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A NEW IMAGE COLOR ANALYSIS METHOD BASED ON MANIFOLD LEARNING

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ABSTRACT

In this paper, the main application image processing, manifold learning and the method of Gaussian mixture model for dimensionality reduction and cluster analysis, the image color information are all studied. First, the color data access algorithm is introduced, secondly, the manifold learning in the local linear embedding (LLE) algorithm is used in color analysis; then the results of an evaluation criteria, LLE parameters in the criteria automatic selection algorithm are presented; meanwhile, the result of the operation of the different color space LLE are also tested and analyzed. Finally, the application of a Greedy EM-based Gaussian mixture model for improving the operation of the HSI space under LLE results of experiments is analyzed. It indicates that the algorithm can automatically determine the number of clusters, and achieve a better clustering result.

Keywords: *Manifold Learning; Locally Linear Embedding; Color Space; Gaussian Mixture Model*

1. INTRODUCTION

The diagnosis is one of the TCM diagnostic methods have clinical value in medicine. In recent years, with the rapid development of computer science and technology, the Chinese diagnosis has overcome the shortcomings of the past, such as non-quantifiable and subjective, and thus the formation of the automated and objective diagnosis has gradually become possible. Color is characterized by diagnosis in one of the most important information relative to the the other characteristics such as texture, shape, technology and methods, more operational and quantitative identification of the main topic is the application of image processing, manifold learning and Gaussian mixture model and the color. The research has broad application prospects, color data dimensionality reduction and cluster analysis, you can further analyze the link between the pathological color characteristics and disease; the study also reflects the trends of color features, and thus reflects the trend of the disease, with some clinical value.

2. MANIFOLD LEARNING IN COLOR ANALYSIS

2.1 Color Data Acquisition and LLE Algorithm In Its.

The first biological computing is from the sample library of Harbin Institute of Technology Research Centre, select some typical samples of each sample, both sides of the five parts of the base, select the size of 32 × 32 pixels color blocks, Figure 1 for the like the color selected schematic. Then the average pixel color of each color block 1024. We selected a total of 211, 1055 the original data, the data is in RGB color space, the distribution shown in Figure 12.

Manifold learning Locally Linear Embedding (LLE) algorithm to study and analyze color. LLE is simple, set a few parameters, visualization, than the other manifold learning method, and is more suitable for the analysis of the color.

The basic idea of LLE is the local linear embedded map to achieve the global non-linear manifold started. Set of initial data sets for high-dimensional space of N real vector Xi (i = 1, 2... N), mapped to the embedded low-dimensional space vector Yi, (i = 1, 2... N). The specific algorithm is divided into the following three steps [1]:

Search points in the neighbourhood of each vector Xi (whichever are the nearest K points in the neighbourhood or a fixed radius of the spherical neighbourhood).

(2) In the neighbourhood of Xi reconstruction weights Wij in each Xi, so that reconstruction of the minimum cost of error (1).

$$\varepsilon_I(W) = \sum_i \left| X_i - \sum_j W_{ij} X_j \right|^2 \quad (1)$$

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Among them, the weights Wij represents the first points on the i-th point of the reconstruction, Wij meets two conditions: if Xj does not belong to the neighbourhood of Xi, Wij = 0; weight matrix W of each line adds up to a . Obtain W, the process for solving constrained least squares problem.

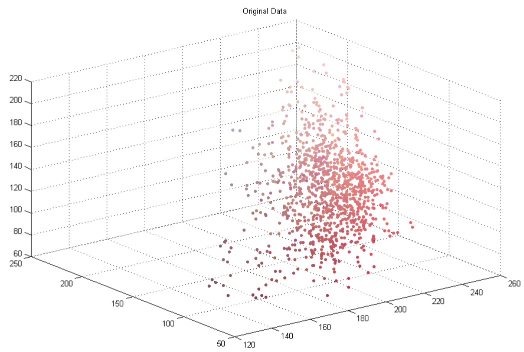

Figure 1 Obtain the raw data in RGB space

$$\varepsilon_{II}(W) = \sum_i \left| Y_i - \sum_j W_{ij} Y_j \right|^2 \qquad (2)$$

Solving for Y is a sparse matrix of eigenvectors of certain constraints. As a result, the LLE problem averts into the strike the smallest non-zero eigenvalue problems, neighbourhood coverage data sets-one mapping in low-dimensional spectral analysis.

Color data in Figure 1 Application LLE algorithm to reduce the dimensions of the K = 5, d = 2 the time to get the results shown in Figure 2.

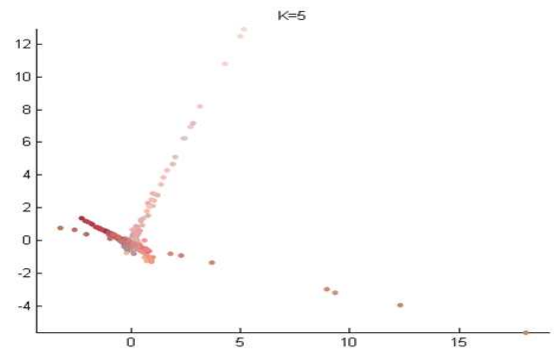

Figure 2 LLE in color data

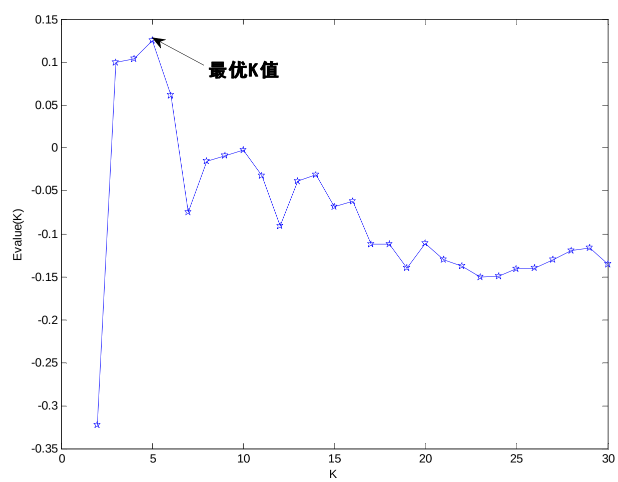

Figure 3 Values score of the original data with different K

2.2. Evaluation Criteria Of LLE Algorithm And Parameter Selection Algorithm Automatically.

This section is an LLE algorithm first proposed evaluation criteria and is used to evaluate different parameters and different color space LLE algorithm dimensionality reduction and visualization, to the LLE algorithm in color analysis of the results in different situations.

Color trends almost linearly in the small neighbourhood, and the local linearity of the LLE algorithm, so that, in a local area, if the results more tend to be a straight line, will be better.

Based on the above ideas, the result of dimensionality reduction is divided into a number of the same size grid, and then calls the shots for each grid component analysis. If the grid points are more linear, the contribution rate of the difference of the first principal component in the PCA and the second principal component should be the greater, the score of the grid should also be higher; grid points, or only a point, the score of the grid is zero. Calculate the principal component of the

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contribution rate of the covariance matrix eigenvalue. Therefore, the definition of grid i scores function as follows:

$$score(i)=\begin{cases}\dfrac{\lambda_1}{\lambda_1+\lambda_2}-\dfrac{\lambda_2}{\lambda_1+\lambda_2}, & \text{More than two points in the network } i\\ 0, & \text{The network} i \text{ did not point or a point}\end{cases} \quad (3)$$

Among them, the grid i calls the shots the first eigenvalue of composition analysis, λ1 and λ2 for the second eigenvalue.

Taking into account some clustering results irregular spread throughout the range, almost all of the grid has a data point distribution, they are not able to draw a linear dimensionality reduction results, although the score of each grid is not high, the score non-zero grid number, the final overall score will be higher. Therefore, the need for such a result a certain penalty, the penalty can be defined for the grid of non-zero number multiplied by a scaling factor. The final overall score function:

$$Evalue=\frac{\sum_i score(i)}{i}-\omega * nonzeronum \quad (4)$$

Among them, the scale adjustment factor, nonzeronum non-zero number of the grid. The higher the overall score, the better the results of the dimensionality reduction.

LLE parameters automatic selection algorithms can be designed on the basis of the above evaluation criteria. The LLE two parameters need to set: the intrinsic dimension d and the number of neighbourhood K. Intrinsic dimension d value the Ambassador mapping results contain too much noise; d value is too small, would have different points in another low-dimensional space may overlap. Color analysis, color space is three dimensional, intrinsic dimensions d = 2 can be. The number of neighbourhood K value selected is too small, continuous topological space is divided into a small space is not adjacent to, and does not reflect the global characteristics; if the K value selected is too large, it will filter out or eliminate the impact of small-scale structure of the original smooth details, similar to conventional PCA, lost a non-linear characteristics. Therefore, the selection of the value of K LLE successfully applied to the color analysis of one of the key points. K value is automatically selected as follows:

Step 1: Select K minimum and maximum possible values of Kmin, of Kmax;

Step 2: run for each K value [Kmin, of Kmax LLE algorithm, calculation Evalue (K);

Step 3: Select makes Evalue (K) the largest value of K;

Step 4: the value into the LLE algorithm to obtain optimal LLE result of the operation.

Figure 3 shows the result of the operation of the data in Figure 1 K, the maximum time to take the 5 Evalue (K), Figure 2, this time the results of the LLE is K = 5 LLE results can be seen that the optimal algorithm to select the results to the human eye observations are consistent.

2.3. The result of the LLE in a different color space.

Commonly used color space, RGB, HSI, the CIE the XYZ, CIE Lab, etc., they have different characteristics, such as RGB display system space, the CIE Lab is more consistent with the human eye color perception approximately uniform space, etc. . This section describes the operation result of the LLE algorithm in the HIS and Lab color space.

HSI (Hue / Saturation / of Intensity, hue / saturation / intensity) model is used to describe the color hue and saturation. First, the data for calculating the RGB color space converted into HSI space H, S, I, value. H, S, three components of the I, the impact factor I (brightness) in the image accounted for smaller H, S two component mapped to [0, 255] interval, the I component is mapped to [0, 25] interval. The original result of the operation of the HSI space is not ideal, after analysis, the LLE algorithm is based on the distance as the criterion, but the HSI model H 0 ° and 360 ° refers to the red. Some color, although similar, but in HSI distance may be but it will very different from far away.

So it is necessary to do some improvements on the original HSI color space, take HSI value is multiplied by, respectively, the sine and cosine, plus the original S and the I component, the new data into a four-dimensional, the former three-dimensional data is mapped to [0, 255] interval, the value of I is mapped to [0, 25] interval.

The L value represents the brightness in the CIE Lab color space, and its value is from 0 (black) to 100 (white). B and a representative of chromaticity coordinate, in which a representative of the red - green axis, b represents yellow - blue axis, their values are from 0-10. RGB to Lab color space, the middle needs to converting the XYZ color space, L

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a, b values of the interval is not the same, before carrying out LLE algorithm, you need to standardize the three components. The final result is shown in Figure 4, leaving the score value of K in the Lab color space, the right picture shows the optimal value of K under the LLE result of the operation. It can be seen that the highest score in the Lab color space values also slightly higher than the highest score value in the RGB space, dimensional results comparable to decline with the HSI color space; the LLE computation results compared to the RGB color space is better able to reflect more color changes and clustering trends.

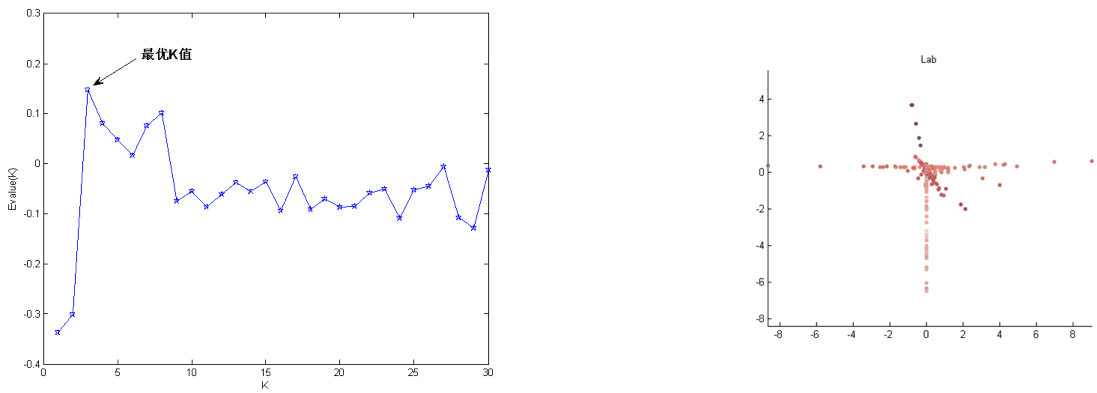

Figure 4 LLE Result Of The Operation In Lab Color Space

3. EM CLUSTERING ALGORITHM BASED ON GAUSSIAN MIXTURE MODEL

The main purpose of manifold learning, such as lowering the dimension of the class space mapping results shows that the color change and a trend of clustering. In order to further analyze the color, also requires a clustering algorithm to the results of LLE for further clustering. Way in view of the vast majority of clustering (e.g. FCM) is the distance to cluster, the last class of the shape is rounded; LLE results reflect the trend is more linear. Therefore, we consider based on the EM Gaussian mixture model (GMM) clustering result of the operation of the LLE. Gaussian mixture clustering results of the shape of the oval, to better reflect the linear clustering.

Gaussian mixture model is based on the EM algorithm; EM algorithm is to solve the model parameters from incomplete data, maximum likelihood estimation method. Every step of the EM algorithm iteration, a step E - expectation step (Expectation Step) and a step of M - Maximum Likelihood steps (the Maximum Likelihood Step), the algorithm in some sense can be reliably converge to a local maximum. In the E-step by the observable variable x and the current parameter estimates, calculate the complete data log likelihood conditional expectation Zik M-step, depending on the value of the E-step calculation makes the log likelihood function value parameter estimation weight, mean, and covariance matrix.

EM-based Gaussian mixture model clustering algorithm is described as follows:

Initialize the mean, covariance and weight; calculate the log likelihood function of the initial value

Repeat

E-step: from the current parameter values Zik:

$$Z_{ik} \leftarrow (\pi_k f(x_i \mid \mu_k, \Sigma_k)) \Big/ (\textstyle\sum_{j=1}^{G} \pi_j f(x_i \mid \mu_j, \Sigma_j)) \tag{5}$$

M-step: re-calculate the maximum likelihood parameter estimates by Zik:

$$n_k \leftarrow \textstyle\sum_{i=1}^{n} Z_{ik} \tag{6}$$

$$\pi_k \leftarrow n_k / n \tag{7}$$

$$\mu_k \leftarrow (\textstyle\sum_{i=1}^{n} Z_{ik} x_i) \Big/ n_k \tag{8}$$

$$\Sigma_k \leftarrow (\textstyle\sum_{i=1}^{n} Z_{ik} (x_i - \mu_k)(x_i - \mu_k)^T) \Big/ n_k \tag{9}$$

Calculate the log likelihood function type:

$$\log p(X \mid \mu, \Sigma, \pi) \leftarrow \sum_{i=1}^{n} \log \left\{ \sum_{k=1}^{G} \pi_k f(x_i \mid \mu_k, \Sigma_k) \right\} \tag{10}$$

Until meet the convergence conditions

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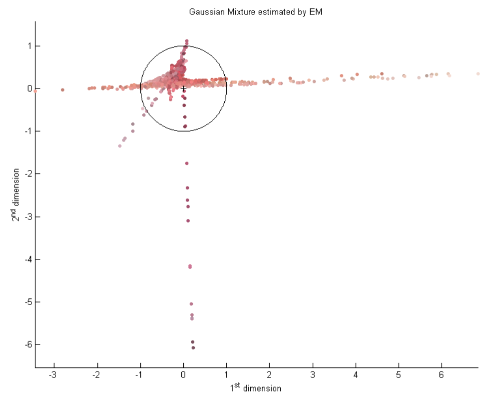
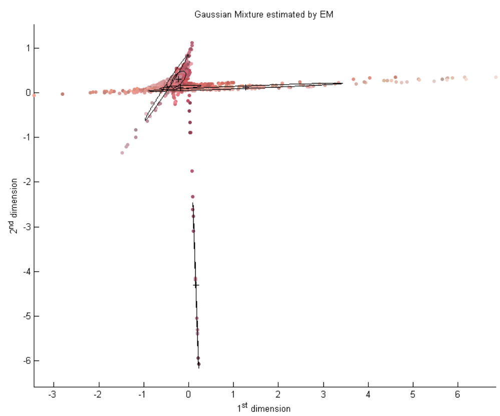
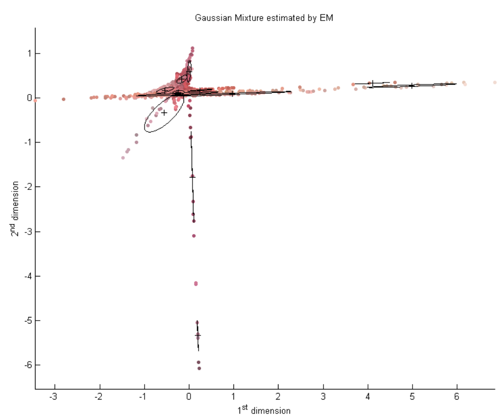


a) K = 1



b) K = 5



c) K = 12

Figure 5 Operation process of EM clustering algorithm based on the Gaussian mixture model

4. EXPERIMENTAL RESULTS.

2.3 improve the results of the LLE operations in the HSI color space optimally, this section will use the results based on the greedy EM Gaussian mixture model clustering.

12 clustering, the likelihood value reaches a local maximum. Part of the computing process is shown in Figure 5, a), b), c). It can be seen that the Gaussian mixture model is able to separate the clustering arrangement of linear trend. Thus the clustering result is the mean μk distribution for the center of the ellipsoid.

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