SUBSPACE CLUSTERING VIA INDEPENDENT SUBSPACE ANALYSIS NETWORK

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Introduction

◆ *As well known, subspace clustering has important significance in the field of machine learning and computer vision. In particular, the effect of subspace clustering on the face recognition task can be better to implementation the AI monitoring. However, most of existing methods based on independent subspace analysis network ignore many useful information embedded in original data.*

◆ *Interest of recent studies*
- *independent subspace analysis network method*
- *spectral clustering-based method*

Problem and motivation

- *Different from the existing methods, we adopt the ISA to learn local translation invariant feature from data and integrate a prior subspace information into the output of the network simultaneously.*
- *We recast the task of extracting the low-dimensional feature into solving an optimization problem of the orthogonal constraint.*

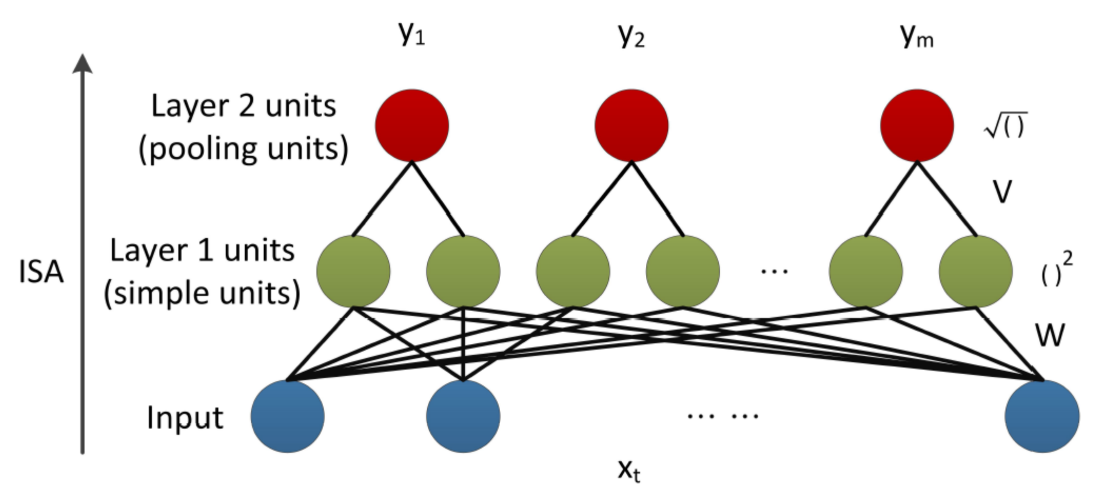


Fig. 1. The neural network architecture of an ISA network.

Proposed method

Our Formulation

- *Given the patches from an image as column vectors to form a new matrix X, and x_t denotes one column of X. We want to extract the feature Y.*

$$\min_{W} \sum_{t=1}^{N}\sum_{l=1}^{m} y_l(\mathrm{x}_t; W, V) + \frac{\lambda}{2}\|Y - YC\|_F^2,\ s.t. WW^T = \mathrm{I}.$$

- *W need to be learned from data, but V is fixed.*

Optimization

- *Obtaining prior structural information*

$$\min_{c_i} \sum_{i=1}^{N} \|\mathrm{x}_i - Xc_i\|_2^2 + \upsilon\|c_i\|_1,\ s.t.\ c_{ii} = 0.$$

- *$\|\bullet\|_1$ denotes l_1-norm that is usually used to achieve sparsity.*
- *Formula supplementation*

$$y_l(\mathrm{x}_t; W, V) = \sqrt{\sum_{j=1}^{k} V_{lj} (\sum_{i=1}^{n} W_{ji} x_i)^2}$$

- *orthogonal constraint*

$$W = (WW^T)^{-\frac{1}{2}} W$$

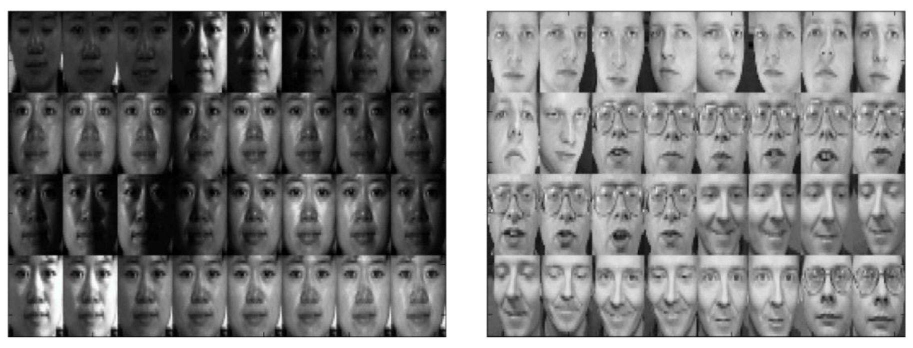
- *Algorithm summarization*

Algorithm 1 Independent Subspace Analysis with Sparsity Prior

Input: A data X, and the tradeoff parameter λ.
Initializing W and V.
Compute the sparsity prior C over X via solving:
$\min_{c_i} \sum_{i=1}^{N} \|\mathrm{x}_i - Xc_i\|_2^2 + \upsilon\|c_i\|_1,\ s.t.\ c_{ii} = 0.$
Do forward propagation to compute Y:
$\mathrm{z}_t^{(1)} = W\mathrm{x}_t$,
$\mathrm{z}_t^{(2)} = Vf(\mathrm{z}_t^{(1)})$,
$y_t = g(\mathrm{z}_t^{(2)}) \in \mathbb{R}^m$.
while not converge **do**
  for $t = 1, 2, \ldots, N$ **do**
    $y_t = g(\mathrm{z}_t^{(2)})$
    $\nabla J_W = V^T[\frac{1}{2} g'(\mathrm{z}_t^{(2)}) + \lambda(y_t - Yc_t) \odot g'(\mathrm{z}_t^{(2)})] \odot f'(\mathrm{z}_t^{(1)})(\mathrm{x}_t)^T$
    $W = W - \mu\nabla J_W$
  end
end
obtain the data segmentation by clustering based on Y.
Output: W and the clustering result.

Simulation experiments

- *Test image data*
  - *CMU-PIE and ORL*



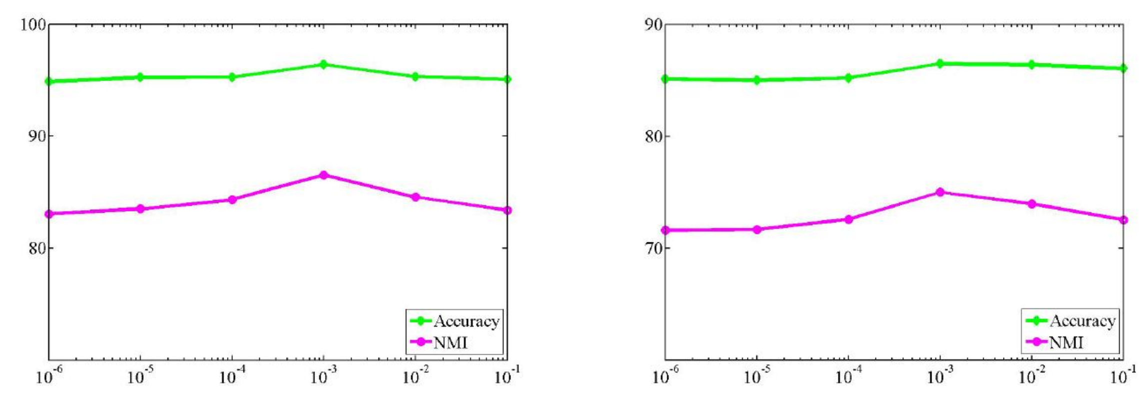
(a) (b)

Fig. 2. Samples on the PIE_pose27 (a) and ORL (b) database.

- *Evaluation Metric:*
  1. *Accuracy*
  2. *Normalized Mutual Information (NMI)*
- *The compared methods*
  1. *sparse subspace clustering (SSC)*
  2. *independent subspace analysis (ISA)*
     - *ISA + k-means (ISAk)、ISA + SSC (ISAs)*
  3. *Ours (independent subspace analysis with sparsity prior, ISASP)*
     - *ISASP + k-means (ISASPk)、ISASP + SSC (ISASPs)*

Results

- *Parameter selection test*



(a) (b)

Fig. 3. Accuracy and NMI (%) (y-axis) of ISASP with different λ (x-axis) on PIE_pose27(a) and ORL(b) dataset.

- *Objective quality test*

Table 1. Clustering results in terms of Accuracy (%) and NMI (%) on PIE_pose27 dataset(mean ± standard deviation).

Algorithm	Accuracy	NMI
K-means	18.33 ± 0.85	40.62 ± 0.79
SSC	82.10 ± 2.30	94.77 ± 0.61
ISAk	58.26 ± 2.78	74.43 ± 1.37
ISAs	84.72 ± 1.69	95.74 ± 0.60
ISASPk	59.68 ± 2.85	75.07 ± 0.89
ISASPs	**86.54 ± 2.92**	**96.38 ± 0.77**

Table 2. Clustering results in terms of Accuracy (%) and NMI (%) on ORL dataset(mean ± standard deviation).

Algorithm	Accuracy	NMI
K-means	58.25 ± 3.56	78.84 ± 1.69
SSC	73.93 ± 2.03	**88.09 ± 0.61**
ISAk	48.85 ± 2.39	68.86 ± 2.14
ISAs	72.53 ± 1.50	84.66 ± 0.45
ISASPk	52.43 ± 2.24	71.46 ± 1.58
ISASPs	**75.00 ± 2.01**	86.48 ± 0.67

Conclusion

In this paper, we presented a novel approach that learns features from original data using ISA network incorporated the sparsity subspace prior. By this, the segmentation of the data can be effectively performed. The experimental results, on two real world datasets, show that our method remarkably outperforms the state-of-the-art methods.

References

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