International Journal of Applied Mathematics and Statistics,
Int. J. Appl. Math. Stat.; Vol. 53; Issue No. 6; Year 2015,
ISSN 0973-1377 (Print), ISSN 0973-7545 (Online)

Pattern Fabric Defect Detection Using Nonparametric Regression

S. Halim[1]

[1]Faculty of Industrial Technology, Industrial Engineering Department,
Petra Christian University, Jl. Siwalankerto 121-131 Surabaya 60238, Indonesia;
Email: halim@peter.petra.ac.id

ABSTRACT

In this paper we proposed a defect detection on the pattern pabric. This defect usually occured since the pattern is shifted, broken, or different to the intended design. To solve this problem, we use comparing signals approch.To do that, we first modeled the images in a 2D nonparametric regression. Moreover, to cope with the correlation between the neighbour of each pixels, we model the errors correlated in their neighbourhoods. The image is divided into two parts vertically, and then a hypothesis test is constructed so that the left image is the same to the right one, against they are significantly different. Similarly, then the image is divided horizontally, and perform the same test for the upper and lower images. To reject or faild to reject the hypothesis we need to measure the distance between two nonparametric regressions. Since the distribution of test statistic under the hypothesis null is not known. In this method we use the standardized modification of the Mallows distance and construct spatial bootstrap for representing the distribution of the test statistic. To preserve the bound of a pixel to its neighbourhood we construct a spatial bootstrap. The reject hypothesis imply that the defects are found in that particular area.

Keywords: 2D nonparametric regression, hypothesis test, mallow distance, spatial bootstrap.

Mathematics Subject Classification: 62G10, 62H35

Journal of Economic Literature (JEL) Classification: C12, C65

1. INTRODUCTION

In recent years, visual inspection on texture has played role in the quality control, since products` quality controls are designed and presented to ensure not giving defect products to customers. In the visual inspection the human doing quality control has been replaced by mechanics and visual vision has been replaced by computer vision.

Finding defects automatically for any types of texture have been researching topics for several years. Some methods have been developed in many fields of interest. Kumar (2008) gave a survey on this topics. Ngan, *et al.* have been worked on this problem using several techniques (2009, 2010a, 2010b). Moahseri *et al.*(2010) used multi resolution decomposition for detecting defect on the texture. Timm and Barth (2011), approached this problem by computing the distribution of image gradients and then computed the Weibull fit and determined the shape and scale of the parameters to detect the defect on the texture. Fu (2009) approached this problem using adaptive local binary patterns. Tang, *et al* (2011) used statistical approach for detecting defect in wood. In line with Tang, Franke and Halim (2007,2008) also used statistical approach, that is by comparing signals and images. To compare those signals, Franke and Halim modelled them as 1D nonparametric regression models and then tested either those signals are significantly the same against they are significantly different. Since the approach of that model is only 1D. That's mean the smoothing procedure in the Franke and Halim model works, line by line.

Therefore, the aim of this article is to enhance the Franke and Halim approach by modelling the images using 2D nonparametric regression, so that the smoothing procedure works for two-dimensional images directly. In the following section we discuss the methods we used for modelling the defect detection on the texture. Illustrations and examples are presented in the fourth section of the paper, and finally we conclude and point out the future research direction in the last section:

2. METHODS

In this proposed method, we first consider the images as signals and model those signals in the nonparametric regression setup. We then wish to test either those signals are significantly the same against they are significantly different. To perform a test, first we need to measure the distance between two nonparametric regression models and use that distance as a statistic test for testing the null hypothesis.

To compare those signals, we first model them as the following nonparametric regression setup, for simplicity we assume that the size of the image is $\boldsymbol{n}$ by $\boldsymbol{n}$.

$$Y_{ij} = m^{I}(x_{ij}) + \varepsilon_{ij},\ \tilde{Y}_{ij} = m^{II}(x_{ij}) + \tilde{\varepsilon}_{ij},\ \ i,j = 1,\dots,n. \tag{1}$$

where Y_{ij} is the image without defect, and $\tilde{Y}_{ij}$ is the defected images; $m^{I}(.)$ and m^{II} are general functions represented the non-defected and defected images respectively. x_{ij} is the grid of pixels; $\varepsilon_{11},\dots,\varepsilon_{nn},\tilde{\varepsilon}_{11},\dots,\tilde{\varepsilon}_{nn}$ are independent with mean zero and finite variance, $Var(\varepsilon_{ij}) = Var(\tilde{\varepsilon}_{ij}) = \sigma^2(x_{ij})$ and uniformly bounded fourth moments $E\varepsilon_{ij},\ E\tilde{\varepsilon}_{ij} \le C < \infty, i,j = 1,\dots,n$

For the sake of simplicity, we only consider the case of equidistant x_{ij} on a compact set, say [0,1] (Detail: Halim (2005)).

2.1. Kernel smoothing

To model an image as a regression, first, we consider an equidistant grid of pixels

$$\boldsymbol{x_{ij}} = (\boldsymbol{i/n - i/2n}, \boldsymbol{j/n - j/2n}) = \boldsymbol{1/n}\,(\boldsymbol{i,j}) - \boldsymbol{1/2n}\,;\boldsymbol{i,j} = \boldsymbol{1},\dots,\boldsymbol{n}$$

(2)

in the unit square $\mathbf{A} = [\mathbf{0},\mathbf{1}]^2$ and a function $\boldsymbol{m}: [\mathbf{0},\mathbf{1}]^2 \to \mathbb{R}$ to be estimated from data, i.e.. the gray levels of the image as follows: $\boldsymbol{Y_{ij}} = \boldsymbol{m}(\boldsymbol{x_{ij}}) + \boldsymbol{\varepsilon_{ij}}; \boldsymbol{i,j} = \mathbf{1},\dots,\boldsymbol{n}$ (3)

where the noise is part of a stationary random field $\boldsymbol{\varepsilon_{ij}}, -\infty < i,j < \infty$, with zero-mean and finite variance.

We use the Gasser-Muerller-type kernel to estimate $\boldsymbol{m}(\boldsymbol{x})$. For that purpose we decompose $\boldsymbol{A}$ into squares $\boldsymbol{A_{ij}} = \{\boldsymbol{x} \in \boldsymbol{A}; (\boldsymbol{i}-\mathbf{1})/\boldsymbol{n} \le \boldsymbol{u_1} \le \boldsymbol{i/n}\,; (\boldsymbol{j}-\mathbf{1})/\boldsymbol{n} \le \boldsymbol{u_2} \le \boldsymbol{j/n}\},\ \mathbf{1} \le \boldsymbol{i,j} \le \boldsymbol{n}$ such that $\boldsymbol{x}$ is the midpoint of $\boldsymbol{A_{ij}}$, then estimate $\boldsymbol{m}$ using: $\widehat{\boldsymbol{m}}(\boldsymbol{x},\boldsymbol{h}) = \sum_{i,j=1}^{n} \int_{A_{ij}} \boldsymbol{K_h}(\boldsymbol{x}-\boldsymbol{u})\boldsymbol{du}\,\boldsymbol{Y_{ij}}$ (4)

where $\boldsymbol{K}: \mathbb{R}^2 \to \mathbb{R}$ is a given kernel function and for the bandwidth vector $\boldsymbol{h} = (\boldsymbol{h_1}, \boldsymbol{h_2})$.

To simplify notation, we write the index in the following way, $z = (i,j)$ such that, (4) can be written as $Y_z = m(x_z) + \varepsilon_z, z \in I_n = \{1, \dots, n\}^2$. Let$\varepsilon_z$, $z \in \mathbb{Z}^2$, is strictly stationary random field on the integer lattice with $\mathbb{E}\varepsilon_z = 0$, $Var\ \varepsilon_z = r(0) < \infty$ and autocovariances $r(z) = cov(\varepsilon_{z'+z}), z, z' \in \mathbb{Z}^2$ (Franke *et al.* [3]). We wish to test either those signals are significantly the same against they are significantly different, i.e., $H_0: m^I(x_{ij}) = m^{II}(x_{ij}) = m(x_{ij}),\ i,j = 1, \dots, n$ against $H_1: m^I(x_{ij}) \neq m^{II}(x_{ij})$ for some i,j

2.2. Performing test

To perform a test, first we need to measure the distance between $\mu_h^I(x)$ and $\mu_h^{II}(x)$ and use this distance as a test statistic for testing the null hypothesis. Following, Haerdle and Mammen (1993), we use standardized L_2-distance between these two estimates, i.e. $T_n = n\sqrt{h}\int\left(\mu_h^I(x) - \mu_h^{II}(x)\right)^2 dx$. Convergence in this distance is equivalent to weak convergence.

2.3. Testing with Bootstrap

We have to decide either those signals are significantly the same (i.e., there is no defect present on a surface) against they are significantly different (i.e., the defect presents on a surface). Typically, a test is performed by calculating some function $T(\mathrm{Y})$ of the data and comparing it with some bound C_α, chosen as the $(1-\alpha)$ quantile of the distribution of $T(\mathrm{Y})$ under the hypothesis H_0. If $T(\mathrm{Y}) \leq C_\alpha$, we accept c as compatible with the data, otherwise we reject it in favor of H_1. α is the prescribed probability of an error of the first kind, i.e., under the H_0, we have $pr(T(Y) > C_\alpha) = \alpha$. Now, constructing the test becomes a problem of determining C_α. However, the distribution of test statistic $T(Y)$ under H_0 is not known. The classical approach to handle this problem is by deriving the asymptotic approximation for unknown distribution that holds for sample size $N \to \infty$. However, this approach practically cannot be applied in signal and image analysis, since the structure of the data has been frequently too complicated.

We then used bootstrap tests, we move from our original data Y to the bootstrap data vector or resample Y^*. The resample Y^* may be artificially generated from the original data and has a similar random structure as Y itself. Then, we consider the test statistic $T(Y^*)$ calculated from the bootstrap data Y^* and determine the $(1-\alpha)$-quantile C_α^* of its distribution: $pr^*(T(Y^*) > C_\alpha^*) = \alpha$, where pr^* denotes the conditional probability given the data Y. The $(1-\alpha)$-quantile C_α^* can be computed numerically using Monte Carlo simulation. (Franke and Halim, 2007).

1. generate a realization $Y^*(b)$ of the bootstrap data and then calculate $T_b^* = T(Y^*(b))$
   repeat for $b = 1, \dots, B$
2. order $T_1^*, \dots, T_B^*$ such that $T_{(1)}^* \leq \cdots \leq T_{(B)}^*$
3. set $C_{\alpha,B}^* = T_{([(1-\alpha)B])}^*$, where $[x]$ denotes the largest integer $\leq x$.

The applicability of the bootstrap data Y^* depends on the way the bootstrap data Y^* are generated as well as the test statistic $T(Y)$ considered. To construct the Y^* for the image, first, we estimated the residual as follows $\hat{\varepsilon}_{ij} = Y_{ij} - \mu^I(x_{ij})$; $\hat{\tilde{\varepsilon}}_{ij} = \tilde{Y}_{ij} - \mu^{II}(x_{ij})$; centering the residual by their sample mean, we achieve $\hat{\varepsilon}_{ij}^0 = \hat{\varepsilon}_{ij} - \frac{1}{n}\sum_{i,j=1}^{n}\hat{\varepsilon}_{ij}$; $\hat{\tilde{\varepsilon}}_{ij}^0 = \hat{\tilde{\varepsilon}}_{ij} - \frac{1}{n}\sum_{i,j=1}^{n}\hat{\tilde{\varepsilon}}_{ij}$

We, then construct out bootstrap samples from $Y_{ij}^* = \mu_g^I(x_{ij}) + \hat{\varepsilon}_{ij}^{*0}$; $\tilde{Y}_{ij}^* = \mu_g^{II}(x_{ij}) + \hat{\hat{\varepsilon}}_{ij}^{*0}$ where $\hat{\varepsilon}_{ij}^{*0}, \hat{\hat{\varepsilon}}_{ij}^{*0}$ are the centering residual.

For the construction of $\hat{\varepsilon}_{ij}^{*0}, \hat{\hat{\varepsilon}}_{ij}^{*0}$; We constructed using the spatial bootstrap to preserve the bond of a pixel to its neighbourhood. First, we compute the spatial covariance matrix of $\hat{\varepsilon}_{ij}$ and $\hat{\hat{\varepsilon}}_{ij}$ and generated both bootstrap residual of them based on that bond.

The spatial covariance of $\hat{\varepsilon}_{ij}$ and $\hat{\hat{\varepsilon}}_{ij}$, is computed between a pair of $\hat{\varepsilon}_{ij}$ and $\hat{\hat{\varepsilon}}_{ij}$ respectively located at points separated by the distance h. The covariance function can be written as a product of a variance parameter, σ^2 times a positive definite correlation function $\rho(h)$, i.e., $Cov(h) = \sigma^2\rho(h)$.

Denote φ the basic parameter of the correlation function and name it the *range parameter*. Some of the correlation functions will have an extra parameterκ, the *smoothness parameter*. $K_\kappa(x)$ denotes the modified Bessel function of the third kind of order *kappa*. In the equations below the functions are valid for $\varphi > 0$and $\kappa > 0$, unless stated otherwise (Diggle and Ribeiro, 2007).

Cauchy	$\rho(h) = \left[1 + \left(\frac{h}{\varphi}\right)^2\right]^{-\kappa}$
Generalized Cauchy	$\rho(h) = \left[1 + \left(\frac{h}{\varphi}\right)^{\kappa 2}\right]^{-(\frac{\kappa 1}{\kappa 2})}$, $\kappa 1 > 0, 0 < \kappa 2 \leq 1$
Cubic	$\rho(h) = 1 - 7\left(\frac{h}{\varphi}\right)^2 - 8.75\left(\frac{h}{\varphi}\right)^3 + 3.5\left(\frac{h}{\varphi}\right)^5 - 0.75\left(\frac{h}{\varphi}\right)^7$ if $h < \varphi$, 0 otherwise
Gaussian	$\rho(h) = \exp\left(-\left(\frac{h}{\varphi}\right)^2\right)$
Exponential	$\rho(h) = \exp(-h/\varphi)$

In this work we chose the correlation $\rho(h)$ as Gaussian model.

Now, the bootstrap test statistics can be constructed as follows (Franke and Halim 2007,2008).

$$T_n = nh^{1/2}\int\left(\mu_h^I(x) - \mu_h^{II}(x)\right)^2 dx \quad \sim h^{1/2}\sum_{i,j=1}^{n}\left(\mu_h^I(x_{ij}) - \mu_h^{II}(x_{ij})\right)^2 \qquad (5)$$

Under the hypothesis $H_{0.}$ we use two forms of the test statistics based on (5) with the bootstrap samples. From now on, we call them as $T1_n$ and $T2_n$ respectively, and we set

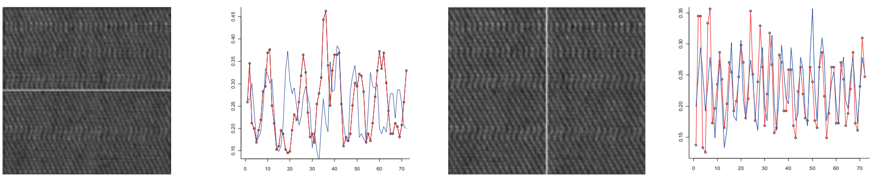
$$t1_n^* = h^{1/2}\sum_{i,j=1}^{n}\left(\mu_h^{*I}(x_{ij}) - \mu_h^{*II}(x_{ij})\right)^2$$

Using one of these two functions then we can set the $C_{\alpha,B}^* = t1_{([(1-\alpha)B])}^*$ and deduce either the hypothesis is rejected (the defect presents in the image) or failed to reject (no defect presents in the image)

3. RESULTS

The idea of detecting defects on the texture`s pattern is the same as we compare the not defected “signal” or series of the texture to the defected one. However, this step can also be applied to the half part of the image, i.e., we divided the image into two parts: Upper and lower part, and also left and right part. We then, comparing the series of the left part to the right one, and of the upper part to the lower one (Figure 1a-b). In this example, we can see that the series are shifted when we compare it from the upper to lower part (Figure 1a-b). However, there is no significantly different of signal when we compare it from left to right one (Figure 1 c-d). The series in Figure b, lead to a conjucture that there is no defect on that line, while in Figure c, lead to a conjecture that there is defect on that line. We then test the conjecture use the proposed hypothesis test explaining in Section 2.3

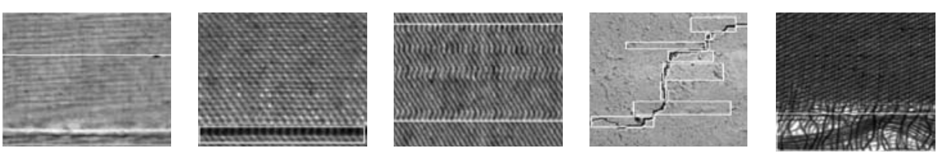
Before testing those series, we first smooth the image using the 2D nonparametric approach, explaining in Section 2.1. We then use that smooth image for constructing the hypothesis test. The hypothesis test is run in each line. Suppose. we take one vector columns from Figure 1a, and let $\mu^{I}(x_{ij}), i = 1. j = 1, \dots, m$ be the first column of the upper image, and called it series I. Let $\mu^{II}(x_{ij}), i = 1. j = m+1, \dots, n$ be the first column of the lower image, and called it series II. We perform a test $H_0: \mu^{I}(x_{ij}) = \mu^{II}(x_{ij}) = \mu(x_{ij}),\ i, j = 1, \dots, n$ against $H_1: \mu^{I}(x_{ij}) \neq \mu^{II}(x_{ij})$. We run the test for $i = 1, \dots, n$. (for simplicity, we let the image size in n by n), and notify in which positions the test reject the hypothesis. Those positions are regarded as the defected area in the image. Similary, the test also run from each row in Figure 1c. Running the test row-wise and columns wise then we we have a set of points which recorded the defect positions in the image. We then take the most four outer points and draw a box thougth those points for detecting the defetc area in the image.



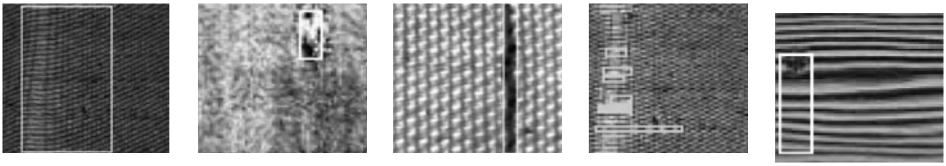
A b c d

Figure 1. The idea of comparing series from the upper to lower part and from the left to the right part

Applying the proposed methods to some defected textures, we are successfully to detect the simple defect as well as the pattern`s defect (Figure 2). Since, we take the outer points for drawing a box to detect the defect area, so in one bix box we can find several defects, i.e. Figure 2a, 2c, 2f. Therefore, we can extend the procedure for finding the defect area, so that we can find several defet areas in a image (see Figure 2d, 2i). Here, we do not use four outer points, but search points in which those points can form a box The proposed model is not running well for detecting defect for wood texture. We need to transform the image using wavelet tansformation first and then perform the test in the wavelet space, then invers the defected area in to the original space (see Figure 2j). The computation in this work was carried out using R-programming (2014).



a b c d e



f g h i j

Figure 2. Some examples of defect detection on pattern fabric

4. DISCUSSION AND CONCLUSION

So far, the methods presented here can handle the simple as well as the pattern defect detection in the texture. However, there are some limitations that these methods cannot overcome, and therefore should be handled in the future work. This method is not successful for capturing many defects on several locations of large texture, capturing in a complex structure such as a defect in the surface of the wood. For capturing many defects on several locations, the procedure for detecting the area of defect shold be impove, so that it can detect many areas of defects at once. So far, the four outer points defect area detection can produce too large defected area due to some small defect in the corner of the image for example. Searching some points which can detect several defect areas should be improved so that, the defected area are not too large, yet not too small to cover the defected area.

For capturing defect in a complex structure, the transformation of the image in the wavelet space is also a challenge to be considered in the future research, Since, inversing the result from the wavelet space to the original space sometime give different result as it is expected.

5. ACKNOWLEDGEMENTS

This research was supported by STEC- Sophia University, Tokyo Japan. The author has gratefully acknowledged to Prof. Akira Kawanaka, from the Sophia University Tokyo for the fruitful discussions during the author stayed in the Sophia University. The author thanks to the anonymous referee for his/her comments that improve the presentation of this paper.

6. REFERENCES

Diggle PJ, Ribeiro P. J., 2007, *Model-based geostatistics*. Springer, New York.

Franke, J., and Halim, S., 2007, Wild bootstrap tests: Regression models for comparing signal and images, *IEEE Signal Processing Magazine,* July 2007, 31-37.

Franke, J., Halim, S. and numerous co-authors, 2008, Structural adaptive smoothing procedure, in *Understanding Complex System*, Springer: Heidelberg.

Fu, R., Shi, M., Wei, H., and Chen, H., 2009, Fabric defect detection based on adaptive local binary patterns, IEEE International Conference on Robotics and Biomimetics (ROBIO), 1336-1340.

Haerdle, W. and Mammen, E., 1993, Comparing nonparametric versus parametric regression fits. *The Annals of Statistics,* **12(4)**, 1926-1947.

Halim, S., 2005, *Spatially adaptive detection of local disturbances in time series and stochastic processes on the integer lattice* Z^2, Dissertation, Technische Universitaet Kaiserslautern, Germany.

Kumar, A., 2008, Computer-vision-based fabric defect detection a survey, IEEE Transaction on Industrial Electronics, 348-363.

Moahseri, B. B. M, Azadinia, S. and Mehbodniya, 2010, A new voting approach to texture defect detection based on multiresolutional decomposition, *World Academy of Science, Engineering and Technology*, **65**, 887-891.

Ngan, H.Y.T., Pang, G.H.K., 2009, Regularity analysis for patterned texture inspection. IEEE Trans. on Autom. Sci. and Eng.,**6(1)**,131-144.

Ngan, H.Y.T., Pang, G.H.K., Yung, N.H.C., 2010a, Performance evaluation for motif-based patterned texture defect detection. IEEE Trans. on Autom. Sci. and Eng., **7(1)**, 58-72.

Ngan, H.Y.T., Pang, G.H.K., Yung, N.H.C, 2010b, Ellipsoidal decision regions for motif-based patterned fabric defect detection. Pattern Recognition, **43**, 2132-2144

R-programming, 2014, www.r-project. org.

Tang, L., Schucany, W. R., Woodward, W. A., and Gunst, R. F., *A spatial bootstrap*, Technical Report, Department of Statistical Science, University of Southern Methodist, [Online] Available: http://*smu.edu/statistics/techreports/tr337.pdf* (retrieved in June 2011)

Timm, F. and Barth, E., 2011, Non-parametric texture defect detection using Weibull features. *Image Processing*: *Machine Vision Applications* IV, 7877, *Proceeding of SPIE. SPIE-IS& T*. San Francisco, USA.