretation of linear features in imageries, (1994) 847–850.

[17]. J. Ma, C. Chen, C. Li, and J. Huang, “Infrared and visible image fusion via gradient transfer and total variation minimization,” *Information Fusion*, vol. 31, pp. 100– 109, 2016.