Unsupervised defect segmentation of patterned materials under NIR illumination

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Abstract. An unsupervised detection method for automatic flaw segmentation in patterned materials (textile, non-woven, paper) that has no need of any defect-free references or a training stage is presented in this paper. Printed materials having a pattern of colored squares, bands, etc. superimposed to the background texture can be advantageously analyzed using NIR illumination and a camera with enough sensitivity to this region of the spectrum. The contrast reduction of the pattern in the NIR image facilitates material inspection and defect segmentation. Underdetection and misdetection errors can be reduced in comparison with the inspection performed under visible illumination. For woven fabrics, with periodic structure, the algorithm is based on the structural feature extraction of the weave repeat from the Fourier transform of the sample image. These features are used to define a set of multiresolution bandpass filters adapted to the fabric structure that operate in the Fourier domain. Inverse Fourier transformation, binarization and merging of the information obtained at different scales lead to the output image that contains flaws segmented from the fabric background. For non-woven and random textured materials, the algorithm combines the multiresolution Gabor analysis of the sample image with a statistical analysis of the wavelet coefficients corresponding to each detail. The information of all the channels is merged in a single binary output image where the defect appears segmented from the background. The method is applicable to random, non-periodic, and periodic textures. Since all the information to inspect a sample is obtained from the sample itself, the method is proof against heterogeneities between different samples of the material, in-plane positioning errors, scale variations and lack of homogeneous illumination. Experimental results are presented for a variety of materials and defects.

1. Introduction
There is no doubt that the human visual system is able to detect local defects in unfamiliar textures, even in the case of not having seen such defects before inspection. Although human visual inspection is less systematic than automated inspection systems at the search stage, it is considered superior at the decision making stage [1, 2]. Most computer vision approaches to texture inspection rely on the prior knowledge of the texture features or the expected defects [3]. As stated by Rohrmus in [4], “the key to inspection robustness is invariance against critical image distortions: rotation and translations, the scaling, and inhomogeneous illumination conditions,” as well as other possible changes in the imaging
system occurred between the acquisition of the defect-free template and the sample to test. These are some major drawbacks of supervised defect detection methods.

Some recent unsupervised defect detection methods decide whether a sample is correct or defective taking exclusively into account the information extracted from the sample itself [5-10]. Since they neither need a defect-free reference nor prior information about the sample structure or the expected flaws, the unsupervised methods overcome the stated drawbacks. Our former paper [8] focused on the unsupervised inspection of periodic textures that appear clearly defined in the frequency domain. In [10] we proposed a unsupervised novelty detection method for defect detection and segmentation in textures using Gabor filters. The method was applicable to both random and periodic textures.

All these supervised and unsupervised methods are useful to detect and locate faults or local defects that alter a small area of the material structure under inspection. But most of them are exclusively applied to uniformly colored materials. The presence of dyed threads or printed patterns such as bands, squares, circles, or drawings of varied colors along with the basic woven structure makes the inspection much more difficult. In a fabric image the signal that corresponds to bands, squares, etc. (superstructure signal) shows high energy and contrast and is superimposed upon a low-energy woven structure signal (basic structure signal). The superstructure signal contributes greatly to the low, middle and high spatial frequencies, whereas the basic structure signal makes a moderate contribution, mainly to the middle and high spatial frequencies. When the fabric is inspected for detection of faults in its basic structure, the superstructure signal contributes with noise that is difficult to smooth, separate or suppress. The machine vision inspection system then fails in either of two ways: a) by underdetection, in which the system cannot detect a fault that is located in a dark area of the fabric image, or b) by misdetection (or false alarm), in which the system misinterprets an edge or an element of the superstructure signal as a fault.

Some effort has been done to detect flaws in dyed patterned fabrics and structural defects in fuzzy or velvet fabrics by means of near infrared (NIR) imaging [11, 12]. In this work, we combine NIR imaging and the unsupervised flaw detection method to tackle the segmentation of defects in periodic and non-periodic materials.

2. Image inspection by infrared camera vision

Most dyes used in yarn dyeing and fabric printing are not NIR absorbers, and their reflectance values are high in the NIR wavelength range. NIR imaging of printed fabrics has been proposed to facilitate the inspection of the basic structure in this kind of material. In [11], NIR illumination was used to reduce the superstructure signal in the image of patterned fabrics. We took advantage of the residual sensitivity of a monochrome CCD camera that reached up to 1000 nm. The light source was an array of NIR LEDs emitting in a band to which the camera was still sensitive. The high contrast that bands, squares, and other printed drawings showed in images captured in the visible range appeared drastically reduced in near infrared images. In the work developed in Ref. 11, a faultless reference sample was required by the segmentation algorithm [13]. The segmentation algorithm included a multiresolution analysis based on Gabor filters for feature extraction [14, 15]. In this work an IR image of patterned materials has been obtained with the experimental setup displayed in figure 1. In this case incandescent bulbs whose spectral radiance is showed in figure 2 illuminate a textile sample. A XenICs camera with an InGaAs sensor that is sensitive to the NIR spectral band of 900-1700 nm captures the IR image with a Computar objective with focal equal to 55 mm. Camera specifications are in table 1.
Figure 1. Setup device. (1) XenICs XEVA-FPA Camera. (2) Telecentric Objective Computar 55 mm. (3) Incandescent light source. (4) Image sample. (5) Computer screen with software for image capture.

Figure 2. Spectral radiance of light source.
Table 1. Technical specifications of the camera.

| XenICs XEVA-FPA Camera - Imaging system for thermo-electrically cooled InGaAs Focal Plane Arrays |
|---|---|
| Array Specifications | |
| Array Type | InGaAs |
| Spectral band | 0.9 to 1.7μm |
| # Pixels | 640x480 |
| Pixel Pitch | 20 micron |
| Pixel operability | > 98% |
| Array Cooling | Uncooled or TE-cooled |
| Camera Specifications | |
| Total dynamic range | 14 bit |
| S/N ratio (low gain, high gain) | (69, 60) dB |

In order to characterize the system formed by the camera and the objective the MTF function has been measured by the slanted edge method using the plug in SE_MTF [16]. Figure 3(a) displays an image of a slanted edge, figure 3(b) displays a horizontal profile of this image, the Edge Spread Function (ESF), figure 3(c) displays the derivate of the ESF, known as the Line Spread Function (LSF) and finally, figure 3(d) displays the MTF of the system obtained by the modulus of the Fourier Transform (FT) of the LSF. As we can see the LSF is a broad function. The imaging quality, typical of this sort of NIR cameras, is not very high as its MTF reveals in figure 3(d).
Figure 3. a) Image of a slanted edge. b) ESF or mean profile of the slanted edge. c) LSF. d) MTF.

Figure 4. Photoresponse and quantum efficiency of the InGaAs sensor of the XenICs camera.

In addition to this, the sensor has some bad pixels that perform incorrectly giving outlier values. It is possible to detect them when imaging a uniformly illuminated white paper (Figure 5). Once these bad pixels have been localized, their values are to be removed from the final binary images of the sample under inspection in order to avoid false alarms.
3. Unsupervised defect segmentation

Image filtering in the Fourier space is applied to achieve an automatic segmentation of flaws in periodic textures such as woven fabrics [8]. In the case of non-woven fabrics or images without periodic structure, Gabor wavelets are applied by means of an unsupervised novelty method for defect detection and segmentation [10]. In both cases no reference image is considered and no prior information about the fabric structure or the defect is required.

Let us consider the sample of Figure 6 as an example to illustrate the potential of the method in the challenging case of a square patterned fabric with periodic woven structure. The method based on image filtering in the Fourier domain [8] has been applied. In the visible spectral band (VIS), the sample appears as it is shown in Figure 6(a), whereas in the NIR spectral band, the sample appears as it is shown in Figure 6(b). Although the fabric pattern is still present in Figure 6(b), the NIR image captured by the NIR camera reveals a flaw that cannot be distinguished in the VIS image. Figure 6 (c) displays the binary output image after removing bad pixels. In this output image, flaws appear clearly segmented.

![Figure 6](image)

**Figure 6.** (a) VIS image of the sample. (b) NIR image, where a flaw can be seen. (c) Output image with bad pixels filtered. This image is shown with reverse contrast for the sake of a better visualization.

Figure 7 displays a sample to illustrate the potential of the method in the case of a material with non periodic structure. This case is a piece of wrinkled patterned paper. Image filtering by means of Gabor filters has been applied [10]. In the visible spectral band (VIS), the sample appears as it is shown in Figure 7(a), whereas in the NIR spectral band, the sample appears as it is shown in Figure 7(b). Notice that the printed pattern disappears and only wrinkles can be observed in the NIR image.
captured by the camera with InGaAs sensor. Figure 7 (c) displays the binary output image, after removing bad pixels, where flaws are segmented.

![Image](a) ![Image](b) ![Image](c)

**Figure 7.** (a) VIS image of the sample. (b) NIR image, where a flaw can be seen. (c) Output image with bad pixels filtered. This image is shown with reverse contrast for the sake of a better visualization.

4. **Conclusions**
We have applied an unsupervised method for detection and segmentation of defects to flawed images, periodic and non-periodic. The method uses NIR imaging, is fully automatic and free of any adjustable parameter. In the case of periodic images the method is based on image filtering in the Fourier domain, and in the case of non-periodic images the method is based on Gabor filters. This unsupervised method is robust against possible heterogeneities between different zones of the material under inspection, in-plane positioning errors, scale variations and lack of homogeneous illumination because all the information is obtained from the sample itself and it does not require the comparison with any other standard reference (faultless) sample or training defect set.

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