A New Approach for Wet Blue Leather Defect Segmentation

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Abstract. In the process plants where beef skin is processed, leather classification is done manually. An expert visually inspects the leather sheet and classifies them based on the different types of defects found on the surface, among other factors. In this study, an automatic method for defect classification of the Wet Blue leather is proposed [1]. A considerable number of descriptors are computerized from the Gray Scale image and the RGB and HSV color model. Features were chosen based on the Sequential Forward Selection method, which allows a high reduction of the numbers of descriptors. Finally, the classification is implemented by using a Supervised Neural Network. The problem formulation is adequate, allowing a high rate of success, obtaining a method with wide range of possibilities for implementation.

1 Introduction

Leather is a raw material for producing a big amount of products from clothes to furniture. Products made of leather are highly appreciated for buyers because in many cases they are hand-made pieces with a high price.

The goal of leather processing plants is to transform the fresh skin (hide), just taken from the animal, in leather sheet to be used in the production of end goods. In figure 1, the main stages in the leather fabrication process are shown. Figure 1(a) shows a stage named Ribera, in which the cow skin is clean from hair and it is hydrated with chemical products to avoid decomposition. At the end of this stage, the sheets are humid and with a blue tone. The hide at this stage is named Wet Blue. Figure 1(b) shows the pre-classification stage, where the Wet Blue leather sheets are manually separated in two categories: good and bad quality. Figure 1(c) shows the draining phase, where the sheets are introduced into a machine to eliminate the humidity excess. Finally, figure 1(d) shows a leather lot already dried.

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(a) (b) (c) (d)

Fig. 1. Leather processing: (a) Ribera (b) Pre-classification (c) Drying (d) Wet Blue leather lot

After the drying stage, an expert visually inspects the leather lot and proceeds to classify it based on the amount of surface defects, zone and area affected by the defect, thickness of the sheet, among other factors. The more defects a sheet has the lower the price. Hence, the classification is a critical task for the economical value of the product. The classification process is exposed to human error because of operator fatigue, his mood, etc. An error in the classification devaluates the product on the eyes of the buyer, sometimes producing 15% return rates [1], implying considerable monetary losses for the leather plants.

The rest of the paper is organized as follow: Section 2 presents related studies and research contribution to the topic. Section 3 presents the proposed method. Section 4 analyzes the results. Finally section 5 displays the conclusions for the study.

2 Related Studies

The proposal presented in [1] is a pioneer study for the leather classification problem. A semi-automatic method is introduced, detecting defects and classifying the leather sheet based on the area affected by the defects. This work requires human intervention for the defect detection.

In [2] a method is proposed based on the use of geometric and statistic descriptors, in addition to the use of decision trees for the classification of the leather surface. The leather classification is done on finished leather stages past the Wet Blue, hence a classification error means the irrevocable loss of the leather piece.

In [3] an identification method is proposed which analyze histogram of the image, using the chi-square criteria. This method compares the distance between the histogram for the analyzed area and the histogram of the areas with defects.

The following studies are a series of recent research for the Project DT-COURO[2], whose goal is to detect defects in Raw Hide leather and Wet blue leather. In [4] software is implemented for the extraction and labeling of samples from the areas with defects, all manually. In [5] a comparison of the performance for several classifiers using first order descriptors from the Concurrence Matrix is performed. The study in [6] adopts as a classifier the Support Vector Machine, focusing on properly tuning the parameters of the classifier by using a stochastic method. Finally, in [7,8] the classification scheme is improved by having a stage selecting features, reducing the amount of descriptors used to 90.

This study presents an automatic method for classifying defects on the Wet Blue leather. The most common defects in Chilean leather plants are considered: Open Cut, Closed Cut, and Fly Bite. Computing a big amount of descriptors is proposed as well as the implementation of a selection stage for features based on the Sequential Forward Selection method, allowing approaching the problem with a much reduced amount of descriptors. For the classification, a Multilayer Perceptron, trained with a method allowing an adequate generalization is adopted. The proposed innovations provided a robust method with a high rate of success, obtaining a method with wide range of possibilities for implementation.

3 Method for Classifying Defects

In this section the different stages of the proposed defect classification method are described. All the stages of a system for pattern recognition are considered, from the sampling to the pattern classification. Four classes for the problem are defined: three of them related to the defects, and one associated to a zero-defect leather.

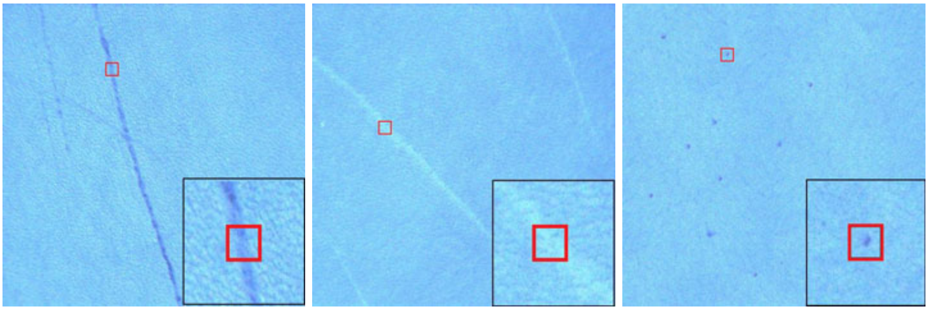
3.1 Capture

To capture the images, a camera with high sensitivity sensor Exview HAD CCD for visual inspection was used [3]. The camera was installed at the top of a hollow cylinder, 30 cms over the leather sheet. Inside the cylinder, an artificial LED lighting was implemented with the goal of keeping always the same lighting conditions and to avoid light flashes on the leather surface.

159 1000x960-píxel images of Wet Blue leather were taken, from which a dataset of 1769 40x40 pixel samples of normal and defective leather pieces was

[2] DTCOURO : `http://www.gpec.ucdb.br/dtcouro`

[3] PointGrey Chameleon: `http://www.ptgrey.com`



(a) (b) (c)

Fig. 2. Leather Defects: (a) Open Cut (b) Close Cut (c) Bite Fly

built. The dataset has 341 samples of Open Cut, 336 Closed Cut, 374 Fly Bite, and 718 normal leather pieces (without defects). Figure 2 presents 3 of the captured samples, each one showing one of the defects.

3.2 Extraction of Features

Following the principle of "The More The Better", a pattern classification problem can be approached by computing a wide amount of descriptors and then using a technique to select features in order to obtain only the relevant descriptors. A big number of features were calculated. Such characteristics were extracted from the Gray Scale image, and from the RGB and HSV channels, for a total of 2002 characteristics. The descriptors extracted can be classified in seven groups: (i) First order statistics, (ii) Contrast characteristics, (iii) Haralick descriptors , (iv) Fourier and Cosine transform, (v) Hu moments with information about intensity, (vi) Local binary patterns, y (vii) Gabor features. Details of the method and the adopted can be found in [9].

3.3 Selection of Features

In this stage the Sequential Forward Selection method (SFS) [10] is adopted. This method allows to rank descriptors based on their contribution to the classification. In order to determine the number of features required to classify the following procedure is followed: a classifier is linked to each class of interest. Classifiers are trained with a determined number of features and the percentage of success in the classification is calculated. Successive trainings of the classifiers are performed, incrementing the number of features based on the ranking provided by SFS.

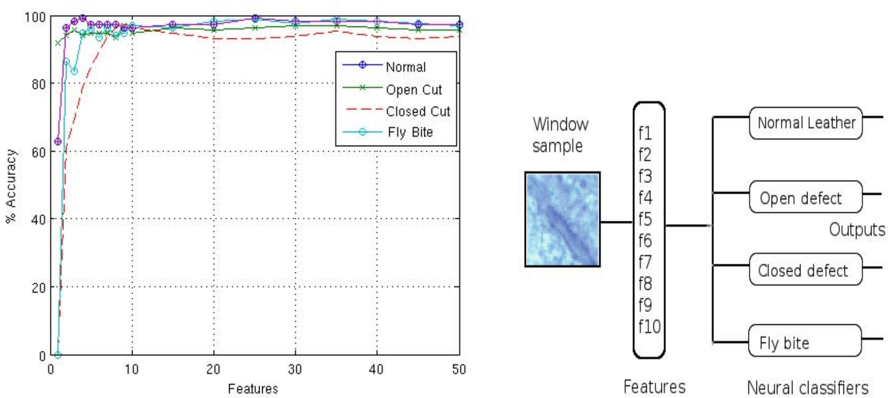
The result of the process above is presented in figure 3(a). Each curve in the figure shows the percentage of success for each one of the 4 classifiers used. It is clearly noticeable that after a determined number of features, the percentage of success does not improve substantially. This behavior allows to determine the number of features. By analyzing the curves, it is determined that only 10 characteristics, from the universe of 2002 initially computed, are required.

3.4 Design for a Robust Neural Classifier

A Multilayer Perceptron was adopted to design the classifiers because this network belongs to a Universal Converger of Functions [11]. For training the Neural Network the Bayesian Regularization algorithm is used because offer a better training speed and a method to determine the number of neurons in the hidden layer, based on the computing the effective parameters of the network. The procedure for training of the neuronal network is described on [12].

The classifier proposed for the problem is composed by 4 Multilayer Perceptron, 3 networks for recognizing defects and another one for identifying the zero-defect leather sheets. A scheme for classification is presented in figure 3(b), where it can be observed that for each window analyzed, 10 descriptors are finally computed. Considering that all the neural networks give and answer, the class for the network which output value is the closest to 1 is chosen.

For the training of the neural classifiers, the set of available samples was divided in a training set and a test set as is shown in the left zone in table 1. The goal is to have a set to train the classifiers and another set to validate the training with samples that haven't been part of the training.



(a) (b)

Fig. 3. (a) Selection of features (b) Classification scheme

4 Results

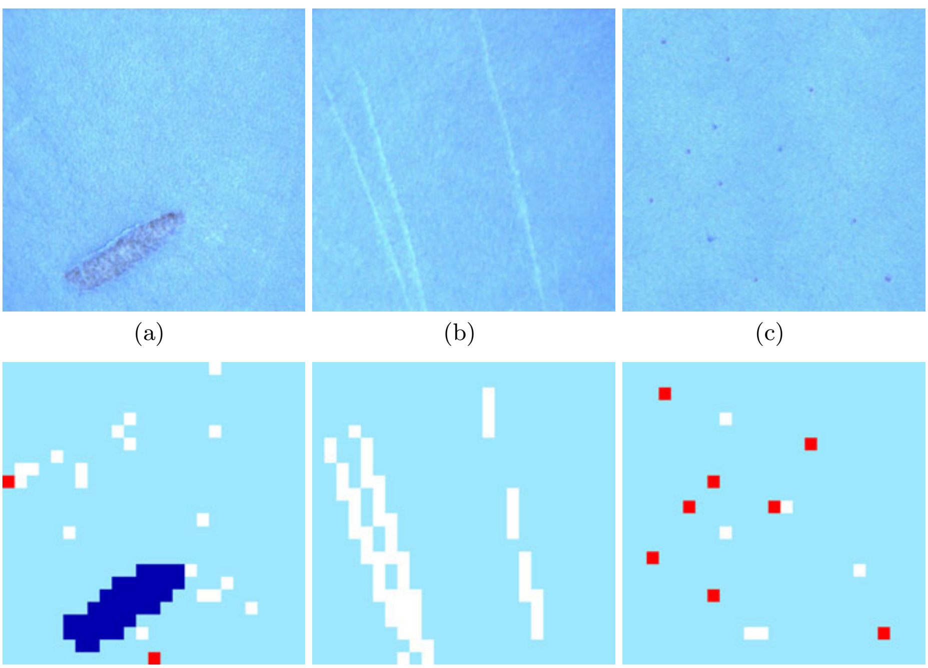
In this section results from the method and experiments executed are presented. From table 1 it can be seen that the method provided very good results for classifying the training set as well as the test set. The percentage of success is above 95%, number that is comparable to the studies quoted but by using

Table 1. Classification Performance

Type of Sample	Samples of Training Set	Samples of Test Set	Training Set Hit (%)	Test Set Hit (%)
Open Cut (OC)	200	141	99.5	94.9
Closed Cut (CC)	200	136	94.5	96.4
Fly Bite (FB)	200	174	95.5	96.4
Without Defect (WD)	600	118	97.3	98.2

a significantly reduced number of descriptors. The importance of having few features is that the classifier has less parameters to adjust and, hence, the times for training and classification are reduced considerably.

In figure 4 results from processing images with defects are shown. The top row in the figure shows the images with defects and the bottom row gives the results after classification. In the images resulting from the classification, the baby blue color represents a leather sheet without defects, the blue represents Open Cut (OC), White represents Closed Cut (CC), and red represents Fly Bite. The classified images have a high percentage of success, with low presence



(a) (b) (c)

(d) (e) (f)

Fig. 4. Results, Top Row: (a) Open Cut (OC) (b) Closed Cut (CC) (c) Bite Fly (BF) Bottom Row: (d) OC Classification (e) CC Classification (f) BF Classification

of errors, which shows the good quality of the discrimination for the selected descriptors and the good training of the classifiers.

5 Conclusions and Future Works

This study has presented an automatic method for classifying defects in Wet Blue leather. Computation for a large set of features is proposed, and then a quite reduced set is selected by using the Sequential Fordward Selection method. The Multilayer Perceptron was selected as a classifier and it was trained by following a procedure that ensures an adequate generalization.

The proposed method contributes to the solution of the defect detection problem in Wet Blue leather, by using new descriptors, applying the Sequential Forward Selection method in the feature selection stage, and with an adequate procedure to train the neural network. Based on all the innovations above, the method has a high reliability detecting defects on leather areas.

Current studies are dealing with a fast stage for finding defects with the goal of recognizing the type of defect in a restricted area, which will allow to improve the speed of the analysis of the leather sheets. Besides the previous goal, the behavior of algorithms with new defects is being studied.

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