Fault detection and qualification of wet blue goatskin

1st Carlos Estevão Bastos Sousa, 2nd Cláudio Marques de Sá Medeiros, 3rd Renato Francisco Pereira,
4th Mateus Alves Vieira Neto, 5th Alcides Andrade Neto
Postgraduate Program in Science Computer
Federal Institute of Education Science and Technology of Ceará
Fortaleza, Brazil
estevao.sousa@ppgcc.ifce.edu.br, claudiosa1965@gmail.com, renato.francisco.pereira@gmail.com
mateus.vieira@ifce.edu.br, alcides.andrade@ifce.edu.br

***Abstract*—Tanneries acquire hides, in most cases, from rural workers, so, due to the informality of the creation, slaughter and extraction of the animal's skin, they receive them with different types and different defect levels. That said, classifying acquired and processed skins becomes a very complex and tiring activity. The leather discrimination process is completely handmade and subjective, too dependent on the experience of the professional responsible for this step, which, due to tiredness, stress and other factors, end up generating several errors in this process. Currently, there are several studies in the literature related to the detection of leather flaws, however, few studies go further and qualify the skins based on the detected problems. In view of this factor, a system based on computer vision and artificial intelligence is proposed in which it obtains an accuracy rate of 95.9 % in the detection of defects in wet blue goatskin and 93.0 % in the identification of the quality level of these parts.**

***Index Terms*—Goatskin, Textile industry, Pattern Recognition**

I. Introduction

The production of leather has increased worldwide, at the same time as there has been a shift in the production base from developed countries to developing countries. Therefore, it is due to a combination of factors related to the availability of raw material, market, costs, among others [1].

Gomes Leal, Penna Rocha and Rocha Junior [2] explain that because it is easy to adapt to the semi-arid climate, the caprine species becomes an excellent option for livestock in the caatinga biome, which is widely found in Brazil and other tropical countries. Several parts of the animal can be used, with emphasis on the meat, milk, offal and skin. In the case of leather, the concern with the management of the goat must be increased, as the skin is easily damaged when there is no care with the control of ectoparasites, places where the animal moves (damage when touching barbed wire fences and spines) and in the slaughter and removal of the skin for further processing.

As Aslam, M. et al. [3], in a changing global scenario, the manufacturing industry constantly demands higher product quality and higher productivity to satisfy customer requirements and reduce rejection costs. The increased demands for objectivity, reliability and efficiency have required the addition of automatic inspection systems in the traditional leather industry. Surface defects reduce the quality and value of the skins.

The defect inspection process is essential in the leather industry to control the quality of finished products. However, the same occurs visually, it is tedious, laborious, time-consuming, causes eye fatigue and, is often prone to human error [4].

In view of the above, the authors propose the development of a computer system using computer vision and artificial intelligence techniques for detecting flaws in goatskin in order to assist tanning professionals. The expectation is that the use of such a tool can contribute to the textile sector, ensuring greater reliability in the quality level of the leather produced.

II. Related works

AMORIM, et al. [5] propose a work to classify flaws in goat leather pieces in two types of images: raw leather and wet blue. For the acquisition of attributes, Gray-Level Co-Occurrence Matrix (GLCM), Gabor filters and two color spaces are used. From the acquired attributes, 3 (three) experiments are carried out. The first consists of classifying the raw data, without pre-processing them, using the classifiers K-Nearest Neighbors (KNN), Fischer classifer (based on Bayes rule) and Support Vector Machine (SVM), in which, it stands out the application of the KNN classifier, with an average accuracy rate of 95.9 % for rawhide skins and 93.76 % for wet blue. In the second experiment, attribute reduction techniques such as FisherFace, Chen Linear Discriminant Analysis (CLDA), Direct LDA (DLDA), Yang LDA (YLDA) and Kernel LDA (KLDA) are applied. Then, the resulting data is again classified with the same classifiers as the first experiment. In this step, the best combination appears through the CLDA and KNN, obtaining an average accuracy rate of 92.2 % for raw leather parts and 90.3 %, for wet blue. The third experiment consists of detecting the flaws, informing their location and comparing them with those reported by the specialist professional, in a visual analysis. As a result, the system found several false positives. The author of the work reports that one of the reasons for which such a problem should occur is the quality of the training set, as it does not have enough samples to discriminate all possible defects.

Edmilson Q. S. Filho, José D. A. Santos and Guilherme A. Barreto [6] propose a model for classifying skin samples in the wet blue stage. The set of images is divided into 7 types of classes in which the author divided them into Upper Class (classes 1 to 5) and Lower Class (classes 6 and 7). The work performed consists of converting the obtained images (3264 x 2448 pixels) to gray levels and, later, resizing them to sizes of 40, 60, 80 and 100 pixels. Then, the characteristics are extracted using the Column-Variance (VAR), Haar wavelet transform (HAAR), Non-Negative Matrix Factorization (NMF), Principal Component Analysis (PCA) and GLCM. After the feature vectors are acquired, the classification is made using the classifiers Least Squares (LS), Extreme Learning Machine (ELM), Regularized Linear Gaussian Classifier (RLGC) and SVM. In the work, there is also the elaboration of the rejection option in order to increase the reliability of the classifiers. The best results of the proposed work have an average accuracy rate of 85.56 %, without the rejection option, through the VAR extractor and ELM classifier. With rejection option, 97.32 %, with PCA and SVM.

Nogueira de Aquino [7] proposes the classification of goatskin samples using 3 (three) variations of the Local Binary Pattern (LBP) method: uniform LBP, rotation-invariant LBP and uniform and rotation-invariant LBP . For the classification, the KNN and SVM classifiers are used. After analyzing the classification from each extractor, it is also proposed to extract characteristics with multi-resolution, that is, the combination of 2 (two) or 3 (three) LBP operators. At the end of the work, it is noticed that the best average accuracy is 86.14 %, obtained from the combination of 3 (three) LBP operators and SVM classifier.

Renato F. Pereira, Cláudio M. S. Medeiros and Pedro P. R. Filho [8] propose defect detection and leather qualification. Initially, they fragment each goat leather into several squares windows with sizes of 51, 101, 151, 201, 251 and 301 pixels. Attribute extraction methods like Gray Level Co-occurrence Matrix (GLCM), Local Binary Patterns (LBP) and Structural Co-Occurrence Matrix (SCM) are applied in each window. Then, the defect classification is implemented by K-Nearest Neighbors (KNN), Multilayer Perceptron (MLP) and Support Vector Machine (SVM). Considering only defect classification, the best accuracy comes from the combination of 51 x 51 pixels windows, LBP extractor and MLP classifier, with an average accuracy of 90 %. For qualification, the authors initially use the trained classifier to identify each defective window contained in the leather sample. Then, they identify the position of each defective window in the sample. Then, they use a mathematical algorithm to identify the convex areas free from flaws in the leather sample. Numerical attributes related to defect-free areas are generated and supplied to an SVM classifier, which obtains an accuracy of 86 % in leather qualification, among the 7 possible categories.

Liong, S. et al. [4] propose a system for detecting and segmenting tick-bite-type defects in bovine leather samples. According to the authors, the proposal to work with this type of defect occurs because this problem is often overlooked by human inspection. The authors use a LED lamp as light source, a 24.2 megapixel camera (2400 x 1600 pixels spatial resolution) to acquire images, a robotic table 6-axis arm (model DRV70L from Delta Electronics, Inc.), and the Mask Region-based Convolutional Neural Network (Mask R-CNN) as learning method. The methodology consists of inserting leather samples manually on a table in which the robotic arm moves in a linear way, from top to bottom, analyzing the pieces and, using the camera, digitizing the image to be analyzed. Thus, from the use of a computer, the detection of regions with this type of defect occurs, in which each identified problem contains its coordinates X and Y saved for later use. With the classification process completed, the robotic arm again passes through the entire piece of leather in order to, from a chalk inserted at its tip, highlight the regions previously detected as defect. In the experiment 84 images are used for training and 500 images for tests, which obtain an accuracy of 70.35 %.

III. Acquisition of sample sets

The authors used the structure developed by Edmilson Q. S. Filho, José D. A. Santos and Guilherme A. Barreto [6] to acquire images of goat leather. The structure, ilustrated in Figure 1, has a table with black background, in order to facilitate the extraction of the background of the object of interest in each image; its own lighting, composed of two fluorescent lamps of 40 W; a camera support instaled 1.5 m above the table's surface; a photograph camera Canon Rebel T3 12.2 MP (55x optical zoom and EF-S 18-55mm lens); and a computer, using the Canon EOS Utility® software.

Fig. 1. Table for digitizing leather samples.

Depending on the availability of goat leather samples in the tannery stock, the authors made 312 photographic records in the JPEG (Joint Photographics Experts Group) format, as can be seen in Table I.

TABLE I
Distribution of the leather samples in image set.

Quality Category	1	2	3	4	5	6	7
Number of Samples	21	44	48	50	49	50	50

The number of samples per quality category is relatively balanced, with an important disadvantage for group 1, which is composed of better quality goat leathers.

IV. Defect detection in goat leather

After acquiring the photographic records of the goat leather samples, the authors open the images in image editing software and, with the participation of professional classifiers, identify and locate each defect found. A file is generated containing the type of each defect, the identification of the image file in which the defect is found and the coordinates X and Y of the location of the defect in the image. This procedure is illustrated in Figure 2.

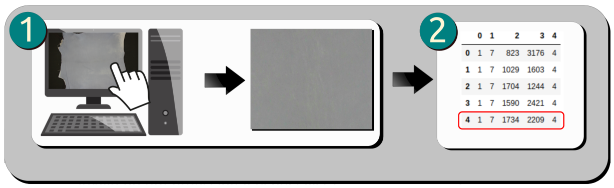

Fig. 2. Procedure performed to prepare the defect report.

Thus, 2250 defect images and 1669 defect-free leather images were cataloged. Then, the authors carried out an exhaustive investigation to define the window size, centered on the coordinates X and Y, most appropriate for the application of attribute extraction methods, seeking the best compromise between execution time and sample characterization.

For each window size, the authors test two methods of extracting attributes and three classifiers based on three different paradigms.

A. Atributes extraction

The attribute extraction methods evaluated are the Local Binary Pattern - LBP [9] and the Gray Level Co-occurrence Matrix - GLCM [10].

D. Huang. et al. [11] states that in recent years, LBP has sparked a growing interest in image processing and computer vision. This method efficiently summarizes local image structures, comparing each pixel with its pixels neighbors. [12] cites that one of the most important properties of this operator is computational simplicity, it makes it possible to analyze images in challenging configurations in real-time.

The GLCM describe texture through a set of characteristics for the occurrences of each level of gray in the pixels of the image considering multiple directions [13]. In this way, the size of the matrix is determined from the distinct number of levels of pixels contained in the original image [14]. Haralick, K. Shanmugam and Dinstein [10] proposed a method to which 14 statistical measures of texture can be obtained from its use, however, only 13 are actually used, since the latter presents computational instability.

For each of the attribute extraction methods, several window sizes were tested. As can be seen in Figure 3 for a particular case, given the coordinates X and Y referring to the central pixel of the regions saved in the report, the window size is defined considering $\frac{T}{2}$ added to the right, left, top and bottom.

Several values were tested for T, with window sizes of 11, 21, 31, 41, 51, 75 e 101 pixels.

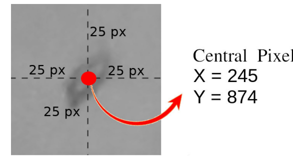

Fig. 3. Example of fragment size used.

B. Classifiers and training/testing data sets

The authors test the effectiveness of the following classifiers: Multilayer Perceptron (MLP), Support Vector Machine (SVM), and Logistic Regression.

For the MLP classifier, several parameters were evaluated: Initial learning rate are tested, ranging from 0.1 to 0.5.; linear or exponential learning rate decay; hyperbolic tangent or logistic function as activation functions; and several numbers of hidden neurons, ranging 2 and 100 neurons.

Regarding the SVM classifier, 4 types of kernel are used; linear, RBF, polynomial and sigmoid. The value of C, that is, the penalty parameter is entered from the following values 0.01, 0.1, 1.0 and 10.

For the Logistic Regression algorithm, the training process stops when achieves 2000 iterations and/or the error rate achieves 10^{-5}.

The authors use 1335 samples from the ”normal” class and 1335 samples from the ”defect” class to compose the training set. The samples were randomly selected from 1669 and 2250 samples, respectively from the ”normal” and ”defect” sets. The authors believe that this balance in the number of samples can avoid trends in the binary classification. The rest of the data, that is, 334 samples of the ”normal” class and 915 samples of the ”defect” class, make up the validation set.

For all classifiers the K-Fold cross-validation technique is used, with a value for K equal 10. The application of this method consists of dividing the total set of training data into K subsets of the same size. Thus, each subset is used for tests, while the rest of the set is applied to estimate the parameters.

C. Results for defect classification

The best results were achieved with the data set formed by applying the GLCM attribute extraction method to windowed images with 51 pixels.

The average results and standart deviation for the hit rates in 50 runs of each of the three classifiers investigated can be seen in the Table II.

TABLE II
Averaged results obtained in the defect identification process.

Classifier	***Acc (%) / Std. (σ)***	
	training	***validation***
Logistic Regression	94.75 $\pm$ 0.32	93.63 $\pm$ 0.56
MLP	94.95 $\pm$ 1.03	95.05 $\pm$ 1.67
SVM$_{RBF}$	96.59 $\pm$ 0.17	95.95 $\pm$ 0.38

The configuration of the MLP networks is as follows: Initial learning rates of the hidden and output layers of 0.5 and 0.3, respectively; linear decay in learning rates; 65 hidden neurons; logistic activation function; and rejection range of 0.1.

In the case of SVM, the best kernel was RBF. The mean of support vectors is 368 and parameter C equal 10.

From here, defect detection will be performed by a support vector machine, on attributes generated by GLCM on image fragments of 51 pixels.

V. Goat leather qualification

For the qualification of goat leather, firstly it is necessary to perform a pre-processing on the sample image, performing procedures for filtering and removing the background. Then, the leather image is fragmented into several 51 pixels windows and a matrix is constructed, in which each element represents a specific window. Each element of the matrix is assigned the value ”0”.

Each window is subjected to the defect detection process presented in Section IV, in which an SVM classifier assigns the value ”0” to the window classified as belonging to the class ”defect” and the value ”1 ”to the window classified as belonging to the” normal ”class.

Then an algorithm is applied to find the fault-free convex regions in the matrix. The detection of these defect-free areas is based on a dynamic programming problem explained by Dhaval Dave [16]. The method is applied recursively until find 5 fault-free convex regions, as is suggested in Figure 4.

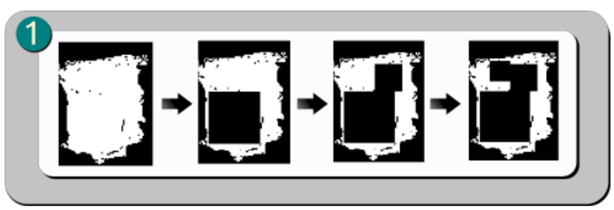

Fig. 4. Detection of flawless regions.

Seven atributes are generated based on defect-free areas. These atributes are listed in Table III.

From here, each goat leather sample image is characterized by the 7 attributes defined in the Table III. Thus, the authors use the MLP and SVM$_{RBF}$ classifiers mentioned before, in addition to the Naïve Bayes classifier to perform the qualification in 7 categories. The results can be seen in the Table IV.

Among the 50 achievements of the Naïve Bayes classifier, the best has an accuracy in the training set of 95 % and in the validation set of 93 %. This is the classifier that will be used to qualify goat leather samples.

TABLE III
Attributes acquired from the process of detecting flawless regions

Attribute	Description
1	Total defect-free area;
2	Total area calculated over 5 greatest defect-free convex regions detected;
3	Area of the largest defect-free convex region detected;
4	Percentage of the largest defect-free convex region detected regarding only the total of defect-free areas;
5	Area of the smallest defect-free convex region detected regarding only the total of defect-free areas;
6	Percentage of the smallest defect-free convex region detected regarding only the total of defect-free areas;
7	Standard deviation calculated over the defect-free areas detected.

TABLE IV
Averaged results obtained in the goatskin qualification process.

Classifier	***Acc (%) / Std. (σ)***	
	training	***validation***
Naïve Bayes	95.79 $\pm$ 0.97	89.56 $\pm$ 2.35
MLP	98.0 $\pm$ 2.64	74.14 $\pm$ 2.97
SVM$_{RBF}$	95.02 $\pm$ 11.99	81.27 $\pm$ 4.59

VI. Conclusions

The best result achieved in defect detection is 95.9 %. Several combinations of image window size, attibute extration method, and classifier were tested. The best combination is image window size of 51 pixels, GLCM and SVM$_{RBF}$ classifier.

With the elaborated set, a higher hit rate obtained from the Naïve Bayes classifier is noted, obtaining approximately 93.0 % accuracy regarding the qualifications of the goat leather samples.

There is an advance in this scenario compared to previous proposals. When considering the cited works [5], [6], [7], [8] and [3]. A higher level of maturity is observed for each proposal developed in terms of solving the problem. This is due to the aforementioned authors, who provided feasible methodologies for the improvement/implementation of solutions for software of decision support for the textile sector.

References

[1] M. Gutterres, “Desenvolvimento Sustentável em Curtumes,” XVI Encontro Nacional da ABQTIC. Porto Alegre - RS, 2003.

[2] Gomes Leal, Penna Rocha and Rocha Junior, “Inovação numa empresa processadora de couro caprino em Pernambuco: limites e potencialidades,”CONIDIS - I Congresso Internacional da Diversidade do Semiárido, 2014

[3] Aslam, M. et al., “On the application of automated machine vision for leather defect inspection and grading: A survey,”IEEE Access, v. 7, p. 176065–176086, 2019.

[4] Liong, S. et al. “ Automatic defect segmentation on leather with deep learning,” CoRR, abs/1903.12139, 2019.

[5] Amorim, W. P. et al. “Attributes reduction applied to leather defects classification,” 23rd SIBGRAPI Conference on Graphics, Patterns and Images, p. 353–359, 2010.

[6] Edmilson Q. S. Filho, José D. A. Santos and Guilherme A. Barreto, “Estudo comparativo de métodos de extração de características para classificação da qualidade de peles de caprinos com opção de rejeição,” XI Simpósio Brasileiro de Automação Inteligente, Fortaleza, Ceará, Brazil, 2013.

[7] Nogueira de Aquino. “Extração de Características de Imagens para Classificação da Qualidade de Couro Caprino Usando Padrão Binário Local,” MastersThesis. Fortaleza, CE, Brazil: UFC, 2017.
[8] Renato F. Pereira, Cláudio M. S. Medeiros and Pedro P. R. Filho, “Goat Leather Quality Classification Using Computer Vision and Machine Learning,” IEEE International Joint Conference on Neural Networks (IJCNN), 2018.
[9] Timo Ojala and Matti Pietikäinen and Topi Mäenpää, “Multiresolution Gray Scale and Rotation Invariant Texture Classification with Local Binary Patterns,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 24, pp. 971 - 987, 2002.
[10] Robert M. Haralick and K. Shanmugam and Its’Hak Dinstein, “Textural Features for Image Classification,” IEEE TRANSATIONS ON SYSTEMS, MAN AND CYBERNETICS, vol. SMC-3, pp. 610-621, 1973.
[11] D. Huang. et al. “Local Binary Patterns and Its Application to Facial Image Analysis: A Survey,” IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), vol. 41, pp. 765-781, 2011.
[12] P. Mohanaiah and P. Sathyanarayana and L. GuruKumar, “Image Texture Feature Extraction Using GLCM Approach.,” International Journal of Scientific and Research Publications. pp. 1-5, 2013.
[13] William Robson Schwartz and Hélio Pedrini, “Método para classificação de imagens baseada em matrizes de co-ocorrência utilizando características de textura,”III Colóquio Brasileiro de Ciências Geodésicas, Universidade Federal do Pará, 2003.
[14] Annadurai, S. “Fundamentals of Digital Image Processing, ”Pearson, Always learning, 2007.
[15] Nobuyuki Otsu, “A Threshold Selection Method from Gray-Level Histograms,”IEEE Transactions on Systems, Man and Cybernetics, Vol.9, pp. 62–66, 1979.
[16] Dhaval Dave, “Maximum size of square sub matrix with all 1’s in a binary matrix,” https://www.gohired.in/2017/12/12/maximum-size-of-square-sub-matrix-with-all-1-in-a-binary-matrix/, 2017, Acess date jan. 2020.