Discriminative Multi-Layer Illumination-Robust Feature Extraction for Face Recognition[☆]

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Abstract

Tackling illumination variation is a major problem and it is also an important challenge for practical face recognition systems. Some related methods consider that lighting intensity components mainly lie in large-scale features, and they use a lot of image decomposition techniques to extract the small-scale illumination-invariant features and remove the large-scale features from original face images. However, it argues that the large-scale features contain a lot useful information which can be further extracted, and the small-scale illumination-invariant features are not robust enough due to they contain some detrimental features (noise, etc.). In this paper, we propose a discriminative multi-layer illumination-robust feature extraction (DMI) model to address this problem. First, we decompose the large-

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scale features into multi-layer small-scale illumination-robust features as a linear combination, and then a weight is assigned to each layer to adjust its importance and influence. The idea is to take full advantage of these useful information in large-scale features for face recognition. Second, we learn a discriminant filter to improve the robustness and statistical discriminative ability of the reconstructed illumination-robust face for face recognition under poor lighting conditions. Extensive experiments on three benchmark face databases and a video image database show that DMI performs better than the related methods, especially in difficult lighting conditions.

Keywords: Face recognition, decomposition technique, illumination-invariant feature, discriminant filter, small-scale

1. Introduction

Face recognition has attracted a great deal of attentions during the past several decades. Various approaches have been proposed, including Eigenface [1], Fisherface [2], Independent Component Analysis (ICA) [3], Laplacianfaces [4] and some regression models [5] [6] [7] [8] [9]. They can improve recognition performance to several kinds of variations. However, the performance of many existing algorithms are highly sensitive to illumination variations. In recent years, a variety of methods have been proposed to solve the illumination problem. The predominant ones include Histogram Equalization (HE) [10] [11], Logarithmic Transform [12]. These methods use traditional image processing model to normalize illumination unbalance, which can improve visual results to some extent, but it is difficult to account for different lighting conditions.

Some methods are proposed to extract the illumination-invariant representa-

tion of face images under varying lighting conditions. Most of them are based on Lambertian reflectance model. Lambertian reflectance model factorizes an image as a multiplication of a light intensity component and a surface albedo component. In general, a face image $I(x, y)$ is regarded as product $I(x, y) = \rho(x, y)S(x, y)$, where $\rho(x, y)$ is the surface albedo and $S(x, y)$ is the final light received at location (x, y) . However, it is difficult to obtain the ρ value of small-scale features from real images. In [13], Wang et al. proposed the SQI model, which extracts intrinsic, illumination-invariant features from a face image based on the QI technique. However, SQI has trouble keeping sharp edges in low frequency illumination fields. In order to preserve sharp edges of images, edge detection technique has attracted a lot of attentions. Le [14] proposed a new hyperbolic distribution and hyperbolic mask for edge detection, in which edge-detection error probability as a function of the half mask size is estimated using both masks in Gaussian- and hyperbolic-distributed pixel-intensity images. The experimental results show that the hyperbolic mask is effective and noise robust for edge detection. In [15], Hegade et al. considered morphological edge detection as pre-processing technique to normalize pose and expression variations, which can improve the performance to some extent for face recognition.

Methods based on two-dimensional function decomposition are well-known and popular. For instance, Chen et al.[16] proposed the logarithm total variation (LTV) model, which utilizes the edge-preserving capability of the total variation model. LOG-DCT [17] proposed by Chen et al. by using image processing techniques to normalize the images to appear stable under different illumination conditions, they employed discrete cosine transform to compensate for illumination variations in the logarithm domain. Based on the common assumption, Gradient-

faces (Gradf) [18] is regarded as insensitive to illumination variant and is extracted from the gradient domain. Chen et al.[19] constructed the intrinsic illumination subspaces from illumination images of intrinsic images, and then proposed a lighting normalization method. In [20], the authors proposed an illumination normalization method based on Weber’s law under varying illumination, which they called Weberface (Webf) is an illumination insensitive representation. Lai et al. [21] considered that the small-scale surface albedo is not robust enough because of containing some detrimental sharp features, and proposed a MLSA algorithm to decompose the surface albedo as a linear combination. Recently, Inspired by the fact that normalized coefficients of the singular value decomposition are insensitive to different lighting conditions, Kim et al. [22] built an illumination-invariant face representation method, called SVD face. In addition, the decomposition methods based on wavelets have been widely used in face recognition. Kwak et al. [23] first used the wavelet decomposition to extract intrinsic features of face images, and then combined Fisherface method and fuzzy integral into a single coherent classification platform for face recognition. Goh et al. [24] proposed wavelet based illumination invariant preprocessing (WIIP) in face recognition. They decomposed a facial image into low and high frequency components using discrete wavelet transform (DWT) decomposition and set the illumination component (low-pass component) as zero. Then both the processed illumination component (low-pass component) and the reflectance component (high-pass component) were used to perform inverse DWT. The experimental results show that these decomposition methods based on wavelets achieve salient performance for face recognition.

Image feature descriptor-based methods have been widely used in face recog-

64 nition due to their great robustness. Typical one like LBP, introduced by Ojala
65 et al. [25], has gained many attentions due to its simplicity and excellent perfor-
66 mance for face recognition. LBP encodes each local 3×3 neighborhood structure
67 into a binary series by thresholding its neighbor pixel intensity with the center
68 one. Instead of binary code, Local Ternary Patterns (LTP)[26], adopted a ternary
69 code pattern to extract illumination-invariant features. Compared with LBP, LTP
70 is less sensitive to noise in uniform regions. Lei et al. [27] focused on LBP-like
71 feature extraction and proposed a novel discriminant face descriptor (DFD), in
72 which the difference of the features between images of the same person are min-
73 imized and that between images from different people are maximized. Different
74 from LBP-based methods, Ren et al. [28] considered that Gabor features in each
75 band can be combined by a vector, and proposed a band-reweighed Gabor kernel
76 embedding algorithm to deal with face recognition with illumination or pose vari-
77 ation. Other feature extraction-based methods such as Local Directional Patterns
78 (LDP) [29], Enhanced LDP [30], Local Directional Number Patterns (LDN) [31],
79 AHELDLP [32], WFSMS [33] also have gained much attention because of their
80 robustness to several kinds of variations, but they still have some room to improve
81 the performance when illumination variation dominates the main variation.

82 It can be seen that LTV, LOG-DCT, Graf and Webf conclude that light intensi-
83 ty mainly lies in large-scale component of an image. Although these methods can
84 obtain good results to some extent, they are unrobust to reference images under
85 difficult lighting conditions and sensitive to some sharp detrimental noise pixels
86 (e.g. shadow casts by big facial organs, shadow borders). In the field of signal
87 processing, noise usually exists in the small-scale features. This is why many
88 noise robust models [34] [35] have been proposed to overcome this problem. In

Figure 1: Comparisons between schemes of LTV, S&L and DMI. (a): LTV retains small-scale component and removes large-scale component. (b): S&L combines smoothed small-scale component and normalized large-scale component. (c): DMI retains small-scale component and decomposes large-scale component into multi-layer illumination-robust features, and then takes them as a linear combination.

89 addition, these existing methods still lack statistical discriminant face informa-
90 tion. Hence, the performance is unstable in complicated situations when lighting
91 conditions are extremely poor.

92 In this paper, we propose an illumination-robust feature extraction method
93 with statistical discriminant face information named discriminative multi-layer
94 illumination-robust feature extraction (DMI) for face recognition under poor light-
95 ing conditions. The flowchart of our proposed method is shown in Figure. 1c. It
96 is worth mentioning that the proposed DMI is different from other illumination-
97 invariant feature extraction methods [13][16][21]. First, these methods only retain
98 small-scale component and remove large-scale component, while we argue that
99 large-scale component contains useful information for face recognition, which can
100 be further extracted, instead of discarded. Second, they do not learn discriminant
101 filter, while DMI learns a discriminative filter to remove noise from the recon-
102 structed illumination-robust face image and improve the statistical discriminative
103 ability. In addition, S&L [36] also argues that large-scale component is useful for
104 recognition. But it only uses LOG-DCT algorithm to preprocess the large-scale
105 component, which is difficult to separate the extrinsic illumination variations and
106 intrinsic facial from large-scale component. We summarize the favorable proper-
107 ties and main contributions of DMI as follows.

108 1. Proposing a multi-layer decomposition algorithm. It decomposes the large-
109 scale component as a linear combination of several detailed layers and can extract
110 different kinds of beneficial and illumination-robust features in different layers,
111 which are ignored by traditional illumination-treating methods (e.g. LTV, LOG-
112 DCT, etc).

113 2. Introducing a weighting strategy. Since each illumination-robust feature

114 layer contains different discriminant information for face recognition. A weight is
115 allocated to each layer to control the importance and influence of this layer. A lin-
116 ear sum of all the weighted layers form the reconstructed illumination-robust face
117 image. The weight in each layer can be integrated into within-class scatter matrix
118 and between-class scatter matrix of small-scale illumination-robust features.

119 3. Introducing a discriminative filter. Considering that noise usually exist-
120 s in the small-scale illumination-robust features, our method learns a discrimi-
121 nant filter to remove noise from the reconstructed illumination-robust face and
122 improve the statistical discriminative ability for face recognition under poor light-
123 ing conditions. Similarly, the learned discriminant filter can also be integrated
124 into within-class scatter matrix and between-class scatter matrix of small-scale
125 illumination-robust features.

126 4. Proposing an illumination-robust face recognition system. We develop a
127 discriminant criterion function and propose an effective DMI algorithm to deter-
128 mine all the weights and the discriminant filter matrix simultaneously.

129 The rest of the paper is organized as follows. In section 2, we propose the
130 DMI model and develop a discriminant criterion function to select the suitable
131 layer weights and the discriminant filter matrix. Section 3 reports experimental
132 results on benchmark databases, followed by the conclusion in section 4.

133 2. Discriminative multi-layer illumination-robust features extraction

134 In this section, each step of the proposed method is described in detail. In sec-
135 tion 2.1, we first introduce the theoretical background, and we further discuss the
136 motivation in section 2.2. Then the weighted-layer small-scale illumination-robust
137 feature extraction method is proposed in section 2.3. In section 2.4, a discriminant

filter learning method is proposed. In order to determine all the layer weights and the discriminant filter matrix simultaneously, we propose an effective DMI algorithm based on a statistical discriminant Fisher criterion function in section 2.5. In section 2.6, we take a comparison analysis between the proposed DMI and the related works.

2.1. Theoretical Background

We first introduce the reflectance model, which is the theoretical basis of removing varying illumination for face images. Then we discuss the Logarithmic Total Variation (LTV) [16] model, which serves as the basis of our proposed method.

The reflectance model defines the pixel value as a production of reflectance and illumination component as follows:

$$I(x, y) = R(x, y)L(x, y), \quad (1)$$

where $I(x, y)$ is face image pixel value, $R(x, y)$ and $L(x, y)$ denote the reflectance component and illumination effect at each point (x, y) , respectively. Here, $R(x, y)$ only depends on the characteristics of the surface of the object, so it can be regarded as intrinsic representation of a face image and contains illumination invariant features. The objective is to separate the reflectance component R and the illumination effect L from real image for face recognition.

Inspired by the SQI, Chen et al.[16] proposed LTV model, which makes use of the edge preservation and multi-scale decomposition capability of the TV- L^1 [37] model. In LTV model, based on reflectance model, the following decomposition

is obtained:

$$\begin{aligned}
I(x, y) &= R(x, y)L(x, y) \\
&= \left(\frac{R(x, y)}{\rho_l(x, y)} \right) (\rho_l(x, y)L(x, y)) \\
&= \rho(x, y)S(x, y),
\end{aligned} \tag{2}$$

154 where $\rho_l(x, y)$ denotes the albedo of large-scale skin areas and background. $\rho(x, y)$
155 is the surface albedo, which only contains the small intrinsic facial structures and
156 $S(x, y)$ is the final light received at location (x, y) , which contains large intrinsic
157 structures as well as extrinsic illumination.

The objective of LTV is to retain the small intrinsic facial structure ρ and remove the large-scale component S . To apply the additive TV- L^1 model to the multiplicative model, LTV takes a logarithm transform on both sides of (2):

$$\begin{aligned}
f(x, y) &= \log I(x, y) \\
&= \log \rho(x, y) + \log S(x, y) \\
&= v + u.
\end{aligned} \tag{3}$$

Then applying the TV- L^1 model, $f(x, y)$ is decomposed as follows:

$$\hat{u} = \arg \min_u \int |\nabla u| + \lambda |f - u| dx, \tag{4}$$

$$\hat{v} = f - \hat{u}, \tag{5}$$

where $\int |\nabla u|$ is the total variation of u , scalar threshold λ controls the selection of features with unknown intensity values. After getting $\hat{v}$, exponent transform is performed on it to finally get the small-scale surface albedo ρ as follows:

$$\rho(x, y) = \exp(\hat{v}).$$

158 Figure. 1a illustrates the pipeline of the LTV method.

Figure 2: The extraction process of the small-scale illumination-invariant features ρ_1 and ρ_2 . In the first experiment, ρ_1 is used as facial features for recognition. In the second experiment, we regard $\rho_1 + \rho_2$ as facial features for recognition. Experimental results are provided in Table 1.

2.2. Motivation

Many existing methods attempt to separate the reflectance component and illumination effect from real images, unfortunately, estimating ρ or S from I is an ill-posed problem [38]. To address this problem, LTV utilizes the multi-scale decomposition ability of the $TV-L^1$ model to extract the small-scale feature ρ . It is effective to some extent, but many noise exist in the small-scale features, which leads that the small-scale feature ρ is not robust enough. What's more, the large-scale component S is removed by LTV, containing not only extrinsic illumination and shadow borders, but also some intrinsic facial structures (illumination-invariant features), which are beneficial for face recognition. This implies that these illumination-invariant features can be further extracted from the large-scale component S . To verify this point, we conduct two experiments of face recognition using the Extended Yale B database (The detailed description of the database can be seen in section 3.1). The Subset 1 is used for training, the other 4 Subsets are used for testing, respectively. All the images from the Extended Yale B

Table 1: Face recognition on the Extended Yale B database use ρ_1 and $\rho_1 + \rho_2$, respectively.

Features	Subset 2	Subset 3	Subset 4	Subset 5
ρ_1	99.12	96.71	86.28	89.66
$\rho_1 + \rho_2$	99.56	97.81	91.92	92.86

174 database are decomposed into small-scale component ρ_1 and large-scale compo-
 175 nent S_1 . In the first experiment, only the small-scale component ρ_1 is directly
 176 used as facial features for recognition. In the second experiment, we decompose
 177 the large-scale component S_1 into small-scale illumination-invariant feature ρ_2
 178 and large-scale light intensity component S_2 via the TV- L^1 model again. Then
 179 we regard the linear combination of small-scale illumination-invariant features ρ_1
 180 and ρ_2 as facial features for recognition. Figure. 2 illustrates how the small-scale
 181 illumination-invariant features ρ_1 and ρ_2 are extracted, and the recognition results
 182 are shown in Table 1. As shown, we can find that the recognition rates of 99.12%,
 183 96.71%, 86.28% and 89.66% are got from Subset 2 to Subset 5, respectively in
 184 the first experiment. In the second experiment, we use the linear combination of
 185 small-scale illumination-invariant features ρ_1 and ρ_2 as facial features for recog-
 186 nition, the recognition rates of 99.56%, 97.81%, 91.92% and 92.86% are obtained
 187 from Subset 2 to Subset 5, respectively. It is clear that the $\rho_1 + \rho_2$ achieves higher
 188 recognition rates than ρ_1 . The superiority of $\rho_1 + \rho_2$ is getting more significant
 189 than ρ_1 when lighting conditions are getting worse from Subset 3 to Subset 5.

190 From the experimental results we have the conclusions that: 1) The large-scale
 191 component S_1 contains a lot of useful information for face recognition, and these
 192 information (small-scale illumination-invariant features) as facial features should
 193 be further extracted, instead of discarded. 2) The linear combination of multi-layer

194 small-scale features help to get higher recognition rates for images with extreme
 195 illumination changes. Therefore, taking full advantage of these information is
 196 very important for face recognition. Based on the multi-scale decomposition, we
 197 can further decompose the large-scale component and reconstruct illumination-
 198 robust face image.

199 2.3. Weighted-layer small-scale illumination-robust features extraction

200 In this subsection, we first demonstrate how a face image can be decomposed
 201 into multi-layer small-scale illumination-robust features and large-scale lighting
 202 intensity component. Based on LTV [16] model, a face image I can be decom-
 203 posed into l layers of different small-scale illumination-robust features as Algo-
 rithm 1:

Algorithm 1 Face Image Multi-Layer Decomposition

Input: a face image I ($I = \rho \cdot S$);

1. Take the logarithm transform:

$$f(x, y) = \log I(x, y), f = u + v,$$

$$u = \log S, v = \log \rho, \hat{u}_0 = f.$$

for $k = 1$ to l **do**

2. Solve for u and v in the TV- L^1 model:

$$\hat{u}_k = \arg \min_{u_k} \int |\nabla u_k| + \lambda |\hat{u}_{k-1} - u_k| dx$$

3. Obtain the illumination-robust feature of the k th layer:

$$\hat{v}_k = \hat{u}_{k-1} - \hat{u}_k$$

4. $I_k = \hat{v}_k$

end for

Output: $I_k: 1 \leq k \leq l$

204

205 λ is a scalar threshold, which controls the selection of features with unknown
 206 intensity values [16]. Hence, selecting an appropriate λ for extracting the small-
 207 scale facial features is very meaningful. Finally, the l layers small-scale facial
 208 features $\{I_k: 1 \leq k \leq l\}$ are obtained. Note that SOP [39] also decomposes
 209 multi-scale features based on LTV model, but it only considers the small-scale
 210 component and ignores the large-scale component.

Since each small-scale illumination-robust feature layer (I_k) contains different discriminant information for face recognition, we assign a weight to each layer to adjust its importance and influence:

$$I = \sum_{k=1}^l \alpha_k I_k, \quad \forall \alpha_k \geq 0. \quad (6)$$

However, selecting suitable layer weights $\{\alpha_k: 1 \leq k \leq l\}$ simultaneously is a formidable task. Based on Fisher criterion [40], we develop a criterion function to determine all the weights. It should be noted that the proposed criterion function is different from Fisher criterion, which can be formulated to minimize the trace ratio of the within-class scatter S'_w to the between-class scatter S'_b , and simultaneously embed nonnegativity constraint on the weights. Let $I^{i,j}$ be the small-scale illumination-robust feature of the j th sample from class i , and m^i denotes the mean feature of the i th class. Then the within-class scatter S'_w can be defined as

$$S'_w = \sum_{i=1}^c \sum_{j=1}^{n_i} (I^{i,j} - m^i)(I^{i,j} - m^i)^T, \quad (7)$$

211 where c is the number of face classes and n_i is the number of samples from the i th
 212 class.

Let $I_k^{i,j}$ be the k th layer of the small-scale illumination-robust feature $I^{i,j}$, and denote m_k^i as the k th layer of the mean feature m^i . Assigning a weight to each

layer, $I^{i,j}$ and m^i can be represented as $I^{i,j} = \sum_{k=1}^l \alpha_k I_k^{i,j}$ and $m^i = \sum_{k=1}^l \alpha_k m_k^i$, respectively. Substituting them into (7), we get

$$\begin{aligned} S'_w &= \sum_{i=1}^c \sum_{j=1}^{n_i} \left(\sum_{k=1}^l \alpha_k I_k^{i,j} - \sum_{k=1}^l \alpha_k m_k^i \right) \left(\sum_{k=1}^l \alpha_k I_k^{i,j} - \sum_{k=1}^l \alpha_k m_k^i \right)^T \\ &= \sum_{i=1}^c \sum_{j=1}^{n_i} \left(\sum_{k=1}^l \alpha_k (I_k^{i,j} - m_k^i) \right) \left(\sum_{k=1}^l \alpha_k (I_k^{i,j} - m_k^i) \right)^T. \end{aligned} \quad (8)$$

In order to obtain a simpler form, we calculate the vector $A_k^{i,j} = I_k^{i,j} - m_k^i$, and denote $\alpha = [\alpha_1, \alpha_2, \dots, \alpha_l]^T$. Inserting them into (8) deduces:

$$S'_w = \sum_{i=1}^c \sum_{j=1}^{n_i} (A^{i,j}) \alpha \alpha^T (A^{i,j})^T, \quad (9)$$

213 where matrix $A^{i,j} = [A_1^{i,j}, A_2^{i,j}, \dots, A_l^{i,j}]$.

Similarly, let m be the total mean feature of the sample set, and denote m_k as the k th layer of the total mean feature m . Then m can be represented as $m = \sum_{k=1}^l \alpha_k m_k$. Therefore, we can define the between-class scatter S'_b as follows:

$$\begin{aligned} S'_b &= \sum_{i=1}^c n_i (m^i - m)(m^i - m)^T \\ &= \sum_{i=1}^c n_i \left(\sum_{k=1}^l \alpha_k (m_k^i - m_k) \right) \left(\sum_{k=1}^l \alpha_k (m_k^i - m_k) \right)^T \\ &= \sum_{i=1}^c n_i (B^i) \alpha \alpha^T (B^i)^T, \end{aligned} \quad (10)$$

214 where matrix $B^i = [B_1^i, B_2^i, \dots, B_l^i]$, and the vector $B_k^i = m_k^i - m_k$ ($k =$
215 $1, 2, \dots, l$).

216 2.4. Discriminant filter learning

217 After face image multi-layer decomposition, the small-scale illumination-robust
 218 component in each layer contains not only beneficial facial features, but also some
 219 detrimental features (noise) [21]. Such bad features would have a negative effect
 220 for face recognition. Similarly to [27] [41], we propose a discriminant filter learn-
 221 ing method to deal with this problem. Given a reconstructed multi-layer weighted
 222 illumination-robust face image I , its filtered image is denoted as $f(I)$.

Under linear assumption, suppose the discriminant filter matrix to be W , and the filtered image can be represented as $f(I) = W^T I$. With the learned discriminant filter, the noise existed in the reconstructed illumination-robust face can be removed and the statistical discriminative ability is improved for face recognition under poor lighting conditions. By appropriate formulation, this problem can also be formulated as minimizing the trace ratio of the within-class scatter S_w'' to the between-class scatter S_b'' , which are represented as follows:

$$\begin{aligned} S_w'' &= \sum_{i=1}^c \sum_{j=1}^{n_i} (f(I)^{i,j} - f(m)^i) (f(I)^{i,j} - f(m)^i)^T \\ &= \sum_{i=1}^c \sum_{j=1}^{n_i} W^T (I^{i,j} - m^i) (I^{i,j} - m^i)^T W, \end{aligned} \quad (11)$$

$$\begin{aligned} S_b'' &= \sum_{i=1}^c n_i (f(m)^i - f(m)) (f(m)^i - f(m))^T \\ &= \sum_{i=1}^c n_i W^T (m^i - m) (m^i - m)^T W, \end{aligned} \quad (12)$$

223 where $f(I)^{i,j}$ is filtered image for the j th sample of class i , $f(m)^i$ is the mean
 224 filtered image of the i th class, and $f(m)$ is the total mean filtered image of the
 225 sample set.

By combining (9)-(12), the within-class scatter S_w and the between-class scatter S_b can be represented as follows:

$$S_w = \sum_{i=1}^c \sum_{j=1}^{n_i} W^T (A^{i,j}) \boldsymbol{\alpha} \boldsymbol{\alpha}^T (A^{i,j})^T W, \quad (13)$$

$$S_b = \sum_{i=1}^c n_i W^T (B^i) \boldsymbol{\alpha} \boldsymbol{\alpha}^T (B^i)^T W. \quad (14)$$

According to the Fisher criterion, smaller within-class scatter and larger between-class scatter will be to better recognition results in an average sense. Therefore, we can define the constrained optimization problem for DMI as follows:

$$\min_{W, \boldsymbol{\alpha}} Tr(S_w) \quad (15)$$

$$\text{s.t. } Tr(S_b)=1 \text{ and } \boldsymbol{\alpha} \geq 0.$$

2.5. Optimization algorithm

Since it is difficult to directly solve the optimization problem in (15), we instead utilize an iterative, two-step strategy to alternately optimize W and $\boldsymbol{\alpha}$. At each iteration, one of the variables W and $\boldsymbol{\alpha}$ is fixed, while the other is updated, and then the roles of W and $\boldsymbol{\alpha}$ are exchanged. Iterations are repeated until convergence or the maximum number of iterations is reached.

On optimizing W . We could first assume that each layer feature is the same importance, and initialize the weight vector $\boldsymbol{\alpha} = [1, 1, \dots, 1]^T$. The optimization problem in (15) is then reduced to

$$\min_W Tr(W^T S'_w W) \quad (16)$$

$$\text{s.t. } Tr(W^T S'_b W)=1,$$

where

$$S'_w = \sum_{i=1}^c \sum_{j=1}^{n_i} (A^{i,j}) \boldsymbol{\alpha} \boldsymbol{\alpha}^T (A^{i,j})^T, \quad (17)$$

$$S'_b = \sum_{i=1}^c n_i (B^i) \boldsymbol{\alpha} \boldsymbol{\alpha}^T (B^i)^T. \quad (18)$$

Intuitively, this optimization problem in (16) can be reduced to a trace ratio problem:

$$\min_W \frac{\text{Tr}(W^T S'_w W)}{\text{Tr}(W^T S'_b W)}. \quad (19)$$

Consequently, according to [42], [43] and [44], the optimization problem can be transformed into solving the generalized eigenvalue problem. The columns of the optimal $W^* = [w_1, w_2, \dots, w_{c-1}]$ are the eigenvectors with the $c - 1$ smallest eigenvalues in

$$S'_w w = \lambda S'_b w. \quad (20)$$

On optimizing $\boldsymbol{\alpha}$. Once the matrix W is updated, we could fix W and use the property $\boldsymbol{\beta}^T \boldsymbol{\beta} = \text{trace}(\boldsymbol{\beta} \boldsymbol{\beta}^T)$ for a column vector $\boldsymbol{\beta}$, the optimization problem in (15) is reduced to

$$\min_{\boldsymbol{\alpha}} \boldsymbol{\alpha}^T \tilde{S}_w \boldsymbol{\alpha} \quad (21)$$

234

$$\text{s.t. } \boldsymbol{\alpha}^T \tilde{S}_b \boldsymbol{\alpha} = 1 \text{ and } \boldsymbol{\alpha} \geq 0,$$

where

$$\tilde{S}_w = \sum_{i=1}^c \sum_{j=1}^{n_i} (A^{i,j})^T W W^T (A^{i,j}), \quad (22)$$

$$\tilde{S}_b = \sum_{i=1}^c \sum_{j=1}^{n_i} n_i (B^i)^T W W^T (B^i). \quad (23)$$

The additional constraints $\boldsymbol{\alpha} \geq 0$ cause that the optimization problem can not be formulated as a generalized eigenvalue problem. It becomes a non-convex

quadratically constrained quadratic programming problem which is known to be hard to solve. However, the non-convex problem can be relaxed to a convex program by adding an auxiliary matrix $C = \alpha\alpha^T$ of size $l \times l$. The problem (21) can then be posed as:

$$\begin{aligned} & \min_{\alpha, C} \text{trace}(\tilde{S}_w C) \\ & \text{s.t.} \begin{cases} \text{trace}(\tilde{S}_b C) = 1 \\ \begin{pmatrix} 1 & \alpha^T \\ \alpha & C \end{pmatrix} \succeq 0 \\ \mathbf{e}_k^T \alpha \geq 0, \quad k = 1, 2, \dots, l \end{cases} \end{aligned} \quad (24)$$

where $\mathbf{e}_k$ is a column vector whose elements are 0 except that its k th element is 1. This is a semi-definite programming (SDP) relaxation of the non-convex problem, which can be efficiently solved by SDP (Refer to [45] [42] for the details).

The whole algorithm of DMI is illustrated in Algorithm 2.

2.6. Comparison Analysis of LTV, S&L(LOG-DCT) and DMI

Considering that LTV [16] and S&L(LOG-DCT) [36] serve as the basis of our the proposed DMI, we take a comparison analysis of LTV, S&L(LOG-DCT) and DMI.

1) *Connections to LTV and S&L(LOG-DCT)*: LTV takes advantage of the TV- L^1 model to decompose a face image into small-scale component and large-scale component in logarithm domain, which utilizes the edge-preserving capability of total variation model. Both S&L(LOG-DCT) and DMI also use the multi-scale decomposition capability of the TV- L^1 model. Moreover, DMI, LTV, and S&L(LOG-DCT) are based on the same idea that the small-scale component and

Algorithm 2 DMI algorithm

Input: The number of layers l and iteration $\mathcal{T}$ are set in advance.

Output: Layer weights vector $\alpha \in R^{l \times 1}$ and filter projection $W \in R^{d \times p}$, where d is dimension of illumination-robust face and p is the number of filter vectors.

1: **Initialize:** $\alpha = [1, 1, \dots, 1]^T$, assuming that each layer feature is the same importance;

for $t = 1$ to $\mathcal{T}$ **do**

2: Compute within-class scatter matrix S'_w in (17) and and between-class scatter matrix S'_b in (18);

3: W is optimized by solving the generalized eigenvalue problem in (20);

4: Compute within-class scatter matrix $\tilde{S}_w$ in (22) and between-class scatter matrix $\tilde{S}_b$ in (23):

5: α is optimized by solving optimization problem in (24) via SDP;

end for

6: **Return:** α and W .

250 large-scale component can be separated from real image based on reflectance
251 model.

252 2) *Comparison Analysis:* LTV only regards the small-scale component as
253 facial feature for recognition, but large-scale component is ignored. However,
254 S&L(LOG-DCT) finds that both the small-scale component and large-scale com-
255 ponent are important for recognition, so S&L(LOG-DCT) performs a threshold-
256 average filtering on the small-scale component and uses the LOG-DCT algorithm
257 to preprocess the large-scale component. Finally, the normalized image is recon-
258 structed by combining the smoothed small-scale component and the normalized
259 large-scale component. However, it is difficult to separate the extrinsic illumi-

nation variations and intrinsic facial structures from the large-scale component,
 and it is not effective to remove the detrimental features (noise, etc.) from the
 reconstructed face image, which may lead LTV and S&L(LOG-DCT) methods to
 being unrobust to different lighting conditions. However, as can be seen in sec-
 tion 2.2, experiments show that the large-scale component contains a lot useful
 information for face recognition, and these information can be further extracted
 via the decomposition capability of the $TV-L^1$ model. Therefore, DMI decom-
 poses the large-scale component into multi-layer small-scale illumination-robust
 features as a linear combination, and then a weight is assigned to each layer to ad-
 just its importance and influence. Finally, the detrimental features can be removed
 from the reconstructed illumination-robust face via a discriminant filter learning
 method. The results provide an intuitionistic view that DMI is more robust to d-
 ifferent lighting conditions than LTV and S&L(LOG-DCT), especially in difficult
 lighting conditions. Comparisons between schemes of LTV, S&L(LOG-DCT) and
 DMI are shown in Figure. 1.

3. Experimental results

The purpose of the presented experiment is to verify the following two points:
 i) the large-scale component contains useful information for face recognition,
 which can be further extracted, instead of discarded; ii) discriminant filter learning
 is effective to remove the noise from the reconstructed small-scale illumination-
 robust face.

We compare our DMI with some of state-of-the-art illumination-treating-based
 and feature learning-based methods: LOG-DCT [17], LTV [16], Gradf [18], LBP
 [25], Webf [20], S&L [36], LTP [26], DFD [27], MOST [28] and SVD face (SF)

284 [22]. The four databases: Extended Yale B [46], Face Recognition Grand Chal-
 285 lenge (FRGC) v2 [47], CAS-PEAL-R1 [48] and Oulu-CASIA-NIR-VIS database
 286 [49] are used to demonstrate the performance of different methods.

287 3.1. Databases

288 1) *Extended Yale B*: The Extended Yale B [46] consists of 2414 frontal-face
 289 images of 38 subjects. These images are divided into 5 Subsets according to their
 290 lighting conditions (the angle between the light source direction and the central
 291 camera axis). In our experiments, the cropped 192×168 face images are cap-
 292 tured under various laboratory-controlled lighting conditions and different facial
 293 expressions, and each image is further downsampled to 96×84 pixels (except
 294 for LBP and SF). We select the Subset 1 for training, and the other 4 Subsets for
 295 testing, respectively. Figure. 3 shows some cropped images on this database.

Figure 3: Cropped face images of two subjects from subsets 1-5 of the Extended Yale B database.

296 2) *FRGC-v2*: FRGC-v2 [47] is a large data set, which consists of 50,000 im-
 297 ages of 625 subjects. These images were obtained in different period, under con-
 298 trolled and uncontrolled variations (illumination, expression, occlusion, etc.). In
 299 our experiment, we take a subset with uncontrolled variations, which were ob-
 300 tained in large lighting variations (hallways, atriums, outside, etc.), ageing and
 301 image blur. It contains 1375 images of 275 subjects and 5 images for each. These

Figure 4: Cropped face images of the FRGC database.

302 images are cropped and resized with dimension 100×100 and each image is fur-
 303 ther downsampled to 50×50 pixels (except for LBP and SF). In each recognition,
 304 3 images per subject are selected for training and the left 2 for testing. There are
 305 $C_5^3 = 10$ turns of recognition in all, where C_b^a denotes the combinatorial number
 306 of choosing a elements from b elements. Figure. 4 shows some cropped images
 307 on this database.

308 3) *CAS-PEAL-R1*: The CAS-PEAL-R1 [48] face database consists of 30900
 309 images of 1040 subjects (595 males and 445 females). These images were ob-
 310 tained in different variations, including pose, expression, accessory, and lighting.
 311 In our experiment, we take a subset with different lighting variations, which con-
 312 tains 1404 images of 156 subjects and 9 images for each subject. All the images
 313 are cropped to 120×100 size, and each image is further downsampled to 60×50
 314 pixels (except for LBP and SF). In each recognition, we randomly select 7 sam-
 315 ples per subject for training, and the left 2 samples for testing. The experiments
 are repeated 10 times. Figure. 5 shows some cropped images on this database.

Figure 5: Cropped face images of the CAS-PEAL-R1 database.

316

317 4) *Oulu-CASIA-NIR-VIS*: The Oulu-CASIA-NIR-VIS database [49] contains

318 videos with six different illuminations and expressions from 80 subjects between
319 23 to 58 years old captured with two imaging systems. These video sequences
320 consist of about 80000 frontal facial images from 80 subjects (73.8% of them are
321 males).

322 In our experiment, we select a subset of the database that consists 1440 im-
323 ages of 80 subjects and 18 images for each subject. Each subject has two sessions
324 of images and 9 images for each session. The first session contains NIR (Near
325 Infrared) images under three different illumination conditions: normal illumina-
326 tion, weak illumination (only computer display is on), dark illumination (all lights
327 are off). The second session contains VIS (Visible Light) images under the same
328 illumination conditions as the first session. Thus, some of them are blurry and
329 low-resolution images. All the images are cropped to 80×70 size, and each im-
330 age is further downsampled to 40×35 pixels (except for LBP and SF). In each
331 recognition, we randomly select half of the images for training and the remainder
for testing. Some images are shown in Figure. 6.

Figure 6: Some images of one subject in Oulu-CASIA-NIR-VIS database. The first row contains NIR (Near Infrared) images under three different illumination conditions: dark illumination, normal illumination, weak illumination. The second row contains VIS (Visible Light) images under three different illumination conditions: dark illumination, normal illumination, weak illumination.

332

Table 2: Mean recognition rates of DMI with different l on the Extended Yale B database (%).

Method	Subset 2	Subset 3	Subset 4	Subset 5	Total
DMI($l=4$)	100	99.12	96.43	97.37	97.82
DMI($l=5$)	100	99.12	96.99	97.74	97.98
DMI($l=6$)	100	99.12	96.99	97.37	97.98
DMI($l=7$)	100	98.03	96.24	97.74	97.93
DMI($l=8$)	100	99.12	96.24	97.56	97.87

Table 3: Mean recognition rates of DMI with different l on the FRGC database (%).

Method	DMI($l=4$)	DMI($l=5$)	DMI($l=6$)	DMI($l=7$)	DMI($l=8$)
Mean	82.41	82.57	82.22	81.91	81.93

3.2. Robustness analysis and discussion

In this section, we first analyse the robustness of our weight-selection mechanism for the proposed DMI model. Then the FRGC database is used to verify the robustness of DMI against noise. In addition, we discuss the effectiveness of layer weights and discriminant filter individually.

1) Robustness analysis to different number of layers l : The selection of the number of layers l must be appropriate. If the layer size l is too small, the useful information will not be effectively extracted from the large-scale component. If the layer size l is too large, it will lead to high computational complexity. Considering these, we set $l=4,5,6,7,8$. For each value of l , the controlled Extended Yale B database and uncontrolled FRGC database are used to demonstrate the robustness to different number of layers l . Following the recognition protocol in section 3.1, the experimental results of DMI with different number of layers l are shown

Table 4: Recognition rates (Mean $\pm$ STD) and descent rates (DR) for different methods against noise on the FRGC database (%).

Method	$\sigma = 0.001$		$\sigma = 0.01$	
	Mean $\pm$ STD	DR	Mean $\pm$ STD	DR
LOG-DCT	64.45 $\pm$ 1.6480	8.15	34.27 $\pm$ 1.6054	49.95
Gradf	67.06 $\pm$ 3.2202	9.82	57.32 $\pm$ 2.4097	22.92
LTV	57.35 $\pm$ 2.0669	8.15	17.73 $\pm$ 1.3546	67.30
S&L	62.22 $\pm$ 2.1322	2.37	49.91 $\pm$ 1.4140	21.69
LBP	11.24 $\pm$ 2.7159	20.41	0.57 $\pm$ 0.1520	99.22
Webf	63.01 $\pm$ 2.2505	5.19	51.40 $\pm$ 2.3892	22.66
DMI	80.38$\pm$1.7732	2.65	72.44$\pm$1.6786	12.27

in Table 2 and Table 3. As can be seen, the difference of the recognition rates of different layer size l is not greater than 1% on the same subset of the Extended Yale B and the mean recognition rates are around 82% on the FRGC database. All these results show that our weight-selection mechanism is robust to a small change of layer size l .

2) *Robustness analysis to different levels of noise*: We evaluate the robustness of the proposed method against noise. Similarly to [50] [51], we adopt the common way of adding white Gaussian noise to the face images of the testing set but not the training set on the FRGC database. To intuitively compare the robustness of the different methods against noise, a descent rate is defined as follows:

$$DR = \frac{rr - rr'}{rr} \times 100\%,$$

where rr denotes the recognition rate of the method without noise, and rr' is the recognition rate with the white Gaussian noise. The recognition protocol is used

Table 5: The effectiveness comparison of layer weights and discriminant filter on the Extended Yale B database (%).

Method	Subset 2	Subset 3	Subset 4	Subset 5	Total
LTV	99.12	96.71	86.28	89.66	90.69
S&L	100	99.12	87.97	87.03	93.07
DMI ^{α}	100	97.81	96.43	95.30	97.72
DMI ^{W}	100	97.81	95.68	96.05	97.27
DMI	100	99.12	96.99	97.74	97.98

as described before, and the experimental results for different methods with different levels of noise (The mean of Gaussian noise is zero and the variance σ is set to 0.001 and 0.01, respectively.) are shown in Table 4. As can be seen, the recognition rates of these methods decrease with the increasing of level of Gaussian noise. However, DMI, due to the use of discriminant filter, has the highest recognition rate and the lowest descent rate. It is obvious that the robustness of DMI against noise is notable as it outperforms the other methods for every level of noise.

3) *Impact analysis of layer weights and discriminant filter*: We investigate the effectiveness of layer weights and discriminant filter individually. First, we only apply the weight-selection mechanism without discriminant filter, denoted as DMI ^{α} . In this case, the discriminant filter matrix is set to be $W = E$, where E is the identity matrix. Second, we apply the discriminant filter without weight-selection mechanism, denoted as DMI ^{W} . In this case, the layer weights α is set to be $\alpha = [1, 1, \dots, 1]^T$ so that each layer illumination-invariant feature is treated equally. LTV and S&L(LOG-DCT) are compared with our method. The compared

Figure 7: Recognition rates for different methods on Extended Yale B database.

369 results on Extended Yale B database are given in Table 5. As can be seen, both
370 layer weights and discriminant filter help to improve the face recognition perfor-
371 mance, compared with LTV and S&L(LOG-DCT), especially in extremely harsh
372 lighting conditions(Subsets 4 and 5). The combination of them further enhances
373 the face recognition rate, indicating that the proposed DMI is effective for face
374 recognition under different lighting conditions.

375 3.3. Comparisons between DMI and other methods

376 In this section, compared results between DMI and other methods on four
377 databases are given.

378 *1) Compared results on the Extended Yale B database:* Following the recog-
379 nition protocol in section 3.1, recognition rates for different methods on the Ex-
380 tended Yale B database are summarized in Table 6 and Figure. 7. According to
381 the results, we can have the following conclusions:

- 382 • The superiority of DMI on Subset 2 and Subset 3 is not obvious, since

Table 6: Mean recognition rates for different methods on the Extended Yale B database (%).

Method	Subset 2	Subset 3	Subset 4	Subset 5	Total
LOG-DCT	98.9	99.34	88.53	88.53	93.42
Gradientfaces	95.39	91.23	68.8	65.6	79.25
LTV	99.12	96.71	86.28	89.66	90.69
Weberfaces	100	100	95.86	91.17	96.51
LBP	99.56	98.25	41.54	14.66	60.78
LTP	100	99.56	96.80	96.24	98.58
DFD	100	97.81	71.64	73.68	81.43
MOST	100	100	85.36	63.90	72.01
S&L(LOG-DCT)	100	99.12	87.97	87.03	93.07
SF	99.34	96.93	81.39	76.69	87.85
DMI	100	99.12	96.99	97.74	97.98

all these methods achieve the high performance, and the recognition rates are over 91%, some even reach up to 100%. It owes to the good lighting conditions of Subset 2 and Subset 3 and is easy for face recognition.

- The superiority of DMI gets more significant when lighting conditions get harsher from Subset 4 to Subset 5. For instance, the recognition rate of LBP is only 41.54% on Subset 4, DMI is about 55.5% higher than it and 10% higher than LTV, which indicates that DMI can effectively extract illumination-robust features.
- Some feature learning/representation-based methods such as DFD and MOST, are robust to handle face recognition against small illumination variations,

expression or pose variations, but they are degraded seriously under bad lighting conditions. For instance, The recognition rates of DFD are only 71.64% and 73.68% on Subset 4 and Subset 5, respectively. However, the proposed DMI reaches up to 96.99% and 97.74%, respectively. The main reason is that DFD and MOST lack specialized background knowledge and do not extract illumination-invariant features when illumination variation dominates the main variation.

- Figure. 7 shows that the performance of DMI is steadily over these of other methods, no matter when the lighting conditions of the testing samples are good (Subsets 2-3) or harsh (Subsets 4-5), while the performance of other methods are unstable, especially for LBP and Gradientfaces.

2) *Compared results on the FRGC database:* FRGC-v2 is an uncontrolled illumination variations database, which is close to real-world scenarios. Therefore, it is more difficult than the Extended Yale B database for face recognition. Following the recognition protocol in section 3.1, the results of different methods are summarized in Table 7 and plotted in Figure. 8. According to the results, we can find that:

- The performances of feature learning/representation-based methods such as LTP, MOST, DFD, LBP and DMI are much better than image decomposition-based methods such as LTV, LOG-DCT and S&L(LOG-DCT), which demonstrates that feature learning/representation-based methods are effective to handle face recognition on the uncontrolled illumination variation database.
- Compared with image decomposition-based methods such as LTV, LOG-DCT and S&L(LOG-DCT), DMI obtains much better recognition accuracy.

Table 7: Mean recognition rates for different methods on the FRGC database (%).

Method	LOG-DCT	Gradf	LTV	Webf	LBP
Mean	68.47	74.36	62.44	66.46	72.13
S&L	LTP	DFD	MOST	SF	DMI
63.73	75.80	77.42	82.29	62.95	82.57

Figure 8: Recognition rates for different methods on FRGC database.

cies, which indicates that multi-layer decomposition strategy can effectively extract illumination-robust features in different layers.

- DMI obtains the best performance compared with these other feature learning/representation based methods such as LTP, MOST, DFD, LBP, and the recognition rate is 82.57%. We think the superiority of DMI in dealing with uncontrolled face recognition is attributed to the discriminant filter learning.

3) *Compared results on the CAS-PEAL-R1 database:* The lighting conditions on the CAS-PEAL-R1 database are somewhat less harsh than those of the Extended Yale B, but its sharp shadows make it harder for face recognition. Following

Table 8: Mean recognition rates for different methods on the CAS-PEAL-R1 database (%).

Method	LOG-DCT	Gradf	LTV	Webf	LBP
Mean	70.58	73.77	69.49	73.88	82.72
S&L	LTP	DFD	MOST	SF	DMI
74.74	84.52	86.15	86.79	77.66	87.98

Figure 9: Recognition rates for different methods on the CAS-PEAL-R1 database.

the recognition protocol in section 3.1, the mean recognition rates and standard deviations for different methods are given in Table 8. As can we see, LOG-DCT, Gradientfaces, LTV, and Weberfaces all obtain low recognition rates of 70.58%, 73.77%, 69.49% and 73.88%, because these methods directly discard the large-scale component, instead of extract useful information from it. LBP, LTP, DFD and MOST are feature extraction-based methods, whose performance are better than LOG-DCT, Gradientfaces, LTV, Weberfaces, S&L(LOG-DCT) and SF, but they are still lower than DMI. From these results we have conclusion that discriminative weighed-layer illumination-robust features extraction model is effective to handle face recognition against illumination variations.

Table 9: Mean recognition rates for different methods on the Oulu-CASIA-NIR-VIS database (%)).

Method	LOG-DCT	Gradf	LTV	Webf	LBP
Mean	67.78	84.44	69.31	80.28	85.66
Method	S&L	LTP	MOST	SF	DMI
Mean	72.64	85.28	86.53	83.33	86.94

The recognition rates under the 10 different reference sets are shown in Figure. 9. we can find that DMI is always much better than most other state-of-the-art methods. Although LBP, LTP, DFD and MOST are slightly better than DMI on three of these reference sets, it is very unrobust and sensitive when the lighting conditions of reference sets are changing. For example, LBP only obtains recognition rates of 62.18% and 67.63% on the 3rd and 10th reference sets, respectively. And our method can get recognition rates about 90% on all reference sets, it shows that DMI is robust and effective to reference sets under different lighting conditions.

4) *Compared results on the Oulu-CASIA-NIR-VIS database:* Oulu-CASIA-NIR-VIS is a video image database with different illumination and expression variations, which is close to real-world scenarios. Thus, it is more difficult than some other controlled illumination variations databases for recognition. According to the results in Table 9, we can find that:

- LTV, LOG-DCT and S&L(LOG-DCT) get poor performance on the video image database, because they mainly use single-layer image decomposition-based methods to extract the illumination invariant features.
- The methods based on feature learning/representation such as MOST, D-

454 MI and LTP significantly improve the performance compared with these
455 traditional illumination-treating methods, which demonstrates the power of
456 feature learning/representation on this database.

- 457 • The DMI obtains the best recognition performance among the compared
458 methods, the recognition result is 86.94%. It indicates that the DMI model
459 is able to extract more discriminative and proper information for face recog-
460 nition against different illumination conditions on video image scenario.

461 **4. Conclusion**

462 In this paper, we propose an illumination-robust feature extraction method D-
463 MI with discriminant face information for face recognition under poor lighting
464 conditions. First, we use the decomposition capability of the TV- L^1 model to sep-
465 arate an original image into small-scale component and large-scale component.
466 Some existing methods directly retain the small-scale component and remove the
467 large-scale component (e.g. LOG-DCT and LTV). However, experimental re-
468 sults show that large-scale component contains some useful information for face
469 recognition, which can be further extracted. Therefore, we further decompose
470 the large-scale component into multi-layer small-scale features as a linear com-
471 bination. Second, we assign a weight to adjust the importance and influence of
472 each layer. Finally, we learn a discriminant filter to remove noise from the re-
473 constructed illumination-robust face image. Experiments show that our weight-
474 selection mechanism is robust, and both layer weights and discriminant filter help
475 to improve the face recognition performance. Moreover, the combination of them
476 further enhances the face recognition rate, especially in extremely harsh lighting
477 conditions.

478 How to fuse multi-layer illumination-robust features to form a more compact
479 and effective representation is a challenging task. Besides the scheme proposed in
480 this paper, better ways of feature combination could be developed. For instance,
481 could there concatenate directly the multi-layer illumination-robust features? If
482 the answer is yes, how to overcome the huge dimensionality and computational
483 problem. In addition, kernel methods have become popular in face recognition.
484 Instead of linear combination, how to introduce nonlinear combination into the
485 decision function? Our ongoing work will focus on these topics.

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