2013 IEEE Workshop on Advanced Robotics and its Social Impacts (ARSO)
Shibaura Institute of Technology, Tokyo, JAPAN
November 7-9, 2013

Fuzzy-based Illumination Normalization for Face Recognition

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Abstract—**In this paper, we address the problem of reducing the effect of illumination especially for human face recognition. We create an adaptive contrast ratio based on Fuzzy by considering two models of individual face as input, appearance estimation model and shadow coefficient model. We then apply a Genetic Algorithm to optimize the Fuzzy's rule. Principal Component Analysis (PCA) and Nearest Neighbor (NN) based on correlation distance are used as the classifiers. We test our algorithm for both still image and natural scene video to show its feasibility for real time system. The experimental results are also provided to prove the robustness and performance of our algorithm in order to recognize desired person under variable lighting conditions.**

I. Introduction

In recent years, service robot started being developed for the purpose of assisting human. Frequently, the robot is equipped with the ability to detect, track and follow the object or target. Some of them are also equipped with a camera in order to visually detect, track and recognize the target. Many platforms already developed to fulfill those requirements, but performing recognition is very difficult to implement for both indoor and outdoor use. The main problem in real situation is the changing of illumination is very difficult to controlled and unpredictable. Frequently, the changing of illumination surrounding the object makes the visual appearance of object different in some parts (see Fig. 1). Based on [1], we can classify the object appearance into four main types: diffuse reflection, specular reflection, attached shadow and cast shadow.

The most common method used to normalize the effect of illumination is based on Histogram Equalization (HE). HE performs very well in order to enhance the contrast of an image. But it cannot adapt to local brightness features of the input image. A local based histogram equalization called Adaptive Histogram Equalization (AHE) [2] and Block-based Histogram Equalization (BHE) [3] were proposed to compute the histogram of local image region.

Fig. 1: Different visual appearances caused by different illumination conditions

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Since reflectance model based on Lambertian illumination model become very popular, some researchers developed their own methods to address illumination problem that recently become very famous. [4], [5], [6], and [7] proposed Quotient Image (QI) based techniques and its variations to produce normalized facial image from uncontrolled illumination image. At the same time, retinex based method and its improvements were also proposed by other researchers [8] and [9] as a solution to address the problem of uncontrolled illumination for face recognition.

Another improvement shown in [10] is still based on Lambertian illumination model by factorizing a single face image to obtain the illumination invariant facial structure. The advantage of discrete cosine transform in logarithm domain [11] is also utilized in order to compensate the illumination effect before undertaking the face recognition process. On the other hand, statistical approaches [12] and [13] were also taking part in order to provide illumination compensation technique in different ways.

In this paper, we use illumination model proposed in [14] in order to detect and reduce illumination effects from single image of natural scene. We modify the way to get appropriate illumination ratio (r) by reasoning a pair of data provided by models. We produce an adaptive contrast ratio that optimal for each condition. By applying this contrast ratio to an uneven illuminated face image, a shadow-free face image can be obtained by relighting each pixel based on the lighting model. The proposed method is composed of some novel algorithms: (1) generating models from single input image, (2) generating an adaptive contrast ratio using Fuzzy based approach, and (3) optimizing fuzzy rules using genetic algorithm.

The rest of this paper is organized as follows. We present Illumination model and it's modification in section II, followed by Shadow and Reflection Detection in section III. Section IV discusses about Fuzzy-Genetic Framework. We then show the experimental result in section V, and conclusions of our work and possible future work are described in section VI.

II. Illumination Model

In general, reflectance model can be expressed as:

$$I = L\,R, \tag{1}$$

where : I is an image captured by a camera,
L is illumination that comes to surface of object, and
R is reflectance property as the surface's characterristic

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Our approach is based on a simple illumination model where lighting consists of directed light and environment light [14]. We use this approach in order to modify reflectance model [15] where image *I(x,y)* is the product of two components, illumination *L(x,y)* and reflectance *R(x,y)*.

$$I_i = (t_i L_d \cos(\theta_i) + L_e) R_i, \tag{2}$$

where I_i is a scalar representing the value for the i-th pixel in grayscale space. Similarly, both L_d and L_e are also scalars, each representing the intensity of the direct light and the environment light, also measured in grayscale space. R_i is the surface reflectance of that pixel, also a scalar in grayscale space. θ_i is an angle between the direct lighting direction and the surface normal. t_i is a value between 0 and 1 indicating how much direct light gets to the surface.

For simplification, we define $k_i = t_i \cos(\theta_i)$, hereinafter we will always refer to k_i as the shadow coefficient for the i-th pixel. $k_i = 1$ for pixels in non-shadow regions.

$$I_i = (k_i L_d + L_e) R_i. \tag{3}$$

We have two models of pixel corresponding to the presence of light: shadow-free pixel, shown by (4) and shadowed pixel, shown by (5).

$$I_i = (L_d + L_e) R_i, \tag{4}$$

and,

$$I_i^* = (k_i L_d + L_e) R_i. \tag{5}$$

Based on (4) and (5), we can make a new relationship between shadow-free and shadowed pixels as:

$$I_i = (L_d + L_e) R_i \frac{(k_i L_d + L_e)}{(k_i L_d + L_e)} = \frac{(L_d + L_e)}{(k_i L_d + L_e)} I_i^*. \tag{6}$$

We can see that a shadow-free pixel can be generated from shadowed pixel by a specific ratio. If we use $r = \frac{L_d}{L_e}$ to simplify (6), then

$$I_i = \frac{(r+1)}{(k_i r + 1)} I_i^*. \tag{7}$$

Based on [14], the illumination ratio (r) can be defined by two near neighbor pixel. But it must be noted that their algorithm is used for partially shadowed area. When the most part of image is covering by shadow, it is very difficult to find different illuminated pixels from a pair of location, and of course it takes much time. To make it possible, it is important to differentiate reflectivity and normal appearances by comparing its values with estimated normal intensity (appearance) values in the same position. Since we only use single image, it is necessary to decompose the image into two models. Then, we can apply fuzzy for reasoning those two models to meet an appropriate contrast ratio.

III. Shadow And Reflection Detection

To differentiate normal and reflection regions, a shadow coefficient model is used. The direct illumination is highly dependent on the angle between the incoming light and the surface's normal, which are hard to estimate from single image, we use the normalized intensity value as an approximation, that is,

$$k_i = \frac{I_i}{255}, \tag{8}$$

where *Ii* is the i-th pixel's intensity value in gray level and *ki* is its normalized version. By using this normalization, we can detect normal natural color of face skin in gray level, the shadowed region and region with high level of reflection, as shown in Fig. 2.

Then, we also propose the use of block-overlapped histogram equalization to estimate normal appearance of human face with locally contrast adjustment. A block size of 12 x 12 pixels is applied to the image. To avoid discontinuity between adjacent block, the block is moved in overlap to adjacent block every 6 pixel. As same as the standard block-overlapped histogram equalization (BHE) [16], we apply weighted sum of neighboring adjacent blocks to smooth the boundaries in order to reduce blocking effect. The BHE'd image is shown in Fig. 3.

$$T_i \in T = BHE(I^*), \tag{9}$$

where T_i is the i-th pixel's intensity value as the element of T (appearance estimation model or BHE'd image).

IV. Fuzzy-Genetic Framework

As we mentioned at section II, illumination ratio r is a main factor that should be obtained. Estimation of r is necessary to produce an appropriate approximation of contrast ratio. Based on real case of human face under uneven illumination condition, two kind of information have been used to address the shadow and reflection problems. We already have BHE-based appearance estimation model and color normalization based shadow coefficient model.

Appearance estimation model and shadow coefficient model have values within range $0 \le T_i \le 255$ and $0 \le k_i \le 1$ respectively. Where *Ti* is an intensity value of BHE'd image at i-th pixel and *ki* is a normalized intensity value at i-th pixel. We cannot directly use them to produce appropriate contrast ratio in order to address illumination problem. But, we need to think about what should be happened if both of information combined.

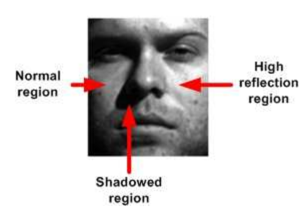

Fig. 2: Shadow and Reflection detection

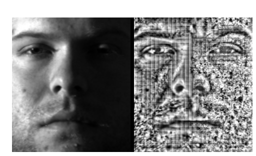

Fig. 3: Block-based Histogram Equalization; (a) original image, (b) BHEd image

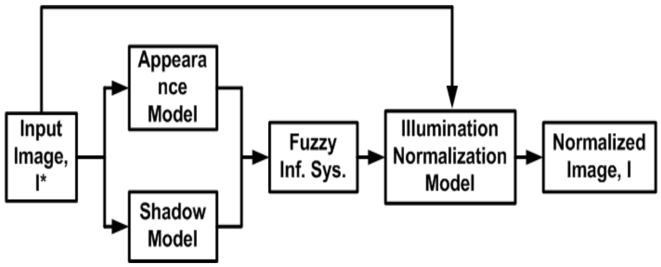

Fig. 4: Proposed system

Because of getting r needs highly complex combination and also involving large number of data as representative of pixel's number, a Fuzzy Inference System (FIS) is proposed to handle this problem. In this section, the optimal r can be approximated through FIS. We use the gray level value of appearance estimation model (T_i) and normalized value of shadow coefficient model (k_i) of the facial region as the input values of FIS. Since FIS produces an appropriate r value corresponding to both inputs, the original input image with uneven illumination can be normalized as a better image. The procedure for the proposed algorithm is shown in Fig. 4.

Each input image, I* with size P x Q pixels is transformed into the appearance model and the shadow model. Each pixel's information from both models is used as input of fuzzy logic system to estimate r for illumination normalization model. Each pixel of input image is processed by its corresponding position of r value.

A. Membership Function

To determine the optimal value of r for the illumination normalization model, we classify the appearance estimation values by using five memberships: very dark (VD), dark (D), medium (M), bright (B) and very bright (VB), and the shadow coefficient values also classified by using five memberships: very low (VL), low (L), medium (M), high (H) and very high (VH). By considering its simplicity and an assumption that this case still can be approached using linear equation, we adopt a linear design for fuzzy membership functions by using triangular shapes, which are most widely used in fuzzy applications, as shown in Fig. 5.

B. Fuzzy Rules

Since the fuzzy membership functions have five memberships for each model, then, our fuzzy has 25 combinations of rule. The rules ($\boldsymbol{R}$) can be described as a vector as follows

$$\boldsymbol{R} = \{R_1, R_2, R_3, \ldots\ldots, R_{25}\}. \quad (10)$$

As in ordinary fuzzy systems, rules are frequently determined at initial state, but it makes the rules too stuffy and not adaptable. While the rule is formed by using data driven approach, rules can be formed as required, but still needs another optimization process. To meet the optimal solution, we choose the data driven approach to create our fuzzy based adaptive contrast ratio. This approach will adaptively normalize paired information provided by each corresponding pixel position from both model. The combination of fuzzy rules is shown in Fig. 6.

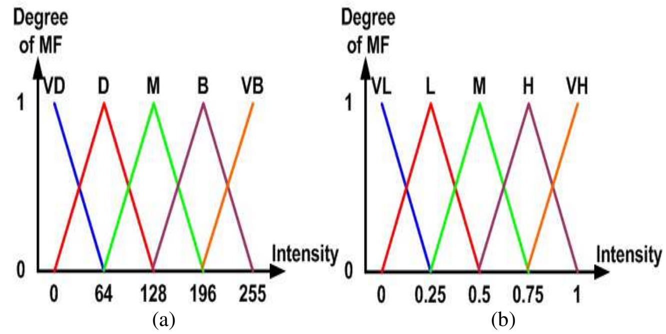

Fig. 5: The membership functions of the proposed fuzzy logic system for (a) appearance model, and (b) shadow model.

C. Optimizing Rules of Fuzzy

As describe in section I, the changing of illumination direction causes the visual appearance of the same face will be different in some parts. Therefore, the effect of illumination direction should be studied. Yale B face database [17] is one of very famous faces database corresponding to illumination problem. This database contains 38 subjects with 64 different illuminations variant. The light source used in the database is a single light source by considering its position respect to camera in the azimuth and the elevation angles.

For the optimization purpose, a set of illumination dataset respect to one subject or person is chosen. Based on this approach, we have 64 objects to be normalized. The main target is how to bring all different appearance images to be one common appearance image. By remembering that each image size of P x Q pixels, we have P x Q x 64 combinations. If P = 168 and Q = 192, we have 2,064,384 combinations. It is really very huge number of data, and impossible to calculate manually.

To produce a rule that satisfies all combinations as an optimal solution, a Genetic Algorithm (GA) is used [18]. GA is used to find an optimal set of rule which fits to 64 illumination conditions. We propose a data driven based GA's training method (see algorithm 1) to optimize fuzzy rules. We modify the fitness function to allow direct intervention for a set of data pairs. The most optimal solution is not the only optimal solution to single problem, but the solution that applies to all problems.

We use the rule $\boldsymbol{R}$ as the coding of genes to be optimized. GA uses the common procedures such as selection, cross over and mutation to find the optimal solution of $\boldsymbol{R}$ from a number of populations. Each individual, X in the population is evaluated for each input using our illumination normalization model. Based on the evaluation result, fitness function can be generated. We use correlation based distance to compute the fitness value.

$$f(X, m) = corr(I_{norm}^1, I_{norm}^m), \quad (11)$$

where : $f(X, m)$ is the fitness value for X-th individual respected to input m-th
I_{norm}^1 is the 1st normalized image, and
I_{norm}^m is the m-th normalized image, m = 2, 3, 4, …, 64

		Shadow				
		VL	L	M	H	VH
Texture	VD	R1	R6	R11	R16	R21
	D	R2	R7	R12	R17	R22
	M	R3	R8	R13	R18	R23
	B	R4	R9	R14	R19	R24
	VB	R5	R10	R15	R20	R25

Fig. 6: Fuzzy Rules

Then, each fitness value that corresponds to each input is averaged together based on its rank to get the shared fitness value, $fs(X)$. Thus, crossover and mutation operators are performed to optimize each individual. The process is iterated 10,000 times. The changing of shared fitness value is also recorded for 10,000 iterations as shown in Fig. 7.

$$fs(X) = \frac{1}{M}\sum_{m=1}^{M} f(X,m), \tag{12}$$

where : $fs(X)$ is shared fitness value for individual X-th
M is the number of input

V. Experimental Results and Discussion

In our experiment, we evaluate both still images and real scene videos for testing the feasibility and performance of our system in order to normalize illumination effects. We use Yale B Face database and MIT Face database [19] as representative of still image database to measure the recognition rate. We also use two real scene video that captured surrounding our campus to represent indoor and outdoor scene to test our system for natural situations.

A. *Experimental Setup*

A.1 Still image dataset

We test our algorithm on two face databases, Yale B Face database and MIT Face database. Only the frontal images with illumination variation are selected and manually cropped. Each image is cropped in size of 168 x 192 pixels. Yale B Face database has 64 illumination variations for each of 38 persons. While MIT Face database has 36 illumination variations for each of 10 persons. We use two kinds of classifier, the nearest neighbor with correlation coefficient as its distance measurement and principle component analysis (PCA) [20] with 9 principle components.

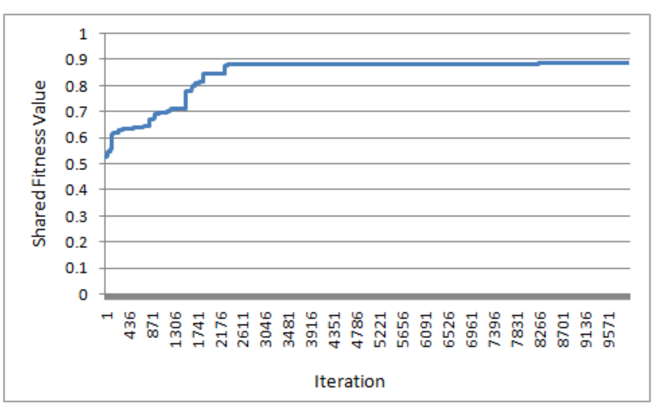

Fig. 7: GA's shared fitness value

Algorithm 1: Genetic Algorithm for Fuzzy Rules Optimization

Input : Number of population at t-th iteration, P_t
Number of dataset, M
Raw input image, I_m^*
Normalized image, I_m

Output : Solution, X_1

Step 1 : Start with a random initial population P_0, Set M = 64, Set t = 0

Step 2 : If the stopping criterion/iteration satisfied, return P_t, $X_1 \in P_t$ is the optimal solution

Step 3 : Apply illumination normalization model to each pixel of raw input image as follows:

$T = appearance(i^*)$

$k = shadow(i^*)$

$r = fuzzy(t,k)$

$i = \frac{r+1}{k.r+1} i^*$, where $i \in I_m, i^* \in I_m^*, k \in K \; and \; r \in R$

Step 4 : Evaluate fitness of the population as follows :

Step 4.1 : Assign a fitness values to each solution based on the each dataset fitness (f) as follows:

$f(X,m,t) = corr(I_{norm}^1, I_{norm}^m)$

Step 4.2 : Calculate the shared fitness value (fs) of each solution $X \in P_t$ as follows:

$fs(X,t) = \frac{1}{M}\sum_{m=1}^{M} f(X,m,t)$

Step 4.3 : Assign a rank r(X,t) to each solution $X \in P_t$ based on its shared fitness value

Step 5 : Use stochastic selection method based on *fs* to select parents for the mating pool. Apply crossover and mutation on the mating pool until offspring population Q_t of size N is filled. Set $P_{t+1} = Q_t$

Step 6 : Set t = t + 1, go to step 2

We use only one frontally illuminated image as a template from 10 persons in Yale B Face database and 10 persons in MIT Face database. All the images have been converted to normalized images by using proposed method before undertaking the recognition process. Each normalized image is resized to 64 x 64 pixels. As comparative methods, no normalization process, Histogram Equalization (HE), Block-based Histogram Equalization (BHE) [3], BHE + 2D Face Model [3], Single Scale Retinex (SSR) [8], Self Quotient Image (SQI) [5], Classified Appearance-based Quotient Image (CAQI) [6], Optimized-SQI [7], Logarithmic Total Variation (LTV) [10], Discrete Cosine Transform (DCT) [11], and Block Difference of Inverse Probabilities (BDIP) + Block Variation of Local Correlation (BLVC) [12] are included.

A.2 Video dataset

We also test our algorithm on two natural situations to prove that our system can be also used in real time. Two kinds of video which represent indoor and outdoor scene are captured at our campus. Indoor video is taken in a corridor with various lighting conditions, such as indoor lighting, light from outside coming in through the window and hallway without light. The outdoor video is taken on road pavement for pedestrian. Each video is captured in size of 640 x 480 pixels. To detect and crop a face, Haar Cascade technique has been used. As the training data, we provided 2,400 positive images and 4,500 negative images that have been converted to normalized images by using our proposed method.

B. *Experimental Results*

B.1 Results of Still Image dataset

In the experiment using still image from Yale B Face database (see Fig. 8), we can see that our method can make each illumination variations produce almost homogeneous image where each detail information of the face can be presented more consistent. We can keep the details for each person in order to produce stronger textures for face recognition purpose. More uniform color also can be obtained after normalization process. By applying the proposed method to MIT Face database (see Fig. 9), we can see that the results in more consistent. Illumination effects that appear in MIT face database are more moderate if compared to Yale B face database. We then compare it with other well-known methods to prove its improvement as shown in Table 1.

Based on the results shown in Table 1, our algorithm can reach the highest recognition rate compared to the others for both Yale B Face database and MIT Face database using correlation based nearest neighbor and principle component analysis. Even though Optimized-SQI and LTV can reach higher recognition rate, but they used more than one reference image as training images for PCA. Since we also used MIT Face database in our experiment, some methods have no available result respected to that database. The high recognition rates obtained by using NN and PCA show us that our algorithm is capable to keep the facial shape (e.g. eyes, eyebrows, nose, nostril and mouth), strengthen the texture and produce a uniform color for each output image.

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

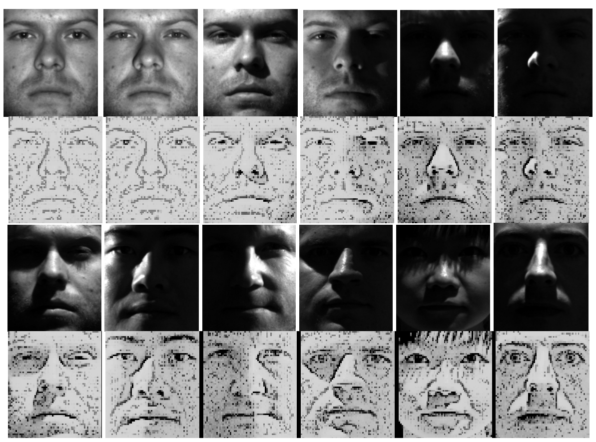

Fig. 8: Example results of Yale B Face database; (a) illumination variations of first person, (b) reconstructed images of (a), (c) illumination variations of different persons, (d) reconstructed images of (c)

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

Fig. 9: Example results of MIT Face database; (a) illumination variations of first person, (b) reconstructed images of (a), (c) illumination variations of different persons, (d) reconstructed images of (c)

TABLE I. Face recognition results using NN and PCA for Yale B and MIT Face databases

Method	Yale B Face database		MIT Face database	
	NN	PCA	NN	PCA
None	57.97 %	49.06 %	95.28 %	80.56 %
HE	70.00 %	67.34 %	91.67 %	92.78 %
BHE [3]	N/A	77.50 %	N/A	N/A
BHE + 2D Face Shape Model [3]	N/A	96.40 %	N/A	N/A
SSR [8]	91.40 %	43.13 %	100.00 %	94.72 %
QI [4]	N/A	74.34 %	N/A	N/A
SQI [5]	93.59 %	60.00 %	100.00 %	100.00 %
CAQI [6]	N/A	97.40 %	N/A	N/A
Optimized-SQI [7]	N/A	99.47 %*	N/A	N/A
LTV [10]	N/A	99.25 %*	N/A	N/A
DCT [11]	N/A	98.11 %*	N/A	N/A
BDIP + BVLC 1 & 2 [12]	N/A	98.00 %*	N/A	N/A
Proposed	**99.84 %**	**98.59 %**	**100.00 %**	**100.00 %**

B.2 Results of Video dataset

We also tested our algorithm in natural scene situations by applying it to normalize uneven illumination in a video sequence. By combining our algorithm with the Haar Cascade method, we normalize each frame of video sequence before undertaking face detection and cropping the face. After a face or some faces detected, then system will automatically cropping the face region and compare the cropped result with a single image or sets of reference images. We then apply correlation based NN as face classifier.

We divide our experiments into two parts: indoor and outdoor experiment. For the experiments, we capture several reference person images before running the system, as shown in Fig. 10. All reference and cropped images are resized to 64 x 64 pixels, and each new cropped image is compared to each reference image by using nearest neighbor based on the correlation distance. Fig. 11 and Fig. 12 show the results for indoor and outdoor experiments respectively.

Actually, it is still very difficult to use the system directly for real situations. In real situations, it is very difficult to keep the same alignment of cropped images, prevent the change of face rotation, and expression. Since our system still focused to illumination problem, we limit our experiments for illumination normalization purpose only. One of the main ob-

(a) (b) (c)

Fig. 10: Reference images for indoor and outdoor experiments; (a) person #1, (b) person #2, and (c) person #3

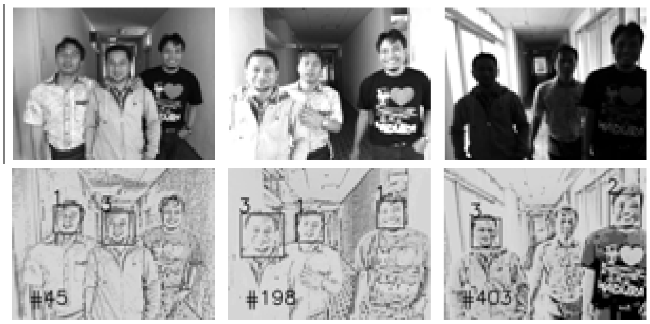

Fig. 11: Examples of test scenes processed with our algorithm for indoor experiment. Each frame shows us the detected face and its recognition results.

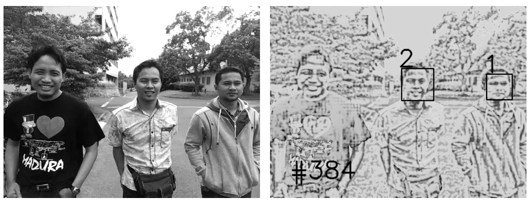

Fig. 12: Examples of test scene processed with our algorithm for outdoor experiment. The frame shows us the detected face and its recognition results.

TABLE II. Recognition rate of indoor and outdoor experiment for intra-personal and inter-personal relationship

Person	**Detected as person no- (%)**					
	Indoor			**Outdoor**		
	1	**2**	**3**	**1**	**2**	**3**
1	**73.6**	11.1	15.3	**83.5**	8.7	7.8
2	23.5	**50.0**	26.5	18.8	**63.5**	17.8
3	12.5	24.3	**62.9**	**57.1**	27.4	15.4

jectives has been achieved, i.e. normalize the lighting effects. For face recognition, the results are still very dependent on a few things that have been mentioned above. Table 2 shows us the recognition rates produced by our system for both indoor and outdoor experiments. For indoor experiment, the system can achieve better result compared to outdoor experiment, especially for testing the third person. When we pay attention to the sequence of videos, some factors causing a low recognition rate are face rotation and distance between camera and the objects. Since our system uses a fixed focus monocular camera while the face databases use a single reference image per person with frontally upright face image and ignoring the face and the head rotation, it is very difficult to enhance the captured image to make it clearer and sharper.

VI. CONCLUSION

We have presented a novel algorithm for reducing the effect of illumination especially for human face recognition based on fuzzy. Our algorithm can successfully normalize unevenly illuminated image to a homogeneous appearance image with high details, small noise and keep important information such as shape, texture and color all at once. Still image based testing result shows that our algorithm is robust enough in order to normalize uneven illumination effect both moderate and hard illumination.

On the other hand, experimental results using real scene situations are less so satisfying. It still needs to be improved, especially for how to maintain the bounding box remains stable. The face orientation also becomes our attention, since the little changing in orientation will produce miss-detection and miss-classification.

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