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FEATURE EXTRACTION OF DISEASED LEAF IMAGES

PATIL J.K.[1] AND RAJ KUMAR[2]

[1]Bharati Vidyapeeth (Deemed Univ.), Pune, MS, India.
[2]Defence Institute of Advanced Tech., Deemed University, Girinagar, Pune-25, MS, India.
*Corresponding Author: Email- jayamala.kp@gmail.com

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Abstract- Image feature extraction is an important key in success of Content Based Image Retrieval (CBIR) systems . The low level visual features of an image can be extracted from color, texture & shape of the image. These features can be used during retrieval to compare query image and other images in the database. This paper describes the method for extraction of color & texture features of diseased leaves of maize. Color features are extracted by computing first, second & third order moments of HSV histogram of an image. The textures features like correlation, energy, inertia & homogeneity are obtained by computing gray level co-occurrence matrix of an image.
Keywords- Color, Texture, Histogram, Co-occurrence matrix

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Introduction

The position of the any country in the world depends on its economy and the economy of most of the countries depends on agricultural production. In country like India the farmers have wide diversity to select their crop for cultivation to produce maximum yield depending on environment available. Then also the production get affected by diseases of the crop. The diseases of the crop are caused by pathogens, deficiency of nutrients, fungi etc. Detecting diseases at early stages enables to overcome it and treat it appropriately. This process requires an expert to identify the disease, describe the method of treatment and protection. Identifying the plant disease is not easy task. It requires experience and knowledge of plants and their diseases. It also requires accuracy in describing the symptoms of plant diseases. A person can depend on a system which has experience and knowledge, called an Expert System. An expert system can be:

- An excellent farmers
- Agricultural advisor
- Electronic or Computerized expert system

An excellent farmers precisely catch the change of the crops in the growing process and they manage the cultivation in proportion to the change in order to cultivate the agricultural products of high quality. Since sensing the delicate change of crops is acquired through the observation by the visual sense in their long cultivation experience, it is difficult for them to transmit the understood technique to future generations as a general cultivation one[1].

If farmers decide to take advice from agricultural expert regarding the treatment of incidence of pest /disease/trait to their crop/plant in order to increase the crop productivity then he may face following situations[2]:

- Sometimes they have to go long distances for approaching the expert.
- Even though they go such distances expert may not be available at that time.
- Sometimes, the expert whom a farmer contacts, may not be in a position to advise the farmer with the available information and knowledge.

In these cases seeking the expert advice is very expensive and time consuming.

Electronic expert systems enables farmers in identifying type of diseases; making the right decision and selecting the proper treatment. The expert systems are intelligent computer programs that are capable of offering solutions or advices related to specific problems in given domain, both in a way and at a level compara-

ble to that of human expert in a field. One of the advantages of using Electronic expert systems is its ability to reduce the information that human users need to process, reduce personnel costs and increase throughput. Another advantage of expert system is that it performs tasks more consistently than human experts[3]. The electronic expert systems can be thought of as Content Based Image Retrieval (CBIR) Systems. CBIR systems are computer vision applications where the desired images are retrieved from large collection of the images on the basis of the features that can be automatically extracted from the images themselves. CBIR involves two steps:

Feature Extraction: Extracting image features to a distinguishable level

Matching: Matching these feature to produce a result that is visually similar to the query image

This paper focuses on the feature extraction of the diseased leaf images.

Image Feature

The feature is a function of one or more measurement which specifies some quantifiable property of an object. It quantifies some significant characteristics of the object. The features are broadly classified in to two groups:

- Low level features: These can be extracted directly from the original image.
- High level features: These can be extracted from low level features[4].

The image features are also classified as:

- General features: These are application independent features like color, texture and shape.
- Domain specific features: These are calculated over entire image or regular sub-area of an image.

The rest of the paper discusses on the extraction of the color & texture feature.

Color: Color is one of the most widely used feature in image retrieval because of its robustness, effectiveness, & computational simplicity. The color of the image is represented through some color model. The commonly used color models are RGB (red, green, blue), HSV (hue, saturation, value) and Y, Cb, Cr (luminance and chrominance) .hence for any color image the color contents are characterized by 3-channels from some color model. The color feature can be described by color histogram[4,5,6], color correlogram[7],Color moment[6,8,9,10],color structure descriptor scalable color descriptor[4].

The color moment has the lowest computational complexity ; hence it is suitable for image retrieval.

Texture: Texture is a very interesting image feature that has been used for characterization of images, with application in content-based image retrieval. There is no single formal definition of texture. The major characteristic of texture is the repetition of a pattern or patterns over a region in an image. The elements of patterns are called textons. The size, shape, color, and orientation of the textons can vary over the region. The difference between two textures can be in the degree of variation of the textons. It can also be due to spatial statistical distribution of the textons in the image. The texture can not have the capability of finding similar images but it can be combined with another visual attribute like color to design effective retrieval methods. The structure can be statistically represented by Fourier power spectra, gray level co-occurrence metrics[11,12], shift-invariant principal component analysis[4], fractal model, multi-resolution filtering like Gabor[6] and wavelet transform.

Feature Extraction

In this paper we are proposing combination of color features derived from histogram moments & texture features derived from co-occurrence matrix.

Color Features Extraction : many methods are available to extract color information from an image. One of the method is color histogram.. color histogram provides the distribution of colors within image or within interested region of an image. The important property of histogram is that it is invariant to rotation, translation & scaling . The color histogram H for an image is defined as

$$H = \{h[1], h[2], \ldots . h[i], \ldots . h[N]\} \qquad (1)$$

Where,

$'i'$ represents a color in the color histogram,

$h[i]$ is the number of pixels in color $'i'$ in the image, N is the number of bins in the color histogram.

To compare images of different sizes, the color histogram needs to be normalized[4]; it leads to better views of structure in the image[6]. The normalized color histogram H' is defined as :

$$h'[i] = \frac{h[i]}{XY} \qquad (2)$$

In order to reduce the feature vector dimension center moments are used to describe histogram. The center moment and mean is defined[6] as:

$$\mu_n = \sum_{i=0}^{L-1} (z_i - m)^n \, h(z_i) \qquad (3)$$

$$m = \sum_{i=0}^{L-1} z_i \, h(z_i) \qquad (4)$$

Where ,

$'$ n' is moment order,

$, h(z_i)'$ is normalized histogram ,

$'z_i'$ is gray level

'm' is mean

As per (3), zero order moment is 1 and first order moment is zero; hence mean, second order moment called variance & third order moment called skewness are used in this paper. These are sufficient to describe the histogram distribution .

Feature extraction can be achieved by using different color models . But due to its perceptual uniformity, we perform the feature extraction in HSV space[13]. The HSV color space is a non-linear transform of the RGB-cube. It is widely used in the field of color vision. The chromatic components hue, saturation and value correspond closely with the categories of human color perception. The HSV values of a pixel can be transformed from its RGB representation according to the following equations :

$$H = \text{arcten}\frac{[3^{\frac{1}{2}}(G-B)]}{[(R-G)+(R-B)]} \quad (5)$$

$$S = 1 - \frac{\min(R,G,B)}{V} \quad (6)$$

$$V = \frac{(R+G+B)}{3} \quad (7)$$

To get color moment feature set following steps are executed

- The RGB images is preprocessed .
- The image is converted into HSV Component.
- Histogram equalization is done for three component
- Calculate first , second & third order moment for the three components' histogram respectively.
- Steps 1 & 4 are executed for all images.

Texture Feature Extraction: To extract texture features gray level co-occurrence matrix is used.

It considers the spatial relationship of pixels. It is also known as the gray-level spatial dependence matrix. The co-occurrence matrix C(i,j) counts the co-occurrence of pixels with gray values i and j at a given distance d. The o-occurrence matrix is defined as[4] :

$$C(i,j) = \text{cord}\left\{\begin{array}{c} ((x1,y1),(x2,y2)) \in (XY) \times ((XY) \\ \text{for } f(x1,y1) = i, f(x2,y2) = j \\ \\ (x2,y2) = (x1,y1) + (d\cos\theta, d\sin\theta); \\ \text{for } 0 < i,j < N \end{array}\right\} \quad (8)$$

Where,

d' is a distance defined in polar coordinates(d, θ) with discrete length and orientation. Practically θ takes values as 0°,45°, 90°,135°, 180°, 225°,270° and 315°.

$\text{cord}\{.\}$ is number of elements in the set.

The dimension of the co-occurrence matrix is N $\times$ N Hence the computational complexity of the co-occurrence e matrix depends on the number of gray scales used for quantization. Various features like energy, inertia, correlation, entropy can be extracted from the co-occurrence matrix to reduce the dimensionality of feature set. The formal definition of the above features is [14]:

$$\text{Inertia} = \sum_i \sum_j (i-j)^2 \; c(i,j) \quad (9)$$

Inertia is also known as variance and Contrast. It measures the local variations in the gray-level co-occurrence matrix.

$$\text{Correlation} = \frac{\sum_i \sum_j (i-\mu_i)(j-\mu_j)c(i,j)}{\sigma_i \; \sigma_j} \quad (10)$$

It measures the joint probability occurrence of the specified pixel pairs.

$$\text{Energy} = \sum_i \sum_j c(i,j)^2 \quad (11)$$

It provides the sum of squared elements in the gray-level co-occurrence matrix. It is also known as uniformity or the angular second moment.

$$\text{Homogeneity} = \sum_{i,j} \frac{c(i,j)}{1+|i-j|} \quad (12)$$

It measures the closeness of the distribution of elements in the gray-level co-occurrence matrix to the gray-level co-occurrence matrix diagonal.

For equation (9)-(12)

$$\mu_i = \sum_i i \sum_j c(i.j)$$

$$\mu_j = \sum_j j \sum_i c(i.j)$$

$$\sigma_i = \sum_i (i-\mu_i)^2 \sum_j c(i,j)$$

$$\sigma_j = \sum_i (j-\mu_j)^2 \sum_j c(i,j)$$

Following steps are executed to get the texture features:

- Convert RGB color image to gray image.
- Obtain co- occurrence matrix for different offset values specified by of 'd' (distance between the pixel of interest and its neighbor) and angle 'α'.
- From the properties of co-occurrence matrix obtain the statics like correlation, inertia (contrast), energy & homogeneity.
- Repeat Steps 1 to 3 for all images.

Experimental Results

The experiment is carried with diseased leaf images of Maize in MATLAB image processing toolbox. For experimentation 10 different leaves of the MAIZE affected by gray spot & common rust disease are used. The diseased leaves are as shown in figure 1 .

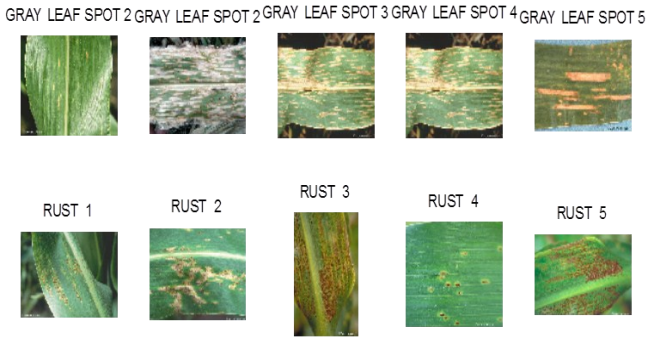

Fig. 1- Diseased Leaf Images of Maize

Color Moments: For each of the diseased leaf color moments are calculated by executing steps (1) to (5) given in section 3. Only first order (M1-Mean) second order (M2-Varience) & third order (M3- Skewness) moments of equalized histogram of HSV images are computed. Hence for single leaf total 9 moment features are obtained.

Figure2 gives the details of execution. For all images same steps are executed and color moment feature are obtained which are tabulated in table1.

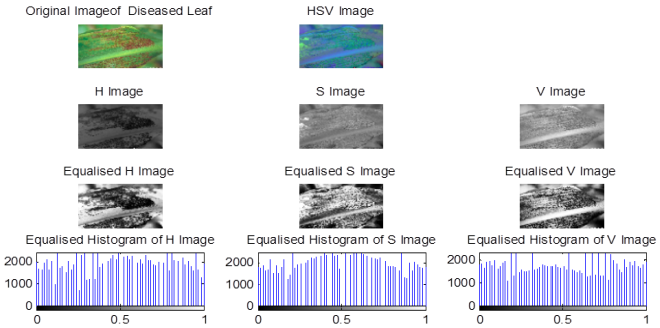

Fig. 2- Execution flow for Color Histogram Moment feature extraction

Table 1- HSV Histogram Moments

Image	H			S			V		
	M1	M2	M3	M1	M2	M3	M1	M2	M3
Gray leaf spot1	0.4567	1	1.1994	0.4567	1.0181	1.2159	0.4567	0.9598	0.3267
Gray leaf spot2	0.5552	2.326	4.27	0.5552	1	1.1832	0.5552	0.9982	0.6066
Gray leaf spot3	0.5906	1.254	1.6605	0.5906	1.1277	1.4586	0.5906	1.1083	1.0536
Gray leaf spot4	0.4573	1.349	2.0154	0.4573	0.8802	1.1444	0.4573	0.827	0.5833
Gray leaf spot5	0.5198	1.67	2.9348	0.5198	0.9796	1.1735	0.5198	0.9653	0.956
RUST1	0.4843	1.062	1.3692	0.4843	0.9159	1.101	0.4843	0.855	0.4931
RUST2	0.5231	1.193	1.6412	0.5231	1.0904	1.381	0.5231	0.9319	0.5675
RUST3	0.4714	1.254	1.8169	0.4714	1.838	1.9743	0.4714	0.8369	0.7606
RUST4	0.5889	1.719	2.5712	0.5889	1.4089	1.8678	0.5889	1.2345	1.4696
RUST5	0.4522	0.85	1.0132	0.4522	0.8813	1.0761	0.4522	0.8126	0.6471

Texture feature: The texture feature are obtained from gray level co-occurrence matrix of each diseased leaf image by executing steps (1) to(4) of section 3.

These steps are executed for all 10 images for d=1 & various values of α (0º,45º,90º &135º) . Table 2 gives the details of texture feature obtained.

Conclusion

This paper describes a possible approach for extraction of low level image features like color & texture. This approach can be used for the agricultural applications like detection & classification of diseases of plant parts like leaf with suitable classifier like 'Nearest Neighbor Classifier'. Further these features can be used for image retrieval in CBIR systems.

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Table 2- Texture Features

Features \ Image	Gray leaf spot1	Gray leaf spot2	Gray leaf spot3	Gray leaf spot4	Gray leaf spot5	RUST1	RUST2	RUST3	RUST4	RUST5
					d=1,α=0º					
Inertia	0.18418	0.56311	0.16664	0.18949	0.14711	0.28169	0.16401	0.257	0.15378	0.16985
Correlation	0.96424	0.83973	0.97169	0.91895	0.91243	0.92329	0.94022	0.78451	0.78333	0.86273
Energy	0.12415	0.10353	0.14572	0.21925	0.31835	0.13394	0.20049	0.24401	0.34637	0.26533
Homogeneity	0.91087	0.80223	0.92585	0.91384	0.93255	0.88875	0.92666	0.88772	0.92803	0.92054
					d=1,α=45º					
Inertia	0.45405	0.59875	0.47043	0.271	0.26567	0.36141	0.35794	0.33347	0.30284	0.26719
Correlation	0.91145	0.82979	0.91976	0.88404	0.84136	0.90175	0.86946	0.72031	0.57241	0.78072
Energy	0.082156	0.09987	0.10754	0.19646	0.2802	0.12541	0.15988	0.22402	0.27602	0.23627
Homogeneity	0.81092	0.79336	0.83723	0.88147	0.88598	0.87044	0.85948	0.86324	0.86287	0.88749
					d=1,α=90º					
Inertia	0.42569	0.23939	0.43716	0.29517	0.22254	0.2263	0.31203	0.20191	0.29496	0.23479
Correlation	0.91696	0.93222	0.92538	0.87392	0.86703	0.93848	0.88612	0.83055	0.58352	0.80741
Energy	0.0444	0.14207	0.1107	0.19349	0.29252	0.14177	0.166	0.26528	0.27893	0.24607
Homogeneity	0.82001	0.89143	0.84593	0.87551	0.90309	0.90443	0.87014	0.91039	0.8659	0.89833
					d=1,α=135º					
Inertia	0.48664	0.62721	0.47263	0.40334	0.27136	0.28792	0.33374	0.30134	0.33877	0.29875
Correlation	0.9051	0.8251	0.91939	0.82741	0.83798	0.92173	0.87827	0.74724	0.52169	0.75481
Energy	0.079344	0.098815	0.10683	0.1769	0.27952	0.13024	0.16165	0.2329	0.26468	0.22568
Homogeneity	0.80229	0.78861	0.83485	0.84792	0.88916	0.88484	0.86351	0.8745	0.84947	0.875