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Low Resolution Face Recognition and Reconstruction via Deep Canonical Correlation Analysis

Overview

Background
- Low-resolution (LR) face identification is always a challenge in computer vision.
- Many existing super-resolution (SR) methods, which aim at achieving high-resolution (HR) facial images or recognition features from LR ones, have been proposed to overcome the LR problem.

Motivations
- Canonical correlation analysis (CCA) is a classical but powerful learning method, which seeks basic vectors for two sets of variables, such that their projections onto these basic vectors have maximum correlation.
- Huang et al. [1] first employed CCA in LR-FSR problem, and achieved a promising result.
- However, CCA is a linear learning approach in essence, thus difficult to measure the nonlinear relationships between HR and LR facial images.
- Unlike previous work [2], we propose a novel deep CCA based LR face recognition method, where the nonlinear correlation between HR and LR facial images can be well depicted by two kernel mappings.

Contributions
- We propose a new LR FSR approach based on deep CCA (DCCA). The method can simultaneously recognize and reconstruct LR faces.
- The proposed method can learn flexible nonlinear representations by passing HR and LR facial features via multiple stacked layers of nonlinear transformation.
- We apply a radial basis function (RBF) based neural network to build a regression model to overcome the irremovability in [2].
- In addition, we also design two residual compensation methods for identification and vision enhancement, respectively.

A number of experimental results on benchmark databases have demonstrated the effectiveness and robustness of our method.

Details of Our Method

Our approach employs a two-step framework: in the first step, we carry out facial feature images recognition. In the second step, we adopt different residual calculation methods according to the purpose of identification and vision enhancement.

Training
1. HR and LR face set are $I^H, I^L \in \mathbb{R}^{m \times n}$, and $F^H, F^L \in \mathbb{R}^{m}$ from training sets.
2. Center the HR and LR training images by $\mu^H, \mu^L$; $\mu^H = \frac{1}{m} \sum_{i=1}^{m} I^H_i$, and $\mu^L = \frac{1}{m} \sum_{i=1}^{m} I^L_i$.
3. Empty PCA to extract the global facial features by $X^H = (I^H - \mu^H)^\top$ and $X^L = (I^L - \mu^L)^\top$.
4. Use DCCA to learn flexible nonlinear representations to enhance consistency, as follows:
$$Z^H = A^H X^H, Z^L = A^L X^L, A^H, A^L \in \mathbb{R}^{m \times m}$$

5. We get the correspondences between $Z^H, Z^L$ and $F^H, F^L$. The distance $D_{\text{SRDCCA}}$ is calculated by
$$D_{\text{SRDCCA}} = \sum_{i=1}^{m} |Z^H_i - Z^L_i|^2$$

6. The preliminary reconstruction image can be expressed as $\tilde{I} = H \times Z^L = H \times (A^L)^\top (I - \mu)^\top$

Experimental Results

- We also design the proposed method containing residual compensation as SRDCCA-RC, and the method without residual compensation as SRDCCA.
- We carry out our SRDCCA and SRDCCA-RC methods on the CMU PIE and Yale-B databases to test recognition performances. The manual weights (SN) classifier is used in all the experiments. The results are recorded in Fig.2, Fig.3, and Fig.4.
- We evaluate the effect of our method by reconstructing the images on the CAS-PEAL database. The peak signal to noise ratio (PSNR) result is illustrated in Fig.5.

References