DIFFERENT CLASSIFIERS FOR THE PROBLEM OF EVALUATING CORK QUALITY IN AN INDUSTRIAL SYSTEM

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Abstract: In this paper we study the use of different classifiers to solve a classification 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 classifiers, which we present in this paper, work with several quality discriminators (features), that we think could influence cork quality. These discriminators (features) have been checked and evaluated before being used by the different classifiers that will be exposed here. In this paper we attempt to evaluate the performance of a total of 4 different cork quality-based classifiers in order to conclude which of them is the most appropriate for this industry, and therefore, obtains the best cork classification results. In conclusion, our experiments show that the Euclidean classifier is the one which obtains the best results in this application field.

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), for its geographical situation, the cork industry is one of its more 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.

For this purpose we have performed a study of the features that could better inform us about the cork quality. We have focused this study on an analysis of thresholding techniques (segmenting the different cork defects) and textural features, in addition to other features (like holes and different-area defects). From this study we conclude that the features that better define the cork quality are: the total cork area occupied by defects, the cork texture

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contrast, the cork texture entropy, and the biggest size defect in the cork stopper/disk.

Later, and with these results, an analysis of different possible classifiers has been made. The studied classifiers have been a Back-Propagation neural network, the K-means classification algorithm, a K-nearest neighbours classifier and the minimum Euclidean distances classification algorithm. In this paper we evaluate all these classification algorithms with the purpose of knowing which of them is the most appropriate for our application environment.

The rest of the paper is organized as follows: section 2 describes briefly the tools and the data used for the development of our experiments. In section 3, we present the features used by the classifiers. Then, section 4 shows the theoretical bases for the analysis we have made and other important details. Finally, section 5 presents the final results statistical evaluation for each classifier, while section 6 exposes the conclusions and future work.

2 TOOLS AND DATA

At present, the computer vision system we use to acquire the cork stopper/disk images is formed by the elements shown in figure 1: 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).

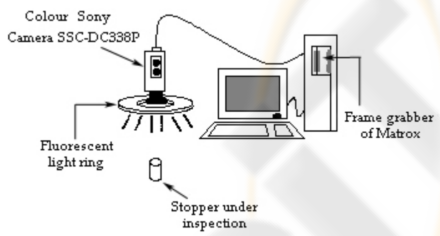

Figure 1: Computer vision system.

On the other hand, 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 know which classifier obtains the most similar classification results.

3 USED FEATURES

In order to develop our classifiers study, different feature extraction methods were analysed: thresholding techniques, statistical texture analysis, etcetera.

Regarding automatic thresholding, we carried out a study of global and local thresholding techniques (Sonka, 1998) (Sahoo, 1988). The objective was to extract the defect area from the cork area, thus being able to extract the percentage of the cork area occupied by defects (an important feature in cork quality discrimination). 11 global thresholding methods were studied: *static thresholding, min-max method, maximum average method, Otsu method, slope method, histogram concavity analysis method, first Pun method, second Pun method, Kapur-Sahoo-Wong method, Johannsen-Bille method and moment-preserving method*. In general, global thresholding methods are very limited in our problem. For a good global thresholding we need bimodal histograms, and the results obtained with unimodal histograms have been quite bad. These methods are suitable for the cork stopper/disk area extraction from the image background. In this situation we can find that all conditions for a good operation are fulfilled, but they are not suitable for the defect area extraction from the cork area. As for local thresholding, two methods have been studied: *statistical thresholding method and Chow-Kaneko method*. 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 was static thresholding method with a heuristically fixed threshold in the gray level 69.

With regard to texture analysis (Haralick, 1973) (Shah, 2004), two main methods have been studied, both based on statistical texture analysis. The first was a method based on simple co-occurrence matrices and another was a method based on rotation-robust normalized co-occurrence matrices. Furthermore, we have studied nine quality discriminators (textural features) for each method: *energy, contrast, homogeneity, entropy, inverse difference moment, correlation, cluster shade, cluster prominence and maximum probability*. The best obtained results were with the contrast and the entropy, both calculated by using rotation-robust normalized co-occurrence matrices.

In addition to the total area occupied by defects (obtained after doing an image thresholding with the previous methods) and the texture analysis of the cork area, other features were analysed too. Concretely, additional studies were made on: *holes (perforations) in the cork area and size of the biggest defect in the cork*. In the case of cork holes, a quantitative comparison is done between the theoretical area of cork (computed using the cork stopper/disk perimeter) and the real area of cork. If the real area is smaller than the theoretical one (surpassing certain threshold) we consider that the cork has holes. In order to calculate the biggest defect in the cork stopper/disk, the followed methodology is to perform successive morphological erosions on the thresholded image (defects area). In each iteration, we control the remaining defect percentage. In this way, we can quickly observe the size that could have the biggest defect of the cork, analysing the number of required iterations for eliminating almost all the defect pixels (or required iterations for reaching certain threshold of defect pixels). The best results obtained in this case (the evaluation of these two additional features) were for the size of the biggest defect in the cork.

In conclusion, after an exhaustive feature study, the features chosen to be used in our classifier study were: the total cork area occupied by defects (thresholding with heuristic fixed value 69), the textural contrast, the textural entropy and the size of the biggest defect in the cork.

4 METHODS

In this paper, in order to classify a cork disk in a specific class, we will use the corresponding classification algorithm base on the four features selected: defects area, contrast, entropy, 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.

4.1 Neural Classifier

Concretely, we have developed a Back-Propagation neural network. An artificial neural network represents a learning and automatic processing paradigm inspired in the form in which the nervous system of the animals works. It consists in 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, very suitable for pattern recognition and class detection. The network designed for this study has the following architecture:

- One input layer that is the one that receives external signals, which will be the four features selected during the course of this work. Therefore, the input layer has *4 neurons*.
- One hidden layer, whose number of neurons is based on the proportion given by the following equation:

$$N^{o}\,hidden\,neurons = \frac{N^{o}\,input\,neurons \times N^{o}\,output\,neurons}{2}$$

  Therefore, and knowing that the output layer has 3 neurons, the number of hidden neurons should be 6. But, at the end, we decided to increase the number of neurons in the hidden layer and increase the complexity of the weight matrix. In this way, we make easier the learning for the network. Due to this fact, our hidden layer has *7 neurons*.
- One output layer that gives back the results obtained by the neural network in binary format. As the classes to classify are seven, only *3 neurons* will be necessary to codify the results correctly.

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, we present to the network pairs of patterns (an entrance and its corresponding wished exit). While we are 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 phase, we can run the neural network.

4.2 K-Means Classifier

As always, we have studied this classifier for the four selected features. We have decided to study the reliability of this classifier 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 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-means classification algorithm is a simple algorithm, but very efficient, and due to this fact it has been so used.

Beginning from a set of p objects to classify X_1, X_2, …, X_p, the K-means classification algorithm makes the following steps:

Step 1

Knowing previously the number of classes, we say K, K samples are randomly chosen and clustered into arrays (see the following equation), and these arrays will be the centroids (due to the fact of being the only elements) for each class.

$$\alpha_1 : Z_1(1); \alpha_2 : Z_2(1); \cdots \alpha_K : Z_K(1)$$

Step 2

Being this algorithm a recursive process with a counter n, we can say that in the generic iteration n we allocate all the samples $\{X\}_{1\leq j\leq p}$ among the K-classes, as we can observe in the following equation:

$$X \in \alpha_i(n) \, sii \, \|X - Z_i(n)\| < \|X - Z_i(n)\| \, \forall i = 1,2,\ldots,K / i \neq j$$

In the previous equation we have indexed the classes (that are dynamic classes) and their centroids.

Step 3

In the moment we have allocated all the samples among the different classes, it is necessary to update the class centroids. With this calculation, we are looking for to minimize the profit index that is shown in the following equation:

$$J_i = \sum_{X \in \alpha_i(n)} \|X - Z_i(n)\|^2$$

This index can be minimized using the sample average of $\alpha_i(n)$ (see the following equation):

$$Z_i(n+1) = \frac{1}{N_i(n)} \sum_{X \in \alpha_i(n)} X$$

Being $N_i(n)$ the number of samples in class α_i, after the iteration n.

Step 4

We check if the classification algorithm has reached the stability, as it is shown in the following equation:

$$Z_i(n+1) = Z_i(n) \, \forall i = 1,2,\ldots,K$$

If it does, the algorithm finishes. If not, we return to step 2 for repeating all the process again.

Finally, we have to say that, for the centroids allocation, the distance shown in the following equation was used. This is the Euclidean distance scaled with the standard deviation instead of with the variance, which gave better results in a previous study.

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

4.3 K-Nearest Neighbours Classifier

As for the classification algorithm based on the K-nearest neighbours, we can say that also works with the four best features obtained in the study about cork quality, above-mentioned. The distance selected for this experimentation was the Euclidean distance scaled with the standard deviation (showed before). We have decided this according to the results obtained for the Euclidean 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. The used distance more suitable for this method is the Euclidean 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).

A first brute-force approach for this algorithm computes the distance between the unknown feature vector and all the samples in the database (training set), it stores all these distances, and then it classifies the unknown vector in the class whose samples gave more minimum distances (in this case, many distances have to be examined). One of the advantages of this approach is that new samples can be added to the database at any time, but it also has a higher calculation time.

A better approach 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 have most of the K-neighbours. This has been the approach implemented in our classification algorithm.

4.4 Euclidean Classifier

This classifier is one of the simplest and most efficient classifiers. This classifier has also been used to observe the tendency (goodness) of all the features previously studied, analysing which of all the studied features were more suitable for cork quality discrimination.

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 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 in section 4.2).

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

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

The best results were obtained by the two last distances, but the modified scaled Euclidean distance was chosen for being more balanced in the results.

5 RESULTS

The results of this section have been obtained using the 4 classification algorithms previously explained. We present these results by means of confusion matrices (Shapiro, 2001), due to their 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.

5.1 Neural Classifier

The experimental results that are shown in this section correspond to a simplified version of the neural network. This decision was taken due to the non convergence of the network, when it was tried to learn the seven cork quality classes. Although we normalized the input data in a range from 0 to 24, and made a preselection of the cork disks that were more adapted to be training patterns, the convergence was impossible.

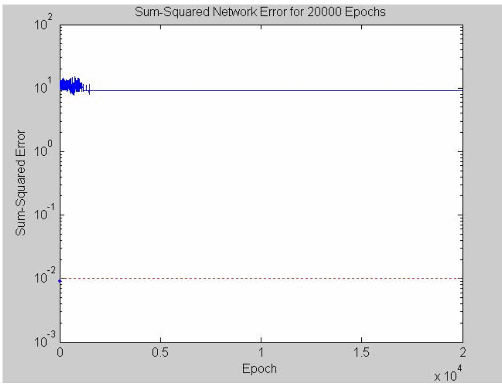

Figure 2: Graph showing the non convergence.

As it can be observed in figure 2, with the first version of the neural network, it was impossible to reach the convergence of the network, and the error introduced in the classification was too high. The dotted line shows the level of ideal error established (0.01), and the solid line shows the real error in the classification (around 10 points). The shown result was obtained after 20000 iterations of the network.

After multiple tests with the neural network, it was verified that, probably due to the overlapping between contiguous classes, the network was only able to learn two classes, for example, class 0 and class 3.

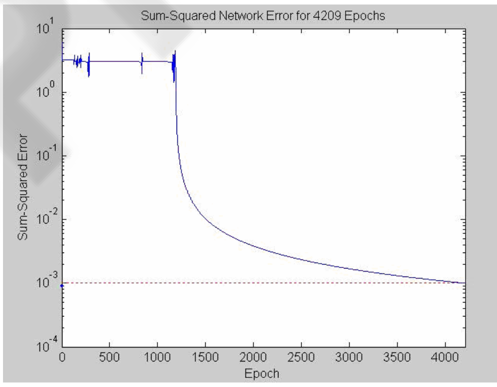

Figure 3: Graph showing the convergence of the network.

As it is shown in figure 3, with this second version (and even after having lowered the maximum level of error to 0.001), the neural network reaches the convergence quickly, in only 4209 iterations.

After this explanation, we can present the results of the confusion matrix. Table 1 shows the confusion matrix for the neural classifier. As it was expected, we have obtained quite bad results due to the class overlapping. Since the neural network only recognizes two classes, all the corks are classified in class 0 or class 3. Anyway, the results are coherent, it can be observed as classes 0 and 3 are classified mainly in themselves. Classes 4, 5 and 6, which are more distant from class 0, are classified mainly in class 3. And classes 1 and 2 are those that present more confusion between class 0 and 3 for being between them.

Table 1: Confusion matrix for the neural classifier.

	C0	C1	C2	C3	C4	C5	C6
C0	36	0	0	14	0	0	0
C1	28	0	0	22	0	0	0
C2	15	0	0	35	0	0	0
C3	12	0	0	38	0	0	0
C4	8	0	0	42	0	0	0
C5	3	0	0	47	0	0	0
C6	2	0	0	48	0	0	0

In conclusion, table 2 presents the final results, with a wrong classification percentage of 78.85%.

Table 2: Total results for the neural classifier.

	C0	C1	C2	C3	C4	C5	C6	TOT.
Wrong	14	50	50	12	50	50	50	**276**
Right	36	0	0	38	0	0	0	**74**

5.2 K-Means Classifier

Table 3 displays the confusion matrix for the K-means classifier.

Table 3: Confusion matrix for the K-means classifier.

	C0	C1	C2	C3	C4	C5	C6
C0	39	0	8	3	0	0	0
C1	25	0	15	9	0	0	1
C2	5	0	20	23	0	1	1
C3	1	0	7	24	4	3	11
C4	0	0	3	9	12	19	7
C5	0	0	0	7	17	24	2
C6	0	0	1	6	17	22	4

The confusion matrix we have obtained offers good results, although we can observe that there is a class that almost disappears, class 1. Nevertheless, the other classes have many right classifications, except class 6. In this sense, a great absorption power of class 5 over classes 4 and 6 is observed. The matrix presents only a little dispersion, which is very positive for the classification.

In conclusion, the final wrong classification percentage is 64.85% (table 4).

Table 4: Total results for the K-means classifier.

	C0	C1	C2	C3	C4	C5	C6	TOT.
Wrong	11	50	30	26	38	26	46	**227**
Right	39	0	20	24	12	24	4	**123**

5.3 K-Nearest Neighbours Classifier

For the calculation of the best size of K, three possible values have been checked. The chosen values were the following:

- A *little* value, K=10.
- A *big* value, K=49, the number of cork disks in a class (50) minus the disk under study.
- A *medium* value, K=20.

After a preliminary test, we finally concluded that the best size of K is K=20. Once we have chosen the value of K, we have done our experiments using the Euclidean distance that has generated the best results, the scaled Euclidean distance according to the standard deviation (see equation in section 4.2).

Table 5 presents the confusion matrix for the K-nearest neighbours classifier. As we can observe in the matrix, we have obtained good results. The matrix has a strong classification tendency around the main diagonal for all the classes, although it would be possible to say that still there are many erroneous classifications in some classes.

Table 5: Confusion matrix for the K-nearest neighbours classifier.

	C0	C1	C2	C3	C4	C5	C6
C0	38	9	3	0	0	0	0
C1	24	15	11	0	0	0	0
C2	8	12	20	9	1	0	0
C3	1	8	10	16	10	2	3
C4	1	0	4	13	15	7	10
C5	0	0	2	7	12	10	19
C6	0	0	4	4	11	16	15

In conclusion, the final error rate (table 6) is 63.14%.

Table 6: Total results for K-nearest neighbours classifier.

	C0	C1	C2	C3	C4	C5	C6	TOT.
Wrong	12	35	30	34	35	40	35	**221**
Right	38	15	20	16	15	10	15	**129**

5.4 Euclidean Classifier

The obtained confusion matrix (table 7) presents quite positive results. Using a classifier based on scaled Euclidean distances with the standard deviation, we can 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 7: Confusion matrix for the Euclidean classifier.

	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 8, with a final wrong classification percentage of 61.42%.

Table 8: Total results for the Euclidean classifier.

	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**

6 CONCLUSIONS AND FUTURE WORK

The automatic 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 causes that cork quality depends on many combined factors, and among them, cork texture, defect area, size of the biggest defect,...

In this paper we have performed a deep survey about several classifiers that includes each of these features (the best features we have found in a previous research). Concretely, we have focused on four important classifiers in the image processing field.

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 final conclusion, we can say that the Euclidean classifier has been the more reliable in our application field. Figure 4 presents the wrong classification percentage obtained by the different classifiers. This graph also includes the wrong classification percentage that a random classification would have obtained if it was used.

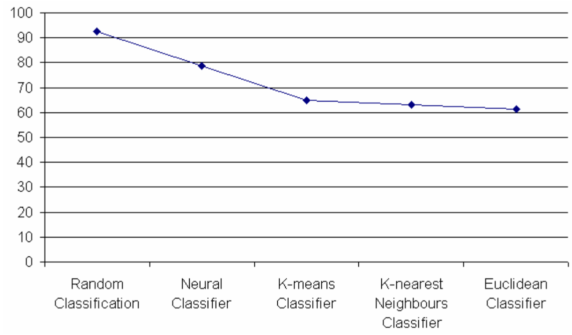

Figure 4: Final results for the studied classifiers.

As we can observe in the previous graph, the Euclidean classifier has produced the best results, but it is worthy to say that all the studied classification algorithms improve the results obtained by a random classification, although the goodness of the obtained results widely varies between some classifiers and others.

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

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 results.

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