Review and Outlook for Texture Analysis Methods

Markus Vogelbacher

Vision and Fusion Laboratory
Institute for Anthropomatics
Karlsruhe Institute of Technology (KIT), Germany
markus.vogelbacher@kit.edu

Technical Report IES-2012-02

Abstract:

The description and analysis of textures is a widely discussed topic. Different methods have already been developed but there are still a lot of opportunities to develop new approaches. For this reason, in this report at first an overview of the standard methods for the analysis of textures is given. Based on that, new ideas and opportunities are presented which extend these methods but also represent totally new approaches. In the field of structural-statistical textures the change in the structural arrangement scheme is described analogously to the modulation of signals in communications technology. A basic fundament is the representation of an image signal by a two-dimensional extended Fourier series whose parameters can be obtained using unmodulated texture primitives. Another subject is the determination of parameters in the modeling of textures using AR-models. This estimate is carried out using the Support Vector Regression (SVR) and, thus, offers an alternative to the in the field of texture analysis widely used Least-Square (LS) and Maximum-Likelihood (ML) estimation methods. In the field of optical inspection of textiles an approach will be introduced, which enables the assessment of tissue properties and the detection of errors. The assessment is not based on the derivation of features from the methods of texture analysis, but uses the possibilities of the image acquisition by a variable illumination.

1 Introduction

For the term *texture* there is no clear definition. The word comes from the Latin *textura* and literally means *tissue*. Textures, e.g., on surfaces, are very familiar to us from everyday life and often they are described by various adjectives such as

(a) (b) (c)

Figure 1.1: Examples of texture types: (a) structural, (b) structural-statistical, (c) statistical.

coarse, fine, grainy, directed, wavy, etc.. Also in image processing the classification, segmentation, modeling, and fault detection of textures is an important part of the inspection and evaluation of surfaces.

As already mentioned, there is no generally accepted definition for texture, but basically, any two-dimensional structure with certain deterministic or statistical regularities can be characterized as such. According to this definition, a basic separation of textures can be made into the following types (Fig. 1.1):

- Structural texture type
- Structural-statistical texture type
- Statistical texture type

A structural texture type can thereby be described by a given elementary sample, which is also known as texture primitive or texel, arranged at a fixed local arrangement scheme. If the primitive or the arrangement scheme is subject to certain stochastic variations, we speak of a structural-statistical texture type. If none of these is recognizable, e.g., the texture is a sample function of a random process, it is seen as statistical texture type. Basically, it can be stated that in the transition from the statistical to structural-statistical and to structural texture type the knowledge about the texture increases.

The various types of texture can be characterized by various methods. The introduction to this standard methods of texture analysis is carried out in Section 2. Section 3 deals with two approaches: the first introduces a way of describing/modeling structural-statistical texture types and the second offers an alternative to the existing methods for parameter estimation at autoregressive (AR)-models.

Another approach to assess semi-finished textile surfaces is part of Section 4. The tissue properties are assessed and errors are detected by using the properties of the textured surface even at the image acquisition. A summary and outlook are given in Section 5.

2 Overview and Insight into the Methods of Texture Analysis

The separation into different texture types shows the diversity in the evaluation of textures that must be considered. A single procedure for texture analysis, which allows an assessment of all the properties of all types of texture, does not exist. Rather the methods are based on the existing texture type. Below, some classic texture analysis approaches are presented, which can be divided into the following categories:

- Statistical methods
- Structural/spectral methods
- Use of special masks
- Texture models

This methods can be used for classification, segmentation, or defect detection.

2.1 Statistical Methods

To represent texture, various properties are determined mainly describing the spatial dependence of the gray values within a particular neighborhood. With these properties in further steps, e.g., classification can be made.

As the visual perception of a texture by humans are strongly dominated by differences in the statistics of the first and second order and differences in higher order statistics are perceived very rarely, histogram properties such as the mean, the variance, the autocorrelation function, or the edge density are used for the evaluation of a texture. The measurement of these properties in a particular window which is slided over a texture can, e.g., enable the segmentation of a texture or the detection of defects by considering the deviations of the properties depending on the window position.

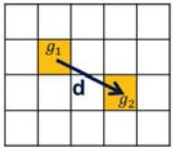


Figure 2.1: Displacement **d** for the determination of the gray level co-occurrence matrix.

A process which is concerned with the assessment of the neighborhood of a pixel involves setting up a gray level co-occurrence matrix (GLCM) [HSD73, Bey11]. The gray values of two pixels $g_1 = g(\mathbf{x})$ and $g_2 = g(\mathbf{x} + \mathbf{d})$ are considered, which have a certain displacement **d** to each other (Fig. 2.1).

The elements of the GLCM $\mathbf{C_d}$ can be determined as follows:

$$c_{\mathbf{d},ij} = |\{\mathbf{x}|g(\mathbf{x}) = i, g(\mathbf{x} + \mathbf{d}) = j, \forall \mathbf{x}, \mathbf{x} + \mathbf{d} \in \Omega\}|$$

The element $c_{\mathbf{d},ij}$ describes the number of pixels **x** in the domain Ω of the image with $g_1 = g(\mathbf{x}) = i$ and $g_2 = g(\mathbf{x} + \mathbf{d}) = j$. An example of the determination of such a GLCM is shown in Fig. 2.2.

Since the determination of GLCMs compares values of pixel pairs they belong to statistics of second order. By normalizing the matrix by

$$\mathbf{C}_{\mathbf{d}}^{\text{norm}} = \frac{\mathbf{C_d}}{\mathbf{1}^{\mathrm{T}}\mathbf{C_d}\mathbf{1}},$$

this can be interpreted as estimation for the second order composite likelihood.

0	0	0	0
0	1	1	0
0	2	2	0
0	0	0	0

(a)

	0	1	2
0	6	1	1
1	1	1	0
2	1	0	1

(b)

Figure 2.2: Example of the determination of a GLCM with $\mathbf{d} = (1\ \ 0)^T$: (a) starting image $g(\mathbf{x})$, (b) co-occurrence matrix $\mathbf{C_d}$ (green column corresponds to the gray value at the point **x** and orange line corresponds to the gray value at the point $\mathbf{x} + \mathbf{d}$).

m_1	m_2	m_3
m_8	m_0	m_4
m_7	m_6	m_5

Figure 2.3: Local Binary Pattern: defining the neighborhood m_1 to m_8 for central pixel m_0.

To use the GLCM to analyse textures, various features such as the Haralick-features [Har79] can be derived:

- Energy:

$$\mathbf{1}^{\mathrm{T}} \left[c^2_{\mathbf{d},ij} \right] \mathbf{1}$$

- Entropy:

$$-\sum_i \sum_j c_{\mathbf{d},ij} \, \mathrm{ld}(c_{\mathbf{d},ij})$$

- Contrast:

$$\sum_i \sum_j |i-j|^a \, c^b_{\mathbf{d},ij} \quad \text{(typically } a=2,\ b=1\text{)}$$

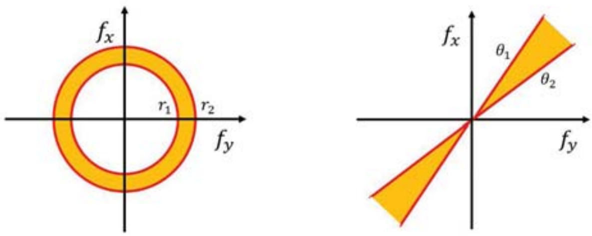
- Other features: maximum, homogeneity, inverse difference moment, correlation [Har79].

Another method, which attracts also the comparison of the gray values of a pixel pair, is called Local Binary Pattern (LBP) [WH89]. The gray values of pixels that are within a certain distance from a central pixel are considered (Fig. 2.3).

A comparison of gray values delivers a binary encoding for the pixel area. For the considered neighborhood of Fig. 2.3 the result is:

$$LBP(m_0) = \sum_{i=1}^{8} \kappa(m_i) 2^{i-1}, \quad \kappa(m_i) = \begin{cases} 1, & m_i \geq m_0 \\ 0, & \text{else} \end{cases}$$

Evaluating for example histograms of LBPs enables the assessment of a texture.



(a) (b)

Figure 2.4: (a) Ring and (b) Wedge filter to select specific frequencies in the periodogram.

2.2 Structural/Spectral Methods

The analysis of structural textures is based on the detection of the texture primitive and the arrangement scheme. The determination of the primitive or the size of the primitive can be derived from various properties such as GLCM, the autocorrelation function or using the Renyi entropy [GP03]. In most cases an accurate determination of the primitive is very difficult. The analysis of the arrangement scheme can be performed using the periodogram/Fourier transform, so that a determination of the frequency and the orientation of the texture is possible.

For most analysis, a detailed consideration of a certain frequency range is needed. This can be achieved by using so called Ring/Wedge filters [RH99], which put the focus on frequencies between two radii or within a certain angle (Fig. 2.4).

For the detection of structural features other transformations such as the Hough or Radon transform can be used as well. If the primitive and the arrangement scheme is known, the texture can be completely recovered from it.

2.3 Use of Special Masks

One way to assess textures is the use of heuristically derived masks. These are included in the texture energy measure by Laws [Law80] and can describe properties such as level, edge, spot, wave, and ripple. In this context, the required convolution kernels can have different length. As an example the convolution kernels of length five are listed. The designation of the convolution kernels refers to the first letter of each property.

$$
\begin{aligned}
\mathbf{l}_5 &= (1 \quad 4 \quad 6 \quad 4 \quad 1)^{\mathrm{T}} \\
\mathbf{e}_5 &= (-1 \quad -2 \quad 0 \quad 2 \quad 1)^{\mathrm{T}} \\
\mathbf{s}_5 &= (-1 \quad 0 \quad 2 \quad 0 \quad -1)^{\mathrm{T}} \\
\mathbf{r}_5 &= (1 \quad -4 \quad 6 \quad -4 \quad 1)^{\mathrm{T}} \\
\mathbf{w}_5 &= (1 \quad -2 \quad 6 \quad 2 \quad -1)^{\mathrm{T}}
\end{aligned}
$$

By calculating the dyadic product of two convolution kernels with desired properties the so called Laws matrices are obtained. The convolution of a gray-scale image with these Laws matrices and then calculating the resulting image energies allows the classification of different textures.

2.4 Texture Models

The description of an existing texture by using a model can be tackled by different approaches. Firstly, a texture can be described by a fractal model. Accordingly, the texture is treated as a structure that consists of non-overlapping and reduced copies of itself. The measurement of the self-similarity in concrete the fractal dimension

$$D = \frac{\log(N_r)}{\log(\frac{1}{r})}$$

delivers a characteristic of the texture [PGS06]. N_r denotes the number of copies of the non-overlapping structure reduced by a factor r.

A widely used model for textures is given by Markov Random Fields (MRF). A statistical dependence of the gray value of a pixel to the gray values of its neighborhood is produced [CJ83]. The choice of the neighborhood is a very important variable for the quality of the model output.

The autoregressive (AR)-model [MJ92] is an instance of the MRF model. A detailed description is given in Section 3.

3 Possible Enhancements of Existing Texture Analysis Methods

3.1 Texture Modulation

The description or the designation of a model for a structural-statistical texture type is a hardly studied area in the field of texture analysis. Below, an approach which interprets the structural-statistical texture as modulation of a structural texture is presented. The structural texture is modeled by using a two-dimensional Fourier series. The local changes of the arrangement scheme, which create the structural-statistical texture, will be considered by a modulation term.

The basis of this idea lies in the communications technology. A signal $x(t) = a_0 \cos(2\pi f_0 t + \varphi_0)$ can be affected by an amplitude (AM) $x_{AM}(t)$ or frequency modulation (FM) $x_{FM}(t)$. The modulating signal used in this case is denoted by $v(t)$. AM and FM can be described as follows:

$$x_{AM}(t) = [a_0 + a_1 v(t)] \, \cos(2\pi f_0 t + \varphi_0),$$
$$x_{FM}(t) = a_0 \cos(2\pi f_0 t + \Delta\Omega \, V(t) + \varphi_0),$$
$$\text{with } V(t) = \int_0^t v(t') \, dt' \text{ and } \Delta\Omega = \text{frequency deviation.}$$

By calculating the analytical signal $x^+_{AM}(t)$ or $x^+_{FM}(t)$ with the Hilbert transform

$$\mathcal{H}\left\{\cos(2\pi f_0 t)\right\} = \sin(2\pi f_0 t),$$
$$x^+_{AM}(t) = x_{AM}(t) + j\mathcal{H}\left\{x_{AM}\right\} = [a_0 + a_1 v(t)] \; e^{j(2\pi f_0 t + \varphi_0)},$$
$$x^+_{FM}(t) = x_{FM}(t) + j\mathcal{H}\left\{x_{FM}\right\} = a_0 \, e^{j(2\pi f_0 t + \Delta\Omega \, V(t) + \varphi_0)},$$

and by using the complex envelope

$$s(t) = \frac{1}{\sqrt{2}} \, x^+(t) \, e^{j2\pi f_0 t},$$
$$\text{for } x^+_{AM}(t): \quad |s(t)| = |a_0 + a_1 v(t)| \, ,$$
$$\text{for } x^+_{FM}(t): \quad Im\left\{\ln s(t)\right\} = \Delta\Omega \, V(t) + \varphi_0,$$

the modulating signal can be obtained again. Demodulation is possible, too [Kam11].

The idea is in the first step to extend the approach to the modulation of any one-dimensional signal and in the second step for any two-dimensional signal/texture.

In order to determine the analytical signal the simple correspondence to the Hilbert transform of $\sin$ and $\cos$ is still to be exploited.

With the representation of an arbitrary periodic signal by means of a Fourier series in amplitude-phase-notation a modulation for any one-dimensional signal can be achieved analogously to a simple $\cos$-signal in the communication technology:

$$x(t) = \frac{a_0}{2} + \sum_{n=1}^{\infty} A_n \cos(n2\pi f_0 t - \varphi_n)$$

$$\text{AM:} \quad x^+_{AM}(t) = v(t) \left[\frac{a_0}{2} + \sum_{n=1}^{\infty} A_n \, e^{j(n2\pi f_0 t - \varphi_n)} \right]$$

$$\text{FM:} \quad x^+_{FM}(t) = \frac{a_0}{2} + \sum_{n=1}^{\infty} A_n \, e^{j(n(2\pi f_0 t + \Delta\Omega \, V(t)) - \varphi_n)}$$

a_0, A_n and φ_n describe the Fourier coefficients of the unmodulated signal.

Just like in the one-dimensional space, every two-dimensional periodic signal or in specific a texture can be expressed by means of a two-dimensional Fourier series. The creation of the analytical signal can be replaced by the direct use of the complex 2D Fourier series:

$$f(x,y) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} E_{mn} \, e^{j(m2\pi f_x x + n2\pi f_y y)},$$

$$\text{with } f_x = \frac{1}{T_x}, \; f_y = \frac{1}{T_y} \text{ , and}$$

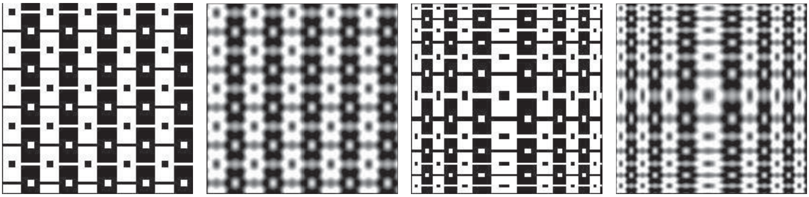
$$E_{mn} = \frac{1}{T_x T_y} \int_{-T_y}^{T_y} \int_{-T_x}^{T_x} e^{-j(m2\pi f_x x + n2\pi f_y y)} f(x,y) \, dx \, dy.$$

By introducing a modulation term, the modulation of a two-dimensional signal can be described by an extended 2D Fourier series. For example for the frequency modulation:

$$f_{FM}(x,y) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} E_{mn} \, e^{j(m(2\pi f_x x + \Delta\Omega_x \, V_x(x)) + n(2\pi f_y y + \Delta\Omega_y \, V_y(y)))},$$

$$\text{with } V_x(x) = \int_0^x v_x(x') \, dx', \; V_y(y) = \int_0^y v_y(y') \, dy'.$$

In Fig. 3.1, an example of modeling a 2D-modulated signal is given in which the modulation of the arrangement scheme is known.



(a) (b) (c) (d)

Figure 3.1: Application of the extended Fourier series to a texture with a known modulated arrangement scheme: (a) unmodulated original texture, (b) model of the extended Fourier series of the unmodulated original texture, (c) modulated original texture, (d) model of the extended Fourier series of the modulated original texture.

It turns out that this approach can represent structural-statistical textures with known modulated arrangement scheme. However, the simple demodulation, as known from the communication technology, is no longer possible. For derivation of the modulating signal from the model of the extended Fourier series, it is necessary to find other methods. Such methods may be derived from similar applications such as the estimation of a time-frequency distribution using the short-time Fourier transform or the Wavelet transform [LT96], the adjusting of the phase of the extended Fourier series with the aid of a phase locked loop, or the use of distribution densities for point fields [SS92]. The possible applications of these various methods must be investigated in further steps. Furthermore, the introduction of a combined x, y-modulation is necessary, since in the previously considered case the modulation is divided into separated x- and y-direction ($V_x(x)$ and $V_y(y)$).

3.2 Alternative Parameter Estimation for AR-Texture Models

AR-models are well-known for the analysis of statistical textures [Bey11]. The intensity at a discrete location g_{mn} can be modeled as follows:

$$\begin{aligned} g_{mn} &= \sum_{(k,l)\in U} a_{kl}\, g_{m-k,n-l} + e_{mn} \\ &= \mathbf{a}^{\mathrm{T}}\gamma_{mn} + e_{mn}, \\ \text{with} \quad \mathbf{a} &= (...,a_{kl},...)^{\mathrm{T}} \quad \gamma_{mn} = (...,g_{m-k,n-l},...)^{\mathrm{T}}. \end{aligned}$$

U describes the causal environment, $|U|$ the order (number of elements in the considered environment), a_{kl} the weighting factors or AR coefficients, and e_{mn} a weakly stationary additive white noise

$$E\{e_{mn}\} = 0, \quad E\{e_{mn}\, e_{m+i,n+j}\} = \sigma^2 \delta_i^0 \delta_j^0.$$

A causal environment in this context means that for a point (m, n) all points $(m-k, n-l)$ in front of it are known. As a result, the modeled image can be determined by recursive implementation of the AR-model. The texture parameters **a** and σ allow the modeling and therefore may be regarded as texture features. An important step in setting up the AR-model represents the parameter estimation of the AR coefficients. In practice, two main methods are used:

- Least-Square (LS)
- Maximum-Likelihood (ML)

The goal of the estimation using LS is to minimize the variance of the prediction error $e_{mn} = g_{mn} - \mathbf{a}^{\mathrm{T}} \boldsymbol{\gamma}_{mn}$. This leads to the following result [JBS09]:

$$\begin{aligned} Var\{e_{mn}\} = Var\left\{g_{mn} - \mathbf{a}^{\mathrm{T}} \boldsymbol{\gamma}_{mn}\right\} \rightarrow Min \\ \rightarrow \hat{\mathbf{a}} = \left(\sum_{m,n} \boldsymbol{\gamma}_{mn}\, \boldsymbol{\gamma}_{mn}^{\mathrm{T}}\right)^{-1} \sum_{m,n} \boldsymbol{\gamma}_{mn}\, g_{mn} \end{aligned}$$

The ML estimate iteratively calculates the coefficients with $\hat{\mathbf{a}}$ as iteration start and delivers better results than the LS estimation [JBS09].

At this point an alternative variant for parameter estimation of AR-texture models is presented, which is already known from the system technology, namely the estimation using Support Vector Regression (SVR) [RAMRdPC$^+$04]. The aim is to minimize the total error R resulting from the model. The total error R consists of a loss function $\xi^{(*)}$ (for upper and lower bound) and a regularization term for the AR coefficients:

$$R = \frac{1}{2}\left\|\mathbf{a}\right\|^2 + C \sum_{i=1}^{N} (\xi_i + \xi_i^*) \qquad N\text{: Number of training data}$$

By introducing the loss function also outliers are allowed similar to the *soft margin* approach at Support Vector Machines (SVM). The constant C controls the balance between the loss function and the regularization term and, thus, the tolerance of outliers. The loss function can be set up differently, a common approach is the ϵ-insensitive loss-function:

$$\xi^{(*)} = \begin{cases} |e_{mn}|, & e_{mn} \geq \epsilon \\ 0, & \text{else} \end{cases}$$

The total error R must be minimized under the constraints:

$$\begin{aligned} g_{mn} - \mathbf{a}^{\mathrm{T}}\boldsymbol{\gamma}_{mn} &\leq \epsilon + \xi_{mn} \\ -g_{mn} + \mathbf{a}^{\mathrm{T}}\boldsymbol{\gamma}_{mn} &\geq \epsilon + \xi^*_{mn} \\ \xi^{(*)} &\geq 0 \end{aligned}$$

This optimization problem under constraints can be solved by using Lagrange multipliers $\alpha^{(*)}$. The corresponding Lagrange function is given by:

$$\begin{aligned} L(a, \alpha, \alpha^*, \eta, \eta^*, \xi, \xi^*) = \frac{1}{2}\left\|\mathbf{a}\right\|^2 &+ C\sum_{i=1}^{N}(\xi_i + \xi_i^*) \\ &- \sum_{i=1}^{N}\alpha_i(-g_i + \mathbf{a}^{\mathrm{T}}\boldsymbol{\gamma}_i + \epsilon + \xi_i) \\ &- \sum_{i=1}^{N}\alpha_i^*(g_i - \mathbf{a}^{\mathrm{T}}\boldsymbol{\gamma}_i + \epsilon + \xi_i^*) - \sum_{i=1}^{N}(\eta_i\xi_i + \eta_i^*\xi_i^*) \end{aligned}$$

In order to optimize, this equation is minimized with respect to **a** and $\xi^{(*)}$, i.e.,

$$\frac{\partial L}{\partial \mathbf{a}} = 0 \quad \text{and} \quad \frac{\partial L}{\partial \xi^{(*)}} = 0.$$

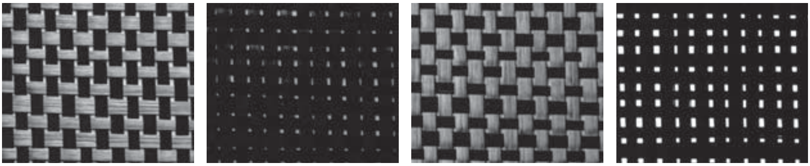
The result of the optimization is:

$$\begin{aligned} \mathbf{a} &= -\sum_{i=1}^{N}(\alpha_i^* - \alpha_i)\,\boldsymbol{\gamma}_i, \\ g_{mn} &= -\sum_{i=1}^{N}(\alpha_i^* - \alpha_i)\left\langle\boldsymbol{\gamma}_i, \boldsymbol{\gamma}_{mn}\right\rangle, \\ &\text{with} \quad 0 \leq \alpha_i^{(*)} \leq C. \end{aligned}$$

After the insertion of the result of **a** to the original equation $L(a, \alpha, \alpha^*, \eta, \eta^*, \xi, \xi^*)$, it can be maximized with respect to the Lagrange multipliers $\alpha^{(*)}$:

$$\frac{\partial L}{\partial \alpha^{(*)}} = 0$$

The $\alpha^{(*)}$ can be obtained and used for estimating the AR coefficients by inserting into the equation for **a**. This procedure has to be applied for various examples



(a) (b) (c) (d)

Figure 4.1: Example for the investigation of a weave structure by variable lighting: (a) perpendicular to weft yarns, (b) not perpendicular to a yarn direction, (c) perpendicular to warp yarns, (d) transmitted light [VWZ12].

from the field of texture analysis and compared with the results of the classical LS and ML estimation methods in further work. Another development potential that has to be examined in this context is the additional introduction of a non-linear extension as known from the classical SVM [SS02].

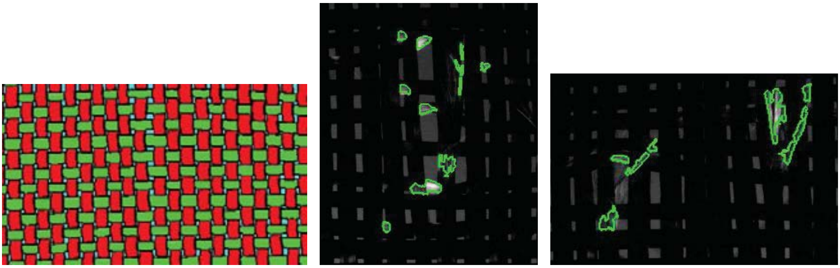
4 Procedure for Assessing Semi-Finished Textile Surfaces

The visual inspection of textiles is an important part of the texture analysis. Various methods, also presented in Section 2, are used to allow the assessment of the quality of the weave structure or the detection of errors. Examples can be found in [VWZ12].

Also in [VWZ12] an approach is unveiled which goes another way and begins with the image acquisition. Selecting a suitable illumination strategy allows to trace back subsequent steps for assessing the weave structure or the detection of errors to the lighting direction. By taking a series of images, in which the direction of illumination is varied systematically, a reflection characteristic and, thus, an orientation can be assigned to each surface location. The application of such a lighting strategy is based on studies by Lindner, Arigita and Puente León [LAPL05, LPL06].

Examples of a lighting series for weave structure can be seen in Fig. 4.1. The result of a segmentation of the warp and weft yarns as well as the detection of errors in such a series are shown in Fig. 4.2.

The presented weave structure is a structural-statistical texture as desribed in Section 1. Both the texture primitive and the arrangement scheme are variable. The



(a) (b) (c)

Figure 4.2: Evaluation of a lighting series: (a) segmentation result for yarn spaces (blue), warp (red) and weft threads (green), (b) detection of distortions, (c) detection of damages [VWZ12].

assessment of the degree of variation is not based on a mathematical description (Section 3.1), but on the use of optical properties and following further treatment.

5 Conclusion and Outlook

This report provides an introduction to the basics of texture analysis. Although no universal definition for the term of texture can be given, it was described what a texture is all about and in what types they can be divided to. Moreover, it was shown in an overview which different methods can be used to investigate textures.

In addition to the existing methods new approaches were shown that offer on the one hand the modeling of structural-statistical texture types and on the other an alternative to the estimation techniques used in the field of AR-models for textures. The application, the development, and the resulting advantages and disadvantages of these approaches must be pursued in subsequent studies.

At the end it was shown that texture analysis can not only be carried out by the analysis of image data, but also by the choice of an appropriate lighting strategy and the corresponding information. For the inspection of textiles the approach of using the reflection characteristic has to be further considered.

Bibliography

[Bey11] J. Beyerer. Lecture: Automatische Sichtprüfung und Bildverarbeitung. *Karlsruher Institut für Technologie, Lehrstuhl für Interaktive Echtzeitsysteme*, 2011.

[CJ83] G.R. Cross and A.K. Jain. Markov random field texture models. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, PAMI-5(1):25–39, 1983.

[GP03] S.E. Grigorescu and N. Petkov. Texture analysis using Renyi's generalized entropies. *International Conference on Image Processing*, 2003.

[Har79] R.M. Haralick. Statistical and structural approaches to texture. *Proceedings of the IEEE*, 67(5):786 – 804, 1979.

[HSD73] R.M. Haralick, K. Shanmugam, and I. Dinstein. Textural features for image classification. *IEEE Transactions on Systems, Man and Cybernetics*, SMC-3(6):610–621, 1973.

[JBS09] M.S. Joshi, P.P. Bartakke, and M.S. Sutaone. Texture representation using autoregressive models. *International Conference on Advances in Computational Tools for Engineering Applications*, pages 386–390, 2009.

[Kam11] K.D. Kammeyer. *Nachrichtenübertragung*. Vieweg+Teubner Verlag, 2011.

[LAPL05] C. Lindner, J. Arigita, and F. Puente León. Illumination-based segmentation of structured surfaces in automated visual inspection. In *Society of Photo-Optical Instrumentation Engineers (SPIE) Conference Series*, volume 5856, pages 99–108, 2005.

[Law80] K. Laws. *Textured Image Segmentation*. PhD thesis, University of Southern California, 1980.

[LPL06] C. Lindner and F. Puente León. Segmentierung strukturierter Oberflächen mittels variabler Beleuchtung. *Technisches Messen*, 73:200–207, 2006.

[LT96] P.J. Loughlin and B. Tacer. On the amplitude- and frequency-modulation decomposition of signals. *Journal of the Acoustical Society of America*, 100(3):1594–1601, 1996.

[MJ92] J. Mao and A.K. Jain. Texture classification and segmentation using multiresolution simultaneous autoregressive models. *Pattern Recognition*, 25(2):173–188, 1992.

[PGS06] M. Petrou and P. Garcia Sevilla. *Dealing with Texture*. John Wiley & Sons, Ltd, 2006.

[RAMRdPC+04] J.L. Rojo-Alvarez, M. Martinez-Ramon, M. de Prado-Cumplido, A. Artes-Rodriguez, and A.R. Figueiras-Vidal. Support vector method for robust ARMA system identification. *IEEE Transactions on Signal Processing*, 52(1):155–164, 2004.

[RH99] T. Randen and J.H. Husoy. Filtering for texture classification: A comparative study. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 21(4):291–310, 1999.

[SS92] D. Stoyan and H. Stoyan. *Fraktale, Formen, Punktfelder: Methoden der Geometrie-Statistik*. Akademie Verlag, 1992.

[SS02] B. Schölkopf and A.J. Smola. *Learning with Kernels: Support Vector Machines, Regularization, Optimization, and Beyond*. MIT Press, 2002.

[VWZ12] M. Vogelbacher, S. Werling, and M. Ziebarth. Beurteilung textiler Flächenhalbzeuge mittels variabler Beleuchtung. In *Forum Bildverarbeitung*, pages 193–204, 2012.

[WH89] L. Wang and D.C. He. Texture classification using texture spectrum. *Pattern Recognition*, 23(8):905–910, 1989.