ROBUST FACE RECOGNITION USING WAVELET AND DCT BASED LIGHTING NORMALIZATION, AND SHIFTING-MEAN LDA

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Abstract: This paper presents an integration of Wavelet and Discrete Cosine Transform (DCT) based lighting normalization, and shifting-mean Linear Discriminant Analysis (LDA) based face classifiers for face recognition. The aims are to provide robust recognition rate against large face variability due to lighting variations and to avoid retraining problem of the classical LDA for incremental data. In addition, the compact holistic features is employed for dimensional reduction of the raw face image. From the experimental results, the proposed method gives sufficient and robust achievement in terms of recognition rate and requires short computational time.

1 INTRODUCTION

The existing face recognition methods (Zhao et al., 2003; Chen et al., 2005; Yu and Yang, 2001; Wijaya et al., 2010; Pang et al., 2005; Zhao and Yuen, 2008) still leave several problems such as low performance for large face variability due to large lighting variations and requiring long computational time for retraining of incremental data.

In terms of large face variability due to large lighting variations, a comparative study of different pre-processing approach to illumination compensation has been proposed for solving this problem (del Solar and Quinteros, 2008). In addition, robust preprocessing for illumination compensation of face image which was based on low-pass filter has been proposed and it provided robust achievements over the SQI (Kurita and Tomikawa, 2010). However, it still has the difficulty to determine the type of low-pass filter that is suitable for those algorithms. An alternative method which was based on the local mean has been proposed for overcome this problem and works well for data from YaleB database (Wijaya et al., 2010). However, the performances of mentioned methods are not optimum yet especially for data which contain large illumination.

Regarding to retraining problem, several methods have been proposed (Pang et al., 2005; Zhao and Yuen, 2008; Wijaya et al., 2010). An algorithm called as incremental LDA (ILDA) was presented to avoid this problem (Pang et al., 2005) which is redefined the within-class scatter (S_w) formulation, made simplification of calculating the global mean, and determined the projection matrix (W) using singular value decomposition (SVD). An improvement of ILDA strategy was proposed called as generalized SVD incremental LDA (GSVD-ILDA) which determined W of incremental data using generalized SVD(Zhao and Yuen, 2008). The GSVD-ILDA needed less computation time than that of ILDA. Another strategy was proposed to solve the retraining problem using the constant global mean for all data samples to obtain the between class scatter, S_b (Wijaya et al., 2010). It also implemented compact holistic features (HF) for dimensional reduction of the raw image which compressed the original size of image into 90%. The HF could provide good enough achievements in terms of recognition rate and required short processing time. The sufficient spanning sets ILDA (Kim et al., 2011) also has been presented to overcome retraining problem of incremental data which works using sufficient spanning sets for converting the large eigen problem of classical LDA into a smaller eigen problem. Furthermore, a new incremental LDA which was based on least square solution to LDA called as LS-ILDA was presented to avoid the eigen analysis bottleneck on conventional LDA (Liu et al., 2009). However, they requires less computational complexity when the input data size (n) is much larger than the total data classes (L) and the LS-ILDA determined the optimum

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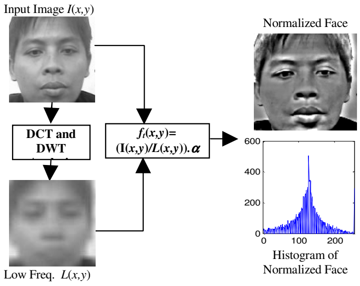


Figure 1: Lighting normalization process.

W just from total scatter matrix and the updating process has to be done by inserting one sample.

In this paper, we present an integration of discrete wavelet transforms (DWT) and DCT based lighting normalization with shifting-mean LDA (SM-LDA)-based face classifiers for robust face recognition. The DCT and Wavelet based lighting normalization which are simple and fast lighting normalization are proposed for solving the remaining problem of large face variability due to lighting variations. Next, the SM-LDA which is a new approach for avoiding to recalculate the S_w and S_b for each incremental data is proposed for solving retraining problem of conventional LDA. In this research, to solve eigen analysis bottleneck on conventional LDA, the compact holistic features is implemented as dimensional reduction of raw face image. In this case, the dimensional of the raw face image is reduced into 53 coefficients from 16384 coefficients.

2 DWT AND DCT BASED LIGHTING NORMALIZATION

The existing methods for lighting normalization still does not work well yet for large face variability due to lighting variations especially for data which contain large illumination such as sub-set 4 of YaleB database (face images set which the angles of the light source direction are up to 77^0 from the camera).

To solve this problem, we develop simple lighting normalization algorithm as shown in Fig.1, which is based on the frequency transformation analysis. The main goal is to improve recent existing methods such as modified local binary pattern (mLBP) and local mean methods. This idea comes from the description of low-pass filter-based algorithm (Kurita and Tomikawa, 2010) which explains that the illumination information of the image is placed on the low frequency component of the face image. As known that the DCT and DWT have good capability to extract the frequency content of the image which have much energy compactness.

Suppose the original image is $I(x,y)$, the illuminant component is $L(x,y)$, and the normalized image is defined as $f_t(x,y)$. The lighting normalization starts from the YCbCr transformation because the RGB is not required and the lighting just affects the contrast and brightness of the image, which is placed in the intensity (Y) component. Next, from the Y component, the illuminant component is extracted by both DCT and multi-resolution DWT using the following procedures:

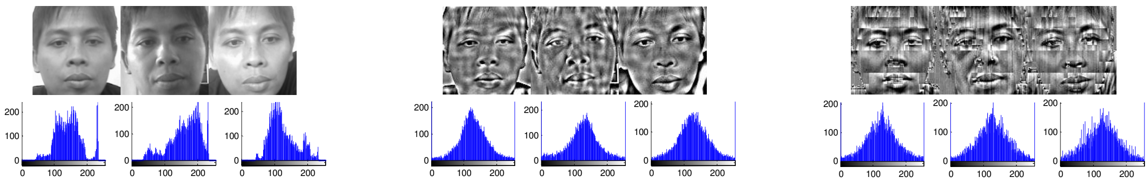
- Performing the DCT and multi-resolution DWT of the Y component then select small m coefficients, which contain 99% of total energy.
- Reconstructing the image from the selected coefficients using inverse DCT and multi-resolution DWT algorithm.

Next, dividing the original image $(I(x,y))$ that represents the input stimulus with the low frequency extraction output $(L(x,y))$ that represent the illuminant or perception using: $f_t(x,y) = I(x,y)/L(x,y).\alpha$, where the α is constant coefficient for making centring the image intensity. Finally, stretching the $f_t(x,y)$ to get the uniform contrast and brightness, as shown in Fig. 2(b and c) for DCT and DWT based lighting normalization, respectively.

The DCT and DWT can work for lighting normalization because the most of the illuminant components are well extracted, as shown in the Fig. 3(a and b). From those images, we can see that the illumination part of the input images is exactly extracted by the DCT and DWT-based methods. From the output of the lighting normalization (see Fig. 2(b and c)) show that all of the images have almost the same brightness and contrast, which is shown by almost identical histogram data for DCT-based and multi-resolution DWT-based algorithms, respectively. In addition, these methods still leave clear facial features such as eyes, mouth, nose, face outline, and face texture. It means the proposed lighting normalization tend to overcome the large variations of face images due to the lighting variations. In other words, the proposed methods tend to provide and better and robust achievements in terms of recognition rate than the previous methods because the most significant discriminant information such as local facial features still exist after normalization.

3 SHIFTING-MEAN LDA

Briefly, the LDA methods works as follows: suppose we have data set which have L classes and each class



(a) Input images (b) DCT-based method (c) Multi-resolution DWT-based method

Figure 2: The input and output of lighting normalization and their histogram.

(k-th) has N_k samples. From the data set, the optimum W, which has to satisfy the Fisher criterion (Eq. 1), can be determined by eigen analysis of inverse S_w time S_b and then select m orthonormal eigenvectors corresponding to the largest eigenvalues (i.e. $m < n$), where n is the dimensional of input vector, x_i^k.

$$J_{LDA}(W) = \underset{W}{arg\,max} \frac{|W^T S_b W|}{|W^T S_w W|} \tag{1}$$

Where both of the $S_w = \frac{1}{N}\sum_{k=1}^{L}\sum_{i=1}^{N_k}(x_i^k - \mu_k)(x_i^k - \mu_k)^T$ and $S_b = \sum_{k=1}^{L} P(x_k)(\mu_k - \mu_a)(\mu_k - \mu_a)^T$ with $P(x_k) = N_k/N$, $N = \sum_{k=1}^{L} N_k$, $\mu_k = \frac{1}{N_k}\sum_{i=1}^{N_k} x_i^k$, and $\mu_a = \frac{1}{N}\sum_{k=1}^{L} N_k \mu_k$.

(a) DCT-based (b) MR-DWT-based

Figure 3: Low frequency extraction outputs.

By using this LDA algorithm for face recognition, good and stable recognition rate for both small and large sample size data (Chen et al., 2005; Yu and Yang, 2001) can be achieved. However, it need retraining process for incremental data. To avoid the retraining problem and to decrease its computational load, we can simplify the S_b using the shifting-mean algorithm as follows.

$$\begin{aligned} S_b &= \frac{1}{N}\sum_{k=1}^{L} N_k(\mu_k - \mu_a)(\mu_k - \mu_a)^T \\ &= \frac{1}{N}\sum_{k=1}^{L}\left(N_k \mu_k \mu_k^T\right) + \alpha \mu_a \mu_a^T - r\mu_a^T - \mu_a r^T \\ &= \frac{\Theta}{N} - \mu_a \mu_a^T \end{aligned} \tag{2}$$

where, $\Theta = \sum_{k=1}^{L} N_k \mu_k \mu_k^T$, $\alpha = N$, $r = \sum_{k=1}^{L} N_k \mu_k$, and $\mu_a = \frac{1}{N}\sum_{k=1}^{L} N_k \mu_k = \frac{r}{N}$. If a new class, x^{new}, comes into the system, the S_b can be updated as follows.

$$\begin{aligned} S_b^u &= \frac{1}{L + N_{new}}\left(\Theta + N_{new}\mu_{new}\mu_{new}^T\right) - \mu_a^u(\mu_a^u)^T \\ &= \frac{1}{L + N_{new}}\left(\Theta_{old} + \Theta_{new}\right) - \mu_a^u(\mu_a^u)^T \end{aligned} \tag{3}$$

where $\Theta_{old} = \Theta$, $\Theta_{new} = N_{new}\mu_{new}\mu_{new}^T$, and

$$\mu_a^u = \frac{1}{L + N_{new}}\left(L\mu_a + N_{new}\mu_{new}\right). \tag{4}$$

By using this simplification, the updated S_b has exactly the same scatter as the original. In detail, to update the S_b using Eq. 3, we just need to calculate the Θ_{new}, μ_a^u, and $\mu_a^u(\mu_a^u)^T$ which require $(2n^2)$ multiplication operations and $(n^2 + n)$ additions. However, the original one requires $(L+1)n^2$ multiplications and $(L+1)n^2$ additions.

In addition, the S_w, which does not depend on the global mean, can be redefined as follows:

$$\begin{aligned} S_w^u &= \frac{1}{N + N_{L+1}}\left\{\sum_{k=1}^{L} S_w^k + S_w^{L+1}\right\} \\ &= \frac{1}{N + N_{L+1}}\left\{S_w^{old} + S_w^{new}\right\}, \end{aligned} \tag{5}$$

where $S_w^k = \sum_{i=1}^{N_k}(x_i^k - \mu_k)(x_i^k - \mu_k)^T$, $S_w^{old} = \sum_{k=1}^{L} S_w^k$, and $S_w^{new} = S_w^{L+1}$.

Finally, the optimum W is obtained by substituting the S_b^u and the S_w^u of LDA eigen analysis and then select several large eigen vectors which correspond to the largest eigen values. This optimum W is called as shifting mean LDA projection matrix (W_{SM-LDA}). The projected features of the both training and querying data set can be performed using the W_{SM-LDA} as done by the original LDA.

4 THE FACE RECOGNITION ALGORITHM

In order to know the effectiveness of the proposed methods, we integrated both of them for face recognition which consists of two main components: face pre processing and feature extraction and classification, as shown in Fig. 4.

The algorithm starts from localizing of face location, next detecting the eyes coordinates from the localized face image, and finally cropping the face image which is done by respecting to the detected eyes

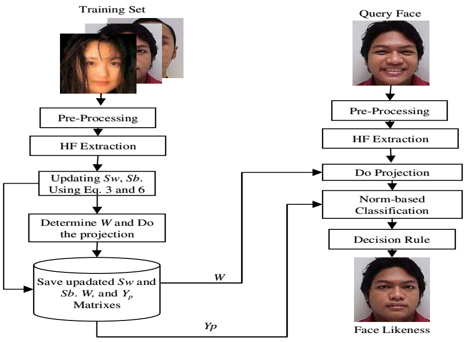


Figure 4: The block diagram of the proposed face recognition.

coordinates. Next, the cropped face images is normalized using the mentioned algorithm (Section 2) to remove non-uniform lighting effect on face image. Finally, a compact holistic feature (HF) of face image that is based on frequency and moment analysis of entire face is implemented as dimensional reduction of raw face image. The HF consists of the dominant frequency content of the face image extracting by DCT and moment information that provides invariant measure of face images shape. The HF with considering the invariant moment set provides higher discriminatory power than without moment information (Wijaya et al., 2010).

The face classification consists of training and recognition process. In the training process, the system defines the optimum W using shifting-mean LDA based algorithm as described in section 3 with the HF as the raw input. Then, the extracted HF and the determined optimum W are saved into database for the next process.

In the recognition process, the Euclidean distance based on nearest neighbour rule is implemented for face classification. In this case, the negative samples (non-training faces and non-face images) are used to define the threshold for face verification. If the minimum score is less than the defined threshold the input data is verified as known face (registered ID) and other wise is concluded as negative face or unknown face.

In order to get better recognition rate, score fusion mechanism is implemented for face verification as follows.

$$S_f = \alpha S_1 + \beta S_2 + \gamma S_3 \tag{6}$$

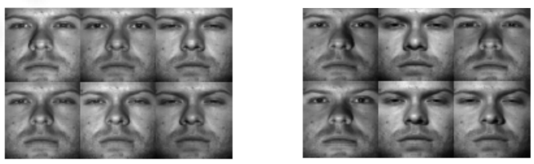
where, S_f is the final score, S_1, S_2, and S_3 are the matching score between the three kind of features vector (Y, Cb, and Cr components) of the querying and training of the face images. The Cb and Cr components are considered in order to cover the skin color information of the face image. The weight coefficients (α, β, and γ) are determined using the following equation. The main aim of this equation is to balance the contribution of three kinds of features vectors in face verification.

$$w_i^n = (w_i - min(\lfloor w_1 \rfloor, \lfloor w_2 \rfloor, ..., \lfloor w_j \rfloor))^2 \tag{7}$$

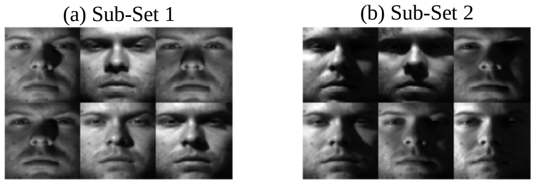
where w_i is the i-th feature vector score, j is number feature vectors of each face image, and finally the $\alpha = w_1$, $\beta = w_2$, and $\gamma = w_3$.

5 EXPERIMENTS AND RESULTS

The first experiment was carried out on the YaleB database (Lee et al., 2005) to investigate the performance of the proposed lighting normalization against to any variations of lighting condition and to compare its achievements with some established methods, such as histogram equalization (HE), modified Local Binary Pattern (mLBP(del Solar and Quinteros, 2008)), and Local Mean(Wijaya et al., 2010). The Yale-B database was divided into four different sub-sets according to the angle of the light source direction forms with the camera axis. In detail, the sub-set 1, 2, 3 , and 4 are the face images set which the angles of the light source direction are up to 12^0, up to 30^0, up to 60^0, and up to 77^0, respectively from the camera. An example of face variability due to lighting variation of YaleB database can be seen in Fig. 5. In this test, the subset 1 was chosen as training data and the remaining sub-sets were selected as testing data.



(a) Sub-Set 1 (b) Sub-Set 2



(c) Sub-Set 3 (d) Sub-Set 4

Figure 5: Example of face with large lighting variations of Yale database.

The experimental results show that the proposed lighting normalization can improve significantly the existed methods, such as mLBP and Local Mean as shown in Table 1. The significant improvement of recognition rate is given by sub-set 4, because face images of this sub-set contains large lighting variations such as large illumination. It can be achieved because the DCT and multi-resolution DWT-based

Table 1: The effect of lighting normalization on the recognition rate for YaleB database.

No	Methods of Normalization	Recognition Rate (%)			
		1 vs 2	1 vs 3	1 vs 4	Average
1	HE	95.39	60.13	13.69	56.39
2	mLBP	100	100	78.71	92.90
4	Local Mean	100	100	80.40	93.47
5	DCT-Based	100	100	87.71	95.90
6	DWT-Based	100	100	95.71	98.57

note:*i* vs *j* means sub-set *i* versus sub-set *j*

lighting compensation can remove most of the illuminant information of the input image, which is placed in low frequency component. Between the DCT and DWT, the multi-resolution DWT provide better improvement because the wavelet analysis has good frequency resolution and poor time resolution at low frequencies analysis. Therefore, it can extract well the illuminant component which is mostly placed low frequency component, as shown in Fig. 3. It means any lighting condition of face images are normalized into almost the same contrast and brightness by the proposed lighting normalization method. Based on this experimental result, we will implement the DWT-based lighting normalization for pre-processing of the face images in the all next experiments.

In addition, the integration of DWT-based lighting normalization and SM-LDA provide robust result over the previous methods (see Fig. 6) when the experiment was done in three challenges databases: ITS- Lab. Kumamoto University(Wijaya et al., 2010), INDIA(Jain and Mukherjee, 2002) databases representing small size database and FERET(Philips et al., 2000) database representing large size database. This experiment is done to support the previous result as presented Table 1. The result shows that, the proposed lighting condition can improve the previous lighting normalization, by about 1% of the baseline method (local mean). It can be achieved because two reasons:

- the DWT-based normalization can perfectly extracted the non uniform lighting effect on the face images because the DWT works as filter-bank to remove the low frequency component, and
- the DWT can extracted not only the low frequency component but also where is the frequency exist. It means the DWT work as time window fast Fourier transforms. Therefore, it is better to used for extracting the non uniform lighting effect on the face images than that of the local mean method because the local mean extracts lighting component in the blocking image which depends on the block size and the block size is not always cover all of the illumination part.

The third experiment was carried out using data from ITS- Lab., INDIA, and FERET databases. From these data, half of the samples were selected as the training sample and remaining as test samples. In this test, we investigate the effectiveness of the score fusion to improve the recognition rate of the single features-based face recognition method. The experimental result shows that the score fusion of three features (Y, Cb, and Cr) can improve significantly the recognition rate for all tested database, as shown in Table 2. It means that the score fusion make the system consider much more discriminant information for face verification than that of the without fusion. In addition, by fusing the chrominant (Cb and Cr) components of the face image means that the system includes the skin information in the face classification.

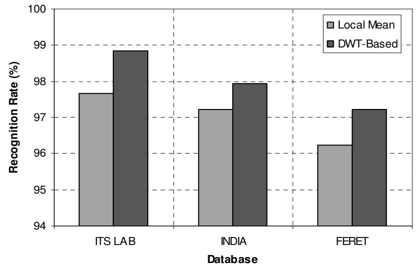


Figure 6: The robust recognition rate of our approach compared to that of base line on several databases.

Table 2: The effect of the score fusion on the recognition rate of the integration proposed face recognition.

No	Databases	Recognition Rate (%) of			
		Y	Cr	Cb	Fusion
1	ITS	98.31	96.27	94.93	98.84
2	INDIA	90.96	93.41	93.03	97.93
3	FERET	91.27	92.53	91.96	96.85

In order to show that the SM-LDA can solve the retraining problem, the next experiments were done to investigated the effect of processing time of S_b recalculation to the processing time of entire LDA. In this experiment, we determined the time ratio between the processing time of S_b recalculation and the processing time of entire LDA.

The time ratio as function of number of incremental data was determined using combined data from all mentioned databases. From this data, 100 classes were selected for initial training set and 1900 classes were selected for incremental data which was inserted into the system step by step (each step was 100 classes). The S_b and S_w recalculation time and entire training time of CLDA were determined the same as done in previous one. The results shows that time ratio of CLDA increases significantly while that of our the proposed method is almost constant for each incremental data, as shown in Fig. 7. It means the SM-LDA requires very short computation time for S_b and S_w recalculation when new classes are added into the system.

From this achievement, the S_b and S_w recalculation of CLDA greatly affect the entire LDA processing time while that of our proposed method does not

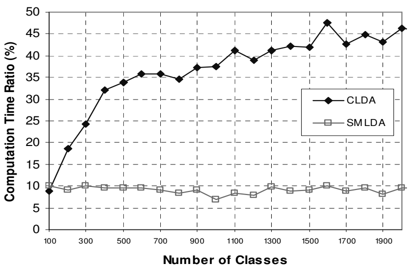
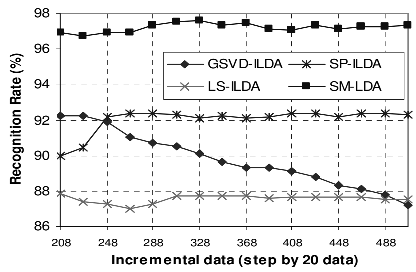


Figure 7: The time ratio as function of inserted data.

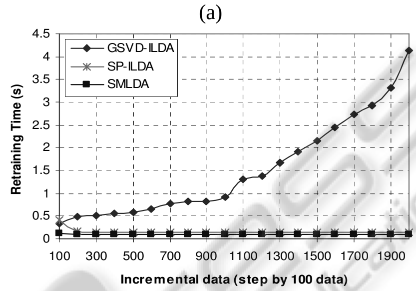
affect the entire LDA processing time at all. In this case, the eigen analysis does not create a bottleneck for the computational cost of LDA, because the size of features vector is much less then total data samples (the features vector size is 53 elements while $M > 1000$ images). It can be achieved because the S_b recalculation process of our proposed method just contains summation of the Θ_{old} and the Θ_{new}, and vector multiplication $(\mu_a^u(\mu_a^u)^T)$ as shown in Eq. 3. In addition, the S_b recalculation is just summation of both S_w^{old} and S_w^{new}. Based on this experimental result, our proposed method could solve the retraining problem of CLDA.

In order to show that the integration of the proposed lighting normalization provides robust recognition rate than that of recent sub-space methods for incremental data (GSVD-ILDA, SP-ILDA, and LS-ILDA methods), the next experiment was performed. It was done in FERET face database with face features of 53 elements and the training was performed gradually: firstly, it was trained 208 face classes and then added gradually 20 new face classes to the system until 508 face classes. In addition, the DWT-based lighting normalization and the score fusion were implemented in this test. In order to know the retraining time, the experiment was done using data from all mentioned databases (consist of 2000 classes) with face features of 53 elements and the training was performed gradually: firstly, 100 face classes was setup as initial training and then 100 classes is inserted for each step until reaching 2000 classes

In term of recognition rate, the SM-LDA provides higher stable recognition rate than that of the recent subspace methods for incremental data, as shown in Fig. 8(a). This result supports our previous achievements, which proves that our proposed method has the same structure as conventional CLDA but they have simpler computational complexity. This approach is an alternative algorithm for features cluster of large sample size databases, which requires much retrain processing such as for incremental data. In addition, the recent establish methods have less recognition rate than our proposed method because the optimum W of



(a)



(b)

Figure 8: The robust recognition rate and retraining time of the proposed method compared to two established methods for incremental data.

GSVD-ILDA is provided by computing the best rank k-th approximation of the matrix $X = [A, B]$ for each incremental data B; the W of LS-ILDA is just determined from total scatter matrix without considering the S_b at all; and W of SP-ILDA is also defined from the total scatter and S_b. The total scatter matrix represents the global covariance matrix of the training set which provides the same information as that of the PCA and the S_b provides the null space information. Therefore, the recognition rate of SP-ILDA is better than GSVD-ILDA and LS-ILDA.

In term of retraining process, our proposed method provides much the same retraining time as SP-ILDA and less than GSVD-ILDA, as shown in Fig. 8(b). It can be achieved because the GSVD-ILDA requires higher time complexity than SP-ILDA and our proposed method. The GSVD-ILDA needs $O(nqk + n(L+M)t + q^2n + k^3)$, where t and k are number of selected leading principle sub matrix of SVD decomposition, as detail described in the ILDA algorithms(Zhao and Yuen, 2008), while the SP-ILDA requires $O(d_{T,1}^3 t + d_{B,1}^3 + nd_{T,3}d_{b,3})$, where the $d_{T,1}$, $d_{T,3}$, and $d_{B,1}$ are equal to n and the $d_{B,3} < n$, and our proposed method require $O(n^3)$. Even though our proposed method time complexity is greatly affected by the eigen analysis time complexity ($O(n^3)$ but the dimensional size of data input (n) is much less than total data samples (M). Therefore, the computational time of our proposed method (0.13 second) is much the same as that of SP-ILDA (0.16 second) for $n \ll L \ll M$. In other words, the eigen analysis does not create a bottleneck for the computational time of the SM-LDA method, because the size of HF vector is much less then total data samples. In this test, the size of n is 53 elements, the L is 2000 and the M is 10000 images.

The retraining time of LS-ILDA can not be compared with that of GSVD-ILDA, SP-ILDA, and our proposed method because the retraining was done by insert a block of data consisting of 100 classes and each class consisting of 5 face images. In case of retraining experiment using 1 face image insertion, the LS-ILDA requires almost the same retraining time as that of GSVD-ILDA, SP-ILDA, and SM-LDA for 200 data classes data training initial which each class consists of 5 face images (the M is 1000, L is 200, and n is 53). For one sample insertion, the retraining time of LS-ILDA is 0.19 second while the GSVD-ILDA, SP-ILDA, and SM-LDA just require 0.31, 0.17, and 0.13 second, respectively. As our evaluation of the LS-ILDA, it has computational complexity $O(\min(M,n) \times n) + O(M \times L \times n)$ for each updating W when training data have $M \gg \text{Ł} \gg n$. If the retraining is done by inserting a block data consisting of q samples ($q \gg n$) into the LS-ILDA method, it requires much longer time complexity than SM-LDA $(q\{O(\min(M,n) \times n) + O(M \times L \times n)\} > O(n^3)$ for updating the W. Suppose $q = 500$ and $n = 53$, time complexity of LS-LDA becomes almost 500 times of our proposed method.

6 CONCLUSIONS AND FUTURE WORKS

From the experimental result, we can conclude as follows. Firstly, the proposed lighting normalization is an alternative solution for large face image variability due to lighting variations. Secondly, the face recognition, which considers much more features, tends to provide better achievement than that of single features. Thirdly, the SM-LDA based classifier can solve the retraining problem of CLDA on incremental data which provides stable recognition rate over recent ILDA methods. Finally, the integration of the proposed lighting compensation and shifting-mean LDA classifier as well as fusion score for face recognition give sufficient and robust enough achievement in terms of recognition rate and it also requires short processing time.

In future, the research will be continued for avoiding the eigen analysis in determining the optimum projection matrix and finding another strategy to solve retraining problem on incremental data which belong to known class (old data). Furthermore, more experiments are required to know the robustness of the proposed lighting normalization against to large variability face due to lighting variations, such as the test using data from FRGC data set.

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