Robust Sparse Learning Based on Kernel Non-second Order Minimization

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Introduction

(a) (b) (c) (d)

Fig.1 Face image with different types of corruption.

Motivations

- Existing mean square error based methods and robust function (e.g., correntropy induced metric) based methods are sensitive to outliers, pixel corruptions, non-Gaussian noise, impulsive noise.

Contributions

- A non-second order statistic measurement based on the information theoretic learning is proposed to better fit the representation error. Thus, the proposed model is robust against various corruptions in the facial images.
- A robust classifier based on the proposed metric is developed
- An efficient optimization strategy is designed to solve the proposed model.

Proposed method

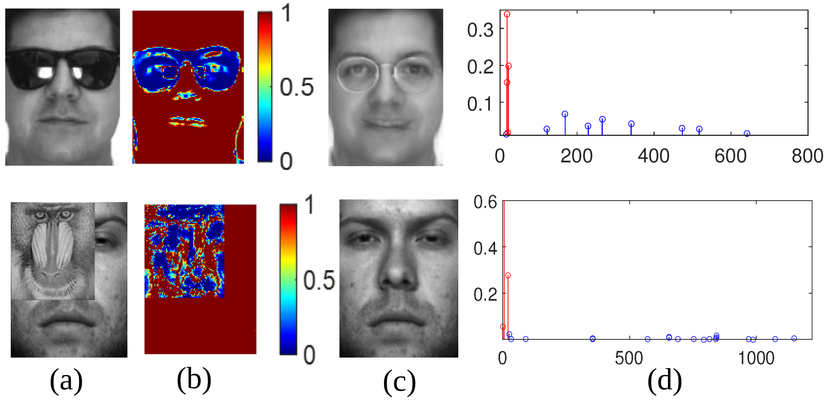
Kernel non-second order loss (KNS-loss):

$$J_{KNS-loss}(A-B) = 2^{-p/2}E[\|\varphi(A)-\varphi(B)\|_H^p] = E[\left(1-k_\sigma(A-B)\right)^{p/2}]$$

KNS-SR:

$$J_{KNS-loss}(\alpha) = \frac{1}{m}\sum_{j=1}^{m}\left(1-k_\sigma\left(y_j-\sum_{i=1}^{n}d_{ij}\alpha_i\right)\right)^{p/2}+\lambda\|\alpha\|_1$$

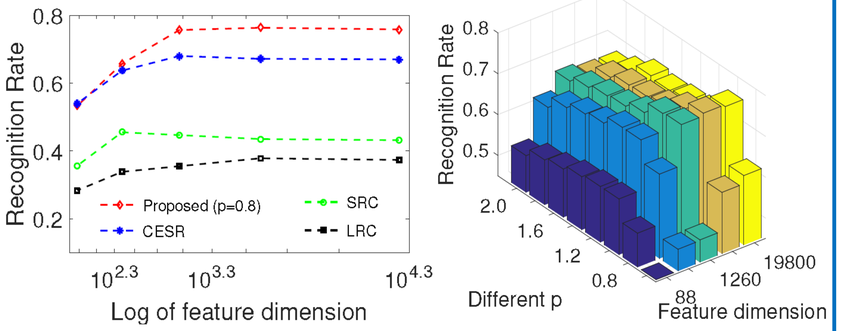
Implementation details



(a) (b) (c) (d)

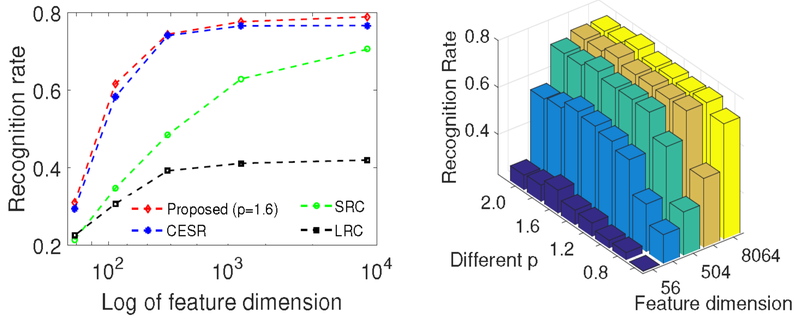
Fig.2 Sparse representation of the proposed method on AR database (first row) and Extended Yale Face database B(second row).(a) original images with sunglasses/block occlusion, (b) weight images, (c) reconstructed images, and (d) sparse coefficients.

Experimental results



(a) (b)

Fig. 3 Results on the AR database. (a) Recognition rates of different methods under different number of features; (b) Recognition rates of the proposed method under different p.



(a) (b)

Fig. 4 Results on the ExtYB. (a) The recognition rates of all methods under different number of features; (b) The recognition rates of the proposed method under different p.

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