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Non-parametric texture defect detection using Weibull features

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ABSTRACT

The detection of abnormalities is a very challenging problem in computer vision, especially if these abnormalities must be detected in images of textured surfaces such as textile, stone, or wood. We propose a novel, non-parametric approach for defect detection in textures that only employs two features. We compute the two parameters of a Weibull fit for the distribution of image gradients in local regions. Then, we perform a simple novelty detection algorithm in order to detect arbitrary deviations of the reference texture. Therefore, we evaluate the Euclidean distances of all local patches to a reference point in the Weibull space, where the reference point is determined for each texture image individually. Thus, our approach becomes independent of the particular texture type and also independent of a certain defect type.

For performance evaluation we use the highly challenging database provided by Bosch for a contest on industrial optical inspection with different classes of textures and different defect types. By using the Weibull parameters we can detect local deviations of texture images in an unsupervised manner with high accuracy. Compared to existing approaches such as Gabor filters or grey level statistics, our approach is not only powerful, but also very efficient such that it can also be applied for real-time applications.

Keywords: defect detection, texture images, Weibull distribution, optical inspection, non-parametric models, novelty detection

1. INTRODUCTION

Over the last decade, automated optical inspection has proved to reduce the cost of industrial quality control significantly. Especially, automated defect detection in textured surfaces has gained increasing importance in industrial production. One of the major applications of texture defect detection is surface inspection, *e.g.* inspection of semi-conductor components or textile inspection. Although automated inspection systems have advantages over human inspection such as reliability and repeatability, they are often highly adapted to a certain texture pattern and defect type. Hence, these systems fail if the problem changes and new types of defects arise.

Texture defects can be either non-textured areas or areas that locally differ from the background texture of the surface. Often the defects are subtle and very hard to identify even manually and thus well-defined defect specification and pixel-wise defect labelling are usually not available. In Fig. 1 some example surfaces are shown such as textile, wood, or steel with different types of defects.

Several approaches for texture defect detection have been proposed; generally, they can be separated into two categories: local and global approaches. Since global approaches are applied to the whole image, they often yield better performance for problems such as shade or tonality analysis, and they perform poorly in texture defect detection. Hence, approaches that evaluate local texture characteristics are often applied; they can be separated into statistical approaches (*e.g.* grey level statistics, fractal dimension), spectral approaches (*e.g.* Gabor filter,

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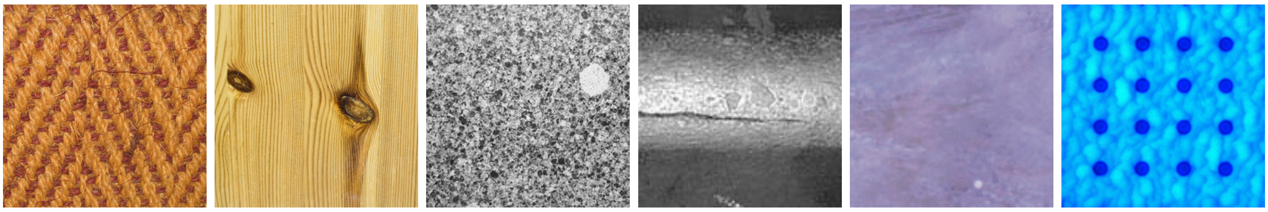


(a) textile (b) wood (c) stone (d) steel (e) ceramic (f) LED

Figure 1. Example textured surfaces with different types of (subtle) defects. Note, that some defects may only be visible in the electronic version.

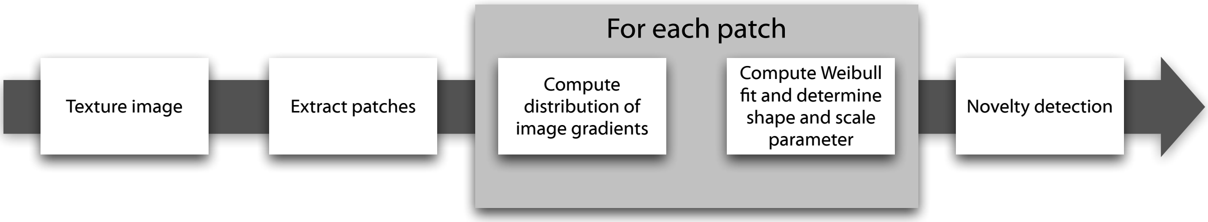


Figure 2. Scheme of our novel method for texture defect detection.

Fourier analysis), and model-based approaches (*e.g.* Markov random fields, model-based clustering). However, these approaches are often complex and adapted to a certain defect type and thus fail to detect miscellaneous types of defects.

Recently, Scholte *et al.* reported that brain responses strongly correlate with Weibull image statistics when processing natural images.[1] Several other researchers also reported that Weibull parameters estimated from the distribution of magnitudes of image gradients yield accurate results for texture classification.[2–5] But so far, the Weibull parameters have not been applied to the problem of texture defect detection.

In this work, we propose a simple, non-parametric approach to texture defect detection by using Weibull parameters. Therefore, we make the following contributions: (i) novel method for computing local features that capture texture characteristic and (ii) fast novelty detection. The steps involved in our novel defect detection approach are depicted in Fig. 2. First, we extract local image patches of a given texture image, where the patch size is automatically determined. Then, for each local image patch we compute image gradients and the distribution of their magnitudes. Afterwards, we compute a Weibull fit for the distribution of gradient magnitudes in order to obtain the scale and shape parameters. Based on these two Weibull features we perform an outlier detection, which evaluates the Euclidean distance of each local patch to the median in the Weibull space. If the maximum distance is larger than a threshold, the current image patch is considered as defective (negative); the threshold is automatically determined by minimising a cost-function. Compared to existing approaches our approach is by orders of magnitude more efficient and does not involve any kind of learning or further parameters.

We evaluate the performance of our method by using the highly challenging database of the contest “weakly supervised learning for industrial optical inspection”[*], which was introduced at the DAGM 2007. The images were proposed by Bosch and consist of different texture classes and different defect types. We demonstrate that our method is able to detect arbitrary deviations from the reference (background) texture.

2. TEXTURE DEFECT DETECTION

Detecting defects in textures is a very challenging problem in computer vision. Although several methods for texture defect detection have been proposed, recent reviews[6,7] have shown that there is a clear need for standard

[*] `http://hci.iwr.uni-heidelberg.de/Benchmarks/gt/detail/?gt_id=2`

evaluation and for standard benchmark datasets in order to avoid highly adapted methods. Supporting these aspects, we generally define the requirements for texture defect detection as follows:

1. Not only a single defect type needs to be detected, but arbitrary defects must be detected.
2. The method must not be adapted to a specific background texture, instead it must perform well on various background textures.
3. There is no defect specification and the defects are weakly labelled (not pixel-wise).
4. Class-dependent costs must be incorporated (samples with missing defects are worse than defect-free samples classified as defective).
5. All parameters, *e.g.* for filtering, feature extraction, or learning, must be determined automatically.

In addition to the above mentioned requirements, our defect detection method has the following properties:

6. No separation into different classes of background textures is required – our method can work on each texture image individually.
7. No exhaustive training set is required – our method works even if only a single defect image is available.

However, most approaches for texture defect detection do not meet all these requirements and therefore we will give only a brief overview of the most important techniques in this field.

2.1 Related Work

Generally, methods for texture defect detection – sometimes also called texture *analysis* – can be separated into three groups: statistical, spectral, and model-based techniques. Historically, statistical methods that evaluate the spatial distribution of pixel intensities were the first techniques to analyse texture images. Numerous statistical methods have been proposed, and they have successfully been applied to several computer vision applications such as texture defect detection.[8–10] The most popular statistical methods use first order statistics such as mean, variance, or range and other histogram-based computations together with the second order statistics based on the spatial grey-level co-occurrence matrix.[11–13] Moreover, the local binary pattern operator,[14,15] which capture local image contrast, or autocorrelation, which evaluates the correlation between the image itself and the translated image, can be used for evaluating the spatial distribution of pixel intensities.

Spectral approaches often imply a bank of filters that are applied to the image, where the energy of the filter responses is used as feature. A variety of different filters are used as basis for further evaluation of texture images such as gradient filters, Gabor filters,[16,17] or eigenfilters.[18] Moreover, the Fourier transform can also be used for computing spectral features for defect detection; due to its noise robustness and translation invariance features based on the Fourier transform are commonly used for periodic textures.

If prior knowledge is available about the underlying process that generates the texture pattern and if this pattern can be defined by a stochastic model, then model-based approaches naturally yield very accurate results in texture analysis. For example, stochastic models based on the Gaussian Markov random field have been successfully used to model natural and hand-made textures.[19] However, these models yield poor performance for the problem of texture defect detection, especially if the defects are subtle and differ only slightly from the stochastic background texture.

State of the art computer vision approaches often involve several methods before feature extraction such as denoising or edge detection and thus cannot be clearly assigned to one of the three groups.

2.2 Weibull Image Statistics

Recent studies have shown that natural image statistics as well as stochastic texture perception can be analysed by using a Weibull distribution. For example, Geusebroek and Smeulders[4,5] found that the gradient magnitude distribution of 54 materials out of 61 (88%) in the Curet collection[20] consistently follow a Weibull distribution. Overall, they report that spatial image statistics change from a power-law to a normal distribution through the Weibull type distribution as the complexity of the scene increases and can therefore be applied to texture analysis. Furthermore, it has been shown that Weibull image statistics yield accurate results for unsupervised image segmentation, image classification, and even for the analysis of visual content.[2,3] A significant study has been conducted by Scholte *et al.*,[1] in which they demonstrate that the distribution of contrast values in natural images generally form a Weibull distribution. More suprisingly, they found that parameters of the Weibull distribution strongly correlate with EEG responses of subjects viewing these images.

Although it seems reasonable to analyse the contrast in image patches by evaluating Weibull statistics, it remains unclear if Weibull statistics yield accurate results for the problem of detecting subtle, miscellaneous defects in texture images. Therefore, we will employ Weibull statistics to image patches and perform novelty detection based on parameters of the Weibull distribution.

In this work, we will use the parametrized Weibull distribution with the following probability density function

$$p(x) = \frac{\beta}{\alpha}\left(\frac{x}{\alpha}\right)^{\beta-1} \mathrm{e}^{-\left(\frac{x-\mu}{\alpha}\right)^{\beta}} \quad , \tag{1}$$

where $x > 0$ is the edge response of a Gaussian derivative filter, μ the origin of the contrast distribution, $\beta > 0$ the shape parameter, and $\alpha > 0$ the scale parameter. The origin μ is usually close to zero for natural images, however, we eliminate this parameter by stretching the contrast to full range. In Fig. 3 the Weibull distributions of different shape and scale parameters are shown. Apparently, the parametrized Weibull distribution captures a variety of different distributions such as power-law or Gaussian.

The Weibull distribution can be used to analyse image contrast by performing a Weibull fit to the distribution of edge responses, *e.g.* obtained by a Gaussian derivative filter. Commonly, the shape and scale parameter are determined by maximum likelihood estimation[21] and used as image features (see Fig. 4).

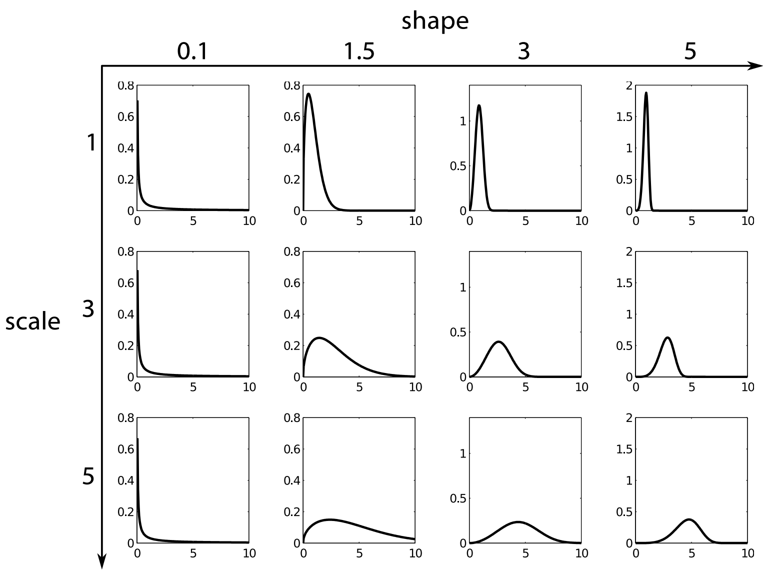


Figure 3. Weibull distributions for different scales and shapes. A distribution similar to the power-law arises for small shape values (less than 1), whereas a Gaussian distribution is approximated by shape values around 3; intermediate shape values yield a typical Weibull type distribution.

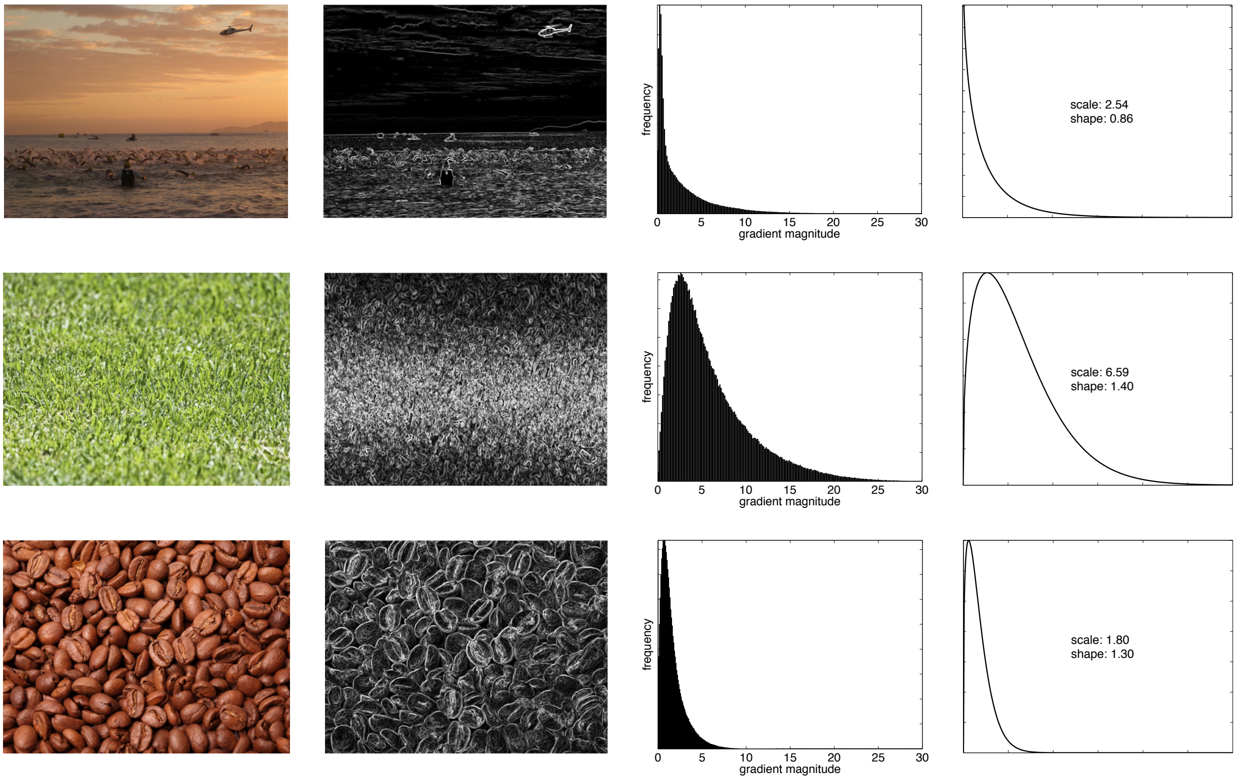


Figure 4. Example of three different natural images (first column) with significantly different visual appearance indicated by their Weibull parameters, shape and scale, respectively. The gradient magnitudes (second column) are used to compute a histogram (third column) from which a Weibull fit is estimated (fourth column). Whereas the gradient magnitude histogram of the first image (swimmer) equals a power-law distribution, the magnitudes of the second (grass) and third image (coffee beans) follows a Weibull distribution. Not only the different visual contents of the first image and the other two images is recovered by significantly different Weibull parameters, but also for the distinction between fine textures (grass) and coarse textures (coffee beans) the Weibull parameters can be used. The Weibull parameters are determined by a maximum likelihood fit to the distribution of gradient magnitudes.

Since texture defects are usually subtle and small, we extract local image patches for which we estimate the Weibull parameters of the distribution of edge responses (see Fig. 5). We apply first-order directional Gaussian derivative filters G_x, G_y to the image I

$$G_1 = \frac{\partial G(x,y)}{\partial x} \quad , \qquad G_2 = \frac{\partial G(x,y)}{\partial y} \quad , \qquad G(x,y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \tag{2}$$

in order to compute the gradient magnitude

$$|\nabla I(x,y)| = \sqrt{[I(x,y) \otimes G_1(x,y)]^2 + [I(x,y) \otimes G_2(x,y)]^2} \ . \tag{3}$$

By estimating the Weibull parameters of the distribution of local gradient magnitudes we obtain samples in the space of the shape and scale parameters, respectively. The basic idea is that within this space samples from defective image regions build clusters, whereas samples originating from defective regions significantly deviate from the background sampels. Hence, a simple novelty detection can be applied to detect defective regions.

2.3 Novelty Detection

Several methods for novelty detection have been proposed such as support vector data description (SVDD),[22,23] one-class MaxMinOver (OMMO),[24] or one-class support vector machine (OC-SVM).[25] Although these methods

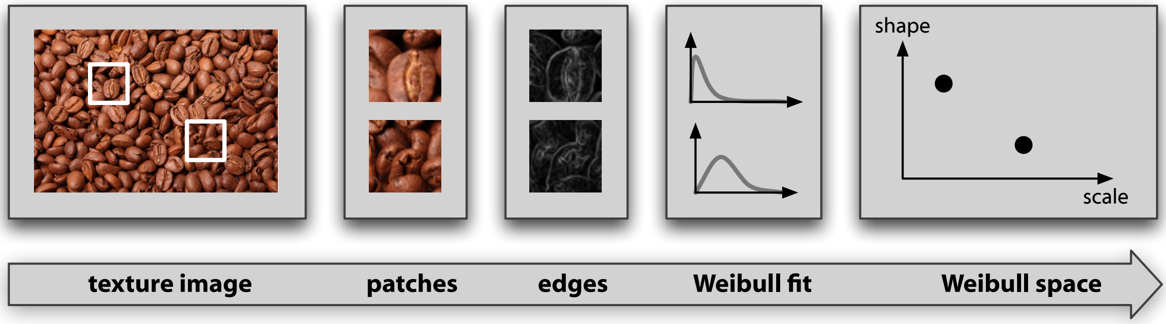


Figure 5. Extraction of local texture characteristics. We first extract local image patches and compute their gradient magnitudes. Then, the distribution of local gradient magnitudes is captured by fitting a Weibull distribution via maximum likelihood estimation. By exploring the space that is determined by the Weibull parameters defective regions can be detected.

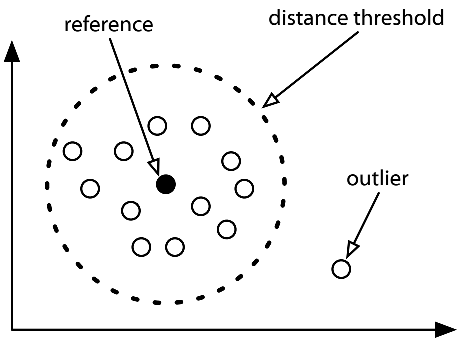


Figure 6. Novelty detection by analysing the distances to a reference point and rejecting samples that have larger distance than a threshold.

yield superior results in several benchmarks, we are interested in a simple model that detects novel samples and can also be applied even if only a single image of the texture class is available. Hence, we are not restricted to a certain class of textures, and we can perform defect detection for each image individually.

A straightforward method for novelty detection involves the computation of a hypersphere and is described as (see Fig. 6):

1. Compute a reference point from all samples such as mean, centre of mass, or median.

2. Determine a threshold for the maximum distance of a defect-free sample to the reference point.

Although this method is very simple, it yields accurate results if the samples are symmetrically distributed around the reference. Furthermore, there is only one free parameter, which can be determined by analysing the variance of defect-free samples or by minimising the classification error if outlier samples are available. For this work, the reference point is represented by the median, since few outliers (defective samples) might have a strong influence on the mean and this would yield poor robustness and stability.

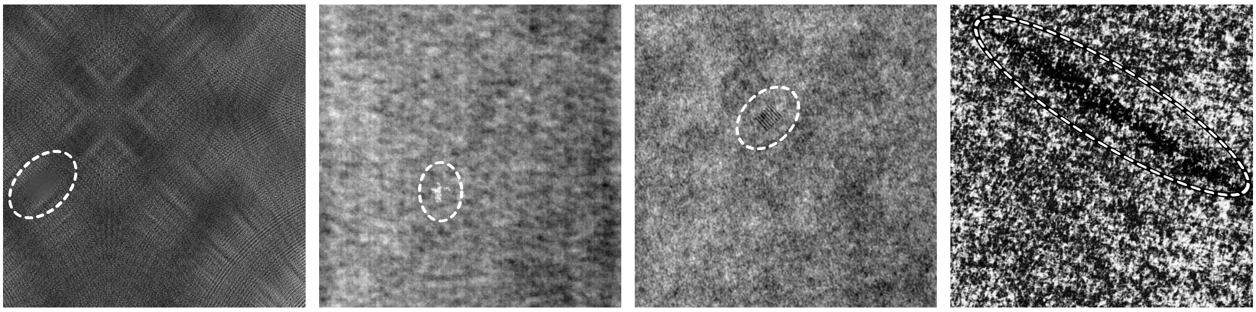


Figure 7. Example images for the classes of textures used for the experiments. Defects are weakly labelled by ellipses and contain also defect-free regions. The four texture classes significantly vary concerning the background texture as well as concerning the defect characteristics. Whereas defects for the first three texture classes are small, the defects of the fourth class have a large extent and cover larger image regions.

3. EXPERIMENTS & RESULTS

For the experiments we will use four classes of texture images provided by Bosch for the DAGM 2007 contest called "Weakly supervised learning for industrial optical inspection"[†]. This contest contains one of the most challenging images concerning defect detection provided so far, which is proven by the fact that only the contest winner provided acceptable results. Unfortunately, explicit information about the winning method as well as detailed result evaluation have not been published. In order to further promote this challenging dataset, we will elaborate our novel method and discuss the results.

The texture classes we use in this work can be described in the following way (see Fig. 7):

Class 1 Defective regions are rather homogeneous with intermediate grey levels and elliptic shape, whereas the defect-free background texture contains high-frequency structures with grey levels of high contrast.

Class 2 Defective regions are bright and with fractal shape, whereas the background contains a speckle pattern of medium size and a global linear gradient with different orientations.

Class 3 Defective regions contain grating-like structures of varying contrast, whereas the background consists of speckle pattern (small size) and globally varying local contrast.

Class 4 Defective regions are dark and with elongated shape, whereas the background contains large speckles with high contrast.

For each texture class the defect size is not constant, but varies to a limited extent. Furthermore, the defects are only weakly labelled by a surrounding ellipse, *i.e.* pixel-wise defect locations are not available and the labelled region also includes defect-free areas. Each texture class consists of 1000 defect-free and 150 defective greyscale images (512×512 pixel).

3.1 Experiment Settings

For the novel texture defect detection approach we have to determine three parameters: size of the local image patches, width of Gaussian derivative filter, and distance threshold for novelty detection. Although the defects are only weakly labelled, we use the defect statistics to automatically set the patch size. Therefore, we compute the minimum minor axis of all defects and round it to the next power of 2 for computational reasons, which yields a patch size of 32×32 pixel for all classes. Furthermore, the overlap of local patches has to be determined in order to avoid border artefacts. Unfortunately, the number of image patches grows exponentially with increasing the overlap, which becomes computationally intractable for real-time applications. For a compromise, we use an overlap of 50% but slight changes of the overlap do not significantly change the results.

[†] http://hci.iwr.uni-heidelberg.de/Benchmarks/gt/detail/?gt_id=2

In order to obtain gradient magnitudes, we apply directional Gaussian derivative filters to the image. The size w and the standard deviation σ of these Gaussian filters are chosen according to the patch size p, where we use the following relationships $w = \text{ceil}(p/11)$ and $\sigma = w/5$. These relationships were experimentally evaluated, but slight changes will yield similar results.

Furthermore, we employ asymmetric costs for classification errors, since a missing defect (false positive) is worse than detecting a defect for a defect-free sample (false negative). According to the terms of the contest, we use the following costs: (i) false positive (ground truth: -1, predicted: +1) are penalised with cost = 20 and (ii) false negative (ground truth: +1, predicted: -1) are penalised with cost = 1.

The novelty detection is performed such that the texture image is classified as defective if the maximum distance to the median (in the Weibull space) of all patches is larger than a threshold, and we optimise this threshold by minimising the total costs. Since our novel defect detection method doesn't involve any kind of learning scheme, we can use all 1150 images of each texture class for estimating the classification error.

3.2 Results & Discussion

We already discussed that Weibull image statistics can be used to classify visual content, but how do they perform for measuring local texture deviations? In Fig. 8 an example image of the first texture class is shown; whereas the Weibull fit of local patches in the defective region yields shape < 1.9 and scale > 17, patches in the defect-free regions have shape > 2 and scale < 14. This indicates that the Weibull features can successfully describe local texture deviations.

In Fig. 9 the distribution of Weibull features of all local patches within a defective image is shown. There, the four patches with maximum distance to the median are detected, and its location within the image is shown. Clearly, the defect-free patches build a single cluster and defective patches can easily be identified as outliers; this holds for all four texture classes. However, if the pattern of the background texture shows large variations, some defect-free patches also have a larger distance to the median (see Fig. 9 first and second column).

We further evaluate also receiver operator characteristics (ROC) for all texture classes in order to demonstrate the performance for different distance thresholds (see Fig. 10 and Tab. 1). Therefore, we compute the equal error rate (EER), which represents the optimised error rate for which positive and negative errors are identically important, and we compute the area under the curve (AUC) of the ROC, which corresponds to the overall performance of the approach independent of a certain threshold. Furthermore, we apply asymmetric weights and optimise the total cost (TC).

For the first texture class we obtain an EER of 8.5%, AUC of 0.96, and a total cost of 190, which indicates that the combination of defect type and background pattern is very challenging – some defects are hard to detect even manually (see Fig. 7). The results for the second and third texture class are almost perfect regarding EER (0.1%, 1.3%) and AUC (0.99 for both) and also the total costs are very low (2, 28). Also for the fourth class our method yields high accuracy (EER 3.2%, AUC 0.99, TC 51). These results prove that our method can successfully deal with different challenging defect types on varying background textures and yield accurate results in detecting defects in texture images.

4. CONCLUSIONS

We propose a novel approach for defect detection in texture images. Our approach evaluates the distribution of local gradient magnitudes based on a Weibull fit. The two Weibull parameters are used to perform a simple novelty detection. Therefore, we compute the median of all samples in the Weibull space and reject an image of the maximum distance to the median is larger than a threshold.

We exhaustively evaluate the performance of our novel method on the very challenging dataset provided by the DAGM 2007 contest. Our method yields accurate results for all texture classes, whereas two classes are classified with an equal error rate of less than 1.3%. Due to large variances of the background pattern within each texture class and the subtle defects our novel method proves to be robust and yields high accuracy. Therefore, our approach successfully deals with complex textures and detects even slight deviations. Note that our novel method does not involve any sophisticated learning algorithms and hence there is no need for training and exhaustive parameter optimisation. Moreover, due to its efficiency our approach can even be applied to real-time applications.

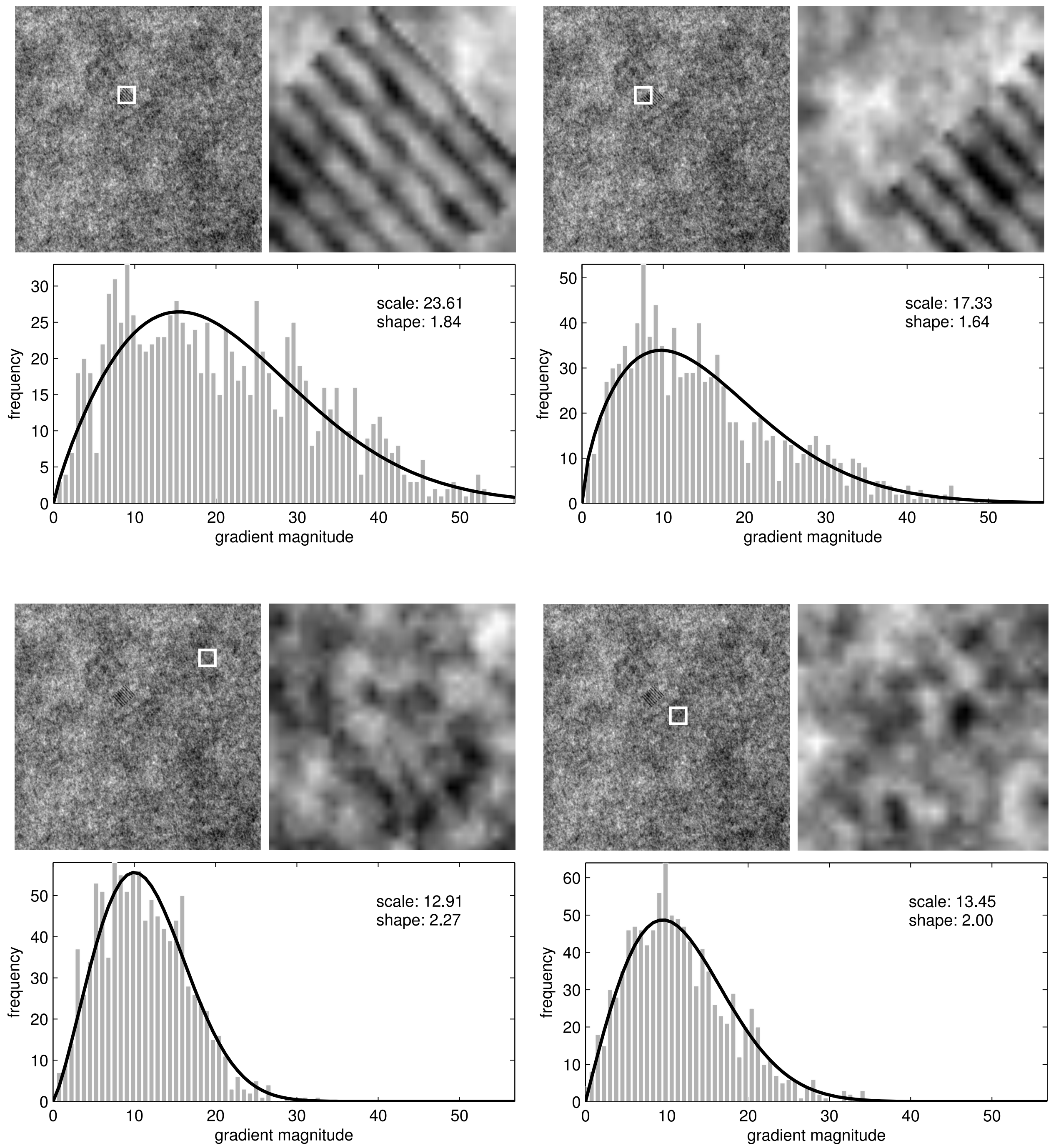


Figure 8. Example image of the first texture class containing a (grating) defect. The first and second row show two local patches at the defective region and their Weibull fit to the distribution of gradient magnitudes. The third and fourth row depict two defect-free patches and the corresponding Weibull fit. Obviously, the distributions of gradient magnitudes for defective and defect-free patches differ and hence the Weibull features shape and scale yield significantly different values.

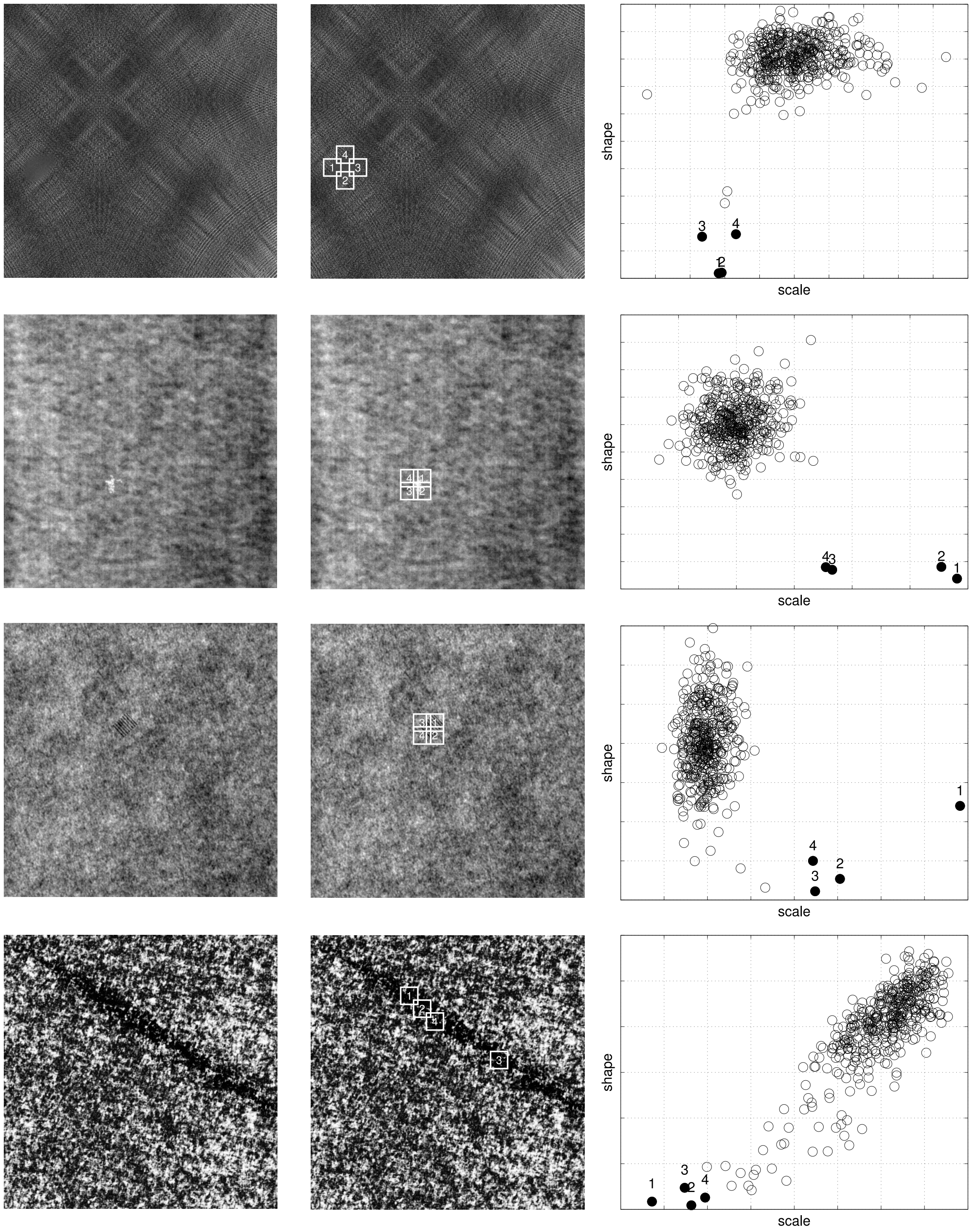
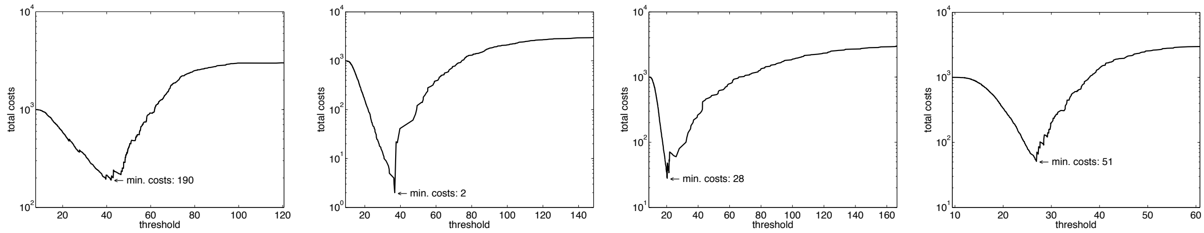


Figure 9. Demonstrating the usefulness of local Weibull parameters for defect detection. For each texture class one example defective image is shown (first column) – see Fig. 7 for defect description and defect location. The distribution of Weibull features for all local patches (third column) forms a cluster such that outliers can be identified easily by analysing the distance to the median. The four samples with maximum distance to the median are depicted in the Weibull space (third column) as well as their corresponding location in the image (second column).



(a) class 1 (b) class 2 (c) class 3 (d) class 4

Figure 10. Total costs for varied distance thresholds of each texture class. For the best thresholds the total costs are between 2 and 190, which means that 2 out of 1000 defect-free images are classified incorrectly in the case of class 2.

class no.	EER	AUC	TC	FP	FN	FN*
1	8.5%	0.96	190	3	130	47.0%
2	0.1%	0.99	2	0	2	0.2%
3	1.3%	0.99	28	0	28	2.8%
4	3.2%	0.99	51	0	51	5.1%

Table 1. Performance evaluation of the novel defect detection approach applied to four texture classes. Based on the receiver operator characteristic the equal error rate (EER) corresponds to the error rate when positive and negative samples are weighted identically, whereas the area under curve (AUC) captures the overall performance for every possible class weighting. By optimising the distance threshold such that the sum of false positives (FP) and false negatives (FN) reaches its minimum, we retrieve the total costs (TC). Note that for optimising total costs asymmetric weights have been applied here, false negatives count 1 and false positives count 20. The false negative rate (FN*) at 100% true negative rate indicates the amount of defect-free images where a defect has been detected, while every defective image has been correctly classified.

REFERENCES

[1] Scholte, H., Ghebreab, S., Waldorp, L., Smeulders, A., and Lamme, V., "Brain responses strongly correlate with weibull image statistics when processing natural images," *Journal of Vision* **9**(4), 1–15 (2009).

[2] Yanulevskaya, V. and Geusebroek, J., "Significance of the weibull distribution and its sub-models in natural image statistics," in [*Proceedings of the Fourth International Conference on Computer Vision Theory and Applications (VISAPP)*], **1**, 355–362, INSTICC Press (2009).

[3] Ayed, I., Hennane, N., and Mitiche, A., "Unsupervised variational image segmentation/classification using a weibull observation model," *IEEE Transactions on Image Processing* **15**(11), 3431–3439 (2006).

[4] Geusebroek, J. and Smeulders, A., "A six-stimulus theory for stochastic texture," *International Journal of Computer Vision* **62**(1), 7–16 (2005).

[5] Geusebroek, J. and Smeulders, A., "Fragmentation in the vision of scenes," in [*Proceedings of the Ninth IEEE International Conference on Computer Vision*], 130–135, IEEE Computer Society (2003).

[6] Xie, X., "A review of recent advances in surface defect detection using texture analysis techniques," *Electronic Letters on Computer Vision and Image Analysis* **7**(3), 1–22 (2008).

[7] Kumar, A., "Computer-vision-based fabric defect detection: A survey," *IEEE Transactions on Industrial Electronics* **55**(1), 348–363 (2008).

[8] Ng, H., "Automatic thresholding for defect detection," *Pattern Recognition Letters* **27**(14), 1644–1649 (2006).

[9] Kim, C. and Koivo, A., "Hierarchical classification of surface defects on dusty wood boards," *Pattern Recognition Letters* **15**(7), 713–721 (1994).

[10] Swain, M. and Ballard, D., "Color indexing," *International Journal of Computer Vision* **7**(1), 11–32 (1991).

[11] Haralick, R., Shanmugam, K., and Dinstein, I., "Textural features for image classification," *IEEE Transactions on systems, man and cybernetics* **3**(6), 610–621 (1973).

[12] Siew, L., Hodgson, R., and Wood, E., "Texture measures for carpet wear assessment," *IEEE Transactions on Pattern Analysis and Machine Intelligence* **10**(1), 92–105 (1988).

[13] Conners, R., McMillin, C., Lin, K., and Vasquez-Espinosa, R., "Identifying and locating surface defects in wood: Part of an automated lumber processing system," *IEEE Transactions on Pattern Analysis and Machine Intelligence* **5**(6), 573–583 (1983).

[14] Ojala, T., Pietikäinen, M., and Harwood, D., "A comparative study of texture measures with classification based on featured distributions," *Pattern Recognition* **29**(1), 51–59 (1996).

[15] Ojala, T., Pietikäinen, M., and Mäenpää, T., "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," *IEEE Transactions on Pattern Analysis and Machine Intelligence* **24**(7), 971–987 (2002).

[16] Bodnarova, A., Bennamoun, M., and Latham, S., "Optimal gabor filters for textile flaw detection," *Pattern Recognition* **35**(12), 2973–2991 (2002).

[17] Bovik, A., Clark, M., and Geisler, W., "Multichannel texture analysis using localized spatial filters," *IEEE Transactions on Pattern Analysis and Machine Intelligence* **12**(1), 55–73 (1990).

[18] Ade, F., "Characterization of textures by Eigenfilters," *Signal Processing* **5**(5), 451–457 (1983).

[19] Cross, G. and Jain, A., "Markov random field texture models.," *IEEE Transactions on Pattern Analysis and Machine Intelligence* **5**(1), 25–39 (1983).

[20] Dana, K., Van Ginneken, B., Nayar, S., and Koenderink, J., "Reflectance and texture of real-world surfaces," *ACM Transactions on Graphics (TOG)* **18**(1), 1–34 (1999).

[21] Gove, J., "Moment and maximum likelihood estimators for weibull distributions under length-and area-biased sampling," *Environmental and Ecological Statistics* **10**(4), 455–467 (2003).

[22] Tax, D. M. J. and Duin, R. P. W., "Support vector domain description," *Pattern Recognition Letters* **20**(11-13), 1191–1199 (1999).

[23] Tax, D. M. J. and Duin, R. P. W., "Support vector data description," *Machine Learning* **54**(1), 45–66 (2004).

[24] Labusch, K., Timm, F., and Martinetz, T., "Simple incremental one-class support vector classification," in [*Proceedings of the 30th DAGM-Symposium on Pattern Recognition*], Rigoll, G., ed., *Lecture Notes in Computer Science* **5096**, 21–30, Springer (2008).

[25] Schölkopf, B., Platt, J., Shawe-Taylor, J., Smola, A., and Williamson, R., "Estimating the support of a high-dimensional distribution," *Neural Computation* **13**(7), 1443–1471 (2001).