Illumination Normalization of Face Images with Cast Shadows

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Background

Illumination normalization for face recognition

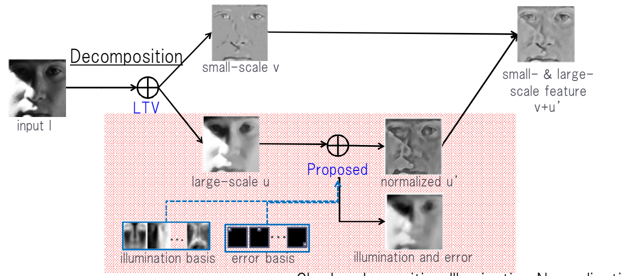
- Shadings are low-frequency components of images, i.e., ***large-scale features***
- Most of methods (e.g, SQI, DCT, TT, LTV) are based on high-frequency components of images, i.e., ***small-scale features***
- Recently, it is reported that the method ***based on both small- and normalized large-scale features*** works better [Xie et al., 2011]

Difficulty of cast shadows

- In the presence of cast shadows, Illumination can not be approximated by low dimensional subspace
  - Occluder can be arbitrary

- Existing methods using illumination subspace (e.g. Non-Point Light Quotient Image [Wang et al. 2004] used in normalization of large-scale features in [Xie et al. 2011]) fail to normalize images with cast shadows

Normalization using Small- and Large-Scale Features



Shadow Insensitive Illumination Normalization

Decomposition

$$I = \rho S \xrightarrow{\text{Logarithmic transform}} \log(I) = v + u$$

reflectance ρ
shading S

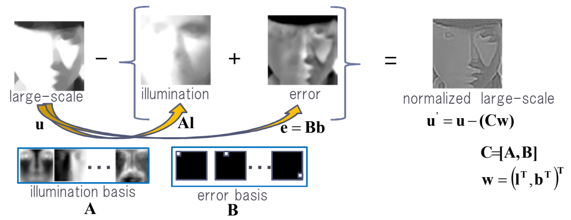
small-scale feature $v = \log(\rho)$
large-scale feature $u = \log(S)$

- This decomposition is obtained by Logarithmic Total Variation (LTV) [T.Chen et al. 2006]

Shadow Insensitive Illumination Normalization

Quotient Image with Error Term

- Remove diffuse lighting on non point light source and *error* components including cast shadows from large-scale features.



Pixel-wise error basis: handle arbitrary shape of error

Algorithm Normalization of large-scale feature

Input: Large-scale feature $\boldsymbol{u}$.
$\hat{l} = \arg\min |\boldsymbol{u} - \boldsymbol{A}\boldsymbol{l}|_2$.
if $|\boldsymbol{u} - \boldsymbol{A}\hat{\boldsymbol{l}}|_2 > \epsilon |\, \boldsymbol{u} \,|_2$ **then**
$\hat{\boldsymbol{w}} = \arg\min |\boldsymbol{w}|_1 \quad \text{s. t. } |\boldsymbol{u} - \boldsymbol{C}\boldsymbol{w}|_2 \leq \epsilon |\boldsymbol{u}|_2$.
$\boldsymbol{u}' = \boldsymbol{u} - \boldsymbol{C}\hat{\boldsymbol{w}}$.
else
$\boldsymbol{u}' = \boldsymbol{u} - \boldsymbol{A}\hat{\boldsymbol{l}}$.
end if
Output: Normalized large-scale feature $\boldsymbol{u}'$.

Fitting Basis Functions

- Fit with minimum usage of error term
  ➡ ***L1-norm minimization*** [Wright et al. 2009]

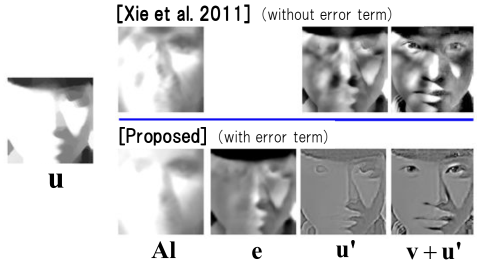
$$\min_{\mathbf{w}} \quad \|\mathbf{w}\|_1$$

$$s.t. \quad \|\mathbf{u} - (\mathbf{C}\mathbf{w})\|_2 \leq \varepsilon \|\mathbf{u}\|_2$$

ε Parameter of tolerance error

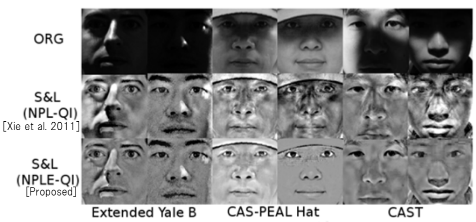
Error term is not constrained to negative: also remove errors other than cast shadows (e.g., specular high lights, and fitting artifacts)

Example Results



Experimental Results

Example



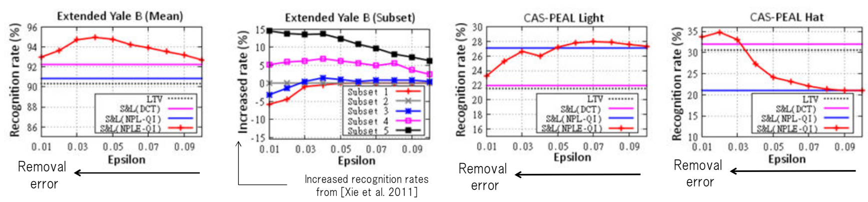
Datasets

- Extended Yale B: 38subjects, 64 lighting conditions
- Multi-PIE: 337 subjects, 21 lighting conditions
- CAS-PEAL: 1040 subjects, lighting probe set and hat images from accessory set
- CAST: 14 subjects, 50 conditions with occluders

Setup

- One image of frontal lighting is registered as a reference image
- Recognition using nearest neighbor classifier based on normalized cross correlation

Results in different settings of ε



Recognition rates of various datasets

Method	Extended YaleB	Multi-PIE	CAS PEAL Light	CAS PEAL Hat	CAST
HE	55.87	57.92	4.37	25.00	18.43
TT [XTan et al. 2010]	86.67	99.46	18.28	24.73	76.00
DCT [Chen et al. 2006]	90.15	99.15	19.66	27.68	81.00
NDF [Chen et al. 2011]	90.57	**99.85**	21.89	32.50	79.71
LTV [Chen et al. 2006]	90.34	98.80	21.58	30.54	82.29
NPL-QI [Wang et al. 2004]	83.69	97.69	23.23	19.46	37.61
NPLE-QI [Proposed]	93.74	99.69	22.60	27.68	67.43
S&L(DCT) [Xie et al, 2011]	92.26	98.85	21.98	32.05	82.86
S&L(NPL-QI) [Xie et al, 2011]	90.83	98.62	**27.06**	21.07	49.71
S&L(NPLE-QI) [Proposed]	**94.71**	99.31	26.62	**33.04**	**84.57**

Summary

- We extend quotient image based illumination normalization taking into account for errors including cast shadows
- Favorable results were obtained

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