Image Segmentation Applied to the Analysis of Fabric Textures

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Abstract

In this work, we are proposing the use of image segmentation to the analysis of the textures of fabrics, with the aim of applying this approach to a fabric fault detection based on image processing.

Keywords: Image Processing, Image Segmentation, Texture Analysis, Textiles, Fabric Fault Detection

To guarantee the quality of textile products as free from defects, the producers have to subject their fabrics to a specific visual inspection made by a trained staff. Sometimes the human inspection is supported by automatic inspection methods [1-3]. Some of these methods can also work during the production processes, that is, directly on the looms. Among the existing industrial inspection systems, let us remember the I-TEX from Elbit Vision Systems, the Barco Vision's Cyclops, and the Zellweger Uster's Fabriscan [4].
In spite of the presence of commercial systems, the research for further improvements of the methods for textile fault detection continues, as evidenced by the recent publications on this subject [5-10]. The reason for the necessity of further studies is motivated by the intrinsic difficulty of having an artificial vision of textiles; this difficulty consists in the fact that fabric faults are often very small and hardly detectable, having a visibility strongly dependent on illumination, reduced by the vibrations of the mounting devices [11-15].
For the analysis of fabric textures, several statistical approaches had been used and developed [16-17], and also methods based on the Fourier analysis, on the Gabor filtering and on wavelets with adaptive bases [18-21]. In addition, an approach based on an image processing, developed for the study of liquid crystals [22], was given in [23-25]. Recently we have also proposed the use of the GIMP Retinex filtering to enhance the visibility of defects [26] (other applications of the Retinex filtering to microscopy, radiography and detection of vehicles in foggy images have been given in [27-31]).
Here, we use another approach to the study of fabric textures, based on an image segmentation for evidencing and measuring the domains present in these textures. Before giving an example, let us discuss shortly the image segmentation.

Image Segmentation In image processing, a segmentation is a method of partitioning an image into multiple sets of pixels, defined as super-pixels, in order to have a representation, which can be simpler than the original one or more useful to the following desired analyses [32]. For this reason, the segmentation of images is used in several applications; in particular, it is used in the medical image processing for stacking and comparing diagnostic results [33-35].
A typical segmentation of an image is a method able to locate objects (the domains), which are

present in the image frame, or the boundaries among the domains. Specifically, the segmentation is a process of assigning a label to every pixel in an image, such that the pixels having the same label share certain characteristics [35]. As a consequence, the result of a segmentation is a set of "segments", or “super-pixels”, that are covering the whole image, or a set of contours, that is of "edges", extracted from the image. In this case, the segmentation gives the "edge detection". Several methods exist for segmentation, as we can appreciate from [35].

Here we use a segmentation based on a thresholding of gray-scale images. By selecting a suitable threshold, the image is converted into a binary (black and white) image. In several cases, this is enough for evidencing the domains among the black or the white pixels. Details of the method of segmentation are given in [36]. In [37-42], we have demonstrated that this segmentation is suitable for the analysis of several textures, in particular, for those that we can define as “vesicular textures”, where some vesicles or voids or empty areas are present. Actually, some “empty” areas can be present in the images of a fabric because of the void among the yarns. Therefore, we can segment the images by considering these voids as the super-pixels. The presence of a defect in the fabric can be evidenced by a change in the distribution of the super-pixels.

Segmenting a fabric texture Let us start the discussion of some examples by processing an image from the Brodatz Album (D103). We can artificially create a defect in it, as shown by the right panel of the Figure 1.

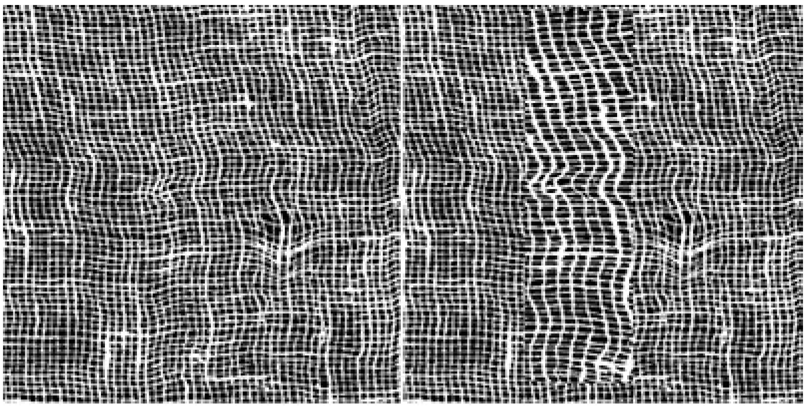

Figure 1: A fabric from Brodatz Album (D103) on the left, and the simulation of a defect on the right. Images are 600x600 pixels.

The two panels of Figure 1 are rendered into black and white images and segmented with the approach detailed in [36-42]. The result of the segmentation is shown in the Figure 2. Each black domain is evidenced in the segmentation by a different color tone (super-pixels). In the case of the “good” fabric, we use green tones; in the case of the “faulty” fabric, we use the red tones. Besides the maps, we can have the distributions of areas of the super-pixels. It is given in the Figure 3.

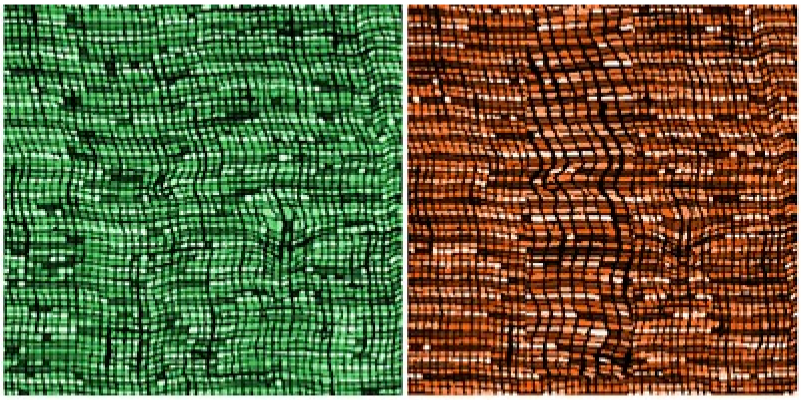

Figure 2: Segmentation of the images in Figure 1.

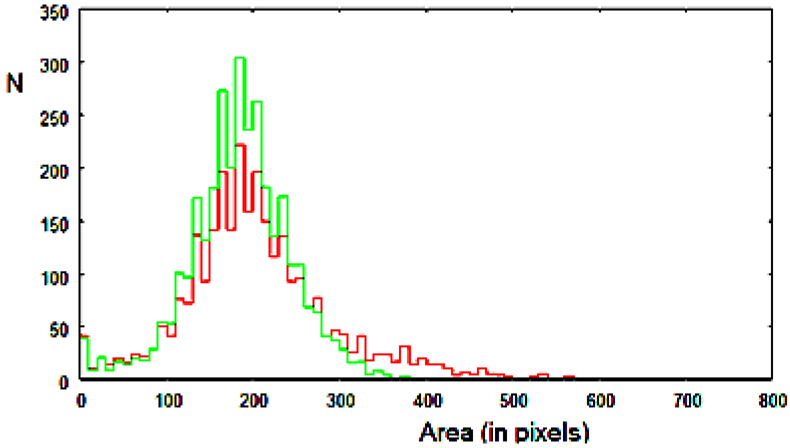

Figure 3: Distributions of areas of super-pixels, in green for the good fabric and in red for the faulty fabric. Areas are spaced in intervals of 10 pixels. N means "number". There is a large number of super-pixels containing about 200 pixels.

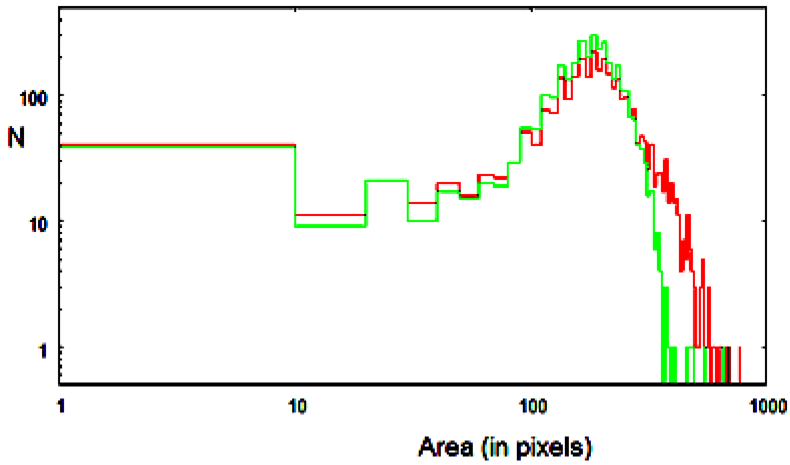

Figure 4: The same as in the Figure 3, represented by means of logarithmic scales.

From the Figure 3 (Figure 4 in logarithmic scales), it is evident that good and faulty fabrics have different distributions of the areas of super-pixels. The distribution of the "faulty" fabric shows the presence of several large domains, whereas the number of the small domains remained unchanged. Since the difference is appreciable, we can imagine that it is possible to detect the presence of faults in the fabric texture by comparing the distribution we obtain from segmentation to a "standard" distribution corresponding to the good texture of the considered fabric.

Other examples Let us consider faulty textures discussed in [23]. Faults in the structure of woven fabrics are deviations from the recurrence of a fundamental unit, and usually appear as subtle lines, dark or bright, in the image frame. The more frequently encountered defects are broken or missing picks. Dust, extraneous staples or oil spots can also be observed.

The first defect we are proposing is the mispick. This is a rather common defect, produced when a yarn is lacking or broken on the loom. It is a defect expanding on the surface fabric and involving several neighbor yarns. Mispicks are easy to find by eye inspection, such as dust and little oil spots. These defects are eye-inspected with back lighting. The same illumination system was used to record images in the Figures 5 and 6 (left panels). In the Figure 5 we give a fabric and in the Figure 6 the same fabric with a mispick.

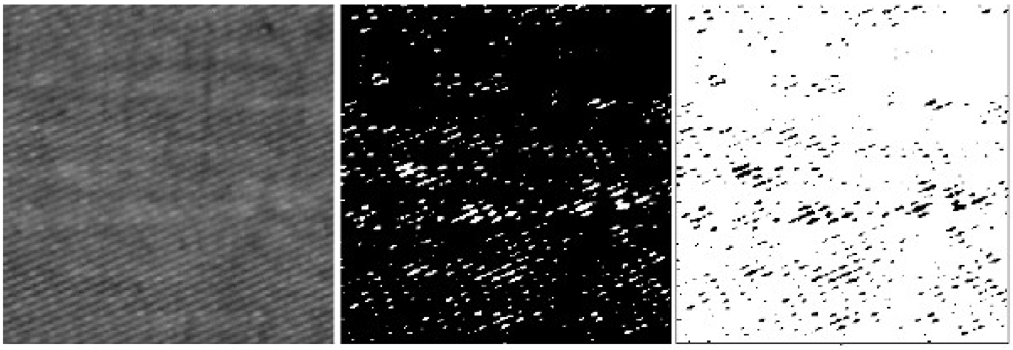

Figure 5: Image of an almost good fabric on the left (600x600 pixels, 600 pixels correspond to 40 mm). In the middle, we see the corresponding binary image obtained by a threshold at the 111 grey-tone. On the right, the inverted image. The black domains represent areas of the fabric, which are transmitting more light.

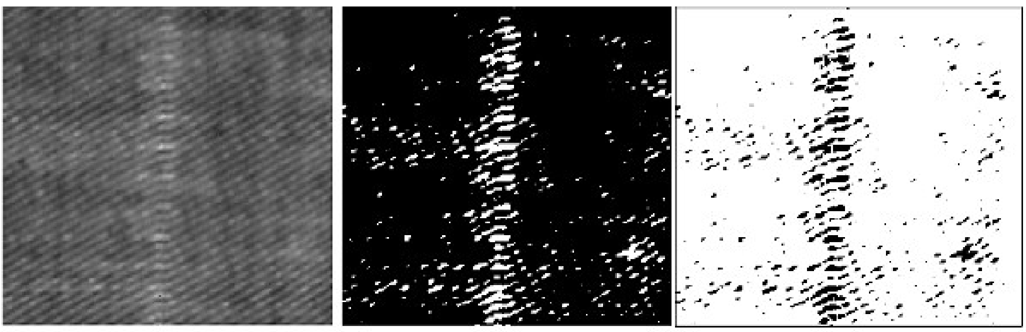

Figure 6: The same fabric of Figure 5 with a mispick (600x600 pixels, 600 pixels correspond to 40 mm). In the middle, we find the binary image obtained by a threshold at 111 grey-tone. On the right, the inverted image. Here too the black domains represent areas that are transmitting more light.

The segmentation of the image on the right of Figure 5 gives us the "good" distribution that we can compare to the distribution coming from the segmentation of the right panel in the Figure 6. Figure 7 gives the maps resulting from the segmentation. On the left, the map is in green tones; on the right, in red tones. Again, the maps look quite different. The Figure 8 allows the comparison of the distributions.

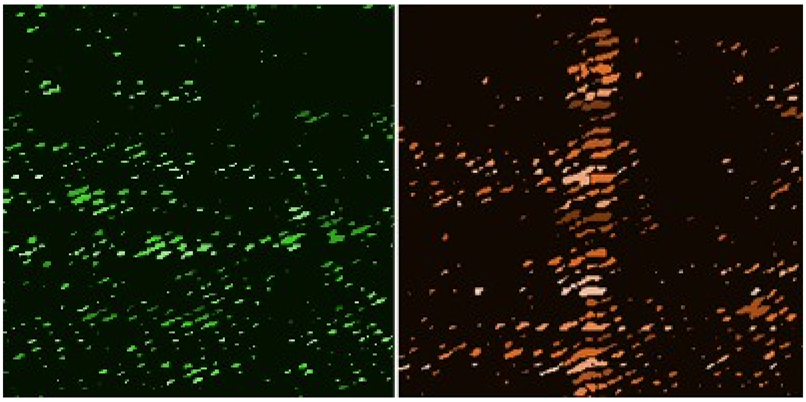

Figure 7: Maps of the segmentation.

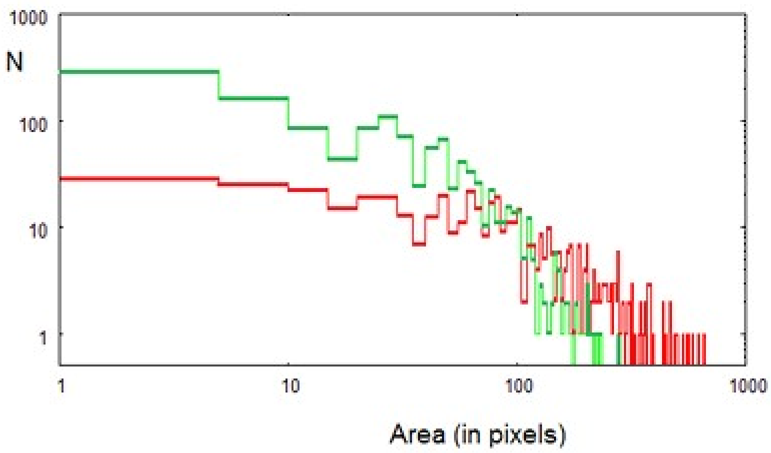

Figure 8: Distributions of areas of super-pixels (in logarithmic scale), in green for the good fabric and in red for the faulty fabric. The faulty texture contains several large super-pixels.

As previously observed for the image from Brodatz album, the distribution of areas of super-pixels obtained by means of an image segmentation allows to distinguish good and faulty textures. Another fabric, where we found a defect (missing pick), is proposed in the Figures 9 and 10. In them, we see also the corresponding binary and inverted images. For both images, the threshold was chosen at the 177 grey-tone. The maps after segmentation are given in Figure 11, and in the Figure 12 the distributions.

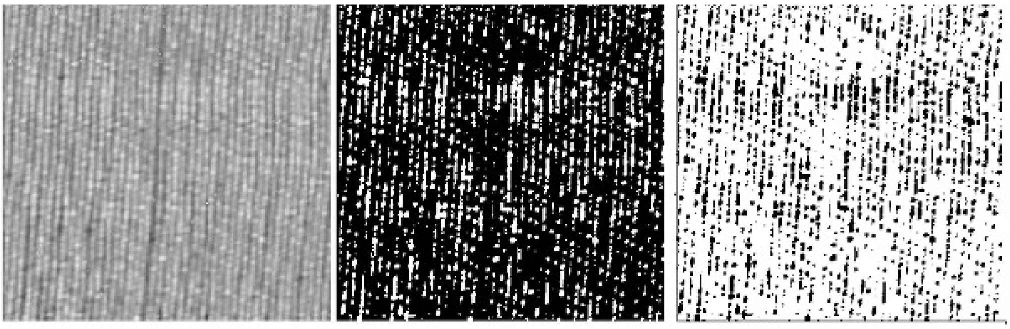

Figure 9: Another fabric. Images 600x600 pixels.

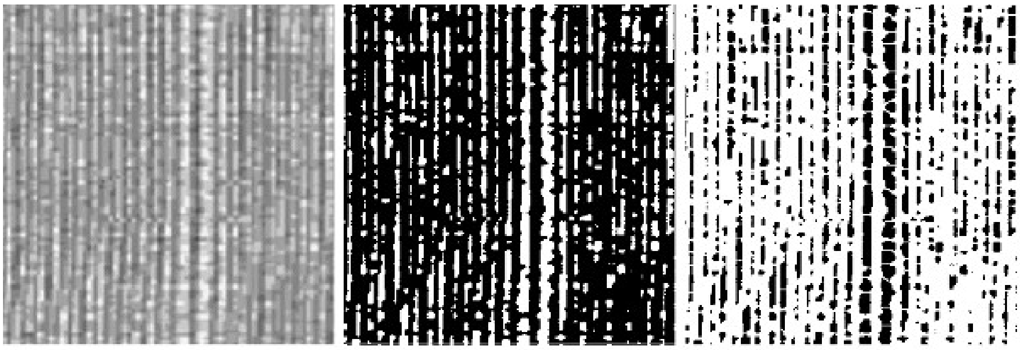

Figure 10: The missing pick. Images 600x600 pixels.

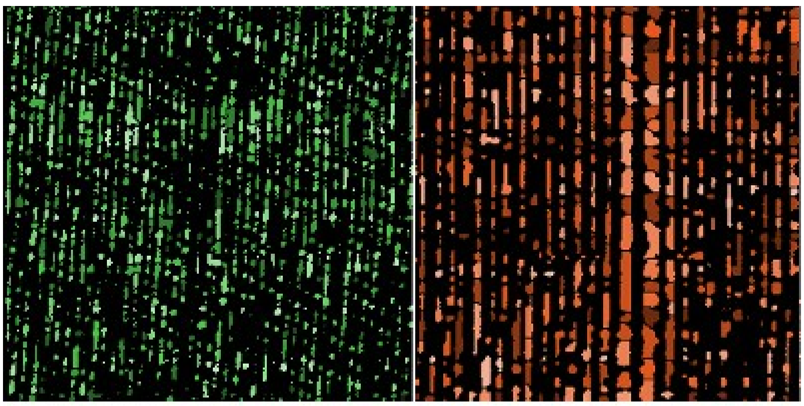

Figure 11: Maps of segmentation.

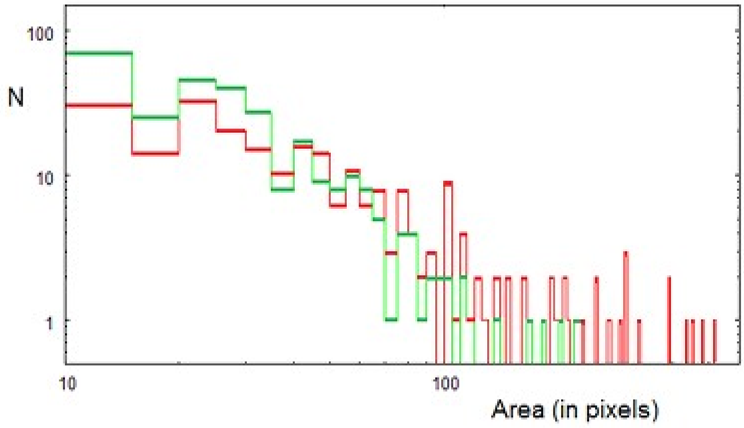

Figure 12: Distributions of areas of super-pixels (in logarithmic scale), in green for the fabric in Figure 10 and fabric in Figure 11. Again, distributions are quite different.

Conclusion As we have seen, the distributions are quite different. However, some points need to be investigated. among them, we have to find a method for the quantification of differences. This can be obtained by considering several images of the same textile, and investigating the corresponding set of distributions. Moreover, it is necessary to study the dependence of segmentation on the chosen threshold and also on physical conditions (illumination, contrast and noise). These seems being the main questions concerning the method, and that require further work. However, it is possible that during this work, other problems arise. In any case, the preliminary investigation here proposed is rather encouraging.

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