# ESTIMATION, DETECTION & COMPARISON OF SOIL NUTRIENTS USING MATLAB

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**Abstract -** *This paper proposes a method for estimation, detection and comparison of soil nutrient analysis quantitatively by following the principle of chromatography technique as chromatogram patterns which are similar to iris patterns, we have adopted iris processing methods for finding the different parameters such as moisture, temperature etc at different layers from the soil sample. Using image processing of soil chromatogram ,we find the soil nutrients and suggest the perfect fertilizer and best suitable crop. Testing of soil nutrients is significantly improving the understanding of soil processes by means of simplifying the soil testing procedures which helps to reduce the cost and time and it will ensure the complete analysis and complete coverage of soil testing in future.*

## 1. INTRODUCTION

Agriculture plays a very important role in India's economy. The chromatogram image processing provides a method in the determination of essential components present in the soil. This information that is provided by decoding the chromatographic image where the fertility of the soil can be maintained by minimizing the use of chemical fertilizers and pesticides there by promoting organic or natural farming. The focus of this paper is on chromatogram image processing, which is a fundamental step for feature extraction. Many algorithms for iris recognition is available which can be applied for chromatographic image. Later many researchers started working in iris image processing which is an important step in iris recognition. Chromatographic image processing includes detection of the centre, normalization and segmentation. To detect chromatogram centre, we used different methods in MATLAB to locate the centre and find different parameters from the soil sample.

## 2.BLOCK DIAGRAM

The original image is transformed into a polar image using the centre of the chromatogram as origin.

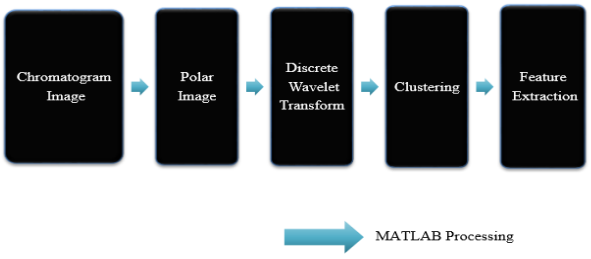



Fig 1: Block diagram

This transformation is done using following equation.

I(x(r,θ),y(r,θ))→I(r,θ)……..(1)
Where(r,θ)=r*cosθ+xc……,(2)
y(r,θ)=r*sinθ+yc……,(3)

where (xc , yc ) is the co-ordinate of the centre of the chromatogram, M is maximum radius which depends on the size of the image and 0≤ θ≤2π, and 0≤r≤M. The DWT analyses is signal based on its content that is used in different frequency ranges. Therefore, it is very useful in analysing repetitive patterns such as texture in the chromatographic image of the soil sample that is being tested or processed. The 2-D image of the chromatographic image transform uses a wavelet functions and its associated scaling function to decompose the original chromatographic image into different channels, namely the low to low(LL), low to high(LH), high to low(HL) and high to high(HH) (A, V, H, D respectively) channels. The process of decomposition can be repeatedly applied to the low to low frequency channel (LL) to generate data at the next level by processing the available data in which the Low pass and High pass filters are used to implement the wavelet transform from the chromatographic image using MATLAB.

The absolute magnitude of the filter output is taken as:
aj(x,y)= | ihj(x,y) | ……(4)
where ihj (x, y) is the jth channel output of the filter. A low pass Gaussian post-filter gp (x, y) is then applied to each aj (x, y) yielding post-filtered energy of the jth filter channel as:
ej(x,y)=aj(x,y)**gp(x,y) ……,…… (5)
where,gp (x, y)= 1 2πσ2 2 e−[x2+y2] 2σ2 2

where ** denotes convolution in 2-D The feature vectors computed from the local energy estimates are (i) mean of A, μ [ej (x, y)] and (ii) variance of V and H, σ [ej (x, y)]. Hence every pixel in the image is represented by a 9-dimensional (3*3) feature vector (3 colour bands, 3 DWT sub bands).

For each region or strip in the segmentation output, we compute the following features:

→ Area = Number of pixels in that region;
→Width = Area / N,
→N = Number of columns in the polar image;
→Area (cm2) = Area / Resolution2 (pixel/cm);
→Width (cm) = Width / Resolution (pixel/cm);

→Colour = Mean of multi-band intensity of the pixels in that region.

## 3. SOURCE CODING

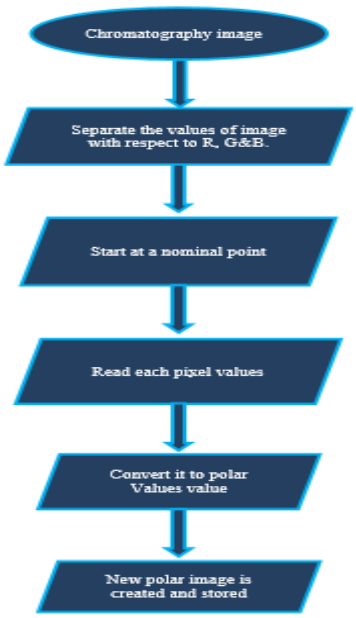



**Fig 2: Polar Image Extraction**

The following are the equations used in this section:
theta = atan2(Y, X)
(equation to find the Angle) ..... (1)
rho = sqrt(X.^2+Y.^2)
(equation to find the radius) ..... (2)

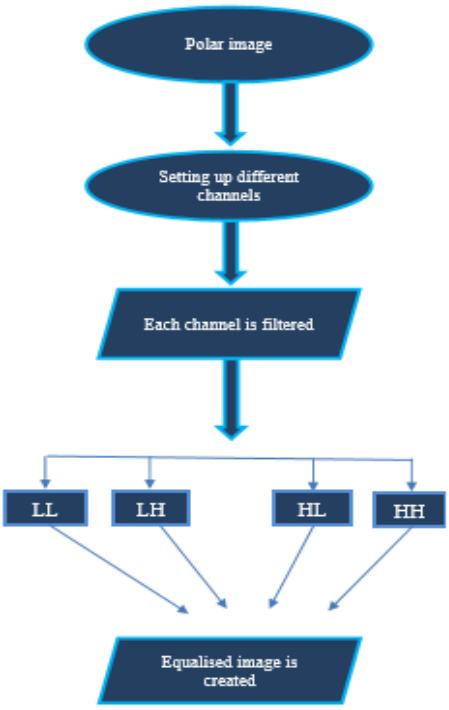



**Fig 3: Equalising the Image**

Wavelets are able to remove noise while preserving the perceptually important features. First, obtain the wavelet transform of a noisy image down to level 5 using a bi orthogonal spline wavelet.
LL: Low channels
LH: Low High channels
HL: High Low channels
HH: High channels

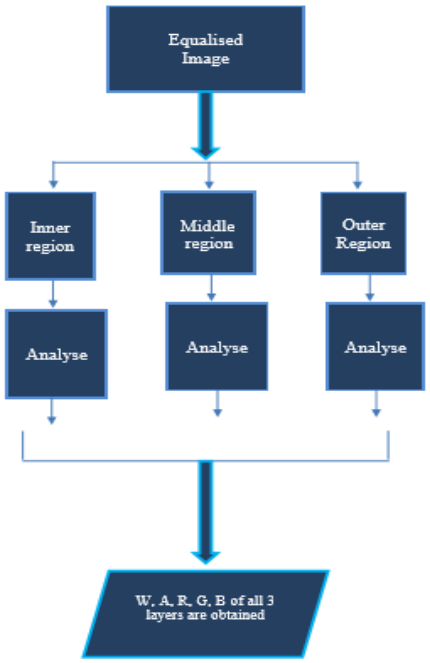



**Fig 4: Parameter Extraction**

Formulas:
Area = Number of pixels in that region;
Width = Area / N,
N = Number of columns in the polar image;
Area (cm2)= Area/Resolution2(pixel/cm);
Width (cm) = Width / Resolution (pixel/cm);
Color = Mean of multi-band intensity of the pixels in that region.
Formula used:
Soil pH index=$[redgreen/blue]$..... (3)
Moisture content=$|((G-B)(B-R))|$..... (4 )
$Nitrogencontent$=$|((R-G)(R-B)/)100/|$..... (5)

## 4. SIMULATION AND RESULT

**Table: 1 : Comparative table**

| Segment Colour Label | Area (cm2) | Width (cm) | Colour | | |
|---|---|---|---|---|---|
| | | | Red | Green | Blue |
| Back Ground | 55.6 | 1.18 | 195 | 179 | 152 |
| Middle | 29.14 | 2.18 | 191 | 125 | 55 |
| Inner | 8.39 | 1.28 | 191 | 168 | 136 |

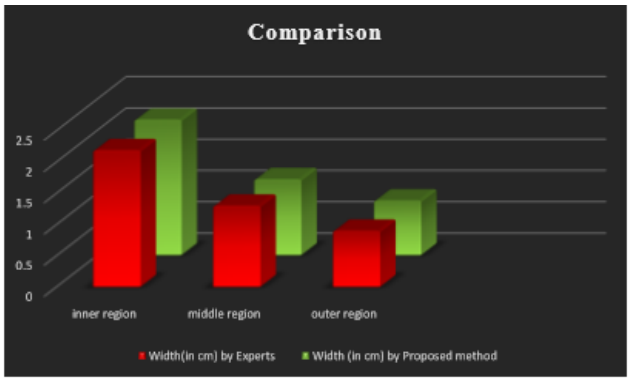
The result of segmentation of the polar image of the chromatogram, in figure. Table shows the features extracted from each segmented strip from different layers. A similar example of this process is shown in figure and table. We neglect the narrow and thin strips of segments formed in the output. These segments are irrelevant in the characteristics of the chromatogram which reflect the soil content. Hence, tables 5.1 and 5.2 give the features of the prominent segments only. The advantage of chromatogram processing (conversion from Cartesian to polar) is now evident, as one can visually compare the spread of the significant regions and compute with ease the geometrical features necessary for soil analysis. In the original circular chromatogram image, these computations would not have been trivial

**Table 2: Nutrients Comparison**

| Parameters | Inner layer | Middle layer | Outer layer |
|---|---|---|---|
| pH | 7.1715 | 27.6664 | 8.4132 |
| Nitrogen (grams/kilogram) | 0.4208 | 1.3535 | 0.549 |
| Moisture content (grams) | 17.6997 | 67.3928 | 24.5280 |
| Temperature (degrees) | 50.8482 | 20.8500 | 43.7402 |

From the extracted R, G, B values for the respective image, using standard formulas the above parameters were obtained and tabulated. Different regions contain information about different nutrient in the soil. Hence by using the parameters such as area, width and RGB values of the image we can calculate the nutrients present in the soil. With further research, we can find many other nutrients present in the soil

**Table:3 Comparing the different regions**




We evaluated the success rate for the proposed method using 50 chromatograms with diverse textures, from 500 chromatograms given by experts. For the two chromatograms in both the figure, comparison of the experimental results with the data given by soil experts is listed in the table . The errors are shown separately for the images in figure (two regions) and figure (three regions). Our experimental results were compared with those obtained manually by experts and the mean and maximum errors obtained for 50 chromatograms are shown in table. Mean error is about 1-2mm while the maximum is about 5mm compared to the chromatogram size of a radius of 75mm (approximately).

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