An Adaptive Two-Stage Approach to Classification of Surface Defects

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Abstract

An adaptive two-stage approach is proposed for the classification of surface defects. In the segmentation phase feature extraction is done and potential defect areas are marked. In the classification phase features describing the shape and internal structure of defects are extracted and defects are classified to different defect classes. The proposed segmentation scheme is taught with examples of faulty-free surface, and the classification scheme with examples of defects. The use of the Self-Organizing Map in segmentation phase makes the proposed method adaptable to different types of surfaces. The results of experiments with base paper samples are encouraging.

1 Introduction

Surface inspection is important in many maintenance tasks but also in many industrial production processes. There are industrial applications from timber grading to machine part inspection. The problem can be divided into two parts, surface classification and fault detection. Both fields have been subjects of active research since the late 1970's [2, 3]. The methods have usually been based on some simple features, as gray values or colours, and on a thresholding logic.

Recently, neural network methods have become popular due to their capability to adapt to new circumstances in an unsupervised way. Some of the methods have been based on a simple one-layer neural network, for example the Self-Organizing Map (SOM) [9]. Visa [16] developed a surface classification method based on a SOM, a Learning Vector Quantization [9], and a long feature vector consisting of texture measures. The same idea was extended to a textured image segmentation by Visa [17]. Later on Yläkoski and Visa developed the method further for timber classification [18].

Self-Organizing Map is also a potential method to process monitoring. Kasslin et al. used a SOM to monitor the state of a electrical device [8]. Alander et al. [1] used a SOM to monitor a coffee maker and Tryba [14] to control a process in chemistry. Vapola et al. used a similar approach but two layers of SOM to monitor an anesthesia system [15].

The most demanding surface inspection problems contain the subproblems: fault detection, fault classification, and process control. These problems can be solved only under certain circumstances. For instance, for running web processes there exist commercial solutions [10, 13, 4]. The proposed approach is aimed at that demanding problem. However, the process control part is not discussed.

2 Overview of the Proposed Method

A two-stage approach is proposed for the classification of surface defects (Figure 1). In the segmentation phase feature extraction is done and potential defect areas are marked. In the classification phase features describing the shape and internal structure of defects are extracted and defects are classified to different defect classes.

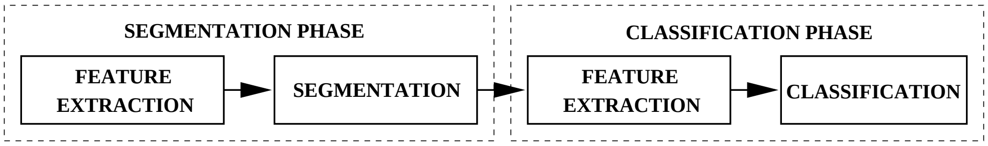


Figure 1: The proposed method consists of two phases.

2.1 Segmentation Phase

Feature Extraction Images of many surfaces can be considered as stochastic textures, hence the co-occurrence matrices [5], also known as the spatial gray level dependence matrices, are used for the texture description. The co-occurrence matrix can be reduced to a set of features to make calculation time and memory requirements smaller [5]. The co-occurrence matrices are calculated locally within a small window that glides across the image. The size of the window should be small so that the lowpass filtering effect due to masking remains tolerable, but it should also be large enough so that the extracted information has statistical significance.

Segmentation The Self-Organizing Map [9] is used to estimate the distribution of features extracted from faulty-free samples. Fault detection is based on the following idea: an unknown sample is classified to a defect if it differs enough from this estimated distribution. What difference is enough is determined by a threshold that is given manually. However, the determination of the threshold is easy. It depends on features and on the desired accuracy of the segmentation. It takes integer values $[0, N]$ (where N is the length of a feature vector). For the complete description of the proposed segmentation scheme see [7].

2.2 Classification Phase

Feature Extraction After the segmentation a binary image is obtained. The obtained defects are characterized by a set of features based on both the original image and the segmented image. Features are selected according to their ability to describe the shape and the internal structure of a defect.

Five shape descriptors are used to characterize the shape of a defect. The descriptors are: convexity, principal axis ratio, compactness, circular variance, and elliptic variance. They are translation, rotation, and scale invariant shape descriptors. Properties of each shape descriptor are discussed and the discriminatory power of their combination is demonstrated in [12]. The internal structure of a defect can be thought as a distribution of gray levels in a defect. This distribution can be characterized as a gray-level histogram,

$$p(i) = \frac{n_i}{n}, \quad i = 0, 1, ..., N-1, \tag{1}$$

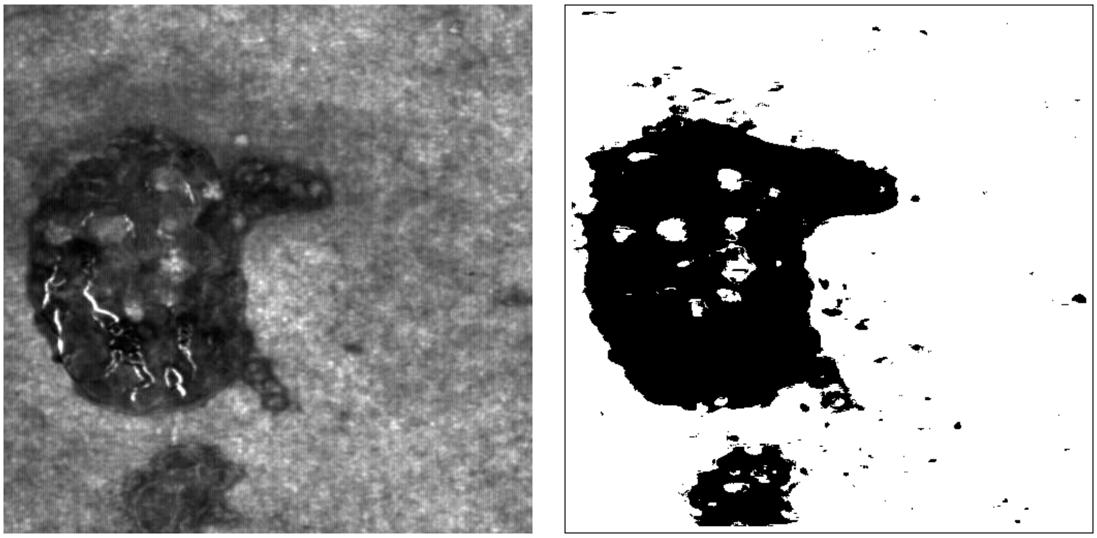
where n_i is the number of pixels having gray level value i in a defect, n is the total number of pixels in a defect, and N is the total number of gray levels.

Classification Classification of defects may be hard even to an expert. There exists several defect classes that overlap in some extent. A covering collection of different defects is also needed to teach the classifier. However, it is hard and time-consuming to collect defects. To get started with few defects and with few defect classes a codebook-based approach is chosen. Separate codebooks are generated for the shapes and for the internal structures. A new defect is then compared with the shape codebook and with the internal structure codebook. If the distance between the best-matching codebook vector and the feature vector of a new defect is small enough then the match is found. When the match is found in both codebooks the classification can be made by combining labels of the best-matching codebook vectors. If the match is found only in another codebook then the classification is not complete. A defect is given a label (i.e., classification) by hand and it is added to the codebook. If the match is not found in neither of the codebooks, then a defect is given two labels (one for the shape and one for the internal structure) and it is added to both codebooks.

In the proposed scheme a defect is classified separately based on its shape and internal structure which simplifies the labeling and the classification. It also allows a new defect to be easily added to the codebooks. However, the size of the codebooks grows linearly with the defect count. This can be avoided by some clustering technique, for example the K-means or the Learning Vector Quantization (LVQ) algorithm [9].

3 Experiments

The proposed classification scheme is demonstrated by samples of base paper. There exist many different kinds of defects, for example holes (clean hole, wire hole etc.), spots (slime spot, light spot, water spot etc.), wrinkles, and streaks. An uneven formation of paper makes the classification more difficult.

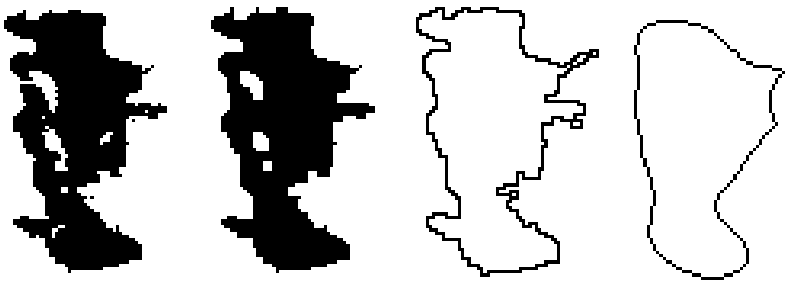


(a) (b)

Figure 2: (a) A base paper image and (b) the segmented image. Defects are marked with black color.

A base paper image is depicted in Figure 2(a). Its size is 512x512 and it is quantized to 32 gray levels. Three features, Energy, Contrast, and Mean, are calculated from two co-occurrence matrices formed at two different displacements, making a total of six features. The different displacements are used to avoid the problem concerning improper spatial resolution [16]. Figure 2(b) shows the segmentation result with the proposed method. Defects are marked with black color.

The segmented image may contain many defects which must be extracted, pre-processed, and classified. In Figure 3(a) is a segmented defect. The basic morphological operations [6], erosion and dilation, are used in processing the defect. To fill up small holes and gulfs in the defect a morphological closing operation (dilation followed by erosion) is applied to the defect (Figure 3(b)). The contour of the defect in Figure 3(c) is obtained by subtracting the closed defect from the dilated defect. Thus the obtained contour is larger than the true contour. Finally the contour is smoothed with the Gaussian filter [11] (Figure 3(d)). This is quite necessary because some of the proposed shape descriptors are sensitive to noise.

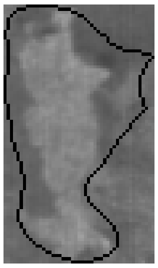


(a) (b) (c) (d)

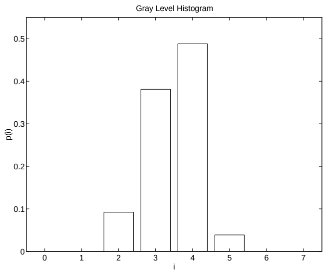
Figure 3: (a) The segmented defect, (b) the defect after closing, (c) the contour of the defect, and (d) the Gaussian smoothed contour of the defect.

The shape features and the internal structure features are then calculated to a defect. An example defect and its features are depicted in Figure 4. The gray levels are requantized to 3 bits. In Figure 5 are the classification results. Figure 5(a) shows the best matching codebook defect when using the five shape descriptors and Figure

5(c) shows the best matching codebook defect when using the Gray Level Histogram. In both cases a very similar defect is retrieved. In Figure 6 are two other examples. First defect is a 'fish-shaped' defect with a dark spot, and the other defect is a big hole with some dark areas around it. The obtained responses from both codebooks seem to be very good. The codebook size was 78.

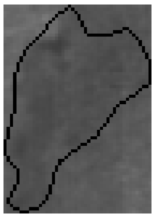


Convexity	0.9035
PC ratio	0.5812
Compactness	0.7287
Circular variance	0.0816
Elliptic variance	0.0371

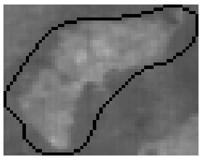


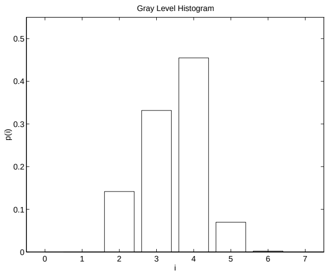
(a) (b) (c)

Figure 4: (a) A defect, (b) the shape descriptors, and (c) the Gray Level Histogram of a defect.



Convexity	0.9128
PC ratio	0.5782
Compactness	0.7325
Circular variance	0.0694
Elliptic variance	0.0316





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

Figure 5: The best matching defects to the defect in Figure 4(a) with respect to (a)-(b) shape and to (c)-(d) internal structure (the Gray Level Histogram).

4 Discussion and Conclusion

The two-stage approach offers advantages when considering real-time processes. Speed requirements of real-time defect detection and classification can be satisfied by splitting the needed procedure into two stages. The defect detection is a suitable part to hardware implementation. It is computing intensive. However, the adaptation is simple and concerns only the codebook vectors. More time can be spend on classifying found defects, because it can be assumed that defects are rare.

The adaptive nature of both the segmentation and classification schemes makes it possible to adapt the proposed method to work with different types of surfaces. The proposed segmentation scheme is taught with examples of faulty-free surface. It may be necessary to reselect features to take into account the specific properties of the surface type. The proposed classification scheme is taught with examples of defects. Shape and internal structure characteristics of defects are learned from examples. It is desirable to have a lot of teaching data available. However, it is usually hard to collect a covering collection of different defects. To alleviate this problem the proposed classification scheme allows new, previously unknown, defects to be added to the codebook gradually during a long period.

The results of experiments with base paper samples are encouraging. The evaluation of the proposed method with more data and the refinement of the defect classification scheme are the main objectives for the future work.

Acknowledgment

The authors wish to thank the Technology Development Centre of Finland for financial support (TEKES's grant 4172/95).

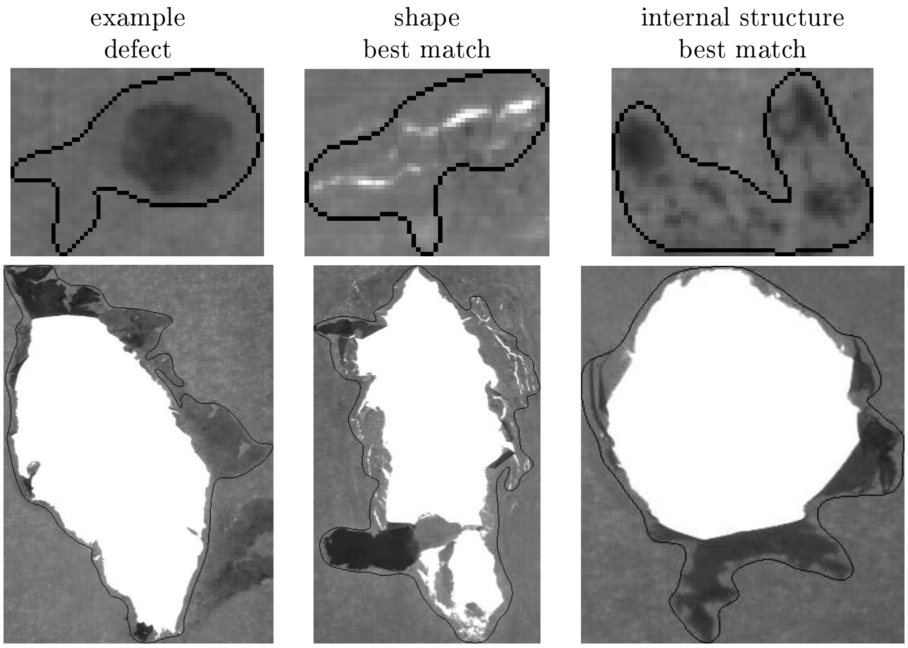


Figure 6: Two example defects (1st column) and the best matching defects with respect to shape (2nd column) and to internal structure (3rd column).

References

[1] J. T. Alander, M. Frisk, and L. Holmström. Process Error Detection Using Self-Organizing Feature Maps. In T. Kohonen, K. Mäkisara, O. Simula, and J. Kangas, editors, *Artificial Neural Networks*, volume 2, pages 1229–1232. North-Holland, 1991.

[2] M. Borghesi, V. Cantoni, and M. Diani. An Industrial Application of Texture Analysis. In *7th International Conference in Pattern Recognition*, pages 420–423, Montreal, Canada, July 30 - August 2 1984.

[3] R. W. Conners, C. W. Mcmillan, and R. E. Vasuez-Espinosa. Identifying and Locating Surface Defects in Wood: Part of an Automated Lumber Processing System. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, PAMI-5(6):573–583, November 1983.

[4] J. E. Graf, S. T. Enright, and S. I. Shapiro. Automated web inspection ensures highest quality nonwovens,. *Tappi Journal*, 78(9):135–138, 1995.

[5] R. Haralick, K. Shanmugam, and I. Dinstein. Textual Features for Image Classification. *IEEE Transactions on Systems, Man, and Cybernetics*, SMC-3(6):610–621, November 1973.

[6] R. M. Haralick, S. R. Sternberg, and X. Zhuang. Image analysis using mathematical morphology. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, PAMI-9(4):532–550, July 1987.

[7] J. Iivarinen, J. Rauhamaa, and A. Visa. Unsupervised segmentation of surface defects. In *13th International Conference on Pattern Recognition*, volume IV, pages 356–360, Wien, Austria, August 25-30 1996.

[8] M. Kasslin, J. Kangas, and O. Simula. Process State Monitoring Using Self-Organizing Maps. In I. Aleksander and J. Taylor, editors, *Artificial Neural Networks, 2*, volume 2, pages 1531–1534. North-Holland, 1992.

[9] T. Kohonen. *Self-Organizing Maps*. Springer-Verlag, Berlin, 1995.

[10] L. Mäkelin, J. Moisio, and J. Järvinen. From hole detection to image processing and information technology. In *Proceedings of 50th Appita Annual General Conference*, volume 1, pages 817–822. The Technical Association of the Australian and New Zealand Pulp and Paper Industry Inc., 1996.

[11] F. Mokhtarian and A. Mackworth. Scale-based description and recognition of planar curves and two-dimensional shapes. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, PAMI-8(1):34–43, January 1986.

[12] M. Peura and J. Iivarinen. Efficiency of simple shape descriptors. In *3rd International Workshop on Visual Form*, Capri, Italy, May 28-30 1997.

[13] H. Ruuska and I. Akerberg. Practical inspection systems for nonwoven diaper linerfabrics. *Tappi Journal*, 78(9):135–138, 1995.

[14] V. Tryba and K. Goser. Self-Organizing Feature Maps for Process Control in Chemistry. In T. Kohonen, K. Mäkisara, O. Simula, and J. Kangas, editors, *Artificial Neural Networks*, volume 1, pages 847–852. North-Holland, 1991.

[15] M. Vapola, O. Simula, T. Kohonen, and P. Meriläinen. Representation and Identification of Fault Conditions of an Anaesthesia System by Means of the Self-Organizing Map. In *Proceedings of the International Conference on Artificial Neural Networks*, volume 1, pages 350–353, Sorrento, Italy, May 26-29 1994.

[16] A. Visa. Identification of Stochastic Textures with Multiresolution Features and Self-Organizing Maps. In *Proceedings of 10th International Conference on Pattern Recognition*, pages 518–522, Atlantic City, New Jersey, USA, June 16-21 1990.

[17] A. Visa. Unsupervised Image Segmentation Based on a Self-organizing Feature Map and a Texture Measure. In *Proceedings of 11th IAPR International Conference on Pattern Recognition*, volume III, pages 101–104, The Hague, The Netherlands, August 30 - September 3 1992.

[18] I. Yläkoski and A. Visa. A Two-Stage Classifier for Wood Boards. In *Proceedings of The 8th Scandinavian Conference on Image Analysis*, pages 637–641, Tromsoe, Norway, May 25-28 1993.