AN APPROACH FOR SOIL CLASSIFICATION THROUGH NN TECHNIQUES

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Abstract

In these days, the content from an image retrieval system has become a challenging task. Many systems based on the text based retrieval systems but the need of an image based retrieval system that takes an image as a input query and retrieves data. Content Based Image Retrieval is an approach for retrieving semantically-relevant images from an image database based on automatically-derived image features. The aim and Objective of the Paper is classifying the soils using Adaptive resonance theory, a Neural Network concept for more efficient and effective results. Forthcoming problems or disasters are easily studied and predicted with help of FL .So that priory we can rescue the human kind and mother earth.

Key words:- BPN, CBIR, Clustering.

I. INTRODUCTION

This section gives an introduction to content based image retrieval system (CBIRS) and the technologies used in them. Image retrieval has been an extremely active research area over the last 10 years, but first review articles on access methods in image databases appeared already in the early 80s[1]. Enser [2] gives an extensive description of image archives, various indexing methods and common searching tasks, using mostly text based searches on annotated images. In [3], an overview of the research domain in 1997 is given and in [4], the past, present and future of image retrieval is highlighted There are several reasons why there is a need for additional, alternative image retrieval methods apart from the steadily growing rate of image production. It is important to explain these needs and to discuss possible technical and methodological improvements. Image retrieval is the process of browsing, searching and retrieving images from a large database of digital images. Advances in data storage and image acquisition technologies have enabled the creation of large image datasets. In order to deal with these data, it is necessary to develop appropriate information systems to efficiently manage these collections. It is simple to identify a desired image from a small collection simply by browsing, but we need more effective techniques with collections containing thousands of items. Image searching is one of the most important services that need to be supported by such systems. In general, two different approaches have been applied to allow searching on image collections: one based on image textual metadata and another based on image content information. The first retrieval approach is based on attaching textual metadata to each image and uses traditional database query techniques to retrieve them by keywords [5,6]. However, these systems require a previous annotation of the database images, which is a very laborious and time-consuming task. Furthermore, the annotation process is usually inefficient because users, generally, do not make the annotation in a systematic way. In fact, different users tend to use different words to describe a same image characteristic. The lack of systematization in the annotation process decreases the performance of the keyword-based image search. Image retrieval systems have not kept pace with the collections they are searching. The shortcomings of these systems are due both to the image representations they use and to their methods of accessing those representations to find images. The problems of image retrieval are becoming widely recognized, and the search for solutions an increasingly active area for research and development.

In recent years, with large scale storing of images the need to have an efficient method of image searching and retrieval has increased. It can simplify many tasks in many application areas such as fingerprint identification biodiversity information systems, digital libraries, crime prevention, medicine, historical research, artificial intelligence, military, education, web image searching. Content-Based Image Retrieval (CBIR) systems [7-9] shown in Fig-1 In these systems, image processing algorithms (usually automatic) are used to extract feature vectors that represent image properties such as color, texture, and shape. In this approach, it is possible to retrieve images similar to one chosen by the user (query-by-example).

There by we can overcome the disadvantages of the text based retrieval systems. The main advantages of this approach is the possibility of an automatic retrieval process, contrasting to the effort needed to annotate images. In this paper it was focused on soil classification of various fields on the earth map/remote sensed image. Generally classification can be done with aid of various filter techniques but in order to calssify the soils we are using an advanced platform called Neural Networks.

II. DIGITAL IMAGE DEFINITIONS

A digital image a[m,n] described in a 2D discrete space is derived from an analog image a(x,y) in a 2D continuous space through a sampling process that is frequently referred to as digitization. The mathematics of that sampling process will be described in Section 5. For now we will look at some basic definitions associated with the digital image. The effect of digitization is shown in Figure1.1

The 2D continuous image a(x,y) is divided into N rows and M columns. The intersection of a row and a column is termed a pixel. The value assigned to the integer coordinates [m,n] with {m=0,1,2,...,M-1} and {n=0,1,2,...,N-1} is a[m,n]. In fact, in most cases a(x,y)--which we might consider to be the physical signal that impinges on the face of a 2D sensor--is actually a function of many variables including depth (z), color (λ), and time (t). Unless otherwise stated, we will consider the case of 2D, monochromatic, static images in this chapter.

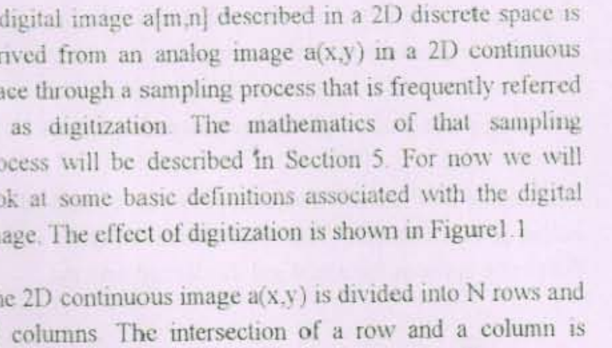


Figure1.1 Digitization of a continuous image. The pixel at coordinates [m=10, n=3] has the integer brightness value 110.

The image shown in Figure 1 has been divided into N = 16 rows and M = 16 columns. The value assigned to every pixel is the average brightness in the pixel rounded to the nearest integer value. The process of representing the amplitude of the 2D signal at a given coordinate as an integer value with L different gray levels is usually referred to as amplitude quantization or simply quantization.

- Common Values
- Characteristics of Image Operations
- Video Parameters
- Common Values

There are standard values for the various parameters encountered in digital image processing. These values can be caused by video standards, by algorithmic requirements, or by the desire to keep digital circuitry simple. Table1.1 gives some commonly encountered values.

Parameter	Symbol	Typical values
Rows	N	256,512,525,625,1024,1035
Columns	M	256,512,768,1024,1320
Gray Levels	L	2,64,256,1024,4096,16384

Table1.1: Common values of digital image parameters

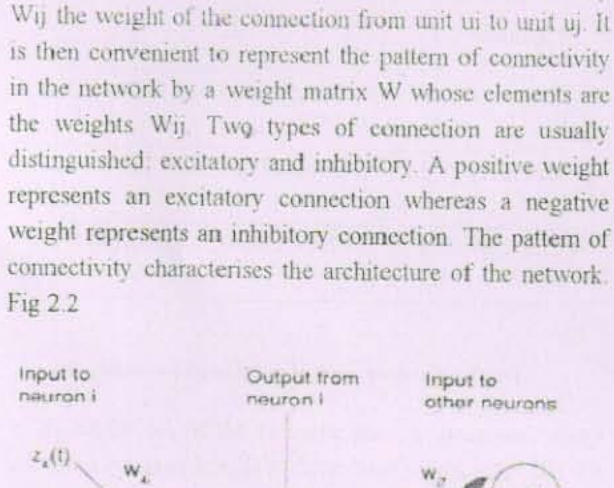
Quite frequently we see cases of M=N=2K where {K = 8,9,10}. This can be motivated by digital circuitry or by the use of certain algorithms such as the (fast) Fourier transform. The number of distinct gray levels is usually a power of 2, that is, L=2B where B is the number of bits in the binary representation of the brightness levels. When B>1 we speak of a gray-level image; when B=1 we speak of a binary image. In a binary image there are just two gray levels which can be referred to, for example, as "black" and "white" or "0" and "1".

III. PROPOSED METHOD

This systems based on features like color, shape, texture, spatial layout, object motion, etc., are cited in[11],[12].Color is one of the most widely used features for image similarity retrieval, Color retrieval yields the best results, in that the computer results of color similarity are similar to those derived by a human visual system that is capable of differentiating between infinitely large numbers of colors. One of the main aspects of color feature extraction is the choice of a color space. A color space is a multidimensional space in which the different dimensions represent the different components of color [13]. Most color spaces are three dimensional. Example of a color space is RGB, which assigns to each pixel a three element vector giving the color intensities of the three primary colors, red, green and blue. The space spanned by the R, G, and B values completely describes visible colors, which are represented as vectors in the 3D RGB color space. As a result, the RGB color space provides a useful starting point for representing color features of images.

IV. BACK PROPAGATION NETWORK – MATHEMATICAL APPROACH

Units are connected to one another. Connections correspond to the edges of the underlying directed graph. There is a real number associated with each connection, which is called the weight of the connection. We denote by Wij the weight of the connection from unit ui to unit uj. It is then convenient to represent the pattern of connectivity in the network by a weight matrix W whose elements are the weights Wij. Two types of connection are usually distinguished: excitatory and inhibitory. A positive weight represents an excitatory connection whereas a negative weight represents an inhibitory connection. The pattern of connectivity characterises the architecture of the network. Fig 2.2



A unit in the output layer determines its activity by following a two step procedure.

First, it computes the total weighted input xj, using the formula:

$$X_j = \sum_i y_i W_{ij}$$

where yi is the activity level of the jth unit in the previous layer and Wij is the weight of the connection between the ith and the jth unit.

Next, the unit calculates the activity yj using some function of the total weighted input. Typically we use the sigmoid function:

$$y_j = \frac{1}{1+e^{-x_j}}$$

Once the activities of all output units have been determined, the network computes the error E, which is defined by the expression:

$$E = \frac{1}{2}\sum_i (y_i - d_i)^2$$

where yj is the activity level of the jth unit in the top layer and dj is the desired output of the jth unit.

The back-propagation algorithm consists of four steps:

1. Compute how fast the error changes as the activity of an output unit is changed. This error derivative (EA) is the difference between the actual and the desired activity.

$$\mathrm{EA}_j = \frac{\partial E}{\partial y_j} = y_j - d_j$$

2. Compute how fast the error changes as the total input received by an output unit is changed. This quantity (EI) is the answer from step 1 multiplied by the rate at which the output of a unit changes as its total input is changed.

$$\mathrm{EI}_j = \frac{\partial E}{\partial x_j} = \frac{\partial E}{\partial y_j} \times \frac{dy_j}{dx_j} = \mathrm{EA}_j y_j (1 - y_j)$$

3. Compute how fast the error changes as a weight on the connection into an output unit is changed. This quantity (EW) is the answer from step 2 multiplied by the activity level of the unit from which the connection emanates.

$$\mathrm{E}W_{ij} = \frac{\partial E}{\partial W_{ij}} = \frac{\partial E}{\partial x_j} \times \frac{\partial x_j}{\partial W_{ij}} = \mathrm{EI}_j y_i$$

4. Compute how fast the error changes as the activity of a unit in the previous layer is changed. This crucial step allows back propagation to be applied to multilayer networks. When the activity of a unit in the previous layer changes, it affects the activities of all the output units to which it is connected. So to compute the overall effect on

the error, we add together all these seperate effects on output units. But each effect is simple to calculate. It is the answer in step 2 multiplied by the weight on the connection to that output unit

$$\mathrm{EA}_i = \frac{\partial E}{\partial y_i} = \sum_j \frac{\partial E}{\partial x_j} \times \frac{\partial x_j}{\partial y_i} = \sum_j \mathrm{EI}_j W_{ij}$$

By using steps 2 and 4, we can convert the EAs of one layer of units into EAs for the previous layer. This procedure can be repeated to get the EAs for as many previous layers as desired. Once we know the EA of a unit, we can use steps 2 and 3 to compute the EWs on its incoming connections.

Working with Back Propagation

The application of the generalized delta rule thus involves two phases. During the first phase the input x is presented and propagated forward through the network to compute the output values yp o for each output unit. This output is compared with its desired value do, resulting in an error signal δp o for each output unit. The second phase involves a backward pass through the network during which the error signal is passed to each unit in the network and appropriate weight changes are calculated.

Weight adjustments with sigmoid activation function.

- The weight of a connection is adjusted by an amount proportional to the product of an error signal δ, on the unit k receiving the input and the output of the unit j sending this signal along the connection:

$$\Delta_p w_{jk} = \gamma \delta_k^p y_j^p.$$

- If the unit is an output unit, the error signal is given by

$$\delta_o^p = (d_o^p - y_o^p)\, \mathcal{F}'(s_o^p).$$

Take as the activation function F the 'sigmoid' function as defined

$$y^p = \mathcal{F}(s^p) = \frac{1}{1+e^{-s^p}}.$$

In this case the derivative is equal to

$$\begin{aligned} \mathcal{F}'(s^p) &= \frac{\partial}{\partial s^p} \frac{1}{1+e^{-s^p}} \\ &= \frac{1}{(1+e^{-s^p})^2}(-e^{-s^p}) \\ &= \frac{1}{(1+e^{-s^p})} \frac{e^{-s^p}}{(1+e^{-s^p})} \\ &= y^p(1-y^p). \end{aligned}$$

such that the error signal for an output unit can be written as:

$$\delta_o^p = (d_o^p - y_o^p)\, y_o^p(1-y_o^p).$$

The error signal for a hidden unit is determined recursively in terms of error signals of the units to which it directly connects and the weights of those connections. For the sigmoid activation function:

$$\delta_h^p = \mathcal{F}'(s_h^p) \sum_{o=1}^{N_o} \delta_o^p w_{ho} = y_h^p(1-y_h^p) \sum_{o=1}^{N_o} \delta_o^p w_{ho}.$$

V. REFERENCE DATA OF SOIL CLASSIFICATION

Table 2.1: Sample training data for soil classification

Table 2.2: Inference results for the soil classification

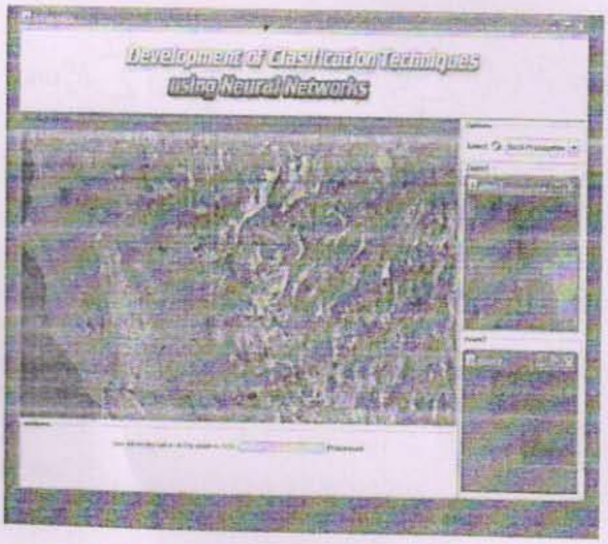
Color of the soil	(Gravel %) 18	(Sand %) 82	(Fine grained particles %) 84	(liquid limit %)59	(plastic limit %)34	IS Classification
0.1	0	0.329	0.869	0.711	0.735	0.203(0.2)
0.1	0	0.341	0.857	0.694	0.705	0.193(0.2)
0.2	0.111	0.692	0.5	0.508	0.529	0.1(0.1)
0.2	0.222	0.682	0.476	0.508	0.529	0.0842(0.1)
0.2	0	0.548	0.654	0.576	0.647	0.289(0.3)
0.3	0	0.756	0.452	0.491	0.529	0.129(0.1)
0.3	0	0.585	0.619	0.61	0.823	0.594(0.6)

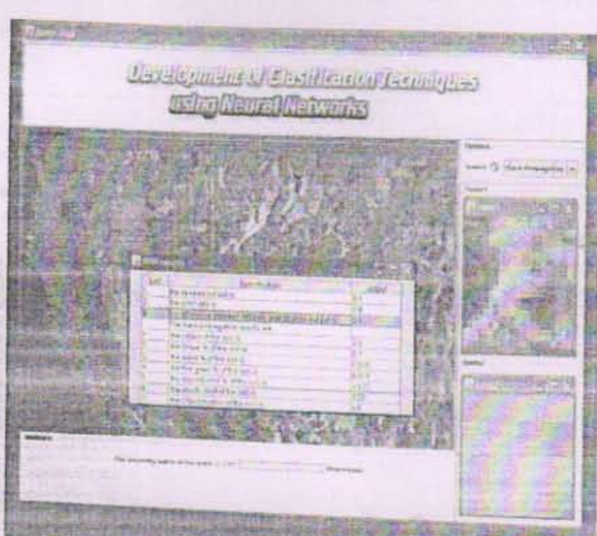
(untrained data)

Table 2.2: Inference results for the soil classification (untrained data)

Color of the soil	(Gravel %) 18	(Sand %) 82	(Fine grained particles %) 84	(liquid limit %) 59	(plastic limit %) 34	IS Classification
0.1	0	0.304	0.892	0.728	0.754	0.204(0.2)
0.1	0	0.951	0.261	0.627	0.676	0.0912(0.1)
0.2	0.222	0.658	0.5	0.525	0.529	0.0887(0.1)
0.2	0	0.536	0.666	0.576	0.647	0.292(0.3)
0.5	0	0.597	0.607	0.61	0.0823	0.592(0.6)

VI. EXPERIMENTAL RESULTS





VII. CONCLUSION

This paper is embedded with Three different domains of sciences i.e Basics of Digital image Processing, Soil Fundamentals, Neural Networks. So in order to study the two important learning techniques (Supervised) we are using the concepts of BPN algorithms. The algorithm which are used in the project are predefined functions, which cannot be altered according to our task. The most important algorithms that are used in this paper is BPN for soil classification as well as image recognition. The BPN algorithm is completely mathematical based tools i.e the functions that are used in these algorithms are predefined one. Presenting these algorithms in java is really a challenging task, working with dynamic image and collecting the relevant data such as position of the pixel, RGB values and converting it into the intensity values and then giving these values as the inputs to the these algorithms through java and verifying the output values with the trained data ends the project.

Even though a large number of commercial and open source applications exist to process remote sensing data. According to an NOAA Sponsored Research by Global Marketing Insights, Inc. the most used applications among Asian academic groups involved in remote sensing are as follows: ESRI 30%; ERDAS IMAGINE 25%; ITT Visual Information Solutions ENVI 17%; MapInfo 17%; ERMapper 11%. Among Western Academic respondents as follows: ESRI 39%, ERDAS IMAGINE 27%, MapInfo 9%, AutoDesk 7%, ITT Visual Information Solutions ENVI 17%.

It is an attempt to study two important learning techniques which plays a vital role in the image processing through these algorithms makes the project more interesting and challenging using Neural Network and Java Flat form.

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