USING 3D FEATURES TO EVALUATE CORK QUALITY

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Abstract: In this paper we study different 3D features in cork material. We do this in order to solve a classification problem existing in the cork industry: the cork stopper/disk quality classification. Cork Quality Standard sets seven different cork quality classes for cork stopper classification. These classes are based on a complex combination of cork stopper defects. In previous studies we only analysed those features that could be detected/acquired with a 2D camera. In this study we work in a 3D environment, in order to extract those features that we could not be extracted in a 2D approach. As a conclusion we can say that the most important 3D cork quality detection feature takes into account dark and deep cork areas (usually, these areas indicate deep and important defects). Furthermore, the 3D features have widely improved the results obtained by similar features with a 2D approach, due to the 3D approach includes more information. This fact allows us to extract more complex features, as well as improve the classification results.

1 INTRODUCTION

Oak is a tree that mostly grows in the western shores of the Mediterranean Sea. Because of this fact, the cork industry has a big economic importance and great research interest in the native zones of this material.

The most important industrial application of cork is the production of disks and stoppers for sealing wines, ciders, and champagnes. In the cork industry, stoppers and disks are classified in different quality classes based on a complex combination of its defects. Due to this high heterogeneity degree, traditionally, the classification process has been carried out by human experts manually.

At the moment, there are several models of electronic machines for the cork stoppers classification in the market. The performance of these machines is acceptable for high quality stoppers/disks, but for medium 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 increases the process price and the production time because a human expert needs a minimum training period of 6 months to attain minimum classification accuracy, although the learning process can last years. Furthermore, a human classifier can introduce some mistakes on the classification due to his/her subjectivity degree. In conclusion, more research efforts are necessary in the automatic cork classification field.

We have to add to these reasons the fact that Spain produces 31% (ASECOR, 2006) of the worldwide cork. All these motivations have lead us to the development of this research, whose final 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.

In this work we try to prove the accuracy of new 3D features in cork quality classification. In previous works (Paniagua-Paniagua et al, 2006a; Paniagua-Paniagua et al, 2006b), a wide study about feature extraction was made. Now, we try to analyse the automatic feature extraction of cork quality, within a 3D approach. We have focused this study on feature extraction, and several new cork quality 3D features have been obtained. We will test the

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performance for each 3D feature, to see the individual reliability of each quality discriminator. However, the main final objective is the development of a system that uses a complex combination of features to make the automatic cork quality classification.

The rest of the paper is organized as follows: section 2 describes briefly the acquisition system and data we have used. In section 3 we present the theoretical bases of this work. Section 4 shows the results and statistical evaluation for the new 3D features studied, while section 5 exposes the final conclusions.

2 TOOLS AND DATA

As a first step, we need to acquire again all the images in our Cork Image Database (CID), but in this case with a 3D approach. For this purpose, we have used a total of 350 cork disks (there are seven different quality classes, 50 disks per class). Furthermore, a laser camera system of the ShapeGrabber Company was used (ShapeGrabber, 2005a; ShapeGrabber, 2005b). The storage is made with “3pi” files, created by the ShapeGrabber Software to represent scanned data in ASCII.

When scanning with the ShapeGrabber system, the data are acquired following the rule: one profile at a time. A profile is the data collected from the processing of one full laser line. The points are ordered in a profile in ascending order along the X-axis. For each of these points, the coordinates of the point (x, y, and z), the intensity value and the order of the point in the profile are given. We will use this information to extract the 3D cork quality features in which this paper is focused on.

3 METHODS

This is the methodology we have followed in this research.

3.1 Background Thresholding

After the data acquisition and before going further in our research, an automatic thresholding algorithm was developed. This was made because the acquired images had some superfluous areas (acquisition surface that does not correspond to cork, see figure 1) that we needed to remove from each of the 3D images in our CID. That is, we needed to delete the background from the 3D cork images, in order to perform the 3D feature extraction research.

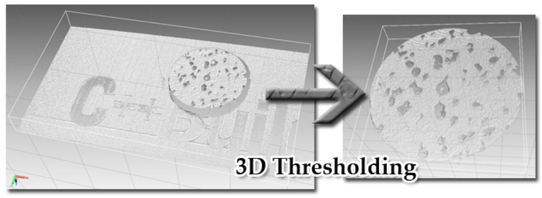

Figure 1: 3D images before and after the 3D thresholding.

To do that, we only consider those 3D points that have a lower depth of Z-axis value than those points that belong to the background.

3.2 Initial Feature Extraction

The following step was the extraction of a 3D feature suitable for doing some preliminary tests with our 3D laser camera. Concretely, the feature extracted is conformed by the *percentage in the cork area occupied by 3D points that are not only dark (intensity) but also deep (coordinate Z)*. A cork stopper with a high value in this feature will glimpse having a low quality, because the higher this value is, more deep defects will exist within the cork.

3.3 Resolution Study

Then, we decided to develop an initial study to discover the optimal resolution value for using the 3D laser-camera in the acquisition of cork images.

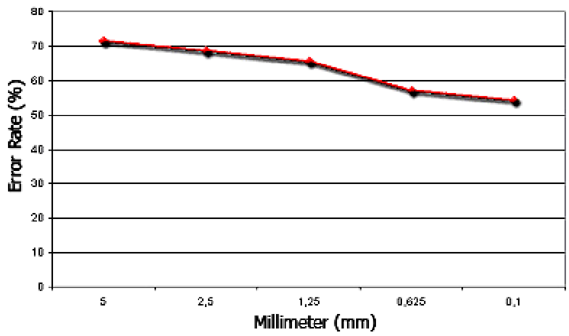

Figure 2: Decreasing error rate tendency when the resolution increases.

Figure 2 shows the error rate obtained in the cork quality classification, using the previous 3D feature and a minimum Euclidean Distance classifier. We can see that when the resolution increases, the error rate decreases.

3.4 Classification Criterion Selection

Our classification system acquires images from both heads of the stopper/disk (see figure 3). Because of that fact, we have carried out studies in which, using our initial 3D feature (see section 3.2), we have selected the optimal stopper-head criterion. The three studied criteria are:

- The feature is computed by choosing the best result obtained between both heads in the acquisition process. The final error rate for this criterion was 59.42%.
- The feature is computed by choosing the worst result obtained between both heads in the acquisition process. The final error rate in this case was 70.28%.
- The feature is computed by choosing an average value from the two obtained in both heads. That is, we have to obtain the feature for each head and make an average between them. In this situation we obtained the best classification, being the error rate 52.57%.

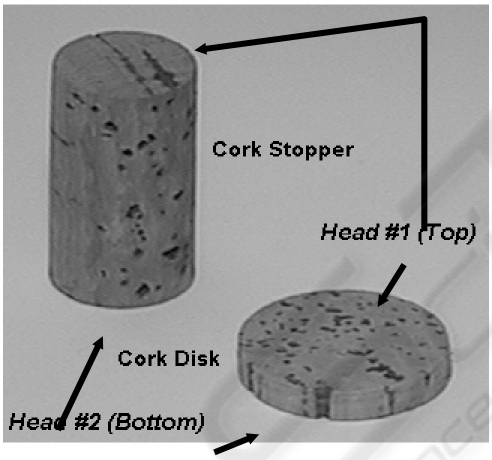

Figure 3: The two heads of a cork stopper/disk.

In conclusion, the best classification criterion is the one that contemplates an average value between both stopper heads. We have used it in all our experiments.

3.5 3D Features Extraction

After making the acquisition of our whole CID with the optimal resolution (in this case, the highest for our 3D camera, 0.1 mm), we perform the last and most important stage: extraction and experimentation of new 3D cork quality features. The studied features have been designed in a heuristic way, by analizing the human experts classifications and considering the visual features they choose in their classifications. The conclusions of this analysis make us chose the following 3D features for our research:

- Maximum depth of the defects within the cork surface (and some variants).
- Weighted sum of the defects according to their relative depth.
- Amount of defect pixels in a concrete depth level.

4 RESULTS

All the results in this section have been obtained by using a classifier of minimum Euclidean distance (Shapiro and Stockman, 2001). We will use confusion matrix in order to show the results.

As for the maximum depth of the defects, it seems logical to think that the depth of the defects (cracks and holes) will make a differentiation between the different cork quality classes, because usually the deeper a defect is, the more important this defect is. However, the obtained results are not as good as we expected (table 1). There is not tendency towards the main diagonal in the confusion matrix, and all the classifications are around classes 0 and 5. The error rate is high (table2), being 80.28%.

Table 1: Confusion matrix for the Maximum Depth.

	C0	C1	C2	C3	C4	C5	C6
C0	21	4	4	2	3	15	1
C1	15	2	6	2	1	24	0
C2	20	3	4	1	1	21	0
C3	14	5	3	2	3	23	0
C4	9	2	2	4	4	29	0
C5	9	2	2	1	0	36	0
C6	3	2	2	2	0	41	0

Table 2: Final results for the Maximum Depth.

	C0	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**TOT.**
Right	21	2	4	2	4	36	0	**69**
Wrong	29	48	46	48	46	14	50	**281**

Because of the bad results obtained, we decided to make an observation of the 3D data in our database. Doing this we realized that it could be possible that the bad results were produced by a side deviation in some cork stoppers. This fact makes the cork stopper sides irregular for the research, as we show in figures 4 and 5.

Figure 4: Deviations in the head surface of the cork disk.

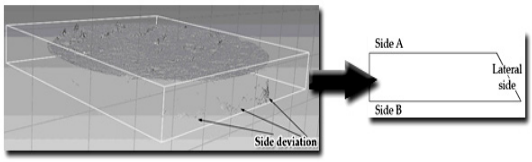

Figure 5: Deviations in the lateral side surface of the cork disk.

But this fact is not strange in industrial environments, due to the cork stoppers production machines can introduce some mistakes in some stoppers, and because cork is a porous material to which the environmental temperature can affect. Due to these deformations in the data, it was decided to make some additional experimentation with this 3D feature. In this new set of experiments we added two important details to the 3D max depth feature: (a) We only considered the very dark pixels (these are clearly defects, and there is not confusion with the deviated sides); (b) Searching for a depth level that was representative, we considered as maximum depth level the maximum depth with at least X dark pixels. That is, we were looking for big deep areas. We tested in our research several different values for X: 10, 25, 50, 100, 150, 175, 200,… Figure 6 shows the results obtained.

As we can see, for the experiment detailed, the best results were obtained in case of X = 200, that is, the maximum depth must have at least 200 dark pixels (error rate = 78%). This value is clearly an inflection point in the graph.

An error rate of 78% improved our previous result (80.28%) but it was still a bad result. For this reason, a second set of experiments was made (figure 7). In this case, we apply the inverse reasoning: we search for a maximum depth with not a lot of pixels, because it seems normal that there are not many very deep defects in a cork stopper, and if many deep defects exist maybe this can be a cluster of pixels due to a cork side deviation and not due to defects. Figure 7 presents the results obtained. Almost all the experiments obtain the same result, an error rate of 66.28%.

Figure 6: First set of experiments with the maximum depth.

This is the best result we have obtained with the maximum depth feature. Observe that cork classification is different from other classification problems, such as character recognition: even a human expert, sometimes, can not make a clear decision about if a stopper/disk absolutely belongs to a certain class or a contiguous one. Therefore, using only one classification feature (the maximum depth) and for this complex classification problem, an error rate of 66.28% is an encouraging result.

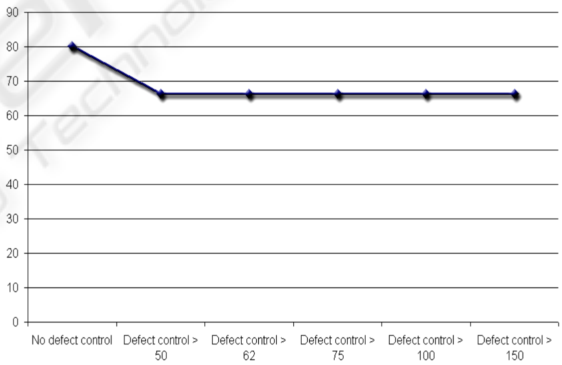

Figure 7: Second set of experiments with the maximum depth.

Regarding the weighted sum of the defects according to their relative depth, we use equation 1. For this 3D feature, we have divided the cork stopper pixels in 7 different depth levels (from 0 to 6), being p_x in the equation the amount of pixels in the X depth level. Each level supposes a different weight in the final sum (if the pixel is deeper, the defect associated with this pixel will be more serious). This feature was chosen in order to consider the possible severity of cork defects. Thus, the greater depth level is, the bigger the severity of those defects is.

$$\text{Weighted Depth} = \frac{(p0*0)+(p1*1)+...+(p6*6)}{\text{total pixels in the stopper area}} \quad (1)$$

Table 3 shows the confusion matrix obtained by this 3D feature, while table 4 shows its final results. The confusion matrix offers very good results. The tendency towards the main diagonal is very clear, except for class 5 due to the influence of classes 4 and 6. The error rate obtained with this feature is 51.14%. This result improves the results we have obtained in previous works (Paniagua-Paniagua et al, 2006a; Paniagua-Paniagua et al, 2006b), showing the importance of using 3D features, and not only 2D features in the cork classification.

Table 3: Confusion matrix for the Weighted Depth.

	C0	C1	C2	C3	C4	C5	C6
C0	35	14	1	0	0	0	0
C1	20	22	7	1	0	0	0
C2	1	10	29	10	0	0	0
C3	0	1	14	33	1	1	0
C4	0	0	1	12	22	4	11
C5	0	0	0	4	20	6	20
C6	0	0	1	4	13	8	24

Table 4: Final results for the Weighted Depth.

	C0	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**TOT.**
Right	35	22	29	33	22	6	24	**171**
Wrong	15	28	21	17	28	44	26	**179**

Finally, we evaluate the 3D feature that considers the amount of defect pixels in a concrete depth level. With this study we want to know if there is some depth level among the defects that is more important in order to obtain a good classification results. In this case we study 5 different depth levels (from 1 to 5): level 0 is not studied because it has not a real importance, being not a defect but the cork surface; in the same way, depth level 6 is not considered because there are not so much pixels for this level in most 3D cork images. Figure 8 displays the final results (error rates after doing a cork classification only based on the defect pixels in a concrete depth level).

Thanks to this study we have empirically proved that the different depth levels have different importance in cork quality classification. We can see that the extreme levels (1 and 5) are the levels with less importance (the worst classification results), and that the defects with a medium depth are the most important in the classification process. In particular, the defect pixels in the second depth level are those that have more importance, obtaining this feature the best result (error rate = 55.42%).

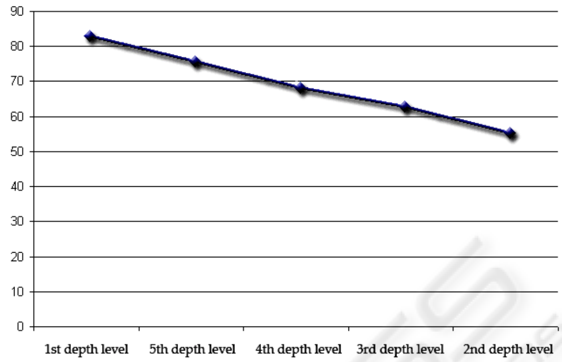

Figure 8: Final results (error rates) for the depth levels study.

5 CONCLUSIONS

The study in the 3D field has improved our cork quality classification. We think this is because in this field the extracted features can be more complex and give more information about the cork quality that those obtained in a 2D environment. After making a deep study about different 3D cork quality features, the obtained results are those displayed in figure 9.

Observe that all the 3D features have obtained certain discriminatory information that improves the cork classification according to its quality (all the features obtain better results than the random classification), although the goodness of the obtained results widely varies. The best result is produced by using the 3D feature "Weighted Depth" (error rate = 51.14%). This result improves our previous works (Paniagua-Paniagua et al, 2006a; Paniagua-Paniagua et al, 2006b), where the best error rate obtained was 65.71%, because of the complex conditions of heterogeneity and overlapping in this classification problem. Moreover, our result even improves other related works, in which the best error rate was 57.5% (Chang et al, 1997). For all these reasons, the result obtained in this research is a very encouraging result. On the other hand, the 3D features offer us new classification details that could not be perceived with our previous 2D works.

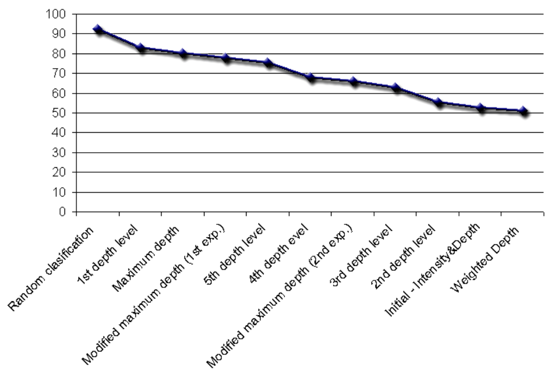

Figure 9: Summary of all the results (error rates) obtained with this study of 3D features.

As future work, we will improve the performance of the system (processing time) by using FPGAs (Vega-Rodríguez et al, 2004), and we will extend our research to other classification factors, as Gabor Wavelets (Tang et al, 2003).

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