Spectral clustering based on high-frequency texture components for face datasets

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Abstract

Spectral clustering is one of the most widely used technologies for clustering tasks, which represents data as a weighted graph, and aims to find an appropriate way to cut the graph apart in order to categorize the raw data. The pivotal step of spectral clustering is to find out the accurate information to estimate the relationship of pairwise data, based on which a graph can be constructed. According to the cognition that different faces are distinguished by the edge contour which can be represented by high-frequency texture components, a novel spectral clustering algorithm via high-frequency signal of human face, named high-frequency spectral clustering (HFSC) is proposed. In HFSC, first the local high-frequency texture components are extracted from samples. Then the relationship of pairwise samples can be estimated with the degree of correlation, which is produced from the image high-frequency information. The graph will be set up with the correlation information. Subsequently the graph cut will be implemented to achieve the final clustering results. Experimental results show that this algorithm outperforms the state-of-the-art clustering methods on several datasets.

1 | INTRODUCTION

The face recognition task has always been a hot research point in artificial intelligent field. Recently, lots of applications have been developed such as payment, smart access control and real-name authentication system, etc. As an important branch of face recognition, the clustering task, which aims to separate different people into different groups, is a fundamental step for the following labels assignment. With the more clear distinction between different faces, the result of face recognition will be more precise. Many types of clustering algorithms are widely applied for diverse domains, such as K-Means [1], subspace clustering [2] and graph clustering [3], etc. Spectral clustering (SC), which is based on spectral graph theory [4], has become a popular algorithm due to its simplicity and high efficiency. Different from other methods, spectral clustering aims to construct a graph to represent the relationship between data points and to find an appropriate way for cutting it apart to gain clustering results.

Based on the practice of predecessors, the result of spectral clustering depends mostly on the similarity matrix estimation [5]. Therefore, the crucial point is the appropriate measurement to approach the similarities of pairwise data points, on which lots of researches have been focusing. Self-tuning spectral clustering has been proposed in [6], in which a local scale is set up for calculating the affinity of pairwise points. Robust path-based spectral clustering was proposed in [7] based on M-estimation for robust statistics and a graph was constructed with a robust path-based similarity measurement. Parallel spectral clustering [8] was designed for distributed systems and...
used a sparse similarity matrix to perform on large data set. In SC-SBM [9], spectral clustering was applied to social network generated from stochastic blockmodel. Unsupervised feature learning via spectral clustering [10] can adaptively learn local feature representations and the intrinsic structures of local image patches, which outperforms the traditional unsupervised feature learning algorithms. An unsupervised method called discriminative subspace matrix factorization for multiview data clustering (DMSMF), is proposed based on nonnegative matrix factorization in [11], which effectively obtains the geometry structure from the low-dimensional subspace. A framework named robust manifold matrix factorization in [12] can achieve the dimensionality reduction and data clustering with a unified low-rank matrix factorization simultaneously.

In practical application of face clustering, multifarious techniques are chosen for feature extraction such as dimensional reduction [13] [14] and deep neural network [15]. When applying those techniques, the number of samples must be guaranteed to be large enough for learning the unique representation. Furthermore, those features are generally lack of interpretability, which means there might be useless or even misleading information for face clustering tasks.

Following the intuition that people recognize a face mainly through its contour which can be represented with the high-frequency texture components of pictures, we attempt to combine human cognition with traditional clustering algorithms by integrating high-frequency extraction into spectral clustering process. In this letter, a novel algorithm named high-frequency spectral clustering (HFSC) is proposed. Firstly, HFSC aims to reveal the intrinsic information which is the most valuable for distinguishing faces by applying high-frequency extraction to each sample. Then a new measurement is proposed to construct the graph, which is calculated with the correlation of high-frequency texture component information. Finally the graph cut is applied for the clustering results.

The main contributions of our work include the following points. Firstly, an extractor is designed to obtain the desired high-frequency texture components of each image, which can describe the essential characteristic and help to achieve a better clustering result. Furthermore, different from the traditional absolute-distance-based Gaussian kernel, a new graph is introduced concentrating on the correlation between the high-frequency texture components of different images, which can reveal a more stable similarity.

The rest of this letter is organized in the following order. In section II, the spectral clustering and high-frequency texture component extraction will be introduced briefly. Then HFSC will be described in detail at section III. Section IV will report and analyse several experimental results. Section V will conclude the letter.

2 | THE RELATED BACKGROUND

In this section, related background knowledge of spectral clustering and high-frequency texture component will be briefly introduced.

2.1 | Spectral clustering

Given a dataset \(\mathbf{x}_1 \cdots \mathbf{x}_N \in \mathbb{R}^{D \times N}\), the target of clustering is to categorize them into \(K\) clusters. A graph \(C\) will be constructed to represent the relationship of data. We can determine a graph by calculating the weighted adjacency matrix (or similarity matrix) \(\mathbf{W} \in \mathbb{R}^{N \times N}\). In the majority of cases, the weight of pairwise points is estimated by Gaussian kernel function, which is defined as \(k(x_i, x_j) = \exp\left(-\frac{||x_i - x_j||^2}{2\sigma^2}\right)\). Spectral clustering aims to find an appropriate way to cut the graph apart in order to get disjointed clusters. A graph cut is defined as

\[
\text{Cut}(C_1 \cdots C_K) = \sum_{i=1}^{K} W(C_i, \overline{C_i}),
\]

where \(W(A, B)\) summarizes the weights of all edges that connect subsets \(A\) and \(B\). In order to ensure that all the subsets \(C_i\) should be “large enough”, a normalization term will be added. So the object function of spectral clustering can be written as

\[
J = \sum_{i=1}^{K} \frac{W(C_i, \overline{C_i})}{\sigma(C_i)}
\]

where

\[
\sigma(C_i) = \begin{cases} 
|C_i| & \text{for } \text{Real} \\
vol(C_i) & \text{for } \text{Nreal} 
\end{cases}
\]

\(|C_i|\) represents the number of vertices in \(C_i\), \(vol(C_i) = \sum_{x \in C_i} d_x\) represents the sum of degrees about all vertices in \(C_i\).

By introducing some intermediate variables, the object function can be effectively converted to an eigenvalue decomposition problem.

2.2 | High-frequency texture component

It is well-known that images consist of structure components and texture components. Structure components indicates dominant structures of images, while texture components contains the information of the morphological details (see Figure 1). The texture component can well reveal the essential characteristic of an image and its information can help to reconstruct the image with compressive sensing methods [16].

The image texture component indeed is the high-frequency information, and many methods can be applied to achieve it. Only the outline is reserved and the information is enough to identify the subjects in the images, especially for human face images.
3 | HIGH-FREQUENCY SPECTRAL CLUSTERING

For most traditional clustering methods, all the information of the data is considered during the procedure. However, when the data is noised, these methods might be disabled, especially when the noise is not sparse or the noise energy is high. For example, when different faces are covered with masks, traditional methods would probably categorize them into the same cluster due to the high energy of masks. In order to overcome this shortcoming of traditional methods, a HFSC method for human face recognition is proposed in this section. The high-frequency texture components of images will be represented to construct a specific graph, and a spectral clustering method will be designed based on the high-frequency information.

To simplify the illustration of our proposed method, in the following parts of this letter, the dataset information.

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**FIGURE 1** Example of the image texture component. (a) Original image. (b) Texture component

Notice that the Gaussian kernel function \( s(x, x_i) = e^{-\frac{||x - x_i||_2^2}{2\sigma^2}} \) is based on the absolute distance, which may result in faulty face clustering in some circumstances (for example, the same person with different light condition). Therefore, the correlation relationship is proposed in this letter to replace the Gaussian kernel function. Denote \( S \) the graph of the dataset, and its element is defined as:

\[
s_{ij} = \frac{\text{vec}(x_i)^T \text{vec}(x_j)}{\sqrt{\|x_i\|_F^2 \|x_j\|_F^2}},
\]

where \( \text{vec}(\cdot) \) represents the vectorization operation, and \( \| \cdot \|_F \) is the Frobenius norm. The element \( s_{ij} \) represents the degree of correlation between the \( i \)th and \( j \)th images. For the diagonal elements, they would always be 1. In order to avoid the misusage of the correlation of itself, the diagonal elements of \( S \) are set to be 0 specifically:

\[
s_{ii} = 0.
\]

Let vector \( f_p (p = 1 \ldots K) \) be the cluster indicators. When the \( q \)th sample \( x_q \) belongs to \( p \)th cluster, the \( q \)th element of \( f_p \) is 1, otherwise is 0. For instance, given a data set whose samples of the same person are adjacent, and there are \( n_D \) samples in the \( p \)th cluster. Then \( f_p = [0, \ldots, 0, 1, \ldots, 0, \ldots, 0]^T \) with \( n_D \) adjacent 1s. Note that

\[
f_p^T f_p = \begin{cases} n_p, & p = q; \\ 0, & p \neq q. \end{cases}
\]

By introducing \( f_p \), some notions can be expressed conveniently as

\[
W(C_p, C_q) = f_p^T S f_q
\]

\[
vol(C_p) = \sum_{i \in C_p} d_i = f_p^T D f_p
\]

\[
W(C_p, \overline{C_p}) = \sum_{i \in C_p} \sum_{k \in \overline{C_p}} c_{ik} = f_p^T (D - S) f_p
\]

where \( D \) is the degree matrix which is a diagonal matrix with the elements defined as the sum of rows or columns of \( S \). So the object function in (2) of Rent and Neat can be rewritten as

\[
f_{Rent} = \sum_{p=1}^{K} \frac{f_p^T (D - S) f_p}{f_p^T D f_p},
\]

\[
f_{Neat} = \sum_{p=1}^{K} \frac{f_p^T (D - S) f_p}{f_p^T D f_p}.
\]

It is worth noting that minimizing these objective functions are NP-hard because of the discrete restriction of \( f_p \). To make these problems solvable, we relax the discrete constraint and seek a
Algorithm 1 The algorithm of HFSC

Input: Data set $X = \{x_1, x_2, \cdots, x_N\} \in \mathbb{R}^{D \times N}$, number of eigenvalues $K_1$, number of clusters $K_2$, KNN parameter $K$, Butterworth filter order $n_1$ and cut-off frequency $D_0$

Output: Clustering label of each data points

Initialize filter by parameters $n_1$ and $D_0$

for all $x_i$ do

Compute the corresponding forms in frequency domain by Equation (4)

Obtain high-frequency texture components by filtering according to Equation (5)

end for

Construct the graph by calculating the element of $S$ by Equation (6)

Compute the degree matrix $D$

Compute the Laplacian matrix $L = D - S$

Symmetrize by $\frac{L + L^T}{2}$ if needed

Compute $F$ by solving Function (12) or (13)

Compute the clustering label by applying K-Means to $F$

continuous solution of $f_p$. For $Rcut$, set $F = \left[ \frac{f_1}{\sqrt{v_1}}, \ldots, \frac{f_K}{\sqrt{v_K}} \right]$ and the optimization objective function is transformed as

$$\min_F Tr(F^T L F) \quad s.t. F^T F = I,$$  \hspace{1cm} (12)

where $L = D - S$ denotes the Laplacian matrix, and $Tr(\cdot)$ denotes the trace operation.

For $Ncut$, set $F = \left[ \frac{f_1}{\sqrt{d_1}}, \ldots, \frac{f_K}{\sqrt{d_K}} \right]$, and the optimization objective function is transformed as

$$\min_F Tr(F^T L F) \quad s.t. F^T D F = I.$$  \hspace{1cm} (13)

The problems above can be solved effectively with eigenvalue decomposition. Subsequently K-means is applied to $F$ for converting it to a discrete cluster result. The main steps of HFSC are summarized as Algorithm 1.

Different from other existing solutions, the texture components extracted with the proposed method have the property of rotation invariance, which means both images and extracted texture components can be rotated in any angles and the information still remains the same. So all samples are handled in the original orientation.

4 EXPERIMENTAL RESULTS

Several experiments are designed for evaluating the effectiveness of proposed algorithm. We choose three real-world datasets for experiments, and the details of implementation and the comparison methods will be introduced in this section.

4.1 Datasets

Four real-world datasets of human faces are adopted, including X26, Yale, YaleB [20] and AR. The brief introductions and partial examples are provided in Figure 2.

(i) X26: X26 dataset contains 260 face images of 10 people in different emotions, illuminations and with covers such as sunglasses or scarfs.

(ii) Yale: Yale data set was published by Yale University, which contains 165 face images of 15 people. The expressions, postures and lights of each person are different in different images.

(iii) YaleB: YaleB is an extension of Yale with more different people and larger scale of number. This dataset contains 2540 pictures of 38 people with different light conditions.

(iv) AR: AR dataset contains 2600 face images of 100 people with different facial expressions, illumination conditions and occlusions (sunglasses and scarf).

4.2 Implementation

For X26, each person has 26 images which are 40 pixels high and 55 pixels wide. For Yale and YaleB, samples are reshaped with 32 pixels for both the height and width. In some cases, due to the limited calculation accuracy, some symmetric matrices may become asymmetric. To avoid that, an extra symmetrize step as $\frac{L + L^T}{2}$ will be taken.

The Butterworth filter is selected as the high-pass filter. According to experimental experience, the feature selection is related to cut-off frequency and the thickness of texture is related to the order of filter. Due to the difference between samples from different datasets, the most suitable filter parameters for different datasets might be different. The selection of the
### Table 1: Clustering performance comparison

| DataSets | Methods | HFSC | K-Means | SC | SSC | RSEC | FastESC | USENC | JSPC |
|----------|---------|------|---------|----|-----|------|---------|-------|------|
| X26      | ACC     | 89.62| 20.00   | 26.92| 71.15| 46.92| 50.00   | 29.62 | 70.38|
|          | NMI     | 85.81| 12.71   | 22.60| 65.50| 50.23| 41.88   | 21.46 | 62.27|
|          | ARI     | 79.05| 2.56    | 4.38 | 52.08| 33.09| 25.81   | 5.48  | 48.28|
|          | F       | 81.10| 13.42   | 18.84| 56.89| 39.81| 34.15   | 16.44 | 53.36|
| Yale     | ACC     | 56.97| 46.67   | 37.58| 51.52| 56.97| 45.45   | 52.12 | 53.94|
|          | NMI     | 58.91| 47.96   | 42.87| 56.59| 56.72| 50.02   | 57.00 | 56.03|
|          | ARI     | 34.76| 22.62   | 18.27| 31.22| 32.39| 23.70   | 32.81 | 32.37|
|          | F       | 39.97| 27.75   | 25.12| 35.61| 36.64| 28.75   | 37.15 | 36.61|
| YaleB    | ACC     | 66.07| 10.69   | 24.61| 50.37| 45.03| 31.36   | 36.41 | 60.40|
|          | NMI     | 75.57| 13.82   | 32.84| 52.45| 52.00| 41.27   | 43.34 | 65.58|
|          | ARI     | 37.23| 1.49    | 4.09 | 19.38| 24.05| 11.18   | 16.74 | 40.71|
|          | F       | 39.51| 4.30    | 8.30 | 22.18| 26.20| 14.58   | 19.36 | 42.45|
| AR       | ACC     | 51.00| 13.12   | 12.77| 78.50| 49.54| 18.23   | 17.81 | 74.27|
|          | NMI     | 68.43| 42.16   | 39.98| 86.44| 68.32| 41.32   | 37.72 | 84.86|
|          | ARI     | 33.02| 4.63    | 3.61 | 63.69| 33.33| 5.92    | 3.40  | 62.22|
|          | F       | 33.75| 5.68    | 4.72 | 64.08| 34.03| 7.17    | 4.71  | 62.61|

4.3 Comparison methods

K-Means and spectral clustering with normalized cut (Ncut) are chosen for the baseline. In addition, classical sparse subspace clustering (SSC) [21] and four related algorithms in recent years are adopted for further analysis, including RSEC [22], FastESC [23], USENC [24] and JSPC [25]. We choose four general performance indicators to evaluate the effect, including accuracy (ACC), normalized mutual information (NMI), adjusted rand index (ARI) and F-measure (F). Accuracy is computed by using the Hungarian algorithm to best map among cluster results and ground true labels. NMI calculates the normalized measure of the similarity between two labels of the same data. ARI estimates the similarity between two clustering. The F-measure calculates the weighted ratio of precision and recall. Generally, higher value means better clustering performance.

4.4 Performance evaluation

The clustering performance comparisons on four datasets are exhibited in Table 1, and the bold numbers highlight the best results.

According to the results, all improved spectral clustering methods perform much better than the baselines, K-means and SC. The clustering effect benefits greatly from the specific graph constructed with the extracted features. Compared to other three spectral clustering related algorithms (RSEC, FastESC and USENC), the proposed method achieves the best performance in all the four datasets. Especially for the dataset X26, HFSC outperforms the second best spectral related methods in terms of ACC and NMI by 39.62% and 35.38%, respectively. When object images contain low-frequency noises, the proposed method can better reduce this impact. In the X26 dataset, samples contain several low-frequency noises such as covered by scarf and sunglasses, which might seriously influence the effectiveness of existing methods. The confusion matrix of the clustering result on the X26 dataset is shown in Table 2. The visualization of confusion matrices is shown in Figure 3. As can be seen in Figure 3, HFSC obtains a clearer block diagonal structure than other three spectral clustering related algorithms. The
to apply the clustering technique with the correlation
between the texture components of different images, which can
provide the essential connection. Experimental results show
that HFSC can achieve a better clustering performance than
other state-of-art spectral clustering algorithms.

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TABLE 2 Confusion matrix for X26 dataset

| True label | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  |
|------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Cluster index |
| 1          | 19  | -   | 1   | 6   | -   | -   | -   | -   | -   | -   |
| 2          | 23  | 3   | -   | -   | -   | -   | -   | -   | -   | -   |
| 3          | 8   | 15  | -   | -   | -   | -   | -   | -   | -   | -   |
| 4          | 24  | 2   | -   | -   | -   | -   | -   | -   | -   | -   |
| 5          | 26  | 2   | 24  | 2   | 26  | -   | -   | -   | -   | -   |
| 6          | 2   | 24  | 24  | 2   | 24  | 2   | 2   | 2   | 2   | 2   |
| 7          | 8   | 1   | 8   | 1   | 8   | 1   | -   | -   | -   | -   |
| 8          | 1   | 1   | 1   | 1   | 1   | 1   | 1   | 1   | 1   | 1   |
| 9          | 1   | 1   | 1   | 1   | 1   | 1   | 1   | 1   | 1   | 1   |
| 10         | 1   | 1   | 1   | 1   | 1   | 1   | 1   | 1   | 1   | 1   |

FIGURE 3 Cluster performances comparison of four spectral clustering
related algorithms for X26 dataset. Solid line blocks delineate the correct
assignment area. (a) HFSC, (b) RSEC, (c) FastESC and (d) USENC.

results of experiments on the AR dataset show that the accu-
cracy of the proposed method is less than SSC and JSPC, both
of which contain a subspace learning term in their models.
The samples of the same object in the AR dataset share an obvious
low-rank component which can be better captured by the sub-
space term.

For comparison, we set the pictures from Yale and YaleB in
the size 32 pixel for both the height and width, but the number
of categories and samples in YaleB are both larger than those
of Yale. Generally, clustering is more challenging when dealing
with a larger dataset, because the features extracted by dimen-
sional reduction may be affected by outliers. As can be seen
in Table 1, the accuracy of all the existing algorithms shows a
significant drop when the dataset changes from Yale to YaleB.
However, the proposed HFSC can still maintain the excellent
performance due to the fact that the local high-frequency tex-
ture components extracted from each single image can effec-
tively reduce the influence of outliers and make the algorithm
more stable.

5 | CONCLUSION

In this letter, a novel high-frequency spectral clustering (HFSC)
algorithm is proposed. Inspired by the natural intuition of
human beings to distinguish different faces, HFSC adapts the
local high-frequency texture component as the principal fea-
tures, enabling the proposed method to work stably for datasets
with different sizes, which is different from other existing fea-
ture extraction techniques. Then a specific graph is constructed

FIGURE 2 Confusion matrix for X26 dataset
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