Recent advances in intelligent inspection of wood boards

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ABSTRACT

Automated Visual Inspection (AVI) is being proposed for the task of inspecting wood sheets for quality control. The motivation for this is that currently, the human graders employed for the task can only perform inspection with an accuracy of around 60%. For wood inspection, AVI operates by employing a camera to acquire an image of the sheet and then utilising appropriate image processing hardware and software routines to find and classify surface defects. A typical AVI framework includes the stages of image acquisition, image enhancement, segmentation, feature extraction, classification and grading. The image acquisition stage obtains an image of the sheet. Image enhancement improves the quality of the acquired image to facilitate segmentation. Frequently, this stage is not used because it is considered more important to obtain high quality images. Image segmentation divides the image into clear wood and defect regions. The result of this stage is called the segmented image which contains objects that represent the defects. Then, feature extraction is employed to calculate numerical values to represent each object. The classification stage determines the type of each object based on its features. Finally, the board is given a grade based on the number of defects found and the size and severity of each one. Grading is a task which can be implemented with the aid of a grading table and a simple expert system. Therefore, it offers few opportunities for research.

This paper gives details of advances in the areas of image acquisition, image enhancement, segmentation, feature extraction and classification for Automated Visual Inspection of wood boards. Artificial intelligence techniques, such as neural networks, genetic algorithms and fuzzy logic, are concentrated upon.

1. INTRODUCTION

Automated Visual Inspection (AVI) is being proposed for the task of inspecting wood sheets for the purpose of quality control. Frequently, the major problem of grading wood boards is their very high rate of production. On a typical line, they travel at speeds of 2-3 metres/second. This makes reliable inspection by human operators very difficult and, in addition, operators quickly become tired and disinterested. Experiments have been performed which confirm that the accuracy of human wood graders is around 60% [Polzleitner and Schwingshakl, 1992].

For wood inspection, AVI operates by employing a camera to scan an image of the sheet and then utilising appropriate image processing hardware and software routines to find and classify surface defects. The framework includes the following stages [Pham and Alcock, 1998]:

- **image acquisition** to obtain an image of the sheet;
- **image enhancement** to improve the quality of the acquired image so that segmentation is easier. Frequently, this stage is not used because it is considered more important to obtain high quality images;
- **image segmentation** to divide the image into clear wood and defect regions. The result of this stage is called the segmented image which contains *objects* that represent the defects;
- **feature extraction** to calculate numerical values to represent each object;
- **classification** to determine the type of each object based on its features;
- **grading** to find the overall grade of the board being inspected based on the number of defects found and the size and severity of each one. Grading is a task which can be implemented with the aid of a grading table and a simple expert system. Therefore, it offers few opportunities for research.

This paper gives details of advances in the areas of image acquisition, image enhancement, segmentation, feature extraction and classification relating to the Automated Visual Inspection of wood boards. Artificial Intelligence techniques, such as neural networks, fuzzy logic and genetic algorithms, are concentrated upon.

2. IMAGE ACQUISITION AND ENHANCEMENT

Image acquisition is the first operation to be performed in the AVI process chain for wood inspection. When capturing an image of the board, it is desirable that the highest possible image quality is obtained. A superior quality image should make defects easier to locate and identify. Without a good quality image, it is difficult to inspect the surface accurately. Figure 1 shows an image of a wood board obtained using front and back illumination.

To acquire high quality images, it is necessary to pay careful consideration to the lighting which could be used and also the configuration of sensors in the system. Ambient lighting can seriously reduce the image quality, whereas well designed lighting enables defects to be more easily identified. Different sensor and lighting configurations are appropriate for detecting different types of defect. When using cameras to capture images, there are also other factors which need to be taken into account, for example, whether colour vision should be employed and the resolution of the images which is required. The image quality can also be reduced by conditions in industrial environments such as dust and dirt.

Image enhancement techniques may be used on the acquired image to make it more suitable for the subsequent processing stages. For wood analysis, this involves accentuating the defects so that they can be more easily differentiated from clear wood by the segmentation module. Morphology is a commonly employed method which can enhance defects [Batchelor and Whelan, 1997]. Morphological opening can be utilised to enhance dark defects whilst morphological closing enhances bright defects. However, most researchers do not utilise image enhancement, preferring instead to acquire an image of the highest possible quality in a highly-controlled environment.

3. SEGMENTATION

Many techniques have been suggested for segmentation but thresholding remains the most commonly utilised. Pham and Alcock [1996] found that thresholding is a useful technique but is not capable of detecting all defect types. Therefore, they proposed a modular approach for segmentation, consisting of four techniques, with each module optimised for different defect types:

- global adaptive thresholding for hard rot;
- multi-level thresholding for holes, rotten knots and splits;
- row-by-row adaptive thresholding for coloured streaks, pin knots, sound knots and worm holes;
- vertical profiling for streaks.

3.1 Global Adaptive Thresholding

For very large dark defects, such as hard rot, it is possible to apply the technique of global thresholding for segmentation. The threshold can be determined from the grey level histogram of the image. There are two basic types of histogram: *unimodal* and *multimodal*. A unimodal histogram has one central peak whereas a multimodal histogram has more than one peak. A special case of the multimodal histogram is the *bimodal* histogram which has two peaks. In the case of a unimodal histogram, it would normally be expected that the clear wood pixels are represented by the central part of the peak with dark defects represented by the tail on the left-hand side and brighter defects by the right-hand tail. An entirely defect-free board should also be represented by a unimodal histogram. With a bimodal histogram, the right peak should represent clear wood pixels and the left peak should represent dark defects. Very bright defects, such as splits and holes, would be denoted by a peak on the far right of a multimodal histogram. To determine the threshold, it is necessary to find the number of peaks contained within it. The reason for this is that the threshold is determined differently depending upon whether the histogram is unimodal or multimodal.

Finding the threshold from bimodal histograms has been widely studied and researchers have reported that the threshold should be placed at the valley in the histogram in order to segment the image [Gonzalez and Woods, 1992]. As previously mentioned, in an image of wood, if the histogram is bimodal then the rightmost peak should represent the clear wood. If the histogram is multimodal then only the two leftmost peaks should be considered. Peaks at the right of the histogram represent open defects such as splits or holes.

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Determining the best threshold from unimodal histograms is a more difficult task and no individual technique is recommended by all researchers. In the case of the images of birch wood, it was noticed that, for an image containing solely clear wood, the histogram approximately forms a normal distribution. From statistical theory it is noted that in a normal distribution, 95% of values will fall within a range of ± 2 standard deviations from the mean [Moore, 1995]. Using this information, the threshold was set at the mean minus two standard deviations.

3.2 Multi-level Thresholding

The second segmentation module used was multi-level thresholding. As well as clear wood pixels forming an approximately normal distribution, it was also observed experimentally that they fall within a range of grey levels in the central part of the histogram. It would be extremely unlikely for a clear wood pixel to have a very small or very large grey level. Therefore, it can reasonably be assumed that these pixels represent defects. Very dark pixels denote defects such as pin knots, sound knot centres and rotten knots. Very bright pixels, obtained when a back-light is used, represent mainly splits and holes. The advantage this method of thresholding is that it is extremely fast in hardware. It may be argued that using fixed thresholds could potentially produce incorrect results because clear wood could have grey levels above or below the chosen thresholds. However, if the thresholds are set at sufficiently high and low values, respectively, then no problems should arise. Indeed, if clear wood pixels do fall outside these thresholds then it is likely that a failure has occurred with a part of the system such as the lighting or the camera. In this case, it is unlikely that any method of segmentation would be able to segment the image reliably and so automatic grading should be stopped until the defective part of the system has been repaired or replaced.

3.3 Row-by-Row Adaptive Thresholding

The third segmentation module used was based on a row-by-row approach. In a real-time system, images from a conveyor belt are usually captured by a line-scan camera. Thus, valuable processing time would be saved if this information could be processed immediately as it is scanned. Practical work was carried out with an area-scan camera with an image size of 512 x 512 pixels but to simulate the operation of a line-scan camera, the image was split into 512 horizontal lines and these were processed in order from top to bottom.

The technique operates by taking the grey levels for the row in the image which is currently being scanned. First, very high and low grey levels in the row are replaced with more intermediate values. Then, the grey levels are smoothed by using averaging. Finally, the difference between adjacent pixels is reduced to below a pre-specified value. This technique gives *expected* values of pixels which can be compared with the actual grey levels of the pixels. If the calculated expected value of a pixel differs widely from its actual grey level then this gives evidence that the pixel represents a defect. The more a pixel's expected grey level differs from its actual grey level then the more likely it is that this pixel represents a defect.

This method finds defects in the horizontal direction but if there is a long horizontal defect then the expected values in the horizontal direction will not differ significantly from their actual values. For this reason, pixels were also compared with previous rows to check if they differed significantly.

3.4 Vertical Profiling

The fourth segmentation module was called vertical profiling. The method is used to detect streaks which are a defect caused in production by a notch in the peeling knife. The streak will be caused parallel to the direction of motion of the sheet on the conveyor belt. Because the sheet is thin, if a strong backlight is used then variations in sheet thickness cause differences in brightness. Therefore, streaks show up on the image as a dark vertical line. Vertical profiling operates by summing the grey levels of each vertical line in the image and creating an array of these values. A dark vertical line in an image can be found by searching for a valley in the profile.

3.5 Post Processing of the Segmented Image

After segmentation has been performed, two problems can be experienced. First, many areas, which are clear wood, may be detected as defects and, second, a defect may be represented by more than one segmented object.

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This gives rise to the need for an object processing stage after objects have been found. Two object processing techniques have been developed to overcome these problems. The techniques were inspired by the artificial intelligence techniques of fuzzy logic and self-organising neural networks.

Accumulation of Evidence is based upon fuzzy logic [Tanaka, 1997]. In fuzzy logic, statements are neither completely true nor false but have a truth value between 0 and 1. For example, the statement "This pixel is part of a defect" is neither true nor false but can be given an *evidence* value of it representing a defect. Then, the more evidence a pixel has, the more likely it is to represent a defect.

The method chosen to determine pixel evidence values was to calculate the difference between a pixel's actual grey level and the grey level that it would be *expected* to have if the whole board were clear wood. This expected value is generated from the grey levels of surrounding pixels and also from the usual grey levels of clear wood pixels i.e. intermediate grey-level values. A method for calculating these expected values is given in [Alcock, 1996]. In summary, the expected value is calculated in three stages:

1. very large and very small grey-level values are replaced with more intermediate values;
2. the image is smoothed using averaging;
3. the grey levels of pixels are adjusted so they differ by no more than a given amount from neighbouring pixels.

The larger the difference between a pixel’s grey level and the expected value, the higher is the evidence of that pixel representing a defect. Clear wood pixels should have zero or very low evidence values. The only defect type which gives any real problems using this method are sound knots. Sound knots do not differ greatly in grey level from clear wood. However, the grey-level values of sound knots can vary greatly across the diameter of the knot so that often their pixel values differ significantly from surrounding pixel values.

The next stage of the process is to group adjacent pixels into objects. Then, for each object, the total evidence is calculated. This is calculated by summing the evidences of all the pixels in the object. If the total evidence of an object is below a specified threshold, then it is removed from the segmented image. Therefore, small objects with grey levels close to those of clear wood are removed. The technique will not remove an object if it is large, because its total evidence will be large, or if its grey levels differ significantly from those of clear wood because this also increases the evidence.

A new method for clustering objects is proposed here which was inspired by a self-organising neural network architecture called *Adaptive Resonance Theory* (ART) [Chan, 1996]. In ART, the first pattern presented to the network creates a new neuron containing the attributes of the pattern. Subsequently, patterns are presented to the network and compared with those stored in existing neurons. If the new pattern is found to be *close* to a stored pattern then the neuron containing that pattern is updated so that its contents represent the new pattern and also all the patterns which were previously covered by the neuron. If the pattern is not deemed to be close to any of the stored patterns then a new neuron is created containing the attributes of that pattern. Whether a new pattern is close to a stored pattern depends upon a *distance function*.

The new object joining method has been implemented to operate in a similar manner to ART. First, four attributes are generated from the Minimum Bounding Rectangle (MBR) co-ordinates of each object. These are derived from the lines which define the position of the object and its MBR. Then, from these co-ordinates, the object's *area of interest* is found, having the same shape as the original but being two thirds larger. The value of two thirds was chosen empirically.

Objects are presented to the clustering neural network in order of size (largest first) and tested to determine whether their MBR co-ordinates are close to the attributes of any existing neuron. Each neuron has four attributes which define the position of its area of interest. The adopted distance function is such that if at least two of the corners of an object's MBR are within the area of interest of a neuron then the object is deemed close to the neuron and is assigned to that neuron.

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The attributes of the neuron are then updated so that its area of interest includes the area that it previously covered and also the area of interest of the new object. Then, the new area of interest of the neuron will be the smallest rectangle that can enclose the areas of interest of both the neuron as it was and the new object. If the new pattern is not close to any existing neuron then a new neuron is created with attributes equal to the co-ordinates of the four corners of the area of interest of the object.

Figure 2 shows the results of applying the segmentation techniques described here to the image shown in Figure 1. It can be seen that all defects are detected, no defect is marked as two regions and no clear wood regions are found.

3.6 Recent Work on Segmentation

The major problems with the technique of row-by-row adaptive thresholding are that it is slow and also time-consuming to understand and implement. Recent work on segmentation by the authors has found that an expected image can be derived using hardware-based functions such as convolutions to enable segmentation to be performed faster. The increased simplicity of this solution also means that there are fewer areas in which it can fail and therefore the technique is more robust.

4. FEATURE EXTRACTION

For the feature extraction stage, it is important to derive the most appropriate features to characterise each defect. Currently, there is no standard set of features and no method to determine which features to utilise.

As mentioned earlier, much research has been performed into improving segmentation and classification techniques. However, relatively little has been carried out on determining the best features to present to the classifier. It is important that features are selected carefully because they are the only information given to the classifier. There should be sufficient features to convey the relevant information to the classifier but features which may confuse the classifier, thus reducing its performance, should be avoided. There is no recommended technique for selection of the best set of features.

However, Castleman [1979] outlined some important factors which should be taken into account when selecting features:

1. for regions of different types, the features should take significantly different values;
2. for regions of the same type, the features should take similar values;
3. the features should be independent. Each feature should represent a different property;
4. the number of features should be kept to a minimum to enable easier classifier training.

Recent research on feature selection has been carried out by Drake and Packianather [1998b]. Their work was based on selecting features according to the first three of the above four criteria. In their method, three statistical measures are calculated for each feature: intra-class variation, inter-class variation and feature correlation. Then, a feature is rejected if any of the following are true:

1. its inter-class variation is below a threshold;
2. its intra-class variation is above a threshold;
3. it is highly correlated with another feature and is the worst performing of the two features.

Other recent work in feature selection for wood defects has employed Genetic Algorithms to derive the optimum feature vector [Estévez, 1998]. In this work, 55 features were originally selected but the genetic algorithm found that only 26 of these were needed for classification. This represents a reduction of more than 50% in the number of features which facilitates faster operation of the final classifier.

To overcome the problem of feature selection, Lampinen and Smolander [1996] employed a self-organising feature map (SOFM) to determine automatically features which can be used for wood defect classification. The pixel values from a window in the image are first passed through a Gabor filter before being presented to the SOFM. The SOFM clusters similar pixel distributions together. The output of the SOFM is then presented to a Multi-Layer Perceptron (MLP) neural network for classification. One problem with this technique is that very large training sets can be produced from each image and it is important to select a subset of these which accurately represent the whole set. Also, it remains to be proved whether features obtained using this method produce better results than those chosen conventionally.

Research was carried out by the authors into developing new features for wood defects and also to validate features which have been suggested before [Alcock, 1996]. The work presented thirty-two features that had been, or could be, employed for characterising wood defects. It then described a method of evaluating the abilities of subsets (vectors) of features to distinguish the various wood defect types. The method, which involved training a neural network to classify feature vectors, was utilised to find the most discriminating subset for this application.

A new type of tonal object features called linguistic features were described. These were compared with conventional first-order statistical features and found to perform better. Overall, the best performance was attained when object features were used together with window features. The best results, of 89.4%, were obtained using twenty-six of the thirty-two features.

5. CLASSIFICATION

The most common classification methods for wood defects have been rule-based classifiers and the MLP. Tests [Cho et al., 1991] comparing these techniques have revealed that the MLP is the superior method of the two. A benefit of the MLP is that it does not need the system developer to specify rules but rather “learns” by itself.

In the work of the authors on employing a MLP for wood defect classification, it was found that the momentum term was not useful for improving classification performance and that varying the number of hidden neurons did not affect results significantly [Alcock, 1996]. The learning rate was the most critical parameter and it was discovered that low values (around 0.1) were needed for good test set classification accuracy.

To improve upon these classification accuracies, the authors suggest the utilisation of Synergistic Classification Systems which combine several classifiers into one classification system. Alcock [1996] combined varying numbers of MLPs and different combining strategies, finding that combining three MLPs gave a small improvement in classification accuracy over just one MLP. Drake and Packianather [1998a] combined several MLPs into a tree structure and also found that it provided an advantage over using just one classifier.

One problem with neural networks is that they just behave as a "black box". That is, they make their decisions but it is very difficult to know why they generated such a decision. A possible future research area is inductive learning [Pham and Dimov, 1997], which derives rules from datasets. These rules enable the reasons why a defect was assigned a given class to be seen.

6. RESULTS

The techniques suggested by Alcock [1996] and Pham and Alcock [1996] for segmentation and classification gave performances of 93% and 92% respectively. This shows a considerable improvement over the 60% grading accuracy achievable by humans.

7. CONCLUSION

This paper has given details of recent research in the field of Automated Visual Inspection of Birch Wood Boards both by the authors and other researchers. It covered the areas of image acquisition, image enhancement, segmentation, feature extraction and classification. Current methods frequently employ artificial intelligence such as neural networks, fuzzy logic and genetic algorithms. Other techniques which have been utilised include modularisation and synergy.

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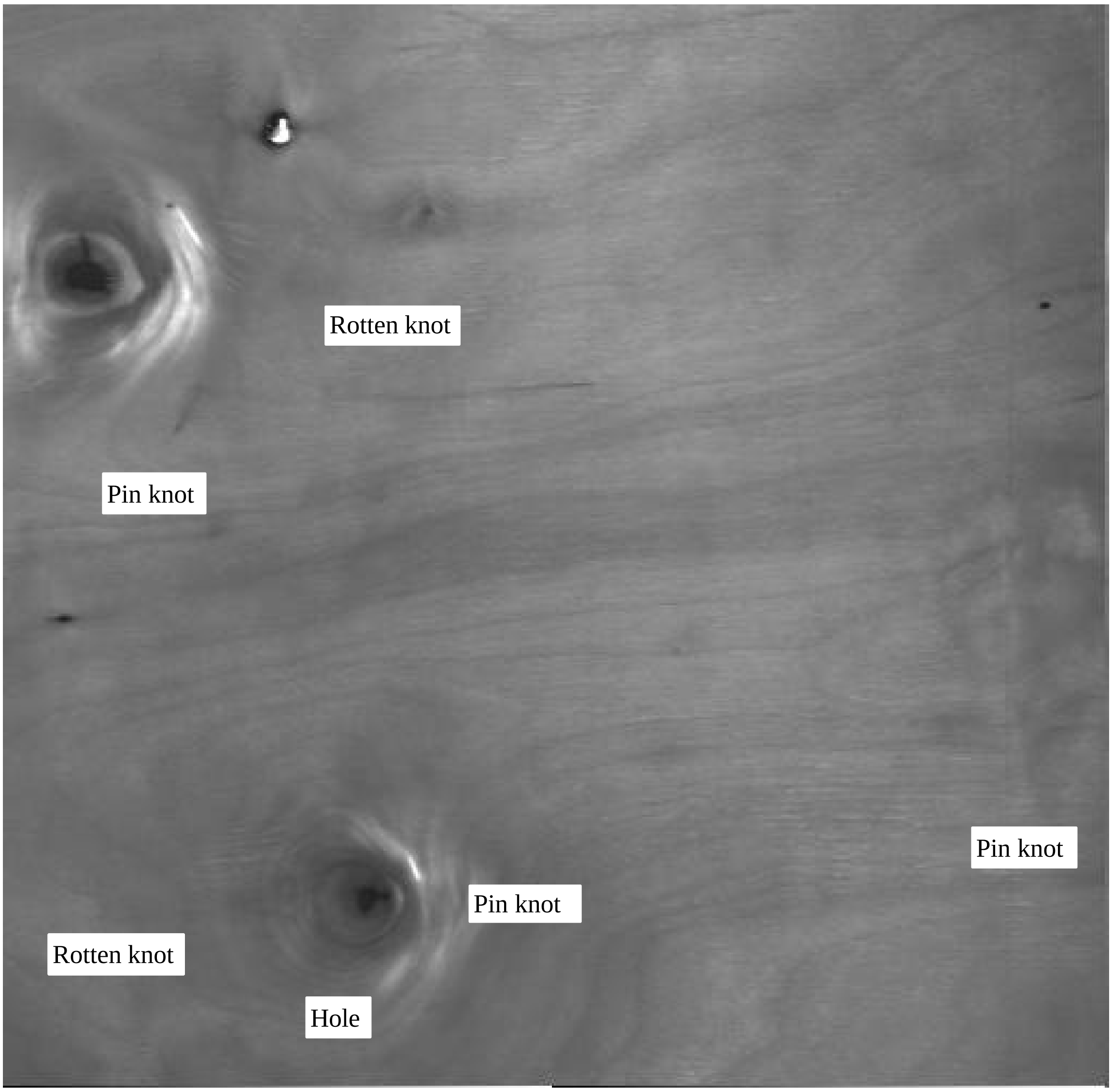

Figure 1 Image of a wood board

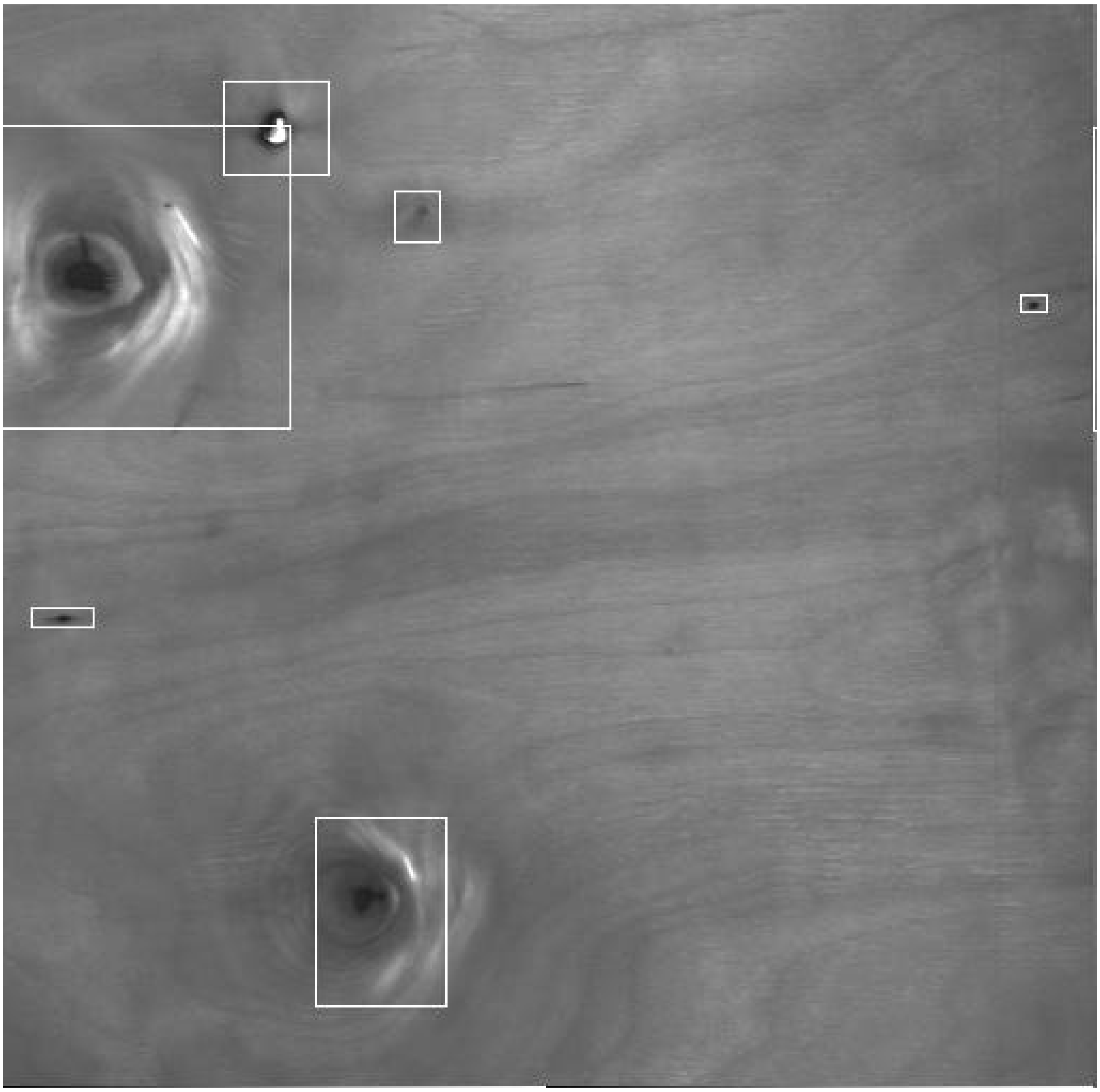

Figure 2 Segmentation of the board shown in Figure 1