CORK PORES AND DEFECTS DETECTION BY MORPHOLOGICAL IMAGE ANALYSIS

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ABSTRACT

The paper presents an application of rank filters to the problem of autometed visual inspection of materials. The aim of the system was to verify the quality of cork planks through the detection, classification and statistical quantification of pores and defects present in the acquired samples. The techniques adopted are a combination of morphological operators, applied to appropriate masks adaptively determined, and rank-order functions.

1. INTRODUCTION

The quality of cork is a determining factor to establish the end use of the raw material and the economy of the processing. The parameters that are considered in the evaluation of cork quality are the porosity and some defects. The porosity corresponds to the presence of the lenticular channels that cross the cork planks radially from the inside to the outside of the plank. In tangential sections of cork, the lenticular channels appear with a more or less circular form and in transverse and radial sections as channels. Their number, dimensions, concentration and distribution are the main factors used to classify cork into quality grades.

The defects that may appear in cork either devaluate it completely for use as a stopper (for instance, insect galeries or tangential cracks) or lower its quality (for instance, the presence of lignous tissues known as nail). The commercialisation of cork after extraction from the tree is based on the visual appreciation of the overall quality of the cork boards. The classification of the cork planks in the industry is done at present by the visual observation of a specialised operator into six grades. An automated classification operation has been introduced so far only for stoppers (then, after production) by image analysis of their lateral surface and a sorting programme using pre-set limits; however, this automated classification is often unreliable, largely due to the few parameters accounted for, and sorting is followed by the visual inspection of an operator whenever an error-free classification is desired.

The industry is unanimous in stressing the importance of the quality evaluation and the need for an automated tool for objective classification of cork planks. Image analysis techniques have been developed for the classification of forest products and the last ten years have seen their introduction in different wood and paper industries. At the moment, experimental work dealing with the problems related to the use of image analysis for cork classification is still exploratory [1-4]. Similarly to what has been done for timber [5], the use of image analysis techniques to the automatic classification of cork defects appears promising. This will require the identification of each defect and its characterization by parameters made available by the software, such as those useful for the characterization of cork porosity. The image analysis techniques applied to cork were based on the measurement of the number of pixels with a grey level above a selected threshold value, thereby classifying the area observed into only two categories: cork and defects (pores and other defects read as pores), quantified by a porosity coefficient. We intend now to introduce a higher specification by differentiating the pores from the defects nail and insect galeries.

2. ADAPTIVE MORPHOLOGICAL FILTERING

Among the various types of morphological filters, the operators based on combinations of Closings and Openings have been already used in the past as effective methods to identify image contours [6] or particular structures [7]. We selected the operator given by the difference between a Close and a Open (*ClO*, *Close less Open*) as the best candidate for the identification of thin structures. As the *ClO* filter is very simple, there are only two elements that can be considered for achieving a spatial adaptivity: the dimension of the mask and its shape. The former parameter is the easier to modify, but does not produce in general the result needed: in fact, it often happens that the thickness of the irregularities to be identified has a size similar to the acceptable variations of the texture. The latter is more interesting, for it is possible to generate and utilize an optimized structuring element, that is, a *ClO* mask that produces a minimum response when applied to an image without irregularities. The implemented algorithm addresses the optimization problem (the goal is to obtain a null response on a regular texture) in a more direct way.

Two hypotheses are first made: (*i*) given a minimum number N_m of non-null elements, every algorithm tends to reach this number in a few steps: it is therefore convenient to keep N_m fixed; (*ii*) since the optimization involves the global image, the computation of the score to be associated to each candidate is based on the average value of the cost function over the all image. Given such rules and a generic cost function J that penalizes the higher outputs of the filter, the algorithm proceeds iteratively by searching for the best swap between two candidates of the mask. In other words, at each step all the pairs of inside-mask and outside-mask elements are exchanged, and the corresponding average cost function is evaluated. If the cost of the current configuration is lower than all the new costs, the algorithm ends, otherwise, the best configuration is chosen and another iteration is launched.

In general, if the search area has a dimension A and the non-null elements are $N_m < A$, then at each iteration it will be necessary to calculate $N_m \times (A\text{-}N_m)$ new configurations, and therefore $N_m \times (A\text{-}N_m)$ values of the cost function. As this way to proceed is very expensive, a sub-optimal solution yielding good results has been developed, based on a separation of the two operations that compose a swap: in practice, the transition from a mask to another is achieved by first finding the best configuration at distance one from the starting point (raising N_m to N_m+1) and then the best configuration at distance one from the intermediate point. In such a way the cost function has to be calculated only $N_m+(A\text{-}N_m)=A$ times.

Concerning the choice of the configuration from which the minimization procedure starts, a reasonable choice (experimentally verified) is to select a symmetrical central block of the desired dimension in the search area: this would not create any a-priori preference in the evolution of the minimization.

Two major points have still to be defined: the selection of a criterion to detect the presence or not of an anomaly, and consequently the definition of a reliable cost function to be used during the optimization procedure. The choice of an effective decision criterion requires the specification of the main properties that characterise a good decision; by studying the outputs of the filter in different situations, three requirements have been identified: (*i*) a pixel must be penalized proportionally to its value; (*ii*) if there is a number of contiguous pixels with non-null value, they must also be penalized proportionally to the number; (*iii*) as this operation has to be performed several times during the optimization, the number and the complecity of the involved operations must be very low. The proposed criterion, called Anomaly Presence Degree is defined as:

$$APD(A) = \sum_{i \in A} f^2(i)$$

where A is a square search area with side L and $f(i)$ is the output of the filter for the i-th pixel. During the analysis phase the image is subdivided in blocks of dimension $L \times L$, and for each block the *APD* parameter is evaluated and compared with a threshold th_{APD}: if the threshold is exceeded, the block is classified as anomalous, otherwise it is

considered regular.
From what was previously said, it is clear that the goal of the adaptation algorithm, if applied to a normal image used for training, is to minimize the maximum *APD* value present in the image: then, the cost function

$$J = \max_{A \in \Theta} \left(APD(A) \right)$$

will be defined, where Θ is the set of square blocks into which the image is subdivided. Once the optimization is completed, the minimum value of J can be used to define the value of the threshold

$$th_{APD} = (1+\alpha) J_{\min}$$

where $\alpha \in (0,1]$ is a constant to be fixed depending on the characteristics of the image to be analysed. This allows one to define the sensitivity to small variations (the lower the value of α, the higher the sensitivity).

3. RANK-ORDER FUNCTIONS ANALYSIS

The other kind of structures, i.e. the circular ones, were identified by measuring the distance between histograms. In some applications, such distance allows to discriminate between textures. A proper distance should comply with the following properties: (*i*) to be zero if and only if the two histograms are exactly equal; (*ii*) to be proportional to the distorsion both for the concentration and for the values; (*iii*) to weight the point differences in relation to their distances from the mean value. The generalised rank function $R_H(z)$ provides exactly the same information as the histogram but has the advantage of making it possible to define an efficient distance measure that complies with all the three requirements, as for instance the Integral Square Error (ISE) and the Integral Absolute Error (IAE).
If a uniform texture is partitioned into sufficiently large blocks, each block is representative of the whole texture: the problem is then to define a prototype of the texture from the analysis of the block histograms. By using the rank distances, a possible strategy is to define as a prototype the rank function computed on the block, and when testing an unknown texture to evaluate the distance between the rank function of its each block and the prototype.
Never standing the semplicity of this solution, a better approach is to use as a prototype the histogram $H^*(x)$ that shows a minimum mean distance from all the block histograms $H_k(x)$. The prototypes $H^*_{ISE}(x)$ and $H^*_{IAE}(x)$ can be computed directly from $H_k(x)$. Now, we denote by D_k the set of discontinuity points of the rank function of the histogram H_k and by Z the ordered set of all the discontinuity points. The rank function F_{H*} related to the optimum histogram H^* is a piecewise constant function and the set of its discontinuity points is contained in Z. Therefore, $F_{H*}(z)$ is a constant, denoted Φ_i, in the range $[z_i, z_{i+1})$; in the same range also the functions $F_k(z)$ are constant and they assume the values $A_k^{\,i}$. Hence, it is possible to compute the rank functions related to the optimal solution in both cases. For the solution based on the ISE, we have that the optimum histogram $H^*_{ISE}(x)$ is given by the rank function:

$$F^*_{ISE}(z) = \frac{1}{N} \sum_{k=1}^{N} F_k(z)$$

In the other case, we have that the optimum histogram $H^*_{IAE}(x)$ is given by the rank function:

$$F^*_{IAE}(z) = med\left(F_1, F_2, \ldots, F_N\right)$$

Sometimes, the first-order statistics of gray levels, when dealing with local histograms of a texture, are not stationary. However, by partitioning the texture in texels with uniform gray level, obtained by dividing the gray levels into classes, these statistics tend to a stable configuration. Therefore, a first-order statistical analysis of such textures should be carried out in each class separately.
Given m classes, for each class i the prototype histogram H_i^* and the related rank function F_i^* are computed. If the block dimensions are comparable with the size of the texel, the distance from the prototype histogram has to be estimated using the following approach.
We denote by F_i^* the prototype rank function of the i-th class. Further, we denote by $F_i(x,y)$ the rank function of the i-th class related to the (x,y) block and by $N_i(x,y)$ the number of samples belonging to the i-th class in the (x,y) block. The

m class rank distance is then defined:

$$d_{ISE}^{m} = \sum_{i=1}^{m} \frac{1}{N_i(x,y)} d_{ISE}\left(F_i^*, F_i(x,y)\right)$$

Images are then partitioned into blocks *N*x*N*, and in order to detect circular structures we use the parameter $\alpha = d_e / d_{max}$, where d_e is the distance from the prototype of such irregularity, and d_{max} is the maximum distance from the prototype of the normal texture blocks. Obviously, for $\alpha > 1$ the irregularity would be correctly identified while for $\alpha \leq 1$ some detection error would be inevitable.
The used distance was:

$$d_{rank}\left(H_l, H_p\right) = \int_0^1 \left(F_{H_l}(z) - F_{H_p}(z)\right)^2 dz$$

4. EXPERIMENTAL RESULTS

The material observed consisted of corkboards with different thickness and porosity obtained in the field during the cork extraction, as well as commercial cork planks, boiled and cut to dimensions, classified into quality grades and representing the three most important thickness classes: 32-40 mm, 27-32 mm and 22-27 mm. The test set consisted of six cork planks obatined in Catalunia, Spain, in 1991, and containing the defects under study. The observations were made on thin slices cut tansversally in the planks with a length of 20 cm and approximately 2 mm thickness. The samples were visually examined by an expert who classified the visible defects in the following categories: (i) nail with horizontal development (tangential in the plank); (ii) nail with vertical development (radial in the plank); (iii) insect galery.
Images of the same samples were acquired and processed in order to have a comparison. Obtained results were quite satisfactory: the detection of all kinds of anomalies was achieved with a high degree of accuracy, making it possible to perform further measurements and classification with a high degree of reliability. The algorithhms developed allow to extract for each defective region a large features' vector for classification purposes. In Figure 1, the processing output regarding the location of pores and defects in one particular case is given as an example.

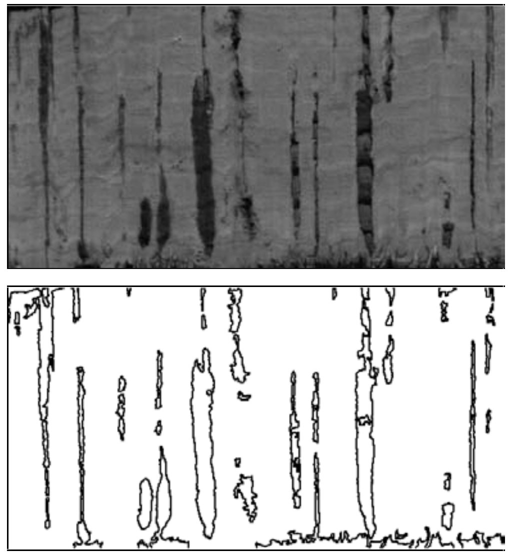

Fig. 1: Original image of a cork plank (radial section) and processing result.

5. REFERENCES

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