Texture Segmentation Based On Fuzzy Grammar for Cork Parquet Quality Control

Manuel J. Ferreira[1], Cristina P. Santos[2], João Monteiro[3]
Department of Industrial Electronics
University of Minho
Campus de Azurem, Guimarães, Portugal
[1]mjf@dei.uminho.pt, [2]cristina@dei.uminho.pt [3]joao.monteiro@dei.uminho.pt

***Abstract-* This paper presents an approach for image texture segmentation based on the wavelets transform and on a fuzzy grammar inference system. It was developed for the Portuguese cork industry, specifically for the quality control in the cork parquet sector. The main purpose was to deal with major quality issues related with texture features. The segmentation procedure reveals a good performance indicated by high classification rates. This approach was integrated in a vision system leading to an industrial prototype that has already been tested, revealing good perspectives of full industrialization.**

I. INTRODUCTION

The cork industry has an important economic impact in the Portuguese traditional industry. This paper presents a texture segmentation procedure, which is part of a quality control vision system developed for the cork industry. This vision unit integrates an automatic classification equipment, specifically able to be used in the cork parquet industry.

There are two cork parquets in the Portuguese cork industry which, due to their great production rates, are the most popular ones. One cork parquet type is composed of three cork layers. The first layer remains in contact with the floor and is called the *BASE* layer. The second layer is visible and is named *UPPER* layer. Finally, a third layer, named *MOTIVE* layer is made of larger and thicker pieces of cork, which are placed randomly above the *UPPER* layer. The other cork parquet type has only two layers - the *BASE* and the *UPPER* layers.

To achieve an effective quality control of these products, several parameters must be evaluated and estimated. The most important of them are: 1) the visibility of the *BASE* layer in the *UPPER* layer (fig. 1a); 2) color drift between same parquet types (fig. 1b); 3) the presence of strange objects such as wood and glue (fig. 1c); and 4) the homogeneity in the visible layer (fig. 1d). The latest one results from the *MOTIVE* layer distribution over the *UPPER* layer. At the present, the quality control of these products is assured by specialized workers, who perform an intensive manual visual inspection of the products. This inspection, besides slowing down the production rate, is very dependent on the worker subjectivity. Therefore, an automatic inspection system is highly important for this sector.

According with the type of materials and with the nature of the quality problems, several computer vision techniques have been developed, based on texture or color analysis. This paper describes the approach developed for texture segmentation and is based on gray level images. Herein, we describe the application of this approach in the following quality control problems: the visibility of the *BASE* layer in the *UPPER* layer (fig. 1a) and 4) the homogeneity in the visible *UPPER* layer (fig. 1d).

The major problem in texture segmentation is the extraction of texture features for the classification procedure. The approach presented in this paper was developed concerning two major constraints: the production speed and the high diversity of texture patterns. This diversity results directly both from the inherent cork granularity of the different layers in the parquet and from the distribution of the *MOTIVE* layer. Consequently, the commercial available vision solutions are not completely appropriated for quality control in the industrial environments. Specifically, their limitations concern the capability to learn "on-line" new texture patterns and to deal with a great number and type of textures.

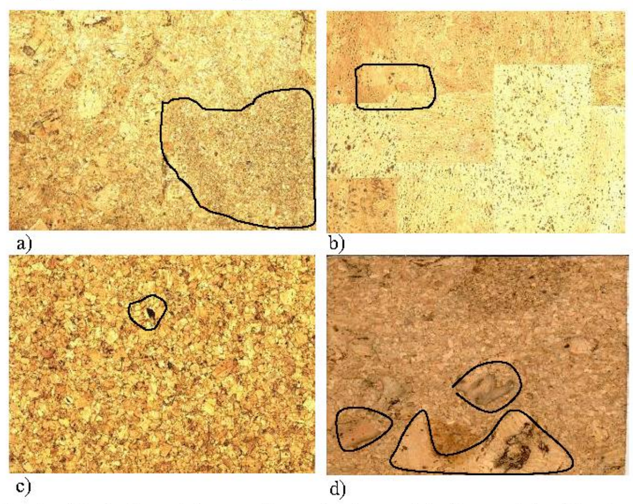

Fig. 1. Illustration of the most important aspects to be considered in the quality control of cork parquet. a) *BASE* appearance. b) Color drift. c) Strange objects. d) Surface homogeneity.

II. SYSTEM ARCHITECTURE

In this paper, a texture segmentation approach based on the wavelet transform and on a fuzzy grammar as a classifier has been developed. Specifically, features are extracted from detail images of wavelet transforms. The developed approach is divided onto two phases (fig. 2): the *learning* and the *execution* phases. In the *learning* phase, a texture is manually selected and a fuzzy rule is generated and stored in the database. In the *execution* phase, the texture under analysis is submitted to each fuzzy rule stored in the database and a texture identification is done. The system is capable of automatically starting a *learning* phase in case an unknown texture is shown to the system.

The *Feature Extraction* module (fig. 2) extracts the feature vector that best describes each texture.

The *Fuzzy Grammar* module uses the extracted feature vector to generate the fuzzy rule that describes the texture. Each rule is stored in a database during the *learning* phase.

In the *Execution* phase, the extracted feature vector is submitted to a *Parsing Procedure module,* developed with the compilers yacc and lex [1]. The vector is submitted to each fuzzy rule stored on the database, and a response value in the interval [0,1], reflecting the grade of membership of the texture, is obtained.

Finally, the *Classification* module uses the output of the parsing and verifies which rule produces a value higher than a pre-defined threshold. In case no rule produces a value higher than this threshold it is assumed that a new type of texture is present. A *learning* phase is automatically initiated and an appropriate fuzzy rule is generated for that texture. The result is a binary image where the blobs correspond to the presence of specific textures.

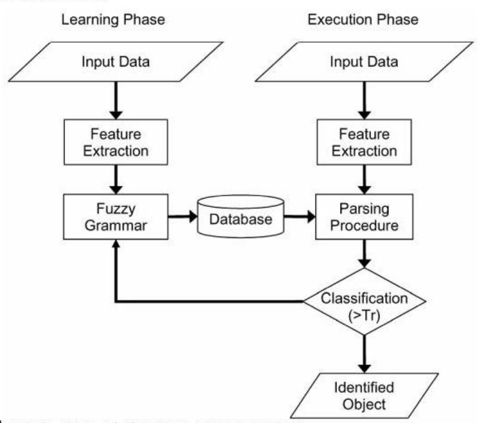

Fig. 2. Architecture of the processing system.

III. FEATURE EXTRACTION MODULE

Besides the classical approaches for texture segmentation, like the statistical, structural and spectral approaches, new ones, based on wavelet transform and Gabor filters [2,3,4], have recently deserved special attention. These are similar to the human vision system, which processes visual information in a multi-scale manner.

In [4], the author realises that the best compromise between processing time and classification rate was achieved with the wavelet transform. These aspects lead to the choice of the wavelet transform for texture segmentation in this industrial application.

[5] present theoretical fundamentals of the wavelet transform applied to signal analysis. The wavelet transform in this domain introduces the concept of variable time window with frequency. Signal events with high frequency are analysed with a higher timing resolution than the ones with lower frequency. To perform the wavelet transform, in the context of image processing, it is necessary to employ a two-dimensional discrete wavelet transform (DWT). As illustrated in fig. 3a, an approximation coefficient, at level m+1 (V_{m+1}xV_{m+1}), is decomposed in four components: the approximation coefficient at level m (V_mxV_m) and the details at level m in three orientation coefficients: horizontal (V_mxW_m), vertical (W_mxV_m) and diagonal (W_mxW_m). These last three components are the detail images used to construct the feature vectors. Fig. 3b shows a cork textured image and the correspondent wavelet transforms. There are several types of wavelets functions that can be used in texture analysis. However, [4] support that the type of wavelet function doesn't produce relevant changes in the analysis.

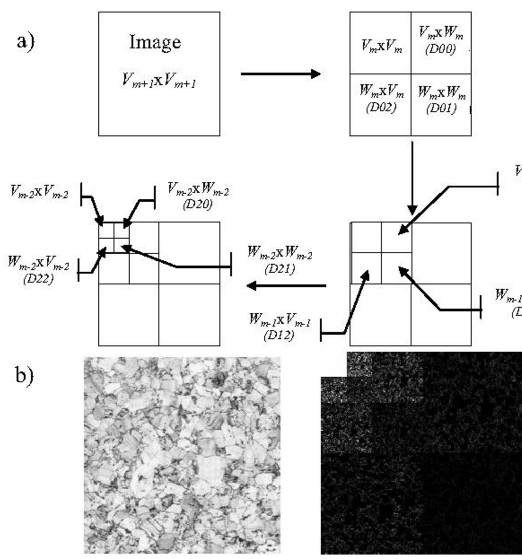

Fig. 3. Wavelet decomposition of an image. a) Final image obtained by the sub-spaces $V_{-i}xV_{-i}$, $V_{-i}xW_{-i}$, $W_{-i}xV_{-i}$, $W_{-i}xW_{-i}$ with i=1,2,3. b) Image of a textured object (up) and the corresponding wavelet transform (down) with three levels of decomposition.

This application uses three levels for the wavelet transform, which results in a total of 9 detail images. The feature vector consists of features extracted from the detail images at each decomposition level. The extracted features are the following parameters: Mean (M), Standard Deviation (SD), Contrast Between adjacent - Next Neighbour - pixels in Vertical (CBNNV) and Horizontal (CBNNH) directions and Contrast Between alternated – Alternated Neighbour - pixels in Vertical (CBANV) and Horizontal (CBANH) directions ((1) to (6)).

Since the classifier is based on a fuzzy inference system, it implies that the magnitude of each element of the feature vector must be in the interval [0,1] and thus a normalization of each feature element is required (7). The feature vector, *FV*, to be presented to the fuzzy grammar module consists of 6 features for each detail image (6x9=54 features): $FV=[\mu_{Mij}, \mu_{SDij}, \mu_{CBNNVij}, \mu_{CBNNHij}, \mu_{CBANVij}, \mu_{CBANHij}]$, with i= 0, 1, 2; j= 0, 1, 2.

$$M = \frac{1}{N}\sum_{i=0}^{N-1} I(i) \tag{1}$$

$$SD = \sqrt{\frac{1}{N}\sum_{i=0}^{N-1}(I(i)-M)^2} \tag{2}$$

$$CBNNH = \frac{1}{N-1}\sum_{l=0}^{Nl-1}\sum_{c=0}^{Nc-1}\left|I(l\times Nc+c+1)-I(l\times Nc+c)\right| \tag{3}$$

$$CBNNV = \frac{1}{N-1}\sum_{l=0}^{Nl-1}\sum_{c=0}^{Nc-1}\left|I((l+1)\times Nc+c)-I(l\times Nc+c)\right| \tag{4}$$

$$CBANH = \frac{1}{N-1}\sum_{l=0}^{Nl-1}\sum_{c=0}^{Nc-1}\left|I(l\times Nc+c+2)-I(l\times Nc+c)\right| \tag{5}$$

$$CBANV = \frac{1}{N-1}\sum_{l=0}^{Nl-1}\sum_{c=0}^{Nc-1}\left|I((l+2)\times Nc+c)-I(l\times Nc+c)\right| \tag{6}$$

$$\mu_F = F/255; \quad F \in \{M, SD, CBNNV, CBNNH, CBANV, CBANH\} \tag{7}$$

where I is the image, N is the number of pixels in the image, Nc and Nl are the number of columns and lines in the image, respectively.

During the *learning phase*, for initial tracking window size specification, it is necessary to consider the type of texture, specifically periodical or random aspects. Therefore, the following was settled for the *learning phase*: 1) initially the user chooses the initial tracking window; 2) this tracking area is divided in non-overlapping windows (NOW), whose size is set by the operator (Fig. 4a); 3) for each NOW the wavelet transform is applied, and the 6x9 features are extracted. Each element of the final feature vector is the result of a feature selection procedure for each NOW; 4) a fuzzy rule is created with this feature vector. In the *execution phase*, the image is also divided in NOW with the same size as the ones of the *learning phase*, but now overlapped (Fig. 4b) by (*dx*,*dy*), where *dx, dy* are the displacements relatively to the previous one. This procedure ensures different grades of performance.

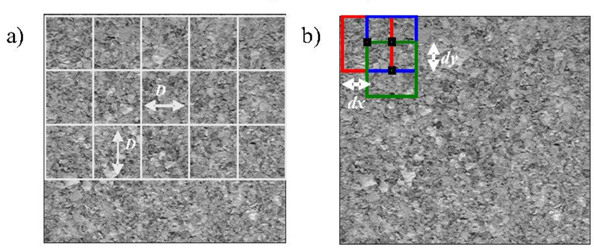

Fig. 4. Decomposition process of the image for the application of the wavelet transform . a) Learning phase. b) Execution phase: Red window *dx*=0,*dy*=0; Blue window *dx*=D/2,*dy*=0; Green window *dx*=D/2,*dy*=D/2.

For all the extracted features, it is fundamental to select *n* representative features from *N* initials, where *n* is much smaller than *N*. This procedure, depicted in fig. 5, enables to eliminate both the non representative features of a particular texture and the redundant ones. Null value and high correlation were the criteria used to eliminate features. The correlation of the feature set is evaluated through the following fuzzy correlation [6]

$$c_{jk} = 1 - \frac{4\times\sum_{i=0}^{N-1}\left(\mu_{ij}-\mu_{ik}\right)^2}{\sum_{i=0}^{N-1}\left(\left(2\times\mu_{ij}-1\right)^2+\left(2\times\mu_{ik}-1\right)^2\right)} \tag{8}$$

where N is the Universe dimension, μ_j is the set of values of feature j and μ_k is the set of values of feature k.

This equation estimates the correlation coefficient between the values of a feature j (μ_j) and the set of values of the feature k (μ_k). If they are strongly correlated only one is selected to be part of the final feature vector. In this work, the threshold used for the correlation coefficient was 0.9.

For a particular texture, in the cases where more than one value for each feature occur (most of the cases), it is necessary to select the value or the values that best describe it. This was done applying a fuzzy c-means algorithm [7,8]. Several attempts, in which concern the number of centres, were evaluated indicating a good description with five centres.

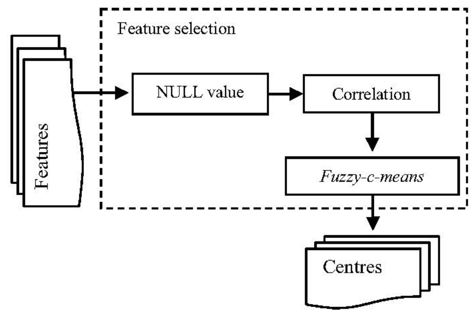

Fig. 5. Schematic representation of the procedure for feature selection.

Figure 6 illustrates the application of the fuzzy-c-means algorithm to the features mean and standard deviation of the detail image D22 for the three layers of cork parquet.

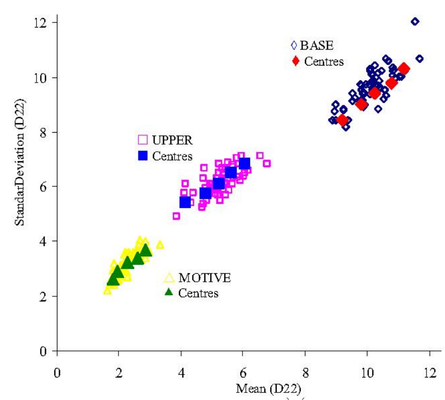

Fig. 6. Fuzzy-c-means application to the features Ī and DP for detail image D22, for three types of cork texture.

IV. Fuzzy Grammar Module

After the extraction of the feature vector that characterizes a texture, it is necessary to classify it according to its attributes. Specifically, the application has to deal with a high diversity of texture objects. To fullfill this constraint, the learning phase must be done with a unique sample of each type of texture.

Regarding the classifiers and recognizers, there are different approaches. The most common solutions use recognizers based on the calculus of metrics like Euclidean, Minkowsky e Mahalanobis distance measures [9]. However, these recognizers, as well as the ones based on neural, fuzzy logic and neurofuzzy networks, demand a great amount of samples from the population to perform learning [7,10,11].

In this work, a fuzzy system modelling approach was developed in which a fuzzy inference system identifies the fuzzy rules representing relationships among the features extracted from the wavelet detail images. There are several approaches that generate these fuzzy rules. The most often applied are based on statistics, neural networks and genetic algorithms [7,11,12]. However, these methods poorly satisfy the needs of this application, specifically the possibility to learn using only a characteristic vector. Therefore, a fuzzy grammar approach [6,7,13] was applied. Fuzzy grammar is a pattern classification syntactic model used to represent the structural relations of patterns and describes the syntax of the fuzzy languages that generate the fuzzy rules. This inference system is capable of generating a fuzzy rule using only one sample of a pattern.

Herein, a brief review of some basics concepts of fuzzy grammar is presented (for full discussion see [7,13,14,15]). Fuzzy grammar GF is a quintuple $GF=(V_N, V_T, P, S_0, \mu)$, in which V_N and V_T are finite disjoint sets of non-terminal and terminal vocabulary respectively, such that $V=V_N \cup V_T$ is the total vocabulary of the grammar. P is a finite set of production rules of the type $\alpha \rightarrow \beta$, with $\alpha \in V_N$ and β is a member of the set V^* of all strings (including the null string ε). $S_0 \in V_N$ is the starting symbol. μ is the mapping of $P \rightarrow [0,1]$, such that $\mu(p)$ denotes the possibility of the current language sentence $p \in P$.

The syntax of the developed language $L(GF)$ includes 4 different steps:

1) The codification of the features to primitives (Table I).

TABLE I

Codification of features to primitives, with i=0,1,2; j=0,1,2

Feature	Primitive
μ_{Mij}	FWDijM
μ_{SDij}	FWDijSD
$\mu_{CBNNVij}$	FWDijCBNNV
$\mu_{CBNNHij}$	FWDijCBNNH
$\mu_{CBANVij}$	FWDijCBANV
$\mu_{CBANHij}$	FWDijCBANH

2) The definition of linguistic terms HistVar:c.

$$HistVar : c \quad = \Pi(x, 0.2, c \times 0.1) \qquad c = 0 \ldots 10 \qquad (9)$$

In the membership function $\prod$ the parameter c is chosen such that the eleven membership functions cover the all universe of discourse, X, and have disjointed maximums.

3) The definition of fuzzy modifiers (FM): "More than", "Less than" and "Between". The FM "More than" LT is defined by

$$\mu_{MT}\langle LT \rangle = \begin{cases} 1 & x \geq L \\ S(x, L-lb, L-lb/2, L & x < L \end{cases} \qquad (10)$$

where L is a threshold value and lb is the bandwidth value of the S membership function [6,7]. The FM "Less than" LT is given by

$$\mu_{LT}\langle LT \rangle = \begin{cases} 1 & x \leq L \\ 1 - S(x, L, L+lb/2, L+lb & x > L \end{cases} \qquad (11)$$

The FM "Between" LT_1 e LT_2, is given by

$$\mu_B < TL_1 >< TL_2 > \; = \begin{cases} 1 - S(x, w_1, w_1 + lb/2, w_1 + lb) & x > w_1 \\ 1 & w_2 \leq x \leq w_1 \\ S(x, w_2 - lb, w_2 - lb/2, w_2) & x < w_2 \end{cases} \qquad (12)$$

where w_1 and w_2 are threshold values [6,7].

4) The definition of fuzzy operators (FO) which establish the relations between the linguistic terms and primitives. The following FO were defined:

a) &, representing the AND of two primitives. It is given by the Yager intersection.

b) >, representing "More than" LT and is given by μ_{MT}<LT>.

c) <, means "Less than" LT and is given by the function μ_{LT}<LT>.

d) | |, describes "Between two" LT and is given by μ_B<LT_1><LT_2>.

e) #, means a "Separator between a" *primitive* and a LT.

f) ( ), imposes a hierarchy in the rule.

Consider texture depicted in Fig. 3b. Fig. 7 illustrates the values of the eleven membership function $\prod$ for the primitive FWD00M (Fig. 7a), primitive FWD21CBNNV (Fig. 7b), primitive FWD22CBNNV (Fig. 7c) and primitive FWD22CBANV (Fig. 7d). Primitive FWD00M has non-zero degrees of membership for LT HistVar:0, LT HistVar:1 and LT HistVar:2. The highest fuzzy value is obtained using LT HistVar:0. Thus, HistVar:0# FWD00M is part of the fuzzy rule which characterizes this texture.

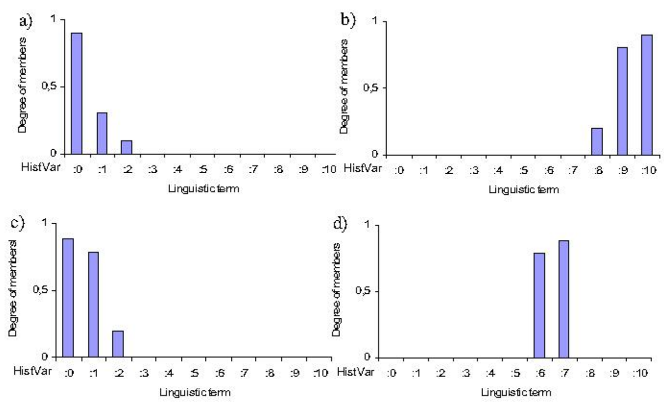

Fig. 7. Membership degree of Linguistic Terms. a) Primitive FWD00M. b) Primitive FWD21CBNNV. c) Primitive FWD22CBNNV. d) Primitive FWD22CBANV

If more than one linguistic term gives fuzzy values superior to 0.75, fuzzy modifiers like "More than", "Less than" and "Between", is applied to combine the obtained results. Accordingly, >HistVar:9# FWD22CBNNV is part of the fuzzy rule which characterizes this texture for primitive

FWD21CBNNV. For primitive FWD22CBNNV, the result will be <HistVar:1# FWD22CBNNV and for the primitive FWD22CBANV the result will be HistVar:6|| HistVar:7# FWD22CBANV.

The final rule will characterize the texture but herein we present part of this rule for detail image D00, created by the fuzzy grammar:

HistVar:0#FWD00M&HistVar:0#FWD00SD&HistVar:0#FWD00CBNNV&HistVar:0#FWD00CBNNH&HistVar:0#FWD00CBANV&HistVar:0#FWD00CBANH.

V. System Evaluation

The system was evaluated and tested using a universe of 100 cork samples (cork parquets of 600 x 300 mm), distributed as follows: 44 samples of parquets for evaluation of the *BASE* layer's visibility in the *UPPER* layer and 56 samples for evaluation of homogeneity in the visible *UPPER* layer.

Fig. 8 to 11 present the results of the system application in order to evaluate the parameters for quality control. Fig. 8 and 9 show graphically the magnitude of the fuzzy rule response for each window under analysis. These graphics exemplify how the rule with the higher value defines the class of the texture that the window belongs. In both cases the classes are clearly discriminated once response values are well apart.

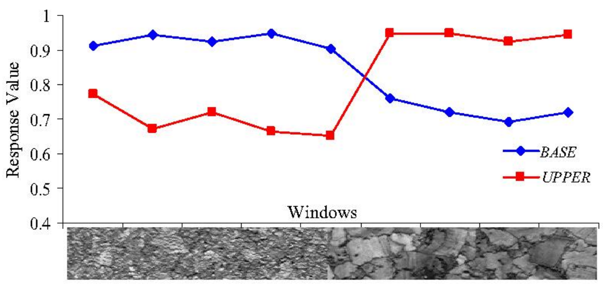

Fig. 8. Response values of the rules, generated for *BASE* and *UPPER* texture, for each window under analysis.

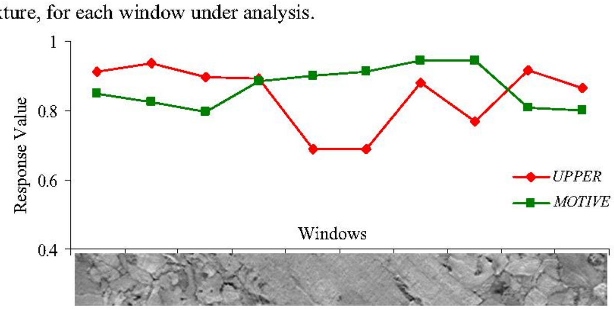

Fig. 9. Response values of the rules, generated for *MOTIVE* and *UPPER* texture, for each window under analysis.

Fig. 10 and 11 show texture images and the segmentation result. In the segmented image, the regions with darker gray level correspond to the presence of *BASE* (fig. 10.b) and larger and thicker pieces of cork (fig. 11b). The presence of false detections in image of fig. 11b, reveals that the system has a higher difficulty to deal with *MOTIVE* layer identification.

Considering the universe of samples under test high classification rates were achieved, specifically 94% for *BASE* detection and 90% for surface homogeneity evaluation.

The feasibility and efficiency of the texture segmentation approach have also been studied by performing a set of experiments using different types of textures and materials (leather, fabric, paper and textures from [16]) [4]. Specifically, textures illustrated in fig. 12a were submitted to this segmentation procedure. A total of 100 patches for each texture were used. Fig. 12b shows the response of each texture rule (gray bars) as well as the overall response of the rule that characterize the other textures (red bars).

A specific advantage of the developed approach is that when a texture is presented to the inference system it gives a response with high value (higher than 0.85) for the rule that describes this texture. In contrast, the rules corresponding to the other textures give low response values. This means that the system creates disjoints rules and assures a good classification.

The system was already applied to a cork inspection machine (fig. 13) in an industrial environment. It used an image size of 1024x1024 pixels – pulnix camera, and a matrox acquisition board, and it was developed in C++. A DLL was created to encapsulate the parsing procedure which was developed with the compilers yacc and lex [1].

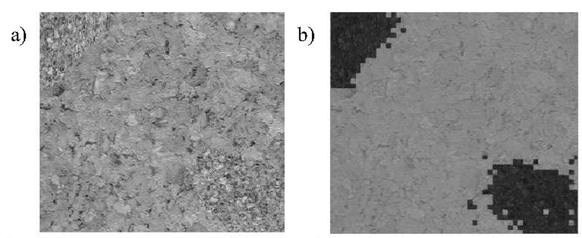

Fig. 10. Texture segmentation of an image with a *BASE* layer. a) parquet image; b) the result segmented image.

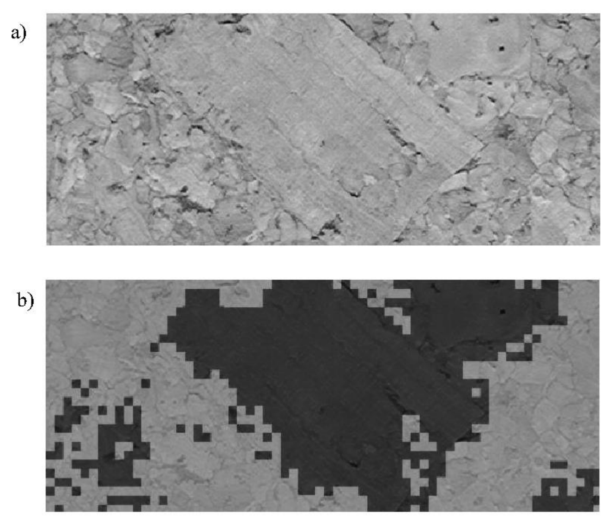

Fig. 11. Texture segmentation of an image with a *MOTIVE* layer. a) parquet image; b) the result segmented image.

VI. Conclusion

In this paper a texture segmentation procedure, to be applied in the quality control of cork parquet industry, was presented. We have used sensing technology to endow an industrial application with a vision system, thus achieving higher flexibility in dealing with the environment. The texture segmentation was based on 6 features extracted for each detail image of the wavelet transform of a gray scale image and on a fuzzy grammar classifier. This procedure was developed to deal with two major quality problems: the visibility of the *BASE* layer in the *UPPER* layer and the homogeneity in the visible *UPPER* layer (distribution of the *MOTIVE* layer). Wavelet transform and fuzzy grammar revealed to be a suitable approach to deal with these problems and simultaneously with the need to reduce expensive time consuming both in the processing and in the off-line *learning* phase. Good classification rates (higher than 90%) were achieved suggesting the efficiency of the inference system when applied to the great diversity of texture that characterizes this Portuguese industrial sector. Another advantage of the approach, when compared to other approaches, was that the learning phase is done with a unique sample of each type of texture.

The presented solution enable to maximize efficiencies and increase the production rate. Further, dependency of final product quality on human subjectivity was eliminated.

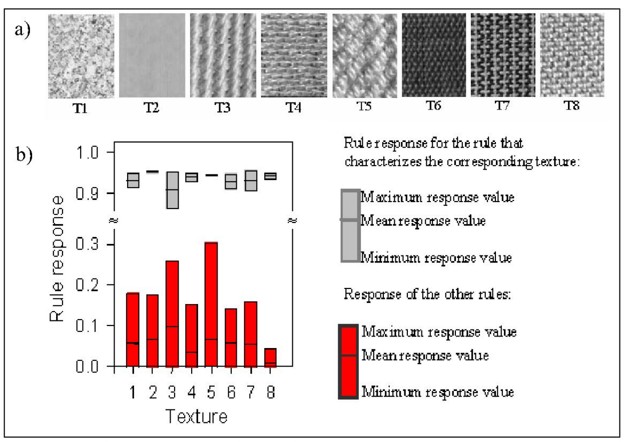

Fig. 12. a) Some examples of the textures used to texture segmentation procedure evaluation. b) Rule response for the images of fig. 12a.

The system was already implemented in a cork inspection machine in an industrial environment. Experiments made with this industrial prototype indicate that full spreading industrialization of this approach is a promising perspective. Some adjustments should be considered, namely improving processing time (to respect the overall industrial needs) and optimizing the integration with the production lines already in function. This can be achieved through an acquisition system based on linear cameras instead of the matrix ones.

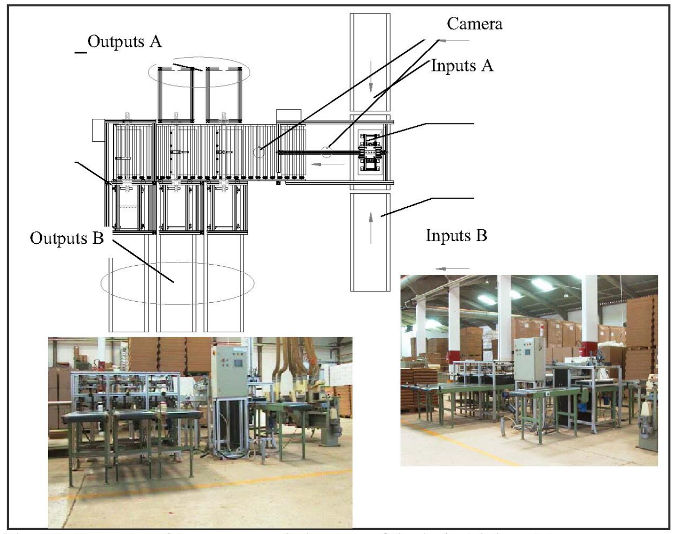

Fig. 13. Layout and two panoramic images of the industrial prototype.

References

[1] Bumble-Bee (1999), *Parser Generator Manual* [online], Bumble-Bee Software, Available from http://www.bumblebeesoftware.com.

[2] Wouwer, G. V. (1998), "Wavelets for multiscale texture analysis", PhD Thesis, Universitaire Instelling Antwerpen, Antwerpen, Belgium.

[3] Teuner, A., Olaf Pichler and Bedrich J. Hosticka (1995), "Unsupervised Texture segmentation of images using tuned matched gabor filters", IEEE transactions on image processing, vol. 4, n. 6, pp. 863-870.

[4] Ferreira, M.J. (2004), *Desenvolvimento de um protótipo para a identificação, classificação e quantificação de defeitos, aplicável em ambiente industrial*, Unpublished Thesis (PhD), Universidade do Minho, Braga.

[5] Benedetto, J J., Michael W. Frazier (1994), Wavelets mathematics and applications: CRC Press, 1994.

[6] Malaviya, A. (1996), *On-line handwriting recognition with a fuzzy feature description language*, PHD Thesis, Technische Universitat Berlin, Berlin.

[7] Bezdek, J.C. & Pal, S.K. (ed) (1992), *Fuzzy Models for pattern recognition*, IEEE Press. New York.

[8] Jang, J. R., Sun, C. T., & Mizutani, E., Neuro-fuzzy and soft computing, a computational approach to learning and machine intelligence: Prentice-Hall, 1997.

[9] Williams, P.S. (1999), The automatic hierarchical decomposition of images into sub-images for use in image recognition and classification, PHD Thesis, University of Western Australia.

[10] Micheli-Tzanakou, E (2000), *Supervised and Unsupervised Pattern recognition, feature extraction and computational*, Industrial Electronics Series, J. David Irwin, Ed., CRC Press, Florida.

[11] Looney, C.G. (2002), "Pattern Recognition", in Hyngsuck Cho, (Ed.), Opto-Mechatronic Systems Handbook: Technical Applications - Handbook Series for Mechanical Enginnering, Vol 10, CRC Press.

[12] Ivancic, F. & Malaviya, A. (1998), "An Automatic Rule Base Generation Method for Fuzzy Pattern Recognition with Multi-phased Clustering", in *IEEE Conference of Knowledge Engineering System*, *Proceedings of KES'98*, IEEE Press, Adelaide, pp 66-75.

[13] Yager, R.R. & Zadeh, L.A. (ed) (1992), An introduction to fuzzy logic applications in intelligent systems, Kluwer Academic, Boston.

[14] Pal, S.K. & Majumber, D.K. (1986), Fuzzy mathematical approach to pattern recognition, Halsted Press Book, John Wiley & Sons, New Delhi.

[15] C. P. Santos, Manuel João Ferreira, Computer Vision and Fuzzy Rules applied to an Industrial Desktop Robot, Assembly and Automation Journal, 2006

[16] Brodatz (1966), P. Brodatz textures: A Photographic album for artists and designers. Dover, New York, 1966, Available in WWW: <URL: http://www.ux.his.no/~tranden/brodatz.html>.