Low-Rank Matrix Recovery with Structural Incoherence for Robust Face Recognition

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Motivation and Contribution

- Real-World Face Recognition (FR)
  (1) BOTH training and test data might be corrupted.
  (2) No prior knowledge on the type of corruption.
  (e.g., sunglasses, mask, etc.).
- Our Proposed Method
  (1) Low-Rank Matrix Decomposition (LR) 
    - Extract representative features for each class.
  (2) Structural Incoherence (SI)
    -> Introduces discriminative features for classification.

SRC for Face Recognition?

- SRC (Sparse Representation-based Classification)
  (1) Sparse representation of input data:
    \[ \min_j \| D_{jk} - A_j \|_F \] (1)
  (2) Classification via class-wise reconstruction error:
    \[ j' = \arg \min_j \| D_{jk} - A_j \|_F \] (2)
  (3) SRC tends to recognize the test input as the class with the most similar training images.
- SRC for Real-World FR?
  (1) SRC requires unoccluded training images for face recognition.
  (2) It would fail if both training and test data have similar types of corruption.

Face Recognition by Low-Rank Matrix Recovery

- Robust PCA (Low-Rank Matrix Recovery)
  Decompose original data \( D \) into a LR matrix \( A \) and a sparse error matrix \( E \), so that \( A \) has a better representational ability than \( D \).
  \[ \min \| A \|_F + \lambda \| E \|_F \quad \text{s.t.} \quad D = A + E \]
- LR for Face Recognition
  (1) Derive \( A \) by performing LR for each of the \( N \) subjects.
  (2) Perform subspace learning (e.g., PCA) on \( A \) instead of \( D \).
  (3) Project training and test data onto the subspace of \( 2 \) and apply SRC for classification.

LR Matrix Decomposition with Structural Incoherence

- We advocate the structural incoherence between the low-rank matrices of different classes.
  (1) We formulate LR matrix recovery with regularization on SI.
  \[ \min \| A \|_F + \lambda \| E \|_F + \gamma \| D_{jk} - A_j \|_F \quad \text{s.t.} \quad D_{jk} = A_j + E \]
  (2) For each class, we solve the following relaxed version.
  \[ \min \| A \|_F + \lambda \| E \|_F + \gamma \| D_{jk} - A_j \|_F \quad \text{s.t.} \quad D_{jk} = A_j + E \]
  (3) Iteratively solve (2) via Augmented Lagrange Multipliers.
  \[ L(A, E, y, y_j) = \| A \|_F + \lambda \| E \|_F + \gamma \| D - A - E \|_F \]
- Visualization (Extended YaleB)
  Projected face data in the subspace spanned by the first two eigenvectors.

Extended YaleB Database (Illumination)

- 38 subjects, 59-64 images each.
  (1) Randomly select 37 images for training.
  (2) Compare to NN, SRC, LLC-SRC and LR w/o SI.

AR Database (Illumination/Expression/Occlusion/Disguise)

- Image of 100 subjects (50 men + 50 women) taken in 2 separate sessions.
  - Each session consists of 7 neutral (illumination and expression), 3 sunglasses and 3 scarf images.
  (1) Sunglasses + Neutral + 1 sunglass + 1 scarf
  (2) Scarf: 7 neutral + 1 scarf
  (3) Sunglasses + Scarf: 7 neutral + 1 sunglasses + 1 scarf
  - Testing: the remaining images of session 1 and 2.
  - Compared to NN, Fishface, SRC, LLC-SRC and LR w/o SI.

Conclusions

- We present a low-rank matrix recovery algorithm with structural incoherence for robust face recognition.
- The proposed SI introduces additional discriminating ability for improved recognition.
- Experiments confirm the effectiveness and robustness of our approach under a variety of variations/corruptions.