MVA2000 IAPR Workshop on Machine Vision Applications, Nov. 28–30, 2000, The University of Tokyo, Japan

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Removing the Intensity Variations Caused by Textures on Textile Surfaces Using Wavelet Shrinkage

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Abstract

In this paper, we propose a new method for visual inspection of textile surfaces; selectively removing the intensity variations caused by textures on textile surfaces. For this purpose we use *Wavelet Shrinkage*, which was originally proposed by Donoho & Johnstone as a method to remove Gaussian white noise. We also propose a modification of Wavelet Shrinkage to selectively remove the intensity variations caused by textures as noise. Once the intensity variations caused by textures on textile surfaces are selectively removed, the remaining processings of inspection can be conducted in the image domain. So we can utilize the image processing methods and techniques developed so far for the visual inspection of other industrial products.

1 Introduction

In this paper, we discuss the visual inspection method of textile surfaces. Although they have long been investigated, they still have problems such as their computational cost or efficacy for practical uses. So, even today, inspection of textile surfaces are mainly performed by the human eye. Even if restricted to the latest studies, we can see many related papers such as [8],[11],[14] *etc.* These methods mainly estimate some textural features and discriminate defects or spots based on them.

In this paper, we propose a different method for the visual inspection of textile surfaces; selectively removing the intensity variations caused by textures on textile surfaces. For this purpose we use *Wavelet Shrinkage*, which uses the wavelet decomposition and reconstruction enabled by the orthonormal wavelet transform. Wavelet Shrinkage was originally proposed by Donoho & Johnstone as a method to remove Gaussian white noise[3], [4]. We also propose a modification of Wavelet Shrinkage to selectively remove the intensity variations caused by textures as noise, suitable for the visual inspection of textile surfaces.

Once the intensity variations caused by textures on textile surfaces are selectively removed, the remaining processings of inspection can be conducted in the image domain. So we can utilize the image processing methods and techniques developed so far for the visual inspection of other industrial products[10]. From the computational standpoint, an efficient algorithm for the orthonormal wavelet transform has been proposed[9]. So our method is computationally efficient.

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2 Wavelet Shrinkage

Wavelet Shrinkage is the method which uses the wavelet decomposition and reconstruction enabled by the orthonormal wavelet transform. We omit the details of the orthonormal wavelet transform. Readers are directed to references such as [2],[12],[13].

Suppose we observe noisy data:

$$y_{i,j} = f_{i,j} + e_{i,j} \qquad i,j = 1, ..., n \tag{1}$$

where $e_{i,j}$ means the noise added to the system and $f_{i,j}$ means the signal which we would like to recover. Hereafter we call $y_{i,j}$ the observed signal (or image), and $f_{i,j}$ the original signal (or image). Here we assume $e_{i,j}$ is expressed as follows:

$$e_{i,j} = \sigma z_{i,j} \qquad i,j = 1, ..., n \tag{2}$$

where $z_{i,j}$ are independently distributed as $N(0,1)$. Eq.(2) means the noise $e_{i,j}$ is Gaussian white noise whose standard deviation is σ.

In the wavelet domain, we can rewrite Eq.(1) as

$$\begin{aligned} \mathcal{W}(y_{i,j}) &= \mathcal{W}(f_{i,j} + e_{i,j}) \\ &= \mathcal{W}(f_{i,j}) + \sigma\mathcal{W}(z_{i,j}). \end{aligned} \tag{3}$$

Here, $\mathcal{W}$ means the two-dimensional orthonormal wavelet transform, of which the two-dimensional extension is described in [9].

When we use the orthonormal basis for the forward and inverse wavelet transform, we can reconstruct the observed signal as

$$y_{i,j} = \mathcal{W}^{-1}\left(\mathcal{W}(f_{i,j}) + \sigma\mathcal{W}(z_{i,j})\right). \tag{4}$$

In addition, $\mathcal{W}(z_{i,j})$ also becomes independently distributed as $N(0,1)$.

Here we call $\mathcal{W}(\cdot)$ wavelet coefficients. In order to remove the added noise, Donoho and Johnstone proposed that only the wavelet coefficients undertaking *soft thresholding* operation $\eta_\lambda(x)$, which is expressed as Eq.(5), should be used for the signal reconstruction.

$$\eta_\lambda(x) = \begin{cases} \mathrm{sgn}(x)(|x| - \lambda) & \text{if } |x| > \lambda \\ 0 & \text{if } |x| \le \lambda \end{cases} \tag{5}$$

Donoho and Johnstone also proposed that the universal threshold λ, which is decided by Eq.(6), should be used in every decomposition channel.

$$\lambda = \sqrt{2\log(n)}\sigma \tag{6}$$

n and σ are identical with those in Eq.(1),(2). Donoho and Johnstone named this de-noising method as Wavelet Shrinkage[3],[4]. Notice that the reason the universal threshold λ is used in every decomposition channel corresponds to the fact that the spectrum energy of white noise becomes flat.

In this paper, we used Symlet8 (Daubechies' 8 tap nearly symmetric wavelet basis[2]) as the orthonormal wavelet basis and the 3-level decompositions.

3 Wavelet Shrinkage for Selectively Removing the Intensity Variations Caused by Textures

In this section, we treat the case that $e_{i,j}$ in Eq.(1), which should be removed as noise, expresses the intensity variations caused by textures. We assume that the perfect textile surface sample, which contains no defects or spots *etc*, can be obtained in advance. In the perfect textile sample, $f_{i,j}$ in Eq.(1) becomes a constant which expresses the DC component.

Some efforts to remove non-white noise by using Wavelet Shrinkage have appeared in several references [6],[7]. The basic idea of these methods lie in that the threshold λs should be selected channel-dependently, because the spectrum energy of non-white noise is no longer flat.

Kolaczyk[7] selected the threshold λs so that they hold the same statistical meaning as Eq.(6). Selecting the threshold λ according to Eq.(6) is conservative, in the meaning that the Wavelet Shrinkage with this universal threshold λ removes almost all Gaussian white noise. However it has been pointed out in some papers that, at the same time, it blurs (or deforms) the original signal $f_{i,j}$ too much. As mentioned before, our aim is to apply Wavelet Shrinkage to the visual inspection of textile surfaces. For this it is more desirable to select the threshold λs so that the Wavelet Shrinkage with these λs might emphasize defects and spots on textile surfaces.

Other methods already proposed[1],[5] are to select the threshold λs so that the Wavelet Shrinkage with these λs might minimize MSE (mean square error) estimated between the original image $f_{i,j}$ and the reconstructed image[1]. Notice that the selected threshold λs vary not only depending on the noise but also on the original image $f_{i,j}$. Although these methods are intended to remove Gaussian white noise, the way of selecting the threshold λs is better fitted for our purposes. Thus we adopted the same method.

In this study, we artificially superimposed the known signal on perfect textile surface samples, then got the observed image $y_{i,j}$, which is shown in Fig.1. The size of this image was 256 × 256. Fig.2(a) shows the zoom-up image around the center points (131,131) of Fig.1, and Fig.2(b) shows the intensity profile along the central horizontal section (y = 128) of Fig.1. In this example, we used a check pattern as the superimposed signal. We calculated the threshold λs so that MSE between the original image $f_{i,j}$, which consists of both the DC component and the superimposed check pattern, and the reconstructed image might be minimized. As will be explained later, minimization was conducted in the wavelet domain, not in the image domain, so as to avoid non-linear optimization. The reason we selected this check pattern as the superimposed signal is that it contains sharp edges, so it represents well the nature of $f_{i,j}$ which is caused by defects, spots and so on.

In addition, instead of using Eq.(5), we will use Eq.(7), (8) as the soft thresholding operation in each decomposition channel.

$$\eta_{\lambda_p}(x) = \begin{cases} x - \lambda_p & \text{if } x > \lambda_p \\ 0 & \text{if } x \le \lambda_p \end{cases} \tag{7}$$

$$\eta_{\lambda_n}(x) = \begin{cases} 0 & \text{if } x \ge \lambda_n \\ x - \lambda_n & \text{if } x < \lambda_n \end{cases} \tag{8}$$

where $\lambda_p > 0 > \lambda_n$.

Here we denote $\hat{y_{i,j}} = \mathcal{W}(y_{i,j})$ and $\hat{f_{i,j}} = \mathcal{W}(f_{i,j})$, then we calculate λ_p and λ_n in each decomposition channel as follows.

$$\lambda_p = \arg\min_{\lambda_p} \sum_i (\eta_{\lambda_p}(\hat{y_{i,j}}) - \hat{f_{i,j}})^2 \quad \text{for all } \hat{f_{i,j}} > 0 \tag{9}$$

$$\lambda_n = \arg\min_{\lambda_n} \sum_i (\eta_{\lambda_n}(\hat{y_{i,j}}) - \hat{f_{i,j}})^2 \quad \text{for all } \hat{f_{i,j}} < 0 \tag{10}$$

Fig.2(c) shows the zoom-up image of the reconstructed image of Fig.1, using the Wavelet Shrinkage consisting of the soft thresholding operation expressed in Eq.(7),(8) with thus estimated λ_ps and λ_ns. Hereafter, we call these reconstructed images as shrunken images. Fig.2(d) shows the intensity profile of the shrunken image of Fig.1.

We compared the performance of our method of removing the intensity variations caused by textures, with that of the low-pass filter. Fig.2(e) shows the zoom-up image of the resulting image, had the low-pass filter been applied to Fig.1. Fig.2(f) shows the intensity profile of the low-pass filtered image of Fig.1. In this case, we used a 2D Gaussian as the low-pass filter. To enable the comparison, the σ of the 2D Gaussian was decided, so that MSE estimated between the original image $f_{i,j}$ and the filtered image might be minimized. Comparing Fig.2(c),(d) with Fig.2(e),(f) we see that the low-pass filter blurs the edges more than the Wavelet Shrinkage and can not fully remove the rough impression caused by the texture. Although Fig.2(c) image is still rough, the impressions have been sufficiently altered from those of Fig.2(a).

[1] However, we can not know the original image $f_{i,j}$ in advance, so we have to use Bayesian framework[1] or Stein's unbiased estimator[5] to minimize MSE. For details, see these papers.

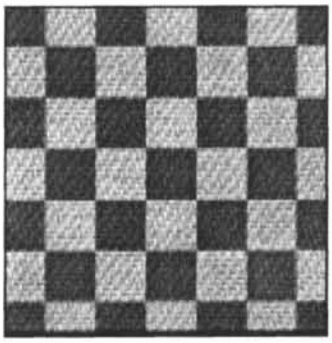


Figure 1: A textile surface with the superimposed check pattern

4 Application to the Visual Inspection of Textile Surfaces

In this section, we apply the method mentioned in the previous section to the visual inspection of textile surfaces.

Fig.3 is an example which has some defects on a textile surface. Fig.4(a) shows the shrunken image of Fig.3. The kind of texture of Fig.3 is the same as that of Fig.1. So we used the same λ_ps and λ_ns which were estimated in the previous section.

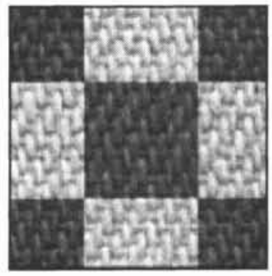
Fig.4(b) shows the binarized image of Fig.4(a). Fig.4(b) is obtained using the following rules. If the pixel values of Fig.4(a) lie in the scope expressed in Eq.(11); mark white. Otherwise; mark black.

$$\overline{u_b} - \sqrt{2\log(n)}\,\sigma_r \leq b \leq \overline{u_b} + \sqrt{2\log(n)}\,\sigma_r \quad (11)$$

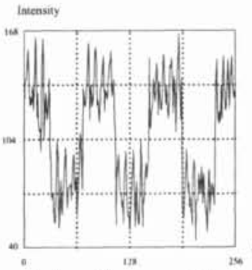
In Eq.(11), $\overline{u_b}$ means the mean of the pixel values of Fig.4(a), and σ_r means the standard deviation of the distribution of the pixel values in the shrunken image of "the perfect sample". n means the total number of the pixels. If the histogram distribution of the shrunken image is approximated by Gaussian distribution, the expected total number of pixels[2] whose values do not lie in the scope expressed in Eq.(11) becomes less than 1 (pixel). So we can treat the pixels whose values do not lie in the scope expressed in Eq.(11) as outliers. If many pixels are classified as outliers, we can conclude that some defects existed on the textile surface. Fig.4(b) shows that the defects were detected correctly as outliers.

For comparison, we made the same experiment using the low-pass filter. Fig.4(c) shows the image produced, when the low-pass filter was applied to Fig.3. For the low-pass filter, we used a 2D Gaussian with the same σ as that used to obtain Fig.2(e). Fig.4(d) shows the binarized image of Fig.4(c) given the same method as that used to obtain Fig.4(b). Fig.4(c),(d) show that the low-pass filter might remove the defects as well as the intensity variations caused by textures. Consequently, the defects were not detected correctly in Fig.4(d).

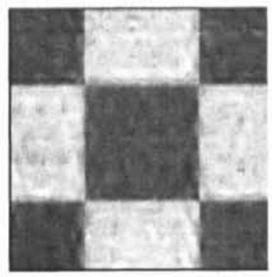
[2]The statistical meaning of $\sqrt{2\log(n)}$ in Eq.(11) is the same as that in Eq.(6).



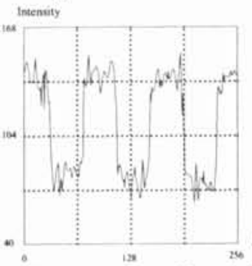
(a) Zoom-up of Fig.1



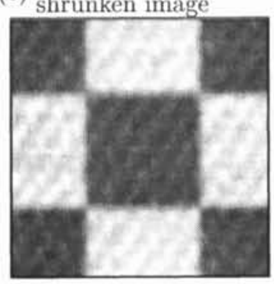
(b) Intensity profile of Fig.1



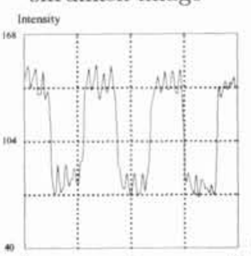
(c) Zoom-up of the shrunken image



(d) Intensity profile of the shrunken image



(e) Zoom-up of the low-pass filtered image



(f) Intensity profile of the low-pass filtered image

Figure 2: The results of removing the intensity variations caused by textures

Notice that the λ_ps and λ_ns (and the σ of 2D Gaussian), which we used in this section, were estimated based on the minimization using the check pattern superimposed on Fig.1. However, as Fig.4(a),(b) show, the Wavelet Shrinkage with these λ_ps and λ_ns is effective on other patterns such as the defects in Fig.3. As mentioned in the previous section, we think this is because the superimposed pattern we used contains sharp edges, so it represents well the nature of $f_{i,j}$ which is caused by the defects.

5 Conclusions

In this paper, we proposed a new method for the visual inspection of textile surfaces; selectively removing the intensity variations caused by textures on textile surfaces. We also proposed how Wavelet Shrinkage could be used for this purpose, and then

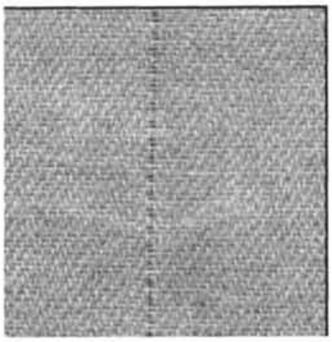
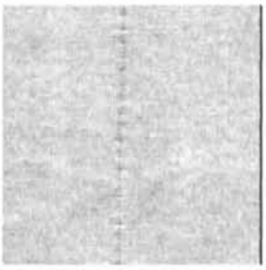


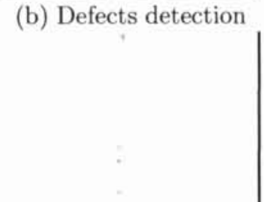
Figure 3: A textile surface containing defects



(a) The shrunken image

(b) Defects detection

(c) The low-pass filtered image



(d) Defects detection

Figure 4: The result of defects detection of Fig.3

showed its effectiveness by comparative experiments.

Our method has several advantages. First, once the intensity variations caused by textures on textile surfaces are removed by Wavelet Shrinkage, the remaining processings of inspection can be conducted in the image domain. So we will be able to utilize the vast accumulation of the image processing methods and techniques developed so far for the visual inspection of other industrial products[10]. In addition, if the remaining processings are conducted in the image domain, it will not be difficult to discriminate defects or spots from the printed patterns on textile surfaces, given that we know these printed patterns in advance. So our method is not restricted to visual inspection of plain textile surfaces, but can be applied to that of textile surfaces with a printed pattern. It is difficult to realize these properties by the methods already proposed using some textural features[8],[11],[14].

Second, as an efficient algorithm for the orthonormal wavelet transform has been proposed[9], our method is computationally efficient. We measured the execution time of our method for 512×512 images on the platform with CPU Intel Celeron 466MHz and OS Linux 2.2.13. It turned out to be about 4 seconds. Considering the rapid progress of microprocessor technologies, we can say that, using our method, we will soon have come to the stage that the visual inspection systems of textile surfaces can be constructed with an ordinary microprocessor.

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