A SOLUTION FOR EVALUATING THE STOPPER QUALITY IN THE CORK INDUSTRY

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Abstract: In this paper we study a possible solution to a problem existing in the cork industry: the cork stopper/disk classification according to their quality using a visual inspection system. Cork is a natural and heterogeneous material, therefore, its automatic classification (usually, seven different quality classes exist) is very difficult. The solution proposed in this paper shows all the stages made in our study: quality discriminatory features selection and extraction, texture analysis, analysis of different (global and local) automatic thresholding techniques and possible classifiers. In each stage we have given more importance to the study of those aspects that we think could influence the cork quality. In this paper we attempt to evaluate each of the stages in our solution to the problem of the cork classification in an industrial environment, and therefore, finding a way to justify the design of our final classification system. In conclusion, our experiments show that the best results are obtained by a system that works with the following features: total cork area occupied by defects (thresholding with heuristic fixed value 69), textural contrast, textural entropy and size of the biggest defect in the cork, all of them working in an Euclidean classifier. The obtained results have been very encouraging.

1 INTRODUCTION

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 the sealed (Fortes, 1993). In the cork industry, stoppers and disks are classified in different quality classes based on a complex combination of their defects and particular features. Due to this, the classification process has been carried out, traditionally, by human experts manually.

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. In conclusion, the stoppers/disks should be re-evaluated by human experts later. This slows down and increases in price the process enormously. Think that, on average, a human expert needs a minimum training period of 6 months to attain a minimum agility, although the learning process lasts years (compare it with other experts: wine tasters, cured ham tasters, etcetera). Another negative aspect is the subjectivity degree added to the classification process due to the necessary human re-evaluation.

We have to add to these antecedents the fact that Spain is the 2nd world producer of cork (CorkQC, 2006), only surpassed by Portugal, and that in Extremadura (a south-western region of Spain), due to its geographical situation, the cork industry is one of its most important industries: it produces 10% of the world cork (ICMC, 2006).

All these motivations have lead us to the development of this research, whose main objective is the construction of a computer vision system for cork classification based on advanced methods of image processing and feature extraction in order to avoid the human evaluation in the quality discrimination process.

The rest of the paper is organized as follows: section 2 describes briefly the data used for the development of our experiments. In section 3, we present the features used by the classifiers. Then,

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section 4 shows our analysis of the different studied classifiers. Finally, section 5 displays the statistical evaluation of the final results obtained by the proposed whole system, while section 6 exposes the conclusions and future work.

2 DATA

The database used in our experiments consists in 700 images taken from 350 cork disks (we have taken two images of each disk, for both heads). There are seven different quality classes, 50 disks in each class. The initial classification, in which this study is based on, 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"). We suppose this classification is optimal/perfect and we want to design a system which obtains the most similar classification results.

3 USED FEATURES

In order to develop our classifiers study, first, different feature extraction methods have been analysed: thresholding techniques, statistical texture analysis and two other heuristic features.

3.1 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, 1998). In our study we evaluate several thresholding techniques with the purpose of knowing which of them is the best for this application field. In this study, in order to classify a cork disk in a specific class, we only use the feature related with the defect area in relation to disk area.

For this comparative thresholding analysis we have studied both global thresholding techniques and local thresholding techniques (Sahoo, 1988). The thirteen thresholding methods that have been studied are the following: slope method (own 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, 1985), Johannsen-Bille method (Johannsen, 1982), moment-preserving method (Tsai, 1985), statistical thresholding method (Fisher, 2004) with different modifications, and Chow-Kaneko method (Chow, 1972).

The results of this study have been obtained by using for each thresholding method a classifier of minimum Euclidean distance (Shapiro, 2001). This classifier is based on the percentage of the defect area in relation to stopper/disk area. Knowing the average value of this feature for each class (cork quality class), we calculate the percentage of defects for each new stopper/disk and the Euclidean distances of this to the mean of each class. The stopper/disk will be classified in the class for which the smallest Euclidean distance has been obtained. The following equation shows the functionality of this classifier.

$$\text{Euclidean Distance} = \sqrt{(x_{ij} - \mu_j)^2}$$

It is possible that this classifier would not produce absolutely satisfactory results, due to we only use a single feature in order to classify the cork stoppers/disks, but this classifier can indicate certainly whether the classification tendency is reasonable or not, that is, the capability as quality discriminator of each of the thresholding methods.

Within global thresholding methods, we find that the most suitable method for cork industry is the moment-preserving method. Figure 1 shows the results (wrong classification percentage) obtained by the different global thresholding techniques. As we can see, all the thresholding techniques have obtained certain discriminatory information, although the goodness of the obtained results widely varies between some thresholding methods and others.

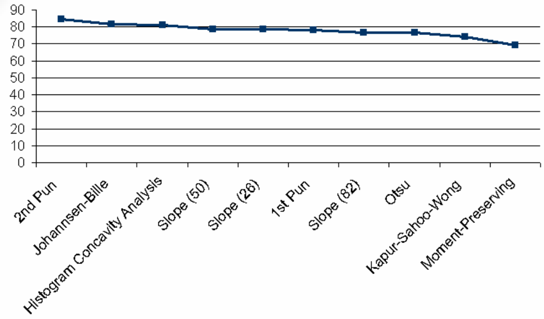

Figure 1: Global thresholding techniques results.

However, we can say that 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 2 displays the wrong classification percentage obtained by the different local thresholding methods.

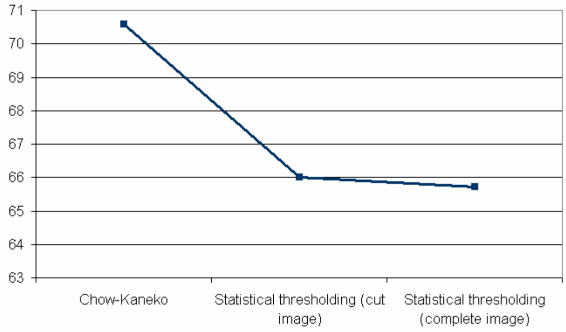

Figure 2: Local thresholding techniques results.

We finish this study comparing the best results obtained by both the global thresholding methods 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. It is worthy to say that, in addition to the studied thresholding methods, we decided to check a static thresholding method with a heuristically fixed threshold. The gray level for the threshold was obtained by using a recursive statistical study, testing what gray levels gave better classification results. Finally, a gray level 69 has been chosen as threshold.

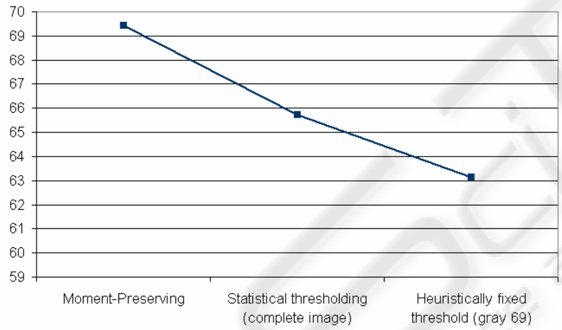

Figure 3: Final results of the thresholding study.

In figure 3 we can observe all these results. In conclusion, the local thresholding methods have been more suitable than the global methods for the solution of our problem. This has been due to they are able to find better thresholds in unimodal histograms. Nevertheless, the increase of the computational cost can make them unsuitable for our problem. 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 gray level 69.

3.2 Texture Analysis

We think cork texture can also be a powerful quality discriminator for the cork stoppers/disks. Between the main methods of texture analysis, structural analysis and statistical analysis (Shapiro, 2001), we have chosen the statistical approach due to the high difficulty to look for given visual patterns (texels) in the cork, since it is a heterogeneous material. The work made in this study is based on second-order gray level texture statistics, proposed by Haralick et al. (Haralick, 1973). In this second study we evaluate a great number of these statistical discriminators 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, we only use the corresponding textural discriminator (stopper/disk texture). In our texture analysis we use statistical quality discriminators based on the co-occurrence matrix. The studied discriminators are obtained by means of calculations using the rotation-robust normalized co-occurrence matrix, and they are the following: Energy (or Angular Second Moment (Shah, 2004)), Contrast (or Inertia), Homogeneity, Entropy, Inverse Difference Moment, Correlation, Cluster Shade, Cluster Prominence and Maximum Probability.

The results of this study have been obtained using the same method that the one used in the thresholding study (see section 3.1). Figure 4 presents the wrong classification percentage obtained by the different statistical discriminators. As we can observe 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, being the best discriminatory features the textural contrast and entropy.

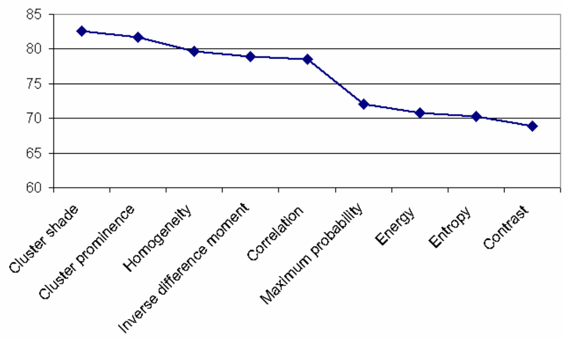

Figure 4: Final results for the studied textural features.

3.3 Other Features

After the previous features studies, we have dedicated the last features study stage to the analysis of other features and processes 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 we found some guidelines that were worthy to evaluate.

The two studied features have been the hole existence in the cork area and the biggest defect size in the cork:

- Hole study: It was observed that the cork stoppers/disks with holes 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 Euclidean classifier, but we have considered the number of hole pixels when we have made the definitive classification. 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, reason why this feature must be combined with another feature that has discrimination power in the rest of classes. In this case, we have chosen the defect area.
- 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. The methodology followed in order to obtain this feature has been making successive binary erosions on the thresholded image, with a 5x5 structuring element (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 obtain easily the size that the biggest defect could have, taking into account the number of iterations required to leave the image in blank.

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

4 CLASSIFIERS

In this last study, in order to classify a cork disk in a specific class, we will use the corresponding classification algorithm based on the four features selected: defects area (using a static thresholding method with a heuristically fixed threshold), texture contrast, texture entropy, the biggest defect size. The four classifiers chosen for this study are the following (Shapiro, 2001) (Sonka, 1998): a Back-Propagation neural network, a K-means classifier, the K-nearest neighbours classification algorithm, and a minimum Euclidean distance classifier:

- *Back-Propagation neural classifier:* The network designed for this study has a *4x7x3 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*.
- *K-means classifier:* This classification 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. We know, a priori, that we have 7 classes, reason why the algorithm is suitable for our necessities.
- *K-nearest neighbours classifier:* This algorithm is part of the methods group known as *correlations analysis methods*. It consists in classifying an unknown feature vector, depending on the sample or K samples of the training set that is/are more similar to it, or what is the same, which is/are nearer to this vector in terms of minimum distance. This is what we know as *rule of the nearest neighbours*. The classification algorithm of the K-nearest neighbours even can be very efficient when the classes have overlapping, and this is very interesting for our problem (cork quality classes). We have evaluated several K sizes (10, 20, 49,…), and the best size was 20.
- *Euclidean classifier:* The classification algorithm supposes several classes with their respective prototypes (centroids). Given an unknown feature vector to classify, the Euclidean classifier will associate this vector to the class whose prototype is closest to it, that is, the prototype whose Euclidean distance is the smallest. Our study have been made for four versions of the Euclidean distance: simple Euclidean distance (see equation below), Euclidean distance with prefiltrate (certain corks were classified directly, without passing the Euclidean classifier, to low-quality classes if a hole in them was detected, that is, we used a set of decision rules in addition to the Euclidean classifier), scaled Euclidean distance (see equation below) and modified scaled Euclidean distance according to the standard deviation (see

equation below). The best results were obtained using the modified scaled Euclidean distance.

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

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

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

According to the experimental results we can say that, in case of cork, there are more suitable classifiers than others, although some of the studied classifiers have been very near in their final results. As conclusion, we can say that the Euclidean classifier has been the more reliable in our application field. Figure 5 presents the wrong classification percentage obtained by the different classifiers.

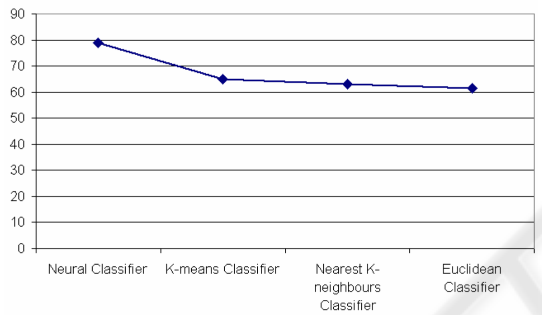

Figure 5: Final results for the studied classifiers.

5 RESULTS

Having made all these previous studies, we can conclude that the best cork classification system is the one based on an Euclidean classifier working with the following quality discriminatory features: the cork area occupied by defects (thresholding with heuristic fixed value 69), the texture contrast, the texture entropy and the size of the biggest defect in the cork.

We present the final results obtained by this system by means of a confusion matrix (Shapiro, 2001), due to its capability to show the conflicts among the different quality categories. Therefore, not only the definition of each class will be displayed, but also the main confusions among them.

The obtained confusion matrix (table 1) presents quite positive results (the main diagonal of the matrix is clearly defined). Using a classifier based on scaled Euclidean distances with the standard deviation, we can also observe that class 6 acquires a great power of absorption, that even affects class 4. On the other hand, we can see a strong discrimination of classes 0, 6 and 3, with a great number of corks classified rightly in these classes.

Table 1: Confusion matrix for the final system.

	C0	C1	C2	C3	C4	C5	C6
C0	33	12	4	1	0	0	0
C1	19	14	13	3	1	0	0
C2	6	9	15	18	2	0	0
C3	1	4	7	23	11	0	4
C4	2	0	1	10	13	3	21
C5	0	0	1	12	7	6	24
C6	1	0	1	7	7	3	31

The total results are shown in table 2, with a final wrong classification percentage of 61.42%.

Table 2: Total results for the final system.

	C0	C1	C2	C3	C4	C5	C6	TOT.
Wrong	17	36	35	27	37	44	19	**215**
Right	33	14	15	23	13	6	31	**135**

In addition to this experiment, which was made on the complete image database, we have made two additional experiments: one with a pre-selection of 40 cork disks per class (280 corks in total) and another with a pre-selection of 20 cork disks per class (140 corks in total). These tests were done because there were corks that were classified badly in a systematic way, therefore, we supposed that the human expert who performed the first cork classification (remember that we have based all our work on this classification) could have made some mistakes (wrong classifications), or that certain cork images could have a very poor quality due to the used acquisition system (camera, illumination, etc.).

The evolution of the obtained results can be seen in figure 6. We can observe a clear decrease in the wrong classification percentage, which makes us think about the possible existence of some errors in our image database. Observe that the results using an image database pre-selected with 140 cork disks (280 images) shows a wrong classification percentage of 45% (very far from the 61.42%).

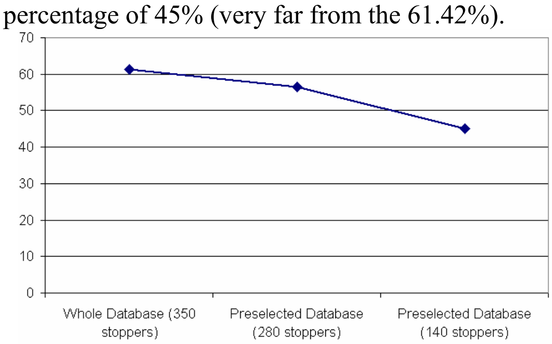

Figure 6: Final results of the database pre-selections.

6 CONCLUSIONS

In this paper we have performed a deep survey to conclude in the best classification system among all the systems proposed. Many possible discriminatory features have been studied in depth, as well as the classifiers to work with them.

As conclusion, figure 7 presents the wrong classification percentage obtained by our system for the different image databases. This graph also includes the wrong classification percentage that a random classification would have obtained.

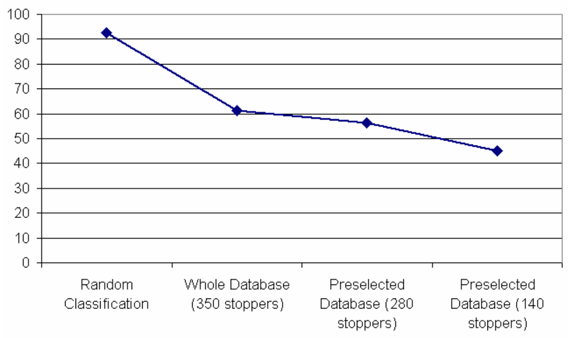

Figure 7: Final results for the studied system.

As we can observe in the previous graph, the pre-selection with 20 disks per class in our proposed system has produced the best results (45% of error rate). Furthermore, the result obtained by the final system highly improves the results obtained by a random classification (around a 90% of error rate).

As future work we have planned to study other classifiers like, for example, fuzzy-neural networks. Also, we do not discard the inclusion and analysis of other features that could improve the classification.

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