Disease Regions Recognition on Mural Hyperspectral Images Combined by MNF and BP Neural Network

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Abstract. Many murals are suffering from some serious diseases such as deep loss, mud besmirch and sootiness nowadays. And it is necessary to identify these regions before conservation and restoration. The purpose of this study was to explore the disease region recognition method using hyperspectral images. A method combined Minimum Noise Fraction (MNF) rotation and Back Propagation (BP) neural network was developed to classify the mural images to several kinds of damaged regions and normal parts. The MNF was adopted to select feature bands while the BP network was constructed and trained to classify the mural images. Some mural images collected in Beijing were utilized for the experiment. And according to the error matrix and sampling analysis, the overall accuracy of this method was 86.6% and the Kappa coefficient was 0.864. And they were higher than the maximum likelihood classification method.

1. Introduction
Mural paintings, survived for hundreds or even over one thousand years, are suffering from different diseases for natural environment or human being’s reason. It is essential to survey and record the current condition of the murals before conservation and restoration. The type, distribution, and the area of each disease should be marked to provide detail support for the next conservation step[1].

Hyperspectral imaging (HSI), which can capture a densely sampled spectral response of the object over a broad spectrum including invisible spectra such as ultra-violet and near-infrared[2], has been used to the digital conservation of murals. And it can be used to detect some surface diseases where the reflectance has changed. In 2009, Lu S. et al. adopted a multi-spectral camera with seven bands to capture images of murals, and proposed a diseases index to extract wall paintings diseases automatically[3]. Goltz D. et al. quantitatively assessed the dyeing regions in two historical documents using spectral imaging techniques, and described how to use pixel unmixing method to evaluate the distribution of stains and to enhance the visibility of lighter stains[4]. Sun M. et al. used near infrared hyperspectral technology to analyze and evaluate the flaking disease of murals in Mogao Grottoes in Dunhuang. The least squares regression, principal component analysis and support vector machine, and artificial neural network were used[5]. Melo D. et al. gave a review about stains and colourants...
produced by fungi colonising paper cultural heritage[6]. Li C. et al. recognized the mud spot disease of Tang dynasty tomb murals image automatically and virtually restored them based on textural features, brightness, colourity[7]. Cornelis B. et al. studied the crack detection and inpainting for virtual restoration of paintings[8]. And Wu M. et al. also restored Tang Dynasty tomb mural in a two-step process including crack detection and image inpainting. They used the morphological transformation which included top-hat and below-hat to detect the cracks of mural by multi-scale morphological transformation, and to improve the order of filling of Curvature-Driven Diffusion algorithm to inpainting the images[9]. Cao J. et al. improved a region growing algorithm for the automatic calibration of shedding disease on temple murals[10].

Therefore, the disease investigation of murals has long been a necessary prerequisite for the conservation and restoration of murals. At present, although there have been some studies on the automatic extraction of murals diseases by means of digital images and multi/hyper-spectral images, there are still many problems to be solved urgently. The automatic extraction of murals diseases is still one of the research hotspots. The purpose of this paper was to introduce a method of diseases recognition by combining MNF with BP neural network. The MNF was used to reduce the dimension of mural hyperspectral image and to select feature vectors as training set of neural network. And the BP neural network was selected to classify the feature image to several classes.

2. Data acquisition and preprocessing

2.1. Data acquisition

The figure 1 was the digital orthophoto map(DOM) of the mural which was painted in Qing Dynasty, located in a temple in Yanqing District, Beijing, China. The lower half of the mural consisted of nine portraits of Arhats and the upper half was a variation of Guan Shiyin Bodhisattva. The characters were interesting and exquisite. However, the mural was not in good condition and was threatened by various diseases shown in figure 2. In figure 2(a), there was a deep loss disease, which led to the complete loss of the paint layer. And an example of the sootiness disease, which made the painting indistinct, was illustrated in figure 2(b). And the figure 2(c) was an image of mud besmirch occurred in the mural. The hyperspectral images which contained the diseases of deep loss, mud besmirch, and sootiness would be dealt with in this paper.

Figure 1. Mural in a temple in District Yanqing, Beijing(Qing Dynasty)

(a) Deep loss
(b) Sootiness
(c) Mud besmirch

Figure 2. Some examples of diseases of mural
2.2. Data preprocessing
The primary data were captured by a hyperspectral imaging instruments named THEMIS-VNIR/400H, which covered the wavelength from 400nm to 1000nm with 1040 bands and spectral resolution 2.8nm. The raw data were the value of reflected radiance of the murals. It should be transformed to reflectance by the formula (1).

\[
R = \frac{R_{\text{raw}} - R_{\text{dark}}}{R_{\text{white}} - R_{\text{dark}}},
\]

where \( R \) was the calibrated reflectance image, \( R_{\text{raw}} \) represented the raw image of reflected radiance, \( R_{\text{dark}} \) indicated the dark current data, and \( R_{\text{white}} \) was the reflected data of standard Lambert reference board.

3. Method
As shown in figure 3, after the reflectance transformation, we got the hyperspectral image with hundreds bands which were highly correlated. It was time-consuming to directly applied them to BP neural network classification. Therefore, MNF transform was used to centralize the information into the first few bands, and then by observing the distribution of eigenvalues, specific bands were selected to participate in the calculation. Further, the structure of the neural network was determined, including the number of layers, the number of nodes in each layer, the dimension of the input eigenvector and the expected output value. Then the training samples were collected for the mural images, and the network was trained. At the last, the hyperspectral image was classified, and the extraction accuracy of the disease was evaluated.

4. Results and analysis
4.1. MNF rotation
Hyperspectral imaging can acquire high spectral resolution electromagnetic reflection signal, and its sensor has very high sensitivity, which would inevitably bring some noise to the data. On the other hand, there is a high correlation between adjacent bands, resulting in data redundancy. Therefore, the hyperspectral images are often transformed by MNF to reduce dimension.
Through the observation of mural data, the first 50 bands and the last 50 bands contained a larger noise than others. So, they were directly eliminated from the data. And then the rest bands were used to conduct MNF transformation. The characteristic bands of MNF had different physical and mathematical meanings. By separating the signal and noise, the spectral features converged towards the class eigenvectors, so that the information was concentrated in some eigenvectors. The change of eigenvalues after MNF transformation was shown in figure 4. It could be observed that the main feature components of the image were concentrated in the first 8 bands, which were shown in figure 5.

Figure 4. Eigenvalue of the hyperspectral images after MNF

![Figure 4](image)

Figure 5. The first to eighth characteristic band of MNF with a deep loss disease

By observing the image of each band and combining the average brightness distribution of each band, we could determine the characteristic band combination which accurately identified the disease. The first six characteristic bands had a good distinction between diseases and non-diseases, and could be used as training data sets. It was found that the disease may be omitted or confused with other categories when the bands selected were less than 6 in the experiment.

4.2. Preparation of training sample set

The research murals contained typical diseases of deep loss, mud besmirch and sootiness. Using the hyperspectral synthetic colour image after dimension reduction, the samples of disease areas and non-disease typical areas (such as red, blue, black, and ground layer areas, etc.) were selected on the images, and their average spectral curves were calculated to explore their separability. The selected samples were combined as training samples, and their distribution on images was shown in figure 6. Finally, the selected sample data consisting of the first six bands after MNF transformation were stored representatively in ASCII file as the training samples. Thus, the preparation of training sample set was completed.
4.3. BP neural network establishing and training
The common used three layers BP neural network was established for disease identification. The input layer consists of six nodes, corresponding to the first six bands of MNF for each kind of selected samples. The determination of the number of nodes in the hidden layer was determined by the complexity of the classification problem. The number of nodes in the hidden layer was set to eight by trials. The output layer corresponded to the target classification number, including disease and non-disease data. And five nodes were set in this paper.

Firstly, the sample data were normalized, and the training expectations for diseases and non-diseases were specified. Then the neural network parameters were set for training. The maximum training times was 1000, the minimum error of training target was 0.0001, and the learning rate was 0.01. The network achieved the training accuracy and the training error reached 0.00006 in 23 training cycles.

4.4. Disease recognition and accuracy evaluation
The images were classified by the trained network and the disease parts of murals were extracted. The original image, classification image and the extraction image of the disease of the ground layer were illustrated in figure 7.

(a) Original colour image     (b) Classification result      (c) The area of deep loss
Figure 7. Recognition result of the deep loss disease area of the mural image

In order to verify the recognition accuracy of the neural network, another validation sample should be selected. By calculating the confusion matrix based on the results of classification and the real values corresponding to the validation sample, it was found that the overall accuracy of the image classification was 86.6%, and the Kappa coefficient was 0.864. Further, the user accuracy of extraction of deep loss was 92%, and the mapping accuracy was 88.5%.
With the same treatment process, the mud besmirch, deep loss, and sootiness in the study area were extracted respectively. The recognition accuracy of the three diseases was more than 80%. Figure 8 to 10 were the results of diseases respectively.

![Image](a) Original colour image  (b) Classification result  (c) The area of mud besmirch and sootiness
Figure 8. Recognition result of mud besmirch and sootiness disease area of the mural image

![Image](a) Original colour image  (b) Classification result  (c) The area of deep loss
Figure 9. Recognition result of deep loss disease area of the mural image

![Image](a) Original colour image  (b) Classification result  (c) The area of mud besmirch
Figure 10. Recognition result of mud besmirch disease area of the mural image

5. Conclusion
This paper combined the MNF transformation and BP neural network to identify the typical diseases of mural. The MNF was adopted to reduce the dimension of the hyperspectral images and to selected the feature vectors as the input of the BP neural network. A common used three layers’ network was established to perform the classification. Experiments on deep loss, mud besmirch, and sootiness were carried out and the results showed that the proposed method achieved high recognition accuracy.

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