CARNEGIE MELLON UNIVERSITY
Pittsburgh, Pennsylvania

Pokerface: Partial Order Keeping and Energy Repressing Method for Extreme Face Illumination Normalization (BTAS'15)

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Marios Savvides

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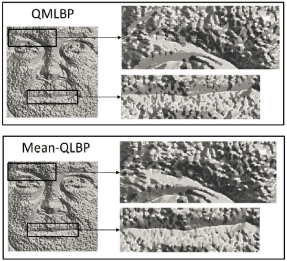

Figure 2: Face features obtained from: Top) QMLBP and Bottom) Mean-QLBP.

Figure 1: From [Zhang et al., 2015] Quaternion-Based LBP for Illumination Invariant Face Recognition

Two Pillars of Quality Illumination Normalization

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Faithfulness

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Expressiveness

Expressiveness means that the illumination normalized image can fully express the identity information of the subject and thus can improve face recognition performance, and most importantly, even when using the simplest possible classifier, *e.g.* nearest neighbor classifier based on normalized cosine distance.

Related Work

[Han et al., 2013]

provided a comparative study on 12 representative illumination preprocessing methods and grouped them into 3 categories:

- (1) grey-level transformation *e.g.* histogram equalization, logarithmic transform,
- (2) gradient or edge extraction *e.g.* Laplacian of Gaussian,
- (3) reflectance field estimation *e.g.* work of [Tan and Triggs, 2010].

The authors have the following conclusion that we also share:
"for face recognition purpose, better visualization effect after illumination preprocessing does not imply higher recognition accuracy."
This reiterates why satisfying both goals is important for a quality illumination normalization method.

Related Work

- [Han et al., 2012]
- [Chen et al., 2011]
- [Wang et al., 2013]
- [Matsukawa et al., 2012]
- [Arandjelović, 2012]

Latest in 2015

- [Zhang et al., 2015]
- [Rizo-Rodriguez and Ziou, 2015]
- [Chen et al., 2015]
- [Punnappurath et al., 2015]
- [Lai et al., 2015]

Main Idea

Intuitive and straight-forward. It aims at transforming a dark image patch to a bright (illumination normalized) one with distinguishable details by keeping the partial orders of the pixels.

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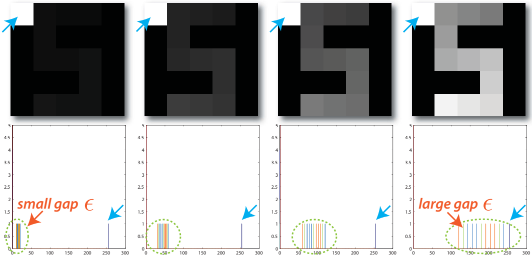

Figure 2: A toy example showing the main idea behind the Pokerface which is to maximize the minimum gap ϵ between adjacently-valued pixels while keeping the partial ordering. The bins inside the green ellipse correspond to the "S" pattern.

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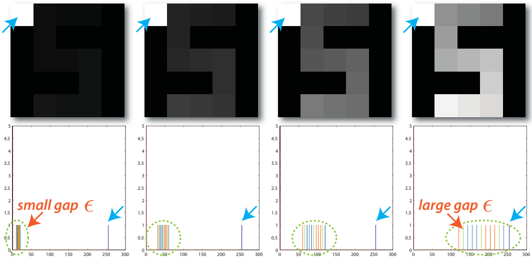

The goal of the Pokerface is exactly to maximize the minimum gap (ϵ) between adjacently-valued pixels while preserving the partial ordering of the pixels. The latter is to guarantee that the local edge information is well preserved when normalizing a dark image to a bright one. We will formulate this optimization problem in the context of order theory.

Overview of the Pokerface

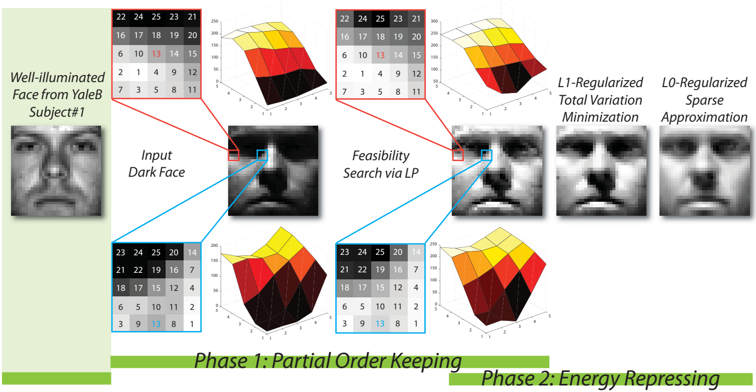

Figure 3: The flowchart of the Pokerface. Phase 1 Partial Order Keeping is accomplished by feasibility search via LP, and Phase 2 Energy Repressing is achieved by ℓ_1-regularized total variation minimization and ℓ_0-regularized sparse approximation. *(Phase 1 does 80% of the job.)*

Definition I

Definition

A binary relation $\mathfrak{R}$ on a nonempty set $\mathbb{X}$ is ***reflexive*** *if $x \ \mathfrak{R} \ x$ for every $x \in \mathbb{X}$. It is* ***antisymmetric*** *if $x \ \mathfrak{R} \ y$ implies $y \ \mathfrak{R} \ x$, for every $x, y \in \mathbb{X}$. It is* ***transitive*** *if $x \ \mathfrak{R} \ y \ \mathfrak{R} \ z$ implies $x \ \mathfrak{R} \ z$, for every $x, y, z \in \mathbb{X}$.*

Definition

A binary relation $\succsim$ on a nonempty set $\mathbb{X}$ is a ***preorder*** *on $\mathbb{X}$ if it is transitive and reflexive. It is a* ***partial order*** *on $\mathbb{X}$ if it is an antisymmetric preorder on $\mathbb{X}$.*

Definition

A ***preordered set*** *is an ordered pair $(\mathbb{X}, \succsim)$, where $\mathbb{X}$ is a nonempty set and $\succsim$ is a preorder on $\mathbb{X}$.*

Definition II

Definition

A preordered set $(\mathbb{X}, \succcurlyeq)$ *is a* ***partially ordered set****, or* ***poset****, if* $\succcurlyeq$ *is a partial order on* $\mathbb{X}$*. (important)*

Definition

Let $(\mathbb{X}, \succcurlyeq)$ *and* $(\mathbb{Y}, \succcurlyeq)$ *be two partially ordered sets. The* ***order-preserving map*** *from* $(\mathbb{X}, \succcurlyeq)$ *into* $(\mathbb{Y}, \succcurlyeq)$ *is a function* $f : \mathbb{X} \mapsto \mathbb{Y}$ *such that* $a \succcurlyeq b$ *implies* $f(a) \succcurlyeq f(b)$ *for every* $a, b \in \mathbb{X}$*. (important)*

Problem Formulation

For every pixel $X_{i,j}$ in the (zero-padded) face image under extreme illumination condition (or "dark face"), we consider an odd-sized $N \times N$ $(N = 3, 5, 7, ...)$ square region around it such that $X_{i,j}$ is the center pixel of the patch. These N^2 pixels in the patch form a partially ordered set $(\mathbb{X}_{i,j}, \succcurlyeq)$.

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Let $Y_{i,j}$ be the counterpart of $X_{i,j}$ in the bright (illumination normalized) face where $(\mathbb{Y}_{i,j}, \succcurlyeq)$ is also a partially ordered set containing the center pixel $Y_{i,j}$ and its neighboring pixels within a patch of the bright face.

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Moreover, let function $f_{i,j} : \mathbb{X}_{i,j} \mapsto \mathbb{Y}_{i,j}$ be an order-preserving mapping from $(\mathbb{X}_{i,j}, \succcurlyeq)$ to $(\mathbb{Y}_{i,j}, \succcurlyeq)$ such that $a \succcurlyeq b$ implies $f_{i,j}(a) \succcurlyeq f_{i,j}(b)$ for every $a, b \in \mathbb{X}_{i,j}$.

Problem Formulation

We adopt a shifting-window approach where we only establish the binary relations between the center pixel and its $(N^2 - 1)$ neighbors, rather than a fully-paired case with $\frac{1}{2}\binom{N^2}{2}$ binary relations.

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Readers can easily verify that establishing the relations between only the center pixel and its neighbors for an $N \times N$ patch under shifting-window, is equivalent to establishing fully-paired relations within each window of width $(\frac{N-1}{2} + 1)$, as depicted in orange color in Figure 4.

Problem Formulation

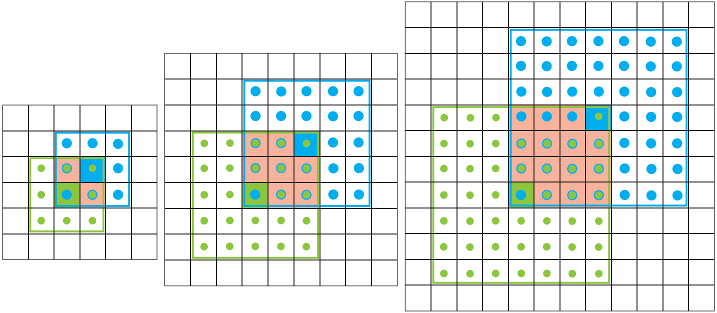

Figure 4: For each $N \times N$ patch, the center pixel is plotted as a colored square, and its neighbors are plotted as dots with the same color. With the window shifting, the orange region is the largest region where pixels inside can have fully-paired binary relations.

Problem Formulation

Now, we can formulate the main idea of the Pokerface using the following optimization where we aim at maximizing the minimum gap (ϵ) between partially ordered pixels while keeping the same partial ordering ($\succcurlyeq$).

$$
\begin{aligned}
\underset{\epsilon}{\text{maximize}} \quad & \epsilon \qquad (1) \\
\text{subject to} \quad & \forall a, b \in \mathbb{X}_{i,j}, \quad \forall i, j, \quad f_{i,j}(a) \succcurlyeq f_{i,j}(b) + \epsilon \\
& 0 \leq \min(f_{i,j}(a), f_{i,j}(b)) \leq \max(f_{i,j}(a), f_{i,j}(b)) \leq 255
\end{aligned}
$$

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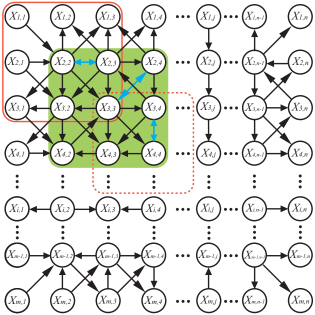
However, this optimization requires explicit knowledge of every mapping function $f_{i,j}$ which is neither efficient nor feasible to learn. Thanks to the reformulation to be discussed next, we can obtain the bright face without explicitly knowing the mapping functions $f_{i,j}$, while, most importantly, satisfying the partial order constraints.

Feasibility Search via LP

Suppose we have a dark face of size $m \times n$ as shown in Figure 5. Each $X_{i,j}$ corresponds to the pixel intensity at location (i, j) and the arrow pointing from $X_{i,j}$ to $X_{k,l}$ means that the pixel intensity at (i, j) is greater than that at (k, l). If (i, j) and (k, l) have the same intensity, the arrow points to both directions and is shown in blue.



Feasibility Search via LP

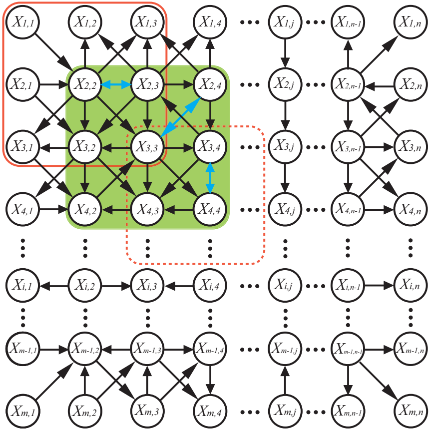


Figure 5: In Phase 1, the illumination normalized image $\mathbf{y} = \{Y_{i,j}\}, \forall i, j$ should have the same partial ordering as the dark face $\mathbf{x} = \{X_{i,j}\}, \forall i, j$.

Feasibility Search via LP

We want our illumination normalization algorithm to preserve the partial ordering in every local image patch. In other words, the bright face image should have exactly the same partial ordering as the input dark face.

Take $X_{3,3}$ for instance, in its 3×3 neighborhood (the green box), these 9 pixels form a partially ordered set $(\mathbb{X}_{3,3}, \succcurlyeq)$, and the partial order characteristic $(\succcurlyeq)$ can be written as the following by comparing the center pixel $X_{3,3}$ to its 8 neighbors:

$$
\begin{array}{lll}
X_{3,3} < X_{2,2} & X_{3,3} > X_{3,2} & X_{3,3} < X_{4,2} \\
X_{3,3} > X_{4,3} & X_{3,3} > X_{4,4} & X_{3,3} > X_{3,4} \\
X_{3,3} = X_{2,4} & X_{3,3} < X_{2,3} &
\end{array}
\tag{2}
$$

Feasibility Search via LP

$$X_{i,j} > X_{k,l} \Leftrightarrow X_{i,j} \geq X_{k,l} + 1.$$

$$X_{i,j} = X_{k,l} \Leftrightarrow X_{i,j} \geq X_{k,l} + 0 \; and \; X_{k,l} \geq X_{i,j} + 0.$$

Therefore, relations in (2) become:

$$\begin{aligned}
&(+1)X_{3,3} + (-1)X_{2,2} \leq -1, && (-1)X_{3,3} + (+1)X_{3,2} \leq -1 \\
&(+1)X_{3,3} + (-1)X_{4,2} \leq -1, && (-1)X_{3,3} + (+1)X_{4,3} \leq -1 \\
&(-1)X_{3,3} + (+1)X_{4,4} \leq -1, && (-1)X_{3,3} + (+1)X_{3,4} \leq -1 \\
&(+1)X_{3,3} + (-1)X_{2,3} \leq -1, && (-1)X_{3,3} + (+1)X_{2,4} \leq 0 \\
&(+1)X_{3,3} + (-1)X_{2,4} \leq 0
\end{aligned} \tag{3}$$

Feasibility Search via LP

Relation (3) is a set of linear constraints that pixel $X_{3,3}$ has to satisfy in order to keep the partial ordering. By scanning through all the pixels in the input dark image, we can generate the complete list of constraints.

According to this setup, let $\mathbf{x}$ be a vector containing all the $X_{i,j}$'s, we can write all of the linear constraints in matrix form: $\mathbf{Ax} \leq \mathbf{b}$, where $\mathbf{A}$ should be a sparse matrix whose non-zero elements are either $+1$ or -1 and the locations of $+1$ and -1 indicate which $X_{i,j}$ and $X_{k,l}$ are being compared. $\mathbf{b}$ should be a vector whose elements are either -1 or 0, indicating the corresponding RHS of the inequality constraints, which is the minimum gap between pairs of pixels. Since we are dealing with 8-bit grayscale image, all the $X_{i,j}$ should be within the range 0 to 255.

Feasibility Search via LP

Recall that $Y_{i,j}$ is the counterpart of $X_{i,j}$, and each patch around $Y_{i,j}$ forms a partially ordered set $\mathbb{Y}_{i,j}$ having the same ordering ($\succcurlyeq$) as $\mathbb{X}_{i,j}$. Let $l_{i,j}^{l}$ be the l^{th} lower-valued neighboring pixel of $Y_{i,j}$, and similarly, $h_{i,j}^{h}$ be the h^{th} higher-valued neighboring pixel of $Y_{i,j}$.

The optimization (1) can be reformulated as:

$$\begin{aligned} &\underset{\epsilon}{\text{maximize}} \quad \epsilon \\ &\text{subject to} \quad (-1)Y_{i,j} + (+1)l_{i,j}^{l} \leq -\epsilon, \quad \forall l, \quad \forall i,j \\ &\qquad\qquad\quad (+1)Y_{i,j} + (-1)h_{i,j}^{h} \leq -\epsilon, \quad \forall h, \quad \forall i,j \\ &\qquad\qquad\quad 0 \leq Y_{i,j} \leq 255, \quad \forall i,j \end{aligned} \tag{4}$$

Feasibility Search via LP

Since we know that each $l^{l}_{i,j}$ and $h^{h}_{i,j}$ is actually some pixel $Y_{k,l}$ in the bright face, whose partial order should be precisely captured by the linear constraints $\mathbf{A}\mathbf{y} \leq \epsilon\mathbf{b}$, $(\epsilon = 1, 2, 3, ...)$, where $\mathbf{y}$ is a vector containing all the $Y_{i,j}$'s. It is worth noting that here matrix $\mathbf{A}$ and vector $\mathbf{b}$ are directly obtained from the partial order characteristics of the dark face.

Feasibility Search via LP

For a known gap ϵ, finding the bright face $\mathbf{y}$ under linear constraints $\mathbf{Ay} \leq \epsilon\mathbf{b}$ is a feasibility search problem [Boyd and Vandenberghe, 2004], which can be efficiently solved using linear programming by setting the objective function to be 0. The feasibility search problem, also called the satisfiability problem, can be regarded as the special case of mathematical optimization where the objective value is the same for every solution, and thus any solution is optimal. We increase ϵ greedily until the solution is no longer feasible.

$$\begin{aligned} &\text{find} \quad \mathbf{y} \\ &\text{subject to} \quad \mathbf{Ay} \leq \epsilon\mathbf{b} \\ &0 \leq \mathbf{y}_s \leq 255, \quad s = 1, 2, \ldots, m \times n \end{aligned} \tag{5}$$

Phase 1: Partial Order Keeping Is Done

That's 80% of the job done.

Phase 2: Energy (of the gradient map after Phase 1) Repressing is achieved by two steps: an ℓ_1-regularized total variation minimization step and an ℓ_0-regularized sparse approximation step.

ℓ_1-Regularized Total Variation Minimization

After Phase 1 of the Pokerface, the intermediate face may show some non-smooth artifacts. This is because during Phase 1, there are no smoothness constraints to be satisfied in the optimization. This is done purposefully, we want a subsequent step down the line to perform the smoothing task, rather than solving a single convoluted multi-purpose optimization.

The concept of total variation (TV) was introduced in computer vision first by Rudin, Osher and Fatemi [Rudin et al., 1992]. However, it is very difficult to be minimized by conventional methods. Therefore, we resort to an iterative *split Bregman* method [Goldstein and Osher, 2009] for solving the total variation minimization problem. The split Bregman method can solve a series of ℓ_1-regularized problem in the form of:

ℓ_1-Regularized Total Variation Minimization

$$\underset{u}{\text{minimize}}\,|\Phi(u)| + H(u) \tag{6}$$

where $|\cdot|$ denotes the ℓ_1 norm, and both $|\Phi(u)|$ and $H(u)$ are convex functions. Following this, the isotropic total variation minimization problem can be formulated as:

$$\underset{u}{\text{minimize}} \sum_i \sqrt{(\nabla_x u)_i^2 + (\nabla_y u)_i^2} + \frac{\mu}{2}\|u - f\|_2^2 \tag{7}$$

where f represents the original noisy image and u is the smooth image after TV minimization. The key to the split Bregman method is that the ℓ_1 and ℓ_2 portions of the energy in Equation (6) are decoupled.

ℓ_1-Regularized Total Variation Minimization

For better visualizing the effect of the penalty coefficient, we rewrite Equation (7) as follows:

$$\underset{u}{\text{minimize}}\, \tau \sum_i \sqrt{(\nabla_x u)_i^2 + (\nabla_y u)_i^2} + \frac{1}{2}\|u - f\|_2^2 \tag{8}$$

We can vary τ to get different levels of smoothing. For large τ, we will end up with very washed out images, and for small τ it will still be noisy as shown in Figure 6. An example of illumination normalized image after ℓ_1-regularized total variation minimization is shown in Figure 3, with much smoother appearance. In the Pokerface, $\tau = 8$.

ℓ_1-Regularized Total Variation Minimization

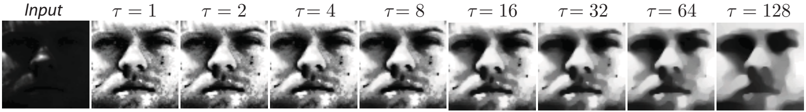


Figure 6: Different levels of smoothing by varying τ in the total variation minimization stage. This example is from YaleB+.

ℓ_0-Regularized Sparse Approximation

We resort to the K-SVD dictionary learning method for obtaining the overcomplete dictionary.

$$\underset{\mathbf{D},\boldsymbol{\alpha}}{\text{minimize}} \|\mathbf{X} - \mathbf{D}\boldsymbol{\alpha}\|_F^2 \text{ subject to } \|\boldsymbol{\alpha}_i\|_0 < K_1, \ \forall i \tag{9}$$

where $\mathbf{X}$, $\mathbf{D}$ and $\boldsymbol{\alpha}$ are the data, the learned overcomplete dictionary and the sparse approximation matrix respectively. Here $\|.\|_0$ is the ℓ_0 pseudo-norm measuring sparsity. The sparse approximations of the data elements are allowed to have some maximum sparsity $\|\boldsymbol{\alpha}\|_0 \leq K_1$.

ℓ_0-Regularized Sparse Approximation

With the learned dictionary $\mathbf{D}$, any intermediate face $\mathbf{y}$ after TV minimization step can be sparsely approximated by the elements of $\mathbf{D}$ following:

$$\boldsymbol{\alpha}_{\mathbf{y}} = \arg\min_{\alpha} \|\mathbf{y} - \mathbf{D}\boldsymbol{\alpha}\| \text{ subject to } \|\boldsymbol{\alpha}\|_0 < K_2 \qquad (10)$$

which can be efficiently solved using any sparse coding algorithm such as the orthogonal matching pursuit (OMP) [Pati et al., 1993]. The sparse approximation of $\mathbf{y}$ is therefore $\hat{\mathbf{y}} = \mathbf{D}\boldsymbol{\alpha}_{\mathbf{y}}$.

ℓ_0-Regularized Sparse Approximation

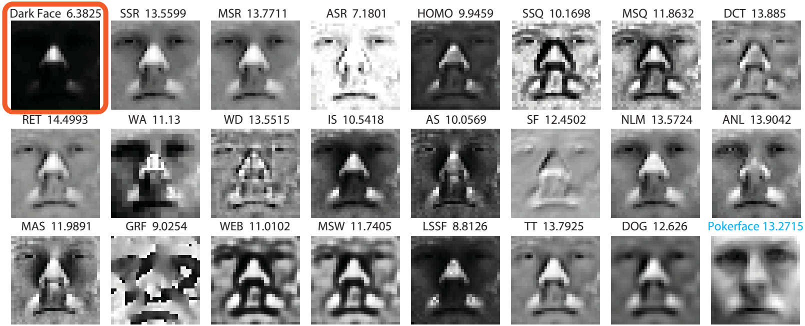


Figure 7: Example from YaleB+ subject #1 showcasing various illumination normalization algorithms. PSNR is also displayed for this particular image.

Faithfulness: Fidelity Experiments (MPIE)

Figure 8: Visual results of the Pokerface on 4 subjects of MPIE under all illumination variations.

Faithfulness: Fidelity Experiments (YaleB+)

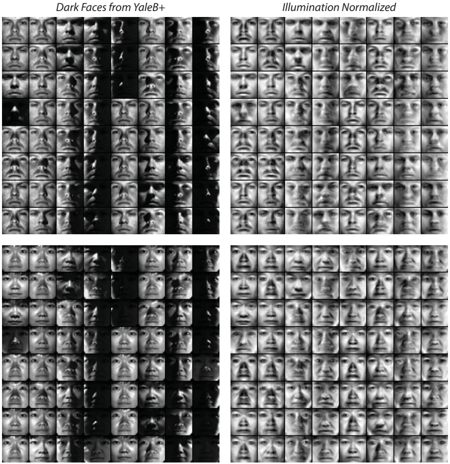


Figure 9: Visual results of the Pokerface on 2 subjects of YaleB+ under all illumination variations .

Expressiveness: Face Verification Experiments (MPIE)

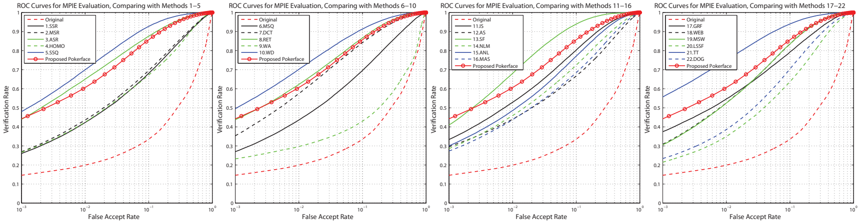


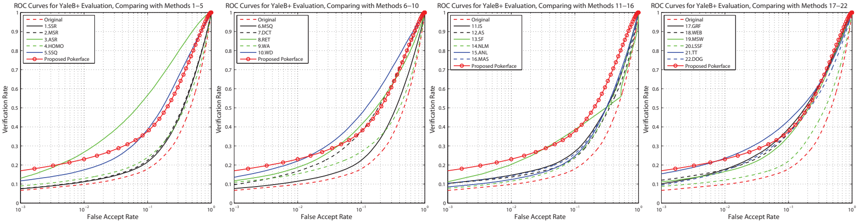
Figure 10: ROC curves for our proposed Pokerface and other 22 competing algorithms on MPIE. These 22 algorithms are split into four sub-figures, and in each sub-figure, ROC curves for the original image performance and the Pokerface performance are plotted for comparison.

Expressiveness: Face Verification Experiments (MPIE)

Method	VR (EER)	Rk_{VR}	PSNR	Rk_{PSNR}	$\sum$	$Rk_{\sum}$	Method	VR (EER)	Rk_{VR}	PSNR	Rk_{PSNR}	$\sum$	$Rk_{\sum}$
Original	0.1457 (0.2017)	—	—	—	—	—	AS	0.2958 (0.2224)	15	12.1041	17	32	19
SSR	0.2633 (0.2070)	20	11.5426	20	40	22	SF	0.4118 (0.0749)	8	11.9702	18	26	15
MSR	0.2672 (0.2044)	19	11.4762	21	40	23	NLM	0.2914 (0.1885)	16	11.6009	19	35	21
ASR	0.4406 (0.1095)	5	8.6825	23	28	16	ANL	0.2999 (0.1585)	14	13.5821	9	23	12
HOMO	0.2674 (0.2185)	18	12.8675	12	30	17	MAS	0.2755 (0.2043)	17	14.0922	5	22	10
SSQ	0.4868 (0.0851)	3	12.2546	16	19	7	GRF	0.3763 (0.1551)	9	8.9773	22	31	18
MSQ	0.4300 (0.1157)	7	12.7599	14	21	9	WEB	0.3131 (0.1299)	12	13.3675	11	23	13
DCT	0.3547 (0.1270)	10	13.5237	10	20	8	MSW	0.3091 (0.1255)	13	14.3141	4	17	5
RET	0.4395 (0.1120)	6	14.0250	7	13	3	LSSF	0.2146 (0.2211)	23	14.8537	3	26	14
WA	0.2307 (0.3710)	22	12.7786	13	35	20	TT	0.5602 (0.0719)	1	12.6407	15	16	4
WD	0.4986 (0.0879)	2	13.9621	8	10	2	DOG	0.2364 (0.1852)	21	14.7781	2	23	11
IS	0.3363 (0.1443)	11	14.0754	6	17	6	Pokerface	0.4445 (0.1217)	4	14.9831	1	5	1

Figure 11: Results including verification rate (VR) at 0.1% false accept rate (FAR), equal error rate (EER), and peak-signal-to-noise ratio (PSNR) are tabulated for experiments on MPIE. VR/PSNR/overall rankings are also shown. $\sum$ column is the sum of $\mathrm{Rank}_{\mathrm{VR}}$ and $\mathrm{Rank}_{\mathrm{PSNR}}$.

Expressiveness: Face Verification Experiments (YaleB+)



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Method	VR	(EER)	Rk_{VR}	PSNR	Rk_{PSNR}	$\sum$	$Rk_{\sum}$	Method	VR	(EER)	Rk_{VR}	PSNR	Rk_{PSNR}	$\sum$	$Rk_{\sum}$
Original	0.0750	(0.4808)	—	—	—	—	—	AS	0.1040	(0.4342)	14	11.6312	15	29	17
SSR	0.0755	(0.4319)	22	10.3763	20	42	23	SF	0.1136	(0.4519)	9	12.9689	5	14	4
MSR	0.0749	(0.4252)	23	10.3884	19	42	22	NLM	0.0766	(0.4207)	21	10.7308	18	39	21
ASR	0.1332	(0.2482)	4	6.4917	23	27	16	ANL	0.0862	(0.4069)	20	12.1193	13	33	18
HOMO	0.0906	(0.4434)	18	11.5867	16	34	19	MAS	0.1043	(0.4047)	13	12.9829	4	17	5
SSQ	0.1181	(0.3160)	6	10.1418	21	27	15	GRF	0.1024	(0.3423)	15	9.0207	22	37	20
MSQ	0.1173	(0.3497)	8	10.9452	17	25	13	WEB	0.1213	(0.3434)	5	12.1227	12	17	7
DCT	0.0973	(0.3374)	16	12.3461	9	25	11	MSW	0.1129	(0.3568)	10	12.2681	11	21	10
RET	0.1174	(0.3441)	7	12.3458	10	17	6	LSSF	0.0879	(0.4397)	19	12.7387	7	26	14
WA	0.1096	(0.4546)	11	12.1002	14	25	12	TT	0.1559	(0.3458)	2	13.2149	3	5	2
WD	0.1382	(0.2963)	3	12.7586	6	9	3	DOG	0.0961	(0.3718)	17	13.2827	2	19	8
IS	0.1047	(0.4117)	12	12.6833	8	20	9	Pokerface	0.1709	(0.3403)	1	13.9678	1	2	1

Figure 13: Results including verification rate (VR) at 0.1% false accept rate (FAR), equal error rate (EER), and peak-signal-to-noise ratio (PSNR) are tabulated for experiments on YaleB+. VR/PSNR/overall rankings are also shown. $\sum$ column is the sum of $\mathrm{Rank}_{\mathrm{VR}}$ and $\mathrm{Rank}_{\mathrm{PSNR}}$.

Conclusions

- We present a practical and effective method for extreme face illumination normalization.
- Pokerface exhibits very high level of faithfulness and expressiveness at the same time, which is outstanding among many competing algorithms.
- Intuitive formulation: it aims at maximizing the minimum gap between adjacently-valued pixels while keeping the partial ordering of the pixels in the dark face.
- We reformulate this optimization as a feasibility search problem which is efficiently solved by LP. Next, a smoothing step involving total variation minimization and sparse approximation is exercised for improved enhancement quality.
- The effectiveness of the Pokerface in terms of both faithfulness and expressiveness is confirmed.

Thank you! Questions?

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Appendix

More related work can be found in
[Juefei-Xu and Savvides, 2015c, Juefei-Xu et al., 2015a, Juefei-Xu et al., 2014b, Juefei-Xu and Savvides, 2015e, Juefei-Xu and Savvides, 2015f, Juefei-Xu and Savvides, 2015a, Juefei-Xu and Savvides, 2015d, Zehngut et al., 2015, Juefei-Xu et al., 2015b, Juefei-Xu et al., 2015c, Seshadri et al., 2015, Venugopalan et al., 2015, Savvides and Juefei-Xu, 2013, Juefei-Xu and Savvides, 2015b, Juefei-Xu and Savvides, 2015g, Juefei-Xu et al., 2014a, Juefei-Xu and Savvides, 2014, Juefei-Xu and Savvides, 2013b, Juefei-Xu and Savvides, 2013a, Juefei-Xu et al., 2012, Juefei-Xu and Savvides, 2012, Juefei-Xu et al., 2011b, Juefei-Xu and Savvides, 2011, Juefei-Xu et al., 2011a, Juefei-Xu et al., 2010]

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