

Segmentation - Offset Based Image Classification

Monika Deswal^{*}, Nitu^{**}, Jitender Singh^{***}

^{*}Assistant Professor (EEE), PDMCEW, Bahadurgarh/ MDU University, Jhajjar, India)

^{**}Student, M.Tech(ECE), GITAM, Kablana/ MDU University, Jhajjar, India)

^{***}Assistant Professor (EEE), GITAM, Kablana/ MDU University, Jhajjar, India)

Abstract

In industrial applications, product identification is the most common thing now days. To kept in mind that we focus on the classification of our industrial product with the help of its texture using segmentation [7] and offset. Texture plays an important role in identifying the characteristics of an image/product. Image has visual features which are characterized as: (i) domain specific features like figure prints, human face etc. (ii) general features like colour, texture, shape. Texture of an image gives us information about the spatial arrangement of intensity values in an image or over the selected region of an image. We will describe the textural features based on gray-tone spatial dependencies.

Keywords: GLCM, Gray tone spatial orientation, Segmentation, Offset.

I. INTRODUCTION

We will classify our product with the help of texture and colour basis. Classification means characterising an image in some valuable form. We will use the concept of image processing in our analysis. There is a significant improvement in the image processing from last few years and its importance is still increasing day by day specially in the field of research. In normal language imageprocessing means processing an image using its features and if we are processing any image it means we need some useful information from it or we need to enhance the image features. So image processing is to convert or alter a image in some valuable form. Once the image is converted then we can apply some propson it like image compression or image enhancement, segmentation, so that we can either enhanced that image or extract some useful information from it.

The paper is organised as follows. In section 2 the overview of gray tone spatial dependency is given. In section 3 the Creating gray tone spatial dependence matrix is summarized. In section 4 Textural features are extracted from gray tone spatial dependence matrices.

II. CLASSIFICATION USING GRAY TONE SPATIAL DEPENDENCY

The image is usually stored as a two dimensional array. $L_x \times L_y$ is the resolution set which contains its pixel values , where $L_x = \{1, 2, \dots, N_x\}$ and $L_y = \{1, 2, \dots, N_y\}$ are spatial domains of X and Y. Image I is the function which assign gary to value, $I: L_x \times L_y \rightarrow G$. We can perform various two dimensional analysis on image I such that

classification, coding, enhancement, segmentation etc. Classification of pictorial data can be done on resolution basis [4]. Our basic aim is to determine the textural features with the help of gray-tone spatial dependencies where tone is associates with brightness. The concept of tone based on varying shade of gray level of resolution cell in an image and texture refers to the spatial distribution of gray level. Both tone and texture are present in an image, but there are possibilities that one concept dominates other at some point. Texture can be fine, coarse, smooth, etc. We will extract the set of textural features from the gray tone spatial dependence matrix of an image. The textural features like contrast, correlation, homogeneity, energy, variance etc. can be calculated that are required to compute any of these features which are proportional to the number of resolution cell in an image.

Texture refers to the arrangement of tonal variation in particular areas of an image. Rough textures consist of a mottled tone where the gray levels change abruptly in a small area. Whereas smooth texture would have very little tonal variation, so the dominant feature is tone [4]. So when small area of an image has little variation in gray tone then the dominant property of that area is tone. But when the small area of an image has large variations in tone then the dominant property of that area is texture. Tone refers to the relative brightness or colour of objects. When the size of the small area of an image is of one resolution cell, then it will have only one discrete feature, so there will be only tone property in that small area. As the number of discrete features in the small area is increases the texture property will dominate the tone property.

III. CREATING GRAY TONE SPATIAL DEPENDENCE MATRIX

Using Image Processing read the image from the sample. Then, determine its general features like colour and textural features. Let us take an image which will have N_x resolution cell in x-direction and N_y resolution cell in y-direction. The gray level of an image is given by N_g .

- 1) Read the image.
- 2) Take some cropped samples of above read image.
- 3) Convert these cropped images in the gray form.
- 4) Determine the GLCM of that image.
- 5) Determine multiple GLCMs by specifying the offset.
- 6) Determine Textural features like:
 - a) Contrast=contrast(image);
 - b) Correlation=corr(image);
 - c) Intensity=mean2(image);
 - d) Histogram=imhist(image);
- 7) To find image's colour feature find the average value of its RGB and then convert the excel of RGB into CSV file.
- 8) After that, we have a classifier for colour feature that is called NN network which has one input (CSV file) and other is target value (what we want to achieve) and provides the desired value.
- 9) This classifier provides to outputs that are (i) good quality (ii) bad quality.

Firstly we read the image our sample. Now if the given sample is in coloured form we need to convert it into gray level using `rgb2gray[2][3]`. After that we will determine the GLCM of the image. It will for the GLCM matrix from the image matrix. The gray-level co-occurrence matrix can give certain properties about the spatial distribution of the gray levels of the texture image. GLCM will determine how often a pixel with the intensity (gray-level) value i^{th} occurs in a specific spatial relationship to a pixel with the intensity value j^{th} . By default, the spatial relationship is defined as the pixel of interest and the pixel to its immediate right (horizontally adjacent). So we will determine multiple GLCMs by specifying the offset. This is done using the angular dependence of neighbouring gray level values which are evaluated at 45 degree increments and at varying distance intervals. The angular subsets are delineated by horizontal (0 degrees), right-diagonal (45 degrees), vertical (90 degrees), and left-diagonal (135 degrees). Distance between the neighbouring resolution cells can be assumed according to the requirement. In the below figure distance is taken as 1.

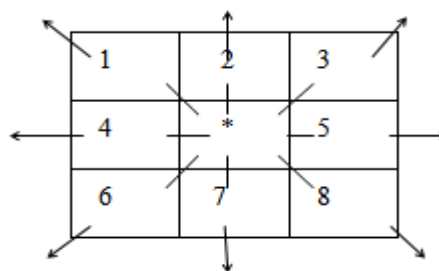


Fig. 1 Resolution cell and eight nearest-neighbour cells

The resolution cells 1 and 5 are 0 degree(horizontal). The resolution cells 7 and 3 are 90 degree(vertical). The resolution cells 8 and 4 are 45 degree(right diagonal). The resolution cells 6 and 2 are 135 degree(left diagonal). Suppose we have the image of 3 X 3. The matrix is given by.

0	0	1	1
0	0	0	1
0	2	2	2
2	3	3	3

The GLCM is created from the image matrix using the angular dependence of neighbouring gray level values which are evaluated at 45 degree increments and at varying distance intervals. The different angles will be 0degree, 45degree, 90degree, 135degree. The distance used in the above example is 1.

0degree

6	2	1	0
2	2	0	0
1	0	4	1
0	0	1	4

45degree

4	2	1	0
2	0	1	0
1	1	2	2
0	2	0	0

90degree

6	4	0	0
4	4	3	0
0	3	0	0
0	0	0	0

135degree

4	0	3	1
0	2	0	0
3	0	0	2
1	0	2	0

**IV. TEXTURAL FEATURES
 EXTRACTED FROM GRAY TONE
 SPATIAL DEPENDENCE
 MATRICES**

Once the gray levelspatial dependence matrices have been made from the image samples then we can extract various textural features from it like contrast, correlation, homogeneity, energy, entropy and many more. This work has been performed on the wood samples. Now we will extend this work further for the floor samples with the effect of light intensity.

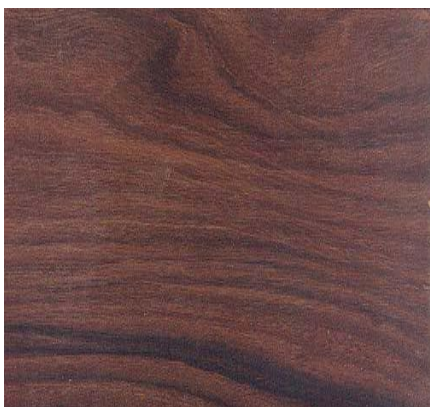
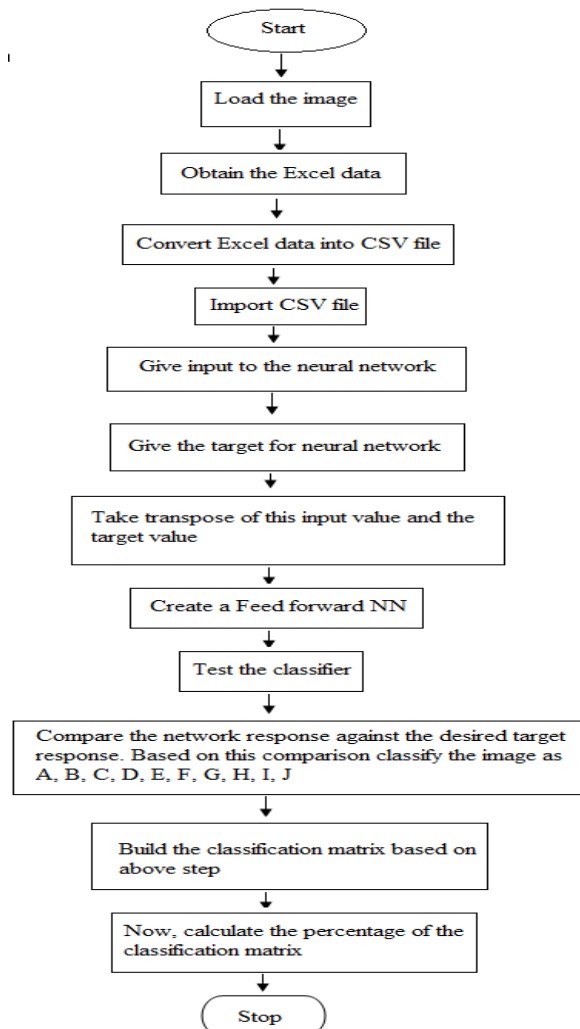


Fig. of various wood samples.

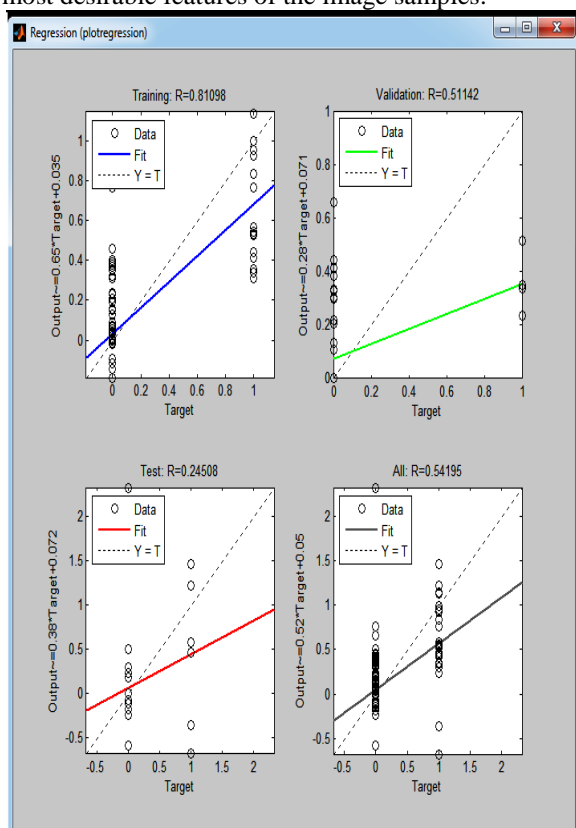


V. RESULT

The result obtained by neural network is shown in Regression window. There it is seen that

there are six control variables as Epoch, Time, Performance, Gradient, Mu, Validation checks. If one of the variables reaches up to its maximum value the training stage stops. As here, variable Epoch reach at its maximum value i.e. 1000 the training stops. The minimum and maximum values of all variables are written on left and right side resp. for corresponding variable. As Epoch variable cause to stop the training so, it is shown with green colour. As in whole training process all can see that total training epochs used to train network are 1000 epochs, total training time period is 37 seconds, system performance reached is $5.42e-13$ (means 5.42 multiplied by 10 raise to power -13), gradient is $1.46e-08$, factor Mu value is $1.00e-09$ and total validation checks are 0. These results shows the performance measurement plots using NN networks. By seeing these plots, take decision to retrain the network or let stay on that result. By retraining and studying these plots, finally decide the training decision and go to next step.

As there are four plots for different-different data points like $output=0.65*target+0.035$, $output=0.28*target+0.071$ etc. As target output minimum and maximum values are -1 & 1 and all data circles are around only these two values, so, regression plot is very good. The accuracy obtained through neural networks is 84.56%. that shows the most desirable features of the image samples.



VI. CONCLUSION

This paper has been described the significance of the image segmentation and offset method used to find a proper way to represent the meaningful contents of image in terms of general features like: human visual perception (colour features) and textural features. This method is can be applied in object recognition, content based image retrieval. The brightness (spatial-tone) of each pixel value correlates with the frequency of occurrence in the original image. For image database, we compare the distance between colour distribution images. This work has been performed on the wood samples.

The methodology introduced in this paper may be implemented for the industrial samples with the effect of light intensity. In which a light is imparted on a small portion of the floor sample to extract the textural feature which define the smoothening and coarseness of that samples.

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