Wood texture classification by Fuzzy Neural Networks

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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. By this methodology we divide the plate image in several rectangular windows or local areas and reduce the number of gray levels. From each local area, we compute the histogram of differences and extract texture features, given them as input to a Local Neuro-Fuzzy Network (LNN). Those features are gotten from the histogram of differences instead of the image pixels due to their better performance and illumination independence. Among several features like media, contrast, second moment, entropy, and IDN, the last three ones have showed better results for network training. Each LNN output is taken as input to a Partial Neuro-Fuzzy Network (PNFN) classifying a pencil region on the plate. At last, the outputs from the PNFN are taken as input to a Global Fuzzy Logic (GFL) doing the plate classification. Each pencil classification within the plate is done taking into account each quality index.

Keywords: Computer Vision, Visual Inspection, Neuro-Fuzzy networks, Texture Classification, Wood classification, Pattern Recognition, Supervised Learning, Backpropagation Neural Network

1. INTRODUCTION

The industry automation tries to develop machines that can do complex tasks like human beings1. 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 analysis2.

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 quality3. 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. The utility of fuzzy sets lies in their ability to model the uncertain or ambiguous data so often encountered in real life4. Neural techniques are being researched for implementing classifiers that minimize the classification error rates, optimize training and classification time, and are adaptive and memory efficient5.
TABLE 1 – Classification results considering 199 plates.

<table>
<thead>
<tr>
<th>Plates Desired</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>S</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>9</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>B</td>
<td>7</td>
<td>27</td>
<td>2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>C</td>
<td>1</td>
<td>2</td>
<td>45</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>D</td>
<td>0</td>
<td>0</td>
<td>4</td>
<td>30</td>
<td>1</td>
</tr>
<tr>
<td>S</td>
<td>0</td>
<td>0</td>
<td>12</td>
<td>5</td>
<td>45</td>
</tr>
</tbody>
</table>

TABLE 2 - Right classification and errors

<table>
<thead>
<tr>
<th>Class</th>
<th>Right Classification</th>
<th>Wrong results</th>
<th>% right</th>
<th>% errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>9</td>
<td>2</td>
<td>81.81</td>
<td>18.19</td>
</tr>
<tr>
<td>B</td>
<td>27</td>
<td>9</td>
<td>75</td>
<td>25</td>
</tr>
<tr>
<td>C</td>
<td>45</td>
<td>9</td>
<td>83.33</td>
<td>16.67</td>
</tr>
<tr>
<td>D</td>
<td>30</td>
<td>5</td>
<td>85.71</td>
<td>14.29</td>
</tr>
<tr>
<td>S</td>
<td>45</td>
<td>17</td>
<td>75.68</td>
<td>24.32</td>
</tr>
<tr>
<td>Total</td>
<td>143</td>
<td>35</td>
<td>80.3</td>
<td>19.7</td>
</tr>
</tbody>
</table>

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.

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

8. REFERENCES


