AUTOMATED VISUAL INSPECTION: WOOD BOARDS.

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Abstract. The majority of scientific papers focusing on wood classification for pencil manufacturing take into account defects and visual appearance. Traditional methodologies are based on texture analysis by co-occurrence matrix, by image modeling, or by tonal measures over the plate surface. In this work, we propose to classify plates of wood without biological defects like insect holes, nodes, and cracks, by analyzing their texture. Each pencil classification within the plate is done taking into account each quality index.

1 Introduction

The industry automation tries to develop machines that can do complex tasks like human beings[1]. One of these is the vision ability. In industrial environment visual techniques are applied mainly in inspection and control, providing important resources to machines. Visual inspection applications refer to feature extraction, dimension measure of mechanical parts, shape classification and surface quality analysis[2].

This paper discusses a visual inspection methodology, by a neuro-fuzzy approach applied on plates of wood used in pencil industry. Nowadays, this inspection is done by trained people taking into account the visual homogeneity of each plate. Visual homogeneity is the wooden fiber distribution, or knots on the board surface, and it results directly the board quality[3,4]. The manual classification depends on humor, tiredness, physical and mental conditions of involved people. The visual homogeneity is used in this paper to define fuzzy variables in automated visual inspection system. The automatic classification time is considered because the system will be applied on the productive process.

The proposed methodology, applies Neuro-Fuzzy techniques, that uses fuzzy sets with artificial neural networks[5].

2 Plate classification

According to the industrial production and by taking into account the product quality and the market demand, the wooden plates used in this paper can be classified, concerning their visual homogeneity, as:

- Plate A: The best ones for pencil manufacturing. They have a better visual homogeneity (figure 1).
- Plate B: These plates need to have homogeneity in the majority of their area (figure 2).
- Plate C: Intermediate plates, and they have longitudinal stripes.(figure 3).
- Plate D: These plates have many longitudinal stripes (figure 4).
- Plate S: The worst plates for pencil manufacturing. Sometimes it is difficult to visually distinguish which area prevails. They will be reject in an industrial production line (figure 5).

Figure 1 - Plate A

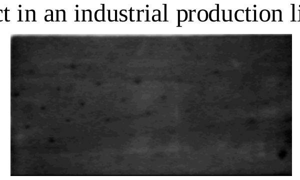

Figure 2 – Plate B

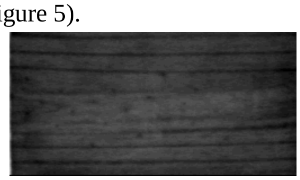

Figure 3 – Plate C

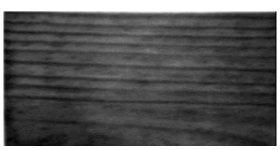

Figure 4 – Plate D

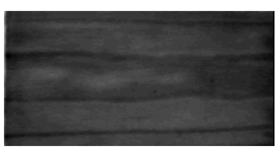

Figure 5 – Plate S

The most of authors have used statistical methods for classifying textures. One example is the use of co-ocurrence matrices [7,8]. The inconvenience with these methods is the great amount of processing time during the classification. The proposed method described in this paper is bounded by real time processing. We have to classify at least 150 plates by minute, due to industry needs.

3 Metodology

The applied approach for quality inspection of the plates is divided in six steps: image acquisition, pre-processing, feature extraction, Local Neuro Fuzzy Network (LNFN), Line Neuro Fuzzy Network or Partial Neuro Fuzzy Network (PNFN) for each area that corresponds to one pencil, and the Global Fuzzy Logic (GFL) for plate classification (figure 6).

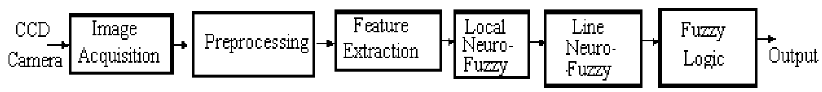

Figure 6 – Neuro-Fuzzy approach for plate inspection

1st Step – Image acquisition. The plate image is acquired by a Hitachi CCD camera and a frame grabber IRIS(DT-2858) with 128x256 pixels of spatial resolution and 256 gray levels.

2nd Step – Preprocessing. It's applied a linear transformation in order to contrast reinforcement[9] .
The gray levels are reduced from 256 to 32 levels by this equation. The advantage of this procedure is the sensibility reduction under to illumination conditions[24].

3rd Step – Feature extraction. The plate is divided in 36 regions with 9 rows and 4 columns. Each row is equivalent to one pencil manufacture. The four columns are empirically chosen. Four features are extracted from each region; three of them are gotten from histogram of difference between pixels and the fourth feature is the sum in each region line. The figure 7 shows these regions over the plate.

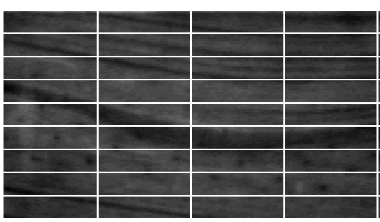

Figure 7 - Regions over the Plate

First order statistics like media, variance and kurtosis, gotten trough image histograms are limited as texture descriptors because it's not taken into account the relative position of all gray levels. Second order statistics like co-ocurrence matrices consider the pixel relative position, but have high computational costs. Working with first order statistics due their simplicity, and increasing their reliability we can establish one gray level local feature. This local feature could be the difference between two image pixels at a defined distance[11]. We can write the difference between two pixels as shown in equation 1:

$$Y(d) = |I(i,j) - I(i+\Delta_x, j+\Delta_y)| \qquad (1)$$

Where d is the established distance: $d = (\Delta_x,\Delta_y)$

So, the histogram $H(y_s,d)$ is the probability of the difference y_s to occur at a distance d. The histogram will concentrate around $y_s = 0$ if the texture is coarse and the distance small relatively to texture element size. The histogram will spread if the texture is fine and the distance is near to texture element size[11]. From the histogram we can extract the Angular Second Moment (ASM), the entropy, and the Inverse Difference Moment (IDM). Unser[10] and Levine[11] show several features that can be extracted from the histogram of difference. These features can be written as:

$$A1 = \Sigma[H(y^2_s,d)] \qquad \text{- ASM (or } 2^{nd} \text{ Moment)}$$

$$A2 = -\Sigma[H(y_s,d) * \log H(y_s,d)] \qquad \text{- entropy}$$

$$A3 = \Sigma[H(y_s,d]/(1+y^2_s) \qquad \text{-IDM (or homogeneity)}$$

As said by Kulkarni[12], all these features measure the image pixel homogeneity.

The fourth feature is the pixel summation in each region line. This summation is normalized by the highest value over all lines.

4th Step – Local Neuro Fuzzy Network. The four extracted features from each region are the inputs to each LNFN as can be seen in figure 10. This network has the input layer, the fuzzification layer, the rule layer, and the output layer. The input layer has four nodes due to the four extracted features. The fuzzification layer gets the membership value for each class, by membership functions generated through a graphical construction over 190 plates. These functions can be seen from figure 8 to 11.

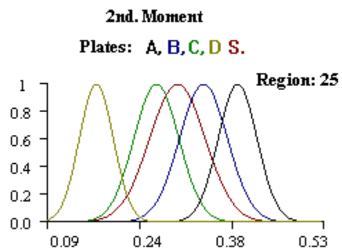

Figure 8 – Membership functions for 2^{nd} Moment.

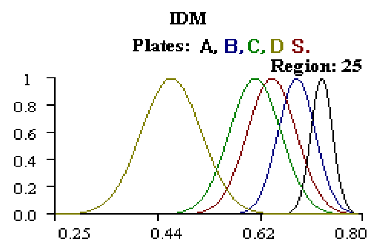

Figure 9 – Membership functions for IDM.

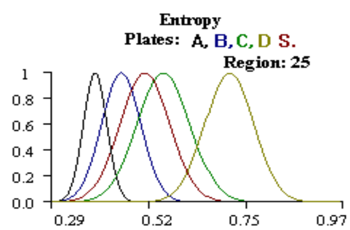

Figure 10 – Membership functions for Entropy.

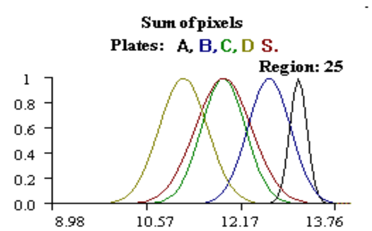

Figure 11 – Functions for Sum of pixels.

Each rule activation is done by the AND connective in the rule layer, and is usually defined as shown in equation 2:

$$\alpha_i = \min\{\mu_{2nd.Moment}, \mu_{Entropy}, \mu_{IDM}, \mu_{Sum\ pixels}\} \quad (2)$$

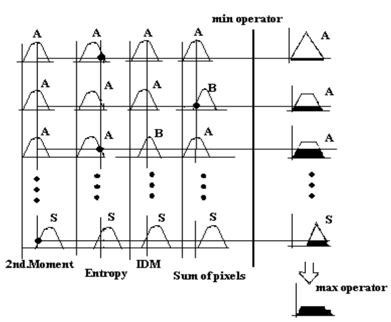

Figure 12 – Mandami Fuzzy Reasoning

In the output layer, the rules are put together by the union operator (OR). This methodology is known as fuzzy reasoning of Mandami, or Min-Max operator. Figure 12 shows the reasoning applied to the proposed work in this paper.

5th Step – Partial Neuro Fuzzy Network or Line Neuro Fuzzy Network. At this step, nine PNFNs are implemented , each one analyzing the four connected regions in a line over the plate. The network inputs are the outputs (A,B,C,D and S) from the LNFNs for each region of that line. The network output classifies a plate area that will produce a pencil in five separate classes.

6th Step – Global Fuzzy Logic (GFL). After each pencil area classification, the software will analyze the plate. This task is done by Fuzzy Logic through IF-THEN rules. Two rules are defined:

R1: If the majority of classified pencils belongs to a class, Then the plate belongs to this class.

R2: If the distribution of classes to one plate is the same, Then the plate belongs to the lower class.

Taking in account that Class S isn't good to pencil manufacture, we have:

R3: If a half of pencils over one plate belongs to S class, and these pencils are neighbor, Then the other plate half will be used to pencil manufacture and the plate will be classified using R1 and R2 rules.

R4: If a half of pencils over the plate belongs to S class and these pencils don't are neighbor, Then the plate will not be used to pencil manufacture and its class will be S.

4 Experimental results and conclusions

We create a simple and effective neuro-fuzzy methodology to classify patterns. The software quickly and easily classifies wooden boards into five classes. With the 199 plates we did the classification task, the results are showed in Table 1. The errors and right classification percentage are showed in Table 2. These results show that our methodology does a good plate classification and we are putting the software to operate on line in an industrial plant. We can't compare our system with other ones because we don't analyze plates with defects like insect holes and cracks. The plates are preprocessed and the approach is applied in the quality control at the end of the industrial process. The results from Table 2 were compared with industry classification and the right results are based on this information. Of course, the classification depends on the specialist over consideration and the results are indeed subjective. A new input could be added to the neural network named demand. The human operator could introduce this value controlling the network output. We could control illumination over the scene and increase network reliability.

Plates Desired\ gotten	A	B	C	D	S
A	9	2	0	0	0
B	7	27	2	0	0
C	1	2	45	3	4
D	0	0	4	30	1
S	0	0	12	5	45

TABLE 1 – Classification results considering 199 plates.

Class	Right Class	Wrong results	% right	% errors
A	9	2	81.81	18.19
B	27	9	75	25
C	45	9	83.33	16.67
D	30	5	85.71	14.29
S	45	17	75.68	24.32
Total	143	35	80.3	19.7

TABLE 2 - Right classification and errors

With the gray levels' reduction and by the difference of histogram, the method is strong and illumination independent. The MIN-MAX neurons are simple mathematical operations. This assures a reasonable speed during process production. The processing time for one plate classification was about 0.39 seconds. Our system classifies 153 plates by minute. This processing time could be reduced by changing the processor. Nevertheless, our system, with the implemented features, shows compatibility with industry needs.

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