

# Attributes Reduction applied to Leather Defects Classification

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**Abstract**—This paper presents a study on attributes reduction, comparing five discriminant analysis techniques: Fisher-Face, CLDA, DLDA, YLDA and KLDA. Attributes reduction has been applied to the problem of leather defect classification using four different classifiers: C4.5, kNN, Naïve Bayes and Support Vector Machines. The results of several experiments on the performance of discriminant analysis applied to the problem of defect detection are reported

**Keywords**-attributes reduction; linear discriminant analysis; leather defect detection;

## I. INTRODUCTION

Attributes reduction is an important step in pattern recognition systems dealing with a large amount of attributes, like image processing and computer vision problems. One of its main goals is the balance between correct classification rates and the time to train or use a classifier. This balance depends on each application, making the conduction of performance experiments for any new application domain very important. In this study, both raw-hide and wet-blue bovine leather defect detection were chosen as the application domains. Raw-hide is an animal skin that has not been exposed to tanning, while wet-blue is the name given to the bovine leather after the first stage of the tanning process. Figures 1 and 2 show some of the defects appearing in wet-blue and raw-hide. The inspection of this leather, usually visual, is crucial in determining the destination of the leather and its price. A computer system is being developed to automate this process, and here some results related to this system's attributes reduction module are presented. Once class information is available for this problem, this work concentrates on Fisher Linear Discriminant Analysis (FLDA) based approaches. In previous studies, this problem also was shown to be prone to the singularity in the within-class covariance matrix, which further let us to sharpen our choice to techniques that can handle this problem.

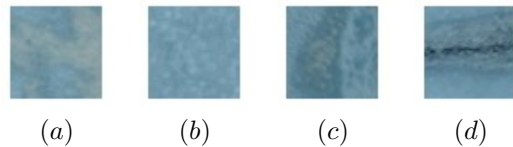


Figure 1. Examples of wet-blue leather defects: (a) scabies (b) ticks (c) hot-iron marks and (d) cuts

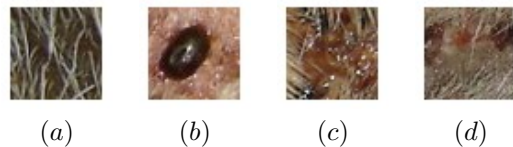


Figure 2. Examples of raw-hide leather defects: (a) scabies (b) ticks (c) hot-iron marks and (d) cuts

We evaluated five attribution reduction techniques: FisherFace, Chen's LDA (CLDA), Direct LDA (DLDA), Yang's LDA (YLDA) and Kernel LDA (KLDA). The techniques have been tested in combination with four classifiers and several attributes based on co-occurrence matrices, interaction maps, Gabor filter banks and two different color spaces. All the tests results were used to compare the performance of the used methods to identify which are best in problems involving singularity problems in the reduction of attributes in cattle leather defect detection. The next sections present a literature review, experimental setup, results, discussion, conclusion and future works.

## II. BOVINE LEATHER

Bovine leather is used in several industries, and Brazil has a large potential growth due to its herd, one of the world's largest. Brazilians classify the leather in three parts: head, flanks and grupon (loin or back). The grupon is the best

part due to its fibers, which have the best texture, uniformity and resistance. The head has too many wrinkles and thicker skin. Finally, the flanks have worst fibers with inferior texture (empty, open and thin), being easier to rupture. For automatic defects analysis, it is usually important to have more precision in the grupon region.

This work focused on raw-hide and wet-blue, which are results from two pre-processing stages of leather treatment. Raw-hide is the initial skin, not yet treated. Wet-blue is obtained after the first tanning phase. Some of the main leather flaws are berne (similar to a round hole, caused by the larvae of a fly known as “berne” or botfly), tick (caused by a clinging insect), scrape cuts (cuts that show, caused by knives during slaughtering), fire branding (caused by identifying marks), open cuts and scars (from barbed wire of whips), veins (from the animals blood problems, where structure or ruptures close to the exterior can show after tanning) and scrabies [1].

From the literature on automatic detection of leather flaws, [2] presents a new technique based on wavelets, which uses a bank of optimized filters, where each filter is adjusted to a certain defect. These filters and the wavelets ranges are chosen based on the maximization of attributes obtained from the flaws and regions of the leather. This kind of method can detect even when a small change in attributes happens. Furthermore, this technique has shown to be fast enough for detection in real time.

In [3] is shown a detection method based on histogram, using the  $\chi^2$  criteria to image analysis and histogram construction. This technique can detect leather flaws based on the evaluation of the difference between gray-scale histogram and other search areas of the image. In [4] is shown a modification on the extraction of attributes called Local Binary Pattern to detect texture defects.

### III. FISHER LINEAR DISCRIMINANT ANALYSIS

Fisher Linear Discriminant Analysis (FLDA) became very common in computer vision and patter recognition applications. It uses information of classes associated to each pattern to linearly extract the most discriminant attributes, this way reducing the amount of attributes in a given problem. FLDA has been extended in many different ways over the last decades, including approaches that enable non-linear analysis through the use of the Kernel trick [5]. In [6], the performance of CLDA, DLDA and YLDA has already been compared, however, the problem studied was face recognition. The feasibility of FLDA for defect detection problems which depends on texture analysis has been studied in [7]. Extensions of FLDA that can handle singular covariance matrices have also been compared in [8].

In the following we briefly review the techniques used in this comparative study. The symbols  $S_w$  and  $S_b$  will be used, from here on, to represent the within-class and between-class covariance matrices. FisherFaces is a two step technique that

performs a Principal Component Analysis (PCA) followed by standard FLDA [9]. CLDA tries to overcome the lost of discriminant information, with the application of PCA as a first step, in FisherFace, by emphasizing and exploring the discriminative information in the null space of  $S_w$  [10]. The main idea behind direct LDA (DLDA) is to discard non-discriminative information in the null space of  $S_b$ . Similar to FisherFaces, YLDA also performs a PCA followed by LDA, however some modifications in the LDA step allow, in some situations, that more discriminative information be retained from the principal components analysis [11]. Kernel-based Fisher Discriminant Analysis (KFDA) uses the kernel trick to implicitly map the feature vectors into a kernel-induced feature space, “before” applying a standard FLDA in this new space.

As an illustrative example, Figure 3 presents the resulting projections from each of the five techniques used in this work. The three situations simulate a two classes classification problem in different levels of discriminability.

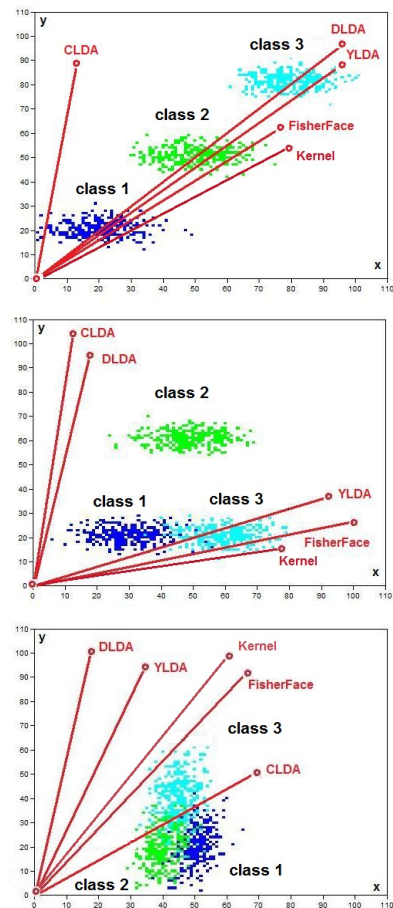


Figure 3. Resulting 3D to 2D projections from each attributes reduction technique

#### IV. EXPERIMENTS, RESULTS AND ANALYSIS

In this work, three sets of experiments using the most common types of flaws on cow leather in the slaughterhouses and tannery plants visited were performed. The experiments were grouped in:

- 1) Experiments 1: Defects classification in Raw-Hide and Wet-Blue;
- 2) Experiments 2: Attribute reduction in Raw-Hide and Wet-Blue;
- 3) Experiments 3: Defects classification compared to human experts.

The images used in this experiment were taken in real-world situations from Brazilian tanneries. Ground-truth classifications of defective regions were provided by field experts and Figure 4 shows some examples of annotated images. In total, 50 different wet-blue leather pieces, from Nelore and Hereford cattle, were used to construct the training and testing datasets. For each of the 8 classes: background, no-defect, hot-iron marks, ticks, open cuts, closed cuts, scabies and botfly larvae; 2,000 samples, consisting of a 40x40 pixel windows, were collected. From each sample, the following attributes were extracted:

- Entropy (*ENT*), inverse difference momentum (*IDM*), dissimilarity (*DISS*), correlation (*CORR*), contrast (*CONT*), second angular momentum (*ASM*) and the inverse difference (*INV*) from co-occurrence matrix varying from 0 to 180 degrees with steps of 10 degrees and distance of 1 pixel resulting in 126 attributes;
- Iteration maps varying from 0 to 180 degrees with steps of 10 degrees and distances 0, 1 and 2 pixels;
- Gabor filters with parameters wave size of (100:256), orientation (45:135), symmetry (90:90), core size of 1.0 and eccentricity 0.5;
- Average values for each color component of HSB (hue, saturation, brightness) and RGB
- Values of the 3-bins 3D histogram for HSB and RGB color space

As for the classifiers, C4.5, K-Nearest Neighbors (kNN), Support Vector Machines (SVM) and Naïve Bayes have been tested, all of them configured with the default parameters for the implementations available in the Weka software [12] and detailed in [13].

##### A. Experiments 1: Defects classification in Raw-Hide and Web-Blue

The first experiment was done to analyze the correct classification ratio (CCR) of the four classifiers without attributes reduction. The results from the classification applied to the raw-hide samples for each learning method are presented in Table I. From the results, all classifiers were efficient, except the Naïve Bayes technique. The best

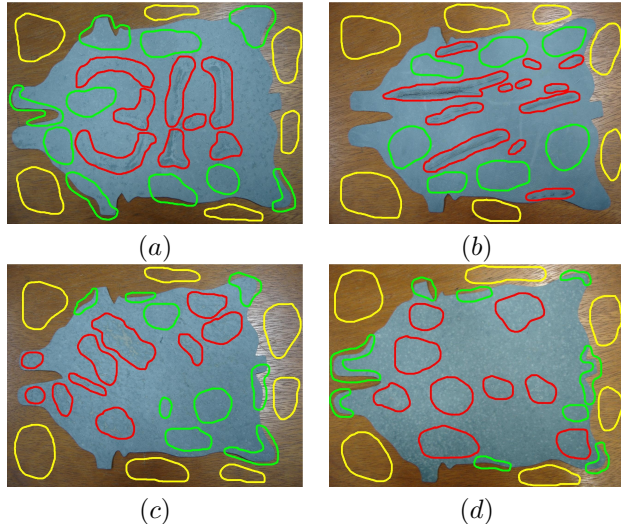


Figure 4. Example of images manually marked with colors red for defect, yellow for background and green for no defect region. (a) iron branding defect, (b) open cut defect, (c) scabies defect and (d) tick defect.

Table I  
CLASSIFIERS CORRECT CLASSIFICATION RATIO (CCR) FOR RAW-HIDE SAMPLES

Classifier	CCR(%)
C4.5	94.73
kNN	95.90
Naïve Bayes	47.37
SVM	90.03

method was kNN, achieving the correct classification ratio of 95.90%.

In a similar way, the same classifiers were used in Wet-Blue images, with the results shown on Table II. As before, it was possible to verify that the techniques for attribute extraction and classification delivered high hit rates, except for the Naïve Bayes method, which again had the smallest CCR, while kNN had again the best correct classification ratio.

Table II  
CLASSIFIERS CORRECT CLASSIFICATION RATIO (CCR) FOR WET-BLUE SAMPLES

Classifier	CCR(%)
C4.5	91.72
kNN	93.76
Naïve Bayes	54.51
SVM	84.53

##### B. Experiments 2: Attribute reduction in Raw-Hide and Wet-Blue

The following experiments were used to compare the different methods for attributes reduction. They were divided into experiments on sample bases were it did or did not occur singularity, in raw-hide and wet-blue. From the experiments

it is noticeable that attributes reduction reduces the learning and classification time without large loss on discriminability amongst the classes' patterns.

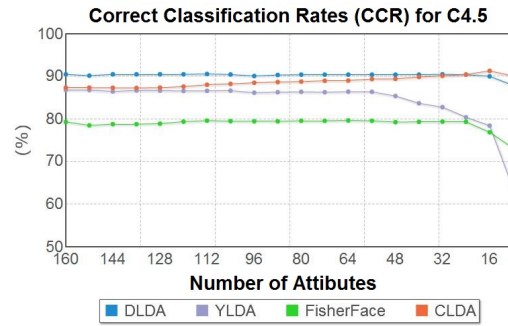
1) *Non singular covariance matrices:* In this experiment, starting at 160, the attributes were progressively reduced in 4% at a time, using each of the attributes reduction techniques: FisherFaces, CLDA, KLDA and YLDA. A 3-fold cross-validation approach, with two repetitions, was used to produce correct classification rates for C4.5, kNN, SVM and Naïve Bayes. The graphics 5 and 6 show the results of attributes reduction using the suggested techniques on cases where  $S_w$  is non singular.

Figures 7 and 8 present the training and testing time for each classifier as the attributes were reduced using FLDA in the wet-blue dataset. In the problem of leather classification there is no clear need for on-line learning and so testing time is more important than training time. These results indicate that C4.5 is significantly faster than the other three techniques when all the attribute are used. However, when less than 16 attributes are used, C4.5 and SVM achieve similar performance in testing time. The training and testing time for the raw-hide dataset are very similar to the wet-blue dataset and were omitted in this paper.

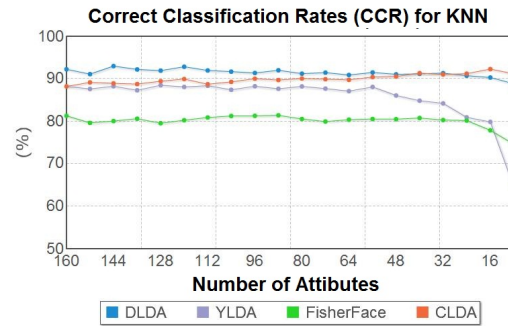
2) *Singular covariance matrices:* For this second comparison of the attributes reduction methods, in order to induce the singularity problem, the training data set has been reduced to 100 samples, for each class, an the attributes set has been augmented with raw pixel information (gray value of each pixel) and the use of more co-occurrence matrices. Table III shows all the attributes extracted for this experiment. Different from the previous reduction experiments, just one reduction has been made, discarding half of the total amount of attribute. This was done in order to enable the comparison with KLDA, that is much slower than the other techniques, and took several days to process just one dataset. As before, we use the correct classification ratio to compare the performance of these methods. The Tables IV and V show the results of attributes reduction (50% reduction) for raw-hide and wet-blue.

Table III  
EXTRACTED ATTRIBUTES FOR THE EXPERIMENT WITH SINGULAR MATRICES

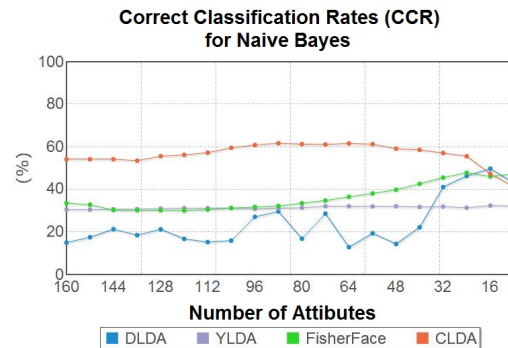
Extraction Method	Quantity of Attributes
Average(H), (S), e (B)	3
Average (R), (G) e (B)	3
HSB Histogram (3-bins)	27
RGB Histogram (3-bins)	27
Iteration maps	7
Co-occurrence Matrix	2520
Gabor Filters	15
Sample Pixels	1600
Total	<b>4202</b>



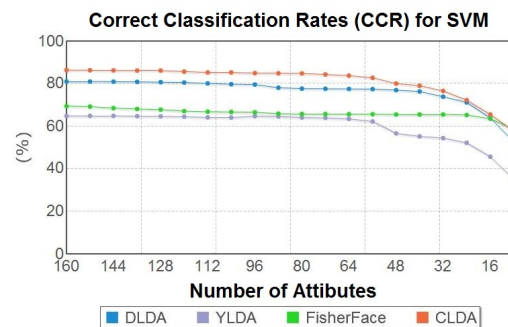
(a)



(b)



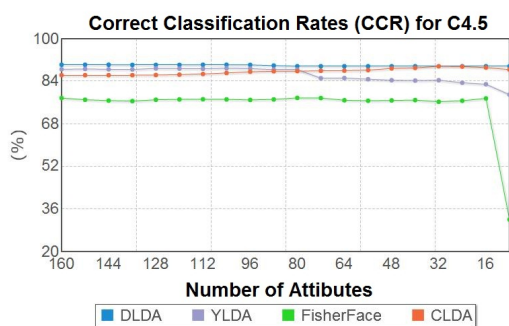
(c)



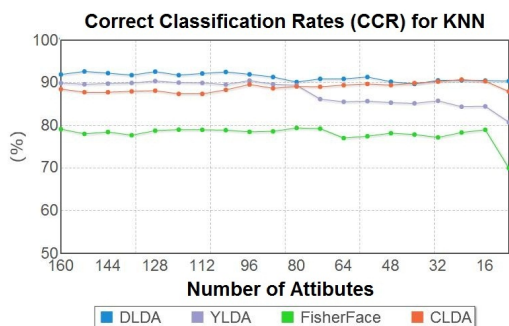
(d)

Figure 5. Correct Classification results for (a) C4.5, (b) kNN, (c) Naïve Bayes and (d) SVM in Raw-Hide

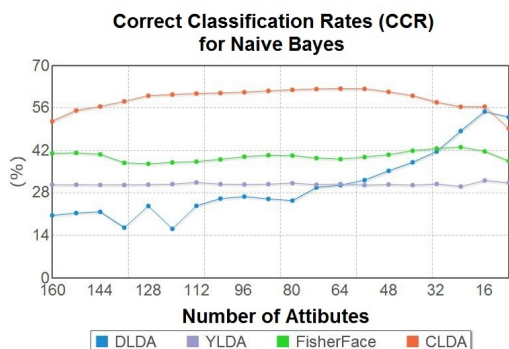




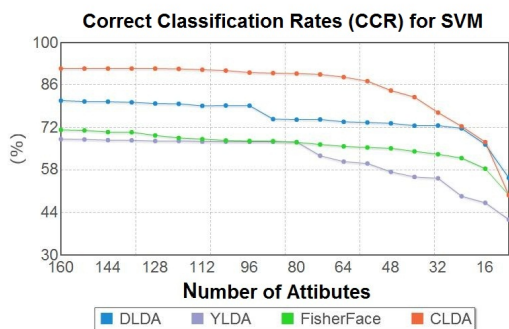
(a)



(b)



(c)



(d)

Figure 6. Correct Classification results for (a) C4.5, (b) kNN, (c) Naive Bayes and (d) SVM in Wet-Blue

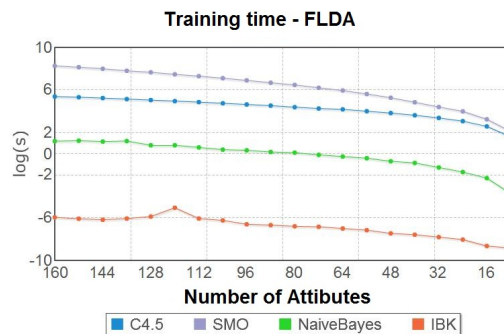


Figure 7. Training time for C4.5, kNN, Naive Bayes and SVM

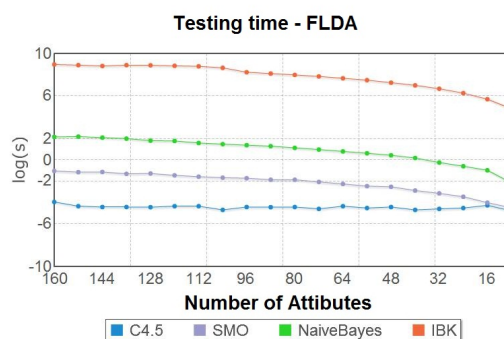


Figure 8. Testing time for C4.5, kNN, Naive Bayes and SVM

Table IV  
CORRECT CLASSIFICATION RATES FOR FOR WET-BLUE IMAGES

Classifier	CLDA	FisherFace	YLDA	DLDA	KLDA
C4.5	85.18	75.96	81.48	88.45	72.24
kNN	90.3	78.21	83.18	88.32	74.21
Naive Bayes	50.14	30.27	39.66	44.74	20.12
SVM	78.11	55.24	67.53	79.88	48.90

Table V  
CORRECT CLASSIFICATION RATES FOR RAW-HIDE IMAGES

Classifier	CLDA	FisherFace	YLDA	DLDA	KLDA
C4.5	87.91	77.75	84.22	88.98	72.78
kNN	92.23	80.5	85.02	90.08	76.73
Naive Bayes	52.75	31.09	42.16	46.85	25.43
SVM	80.02	66.56	69.48	81.76	54.16

### C. Experiments 3: Defects classification compared to human specialists

Experiments were also made to visually compare automatic defect classification to a trained human expert. The parameters of the classification system were set according to the best results from the previous experiments. The training bases were also the same as before. For the test two images were used (see Figure 9) that did not belong in the training base, one for raw-hide and one for wet-blue.

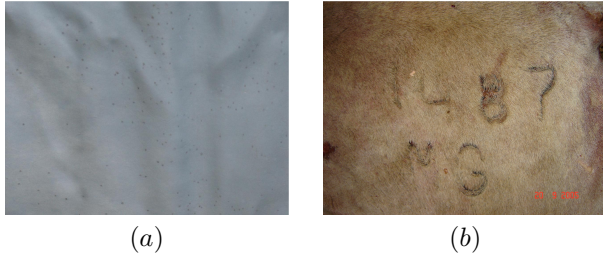


Figure 9. Images used for tests with the automatic classification module. (a) wet-blue (b) raw-hide.

The automatic classification module created, for each image, a copy with marks for all the regions where defects are identified, with different color for each type of flaw. The Figures 10 and 11 show the automatic and manual classifications, respectively.

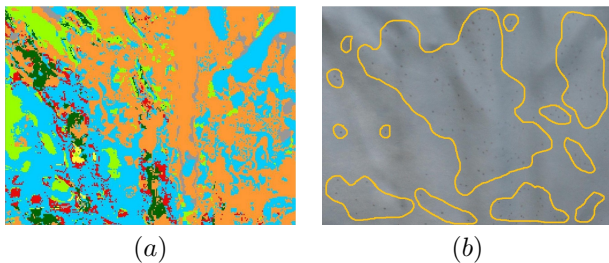


Figure 10. Wet-Blue image, used for tests of the automatic classification module, (a) automatic classification (b) manual classification

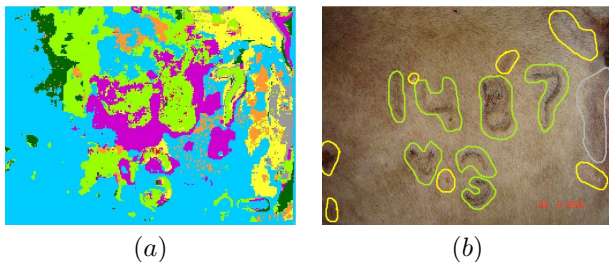


Figure 11. Raw-hide image, used for tests of the automatic classification module, (a) automatic classification (b) manual classification

## V. DISCUSSION

Based on these experiments, we stress the importance of using reduction techniques for applications where the main goal is reliability with low computational cost in classification. Experiments also have shown that even in situations with singularity problems it is possible to reduce the quantity of information while still discriminating well amongst the classes.

During this experiment a problem occurred in the use of Kernel technique (KLDA) applied on the learning base without singularity problem. It took too long to reduce the attributes, not reaching any results after 48 hours executing (in

a 2,3GHz Intel - Core 2 Duo with 2Gb RAM). It was because KLDA makes projections of attributes vectors on the Kernel space, creating new values that are evaluated considering the total quantity of samples. Therefore, the large quantity of attributes and samples turned the calculation infeasible for this base. But for the problem with singularity, where the sample base is about 3.85% the size of the non-singularity base, there were no problems using KLDA.

Analyzing the results for the problem without singularity, there was a large improvement on performance using the reduction methods, giving even results better than the traditional Fisher discriminant analysis. For both classification problems, raw-hide and wet-blue, results obtained were close on classification and very similar on performance, as the quantity of information went decreasing.

For cases with singularity, where reduction was made only once, with half the total of attributes, the techniques were still efficient, because even with 50% of all information it was still possible to achieve high correct classification rates. The techniques with best results in attributes reduction for both formats of performed experiments, with and without singularity problems, were CLDA e DLDA. For wet-blue without singularity, the best cases happened using 24 attributes with 91.47% correct classification ratio for CLDA, e 144 attributes with 92.33% correct classification ratio for DLDA. For raw-hide without singularity, the best cases occurred using 16 attributes with 92.28% correct classification ratio for CLDA, and 136 attributes with 93.32% correct classification ratio for DLDA. For wet-blue with singularity, CLDA gave a correct classification ratio of 90.3% and DLDA gave correct classification ratio 88.32%. For raw-hide with singularity, CLDA gave a correct classification ratio of 92.23% and DLDA gave correct classification ratio 90.08%.

But YLDA also had good results, having in best cases a correct classification ratio of 83.18% for Wet-Blue and 85.02% for Raw-Hide, in cases with singularity, unlike FisherFace and KLDA, which presented the worst results in most of the cases. To classify reduced learning bases, kNN algorithm gave the best results. However it is not efficient on testing times, as shown in the experiments and also in the literature. On the other hand, the C4.5 algorithm has much lower times than kNN but has satisfactory classification performance.

In the experiments, FisherFaces e KLDA methods showed the worst cases. For singularity problems, the best case for FisherFace correct classification ratio was 78.21% for wet-blue and 80.5% for raw-hide. KLDA resulted 74.21% for wet-blue and 76.73% for raw-hide. In case without singularity problems, the worst correct classification ratio was from FisherFace, with 32% for Wet-Blue. Analyzing the learning algorithms, the less efficient was Naïve Bayes, which had the worst performance in most of the reduced learning bases.

In the KLDA case, the low correct classification ratio may

be related to the type of kernel function used, that may be neglecting the most discriminative information, while not directly dealing with the singularity problem. But some works, like [14] and [15] show that the change in the kernel function used, coupled with LDA techniques that deal with the singularity problem, could bring more satisfactory results.

As observed, the images automatically classified by the system present regions that should not be marked, or present defects incorrectly classified, when compared to the ones marked by a human expert, as shown in Figures 10 e 11. That means that for this experiment we had several “false positive” classifications, i.e., the classifier identified as a certain type of defect regions with no defect. This happens for several reasons, but amongst them the quantity and quality of the training set stand out: they are not sufficient to discriminate all flaws. In the raw-hide case, we noticed that all iron branded regions were identified as flaws by the system and the human expert, but the automatic classifier identified the surroundings of the iron scars as scrapes.

## VI. CONCLUSIONS AND FUTURE WORK

A comparison using four LDA reduction strategies and four classifiers applied to the problem of wet-blue defect detection was provided. The results pointed to better performance of CLDA and DLDA, in keeping correct classification rates as attributes were reduced. kNN reached the best CCR using the maximum and the minimum amount of attributes in the test. However, classification times for kNN are shown to be much higher than C4.5, which could justify the use of C4.5 for this problem. We should point out that for the system under development, training time is not as critical as the classification time.

Several problems in using KLDA were found and it has only been used in the experiments with the 800 samples dataset (section B.2). Its CCR results presented the lowest values both for raw-hide and wet-blue images. New experiments, using different kernels and optimized versions of kernel based techniques should be conducted in the future, before discarding them for the problem of leather defects classification.

## ACKNOWLEDGMENT

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