Robust Face Recognition Methods under Illumination Variations toward Hardware Implementation on 3DCSS

H. Ando, N. Fuchigami, M. Sasaki and A. Iwata

Graduate School of Advanced Sciences of Matter, Hiroshima University 1-3-1 Kagamiyama, Higashi-hiroshima, 739-8530, Japan Phone: +81-824-22-7358, E-mail: ando, futigami, sasaki, iwa@dsl.hiroshima-u.ac.jp

1. Introduction

In order to realize highly intelligent information processing systems which can recognize various objects in real-time/real-world, we have been proposed a concept of multi-object recognition system based on 3D custom stack system (3DCSS) presented in the 21st century COE of Hiroshima University [1]. Recently, we have developed a real time human face detection/recognition software system based on eigenfaces methods and implemented it on FPGA [2, 3].

However, there is a problem that the recognition performance of our developed system deteriorates under illumination variations. These variations can not be avoidable in the real world.

In this paper, we propose robust face recognition methods which overcome illumination problem by applying three image processings to input images. We show the effectiveness of proposed methods by numerical simulations.

2. Preprocessing for removing the influence of illumination variations

The Yale Face Database B[4] is a free database for illumination and pose problems. This database contains 5760 single light source images of 10 individuals each seen under 576 viewing conditions (9 poses x 64 illumination conditions). For all the sets in the frontal pose, the coordinates of the left eye, right eye, and mouth in each image have been appended. The examples of frontal images in the database are shown in Fig. 1. 45 images out of 64 is assigned to one of four Subsets according to the light-source directions. The examples of frontal images belonging to each Subset are shown in Fig. 2.



Figure 1: Example of cropped frontal images of 10 individuals in the Yale Face Database B.

As shown in Fig. 2, although all of these images are same individual, the appearance of these images varies strongly according to the light-source directions. We should remove the influence caused by illumination variations in order to achieve accurate face recognition. Therefore, we apply image preprocessing which is combination



Subset 1

Subset 4

Figure 2: Example of cropped frontal images of a single individual in the Yale Face Database B under different illuminations.

of Histogram equalization, Laplacian of Gaussian filter and Contrast adjustment to appearance-based recognition methods.

(1)Histogram equalization

Histogram equalization is most widely used method to enhance biased contrast image that some pixels are concentrated on a narrow range of the pixel intensity. Figure 3(a) shows results of histogram equalization for images shown in Fig. 2. Thus, the quality of the image is improved and feature parts such as eyes, nose and mouth are made more clearly.

(2)Laplacian of Gaussian filter

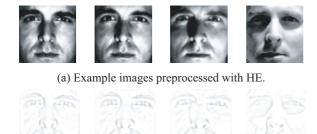
In order to remove the information of pixel intensity while reserving local features that are useful to recognition, we apply Laplacian of Gaussian filter following the histogram equalization (Fig. 3(b)). As shown in Fig. 3(b), local features of each face are reserved and the influence of lighting is almost removed. However, contrast of processed images is biased to a certain range.

(3)Contrast adjustment

In order to improve the contrast of Laplacian of Gaussian filtered images and emphasize the local features, we perform Contrast adjustment. That is, pixel values that the sum total of number of pixels from a maximum/minimum intensity of the image becomes the whole 1% are calculated each other, and these values are newly assigned to be a maximum/minimum intensity of the image. The processed images are shown in Fig. 3(c). As a result, we can create the images by which illumination variations was lessened.

3. Experiments

We performed numerical simulations of human face recognition by using Eigenfaces [2] and Fisherfaces [5] methods with Yale Face Database B. In our experiments, we cropped the original images so that the positions of both the eyes of all images should be equal, and resized them into 64×64 pixels. The images included in Subset 1 were used for training data.



(b) Example images preprocessed with HE and LG.



(c) Example images preprocessed with HE, LG and CA.

Figure 3: Example images with histogram equalization.

In order to compare with other combination of image processing, four kinds of combination were used and evaluated:

- A) No preprocessing (original)
- B) Histogram equalization (HE)
- C) Histogram equalization and Laplacian of Gaussian filter (HE+LG)
- D) Histogram equalization and Laplacian of Gaussian filter and Contrast adjustment (HE+LG+CA).

Moreover, the difference of recognition performance was examined for four evaluation functions:1) Manhattan distance (Man), 2) Euclidean distance (Euc), 3) Normalized correlation (NCorr) and 4) Correlation (Corr).

Table 1 and 2 show recognition rates by using Eigenfaces and Fisherfaces methods, respectively. As shown in Tab. 1, recognition rates were rapidly decreased as change of illumination increased without preprocessing. On the other hand, the recognition rate of 99.74% was achieved in HE+LG+CA under illumination variations. In the case of Fisherfaces (Tab. 2), we achieved the recognition rate of 99.20% in the same way.

From the viewpoint of evaluation functions, the recognition rates in Man was almost equal with the best performance. Therefore, we only have to use the simplest Manhattan distance for evaluation function. This is the advantage for hardware implementation because the calculation of Manhattan distance can be realized by only subtraction.

Thus, we can achieve robust face recognition under illumination variations by using proposed methods. In 3DCSS, the proposed methods can be realized by assigning the chip for the preprocessing as one layer of the former steps of the recognition chip layer.

4. Conclusions

We proposed the illumination invariant face recognition methods by using three image processings. We performed about 99% correct recognition rates by the numerical simulations on Yale Face Database B.

Acknowledgment

We would like to thank Athinodoros Georghiades and acknowledge the use of the "Yale Face Database B".

Table 1: Recognition rate in Eigenfaces								
	Func.	Sub. 2	Sub. 3	Sub. 4	All			
Α	Man	94.07	50.42	27.54	55.73			
	Euc	94.92	52.10	26.09	56.00			
	NCorr	98.31	79.83	38.41	70.40			
	Corr	99.15	79.83	39.13	70.93			
В	Man	100.00	84.03	41.30	73.33			
	Euc	100.00	89.08	36.23	73.07			
	Ncorr	100.00	91.60	36.23	73.87			
	Corr	100.00	92.44	37.68	74.67			
С	Man	100.00	100.00	87.68	95.47			
	Euc	100.00	97.48	76.81	90.67			
	Ncorr	100.00	99.16	79.71	92.27			
	Corr	100.00	100.00	99.28	99.73			
D	Man	100.00	100.00	97.83	99.20			
	Euc	100.00	100.00	97.10	98.93			
	Ncorr	100.00	100.00	97.10	98.93			
	Corr	100.00	100.00	99.28	99.73			
All: including Subset 2, 3 and 4. unit: $[\%]$								

Table 2: Recognition rate in Fisherfaces

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	Func.	Sub. 2	Sub. 3	Sub. 4	All			
Α	Man	100.00	94.96	34.78	74.40			
	Euc	100.00	95.80	35.51	74.93			
	NCorr	100.00	100.00	44.93	79.73			
	Corr	100.00	98.32	39.86	77.33			
В	Man	100.00	100.00	63.04	86.40			
	Euc	100.00	99.16	65.94	87.20			
	Ncorr	100.00	99.16	67.39	87.73			
	Corr	100.00	96.64	64.40	85.87			
С	Man	100.00	100.00	95.65	98.40			
	Euc	100.00	100.00	97.83	99.20			
	Ncorr	100.00	100.00	86.96	95.20			
	Corr	100.00	90.76	56.52	81.07			
D	Man	100.00	100.00	97.10	98.93			
	Euc	100.00	100.00	97.83	99.20			
	Ncorr	100.00	92.44	59.42	82.67			
	Corr	100.00	90.76	60.87	82.67			
All: including Subset 2, 3 and 4, unit: [%]								

All: including Subset 2, 3 and 4. unit:[%]

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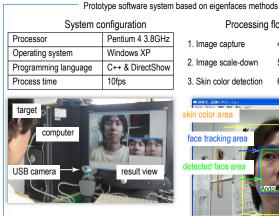
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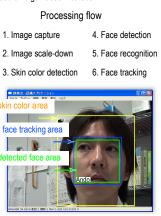
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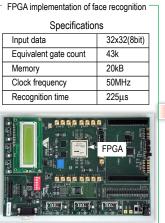
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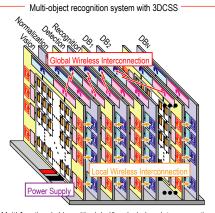
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In order to realize highly intelligent information processing systems which can recognize various objects in real-time/real-world, we have been proposed a concept of multi-object recognition system based on 3D custom stack system(3DCSS) presented in the 21st century COE of Hiroshima University. Recently, we have developed a real time human face detection/recognition software system based on eigenfaces methods and implemented it on FPGA









Multi-functional chips with global/local wireless interconnection

2. Recognition in an uncontrolled environment

There is a problem that the recognition performance of our developed system deteriorates under variations. These variations can not be avoidable in the real world

images under several variations



In this presentation, we focus on the illumination problem and propose robust face recognition methods by applying three image processings to input images.

3. Database for illumination problem

The Yale Face Database B is a free database for illumination and pose problems. This database contains 5760 single light source images of 10 individuals each seen under 576 viewing conditions (9 poses x 64 illumination conditions). 45 images out of 64 is assigned to one of four Subsets according to the light-source directions.



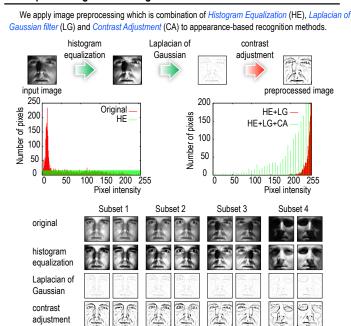


Example of cropped frontal images of a single

individual under different illuminations.

Example of cropped frontal images of 10 individuals.

4. Preprocessing for removing the influence of illumination variations



Example of preprocessed images under illumination variations

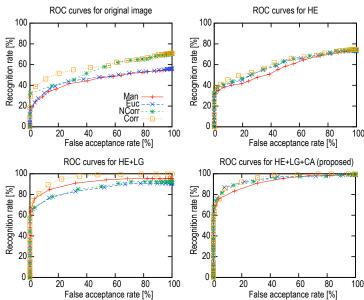
5. Numerical simulation results

We performed numerical simulations of human face recognition by using Eigenfaces and Fisherfaces methods with Yale Face Database B. The difference of recognition performance was examined for four evaluation functions: 1)Manhattan distance(Man), 2)Euclidean distance(Euc), 3)Normalized correlation(NCorr) and 4)Correlation(Corr).

		Recognition rates for Eigenfaces			Recognition rates for Fisherfaces				
		Sub.2	Sub.3	Sub.4	All	Sub.2	Sub.3	Sub.4	All
Original	Man	94.07	50.42	27.54	55.73	100.00	94.96	34.78	74.40
	Euc	94.92	52.10	26.09	56.00	100.00	95.80	35.51	74.93
	NCorr	98.31	79.83	38.41	70.40	100.00	100.00	44.93	79.73
	Corr	99.15	79.83	39.13	70.93	100.00	98.32	39.86	77.33
HE	Man	100.00	84.03	41.30	73.33	100.00	100.00	63.04	86.40
	Euc	100.00	89.08	36.23	73.07	100.00	99.16	65.94	87.20
	NCorr	100.00	91.60	36.23	73.87	100.00	99.16	67.39	87.73
	Corr	100.00	92.44	37.68	74.67	100.00	96.64	64.40	85.87
HE+LG	Man	100.00	100.00	87.68	95.47	100.00	100.00	95.65	98.40
	Euc	100.00	97.48	76.81	90.67	100.00	100.00	97.83	99.20
	NCorr	100.00	99.16	79.71	92.27	100.00	100.00	86.96	95.20
	Corr	100.00	100.00	99.28	99.73	100.00	90.76	56.52	81.07
HE+LG+CA	Man	100.00	100.00	97.83	99.20	100.00	100.00	97.10	98.93
(Proposed)	Euc	100.00	100.00	97.10	98.93	100.00	100.00	97.83	99.20
,	NCorr	100.00	100.00	97.10	98.93	100.00	92.44	59.42	82.67
	Corr	100.00	100.00	99.28	99.73	100.00	90.76	60.87	82.67

All : including Subset 2, 3 and 4. unit:[%]





6. Conclusion

We proposed the illumination invariant face recognition methods by using three image processings. We performed about 99% correct recognition rates by the numerical simulations on Yale Face Database B. Moreover, we should just use the Manhattan distance for evaluation function by using our proposed methods.