Robust Multi-Image Based Blind Face Hallucination

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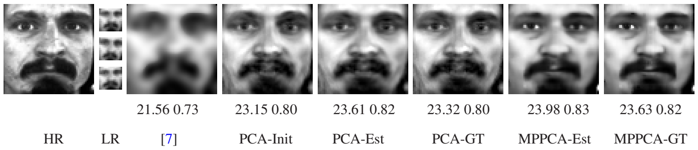

Figure 1: Face SR using multiple simulated LR faces.

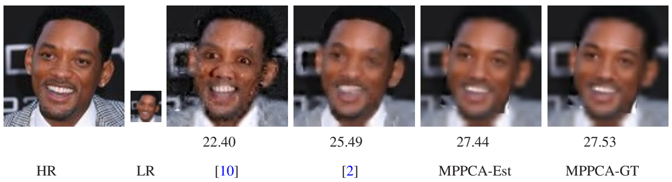

Figure 2: Face SR using single simulated LR face.

Figure 3: Face SR in real LR sequences.

Most previous work on face super-resolution (SR) utilizes only a single low-resolution (LR) face, where the LR face is often manually or automatically aligned and fixed and small blurring kernel is often used. However due to low visual quality of LR faces, there are often significant errors in the initial alignment while fixed and small blurring kernel may not be valid in practice.

We present in this paper a robust multi-image based blind face hallucination framework to super-resolve LR faces in image sequences. The proposed method first explores face PCA subspace, rather than high resolution (HR) image space, for robust deblurring and registration. A new patch-wise Mixture of Probabilistic PCA (MPPCA) prior, rather than weak generic image priors, is then incorporated to improve SR performance.

Mixture of Probabilistic PCA Previous work [1, 5] on face SR using PCA prior can be shown to be a linear estimator to estimate an HR image,

$$\hat{\mathbf{x}} = \mu + \mathbf{K}[\mathcal{Z} - \mathcal{H}\mu]$$

where μ is the mean face, $\mathcal{H}$ is an observation matrix, $\mathbf{K}$ is a dense linear coefficient matrix and each row in $\mathbf{K}$ linearly combines all LR image pixels $\mathcal{Z}$ to estimate an HR pixel. This holistic PCA approach has an over-fitting issue, as all pixels in an LR image are involved to estimate an HR pixel, no matter how far they are spatially away from the HR pixel. The second limitation is that predictions are very rough, where the predicted mean is actually training sample mean while the predicted covariance is an approximation of the covariance of training samples.

We improve the simple PCA prior model by a patch-wise MPPCA model [9], where an HR image is spatially partitioned into local overlapping patches, and patch-wise local MPPCA dictionaries are learnt for each patch. The local patch-wise approach is to address the over-fitting issue of the holistic approach, while MPPCA aims to improve both mean and covariance prediction.

Multi-Image Based Blind Face Hallucination Given a set of LR faces $\mathcal{Z}$, we first estimate both blurring kernel $\mathbf{k}$ and multiple transformations $\mathbf{w}$ by optimizing a variational lower bound of marginalized posterior,

$$p(\mathbf{k},\mathbf{w}|\mathcal{Z}) = \int\int p(\mathbf{x},\mathbf{k},\mathbf{w},\alpha|\mathcal{Z})\, d\alpha\, d\mathbf{x}$$

This is an extended abstract. The full paper is available at the Computer Vision Foundation webpage.

Methods	HMRF [7]	PCA [1, 5]			MPPCA	
Blurring	GT	GT	Est	GT	Est	GT
Trans.	GT	Initial	Est	GT	Est	GT
PSNR	19.67	19.52	21.27	21.51	21.78	22.32
SSIM	0.67	0.72	0.76	0.77	0.79	0.81

Table 1: Comparison of face SR using multiple simulated LR faces.

Methods	Bicubic	[10]	[2]	MPPCA	
Blurring		GT	GT	Est	GT
PSNR	24.78	22.29	26.12	25.85	26.17

Table 2: Comparison of face SR using single simulated LR face.

where high dimensional HR image $\mathbf{x}$ and PCA coefficients α are regarded as latent variables. We utilize reduced dimensionalities of PCA subspace, rather than the high dimensional image space or filter space [4], for blurring kernel and transformation estimation. Given estimated blurring kernel and multiple transformations, learnt patch-wise MPPCA prior is then incorporated to iteratively estimate an HR face.

Results Experiments were carried out in challenging simulated and real LR image sequences. Frontal HR faces from FERET database [6] are used as the training set. Testing set includes BioID database [3], PubFig83 database [8] and real LR image sequences. Examples of face SR using multiple and single simulated LR faces are shown in Fig. 1 and Fig. 2, respectively, whereas face SR in real LR sequences shown in Fig. 3. Performance comparison with previous work [1, 2, 5, 7, 10] is summarized in Table 1 and Table 2.

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