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Image-based classification of paper surface quality using wavelet texture analysis

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ABSTRACT

The characteristics of paper surface play a central role in the overall quality of paper produced in modern paper machines. Among the surface features, paper formation, i.e., the level of homogeneity in the distribution of fibres on the surface of paper, is a key quality parameter, being currently monitored off-line, at low sampling rates relatively to the high production speeds achieved with modern paper machines. Therefore, in this paper, we address the problem of assessing the quality of paper formation, on-line, in situ, in an autonomous, efficient, objective and fast way, using features derived from images collected by a specially designed sensor, coupled with proper classification methodologies. The results obtained clearly demonstrate the potential of the proposed assessment approach either for the more complex three-class classification problem as well as for less demanding, but still important in practice, two-class "Accept"/"Reject" or "Pass"/"Fail" problem.

1. Introduction

Paper formation (the level of homogeneity in the distribution of fibres on the surface of paper) is a key quality parameter for paper products, as it impacts not only the aesthetic evaluation and visual perception of quality by the end users, but also affects other relevant properties such as the average strength of paper (a sheet with poor formation is weaker than a comparable sheet with a better formation), the quality of printing operations (which is inferior for papers with poor formation) and, furthermore, leads to process related problems, such as, for instance, the increase of consumption in coating chemicals, as paper formation gets worse. For these reasons, paper formation constitutes a matter of great concern for paper producers, being therefore routinely measured in the quality control laboratories of modern paper production facilities, either through visual inspection followed by comparison with a previously labelled set of standard samples representing different quality levels of paper formation or, more frequently, with resource to instrumentation that scan the paper sheet, measuring the variation of light transmission through it. This monitoring activity occurs only a few times per day, according to the routine testing plans established in each paper mill. For instance, a possible routine may consist on taken a sample for each paper reel produced, which is then sent to the quality control laboratory, where, after some time, the measurements are performed and results introduced in the product quality information system. This whole process introduces a very significant delay in the supervision and control tasks, in particular when considering the high production rates achieved by modern paper machines, where paper is being currently produced at linear speeds that can be over 100 km/h. Therefore, we can easily conclude that such off-line process monitoring assessment activity presents strong limitations, being rather ineffective in promptly detecting problems in paper formation, which may originate significant losses in the quality of the final product and in the efficiency of the overall production process, when process upsets do arise. In this context, we address in this paper the development of technology for performing paper formation quality assessment, on-line and in situ, in an autonomous, efficient, objective and fast way, using features derived from images collected by a specially designed sensor.

Image analysis is currently a mature field, with many applications in different areas such as industry, medicine, biology, ecology, geology, astronomy, artificial intelligence, etc. The type of problems addressed may be quite distinct, and therefore the nature of the images analysis techniques employed may also vary significantly, from those applied in deterministic, shape recognition problems (De Anda, Wang, & Roberts, 2005), where the segmentation task (i.e., the partition of a image into meaningful regions or segments) plays a central role, passing by those related to image enhancement and noise reduction (Jähne, 1993; van der Heijden, 1994), to the analysis of random textures (Prats-Montalbán & Ferrer, 2007), where the goal is to extract the essential information contained in the randomness of the patterns, more than any localized feature in the image space, a scenario where the images to be analyzed in this paper fit into.

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Several approaches have been recently proposed regarding the analysis of random textures in grey-level images, as well as in colour and hyper-spectral images with various analytical aims, such as regression (Prats-Montalbán, Ferrer, Bro, & Hancewicz, 2009; Ye, Sakai, Sasao, & Asada, 2008), discrimination (Bharati, Liu, & MacGregor, 2004), classification (Antonelli, Cocchi, & Fava, 2004; Pereira, Reis, & Saraiva, 2009), clustering (Tran, Wehrens, & Buydens, 2005), process control (Yu, MacGregor, Haarsma, & Bourg, 2003) and process monitoring (Liu, MacGregor, Duchesne, & Bartolacci, 2005; Reis & Bauer, 2009; Yu & MacGregor, 2004). In these applications involving the analysis of random textures, an important issue regards the computation of quantitative features from the images that, for all practical purposes, correlate well with the different realizations of textures under analysis. In this context, there is some accumulated evidence pointing towards the effectiveness of the so-called wavelet texture analysis (WTA) features in the extraction of information regarding random phenomena contained in textures, being currently considered a state-of-the-art technique in this regard (Bharati et al., 2004). In WTA, features are computed after a preliminary transformation stage of the raw images using the efficient two-dimensional (2D) wavelet transform (hence the name, wavelet texture analysis), whose coefficients, naturally organized by blocks (regarding the scale and directionality of the wavelet basis functions involved) are then summarized by single numbers, according to the block they belong to. Wavelet analysis has been already applied to the analysis of paper formation, but only the wavelet details coefficients for the second decomposition level were used (Bouydain, Colom, & Pladellorens, 1999), something that, according to our results, may seriously hinder the discrimination ability that can be achieved among different levels of quality in paper formation, as shown later on. We have also demonstrated in a previous publication the potential of using WTA features for process monitoring of this characteristic (Reis & Bauer, 2009), and in this article we address the related, but more challenging problem of developing an autonomous and reliable framework for quality assessment of paper formation, using images collected on-line and in situ by properly combining feature extraction and classification methodologies.

This article is organized as follows. In the next section we briefly describe the images analyzed in this paper and the technology used in their collection, and introduce the methods employed in the classification methodologies tested for developing an autonomous assessment system for paper formation quality. Then, we present the results obtained for a variety of combinations of feature extraction and selection methods with several classification methodologies tested, and analyze their consequences for the quality assessment problems under analysis. Finally, we briefly conclude with a summary of the main results obtained and refer some future work worthwhile undertaken in the sequence of the results achieved so far.

2. Materials and methods

2.1. Image acquisition system and data set used in the study

The image acquisition sensor is a critical element for the on-line assessment of paper formation quality. Its function is to capture good quality images in the harsh environmental conditions prevailing in the forming section of the paper machine, which is essentially steamy and wet, with drops erratically flying everywhere around the camera. The technological solution developed for the formation sensor, consists of a digital camera within a housing that is able to rotate at high speed, in order to prevent dirt accumulation on the housing surface. Such design protects the camera from the environmental conditions, ensuring that the sensor will function properly with little maintenance. Camera used was a Jai A10 CL, with a Navitar DO-2595 lens. The strobe light consists of a led array emitting red light (CCS LDL-TP).

With this apparatus, a set of 23 images was collected for analysis. The images regard distinct formation quality levels, 10 from “Good”, 4 from “Poor” and 9 from “Bad” quality levels. In order to increase the sample size in the analysis, each image was then split into 4 sub-images (1/4 of the size of the original ones), after illumination correction to remove any systematic effect due to the particular position of each sub-image in the original image, leading in the end to a final image set with 40 sub-images with “Good” paper formation, 16 with “Poor” quality and 36 with “Bad” formation quality. This image set will be used as such in the three-class classification problem. As to the two-class classification problem, the samples regarding “Poor” and “Bad” formation quality are gathered into a single level, referred as “Not Good” (or alternatively as “Reject” or “Fail”).

2.2. Methods

2.2.1. Wavelet texture analysis

Wavelet texture analysis is based on the application of a 2D wavelet transform to each raw sub-image (Mallat, 1999), which essentially consists of transforming a matrix of numbers (pixel intensities, as we are analyzing single-channel or grey-level images) into another, with the same size (same overall number of wavelet coefficients), containing blocks of coefficients regarding details ($\mathbf{d}_i^j$) for different scales (from the finest to the coarsest scale, which is known as the decomposition depth, J_{dec}) and along three different directions (horizontal, vertical and diagonal; see Fig. 1).

In the present case, the decomposition depth considered in the analysis was $J_{dec} = 5$, and therefore each image will give rise to 16 blocks of data or sub-matrices ($=J_{dec} \times 3+1$; the “1” stands for the block of final approximation coefficients ($\mathbf{a}_1^{J_{dec}}$), containing the lowest resolution version of the image, after removing all the details corresponding to the finer scales). The wavelet adopted was the Symmlet with 6 vanishing moments (Daubechies, 1992; Mallat, 1999). The next stage in WTA is to summarize the information contained in the wavelet coefficients belonging to each of these blocks into a single number, from which a vector of WTA features will result. From the several possibilities available for performing this computation (energy, entropy, averaged l_1-norm, standard deviation) we used the standard deviation, $\omega_i^j = \mathrm{std}(\mathbf{w}_i^j)$, $\omega_i^j = \left\{ \left. \mathbf{d}_i^j \right|_{\substack{i=1:3 \\ j=1:J_{dec}}}, \quad \mathbf{a}_1^{J_{dec}} \right\}$ (this choice was motivated by the fact that the wavelet transform of uncorrelated homogeneous white noise is also white noise with the same standard deviation; therefore by using the standard deviation to summarize the information in each block, we are tactilely using a stochastic uncorrelated frame of reference against which we compare the texture in the images). In summary, by employing WTA, we have compressed the original analysis space composed by 128×128 pixels or intensity numbers in each sub-image, to just 16 numbers, i.e., the set $\{\omega_i^j\}$, that are expected to contain the essential information necessary to discriminate different formation patterns. The extracted WTA features are then ready to be used in the development of a classification framework for paper formation quality assessment.

2.2.2. Classification methodologies

A classification problem is essentially the derivation of a map from the $\mathbb{R}^N$ domain, where N-dimensional observations taken from samples or features computed from them (such as the WTA features) lie, onto the finite set of class labels, $\Omega = \{\omega_1, \omega_2, \ldots, \omega_g\}$