Feature spectrum extraction of human fingernails based on LCTF multispectral imaging

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Abstract: A multispectral imaging system consisting of liquid crystal tunable filter (LCTF) and charge coupled device (CCD) camera was used to collect the images of fingernail samples at intervals of 10 nm during the spectral range of 450—1 000 nm, and a multispectral image of human fingernails containing 56 bands was obtained. The accurate reflectivity information of fingernails was obtained through referring whiteboard comparative measurement method. Principal component analysis (PCA) and band index method were used to reduce the dimension of the sample images respectively and two feature spaces were obtained. Spectral angle mapping (SAM) was used to classify human fingernails in these two feature spaces. The classification accuracy were above 92.5% and 82.9% respectively. Therefore, the feature space obtained by the PCA can be used as the characteristic spectrum of human fingernails, which provides a reliable basis for the analysis of multispectral spectrum of fingernails and human health assessment in the future.

Key words: multispectral imaging; feature spectrum; band index; principal component analysis (PCA); human fingernails

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0 Introduction

Fingernail is an important part of the human body, which maintains close relationship with the torso, viscera, and limb through the meridian blood. Besides, the physiological and pathological information of the human body can be reflected by the change of fingernails[1-2]. Traditional Chinese medicine nail diagnosis[3] refers to that the doctor obtains the intuitive information of nails by observing the color, shape and texture of nails based on subjective experience. Some scholars have found that the infrared spectrum bands[4-5] of nails of some cancer patients and healthy people are different. However, the above two methods can not simultaneously obtain the spatial and spectral information of the target, which is expected to be measured. A large amount of imaging data bands put forward higher requirements on the performance of imaging spectrometer and data processing algorithm. Therefore, the processing of imaging data is particularly important to the rapid extraction of nail information.

At present, there are few reports on the research of human nails using multispectral imaging technology[6].

Multispectral imaging system can obtain fingernail information from both spectral and spatial dimensions, which overcomes the bottleneck of homochromic and heterogeneous spectrum in the traditional science filed. Multispectral fingernail images acquired by multispectral imaging system contain a large amount of data information. The excessive bands make the data redundant, interband correlation strong and time consumed. Therefore, it is necessary to select effective feature bands from a large number of imaging spectral data for rapid identification and classification of human nails.

In this paper, the method for extracting characteristic spectrum[7] of human fingernails based on liquid crystal tunable filter (LCTF)[8] multispectral imaging is extensively studied, which can extract the characteristic spectrum of human fingernails quickly and effectively. In addition, this method can lay a deep foundation for the diagnosis of human fingernails by using multispectral imaging

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technology.

1 Experiment principle and research method

1.1 Experiment principle and equipment

The multispectral imaging system applied in the experiment is mainly composed of the following parts: LCTF, area array charge coupled device (CCD) camera, optical lens, computer control software, halogen light source, reference whiteboard, etc. The principle of the spectral extraction of human fingernails based on LCTF multispectral imaging is shown in Fig. 1.

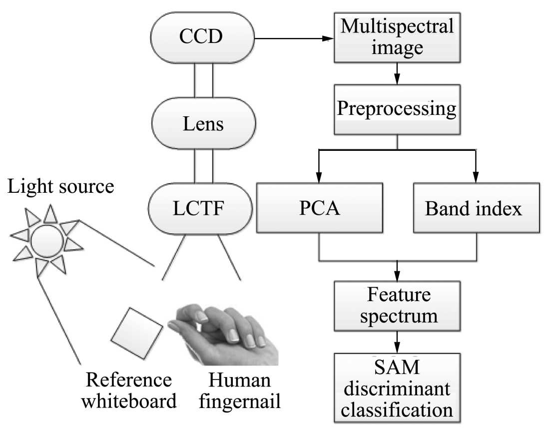

Fig. 1 Principle of extracting characteristic spectrum of human fingernails

20 normal human fingernails were collected and preprocessed as samples by multispectral imaging system. 10 samples were selected as training samples and two feature spaces H_1 and H_2 were obtained by principal component analysis (PCA) and band index method. The testing sample set was composed of 10 other samples points in the region of interest (ROI). In the above two feature spaces, the spectral angle mapping (SAM) sampler was used to classify the testing samples, and the classification accuracy was calculated respectively to verify the accuracy of feature spectrum.

The LCTF in the system is the VariSpecTM of American CRI Company, which can realize fast tuning in the range of 450－1 000 nm, and the full width half maximum (FWHM) is 10 nm. The CCD camera is a Lm165 digital camera made in Lumenera company of Canada with resolution rate of 1 392×1 040, the pixel size of 6.45 μm×6.45 μm and the frame rate of 15 fps. The optical lens is produced by Computar, Japan, with a focal length of 35 mm and a maximum aperture of F1.4. The light source is the SLS201L/M halogen lamp of THORLABS company, USA. The reference whiteboard is a whiteboard of the Coskey series, and its diffuse reflectance is close to 1 at each band.

1.2 Sample collection and image preprocessing

In order to avoid the influence of natural light and other stray lights, the whole experimental process is carried out in the optical darkroom. Multispectral imaging system has a distance of 50 mm with experimental sample. At first, set the parameters of the camera. And then in each band the appropriate exposure time and image gain should also be adjusted on the standard reference whiteboard, so that the camera can generate images in the linear range of photoelectric conversion. Besides, it is necessary to ensure that the gray value of reference whiteboard's images is about 150 pixel, and extract the gray images on the reference whiteboard. Finally, complete the dark current noise test and sample images collection using the exposure time and image gain in the same conditions respectively.

After obtaining the multispectral images of human fingernails, the images were preprocessed. The reflectivity reconstruction[9] can remove the influence from the dark current noise of the camera. Meanwhile, selecting several ROI regions for averaging the gray value to search and remove the influence from the uneven brightness of the fingernails surface and the light scattering.

1.3 PCA

PCA is a kind of orthogonal linear transformation based on a quantity of information, which is frequently applied in multispectral image processing[10]. By selecting the principal components which have great contribution to the original information and comparing and analyzing the load coefficient lines of main components, the less dimension information is substituted for the original multidimensional information, the redundant band is removed, the data dimension is reduced and thus the feature spectrum is obtained. The specific steps are as follows.

1) Standardize the original data and seek the covariance matrix: the covariance matrix of the standard matrix can be understood as the correlation coefficient matrix, which indicates the correlation degree between the attributes;

2) According to the eigenvalues and feature vectors of the covariance matrix, the principal components of the original variables are obtained by

$$F_m = d_{m1}h_1 + d_{m2}h_2 + \cdots d_{mn}h_n, \quad (1)$$

where F_m is the principal component of the first part, d_{mn} is the characteristic vector of the normalized matrix eigenvalue λ_m for the corresponding training sample set;

3) Calculate the contribution rate of each principal component and accumulate them. Then select the main components which have great contribution to the original information by

$$\alpha_m = \frac{\lambda_m}{\sum \lambda_m}. \quad (2)$$

By calculating the contribution rate of the principal components α_m, the principal component's accumulative contribution rate before p was selected up to 99%, indicating the former numbers of the principal components before p represented 99% of the whole information of the original data;

4) The numbers before p correspond to the band with bigger absolute value of the principal component's loading coefficient, indicating that the band has a greater contribution to the original multiband data.

$$L(F_m, H_n) = \sqrt{\lambda_m d_{mn}}, \quad (3)$$

where $L(F_m, H_n)$, as the load factor, is the correlation degree between the main component F_m and the original variable H_n, which is not affected by the original spectral redundancy information and is helpful to identify the effective wavelength for the classification.

1.4 Band index

Band index[11] refers to the ratio of the standard deviation to correlation coefficient of band in imaging spectral data, which is

$$P_i = \frac{\sigma_i}{R_i}, \quad (4)$$

where P_i is the band exponent value of the i band, σ_i is the standard deviation of the i band, R_i is the correlation coefficient of the i band. Assume that ρ_{ij} is a correlation coefficient between band i and j, and the multispectral data is divided into l groups. The number of bands in each group is $b_1, b_2, \cdots, b_l$, and thus

$$R_i = R_w + R_a, \quad (5)$$

$$R_w = \frac{1}{b_l}\sum_{j=1}^{b_l} |\rho_{ij}|, \quad (6)$$

where R_w is the average value of the absolute correlation coefficients between the band i and other bands in the group, R_a is the sum of absolute correlation coefficients between the band i and other bands outside the group.

The bigger the standard deviation of the band is, which can make the dispersion degree greater, the more the spectral information becomes. The smaller the absolute value of the correlation coefficients is, which leads to greater independence and smaller redundancy, the greater the band index value will appear. After calculation, the bands with exponent value ranking in the top several bands can be considered as the characteristic bands of the object to be measured.

1.5 SAM discriminant classification

The SAM[12] method is used to determine the similarity between a measurement spectrum and a reference spectrum, which requires to get the same spectral resolution for the both spectra. Assume that the two samples $\boldsymbol{X}$ and $\boldsymbol{Y}$ each has a capacity of q, where $\boldsymbol{X}$ represents the standard reference spectral vector, and $\boldsymbol{Y}$ represents the spectral vector of image pixels. Besides, the angle between vectors $\boldsymbol{X}$ and $\boldsymbol{Y}$ is defined as θ.

$$\boldsymbol{X} = (x_1, x_2, \cdots, x_q), \quad (7)$$

$$\boldsymbol{Y} = (y_1, y_2, \cdots, y_q), \quad (8)$$

$$\theta = \arccos \frac{\sum_{i=1}^{q} x_i y_i}{\sqrt{\sum_{i=1}^{q} x_i^2}\sqrt{\sum_{i=1}^{q} y_i^2}}, \ \theta \in \left[0, \frac{\pi}{2}\right]. \quad (9)$$

If $\boldsymbol{X}$ is similar to $\boldsymbol{Y}$, the angle of $\boldsymbol{X}$ and $\boldsymbol{Y}$ will be close to 0, and thus $\cos\theta$ is near 1.

2 Experiment results and data analysis

2.1 Reflectivity reconstruction

The acquired fingernail images are reconstructed using comparison method to obtain the reflectivity of each pixel. Then get the average reflectivity in multiple regions of the fingernail samples. Finally, the average reflectivity curves of the samples are reached as shown in Fig. 2.

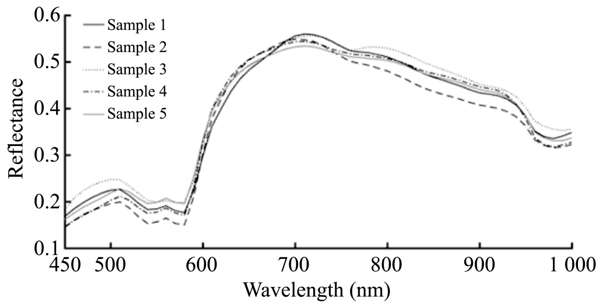

Fig. 2 Average reflectivity curves of 5 fingernails samples

2. 2 PCA for extracting characteristic bands

To avoid the effects from the edge of skin and background on spectral information of fingernails, choose the center of the spectral images as the ROI in 10 training samples. Randomly take 20 data points in each ROI of training sample (the value of the data point is the average value of spectral information with 3 pixels × 3 pixels), and make principal component analysis of data sets composed of 200 data points from 10 training samples. Select the load factor curve corresponding to the principal component with an accumulated contribution rate of above 99%, whose positions of peak and trough indicate that the load factor has a larger absolute coefficient in the corresponding band. In other words, the corresponding band is the characteristic band. The contribution rate of some principal components is shown in Table 1.

Table 1 Partial contribution rate of principal components

No.	Contribution (%)	Cumulative contribution rate (%)
1	86. 05	86. 05
2	11. 03	97. 08
3	2. 33	99. 41
4	0. 25	99. 66
5	0. 12	99. 78
6	0. 07	99. 85
7	0. 03	99. 88
8	0. 02	99. 90
9	0. 01	99. 91
10	0. 01	99. 92

As seen from Table 1, the cumulative contribution rate of the first three principal components adds up to 99. 41%. The fourth principal components and subsequent contribution rates are all less than 1%. It indicates that the first three principal components contain the information close to the original information. The load coefficient curves corresponding to the first three principal components are present in Fig. 3.

As shown in Fig. 3, peaks and troughs appeared at the bands of 510, 550, 570, 580, 640, 660, 710, 850, 960, and 980 nm, which indicates that these bands have more contribution to the overall data than adjacent bands. Therefore, these bands can form the characteristic space H_1 of the human fingernails.

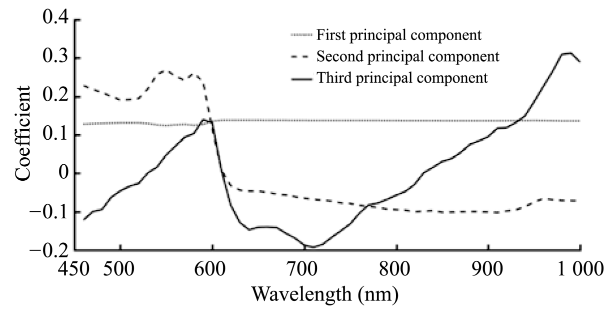

Fig. 3 Load coefficient curves corresponding to the first three principal components

2. 3 Band index method for extracting characteristic bands

Extract 200 original gray values of data points in the above 10 training samples, then calculate the standard deviation and correlation coefficient of each band respectively. Standard deviation can judge the amount of information in each band and the magnitude of the correlation coefficient can be used to characterize the degree of redundancy among the bands. The standard deviation curve and the band index bar of the fingernails sample imaging spectrum data are shown in Figs. 4 and 5 respectively.

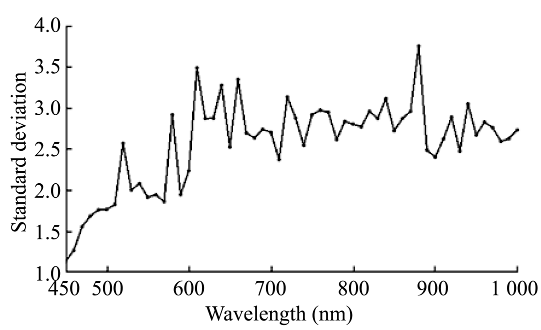

Fig. 4 Standard deviation curve of fingernails sample

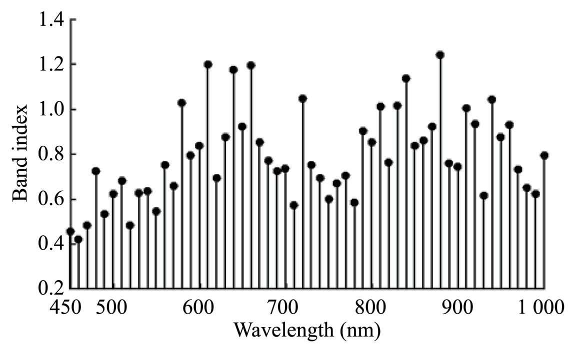

Fig. 5 Band index of fingernails sample

It can be seen from Fig. 5 that the maximum index value at 880 nm is 1.24, followed by 610, 660, 640, 840, 720, 940, 580, 830, and 810 nm. Therefore, the standard deviations at these bands are large and the absolute values of the correlation coefficient are small. In other words, the information of human fingernails is rich and the independence of bands is good. So these bands can form the characteristic space H_2 of the human fingernails.

2.4 SAM for validating characteristic space

In order to verify the accuracy of the two characteristic spaces H_1 and H_2, ten testing fingernails samples were classified and chosen by SAM classifier.

In the standard spectrum of fingernails, the spectra corresponding to the two characteristic spaces H_1 and H_2 were taken as the reference spectra A_1 and A_2 respectively. 10 samples were selected as testing samples, whose center regions in the spectral images were regarded as ROI, and then 100 data points (the average value of the spectral information is 3 pixels× 3 pixels) were randomly taken in each training sample. The test set consisting of 100 data points obtained from each training sample was analyzed by SAM to A_1 and A_2 in H_1 and H_2 respectively. Meanwhile, the accuracies of the characteristic spaces H_1 and H_2 were verified by statistical classification accuracy as shown in Table 2.

Table 2 Ten classification accuracy of testing samples

No.	Classification accuracy(θ=0.28)	
	H_1(%)	H_2(%)
1	92.5	83.3
2	96.3	87.1
3	95.0	85.4
4	95.6	86.7
5	93.1	85.8
6	97.4	89.8
7	95.7	82.9
8	94.2	84.5
9	96.1	86.1
10	95.8	85.2

Table 2 shows that the classification accuracies of 10 testing samples are higher than 92.5% in characteristic space H_1 and higher than 82.9% in characteristic space H_2. Therefore, the characteristic space H_1 can reflect the characteristic spectrum of human fingernails more accurately. In other words, it can be used as the characteristic spectrum of human fingernails for rapid classification and identification of human fingernails.

3 Conclusion

The LCTF multispectral imaging system was used to collect images of 20 human fingernails samples at intervals of 10 nm in the spectral range of 450－1 000 nm. In the experiment, the characteristic spaces of human fingernails were obtained by PCA and band index method from 10 training samples, and the accuracy of the characteristic space was verified by SAM discriminant classification. The results show that bands of 460, 510, 540, 560, 580, 650, 730, 750, 800, 890, and 950 nm can be applied as the characteristic spectrum of the human fingernails, which provides a solid basis for systematic study of the relationship between spectral information of fingernails and human health assessment in the future.

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基于 LCTF 多光谱成像的人体指甲特征光谱提取

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摘　要： 利用由液晶可调谐滤光片(LCTF)和CCD相机组成的多光谱成像系统在450～1 000 nm光谱范围内每隔10 nm采集人体指甲样本，得到包含56个波段的人体指甲多光谱图像。通过参考白板比较测量法进行反射率反演，得到指甲的准确反射率信息，分别利用主成分分析法(PCA)和波段指数法实现样本图像的降维，得到两个特征空间，并利用光谱角度填图法(SAM)在两个特征空间内对人体指甲进行分类，分类准确度分别为92.5%及82.9%。因此，由主成分分析法得到的特征空间可以作为人体指甲的特征光谱，为指甲多光谱图谱分析和人体健康评估提供了可靠的依据。

关键词： 多光谱成像；特征光谱；波段指数法；主成分分析法；人体指甲

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