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An integrated multiscale and multivariate image analysis framework for process monitoring of colour random textures: MSMIA

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A B S T R A C T

We present an integrated approach for conducting on-line and off-line image-based monitoring of processes whose products (raw materials, intermediate or final) consist of colour random textures. The methodology combines the principles underlying wavelet texture analysis and multivariate image analysis into a single framework, able to detect both abnormal changes in texture and colour. By taking into account a scale-dependent description of colour, it can detect subtle changes on how colour interacts with texture across the several length-scales considered. The proposed methodology was studied and characterized following best practice procedures for developing statistical process control methods, where controlled simulated test scenarios are employed to generate normal operation condition (NOC) data, as well as faults of different types and magnitudes. By simulating normal operation and faulty images in this way, it is possible to assess the monitoring potential of the proposed methodology to detect abnormal situations under a diversity of monotonically increasing faulty conditions. Results show that the proposed methodology is able to effectively detect changes in both colour and texture characteristics and one type of monitoring statistics in particular leads the performance in most of the tested scenarios: the PCA statistics for monitoring multiscale textural features. For this reason and for encompassing less computational and programming effort, its adoption is particularly recommended.

1. Introduction

Image acquisition systems offer new perspectives to monitor and control industrial processes, particularly when products naturally present heterogeneous features. This is quite common for solid matrices or multiphase products and several solutions are currently being implemented with success in industry for conducting such tasks in an autonomous way [1–5]. The type of methodology adopted depends on the relevant characteristics of the product depicted in the images. In general, colour related characteristics can be properly handled with Multivariate Image Analysis (MIA) tools [6–11], namely through the analysis of the distribution of pixel scores in a low-dimensional principal component analysis (PCA) subspace, or the associated distances to the PCA subspace [5,7,9,10]. This is an example of a pixel-wise MIA, as pixel integrity is retained during the course of computations. On the other hand, spatial characteristics, in particular those related with image texture, are predominantly considered in grey-level images and involve the analysis of first order statistics extracted from the intensity histograms (e.g., mean, median, variance, skewness, kurtosis) or second order statistics, computed from the grey-level co-occurrence matrix (GLCM) containing information regarding the spatial distribution of features [12,13]. In this case the analysis is performed image-wise, as each image will produce a vector of characterizing features for the image as a whole, and not a distribution of pixel-wise quantities [9,14]. Other methodologies proposed for handling texture phenomena include the use of shifted and staked images [14,15] (an extension of the principle underlying Dynamic Principal Components Analysis, where shifting is performed unidirectionally in the time mode [16]), spectral techniques based on the Fourier transform [17] and Wavelet Texture Analysis (WTA), which is centred on the computation of scale-dependent features from the 2D wavelet decomposition of the image [14,18].

The image-based approaches referred above address exclusively one type of features: colour (through MIA) or spatial (through statistical or transformed-based methodologies). Very few works involve the simultaneous analysis of spectral and spatial features [15,19–21] and all of them were designed to off-line analysis (mostly encompassing a certain classification task). However, increasingly often the acquired images have some degree of spectral resolution (the simplest case being RGB images), and therefore have the potential to characterize more fully the objects under analysis. The problem of characterizing, classifying and monitoring materials with colour random textures appears recurrently. Some examples of images from products consisting of coloured random textures are presented in Fig. 1.

In this context, a framework is proposed here for efficiently conducting process monitoring on-line or off-line, when the interest is

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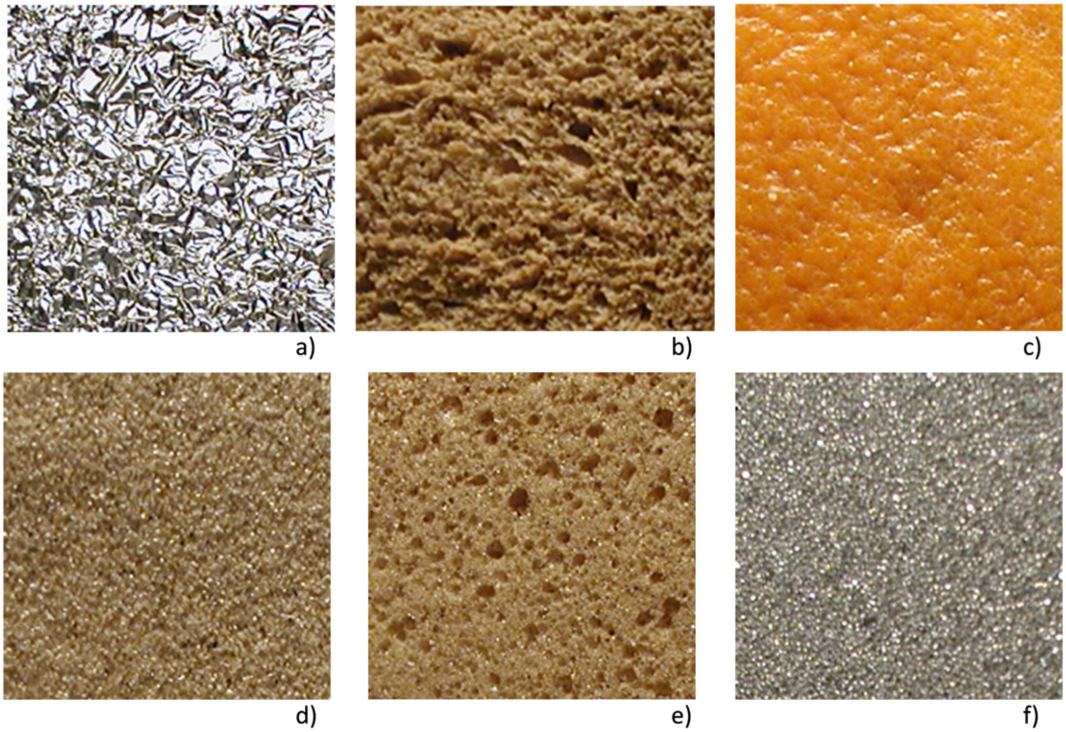

Fig. 1. Examples of images from different random textures: a) aluminium foil; b) brown bread; c) orange peel; d) sand paper; e) sponge; f) styrofoam.
Source: the KTH-TIPS database.

in the assessment of colour random textures of the products under processing: Multiscale and Multivariate Image Analysis (MSMIA). The proposed methodology synergistically combines the state of the art approaches for extracting spectral information and for describing texture. In particular, we propose the integration of MIA [7] with one of the most successful methods for describing texture, WTA [19], in such a way that scale-dependent interactions of colour and texture are efficiently accounted for in the NOC model. Even though these two approaches have already appeared together in a previous work, namely in MR-MIA (I) and MR-MIA (II) [19], the proposed method is fundamentally different in scope, design and implementation, as will be fully discussed in Section 4.

The rest of this article is organized as follows. In the next section we presented the building blocks of MSMIA and describe in detail all the stages of this framework. Then, in Section 3, we present how the methodology will be tested and report the main results obtained (supplementary results are also made available in the journal website). In the following section we discuss the results achieved, compare them with those from current approaches, discuss how to conduct fault diagnosis off-line and clarify the relationship of the proposed methodology with other related approaches (Section 4) and finally conclude the article with a summary of the main features of MSMIA and a prospective view of possible future work (Section 5).

2. Methods

In this section, the methods underlying the proposed image-based approach for process monitoring, are introduced. The first subsection is dedicated to a brief exposition of the multivariate image analysis (MIA) and wavelet texture analysis (WTA) methodologies, mostly for the purpose of clarifying the mathematical notation and nomenclature adopted in this article. Then, in the following subsection, the multiscale and multivariate image analysis (MSMIA) framework, along with its several stages and building blocks, is presented in detail.

2.1. Background on image-based monitoring of colour and texture features

2.1.1. Multivariate image analysis (MIA)

In this article we will address the task of monitoring 2D images composed by several spectral channels. In this context, let us consider that images are composed by a grid with R rows and C columns, and that each cell in such grid, called pixel, contains the intensity levels at K wavelength bands (for instance, $K = 1$ for grey-level images, $K = 3$ for RGB colour images, $3 < K \leq 10$ for multispectral images and $K >> 10$ for hyperspectral images). Thus, one image is represented by a 3-way tensor, $I \in \mathfrak{R}^{R \times C \times K}$. The multivariate image analysis (MIA) approach [7] provides an effective way to describe and handle the correlation structure of the intensity levels in the wavelength channels for all pixels, independently of their location in the image — in fact, the spatial and location characteristics are not handled in the basic formulation of MIA. In this approach, the 3-way tensor is first unfolded into a 2-way one, by application of an invertible unfolding operator, U:

$$U : I \in \mathfrak{R}^{R\times C\times K} \rightarrow X \in \mathfrak{R}^{(R\times C)\times K}. \tag{1}$$

This operator transforms each pixel in I into a row of matrix X, whose columns are the K wavelength channels (Fig. 2). This mapping can be conducted in different ways, but the alternatives do not change the final outcomes of the analysis (only the location of the pixels in the rows of the unfolded matrix).

The inverse operation, U^{-1}, reconstructs the original structure of the image from the 2-way matrix with consistent dimensions.

$$U^{-1} : X \in \mathfrak{R}^{(R\times C)\times K} \rightarrow I \in \mathfrak{R}^{R\times C\times K} \tag{2}$$

The MIA approaches consists in applying PCA to the unfolded matrix X, and analysing the corresponding pixel distribution in the score space. In the case of RGB colour images, the first two principal components are usually enough for describing the main colour features present in the original image. According to the goal of the analysis, the score space