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DISCRETE HOPFIELD NETWORK FOR CLASSIFICATION OF FOOD GRAINS

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ABSTRACT

This paper describes the technique of image analysis of different bulk grain samples with reference to use of neural network for automatic recognition and classification. The HIS model of the image is considered for extracting 18 color features. The classification is carried out using color and texture features. The Co-occurrence matrix is calculated to determine 27 texture features. A Discrete Hopfield Network, a type of Auto-associative neural network is used to recognize and classify given grain samples. It has the capability to learn and to store the data in the form of weights. Patterns (feature vectors) for different classes are stored and the network is tested by giving a test pattern. The network effectively associates the given pattern to the nearest stored pattern. The result of discrete Hopfield network is compared with Back-Propagation network (BP) for same set of grain samples. Computational time for Hopfield network is very less (few seconds). The classification accuracy is better for discrete Hopfield network.

Keywords: Co-occurrence matrix, color and texture features, Hopfield Neural Network.

I. INTRODUCTION

Image processing system became an alternative to manual inspection of grain samples for kernel characteristic properties and the amount of foreign material. During grain handling operations, information on grain type and grain quality are required at several stages before the next course of operation is performed. In the present grain -handling system, grain type and quality are rapidly assessed through visual inspection. This evaluation process is, however, tedious and time consuming.

The decision-making capabilities of a grain inspector (the one who grades the grains) is seriously affected by his/her physical condition such as fatigue and eyesight, mental state caused by biases, work pressure, and working conditions such as improper lighting, climate, etc. Owing to these facts, it is better; this task is carried out automatically. Computers are used successfully for classification of plants, recognition of leaves, gradation of roses, and diagnosis of plant diseases etc. using an artificial neural network approach. A methodology for the classification and gradation of different grains (for a single grain kernel) such as groundnut, Bengal gram, wheat etc. is described [1] [2] [7]. In determining the potential of morphological features to classify different grain species, classes, varieties, damaged grains, and an impurity, using statistical pattern recognition techniques, has been the main focus of much of the published research. Some researchers have tried to use color features for grain identification. Only limited work has been done to incorporate textural features for classification purposes. Efforts have also been made to integrate all these features in terms of a single classification vector for grain kernel identification.

Most of the published research mainly focuses on identifying a grain type from digital images acquired by placing kernels in a non-touching fashion. Such experiments are comparatively easier to perform in controlled situations, as in a research lab, but would be difficult to implement on site because of cumbersome setup requirements. Such systems generally require a device to present kernels in a non-touching manner, an independent conveyor belt assembly, and the typical imaging devices in order to perform the task in real-time. The algorithms for classification of grain type used with such images are based on morphological, color, textural features, and combination of two or more features. The pre-processing operations such as segmentation, background removal, and object extraction, which are a prerequisite to determining morphological features, are some of the most time-consuming operations. On the other hand, if the grain type has to be determined using images of bulk samples, many of the requirements of the previously described system become redundant. The imaging devices are to be mounted at the site and do not require a grain separation device. The image of bulk sample may be acquired by creating a flat layer of grain on a conveyor belt. Moreover, an image of a bulk sample does not contain individual objects in it, so it does not need to be pre-processed for background removal and object extraction.

The grain type classification using images of bulk samples is going to implement in this paper using color and textural features. Previous research suggests that a back propagation neural network is best suited for classification of cereal grains [1] [2] [7]. Based on that, the objective of this paper is to evaluate a neural network based classifier for classification of various types of grains using color and textural features extracted from images of bulk grain samples. The paper involves processing of images of different types of grains.

Extracting the features of the grains and finally developing a suitable neural network model to recognize the different types of grain images. Images of different grains are obtained using camera, and the color and texture features are extracted using image-processing techniques. These features are used to train the Neural Network-based classifier. The developed neural network model is tested for classification of different grains. The work carried out involves application of Image Processing, Pattern Recognition and Neural Network techniques.

Classification involves training and testing. In training phase the patterns which are nothing but set of features are stored in the network as a knowledge base. The strength of classification is tested by applying a test input. It is nothing but a test pattern. As soon as the test pattern is feed to the network the network will automatically find the closest pattern, which is more close to the stored patterns. Then this stored pattern, which is close with the given test pattern, is selected and the corresponding class to which the stored patter belongs is displayed and that is also the class, which the test pattern belongs.

The classification processes adopted by Hopfield is base on energy. Each pattern will have a specified energy, which can be calculated by the expression given in equation 3.1. Depending on this energy the classification is carried out, with the concept that a pattern which energy is close to the energy of the stored pattern is chosen and classified as belong to the class where the particular stored pattern belongs.

II. FEATURES EXTRACTION

The feature extraction algorithm development is done on a computer. The algorithm extracted 18 color and 27 textural features from bulk sample images [1] [2] [7].

Sample images

Ten sample images for each of the rice type are taken. Five images each of the rice types are picked randomly and their corresponding patterns are stored. The image samples shown in figure 1 are the images of those rice's which is to be stored in case of Hopfield network, at the same time this are also the images whose patterns are to be trained in case of back propagation network.

With these images as the input we have to extract the color features and texture features. The forty five combined features of each image are now feed to an artificial neural network. Here in this paper we are going to make a comparison between Hopfield and back propagation.

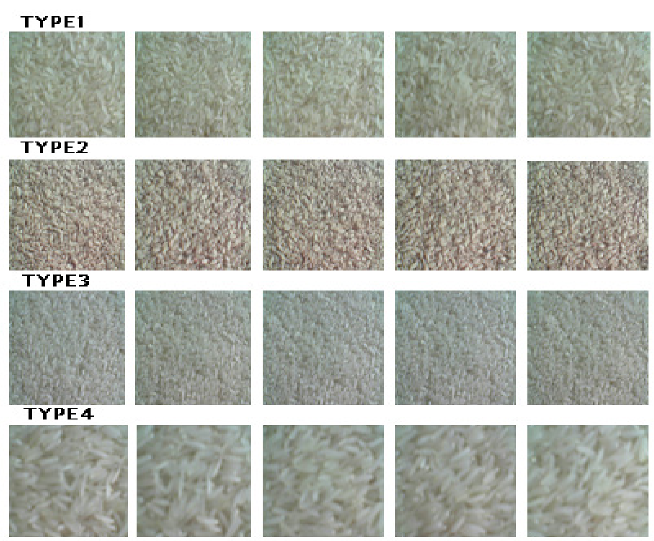

Fig1: stored rice image

Color Feature Extraction

The original 24 -bit color images are of size M*N*3 where M and N are the height and width of image respectively and 3 indicates the three 8-bit color components of the original images, viz. Red(R), Green (G), and Blue (B). From the original images, RGB components are separated and the Hue (H), Saturation (S) and Intensity (I) components are extracted from RGB components.

The components RGB & HSI are of size M*N. The mean, variance and range for all these 6 components are calculated and a total of 18 color features are stored suitably for later retrieval [1] [2]. The steps involved in color feature extraction are given in algorithm 1.

Algorithm 1: Color Feature Extraction

Input: Original 24-bit color image.

Output: 18 color features.

Start
Step 1: Separate the RGB components from the original 24-bit input color image.
Step 2: Obtain the HSI components from RGB components using the equations (2.1), (2.2) and (2.3).

$$\mathrm{H} = \begin{cases} \theta & \text{if } \mathrm{B} \le \mathrm{G} \\ 360 - \theta & \text{if } \mathrm{B} \succ \mathrm{G} \end{cases} \qquad \ldots \quad (2.1)$$

Where,

$$\theta = \cos^{-1}\left\{ \frac{\frac{1}{2}\left[(\mathrm{R}-\mathrm{G}) + (\mathrm{R}-\mathrm{B})\right]}{\left[(\mathrm{R}-\mathrm{G})^2 + (\mathrm{R}-\mathrm{B})(\mathrm{G}-\mathrm{B})\right]^{1/2}} \right\}$$

$$S = 1 - \frac{3}{(R+G+B)}\{\min(R, G, B)\} \qquad \ldots \quad (2.2)$$

$$I = \frac{(R+G+B)}{3} \qquad \ldots \quad (2.3)$$

Step 3: Find the mean, variance, and range for each RGB and HSI components.
Stop.

Texture Feature Extraction

Texture is a connected set of pixels that occur repeatedly in an image. It provides the information about the variation in the intensity of a surface by quantifying properties such as smoothness, coarseness, and regularity [1] [2] [7]. To describe texture features, the most widely accepted models are those that use the co -occurrence and run-length matrices [2]. In this study, we used the co -occurrence matrix. The co -occurrence matrix method of texture description is based on the repeated occurrence of some gray-level configuration in the texture. This configuration varies rapidly with distance in fine textures and slowly in coarse textures. Suppose the part of a textured image to be analyzed is an M * N rectangular window. An occurrence of some gray-level configuration may be described by a matrix of relative frequencies *Pf, d (x, y),* describing how frequently two pixels with gray -levels *x, y* appear in the window separated by a distance *d* in the direction *f.* A Co-occurrence matrix computation scheme is given in Algorithm 2.

Algorithm 2: Calculation of co-occurrence matrix
Pf, d(x,y) from the image f(p,q)
Input: Input gray level image (matrix of size *M*N*)
Output: Co-occurrence matrix *Pf, d (x,y)* for *d=1* in the direction *f* .
Start
Step 1: Assign *Pf, d (x,y)* =0 for all *x,y e [0,L],* where *L* is the maximum gray level.
Step 2: For all pixels *(p1, q1)* in the image, determine *(p2, q2)* which is at distance *d* in direction *f* and perform

$$P_{0,d}(x, y)=\sum_{p=1}^{n}\sum_{q=1}^{m}\begin{cases}1, & \text{if } f(p,q)=x \text{ and } f(p,q+\Delta y)=y\\ 0, & \text{otherwise}\end{cases}$$

… (2.4)

$$P_{45,d}(x, y)=\sum_{p=n}^{1}\sum_{q=1}^{m}\begin{cases}1, & \text{if } f(p,q)=x \text{ and } f(p-\Delta x, q+\Delta y)=y\\ 0, & \text{otherwise}\end{cases} \quad \text{… (2.5)}$$

$$P_{90,d}(x, y)=\sum_{p=n}^{1}\sum_{q=1}^{m}\begin{cases}1, & \text{if } f(p,q)=x \text{ and } f(p-\Delta x,q)=y\\ 0, & \text{otherwise}\end{cases} \quad \text{… (2.6)}$$

$$P_{135,d}(x, y)=\sum_{p=n}^{1}\sum_{q=m}^{1}\begin{cases}1, & \text{if } f(p,q)=x \text{ and } f(p-\Delta x,q-\Delta y)=y\\ 0, & \text{otherwise}\end{cases} \quad \text{… (2.7)}$$

Stop.

$$\text{Energy} = \sum_{x,y} P^2(x, y) \quad \text{…. (2.8)}$$

$$\text{Entropy} = -\sum_{x,y} P(x, y)\log_2(P(x, y)) \quad \text{…. (2.9)}$$

$$\text{Contrast} = \sum_{x,y} |x-y|^2 P(x, y) \quad \text{… (2.10)}$$

$$\text{Inverse difference moment} = \sum_{x,y;x\neq y} \frac{P(x, y)}{|x-y|^2} \quad \text{… (2.11)}$$

$$\text{Correlation} = \frac{\sum_{x,y}[(xy)P(x, y)]) - \mu_x\mu_y}{s_x s_y} \quad \text{... (2.12)}$$

Where μ_x, μ_y are means and s_x, s_y are standard deviations defined by,

$$\mu_x = \sum_x x \sum_y P(x,y)$$

$$\mu_y = \sum_y y \sum_x P(x,y)$$

$$s_x = \sum_x (x-\mu_x)^2 \sum_y P(x,y)$$

$$s_y = \sum_y (y-\mu_x)^2 \sum_x P(x,y)$$

$$\text{Homogeneity} = \sum_{x,y} \frac{P(x,y)}{1+|x-y|} \qquad \text{… (2.13)}$$

III. CLASSIFICATION OF GRAINS

This section explains the ANN architecture, classification models, training, testing, & validation of neural network. ANN's are physical cellular systems, which can acquire, store and utilize experimental knowledge. Neural Networks have found applications in pattern classification, image processing, face and character recognition etc [1] [2] [3] [4].

Neural network model (classifier)

In this paper we are going to implement a Hopfield network [6]. There are four steps in the training process:

i) Assemble the training data.
ii) Create the network.
iii) Train the network.
iv) Test network response to new input.

A typical neural network model developed to classify the grains is as shown in Fig.2. The number of neurons is n, which is equal to the dimensionality of the input pattern vectors (Number of input nodes equals number of input features used).
Thus we should have 45 neurons for 45 features.

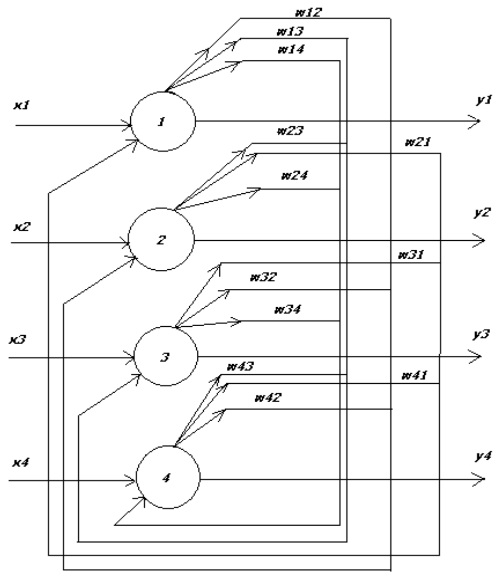

Fig. 2: Hopfield Network Model

Here we purpose a Hopfield network. The Hopfield neural network is a fully connected single layer auto associative network. This means it has one single layer, with each neuron connected to every other neuron. In this paper we will examine a Hopfield neural network with just four neurons. This is a network that is small enough that it can be easily understood, yet can recognize a few patterns. Hopfield neural network is a simple artificial network, which is able to store certain memories or patterns in a manner rather similar to the brain - the full pattern can be recovered if the network is presented with only partial information. Furthermore there is a degree of stability in the system - if just a few of the connections between nodes (neurons) are severed, the recalled memory is not too badly corrupted - the network can respond with a "best guess".

Hopfield network

A Hopfield net is a form of recurrent artificial neural network invented by John Hopfield. Hopfield nets serve as content-addressable memory systems with binary threshold units. They are guaranteed to converge to a stable state. Training a Hopfield net involves lowering the energy of states that the net should "remember". This allows the net to serve as a content addressable memory system, that is to say, the network will converge to a "remembered" state if it is given only part of the state.

The Hopfield neural network is a simple artificial network, which is able to store certain memories or patterns in a manner rather similar to the brain - the full pattern can be recovered if the network is presented with only partial information. Furthermore there is a degree of stability in the system - if just a few of the connections between nodes (neurons) are severed, the recalled memory is not too badly corrupted - the network can respond with a "best guess". Of course, a similar phenomenon is observed with the brain - during an average lifetime many neurons will die but we do not suffer a catastrophic loss of individual memories - our brains are quite robust in this respect (by the time we die we may have lost 20 percent of our original neurons). The nodes in the network are vast simplifications of real neurons - they can only exist in one of two possible "states" - firing or not firing. Every node is connected to every other node with some strength. At any instant of time a node will change its state (i.e. start or stop firing) depending on the inputs it receives from the other nodes. To see this, think of starting the network with just one firing node. This will send a signal to all the other nodes via its connections so that a short time later some of these other nodes will fire. These new firing nodes will then excite others after a further short time interval and a whole cascade of different firing patterns will occur. One might imagine that the firing pattern of the network would change in a complicated perhaps random way with time. The crucial property of the Hopfield network which renders it useful for simulating memory recall is the following: we are guaranteed that the pattern will settle down after a long enough time to some fixed pattern. Certain nodes will be always "on" and others "off". Furthermore, it is possible to arrange that these stable firing patterns of the network correspond to the desired memories we wish to store!

Energy function

An important concept is to conceptualize the recall phase as an energy function.

$$E = -\frac{1}{2}\sum_{ij} W_{ij} a_i a_j \qquad \ldots \qquad (3.1)$$

If we think of the space of all possible states of the network as the configuration space (represented by a "region" then the stored patterns can be thought of as attractors. we can then imagine an energy landscape "above" this configuration space.

The central property of an energy function is that it is always decreasing (or remaining constant) as the system evolves according to its dynamical rule.

Key contribution of Hopfield net

- Conceptualized the network in terms of energy.
- Showed that an energy function exists for this network.
- Processing elements with bi-stable outputs are guaranteed to converge to a stable local energy minimum.
- May consist of a stable oscillating series providing that each state has the same "energy" as the previous one.

Strengths

- The ability to reconstruct entire patterns from partial or incomplete input – making it useful in noisy environment
- Well suited for applications that require the capability to remove noise from large binary patterns.
- Stability under asynchronous updating – making it appealing for integrated circuit implementations.
- Fault-tolerance.
- Applications include pattern matching and classification.

Algorithm:

Step 1: Determining the class.

- How many classes to be classified.
- How many patterns to be stored for each class.

Step 2: Determining the energy.

- Estimation of the stored pattern energy.
- Estimation of the test pattern energy.

Step 3: Energy comparisons.

- Comparing the energy of the test pattern with those of the stored patterns.

Step 4: Retrieving the stored pattern

- The stored pattern, which is having the energy more close to the test pattern, is selected and its corresponding class is displayed.

IV. RESULTS AND DISCUSSION

The results (Fig.3 & Fig.4) show that the Hopfield net is very simple to implement and does not have complex mathematical calculation. The energy function is easily calculated compared to each layer weight updating in Back-propagation network. The maximum computational time for Hopfield network is 9 seconds. But, for Back-propagation is 220 seconds. From the energy comparison bar chart 1, it is clear that the classification is well comfortable and efficient with the concept of comparing the energies. It has been shown that for all the twenty stored patterns the energy level more close to that of the test pattern energy (which is represented at the last) is the pattern where the test pattern belongs.

Fig .3: classifying different grain types

Fig .4: classifying different rice type

The test pattern belongs to eleventh to fifteenth stored patterns. Forty Image samples are taken to check the performance of the Hopfield classifier and the back propagation classifier. Ten for each rice type. It is found that for the same input patterns and for the same images, the Hopfield net is able to classify more accurately. The classification efficiency for both the network is represented in the chart 2 given below. It is found that Hopfield classify better. The first bar in each pair indicates the percentage classifications of Hopfield and the second bar indicates the percentage classification of back propagation network. By increasing the number of training patterns the classification performance of both the network is checked. The classification accuracy is same if both the networks have similar stored and test patterns. The Hopfield network performs better with distorted test patterns.

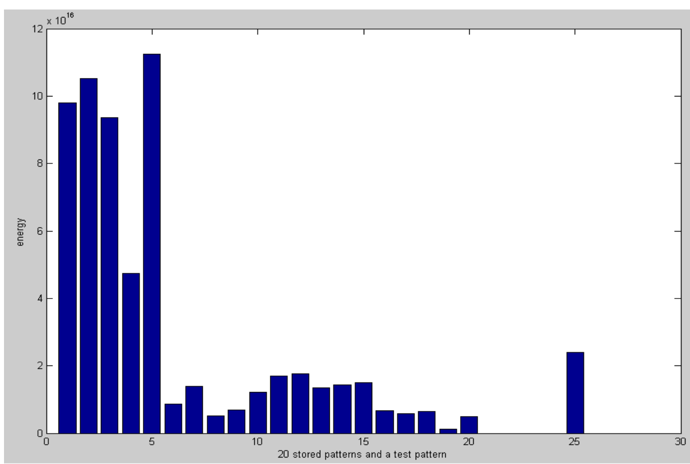

Chart 1: energy comparison of the test pattern and Patterns stored.

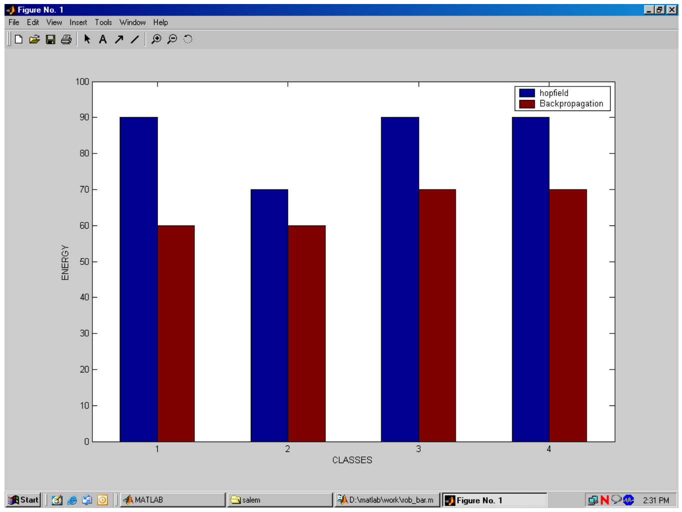

Chart 2: comparing hopfield and back propagation network
Computational time for hopfield ➔ 2.1870 sec
Computational time for B.P ➔ 215.5780 sec

V. CONCLUSION

It is evident that the Image processing systems are capable of replacing the human inspection system because of their high speed, precision and indefatigable operation. Image processing and pattern classification using Hopfield network (Artificial Neural Network) can be coupled together and used in a machine vision system for automatic recognition and classification of different grain samples. Bulk grain samples avoid the need of arranging the grain kernels in a non-touching fashion as in the case for the extraction of morphological features. The consistency of the results of this neural network classifier indicates that they are an apt choice to classify various agricultural products. This paper suggest that Hopfield network is highly suitable for classification of cereal grains

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