

Features Extraction of Soil Image

Sneha Pethkar¹, S. V. Phakade²

¹Department of E&TC Engineering P.V.P.I.T Budhgaon, Maharashtra, India

²Associate Professor, Department of E&TC Engineering P.V.P.I.T Budhgaon, Maharashtra, India

Abstract: In image processing, Statistical, geometrical features are used to describe the texture of an image region. The signal processing methods involve enhancing original image using filters and calculating the features of the transformed images. In this paper, color moment, Hsv, wavelet transform and gabor filter are applied to the original images to extract the texture features of soil images for classification. Results on a database of soil images belonging different types of Soils show that proposed method performs soil classification effectively.

Keywords: color moment, Hsv, wavelet transform, gabor filter

1. Introduction

There is a necessity to classify contiguous intervals (segments) of series data (signals) in a number of engineering problems. Series data has an additional index variable (distance or time) associated with each data value. In standard classification algorithms these situations are often inadequate due to the additional contiguity constraint. Examples are from the following domains: classification of sub-soil layers using Cone Penetration Testing [3], in petroleum engineering, palaeoecology, etc. In these cases measurements are taken from a vertical bore or employing test apparatus that is pushed down the earth and stratigraphical information is preserved in the classification. The problem is solved in two phases: firstly, a segmentation algorithm is utilized to cluster contiguous blocks of instances and then, these segments are classified by domain experts. To automate classification of soil layers from measured data is important. In civil engineering it is a prerequisite to know the soil classes up to some depths prior to any construction. The direct method to identify the soil classes by drilling boreholes and testing soil samples is very expensive. A cheaper alternative is the so-called Cone Penetration Testing (CPT). CPT is one of the most popular soil investigation methods [3]. But all these methods require manual data of soil samples and for classification using expert advice is difficult and expensive also. Different results also occurred due to different expert give result as per their knowledge. For these difficulties or to remove this limitations algorithm can be formed which work efficiently. Which is based on image processing.[2]

This paper is structured as follows, First introduction, in section 2 block diagram, section 3 feature extraction methods. The results are given in section 4

2. Block Diagram

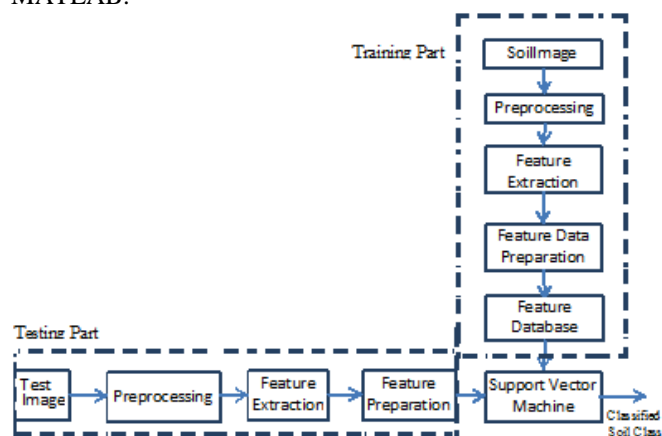
A. Training Part

In training part, first part is to collect different types of soil sample picture. Then preprocesses apply on that soil images. Then develop an algorithm to extract the features of soil sample images using features extraction methods, like Hsv, Color moments-mean sd, Gabor features, Colour auto

correlogram. Then develop database with feature preparation of sample images. Develop an SVM algorithm for deciding class.

B. Testing Part

For testing purpose select any soil sample image. Which will undergoes processes like preprocessing, Feature extraction, feature preparation. Develop an SVM algorithm to find class of soil. Implementation of algorithm may be by using MATLAB.



2.1 Enhancement

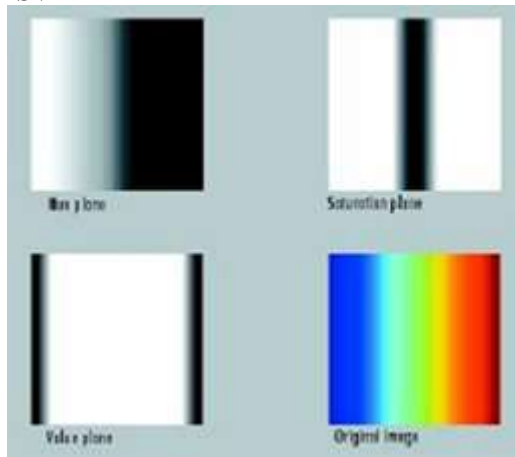
In preprocessing enhancement technique used. Here contrast stretching enhancement technique used. Image enhancement techniques help in improving the visibility of any portion or feature of the image suppressing the information in other portions or features. It involves the modification of digital data for improving the image qualities with the aid of computer. The processing helps in maximizing clarity, sharpness and details of features of interest towards in format on extraction and further analysis.

Contrast stretching often called normalization is a simple image enhancement technique that attempts to improve the contrast in an image by 'stretching' the range of intensity values it contains to span a desired range of values, e.g. the full range of pixel values that the image type concerned allows. It differs from the more sophisticated histogram equalization in that it can only apply a linear scaling function

to the image pixel values. As a result the 'enhancement' is less harsh. Before the stretching can be performed it is necessary to specify the upper and lower pixel value limits over which the image is to be normalized. Often these limits will just be the minimum and maximum pixel values that the image type concerned allows. For example for 8-bit gray level images the lower and upper limits might be 0 and 255.

2.3 Feature extraction methods

2.3.1 HSV



A three dimensional representation of the HSV color space is a hexagon, where the central vertical axis represents the Intensity [9]. Hue is defined as an angle in the range $[0, 2\pi]$ relative to the Red axis with red at angle 0, green at $2\pi/3$, blue at $4\pi/3$ and red again at 2π . Saturation is the depth or purity of the color and is measured as a radial distance from the central axis with value between 0 at the center to 1 at the outer surface. For $S=0$, as one moves higher along the Intensity axis, one goes from Black to White through various shades of gray. On the other hand, for a given Intensity and Hue, if the Saturation is changed from 0 to 1, the perceived color changes from a shade of gray to the most pure form of the of gray by sufficiently lowering the Saturation. The value of Intensity determines the particular gray shade to which this transformation converges. When Saturation is near 0, all pixels, even with different Hues, look alike and as we increase the Saturation towards 1, they tend to get separated and are visually perceived as the true colors represented by their Hues. Thus, for low values of Saturation, a color can be approximated by a gray value specified by the Intensity level while for higher Saturation, the color can be approximated by its Hue. The Saturation threshold that determines this transition is once again dependent on the Intensity. For low intensities, even for a high Saturation, a color is close to the gray value and vice versa. Saturation gives an idea about the depth of color and human eye is less sensitive to its variation compared to variation in Hue or Intensity. Therefore, use the Saturation value of a pixel to determine whether the Hue or the Intensity is more pertinent to human visual perception of the color of that pixel and ignore the actual value of the Saturation.

The formula that transfers from RGB to HSV is defined as below:

$$S = 1 - \frac{3}{R+G+B} (\min(R, G, B))$$

$$V = \frac{1}{3} (R + G + B)$$

$$H = \text{Cos}^{-1} \left\{ \frac{[1/2(R-B) + (R-G)]}{[(R-G)^2 + (R-B)(G-B)]^{1/2}} \right\}$$

The R, G, B represent red, green and blue components respectively with value between 0-255. In order to obtain the value of H from 0^0 to 360^0 , the value of S and V from 0 to 1.

Execute the following formula:

$$H = (H/255 * 360) \text{ mod } 360$$

$$V = V/255$$

$$S = S/255$$

2.3.2 Wavelet

Wavelet is a powerful tool for signal/image analysis. However, the implementation is quite simple. The wavelet transform is performed by convolving a signal with a family of real orthonormal basis function $\psi(x)$ given below

$$W_f(j, k) = \int_{-\infty}^{+\infty} f(x) \psi(x) dx \quad (1)$$

Like the Fourier transform, wavelets also have wavelet series expansion, continuous wavelet transform (CWT), and discrete wavelet transform (DWT). The wavelet is defined based on a scaling function,

$$\phi_{jk} = 2^{1/2} \phi(2^j x - k) \quad (2)$$

From that, we can have a refinement equation via

$$\Phi(x) = \sum_n h(n) \sqrt{2} \phi(2x - n) \quad (3)$$

where the $h_\phi(n)$ is the scaling function coefficient. Then we can have the following equation

$$\psi(x) = \sum_n h(n) \sqrt{2} \phi(2x - n) \quad (4)$$

where $h_\psi(n)$ is called the wavelet function coefficient and is related to $h_\phi(n)$ via

$$h_\psi(n) = (-1)^n h_\phi(1-n) \quad (5)$$

Therefore, the mother wavelet is

$$\Psi_{j,k} = 2^{j/2} \psi(2^j x - k) \quad (6)$$

Equation (6), also known as the mother wavelet, can be used to decompose a signal with its different dilation and translation form. The wavelet coefficients of $f(x)$ can be obtained via

$$c_{j,k} = \int_{-\infty}^{+\infty} f(x) \psi(x) dx \quad (7)$$

$f(x)$ can also be reconstructed via a synthesis procedure, i.e.,

$$f(x) = \sum_{j,k} c_{j,k} \psi(x) \quad (8)$$

A fast algorithm, known as the dyadic filter tree, is commonly used to implement the DWT, in which the signal $f(x)$ is convolved with a high-pass and low-pass filter simultaneously, and the filtered signal is down sampled by a factor of 2. The iterative convolution process is done with the low-pass component until it reaches the level of $l = \log_2 N$,

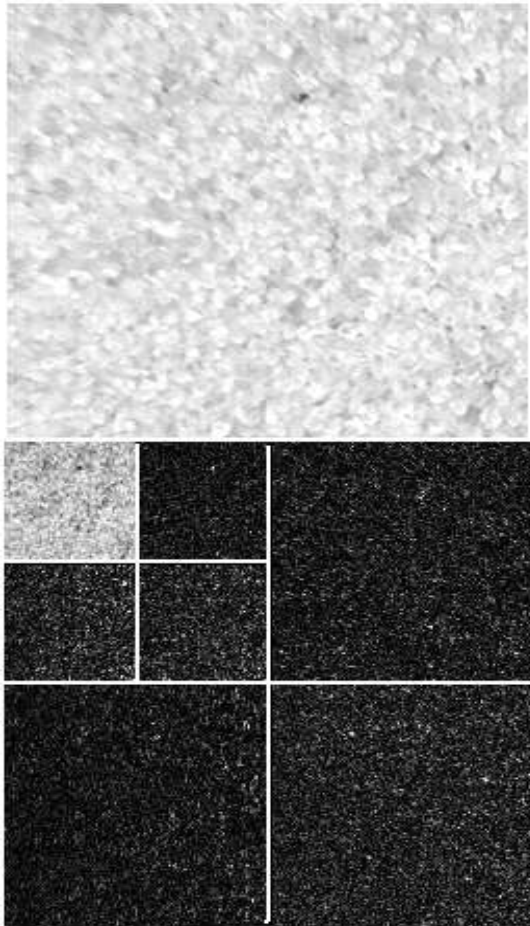


Figure 1: Pyramid-structured wavelet transform of “Sand”.

The same process is applied to the two-dimensional DWT, except that the scaling function and mother wavelet are two dimensional, and the process is to first do the one-dimensional DWT to the rows of $f(x, y)$, then followed by the one dimensional DWT to the resulting columns. Second, the above process is repeated until the level of l , a series of sub-images will be generated. Figure 1 is the pyramid-structured wavelet transform of the sand image.[5]

2.3.3 Gabor

The extraction of texture of an image is accomplished by using a set of Gabor Filters. GABOR Filters are a group of wavelets capturing energy at a specific frequency and a specific direction. The expansion of a signal using this basis provides a localized frequency description, therefore, capturing local features/energy of the signal. Texture features can thus be extracted from this group of energy distributions. A 2D Gabor function $g(x,y)$ and its Fourier transform $G(u,v)$ are defined as follows;

$$G(x,y) = (1/2\pi\sigma_x\sigma_y) \exp[-1/2(x^2/\sigma_x^2 + y^2/\sigma_y^2) + 2\pi jw_x]$$

$$G(u,v) = \exp\{-1/2[(u-w)^2/\sigma_u^2 + v^2/\sigma_v^2]\}$$

Where $\sigma_u = 1/2\pi\sigma_x$ and $\sigma_v = 1/2\pi\sigma_y$

A set of self-similar functions can be generated from dilation and rotation of the Gabor function $g(x,y)$

$$G_{mn}(x,y) = a^{-m}G(x,y) \text{ Where } a > 1$$

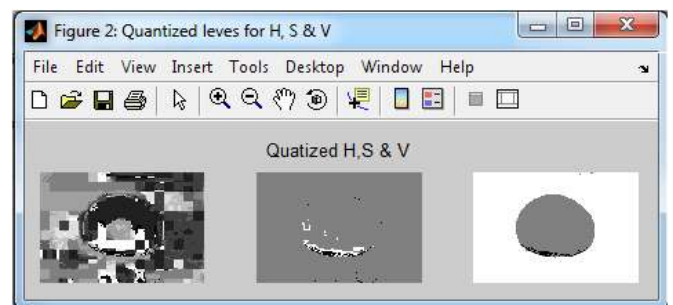
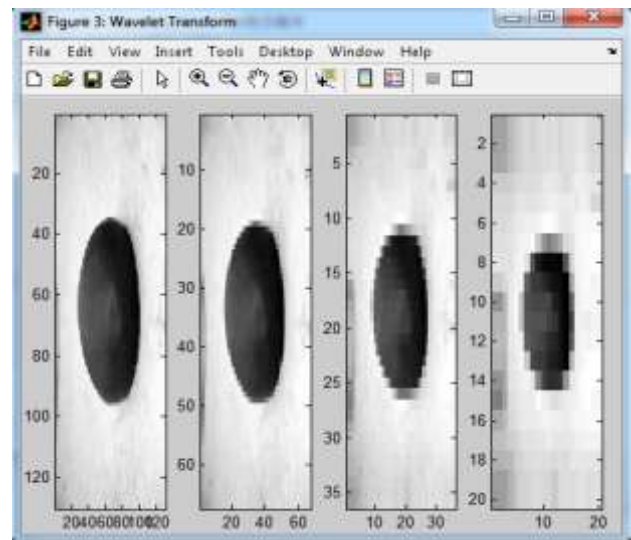
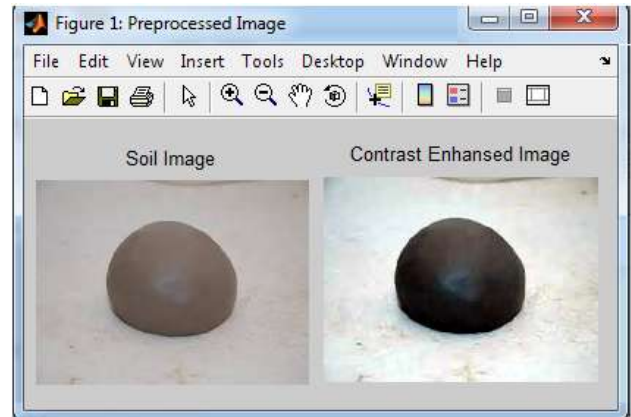
$$X' = a^{-m}(x \cos \epsilon + y \sin \epsilon) \text{ and } y' = a^{-m}(-x \sin \epsilon + y \cos \epsilon);$$

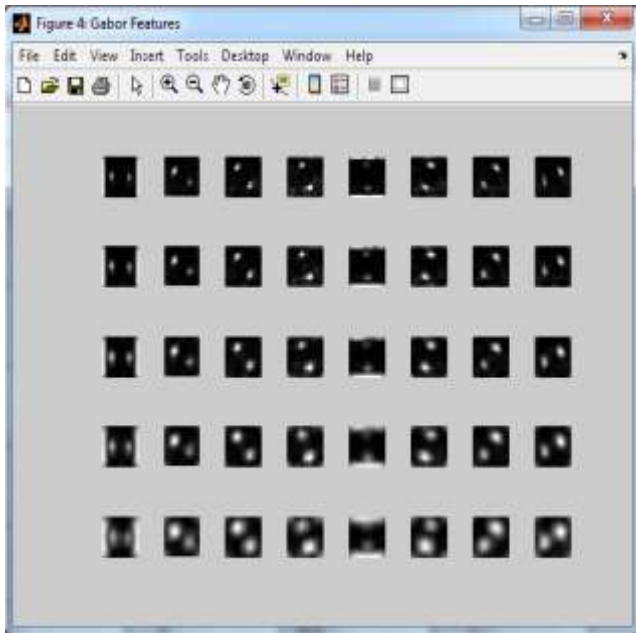
$$\epsilon = n\delta/N;$$

m and n specify the scale and orientation of wavelet respectively with $m=0,1,\dots,M-1$ and $n=0,1,\dots,N-1$. M is the number of scales and N is the number of orientations.

For a given image $I(x,y)$, the discrete GABOR wavelet transform is given by a convolution $W_{mn} = \sum I(x_1,y_1) g_{mn}^*(x_1,y_1)$4 where $*$ indicates complex conjugate. The features obtained are combined as per the description in the proposed algorithm and final results are acquired after the implementation.

3. Results





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4. Conclusion

Generally for finding soil characteristics and classification manual methods are available, but for this experts are required. So as per different experts different results are given.

Features extraction methods used for extract features for study of next level. As many features extraction methods are available but for soil images above extraction methods are better than others.

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