A Deformation and Lighting Insensitive Metric for Face Recognition Based on Dense Correspondences

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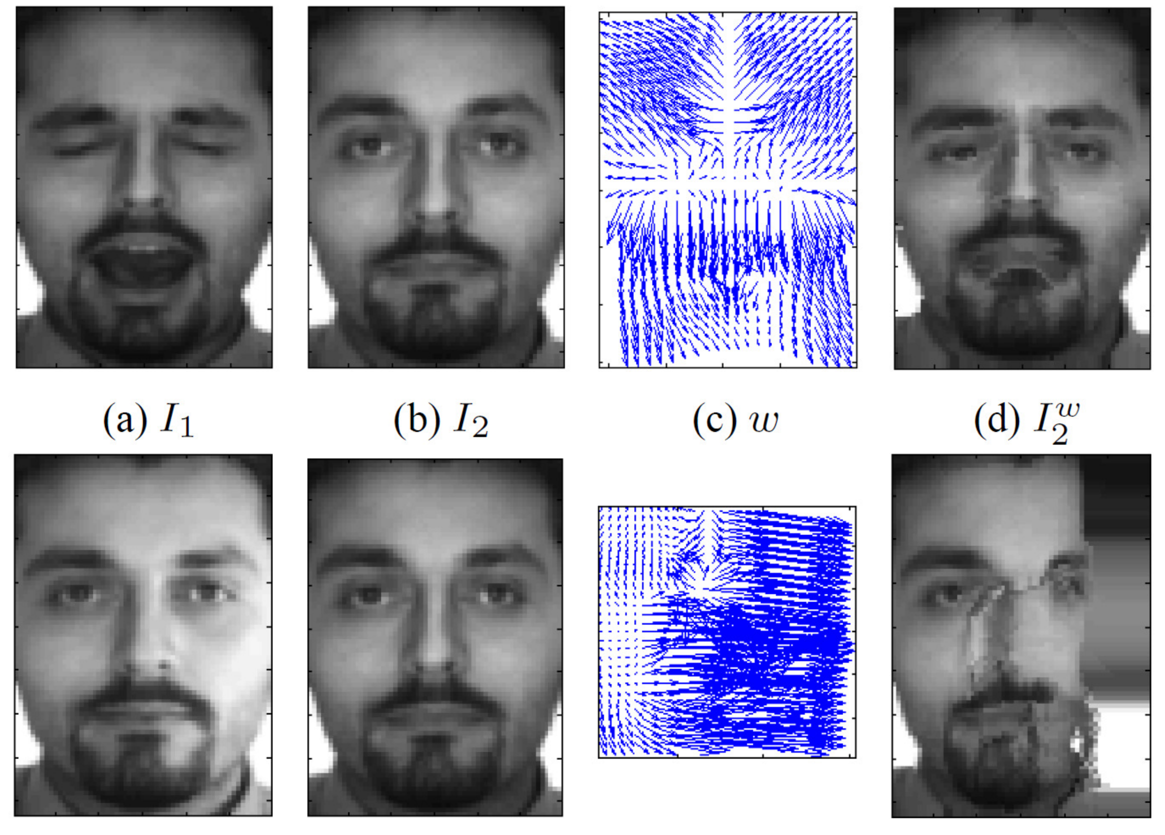
Optical Flow for Face Recognition

Goal: Compute the lowest cost deformation and intensity changes relating two face images, and use these for recognition.

Poor results are achieved when traditional optical flow is used:



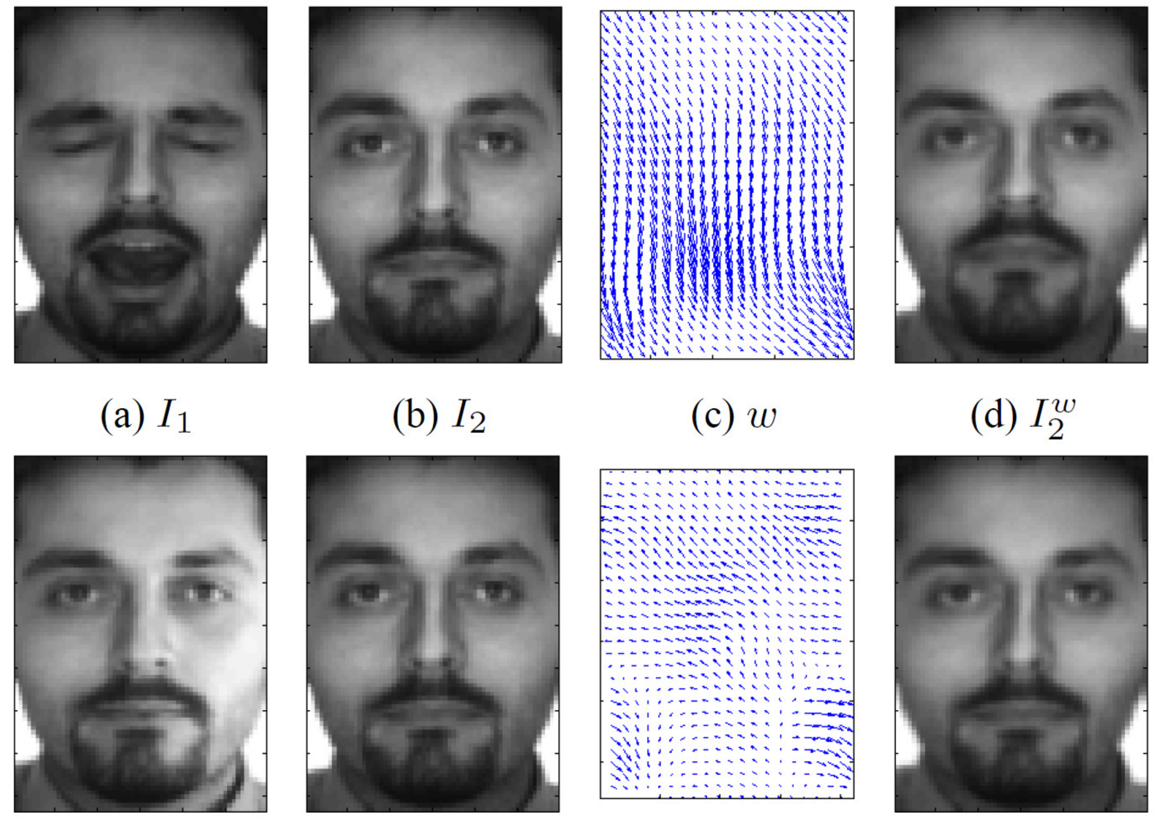
(a) I_1 (b) I_2 (c) w (d) I_2^w

(e) I_1 (f) I_2 (g) w (h) I_2^w

w : *the flow from* I_1 *to* I_2

I_2^w : I_2 *warped backwards along* w *to attempt to match* I_1

The flow calculated with our proposed method is more stable:



(a) I_1 (b) I_2 (c) w (d) I_2^w

(e) I_1 (f) I_2 (g) w (h) I_2^w

References:

[1] J. W. Neuberger. *Sobolev Gradients and Differential Equations, 2nd Edition*. Springer, 2010.

[2] A. Martinez and R. Benavente. The AR Face Database. *CVC Technical Report #24*, 1998.

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The New Deformation and Lighting Insensitive (DLI) Metric

Goal: Define a metric on face image flows that is insensitive to changes in expression and lighting.

$$E_{\text{DLI}}(w) = (1-\lambda)E_b(w) + \lambda E_r(w)$$

Photometric term :

$$E_b(w) = \frac{1}{2}\sum_{ij} \frac{\|\nabla(I_2^w - I_1)\|^2}{\|\nabla I_1\|^2 + \epsilon^2} = \frac{1}{2}\sum_{ij}(E^x_{b_{ij}})^2 + (E^y_{b_{ij}})^2$$

- Invariant to multiplication by a scalar and addition by a constant.
- Insensitive to changes caused by the effects of lighting variation in 3D scenes (ex: changing the location of a light can magnify or weaken the gradient at the edge of a polyhedron, as the two sides forming the edge are exposed to the light differently).

Regularization term :

$$E_r(w) = \frac{1}{2}\langle K^{-1}w,\ w\rangle_G = \frac{1}{2}\sum_{ij}(E^x_{r_{ij}})^2 + (E^y_{r_{ij}})^2$$

- K : a symmetric positive definite matrix (eg a gaussian)
- G : a generalized inner product defined on MxNx2 structures (dimensions of the flow)

Optimization

Use a modified gradient descent algorithm to minimize $E_{\text{DLI}}(w)$.

Sobolev Gradient[1]: $\nabla_K E = K\nabla E$

- Smoother, results in superior rates of convergence.

Optimize over a dual variable α:

$$w_n = K\alpha_n \qquad \textit{(this is a convolution)}$$

$$\alpha_{n+1} = \alpha_n - \Delta t \cdot \nabla E(w_n)$$

Learning for Improved Results

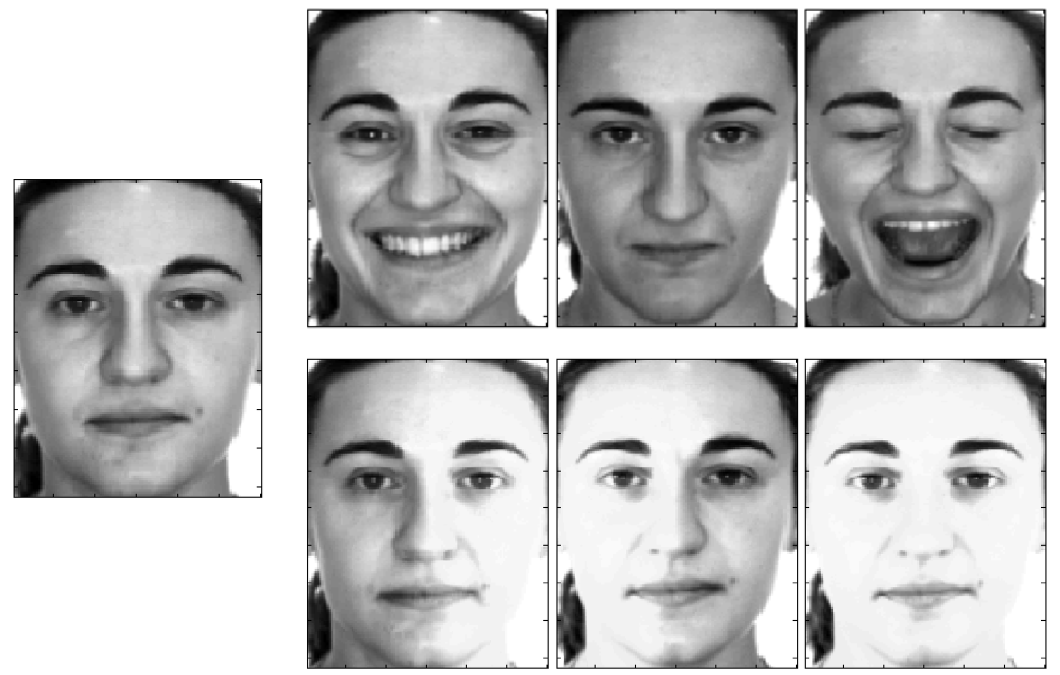
Given pixel matching costs for known image pairs,

- Use Maximum Likelihood estimation to learn typical Gaussian distributions through 4D cost vectors $\vec{E}_{ij} = [E^x_{b_{ij}}\ E^y_{b_{ij}}\ E^x_{r_{ij}}\ E^y_{r_{ij}}]$.
- Assume pixel independence.
- Learn separate models for same-person and different-person image pairs, to calculate probability that two images are from the same person and also from different people.
- The final similarity measure: $S(I_1, I_2) = \dfrac{P_{\text{same}}(\vec{E}(w))}{P_{\text{diff}}(\vec{E}(w))}$

Experiments

Identity of unknown neutral face determined by gallery image resulting in lowest matching cost.

Images from the AR Face Database[2] with variations in expression and lighting.



Variation	*Accuracy*	*Variation*	*Accuracy*
Smile	97.6%	**Left light**	98.8%
Frown	91.6%	**Right light**	99.6%
Scream	79.6%	**Both lights**	98.4%

Cost Function	*Expression*	*Lighting*	*Overall*
Direct	82.0%	96.0%	89.0%
After Learning	89.6%	**98.9%**	**94.3%**
Smile gallery After Learning	86.8%	91.2%	89.0%
Borders removed After Learning	85.1%	96.4%	90.7%