SUPervised classification of defective crankshafts by image analysis

Beatriz Remeseiro¹, Javier Tarrio-Saavedra², Mario Francisco-Fernández², Manuel G. Penedo¹, Salvador Naya², Ricardo Cao²

¹ Departamento de Computación, Universidade da Coruña, España (e-mail: mgpenedo@udc.es, bremeseiro@udc.es)
² Departamento de Matemáticas, Universidade da Coruña, España (e-mail: mariofr@udc.es, salva@udc.es, rcao@udc.es, jtarrio@udc.es)

Abstract: A supervised classification methodology based on image analysis of photographs, dimension reduction procedures and Linear Discriminant Analysis, Naïve Bayes, Logistic regression and Support Vector Machines classification methods has been successfully implemented to identify defective crankshafts in automotive industry.

Keywords: Imaging, artificial vision, quality control, supervised classification, PCA, PLS.

1 Introduction

The aim of this work is to assure the quality of the crankshafts used in automotive industry using an automatic procedure based on imaging and statistics. The proposed methodology seeks for saving time, resources and quality improvement in the productions of crankshafts. Nowadays, the defect inspection of each crankshaft obtained by forge is made manually by operators. The procedure occupies many resources of the forge factory, is extremely time consuming and stressful for operators. In fact, an increasing number of defective pieces could take place due the increasing operator fatigue. It is well-known that crankshafts defects can cause a large number of traffic accidents, thus the quality assurance of these pieces from an statistical quality control and artificial vision point of view is justified. Therefore, the methodology proposed deals with providing a more reliable and automatic process to detect defects in crankshafts in order to increase the profit and the confidence on this type of industry. The present procedure is based on the following steps:

1. Obtaining magnaflux photographs of each crankshaft by means an industrial camera.
2. Processing the images and extracting the relevant features that define each picture. Texture and colour techniques are both used.
3. Applying dimension reduction methods to the feature matrix obtained in the step above mentioned.
4. Fitting of supervised classification methods to posterior estimate which new photograph (corresponding to a specific crank) presents defects (cracks or scratches) or not.

2 Data collection

The magnaflux photographs of each crank are obtained in a special room in the forge factory. Overall 16777 photographs were obtained. This sample corresponds to pieces of the same population. Figure 1 shows an example of magnaflux photograph.

![Figure 1. Magnaflux photograph from a crankshafts.](image)

The aim of this step is to translate the information of each image to numerical matrix where each row is an individual and each column a feature that defines the photograph. In order to obtain this matrix, several low-level features were extracted to distinguish between defective areas and non-defective ones. Taking into account the particularities of the images, the use of color and texture information were considered to extract the low-level features. On the one hand, defective areas have a characteristic green color which motivates the use of color information, and so the Lab color space was considered in addition to grayscale images. On the other hand, defective areas have a different texture from those which are not, and thus two texture extraction methods were considered: uniform histograms and the discrete wavelet transform. In this manner, overall 92 features were obtained and combined in the same matrix. Images were analyzed locally, i.e., square windows of 128x128 pixels were considered. Thus, it is possible to know not only whether a given image defects but also the approximate area where they are. According to the present methodology, an unique image is enough to determine if there is defect or not.

3 Dimension reduction and Classification

Once data were acquired and transformed to a numeric features matrix, the next step is to project the features in the principal components space (PCA) or partial
linear squares space (PLS) (Tarrío-Saavedra et al., 2013; Wehrens, 2011). The resulting new components will be not dependent and are ordered from more to less informative. On the one hand, this permits to work with a lower number of components without losing valuable information and saving computation time. On the other hand, the new components are closer to meet the assumptions of classification methods.

**Figure 2.** Misclassification errors applying LDA to PCA component

**Figure 3.** Misclassification errors applying Log. Regression to PCA components.

**Figure 4.** Misclassification errors applying LDA to PLS components.
Figure 5. Misclassification errors applying Naïve Bayes to PLS components.

Three simple supervised classification methods were chosen attending to the size of the dataset and the requirements of rapid response: linear discriminant analysis (LDA), Naïve Bayes, and logistic regression (Tarrio-Saavedra et al, 2013; Wehrens, 2011). These three methods were applied to the PLS and PCA components datasets. To properly validate these methods, 10 fold cross validation was performed (Tarrio-Saavedra et al, 2013; Wehrens, 2011). Although it provides slightly biased misclassification error estimates (slightly pessimistic) they are characterized by lower variance. Figure 2, 3 4 and 5 show the results applying the classification methods to a wide range of PLS and PCA components. We have obtained a perfect classification (misclassification error = 0) applying LDA to the first 86 principal components. Moreover, if the Logistic Regression method is applied to 16 first principal components, the 96% of the photographs are well classified. Thus, this method could be used to this number of components in order to save computation time and gaining simplicity. Regarding to PLS results, 90% correct classification is obtained using around 18 PLS components and applying LDA and Naïve Bayes.

References
