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QUALITY CONTROL OF WOODEN PLATES BY NEURO-FUZZY APPROACH.

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Abstract: Visual Inspection is an important task for industrial productivity. It could be applied for quality control or for replacing manual work under dangerous or repetitive activity. The classification stage in control quality of the industrial production is often based on the human knowledge and valuation. It seems, therefore, to be a great concern supplying an automated visual inspection system with fuzzy or ambiguous data. The Neuro-Fuzzy system is a good way to do this.

This paper discusses a visual inspection application for the quality control of wooden plates that are used in pencil manufacturing. A Neuro-Fuzzy approach was adopted based on fuzzy variables extracted from human knowledge. Two types of neuron (MIN and MAX) do the basic processing, classifying the plates within compatible time and with the industry requirements.

1 - INTRODUCTION

Classical and Fuzzy proposition basically differs on their output values[1]. The domain of a conventional pattern recognition system is set at true (1) or false (0). Otherwise, the fuzzy domain is set at interval [0,1] where each output value is the membership grade of the variable. Thus, an output zero (0) means that the variable isn't a class member and an output one (1) means 100% of confidence for belonging to the class.

The human brain is able to work with a great amount of visual information, although this information has noise, inconsistency, fuzziness, or probabilistic variables [2]. The brain is reliable and fault tolerant. Even if some brain neurons die daily it has the same performance. However, when the human brain does a repetitive task for a long time, it could fail due to tiredness, humor, mental state and physical condition.

Either for human brain or for digital processing, the images frequently have uncompleted or ambiguous data [3]. One way for implementing an artificial pattern recognition system that approximates brain features, is merging the fuzzy concepts with artificial neural networks [4]. The fuzzy system is able to model uncertainty and ambiguous data frequently found in the real life.

This paper discusses a visual inspection application for the quality control of wooden plates, that are used in pencil manufacturing, by a neuro-fuzzy approach. Several people are trained for inspecting wooden plates taking into account their visual homogeneity during the industrial production of pencils. This visual homogeneity is the visual distribution of fibers and nodes over the plate surface causing its quality [5]. This distribution is visually estimated on the manual classification. We use the visual homogeneity, in this paper, to define fuzzy variables in automated visual inspection. We consider, also, the automatic classification time because the system will be applied directly on the productive process.

2 - WOOD DEFECTS CLASSIFICATION

The majority of industry problems, that uses wood as raw material, is on the quality control. Nodes are natural structures that endanger the end product. Cracks and holes, besides another non visual detectable defects, decrease productivity. The pencil industry, for example, uses wooden plates normally of pine, previous shaped. The visual inspection is doing by a trained human element. The classification speed is about 100 to 120 plates by minute. Several papers have been published with image processing classical algorithms for defect classification or for node study.

Steele et al. [6] use the slope of pixel direction for classifying plates without defects from bad ones. Their work detects holes, cracks and nodes. Applying Steele solution on our wooden plates, the pixel direction has little difference, because our plates are very similar between then. So, the pixel direction didn't give good results for this specific application.

The statistical classifiers are traditionally used for defect classification. Koivo & Kim [5] have used mean, median, and minimum and maximum counting for classifying two or three wood classes. One class represents the good ones (homogeneous) and other ones represents wood with holes or nodes.

By preliminary studies, mean and variance, didn't give sufficient information for classifying our boards. The wooden plates aren't similar. They have a

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strong visual difference. Our classifier works on plates without holes or cracks, but with only texture variation.

Neural networks and Fuzzy logic seem to be good tools. Once the network was trained the execution time is generally small. The objective of this work is real time application.

3 - ARTIFICIAL NEURAL NETWORKS AND FUZZY LOGIC

Fuzzy logic allows to implement classification systems with non binary output within the interval [0,1]. If x is a generic element of an X set, the fuzzy set of A in X is: $A=\{(x,\mu_A(x)) / x \in X\}$ where $\mu_A(x)$ is named the membership function of x in A. The membership function maps each X element in a continuous membership value between 0 and 1.

3.1 - Fuzzy Neurons

The Maximum Fuzzy Neuron does the union of two fuzzy sets (A and B). It's called AND neuron. It takes the input in $X = [x_1\ x_2\ \ldots\ x_n]$ operating over then in the connections with the weights $w = [w_1\ w_2\ \ldots\ w_n] \in [0,1]$ and then does the global AND with these results. This union operator is defined as: $y = AND(x;w)$ or $y = T^n_{i=1}[x_i\ s\ w_i]$ where t and s are used for representing the AND and OR operation, respectively.

The Minimum Fuzzy Neuron does the intersection of two fuzzy sets (A and B). It's called OR neuron. Its function is similar to the AND neuron. It takes the input in $X = [x_1\ x_2\ \ldots\ x_n]$ operating over then in the connections with the weights $w = [w_1\ w_2\ \ldots\ w_n] \in [0,1]$ and then does the global OR with these results. This intersection operator is defined as:

$y = OR(x;w)$ or $y = S^n_{i=1}[x_i\ t\ w_i]$

The task of these neurons is selecting among several output levels, one that corresponds to a given input.

The Competitive Neuron compares its state with a threshold (T) gotten from previous layer and it has a binary output (0 or 1). This operator is defined as:

$$y_m = g[s_m - T] = 0 \quad \text{if } s < T \quad \text{or}$$
$$= 1 \quad \text{if } s \geq T$$
$$T = \max(\,t[c_1, c_2, \ldots\, c_k]\,)$$

where the t is the threshold function $s_m = \sum w_i * x_i$

3.2 - Fuzzy rules

The fuzzy rules could be classified in three types, according to its consequent form [7]:

Type 1: Fuzzy rules with a constant consequence.

R_i : If X_i is A_{i1} and .... and X_m is A_{im}
then Y is c_i

Type 2 : Fuzzy rules with a consequent linear combination.

R_j : If X_j is A_{j1} and .... and X_m is A_{jm}
then Y is $g_j(x_1, \ldots, x_m) = b_0 + b_1x_1 + \ldots + b_mx_m$

Type 3 : Fuzzy rules with a consequent fuzzy set.

R_k : If X_k is A_{k1} and ...... and X_m is A_{km}
then Y is B_k

where X and Y are the input and output variables, respectively. The linguistics terms A_{im} are fuzzy sets with a specific function (triangular, sigmoidal, trapezoidal). The c_i term is a constant value. The g_j term is a linear array of input variables, and the b_m terms are the constant coefficients. The B_k term shows another fuzzy set.

3.3 - Artificial Neural Networks

An Artificial Neural Network (ANN) is a set of nodes connected by direct links. Each node is a processing unit that applies one specific function between its input and its correspondent weight. The ANN's are classified, by their connection type, in feed-forward and back-propagation networks. In the feed-forward type, the signal flows from one output to one input in the next layer. In the back-propagation model there are links from one output to a previous layer input.

A Fuzzy Neural Network is set by the following layers [8]:

- The input layer (fuzzyfication): changes the input signal in a pertinence value to a class by mean of a function.
- The input of MIN (MAX) rules : applies the fuzzy operation AND (OR). The AND and OR rules could be implemented on different layers [7][8] or in the same layer [9]. The AND and OR operations could be also implemented in the same ruler [9].
- The output layer (defuzzyfication) : changes the fuzzy signal in a defined value.

Some researchers have used another layer like the matching layer [8]. This layer has a linguistic node as input with its output going to the rule layer. This layer is described by the difference function between the input and the correspondent weight.

4 - FUZZY VARIABLES FOR WOODEN PLATE CLASSIFICATION

The wooden plates, that we have used in this paper, will be classified in three classes taking into account the market demand.

- The A class plates are the best ones for pencil manufacturing. They have a good visual homogeneity. They don't have nodes, stripes and dark points on their surface (see Fig.1).

- The C class plates are intermediate plates. They have longitudinal stripes. These stripes are visually dark but their total area is smaller than the plate area (see Fig.2).

- The S plates are the worst plates for pencil manufacturing. They have different pigmentation due to nodes, surface defects and stripes. They will be

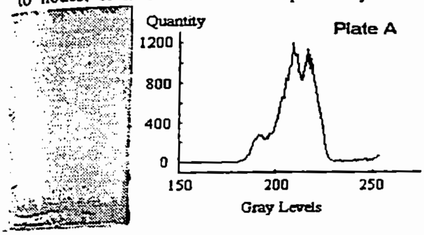

Figure 1- "A" class and its typical histogram

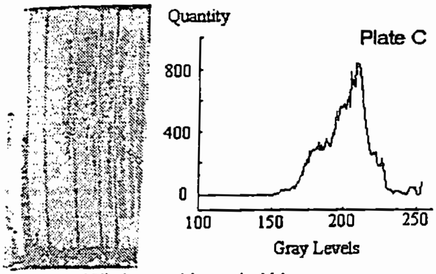

Figure 2 - "C" class and its typical histogram

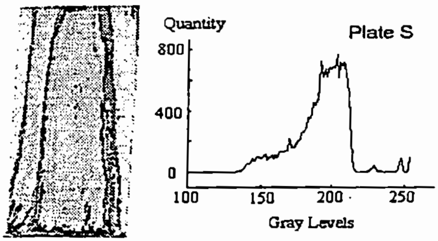

Figure 3 - "S" class and its typical histogram

reject in an industrial production line (see Fig. 3).

The wooden plates have a standard size due to the appropriate pre-processing. We theoretically suppose that the ideal histogram that represents a perfect plate would be shown by the equalized histogram in Fig. 4. The distributed gray levels on the surface would be equals. given security to visual homogeneity.

The pixel quantity on the plate surface is calculated by the area under pulse width of the equalized histogram. It would be constant for all perfectly ideal plates, so the "range width" showed in Fig. 4 would be constant, from plate to plate. A range width increase implies on a gray level change given a great possibility of existing nodes, stripes or defects on the plate surface.

The "elbow" is the limit of the smallest gray level on the plate surface and the highest gray level out of

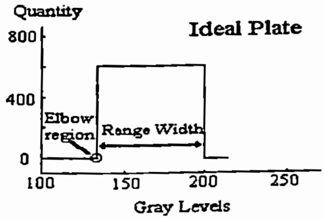

Figure 4 - Equalized histogram for an ideal plate

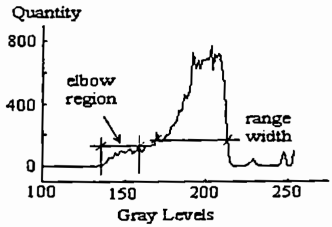

Figure 5 - Extracted features from histogram.

plate. This region width would be zero. Its derivative would be represented by only one point. This is shown by a 90° inclination from the highest level out of plate to the smallest gray level on the plate, considering the equalized histogram. An "elbow region" slope different from 90° would give information about some gray level quantity darker than the gray level under the "range width".

Therefore, changes at these parameters would be changes in the plate visual homogeneity, in a global way. Their quantities are fuzzy variables contributing for classifying the wooden plates.

By sampling the A, C and S plates, we could see by histogram analysis, that "S" class has the "range width" wider than "A" and "C" classes. So, this class has less pixel quantity by each level. "A" class has the "range width" slightly narrower than "C" class.

The most of authors have used statistical methods for classifying textures. One example is the use of co-ocurrence matrices [10][11]. 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.

We extracted the "range width" from histogram, taking into account the gray levels greater than a "K" value, as showed in Fig. 5. This feature gives the plate homogeneity. A narrow "range width" shows that the plate has a small quantity of gray levels. The more the "range width" increase, the more gray levels will be present on the plate surface. So, this quantity is used as a fuzzy variable giving the plate membership related to visual homogeneity.

The second fuzzy variable is extracted from histogram taking the point quantity at "elbow region". This region is gotten checking the peak level from histogram and thus, searching for the beginning of region slope. This quantity shows darker levels than the gray levels under the range width. This means nodes, stripes or defects on the plate surface. The fuzzy variable based on the "elbow region" is an inhibiting variable because this feature is stronger for "S" class.

The third fuzzy variable is need for discriminating the "C" from "A" class. The visual difference between then is the stripes in "C" plate. We do four transversal scans and then we count the number of crossed stripes. For the majority of the "A" class this number is small and for the "C" class this number is big. Moreover, the number of stripes in the "C" class is the same in any scan.

4.1 - Fuzzyfication

The neural network input layer has four nodes. The first one is the range width, the second one is the elbow region, the third one is related with the global contrast and the last one is the number of detected stripes.

By the histogram of 100 plates, front and back, we get the range width distribution showed in Fig. 6. By

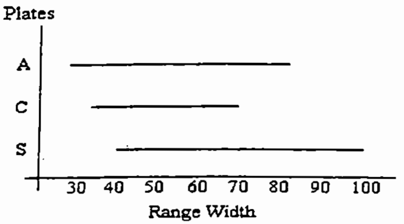

Figure 6 - Range width distribution

this graphic, we get the membership functions for the fuzzy variable named range width, as showed in Fig.7; a bell shaped function and a sigmoidal function.

The second input is the pixel number of elbow region. That's a good separator of bad plates ("S" class). It's an inhibitor input for the fuzzy rules. It does the general rules dependent from a specific input [9].

The third input is gotten by contrast enhancement and then by counting pixels in dark region. This pixel quantity gives the membership functions showed in Fig. 8.

The fourth input is gotten by taken the mean of the four quantities generated by the four transversal scans. That's a good variable for discriminating between "A" class and "C" class plates. The membership function for this fuzzy variable is showed in Fig. 9.

The inputs are then applied to the Neural Network of Fig. 10.

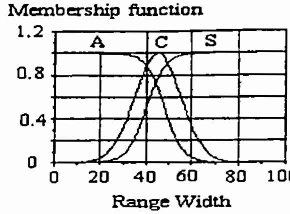

Figure 7 - Membership functions for range width

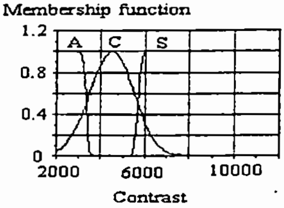

Figure 8 - Membership functions for global contrast

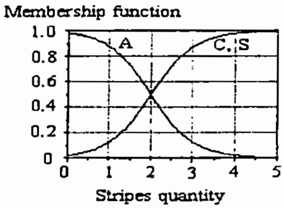

Figure 9 - Membership functions for stripes quantity

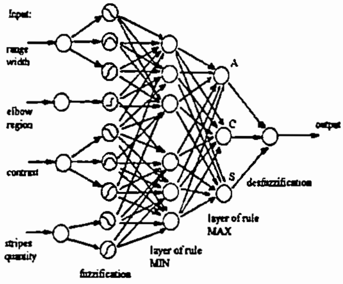

Figure 10 - Classifier based on Neural Network

4.2 - Fuzzy Implementation

The second network layer (fuzzyfication) processes the input through the membership function from each class (A, C, and S).

For fuzzy algorithms implementing we need a set of operators that will handle the fuzzy quantities described by the membership functions. These operators are the intersection (AND), the union (OR) and the implication (IF ... THEN...). The fuzzy rule layer of the network uses the union property described by Jang and Sun [12], that is:

$u_c(x) = \max\,(u_A(x),\, u_B(x))$ where A, B, and C are fuzzy sets.

The minimum fuzzy neurons are used in the output layer of membership functions, that is:

$u_c(x) = \min\,(u_A(x),\, u_B(x))$ where A, B, and C are fuzzy sets.

The last network layer classifies the plates by only one neuron. We are using the sigmoidal function setting up three bands. These bands refer to result of

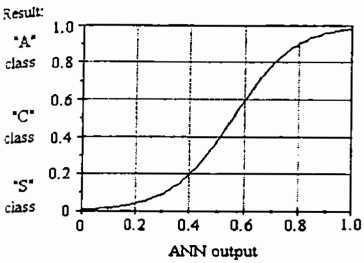

Figure 11- Neural Network output

classification for each plate and have the following values, as we can see from Fig. 11:
from 0.0 to 0.399 - "S" class
from 0.4 to 0.699 - "C" class
from 0.7 to 1.0 - "A" class

5 - EXPERIMENTAL RESULTS

We have used 20 wooden plates (front and back) for network training, previously classified: six plates from "A" class, seven plates from "C" class and seven plates

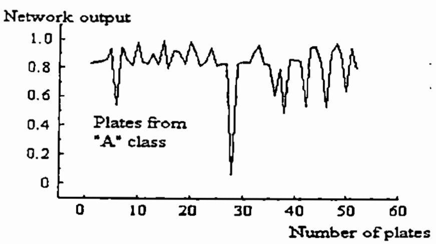

Figure 12 - Plate "A" classification

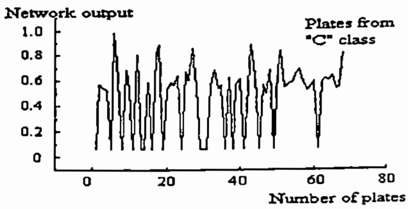

Figure 13 - Plate "C" classification

from "S" class. The output was taken from the intermediate point of output range for each plate (see Fig. 11) with a 0.01% of error.

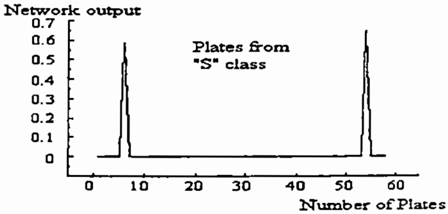

Figure 14- Plate "S" classification

With a test set of 89 plates the system processes 178 images, considering front and back plate sides. in real time. The Fig. 12, 13 and 14 show the network output for classifying plates from "A", "C", and "S" classes. respectively, with the results showed by Table 1.

TABLE 1 - Neural Network classification

Network Classification	Plates from "A" class	Plates from "C" class	Plates from "S" class
as "S" class	1	18	56
as "C" class	6	42	2
as "S" class	45	8	0

For network accuracy and reliability testing, we have taken one plate from each class, randomly, and submitted it 100 times to the network input. The Fig. 15, 16. and 17 show the results to "A"," "C", and "S" class respectively. It can be seen the high accuracy (repeatability) to "S" class. This class is easy to classify by visual inspection, due to node distribution on the surface. The same result was gotten in our implementation.

The "A" and "C" classes got good results. classifying the same plate within the same class all the time, without any error. This is an excellent result because these plates are difficult to classify by human visual inspection.

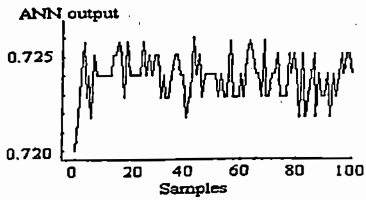

Figure 15 - Network reliability to the same plate from "A" class

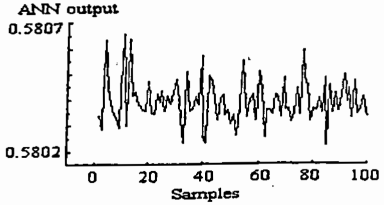

Figure 16 - Network reliability to the same plate from "C" class

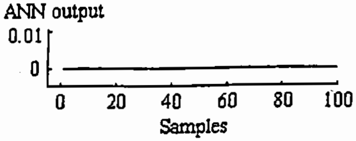

Figure 17 - Network reliability to the same plate from "S" class

6 - CONCLUSIONS

With the 178 images gotten from the 89 plates we did classification task. The errors and right classification percentage are showed in Table 2.

TABLE 2 - Right classification and errors

Class	Right Classification	Wrong results	% right	% errors
A	45	7	86.5	13.5
C	42	26	61.7	38.2
S	56	2	96.5	3.5
Total	143	35	80.3	19.7

These results show the excellent classification rate for "S" class plate, and a good classification rate for "A" class plate. The "C" class plate could be classified as "S" class or "A" class depending on demand. If demand is high, high values from "C" class could classify the plate as "A" class and low values as "S" class. If demand is low all "C" class could be classified as "S" class. 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.

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 is based on a 486 processor with a Data Translation frame grabber, and Hitachi camera mounted over a conveyer belt. It 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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