LANDSAT TM IMAGE RECOGNITION BY USE OF POWER SPECTRUM ANALYSIS

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ABSTRACT

In this paper an approach of Landsat TM-image recognition by use of Optical Power Spectrum Analysis (OPSA) is introduced. The method is based on the fast optical Fourier transform technic, special wedge-ring photodetector array, simple feature extraction method and effective Boolean classifier which is convenient to accomplish by use of firmware. Finally the experimental results of three pattern classes are given in two-dimensional feature space.

THE SPECTRAL CHARACTERISTICS OF WATER, SOIL & VEGETATION

The thematic mapper (TM) which is fixed in the Landsat 4 or 5 is a multispectral scanner[1] . The TM system was originally intended primarily for vegetation mapping applications, which substantially influenced the choice of spectral bands. In this research, the objects of recognition are water, light - toned land and green vegetation area. the spectral reflectance curves of them are shown in [2] . We choose TM-image of band 4 (0.76-0.90 μm) as experimental sample, because this band is full of information and the crossing of its curves is small.

The sampling data curves of power spectrum of typical land and water area image in our experiments are shown in Fig. 1. In TM - image of band 4, since the reflectance of water is small , even the huge wave of sea or river, its exposure and texture is very small . So its optical power spectrum does not have any spatial high frequency (see Fig. 1). As regards the land, because of the crossing of vegetation, bare soil, road, river, sand bank and so on, their reflectances are different, so the texture of land is net-like feature.

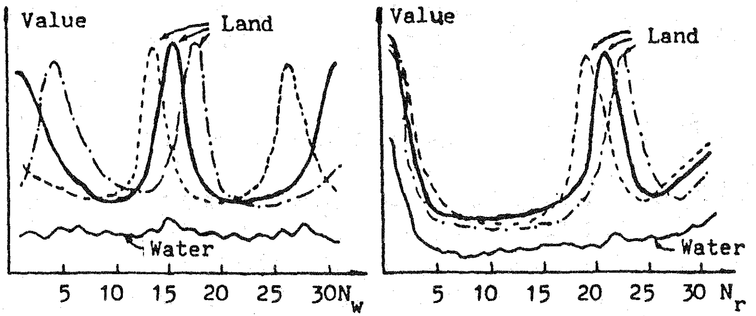
PATTERN SAMPLING BY USE OF OPSA SYSTEM

The pattern sampling of TM-image is by use of Optical Power Spetrum Analysis (OPSA) system [3] . The OPSA system is diagrammed in Fig. 2.

A whole TM-film is divided into 195 (15 X 13) windows. After sampling, every image window is translated into a subset data, so we can obtain 195 subsets of data from a whole TM-film . In Fig. 2, if put the TM-film t(x, y) into the focal plane P_1 of the Fourier transformer, we can get an optical diffraction pattern F(u, v) on plane P_2, the relation may be written as follows:

$$F(u, v) = \iint t(x, y)\exp\left[-2\pi j(ux + vy)/\lambda f\ dxdy \qquad (1)$$

where, $u/\lambda f$ and $v/\lambda f$ are spatial frequency of the diffraction pattern. λ is wavelength of coherent light, f is the focal length of Fourier transform lens.



(a). Directional Sampling (b). Spatial Frenquency Sampling

Fig.1 Sampling Data Curve of Optical Power Spectrum of Typical Land and Water Area Image.

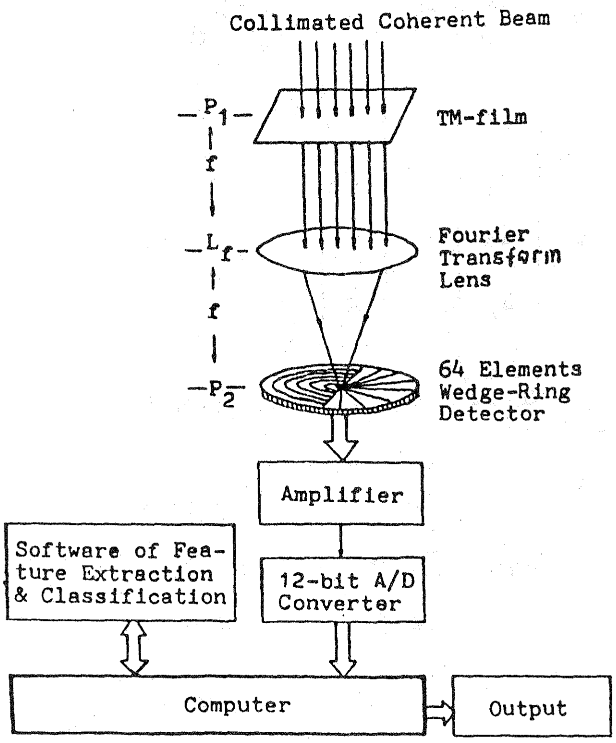


Fig.2 Optical Power Spectrum Analysis System

The optical power spectrum $|F(u, v)|^2$ of every image window is transfered into 64 analog signals by detector with 32 ring elements and 32 wedge elements [4] , then the signals are amplified, digitized and fed into the computer with a subset of data D,

$$D = \{ D_{R1}, D_{R2}, \ldots, D_{R32}, D_{W1}, D_{W2}, \ldots, D_{W32} \} \quad (2)$$

The 32 ring data D_{R1}-D_{R32} are measurements of radial distribution of optical power spectrum, the 32 wedge data D_{W1}-D_{W32} are descriptions of diffractive direction of the spectrum.

FEATURE EXTRACTION FROM SAMPLING DATA

Generally speaking, the original measurements of a pattern may contain a lot of information, some of them do not aid in the classification process and may even hinder it. On the other hand, if use all original measurements to pattern recognition, it would lead to time consuming. So we must separate the useful information from the original measurements and reduce the dimensionality of the data.

In this research, in order to recognize three pattern classes of TM-image, two features F1and F_2 are extracted from sampling data D.

$$F_1 = k_1 \sum_{i=1}^{32} D_{Wi} + k_2 \sum_{i=1}^{32} D_{Ri} \quad (3)$$

$$F_2 = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{bmatrix} \cdot \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ 1 \end{bmatrix}^T \quad (4)$$

where, k_1, k_2 and a_1-a_5 are constant, T means transposition, x_1-x_4 is as follows:

$$x_1 = \max (D_{W1}, D_{W2}, \ldots, D_{W10}) \quad (5)$$

$$x_2 = \max (D_{W11}, D_{W12}, \ldots, D_{W20}) \quad (6)$$

$$x_3 = \max (D_{W21}, DW22, \ldots, D_{W32}) \quad (7)$$

$$x_4 = \max (D_{R17}, D_{R18}, \ldots, D_{R24}) \quad (8)$$

Obviously, x_1-x_4 and F_1, F_2 are simple for computation and easy for accomplishment by use of firmware.

Assuming the time required to perform multiplication is the dominant factor in the total time required for each classification, the classification time is roughly proportional to n(n+1), where n is the dimensionality of the data. Since

$$\frac{m(m+1)}{n(n+1)} = \frac{2 \times 3}{64 \times 65} = 0.0014 \qquad (9)$$

So in this research, the classification by use of two features (m=2) requires only 1.4 per thousand of the time which requires when all 64 measurements are used. Of course, the cost of the feature extraction process must also be accounted for.

BOOLEAN FUNCTION CLASSIFICATION METHOD

In order to use firmware instead of the classified software, a classifier is composed by three Boolean discriminants:

$$Y_W = A \cdot B \qquad (10)$$

$$Y_l = \overline{AB} \cdot (A + C) \qquad (11)$$

$$Y_d = \overline{Y_w + Y_l} = \overline{AB + (\overline{AB} \cdot (A + C))} \qquad (12)$$

Where Yw indicates the water area, such as river, lake and sea. Yl is the sign of light-toned land, including the bare soil, sand bank, new alluvial plain and so on. Y_d represents darktoned land, such as green vegetation area, dark-toned plain (usually the history of the plain is long) and so on. The A, B, C is Boolean state:

$$A = \begin{cases} 1 & \text{if} \quad F_1 \leq H_1 \\ 0 & \quad\quad F_1 > H_1 \end{cases} \qquad (13)$$

$$B = \begin{cases} 1 & \text{if} \quad F_2 \leq H_2 \\ 0 & \quad\quad F_2 > H_2 \end{cases} \qquad (14)$$

$$C = \begin{cases} 1 & \text{if} \quad F_2 \leq H_3 \\ 0 & \quad\quad F_2 > H_3 \end{cases} \qquad (15)$$

Where F_1, F_2 is the extracted feature shown as (3), (4). H_1, H_2 and H_3 are thresholds and $H_2 < H_3$.

EXPERIMENTAL RESULTS

The training set is the 195 subset-data of TM-film 23/ APR/ 84/ D118-038/F4, this is the image of the Yangtze river valley nearby sea. The test set is another 195 subset-data of TM-film 23/ APR/84/D118-039/F4 -- the Qiantang river valley nearby sea. The experimental results are shown in table 1 and table 2, the correct classification rate of the training set is about 95.4%, the correct recognition rate of the test set is about 88.7%.

Table 1. Training Set

True Class

Assigned Class

A \ T	Y_w	Y_l	Y_d
Y_w	136	6	0
Yl	0	22	0
Y_d	0	3	28

Table 2. Test Set

True Class

Assigned Class

A \ T	Y_w	Y_l	Y_d
Y_w	98	0	0
Y_l	0	24	7
Y_d	0	15	51

As an assigned class result, an alphanumeric display of the Yangtze river valley nearby sea is shown in Fig.3.

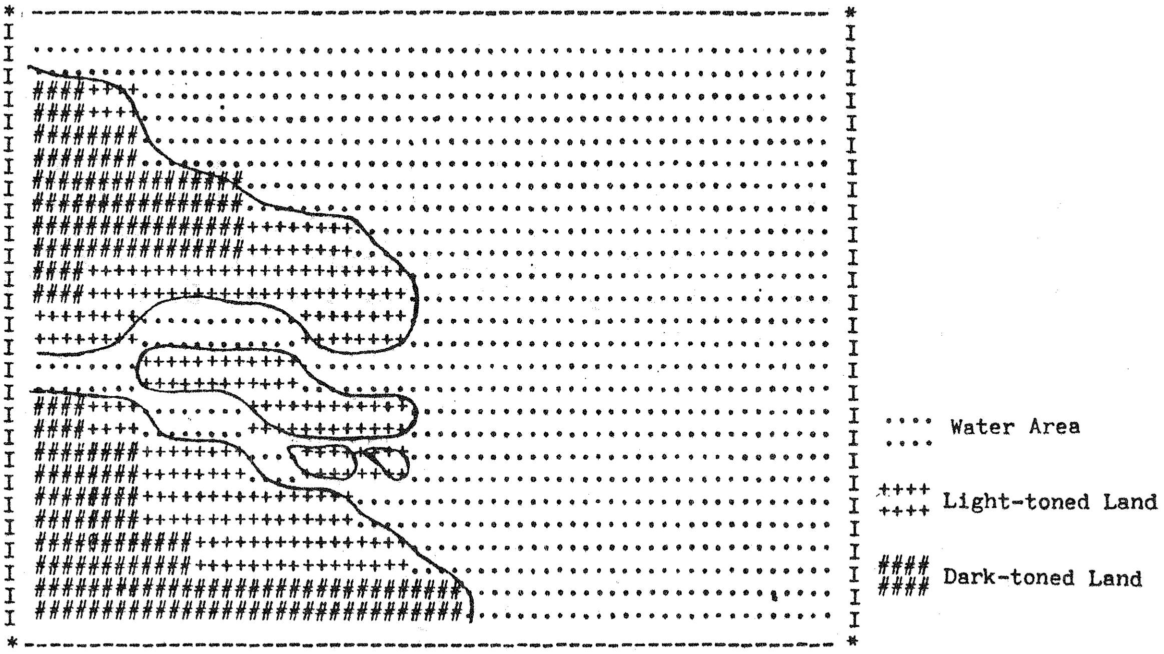


Fig.3 Alphanumeric Coded Display of The Yangtze River Valley Nearby Sea

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