Image recognition with the refined feature of core tensor

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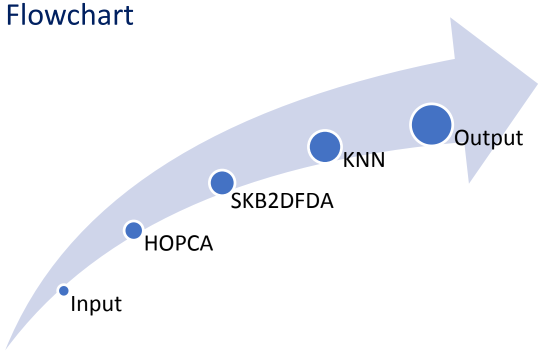
Abstract

In the field of artificial intelligence and machine learning method, people always need a scheme for feature extraction on the high order tensor data reserving more information in image retrieval, object recognition, etc. The reserved information keeping the spatial relationships in different modes when extracting the feature of the data can make the classification more accurate and efficient. Traditional feature extraction on the high order tensor data must be previously expanded into high dimensional vectors such as Principle Component Analysis and Fisher Discriminant Analysis, causing the loss of spatial relation information residing in original high order tensor data. We propose a classification model combining High-Order Principal Component Analysis (HOPCA) and Small Kernel Bilateral Two-Dimensional Fisher Discriminant Analysis (SKB2DFDA) which transformed the feature extraction through HOPCA into the new feature extraction that annihilates some drawback of traditional feature extraction, reduces the computational time, and increases our classification model accuracy.

Flowchart



Problem description

For an image or video database, we want to find the feature in order to spend less computation time and increase recognition accuracy. Firstly, we apply HOPCA to compress the data while maintaining the maximum total scatter. That is, we get a smaller tensor called core feature tensor. In other word, it can represent the original data. Secondly, we refine the core feature tensor by SKB2DFDA which extends from KB2DFDA and reduces the kernel matrix size making the computation speed up. Given a data of k classes $\mathbf{X} = \bigcup_{i\in\{1,\dots,k\}} \{\widehat{X}_i\}$ for $\widehat{X}_i = \bigcup_{j\in\{1,\dots,N_i\}} \{X_t\}$ with $X_t = \begin{bmatrix}\mathbf{x}_1^{(t)} & \mathbf{x}_2^{(t)} & \cdots & \mathbf{x}_q^{(t)}\end{bmatrix}$, $X_t \in \mathbb{R}^{p\times q}$, $t = j + \sum_{n=1}^{i-1} N_n$, and let k be the RBF kernel. We need to solve the eigenvectors of generalized eigenvalue problem $BA = \lambda WA$, where $B = \sum_i N_i V_i V_i^\top, V_i = \frac{1}{N_i}\sum_{X_t\in\widehat{X}_i} G(t) - \frac{1}{K}\sum_{n=1}^{K} G(n), W = \sum_i \left(E - \frac{1}{N_i} 1_{1\times N_i} \otimes \sum_{X_j\in\widehat{X}_i} G\right) E^\top$, and $E = \begin{bmatrix}G(1+s) & G(2+s) & \cdots & G(N_i+s)\end{bmatrix}$ with $s = \sum_{n=1}^{i-1} N_n$.

The key point is the sequence of kernel matrix elements. Define

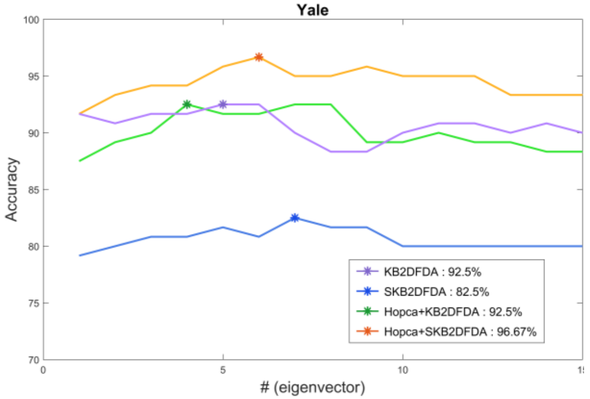
$$G = \begin{bmatrix} k\left(\mathbf{x}_{(1)},\mathbf{y}_1\right) & k\left(\mathbf{x}_{(1)},\mathbf{y}_2\right) & \cdots & k\left(\mathbf{x}_{(1)},\mathbf{y}_q\right) \\ k\left(\mathbf{x}_{(2)},\mathbf{y}_1\right) & k\left(\mathbf{x}_{(2)},\mathbf{y}_2\right) & \cdots & k\left(\mathbf{x}_{(2)},\mathbf{y}_q\right) \\ \vdots & \vdots & \ddots & \vdots \\ k\left(\mathbf{x}_{(qK)},\mathbf{y}_1\right) & k\left(\mathbf{x}_{(qK)},\mathbf{y}_2\right) & \cdots & k\left(\mathbf{x}_{(qK)},\mathbf{y}_q\right) \end{bmatrix},$$

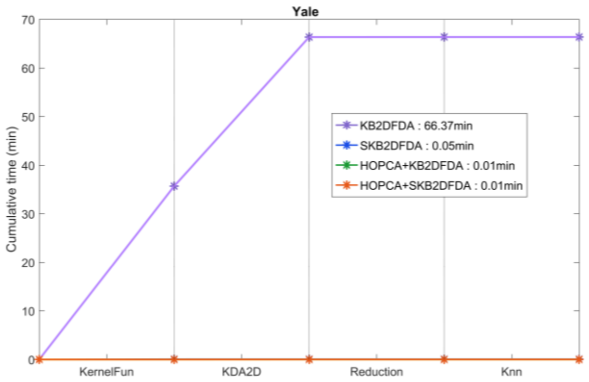
we choose a part of G and form

$$\widetilde{G} = \begin{bmatrix} k\left(\mathbf{x}_{(1)},\mathbf{y}_1\right) & k\left(\mathbf{x}_{(K+1)},\mathbf{y}_2\right) & \cdots & k\left(\mathbf{x}_{((q-1)K+1)},\mathbf{y}_q\right) \\ k\left(\mathbf{x}_{(2)},\mathbf{y}_1\right) & k\left(\mathbf{x}_{(K+2)},\mathbf{y}_2\right) & \cdots & k\left(\mathbf{x}_{((q-1)K+2)},\mathbf{y}_q\right) \\ \vdots & \vdots & \ddots & \vdots \\ k\left(\mathbf{x}_{(K)},\mathbf{y}_1\right) & k\left(\mathbf{x}_{(2K)},\mathbf{y}_2\right) & \cdots & k\left(\mathbf{x}_{(qK)},\mathbf{y}_q\right) \end{bmatrix}.$$

Then, the time of solving generalized eigenvalue problem will be extremely reduced. Meanwhile, the model keeps the accuracy in the same high level.

Results





We test on the ORL, Yale, and COIL-100 databases. The result shows that HOPCA+SKB2DFDA has the best performance.

Conclusions

The proposed classification model combining HOPCA and SKB2DFDA to extract features from the original tensor data and use KNN to be the last step in the classification. The key improvement of SKB2DFDA over KB2DFDA is that the kernel matrix is redefined to reduce the computation time and memory requirements. Using HOPCA to retain the maximum total scatter while compressing the data. After that, SKB2DFDA provides a non-linear mapping method with an RBF kernel to refine the core tensor as a new feature. Experimental results show that applying HOPCA before (HO)FDA except SKB2DFDA will not always perform well. However, it will make SKB2DFDA has higher accuracy than KB2DFDA or HOPCA+ KB2DFDA. The lager size of tensor data is, the more difference between KB2DFDA and SKB2DFDA preforms.

References

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