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A sequential machine vision procedure for assessing paper impurities

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ABSTRACT

We present a sequential, two-step procedure based on machine vision for detecting and characterizing impurities in paper. The method is based on a preliminary classification step to differentiate defective paper patches (i.e., with impurities) from non-defective ones (i.e., with no impurities), followed by a thresholding step to separate the impurities from the background. This approach permits to avoid the artifacts which occur when thresholding is applied to paper samples that contain no impurities. We discuss and compare different solutions and methods to implement the procedure and experimentally validate it on a datasets of 11 paper classes. The results show that a marked increase in detection accuracy can be obtained with the two-step procedure in comparison with thresholding alone.

1. Introduction

Paper may contain particles of various types. In most cases these represent defects and impurities that need to be avoided; in other cases they are purposefully inserted in the paper to give the final product a peculiar visual appearance. In either situation the papermaking industry is increasingly concerned with the development of quick and reliable systems to detect and characterize such inclusions automatically. The growing attention towards environmentally friendly production policies and the consequent rise in production of recycled paper [14] – intrinsically more prone to contain defects – has rendered this need more and more compelling. The detection and characterization of particles can also help to determine the source of impurities in the production process, which can be subsequently amended and eliminated. This may reduce the use of chemicals in the bleaching phase, with beneficial effects on the environment. When speaking of defects, specific international standards [1,2] provide definitions and quantitative means to assess their extent and the quality of the paper. Otherwise, when particles are actually desirable features of the product, their control may be performed in compliance with internal norms of the companies.

In the last twenty years, automatic visual inspection has benefited from the steady development of machine vision, whose applications now embrace a wide range of very diverse industrial products, such as wood [10,17], textile [9], natural stone [7], exterior car parts [13] as well as food and agricultural products [3,18], to cite some. In the papermaking industry, applications of machine vision are not uncommon and have covered, thus far, many problems like curl estimation [38], printability analysis [24], control of stripes and holes [29], sorting of waste paper for recycling [34], recognition of paper manufacturer and lot for forensic comparison [4] and characterization of fibre properties [11,21].

Among the various applications, the identification of impurities has received significant attention, since such defects greatly affect the quality of final products. Within this field, Torniainen et al. [39] described an apparatus to measure dirt points on wet and dry pulp sheets through transmitted light reporting accuracy from 75% to 90%. Likewise, Duarte et al. [12] proposed a system for dirt inspection on pulp and paper based on hiearchical image segmentation. Later on, Campoy et al. [8] presented 'InsPulp-I', an inspection system for the pulp industry. More recently, interesting results have been obtained within the project 'PulpVision' [33], the aim of which is to detect dirt particles in pulp and classify them into different categories (i.e., bark, shives, etc.).

The literature shows that the common strategy to attack the problem consists of a preliminary image thresholding step to separate whatever kind of contraries from the background, followed by further analysis to classify them into one of some predefined categories. For such a strategy to work correctly, one has to implicitly assume that the paper patch under control does actually contain some type of particles; otherwise, if there are no particles at all, any image thresholding procedure is bound to produce unpredictable results, as we show in Fig. 1. To solve this problem, we propose a novel approach in which we first separate

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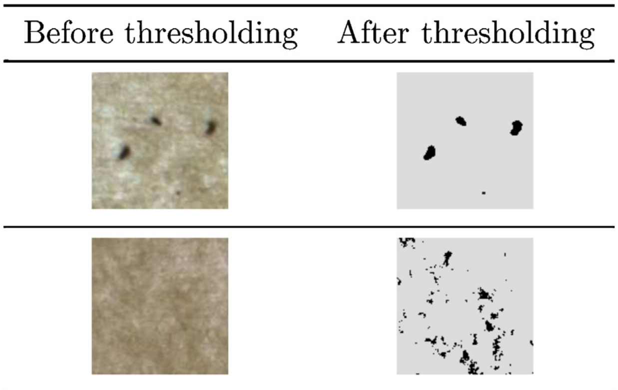

Fig. 1. Effects of thresholding on a defective (first row) and a non-defective (second row) paper patch.

paper areas into defective and non-defective, then proceed to further analyse only the defective ones. Experimentally, we show that the method can provide an average increase in detection accuracy of about 25%.

In the remainder of the paper we first give a general overview of the method (Section 2), followed by a description of the materials and image acquisition devices used in the study (Section 3). In Section 4 we present and compare different solutions to implement the two steps of the method. The experimental activity is detailed in (Section 5), followed by the results (Section 6) and concluding considerations (Section 7). For the purpose of reproducible research, all the data and functions used in this study are available to the public [32].

2. Overview of the procedure

Our approach consists of the following two steps: (1) preliminary classification of surface patches into defective and non-defective; (2) analysis of the defective patches through image thresholding. This solution avoids the problems that arise when paper samples contain no defects at all. In this case direct image analysis through thresholding usually produces unpredictable and utterly unreliable results, as shown in Fig. 1.

The overall procedure is summarized in Fig. 2. The sample to analyse (Fig. 2(b)) is first subdivided into a set of non-overlapping inspection patches of equal area (Fig. 2(b)). The size of the patches can be adjusted to fit specific application needs. Then each patch is classified as defective or non-defective through a supervised classification procedure (Fig. 2(c)). For this step we propose a texture-based approach. Possible implementations are described in Section 4.1. Finally, an image thresholding step permits to assess the extension of the defects (Fig. 2(d)). Different thresholding methods are discussed in Section 4.2. In the experiments (Section 5) we assess the accuracy of the methods proposed for classification and thresholding.

3. Materials

In this study we considered 11 different classes of paper. The characteristics of each class are reported in Table 1. For each class we selected a set of specimens of dimension 150 mm $\times$ 150 mm and acquired them at a resolution of 1600 pixels $\times$ 1600 pixels, which corresponds to a spatial resolution of approximately 370 dpi. This gives a pixel side length of 0.0686 mm, and an area of $\approx$ 0.005 mm^2 – a value far below the minimum of 0.04 mm^2 established by related standards [1,39].

3.1. Imaging system

The imaging system (Fig. 3) is composed of one dome illuminator (Monster Dome Light 18.25″), one industrial CMOS camera equipped with a 12 mm fixed focal length lens (Pentax H1214-M), one backlight illuminator, one base and three pins to support the dome. Inspection can be performed through either transmitted light or reflected light: when working by reflected light, the dome is on and the backlight illuminator is off; when operating by transmitted light the reverse occurs. In either case illumination is provided by LED lights. For each type of paper (see Table 1) the most appropriate inspection method is selected on the basis of the intrinsic properties of the paper (i.e., density) and of the particles (i.e., transparency/opacity).

From the acquired images, and for each class of paper, we manually cropped 48 image patches containing no impurities and 48 patches with impurities of different shape and extension. Each of these patches has a resolution of 128 $\times$ 128 pixels. In the experiments they simulate the inspection areas into which a paper sample is subdivided (see Fig. 2(b)). For each defective patch a binary ground truth of the relevant impurities has been manually determined and cross-validated by two human experts. As a result, the dataset contains 144 images per class, therefore a total of 1584 images. For every class Table 1 reports three images of each of the defective, non defective and ground truth group. The dataset comprises a wide enough range of inclusions as for shape, extensions and type.

4. Methods

The two core steps of our approach belong to two classic problems of image analysis, namely classification and thresholding. Both have been investigated at length and several solutions have been proposed. Yet their conversion into industrial applications is rarely straightforward. In the industry we need methods that are not only accurate and fast, but also conceptually simple, robust and easy to implement. In the following sections we discuss different solutions that comply with these requirements.

4.1. Classification

The aim of this step is to design a two-class classifier capable of discriminating between defective and non-defective paper patches. This involves the choice of an appropriate classifier and the definition of suitable image descriptors.

The selection of a proper classifier is the result of a trade-off among various factors, mainly accuracy, computational demand and robustness. Here we opted for the robust and simple 1-NN with L_2 distance. The ease of implementation, as well as the absence of tuning parameters, make the method particularly appealing for industrial applications. In the specific problem studied here, this method also proved very accurate, as shown in Section 6. Preliminary experiments showed higher accuracy of this method in comparison with linear and SVM classifiers. The interested reader will find the extended results the accompanying website [32].

Our approach to image classification is texture-based: we consider the seven image descriptors detailed in Sections 4.1.1–4.1.5 and summarized in Table 2. All the methods are rotation invariant, since in principle defects can occur at any orientation. In the remainder of the paper let $\mathbf{I}$ indicate a grey-scale image quantized into L intensity values.

4.1.1. Histograms of equivalent patterns

Histograms of equivalent patterns (HEP) is a family of texture descriptors [16] which includes very popular methods such as