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Improving the industrial classification of cork stoppers by using image processing and Neuro-Fuzzy computing

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Abstract This paper presents a solution to a problem existing in the cork industry: cork stopper/disk classification according to their quality using a visual inspection system. Cork is a natural and heterogeneous (remarkable variability among different samples, being impossible to find two samples with the same morphological distribution in its defects) material; therefore, its automatic classification (seven quality classes exist) is very difficult. The solution proposed in this paper evaluates the following procedures: quality discriminatory features extraction and classifiers analysis. Each procedure focused on the study of aspects that could influence cork quality. Experiments show that the best results are obtained by system specific features: cork area occupied by defects (after thresholding), size of the biggest defect within the cork area (morphological operations), and the Laws TEMs E5L5TR, E5E5TR, S5S5TR, W5W5TR, all working on a Neuro-Fuzzy classifier. In conclusion, the results of this study represent an important contribution to improve quality control in the cork industry.

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Introduction

Cork is the biological term for the tissue that the cork tree produces around the trunk. This tree grows on the western shores of the Mediterranean Sea. The cork industry has a strong economic importance and great research interest in the native zones of this material. Spain is the second leading world producer of cork (CorkQC 2008), only surpassed by Portugal, and in Extremadura (a south-western region of Spain), for its geographical situation, the cork industry produces 10% of the world cork (ICMC 2008; ASECOR 2007).

The most important industrial application of cork is the production of stoppers and disks for sealing champagnes, wines and liquors. In fact, according to the experts, cork is the most effective product, natural or artificial, for sealing (Fortes 1993). However, cork is a natural material and it is a challenge to classify cork quality. In the cork industry, stoppers and disks are divided into different quality classes based on a complex combination of their defects and particular features. The most important aspects that influence cork quality are divided into two groups:

- *Quantitative agents*: Bore, density and the condition of the cork surface.
- *Qualitative agents*: These agents are related with the external appearance of the cork, such as shade, porosity, man-made defects, insect marks, etc.

Aspects that can influence cork quality are numerous and very different. Due to this fact, the classification process has been carried out, traditionally, by human experts. At the moment, there are several models of electronic machines for the classification of cork stoppers and disks in the market. The performance of these machines is acceptable for high quality stoppers/disks, but for intermediate or low quality, the number of samples classified erroneously is large. For this reason, the stoppers/disks require re-evaluation by human experts. This slows down and enormously increases the cost of the process. On average, a human expert needs a minimum training period of six months to attain a minimum agility, although the learning process can last for years (compare it with other experts: wine tasters, cured ham tasters, etc.). Another negative aspect is the subjectivity degree added to the classification process due to the necessary human re-evaluation.

Previous studies on cork classification have not yet identified an adequate system for cork quality control. For this reason, this study proposes the construction of a computer vision system for cork classification based on advanced methods of image processing and feature extraction to avoid human evaluation in the quality discrimination process.

Specifically, several studies were performed:

1. *Thresholding study*: several methods of global and local automatic thresholding were used to determine the defect area feature (one of the most used features by the human experts in the industrial environment).
2. *Texture study*: several textural quality discriminating techniques were assessed. These techniques were second-order co-occurrence matrices (Haralick et al. 1973), Laws' Texture Energy Measures (Laws 1980) and Varma and Zisserman's texture recognizer (Varma and Zisserman 2005).
3. *Heuristic features study*: these features come from the human classification observation. The studied features were the hole existence in the cork area and the biggest defect size in the cork.
4. *Classifiers study*: once the quality discriminatory features were selected, a study about the different possible classification algorithms was performed to select the most suitable classifier for our problem. The classification algorithms selected were a Classical Neural classifier, a K-means classifier, a K-nearest neighbours classifier, a Euclidean classifier and a Neuro-Fuzzy classifier (Jang et al. 1997; Monzon and Pisarello 2004).

The results from these studies led to the final classification system. The sections of this paper are organized as follows: 1) overview of the state of the art in this specific research field; 2) tools and the data used for the development of our experiments; 3) features used by the classifiers; 4) analysis of the different studied classifiers; 5) results and statistical evaluation for the proposed system; and 6) conclusions.

Previous studies

Several different studies have assessed different aspects of cork quality control. Rocha et al. (1998) studies focused on the cork stopper quality control by using chemical techniques based on the smell analysis of the material. Corona et al. (2005) analyzed the cork tree trunk to detect the quality of the planks that will be obtained from that tree. Brunetti et al. (2002) controlled the side part of the cork planks applying radiological analysis (X-rays). Pereira et al. (1994) performed a heuristic cork plank analysis to calculate the quality of the planks and the quality of the stoppers that will be manufactured with them. Later, Lima and Gomes-Costa (2005) classified cork planks using a computer vision system based on feature extraction methods using a CCD camera.

Even though many studies have evaluated cork quality, cork stopper classification remains a challenge. The work of Gonzalez-Adrados et al. (2000) (33.33% error rate) focused on the heuristic feature extraction methods combined with Discriminant Analysis. In the case of Vega-Rodríguez et al. (2004), they studied a system that detected a simplified cork quality standard (only 5 classes of the 7 regular classes) that works with a joint system of reconfigurable hardware (FPGAs) and mainly thresholding techniques. Although the processing times are very good, the final performance in terms of error rates is still high (13.94%). In the case of Costa and Pereira (2006), a system was used based on CDA (Canonical Discriminant Analysis) and SDA (Stepwise Discriminant Analysis) techniques, obtaining an error rate of 14%. Chang et al. (1997), however, designed a visual system based on morphological filtering, contour extraction and neuronal networks. In this case the error rates (around 6.7% of error rate) are also higher than those obtained by this study, probably due to the low complexity of the features extracted. Finally, reviewing the system based on feature extraction and Bayesian classifiers for cork quality classification (this system has a simplified cork quality standard, 5 classes) performed by Radeva et al. (2002) shows that the obtained average error rate is 6%.

A different methodology from these previous studies was proposed, using some of their ideas but contributing new ones. In this way, our final system obtains an error rate of 4.28%, surpassing all the previous results from other authors published in the literature. One of the important ideas of our system is the use of a fuzzy neural network as classifier. Real systems (Dragomir et al. 2008), as cork classification, are complex, heterogeneous, and in general, they are hard to model. Soft-computing tools (Kumar et al. 2007; Cheu et al. 2008) that concern computation of an imprecise environment and model very complex systems have gained significant attention in the last years. Many investigators (Bouharati et al. 2008; Asteriadis et al. 2008) aim at overcoming the major Artificial Neural Networks' drawbacks by adding fuzzy logic to these networks. In fact, several studies (Berberoğlu and Satir 2008; Marpu et al. 2008; Lin et al. 2008) show the utility of fuzzy neural networks in classification problems. All these motivations have led to the use of Neuro-Fuzzy computing in our system.

Tools and data

At present, the computer vision system used to acquire the cork stopper/disk images is formed by the following elements: the host (a Pentium processor), a colour Sony camera (SSC-DC338P model), the illumination source (fluorescent-light ring of high frequency—25 KHz—of StockerYale), and a METEOR 2/4 frame-grabber of Matrox, with the software required for the image acquisition (MIL-Lite libraries of Matrox).

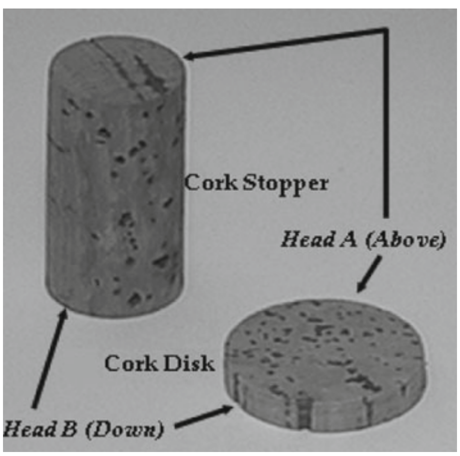


Fig. 1 The two heads in a cork stopper/disk

On the other hand, the database used in our experiments consists of 700 images taken from 350 cork disks (we have taken two images of each disk, one for each head, see Fig. 1).

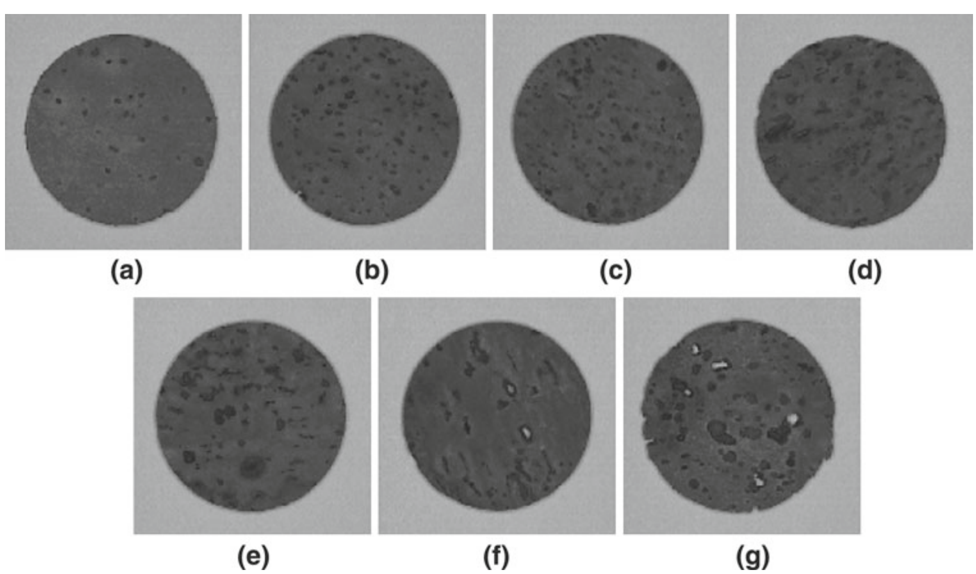
There are seven different quality classes and 50 disks in each class (see Fig. 2). The initial classification, from which this study is based, has been made by a human expert from ASECOR (in Spanish: "Agrupación Sanvicenteña de Empresarios del CORcho", in English: "Cork Company Group from San Vicente-Extremadura"). This classification was assumed to be optimal/perfect and a system which obtains the most similar classification results needs to be designed.

Used features

In order to perform the classifiers study, a deep feature extraction methods study must be developed in order to discover what features can evaluate cork quality. The methods analyzed are as follows: both global and local thresholding techniques, different texture techniques, and two other heuristic feature extraction techniques. Detailed descriptions of these methods are shown in the following sections. Each experiment described was performed under the same conditions:

- The same number of samples, consisting of 700 images divided in 7 different cork quality classes (balanced data, 100 images for each class). Considering as reference other similar studies (Woodford et al. 2004; Asteriadis et al. 2008), it was assumed that this number of samples is relevant enough to have results based in some statistical confidence. As mentioned before, the initial classification of these samples was made by a human expert. These grades were assumed to be ground truth.
- The results for each method (thresholding, texture or heuristic feature method) were obtained using a mini-

Fig. 2 **a** Class 0 disk, **b** Class 1 disk, **c** Class 2 disk, **d** Class 3 disk, **e** Class 4 disk, **f** Class 5 disk, **g** Class 6 disk



mum Euclidean distances classifier (Shapiro and Stockman 2001). This classifier was based on the corresponding single feature in any of the results displayed. Knowing the average value of this feature for each class (cork quality class), 1 the feature for each new stopper/disk and the Euclidean distances of this to the mean of each class (μ_j) was calculated. The stopper/disk was classified in the class for which the smallest Euclidean distance was obtained. The following equation shows the functionality of this classifier (Eq. 1).

$$\text{EuclideanDist.} = \sqrt{(x_{ij} - \mu_j)^2} \tag{1}$$

where x_{ij} is the value obtained for the sample i-th on the class j and μ_j is the mean value for the j-th class. Since this classifier was used with each single feature analyzed, it was possible that the classifier would not produce absolutely satisfactory results. The classifier can glimpse the trend of that feature on cork quality classification (its capability to detect different cork quality classes).

Once the basis of the experiments was set, the different stages and results obtained in each feature extraction method divided by areas could be explained.

Thresholding techniques

The cork stoppers/disks are classified using their defects. These defects can be obtained by means of segmentation techniques, and more concretely, by automatic thresholding techniques (Sonka et al. 1998). In this study several thresholding techniques with the purpose of knowing which of them is the best for this application field were evaluated. In this subsection, in order to classify a cork disk in a specific class, only the feature related with the defect area in relation to disk area was used.

For this comparative thresholding analysis both global thresholding techniques and local thresholding techniques (Sahoo et al. 1988) were studied. Global thresholding uses a fixed threshold for all the pixels in the image, knowing previously the image histogram. Local thresholding, on the other hand, selects an individual threshold for each local region of the image, based on the illumination or intensity values of the pixels in that region or neighbourhood.

The 13 thresholding methods that have been studied are: slope method (our own heuristic proposal) with different minimum slopes, Otsu method (Otsu 1978), histogram concavity analysis method (Rosenfeld 1983), first Pun method (Pun 1980), second Pun method (Pun 1981), Kapur-Sahoo-Wong method (Kapur et al. 1985), Johannsen-Bille method (Johannsen and Bille 1982), moment-preserving method (Tsai 1985), statistical thresholding method (Fisher et al. 2004) with different modifications, and Chow-Kaneko method (Chow and Kaneko 1972). The results of this study have been obtained by using for each thresholding method a classifier of minimum Euclidean distance, as explained in former sections.

Within global thresholding methods, it was found that the most suitable method for cork industry is the moment-preserving method. Figure 3 shows the results (wrong classification percentage) obtained by the different global thresholding techniques, all of them compared with the simulation of the behaviour of a raw cork production line in the cork industry (Cork Random Classification). All the thresholding techniques have obtained certain discriminatory information, although the goodness of the obtained results widely varies among the different methods.

However, according to the experimental results, the local thresholding techniques are more suitable for discriminating cork quality based on the stopper/disk defects, being the statistical thresholding method which has given the best results. Figure 4 displays the wrong classification percentage obtained by the different local thresholding methods.

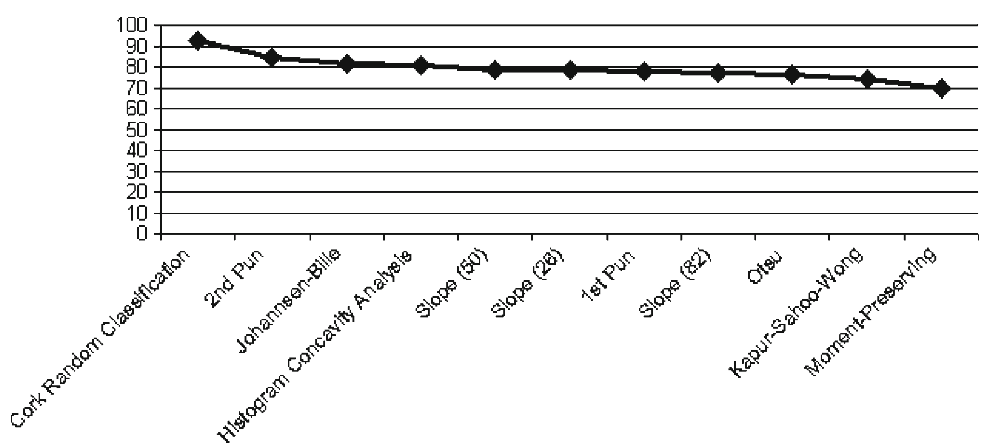


Fig. 3 Global thresholding techniques results

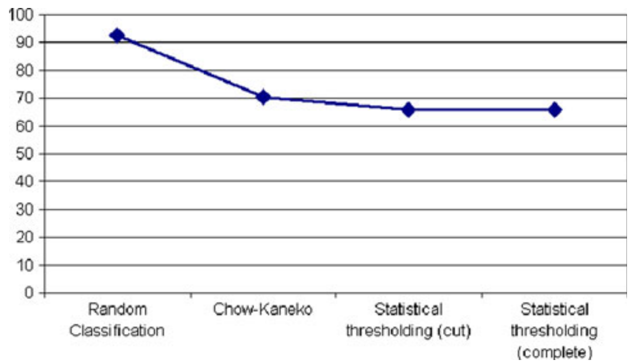


Fig. 4 Local thresholding techniques results

This study was completed by comparing the best results obtained by both the global and the local thresholding methods, in order to select the best thresholding method to obtain our first quality discriminatory feature: the cork area percentage occupied by defects. In addition to the studied thresholding methods, a static thresholding method with a heuristically fixed threshold was checked. The grey level for the threshold was obtained by using a recursive statistical study, testing which grey levels gave better classification results. Finally, a grey level of 69 was chosen as threshold.

In conclusion, the local thresholding methods have been more suitable than the global methods for the solution of our problem. The main difference is that local thresholding allowed identification of the cork area percentage occupied by defects in unimodal histograms (that is, when both the disk area and the defects grey levels are in the same Gaussian distribution of the image's histogram). Nevertheless, the increase of the computational cost can make the local thresholding methods unsuitable for our problem (Niemistö 2004). Taking into account all these considerations, the best of all these methods applied to our problem has been the static thresholding method with a heuristically fixed threshold in the grey level 69.

Texture analysis

It appears that cork texture can be a powerful quality discriminator for cork disks. Among the main methods of texture analysis, different textural features extraction methods were chosen, both structural and statistical (Shapiro and Stockman 2001), in order to discover which one is the most suitable method to find cork quality patterns. The studied techniques are discussed in detail in the next sections.

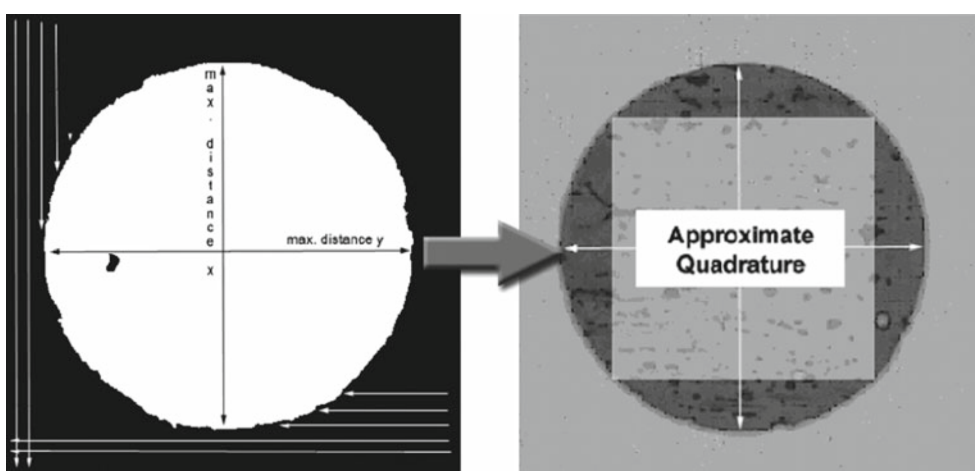
Second order co-occurrence matrix

This stage is based on second-order grey level texture statistics, proposed by Haralick et al. (1973). In this second study, a great number of these statistical discriminators (Wu et al. 1992; Durán et al. 2001; Wood et al. 1988) were evaluated based on textures with the purpose of knowing which of them are most appropriate for the resolution of our problem.

In order to classify a cork disk in a specific class, only the corresponding textural discriminator (disk texture) was used. However, for extracting the different quality discriminators, the approximate quadrature for the disk area had to be found. This was necessary to avoid the strong interaction between the pixels in the background and the pixels in the disk area, because the only pixels that are useful for this study are those that belong to the cork area. This problem was solved by finding the diameters of the disk area (after thresholding the cork image, see Fig. 5), and later doing an approximate quadrature for the disk area.

In the texture analysis, statistical quality discriminators based on the rotation-robust normalized co-occurrence matrix were used. This matrix was calculated by first computing the normalized co-occurrence matrix for a displacement vector with an angle of 0°. Next, its transposed matrix was calculated, and finally an average between both matrices. In this way, the normalized co-occurrence matrix for the angles of 0° and 180° was calculated, and the aver-

Fig. 5 Discovering the stopper/disk area diameters by successive iterations and its approximate quadrature



age between them is a symmetric and invariant matrix to rotations of 180°. This process was repeated for the angles 45°, 90°, 135°, 225°, 270° and 315°. The average matrix for these last matrices was rotational invariant. The studied discriminators were obtained by means of calculations using the rotation-robust normalized co-occurrence matrix, and they were as follows:

1. *Energy*: This is a measure of uniformity of an image. In a uniform image, there are very few dominant grey-tone transitions, hence, the co-occurrence matrix for the image will have few entries of large magnitude. However, for an image which is not uniform, the matrix will have a great number of small entries (and some large entries) and the energy feature will be small. Some authors name this textural feature as Angular Second Moment (Shah and Gandhi 2004). The following equation shows the way to calculate this parameter based on the co-occurrence matrix (Nd).

$$\text{Energy} = \sum_i \sum_j N_d^2\,[i, j] \tag{2}$$

2. *Contrast*: This parameter measures the amount of local variations present in the image. Therefore, if there is a large amount of local variations present in an image compared to another, then its contrast value will be consistently higher than the other. This value is also known as Inertia. The equation below shows the calculation of this feature using the co-occurrence matrix.

$$\text{Contrast} = \sum_i \sum_j (i - j)^2\, N_d\,[i, j] \tag{3}$$

3. *Homogeneity*: It measures the degree to which similar grey levels tend to be neighbours. The following equation presents the way to calculate this parameter based on the co-occurrence matrix.

$$\text{Homogeneity} = \sum_i \sum_j \frac{N_d\,[i, j]}{1 + [i - j]} \tag{4}$$

4. *Entropy*: This is a measure of complexity of an image. A complex image will have greater entropy than a simple image. The associated equation with this parameter is the shown below.

$$\text{Entropy} = \sum_i \sum_j N_d\,[i, j] \log_2 N_d\,[i, j] \tag{5}$$

5. *Inverse difference moment*: The equation below shows the way to calculate this parameter based on the co-occurrence matrix.

$$\text{Inverse difference moment} = \sum_i \sum_j \frac{N_d\,[i, j]}{(i - j)^2} \tag{6}$$

6. *Correlation*: This measures the grey-level linear dependencies in an image. The following equation presents the calculation for this feature using the co-occurrence matrix.

$$\text{Correlation} = \sum_i \sum_j \left[\frac{(i - \mu_i)\left(j - \mu_j\right) N_d\,[i, j]}{\sigma_i \sigma_j} \right] \tag{7}$$

7. *Cluster shade*: The equation below shows how to calculate this parameter.

$$\text{Cluster shade} = \sum_i \sum_j \left(i + j - \mu_i - \mu_j\right)^3 N_d\,[i, j] \tag{8}$$

8. *Cluster prominence*: The equation for this parameter is the following.

$$\text{Cluster prominence} = \sum_i \sum_j \left(i + j - \mu_i - \mu_j\right)^4 N_d\,[i, j] \tag{9}$$

9. *Maximum probability*: The following equation shows how to calculate this parameter based on the rotation-robust normalized co-occurrence matrix.

$$\text{Maximum probability} = \max \sum_i \sum_j N_d\,[i, j] \tag{10}$$

The results of this study have been obtained using the same method as for the thresholding study. Figure 6 presents the wrong classification percentage obtained by the different statistical discriminators. As observed in the graph, texture has certain discriminatory information that improves the cork classification according to its quality, although the goodness of the obtained results widely varies between some textural features and others. The best discriminatory features are the textural contrast and entropy.

The results obtained were not as good as expected, therefore, more complex textural techniques were studied.

Varma and Zisserman's model-based recognizer

The second technique studied was the Varma and Zisserman's model-based recognizer (Varma and Zisserman 2005). This work is based on statistical analysis techniques that try to

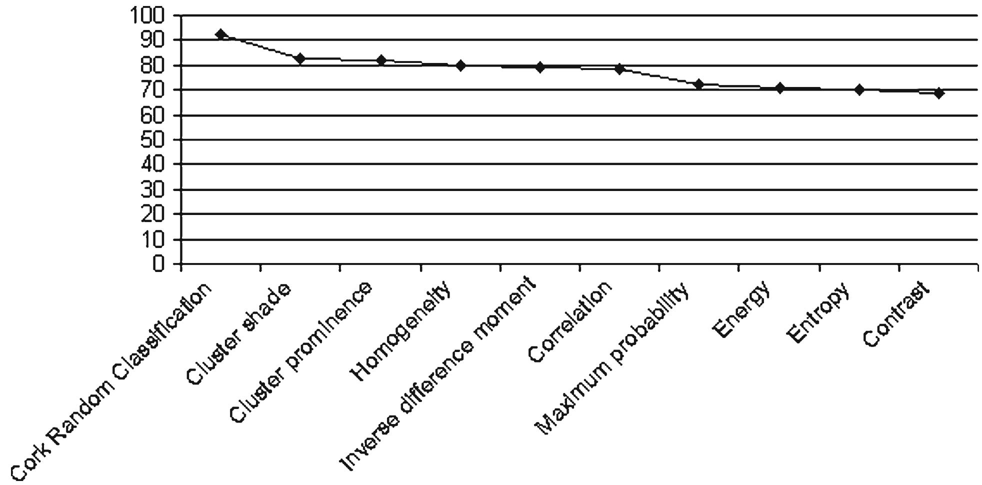


Fig. 6 Final results for the second-order textural features

search similar patterns among different textures. Although Varma–Zisserman textures were initially proposed to classify different materials, our research used their textural approach to classify different kinds of the same material (different cork qualities).

The methodology is divided into the following steps:

1. *Image convolution*: The first step was to convolute the Cork Image Database (CID) with the Gabor-based filter bank designed by Schmid (2001), made up of 13 rotational invariant filters, with the following equation:

$$F(r,\sigma,\tau) = F_0(\sigma,\tau) + \cos\left(\frac{\pi\tau r}{\sigma}\right) e^{-\frac{r^2}{2\sigma^2}} \quad (11)$$

   where F_0 is added to obtain a zero DC (direct current, or continuous current) component with the (σ, τ) pair taking values (2,1), (4,1), (4,2), (6,1), (6,2), (6,3), (8,1), (8,2), (8,3), (10,1), (10,2), (10,3) and (10,4). This initial processing allows searching for similar patterns among the different textures. After the convolution the filter responses for each pixel (13 rotational invariant filters, results in a 13-dimensional array) were stored. These arrays will characterize each pixel in our CID.
2. *Textons calculation*: The most significant vectors of our CID were searched. For this purpose the clustering algorithm K-means was used because of its consecrated fame in specialized literature. This classification algorithm makes reference to the existence of a number of K classes or patterns, and therefore, it was necessary to know the number of classes. The use of 50 textons labels made the algorithm suitable for our needs. Therefore, in this step, the convolution filter responses with labels between the values 0 and 49 were labeled.
3. *Models calculation*: The CID was sequentially studied again. For each image, the convolution filter responses were calculated again, and for each 13-dimensional array the label of the texton that was closest to the array in Euclidean Distance terms was assigned. In order to create a model it was necessary to accumulate the labels obtained for each class in a histogram, creating a model for each one of the seven classes of cork quality.
4. *Classification*: The CID was sequentially studied again, and the model for each image was calculated. The image was classified in the class for which the image model and the class model were closest in Euclidean distance terms. The final results for this method were not satisfying (error rate of 74.85%), even the second-order texture features obtained better results. This research concluded that the Varma and Zisserman's textures, in spite of having enough accuracy for differentiating different materials, did not have a good performance in detecting different qualities of a same material.

Laws texture energy measures

The texture energy measures were developed by Kenneth Ivan Laws at the University of Southern California (Laws 1980) and have been used for many diverse applications (Habib et al. 2004; Maxwell and Brubaker 2003). These measures were computed by first applying small convolution kernels to a digital image, and then performing a nonlinear windowing operation. Those 2-D convolution kernels were typically used for texture discrimination and were generated from the following set of one-dimensional convolution kernels of length five (Fig. 7):

These mnemonics stand for Level, Edge, Spot, Wave, and Ripple. Note that all kernels except L5 are zero-sum. From these one-dimensional convolution kernels, 25 different two-dimensional convolution kernels by convolving a vertical 1-D kernel with a horizontal 1-D kernel were generated. As an example, the L5E5 kernel was found by convolving a vertical L5 kernel with a horizontal E5 kernel. A total of 24 (out of 25) of these two-dimensional convolution kernels

```
L5  =  [  1   4   6   4   1  ]
E5  =  [ -1  -2   0   2   1  ]
S5  =  [ -1   0   2   0  -1  ]
W5  =  [ -1   2   0  -2   1  ]
R5  =  [  1  -4   6  -4   1  ]
```

Fig. 7 Laws uni-dimensional convolution kernels

were zero-sum; the L5L5 kernel was not. These convolution kernels were the base of this study, whose main stages follow:

1. *Image pre-processing*: The first stage in the Laws Texture Energy Measures extraction is to avoid the illumination effects by convolving the original image with a 15 × 15 kernel. For every pixel in the image, the 15 × 15 neighborhood-mean for that pixel was obtained, and the mean was subtracted. This step made the pixel values in the image change to negative values. This was not important because it could be fixed in other stages of this textural analysis.
2. *Apply convolution kernels*: The second stage of the analysis is to apply each of the 25 convolution kernels to the image. The result was a set of 25 greyscale images for each image in the CID.
3. *Performing Windowing Operation, TEM transformation*: After applying the convolution kernels to the image, the energy maps for each image were calculated. Every pixel in the 25 separate greyscale images was replaced with a Texture Energy Measure (TEM) at the pixel. This was done by looking in a local neighborhood of 15 × 15 around each pixel and summing together the absolute values of the neighborhood pixels. A new set of images, referred to as the TEM images, was generated during this stage of image processing. The following non-linear filter was applied to each of the images:

$$E_k(m,n) = \sum_{j=n-7}^{n+7} \sum_{j=m-7}^{m+7} |F_k(i,j)| \tag{12}$$

   where E_k is the TEM-image and F_k is the original image obtained in the convolution stage. With the absolute value that is displayed in the equation, the problem in the pre-processing associated with the possibility of negative values in the pixels was avoided. At this point 25 TEM images from the original image have been generated. These images are denoted by the names of the original convolution kernels with an appended “T” to indicate that this is a Texture energy (i.e. E5L5T).
4. *Energy measures normalization*: All convolution kernels used so far were zero-sum with the exception of the L5L5 kernel. In accordance with Laws’ suggestions, this can be used as a normalization image; normalizing any TEM image pixel-by-pixel with the L5L5T image will normalize that feature for contrast. As the L5L5 kernel is special (it is not zero-sum), it is not usually used for calculating the energy measurement maps. However, it is used to normalize the TEM images calculated in the previous stage. With this calculation, pixel values between 0 and 1 can be obtained and the L5L5T image is typically discarded and not used in subsequent textural analysis.
5. *Combine similar features*: Pairs of energy measures symmetric maps to remove a bias from the features’ dimensionality were obtained. For example: L5E5T is sensitive to vertical edges and E5L5T is sensitive to horizontal edges. If two TEM images are added together, the result is a single feature sensitive to simple “edge content”. Following this example, features that were generated with transposed convolution kernels are added together. These new features were denoted with an appended “R” for rotational invariance. The other four maps were rotationally invariant since their convolution kernels are products from the same filters (and so, symmetric). They are E5E5TR, S5S5TR, W5W5TR and R5R5TR. The result of this stage, is a set of 14 texture features which are rotationally invariant. If these images are stacked up, a data set where every pixel is represented by 14 texture features is obtained.
6. *Calculation of the TEM array*: The last stage consists in extracting one textural feature for each image (now 14 features for each pixel). For this purpose, the mean of each of the textural features was calculated, using only the pixels that are part of the stopper. In order to calculate the mean of the energy measurement features of the stopper pixels, the first step was thresholding the original image. A binarized image was obtained, having only pixel values between 0 and 1 (this value will indicate if the pixel is part of the stopper or not). After that step, the energy measurement maps were analyzed, only summarizing the values of the pixels that are part of the stopper. Figure 8 shows a cork image, a resulting TEM, and finally, the same TEM only considering the pixels in the stopper.
7. *Classification*: The results have been obtained using the same methodology as in the rest of studies (see the beginning of section Used Features). Figure 9 presents the wrong classification percentage obtained by the different Laws TEMs discriminators. As observed in the graph, the results obtained with these textural features clearly improve the results obtained in previous textural studies.

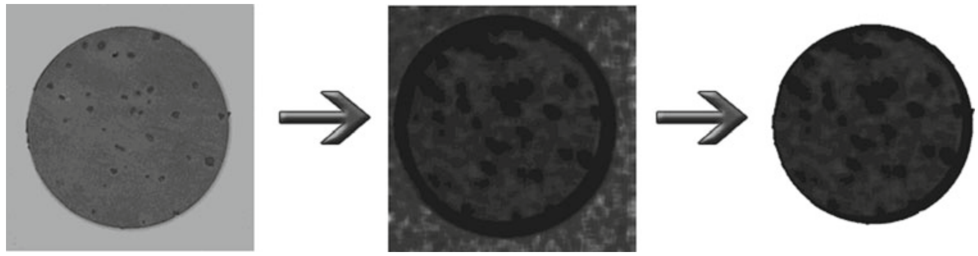


Fig. 8 Thresholding in order to obtain the TEM using only the pixels in the stopper

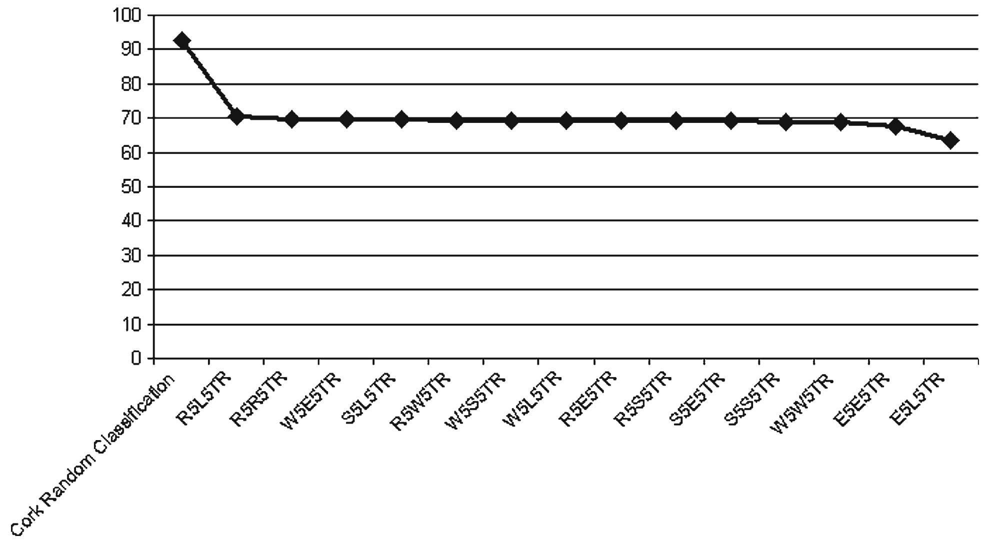


Fig. 9 Final results for the Laws TEMs textural features

Other features

After the previous features studies, the last features study stage was dedicated to the analysis of other features which could give positive results in matter of cork classification. After a deep observation of the classification parameters used by the human experts in their classifications, the following guidelines were evaluated:

- *Hole study*: It was observed that the cork stoppers/disks with holes (Fig. 10a) were relegated to low-quality classes, in spite of their good cork texture or their pore homogeneity. The followed methodology has been to make the classification by means of the usual classifier, but the number of hole pixels were considered when a definitive classification was made. This feature only has some discrimination power in the low-quality cork classes, concretely from class 4 to class 6 which are those that begin to have some holes in their area, which is the reason why this feature must be combined with another feature that has discrimination power in the rest of classes. In this case, the defect area as the combined feature was chosen.
- *The biggest defect size study*: It was observed that those cork stoppers/disks with big defects also were classified in the lower classes, in spite of the possible positive details that they could have (see Fig. 10b). The methodology followed in order to obtain this feature has consisted in making successive binary erosions on the thresholded image (image that only includes the defects), with a 5×5 convolution kernel (each iteration subtracts two pixels from the defect perimeter). In each iteration the remaining image percentage is controlled. In this way, it is possible to easily obtain the size that the biggest defect could have, taking into account the number of iterations required to suppress the entire binary image.

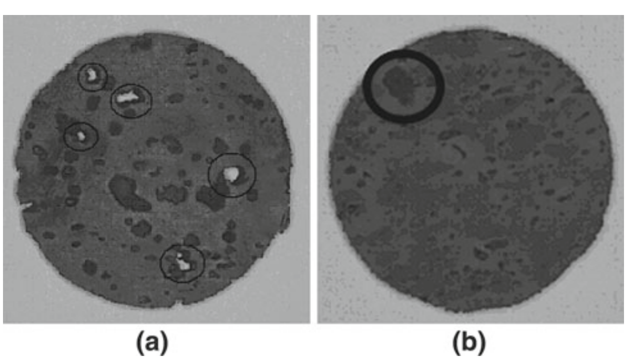


Fig. 10 **a** Cork disk with important holes. **b** Low-quality cork disk due to a big defect

Finally, the optimum feature selected in this study has been the biggest defect size in the cork area.

Assessment of the importance of each classification parameter

The cork classification process has traditionally been carried out by human experts, but cork is a highly heterogeneous material. In the industry, cork stoppers are classified into seven different categories based on a complex combination of their defects and particular features. For this reason, a wide and comprehensive study was performed and analyzed on feature extraction methods. In order to determine which of those features should be included in the final proposed system two different aspects were evaluated:

- Experiments in human perception were performed, in order to detect the major features used by human experts on their grades.
- The classification results of the features obtained were observed and analyzed, based on preliminary studies that showed the initial error rates obtained with a Euclidean Classifier (Paniagua-Paniagua et al. 2006a,b).

Human visual perception

An eye-tracker was used to analyze the gaze patterns of a human expert trained in cork classification, in order to identify visual features of cork samples used by the expert in making decisions. It was assumed that, even using the data obtained from only one human expert, this information would give relevant information about features used in the classification process. This is because in tests with several human experts on cork stopper quality evaluation found that classifications of samples were highly correlated among experts, implying that they used some features consistently. If these could be identified, they might benefit the development of a computer system.

There were two main goals for this stage of the research. The first was to obtain data that would identify the visual features of cork samples that were used by a human expert when making decisions about their quality. The second was to apply these results in the selection of the features that would work in a computer classification system.

Eye-tracking system

The eye-tracking system used in these experiments was a Tobii X50 model (Fig. 11) and the acquisition software provided by the Tobii Company gave very diverse data.

The data that was most relevant for the research were Gaze plots and Hotspot maps.

- *Hotspot maps*: Visualizations summarizing the distributions of the human expert's fixations on the samples.

Fig. 11 Tobii X50 eye-tracker used in these experiments

- *Gaze plots*: Displays of gaze points, fixations and scanpaths superimposed over the samples. Gaze plots provided further information about the positions, sequence and timings of individual fixations.

Experiments

An expert was asked to make decisions about monochromatic images of samples on a monitor screen, and not about real samples. The upper and lower surfaces of each cork disk were displayed together, side by side. Previous experiments with experts showed that they were able to classify images of samples successfully, and so cues such as touch that are only available from real samples were not essential. An advantage of this approach was that it gave the experts the same image information that this system receives to make its calculations, introducing the same biased information.

Results

Analysis and interpretation of the eye-tracking data was carried out in two stages:

1. Identifying samples that were difficult to grade. In order to find the samples that are difficult to grade for the human experts, the number of fixations recorded on each sample (Gazeplots, Fig. 12) were analyzed while inspec-

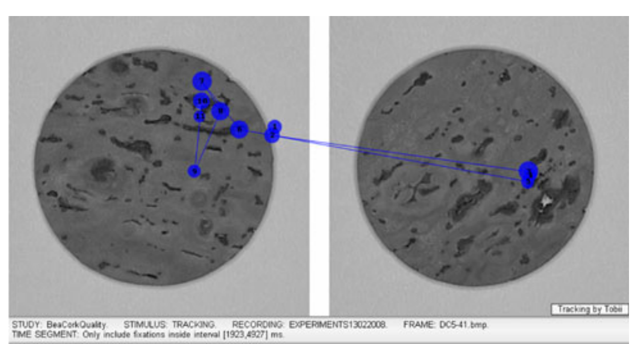


Fig. 12 Gazeplots, showing the direction and fixations on the samples

ting and classifying it. If a sample had a large number of fixation points, it was assumed that it was a relevant feature that the human expert would use as a clue in order to give a grade to the specific sample.

2. Inspecting the Hotspot Maps of the detected difficult samples in order to identify perceptual features that attracted fixations of gaze. Once a set of samples from the dataset that were difficult to grade was decided upon, their Hotspot maps and identified features of the cork surface where gaze had stayed for a longer time were vizualized. These features fell into 5 classes:

   - *A*: Large dark patches in the sample (see Fig. 13a).
   - *B*: Extended light regions in the sample. These regions often contained marked variations in lightness (see Fig. 13b).
   - *C*: Holes in the sample (see Fig. 13c).
   - *D*: Non-defective areas in the sample. Regions containing no defects also attracted fixations (see Fig. 13d).
   - *E*: Extended dark regions in the sample (see Fig. 13e).

Observing these five perceptual features found in the human vision experiment, it was concluded that the major relevant features used by the experts while making their grading on samples, are variations in the intensity, texture and appearance of other relevant structures such as holes and dark patches. This is why the feature selection in the best results obtained from thresholding techniques, texture analysis and other heuristic features was focused upon.

Selected features

All the results obtained in the feature extraction stage were obtained in the same conditions. All the single cork quality features with the same basic classifier, regardless the technique used for its extraction were tested. Although the initial error rates were high due to the simplicity of the classifier used, the results obtained from them can be sorted in terms of global error rate, in order to detect which of those features were the ones having a better performance in terms of cork quality detection.

Using Table 1 as reference, the best results obtained in each stage (with each technique) in order to select the features that will be introduced in the final classification system can be evaluated.

Thresholding techniques

The thresholding technique that showed a better performance was selected in order to extract a feature that could give relevant information about the intensity values and variations in the cork surface. In Table 1 there were three thresholding techniques obtaining good classification results. Only one of those methods needed to be selected, since the information that would be provided by all the features obtained by the different thresholding techniques would be the same. This was why the best of those methods was selected: Static thresholding with a heuristically fixed threshold in the grey level 69.

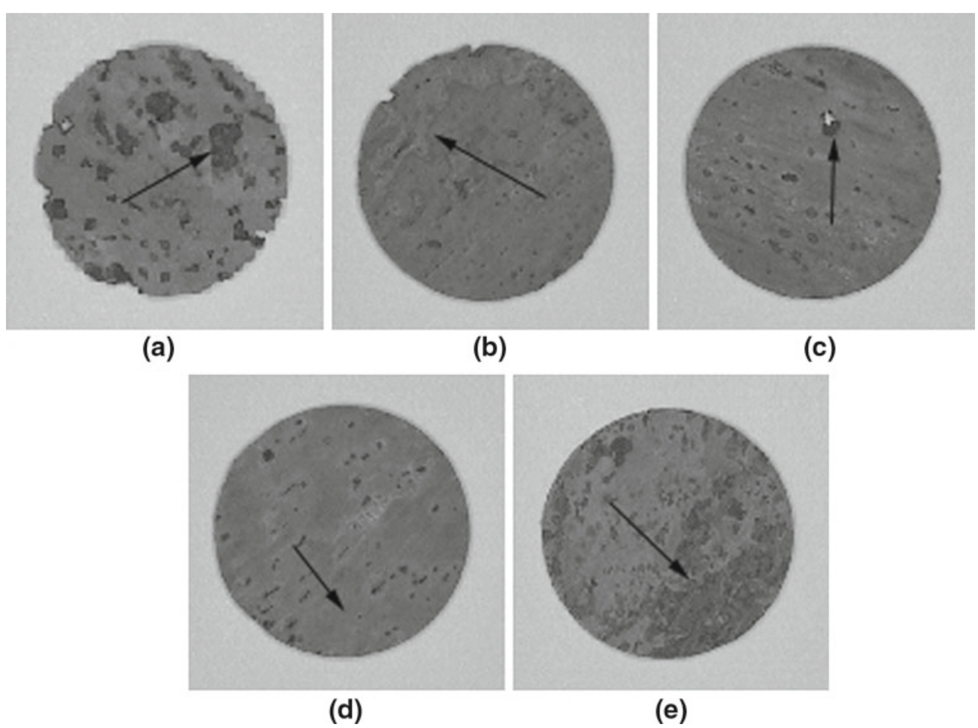


Fig. 13 **a** Large dark patches. **b** Extended light region, with variations in lightness. **c** Holes, **d** Non-defective areas, **e** Extended dark region

Table 1 All the features extracted, sorted by global error rate and divided in the three main classes THR (thresholding techniques), TEX (texture analysis) and HEU (heuristic features)

Cork Random Classification	92.57%
THR: 2nd Pun	84.57%
TEX: Cluster shade	82.57%
TEX: Cluster prominence	81.71%
THR: Johannsen-Bille	81.42%
THR: Histogram Concavity Analysis	80.85%
TEX: Homogeneity	79.71%
TEX: Inverse Difference Moment	78.85%
THR: Slope method 50	78.85%
TEX: Correlation	78.57%
THR: Slope method 26	78.57%
THR: 1st Pun	78%
THR: Slope method 82	76.85%
THR: Otsu	76.57%
THR: Kapur-Sahoo-Wong	74%
TEX: Maximum probability	72%
TEX: Energy	70.85%
THR: Chow-Kaneko	70.57%
TEX: R5L5TR	70.57%
TEX: Entropy	70.28%
TEX: R5R5TR	69.71%
TEX: W5E5TR	69.71%
TEX: S5L5TR	69.71%
THR: Moment-preserving	69.42%
TEX: R5W5TR	69.42%
TEX: W5S5TR	69.42%
TEX: W5L5TR	69.42%
TEX: R5E5TR	69.41%
TEX: R5S5TR	69.14%
TEX: S5E5TR	69.14%
TEX: Contrast	68.85%
TEX: S5S5TR	68.85%
TEX: W5W5TR	68.85%
TEX: E5E5TR	67.71%
THR: Statistical Thresholding (cut)	66%
THR: Statistical Thresholding (complete)	65.71%
HEU: Biggest defect	64.57%
TEX: E5L5TR	63.71%
THR: Static thresholding with a heuristically fixed threshold	63.14%
HEU: Hole study combined with thresholding	62.57%

Texture analysis

Each one of the features extracted gave different information about texture analysis. As Table 1 shows, the Laws TEMs features shows a better classification behavior than other more basic texture analysis techniques studied. That is why the best Laws textural features obtained in order to add them to this system were selected: E5L5TR, E5E5TR, S5S5TR, W5W5TR.

Heuristic features

Table 1 with the final global error rates shows that the two heuristic features discovered by the gaze pattern analysis by human experts, obtained good performance results. Both holes and size of defects were showing relevant cork quality information. However, since holes information was only showing discrimination power in the low-quality cork classes (those with perforations) and it had to be combined with another feature that has discrimination power in the rest of classes, it was not considered for the final system. The defect size was considered as a selected feature for further research.

Classifiers

In order to classify a cork disk in a specific class, the corresponding classification algorithm based on the best features selected was used in this study. In previous sections each single feature was analyzed individually, but from now all results will be evaluated by using the combination of all these six best features selected. The selected features are those that have obtained the best cork classification rates: defects area (using a static thresholding method with a heuristically fixed threshold), the biggest defect size, and the Laws TEMs E5L5TR, E5E5TR, S5S5TR and W5W5TR. The five classifiers chosen for this study are the following (Shapiro and Stockman 2001; Jang et al. 1997): a Back-Propagation classical neural network, a K-means classifier, the K-nearest neighbours classification algorithm, a minimum Euclidean distance classifier and a Neuro-Fuzzy classifier:

1. *Neural classifier*: A Back-Propagation neural network was developed. An artificial neural network represents a learning and automatic processing paradigm inspired by the way in which the nervous system of animals works. It consists of a simulation of the properties observed in the biological neural systems through mathematical models developed with artificial mechanisms (like a computer). In the case of this problem, a Back-Propagation network architecture has been chosen, since it is very suitable for pattern recognition and class detection. The network designed for this study has a $6 \times 7 \times 3$ architecture. The weights associated to the network interconnections are initialized randomly and are adjusted during the learning. The type of learning used by this neural network is supervised. That is, during the network training stage,

some pairs of patterns (an entrance and its corresponding desired exit) are presented to the network. While showing patterns to the network, the weights are adjusted so that the error between the real results and the desired ones is diminished. This process is repeated until the network is stable. After this stage, the neural network using this dataset can be run.

2. *K-means classifier*: The reliability of this classifier was studied because of its fame in specialized literature. This clustering algorithm makes reference to the existence of a number of K classes or patterns, and therefore, it is necessary to know the number of classes. There are seven classes, which is the reason why the algorithm is suitable for this study. K-means algorithm is a simple algorithm, but very efficient, and due to this fact it has been so used.
3. *K-nearest neighbours classifier*: This algorithm is part of the methods group known as correlations analysis methods. It classifies an unknown feature vector, depending on the sample or K samples of the training set that is/are more similar to it, that is to say, those samples that are closer to this vector in terms of minimum distance. This is what is known as the rule of the nearest neighbours. The classification algorithm of the K-nearest neighbours can even be very efficient when the classes have overlapping, and this is very interesting for cork quality classes. The approach for this classification algorithm used in this study is to examine only the K nearest neighbours (samples) to the unknown vector, and to classify it based on those K neighbours. The class of the unknown feature vector will be the one that most of the K neighbours have. Several K sizes (10, 20, 49,…) were evaluated, and the best size was 20.
4. *Euclidean classifier*: This classifier is one of the simplest and most efficient classifiers. This classifier has also been used to observe the tendency (performance) of all the features previously studied, analysing which of all the studied features were more suitable for cork quality discrimination. The classification algorithm sets several classes with their respective prototypes (centroids). Given an unknown feature vector to classify, the Euclidean classifier will associate this vector with the class whose prototype is closest to it, that is, the prototype whose Euclidean distance is the smallest. This study has been made for four versions of the Euclidean distance: simple Euclidean distance (see Eq. 13), Euclidean distance with prefiltrate (certain corks were classified directly, without passing through the Euclidean classifier, to low-quality classes if a hole in them was detected, that is, a set of decision rules in addition to the Euclidean classifier was used), scaled Euclidean distance (see Eq. 14) and modified scaled Euclidean distance according to the standard deviation (Eq. 15). The best results were obtained using the modified scaled Euclidean distance.

$$\text{Euclidean distance} = \sqrt{(x_{i1}-\mu_1)^2+(x_{i2}-\mu_2)^2+\cdots+(x_{iN}-\mu_N)^2} \quad (13)$$

$$\text{Scaled Euclidean distance} = \sqrt{\left(\frac{x_{i1}-\mu_1}{\sigma_1}\right)^2+\left(\frac{x_{i2}-\mu_2}{\sigma_2}\right)^2+\cdots+\left(\frac{x_{iN}-\mu_N}{\sigma_N}\right)^2} \quad (14)$$

$$\text{Modified scaled Euclidean distance} = \sqrt{\frac{(x_{i1}-\mu_1)^2}{\sigma_1}+\frac{(x_{i2}-\mu_2)^2}{\sigma_2}+\cdots+\frac{(x_{iN}-\mu_N)^2}{\sigma_N}} \quad (15)$$

5. *Neuro-Fuzzy classifier*: Previous experimentations with neural networks showed the disadvantages of classical Neural Networks Computing in this application field (cork classification). This study hopes to find some improvement in these previous results by extending the research to Neuro-Fuzzy Computing, which seems to be more suitable to this study. Neuro-Fuzzy (Jang et al. 1997) networks are systems that include both aspects of the neural networks since they are systems with the ability to learn and to generalize, and aspects of fuzzy logic since they work with logical reasoning based on inference rules. The Neuro-Fuzzy networks also incorporate the possibility of working with linguistic variables (if it is necessary for the problem) and, in addition they change the binary treatment that the Artificial Neural Networks (ANNs) do by a diffuse treatment. The basis neural network architecture used in this study is a Back-Propagation and consists of three basic layers (Monzon and Pisarello 2004):

   - The input layer is the one that receives external entrances. This layer has its input in the previously selected features, thus, the input layer will be composed of *6 input neurons*.
   - The intermediate or hidden layers are those that are between the input and the output layer, and each of the neurons of the layer must be completely interconnected to each of the neurons in the previous and the following layers. There are some authors who say that is good to begin the training with a high number of hidden neurons, which can be reduced later, if the network reaches the minimum error in a reasonable time. Research discovered that, for input-output configuration, the optimum number of *hidden neurons* was 33.
   - The output layer gives the class to which an input pattern (cork stopper) belongs, and also the membership degree of the cork stoppers for every quality class. For that purpose a fuzzy membership function is defined, which will allow fuzzy data modeling when a feature can not be classified accurately between two contiguous cork classes. This study has seven cork quality

classes in a 6-dimensional feature space. The weighed distance Z_{ik} for the i-th input pattern to each of the cork quality classes is defined as:

$$Z_{ik} = \sqrt{\sum_{j=1}^{6} \left[\frac{F_{ij} - O_{kj}}{V_{kj}} \right]} \quad \text{for } k = 1 \ldots 7 \quad \text{and} \quad j = 1 \ldots 6 \tag{16}$$

where F_{ij} is the value of the j-th input features component of the i-th pattern. The 6-dimensional vectors O_{kj} and V_{kj} denote the mean and the standard deviation of the j-th input features of the numerical training data for the k-th class. The weighted distance with V_{kj} is used to take care of the variance of the classes so that a feature with higher variance has less significance in characterizing a class. This distance, Z_{ik}, will be stored in a 7-position array, and this vector will define the distance that separates each input pattern from each class. Knowing the Z_{ik} definition, the membership fuzzy function μ_k can be defined for each cork class, in case of an input feature pattern F_i as:

$$\mu_k = 1 - \left(\frac{Z_{ik} - \min_k(Z_{ik})}{\max_k(Z_{ik}) - \min_k(Z_{ik})} \right) \quad \text{for } k = 1 \ldots 7 \tag{17}$$

Obviously, $\mu_k(F_i)$ lies in the interval [0,1]. Here, the larger the distance of a pattern from a class, the lower its membership value to that class. These membership values will be calculated at the same time for every class, and they will be the optimum exit for an input pattern. This exit will shown the membership degree to each cork quality class. With seven classes, layer 7 neurons that present these membership values are needed in the output layer. So, the output layer will need *7 output neurons*.

After evaluating all these different classifiers in this study, it was concluded that the Neuro-Fuzzy classifier is the classifier that obtained the best results. The inclusion of fuzzy logic and the change of the neural network architecture have widely improved the wrong classification percentages obtained by the other classification algorithms, as shown in Fig. 14.

Final results

The Neuro-Fuzzy classifier was the one that obtained the best results using the combination of the six best features selected from the feature extraction methods section. Results are presented by means of a confusion matrix (Shapiro and Stockman 2001), due to their capability to show the conflicts among the different quality categories. Therefore, not only the definition of each class is displayed, but also the main confusions among them. Table 2 shows the results obtained by the fuzzy-neural network. The classification results obtained are highly satisfactory because most of the elements are placed around the main diagonal with few outliers. The dominance of the main diagonal can be observed clearly in the matrix. The final error rate, 4.28%, is also lower than the ones obtained in the other classifiers (see Fig. 14).

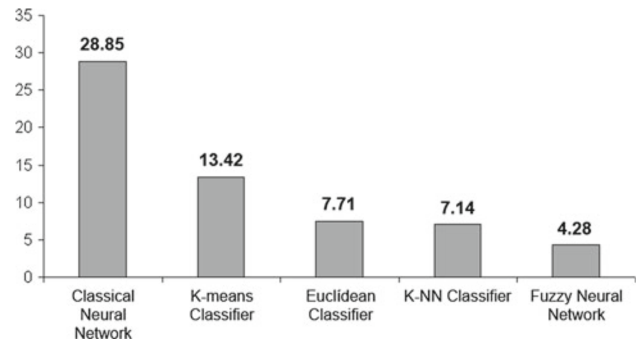


Fig. 14 Final results for the studied classifiers

Table 2 Final results for the Neuro-Fuzzy classifier

	C0	C1	C2	C3	C4	C5	C6	Right	Wrong
C0	49	0	0	1	0	0	0	49	1
C1	0	49	0	1	0	0	0	49	1
C2	0	0	50	0	0	0	0	50	0
C3	0	0	0	48	0	0	2	48	2
C4	0	0	1	0	47	0	2	47	3
C5	0	0	0	2	0	48	0	48	2
C6	0	0	1	2	3	0	44	44	6
Total								335	15

Comparing this error rate with the results obtained by other authors (see section Previous Studies) and also with the ones obtained by the electronic classification machines that exist in the cork industry at present (around 40% error rate for stoppers/disks of intermediate or low quality), this proposal widely improves all these results.

Noise and bias can be introduced in the system due to extensive experimentation, but the samples selected showed diverse and complex information. The high number of samples used along with the diversity of the samples assure the statistical confidence of these results. Furthermore, the final results obtained by this system were evaluated by three human experts on cork quality classification from IPROCOR (in Spanish: "Instituto del Corcho, la Madera y el Carbón Vegetal", in English: "Research Institute for Cork, Wood and Wooden Coal"). All experts agreed on the good results obtained by the system, even considering disagreement on the grading of some specific samples.

Conclusions

The automated visual inspection of cork is a problem of great complexity, in what refers to its quality-based classification, because cork is a natural material, and therefore, highly heterogeneous. This heterogeneity means that cork quality depends on many combined factors, such as texture, defects, surface, etc.

A deep survey about cork features extraction was performed in this study. The second-order grey level texture statistics, many different thresholding techniques (both local and global) in order to obtain the defect area in the cork, the Laws texture energy measures, the Varma and Zisserman's model based recognizer and some heuristic-oriented features have been studied. Finally, for the evaluation of all these features, methodology based on the combined use of the best features and five different classification techniques was proposed. The experimental results show that, in case of cork classification, the best system in this study is the one that combines cork texture, cork defects, and a classifier that allows some cork quality class overlapping (Neuro-Fuzzy classifier). Therefore, a different methodology from the previous studies in this field (section Previous Studies), using some of their ideas but contributing new ones is proposed.

In conclusion, the experiments on real cork stoppers/disks showed the high effectiveness and utility of our approach (with an error rate of only 4.28%), satisfying the needs of human experts in the cork industry. Furthermore, the use of this system could reduce costs, time and also many of the current conflicts in the cork industry due to the lack of a universal standard of quality.

Additionally, the results and conclusions obtained in this study can be useful to other visual inspection researches focused on other natural materials (wood, slate, etc.), because they have common characteristics with the cork (heterogeneity, changing texture according to its quality, defects, etc.).

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