Unsupervised Segmentation of Surface Defects

Jukka Iivarinen[1], Juhani Rauhamaa[2], and Ari Visa[1]
[1]Helsinki University of Technology
Laboratory of Computer and Information Science
Rakentajanaukio 2 C, FIN-02150 Espoo, Finland
E-mail: `Jukka.Iivarinen@hut.fi, Ari.Visa@hut.fi`

[2]ABB Industry Oy
Pulp & Paper Division
P.O. Box 94, FIN-00381 Helsinki, Finland
E-mail: `Juhani.Rauhamaa@fidri.abb.fi`

Abstract

A segmentation scheme to detect surface defects is proposed. An unsupervised neural network, the Self-Organizing Map, is used to estimate the distribution of faulty-free samples. An unknown sample is classified as a defect if it differs enough from this estimated distribution. A new scheme for determining this difference is suggested. The scheme makes use of the Voronoi set of each map unit and defines a new rule for finding the best-matching map unit. The proposed scheme is general in the sense that it can be applied to fault detection of different types of surfaces.

1. Introduction

Surface inspection is important in many industrial production processes. There are applications from timber grading to machine part inspection. The problem can be divided into two independent parts, surface classification and fault detection. Both fields have been subjects of active research since the late 1970's [2, 4, 10]. 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. The reason has been the possibility to use more realistic decision surfaces by neural networks. However, some of the methods have been based on a simple one-layer neural network, the Self-Organizing Map (SOM) [9]. Visa [14], for instance, 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 [15]. Later on Yläkoski and Visa developed the method further for timber classification [17]. The extension of the method consisted of a grammar that described the quality of a surface by the means of defects. SOM has not been a popular method in fault detection, but there are some attempts. Kasslin et al. used a SOM to monitor the state of a electrical device [8]. The sequence of the states of the device, a trace, was visualized on the SOM. The deviations from the ordinary trace were interpreted as faults. Alander et al. [1] and Tryba and Goser [12] used a SOM to monitor a coffee maker to control a process in chemistry. Vapola et al. used a similar approach but two layers of SOM to monitor an anaesthesia system [13].

In this paper the mentioned ideas will be extended to a special case of image segmentation, fault detection. In section two it will be described how to separate the faults from the background. Some results are demonstrated and compared with a thresholding method in section three. The limitations of the suggested method are discussed in section four.

2. The proposed segmentation scheme

The Self-Organizing Map is used to estimate the distribution of features extracted from faulty-free samples. Fault detection is now based on the following idea: an unknown sample is classified as a defect if it differs enough from this estimated distribution. The scheme consist of three different phases, the training phase, the threshold determination phase, and the segmentation phase.

2.1. Segmentation

The segmentation phase can be stated as follows:

1. Extract a feature vector $\mathbf{f}$ for an image pixel.
2. Feed $\mathbf{f}$ into SOM and find the best-matching unit c (Eq. 1 and 2). Show the minimum error e_c as the output.
3. If e_c is larger than the specified limit T, the pixel is classified to a defect.
4. Repeat steps 1-3 for each image pixel.

The limit T is determined by hand, and it depends on features and on the desired accuracy of the segmentation. The segmentation scheme is depicted in Figure 1.

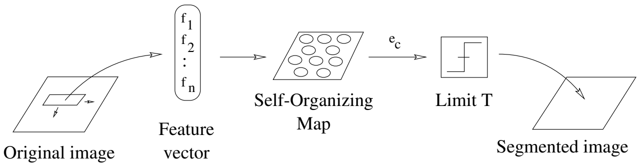


Figure 1. The proposed segmentation scheme.

The matching error e_i for the feature vector $\mathbf{f}(t)$ and the map unit i is defined similarly to the Hamming distance as

$$e_i = \sum_{j=1}^{n} e_{i,j}, \text{ where } e_{i,j} = \begin{cases} 1 \text{ if } (f_j(t) - m'_{i,j})^2 > th_{i,j} \\ 0 \text{ else} \end{cases} \quad (1)$$

$m'_{i,j}$ is defined in Eq. 4 and $th_{i,j}$ in Eq. 6. The best-matching unit c is now chosen to be the unit with the minimum error e_c,

$$e_c = \min_i \{e_i\} \quad (2)$$

If there are several map units with the same minimum error e_c, the one with the minimum Euclidean distance with the feature vector $\mathbf{f}(t)$ is chosen.

2.2. Texture features

Images of many surfaces can be considered as stochastic textures, hence the co-occurrence matrices [6], also known as the spatial gray level dependence matrices, are used for the texture description. The co-occurrence matrix method has been found to be good in classifying stochastic textures [16, 3]. The co-occurrence matrix $M_d(i, j)$ is a second order statistical measure of gray level variation. It indicates the joint probability of gray level occurrence at a certain displacement in an image.

The co-occurrence matrix can be reduced to make calculation time and memory requirements smaller. One approach is to concatenate the rows and columns into two vectors. Another approach is to calculate a set of features [6].

The co-occurrence matrices are calculated locally within a small window that glides across the image. The window size is also a compromise. The size of the window should be small 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.

2.3. Map training

To train the Self-Organizing Map a set of feature vectors $F = \{\mathbf{f}(t) \mid \mathbf{f}(t) = [f_1(t)...f_n(t)]^T,\ t = 0, ..., N-1\}$ is extracted from faulty-free samples. The weight vectors of the map units are initialized to random values evenly distributed in the area of training vector components. The training of the map is done by feeding the training vectors to the map, finding the best-matching unit for each training vector and updating the weight vectors of the best-matching unit and its neighbors [9]. The training set is fed into the map several times. As a result we have a map which has learned an estimate of the distribution of faulty-free samples.

2.4. Threshold determination

In the threshold determination phase each vector component j of each map unit i is assigned a threshold value $th_{i,j}$. All thresholds are determined automatically by the following procedure.

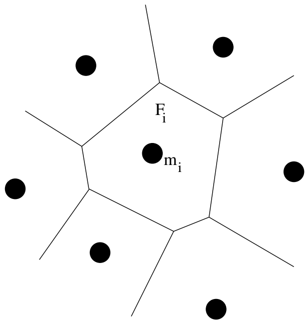


Figure 2. The Voronoi set F_i of the map unit i (in a two-dimensional case).

For each map unit i the set F_i is defined to include only those input vectors $\mathbf{f}(t)$ for which the unit i is the best-matching unit, i.e, the set F_i consists of those input vectors $\mathbf{f}(t)$ which belong to the Voronoi set of the unit i (Figure 2),

$$F_i = \{\mathbf{f}(t) \mid i = \arg\min_k \{\|\mathbf{f}(t) - \mathbf{m}_k\|\}\}, \quad (3)$$

where $\mathbf{m}_k$ is a weight vector of the map unit k. If a uniform distribution is assumed for $f_j(t)$, the jth component of $\mathbf{f}(t) \in F_i$, the mean of the $f_j(t)$ is given by

$$m'_{i,j} = \frac{\min\{f_j(t)\} + \max\{f_j(t)\}}{2}, \ \forall\, \mathbf{f}(t) \in F_i. \quad (4)$$

The confidence interval for $f_j(t)$ is now defined as

$$m'_{i,j} - \frac{d'_{i,j}}{2} < f_j(t) < m'_{i,j} + \frac{d'_{i,j}}{2}, \ \forall\, \mathbf{f}(t) \in F_i, \quad (5)$$

where $d'_{i,j} = d(\max\{f_j(t)\} - \min\{f_j(t)\}), \ \forall\, \mathbf{f}(t) \in F_i$, and d is the confidence level.

We can now define the thresholds $th_{i,j}$ as

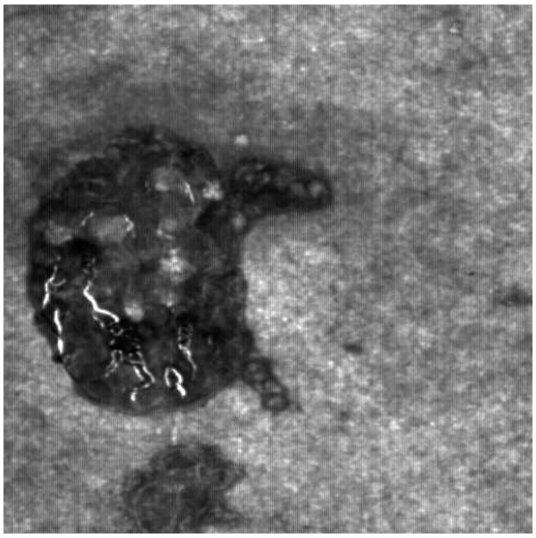
$$th_{i,j} = (\frac{d'_{i,j}}{2})^2 \quad (6)$$

3. Experiments

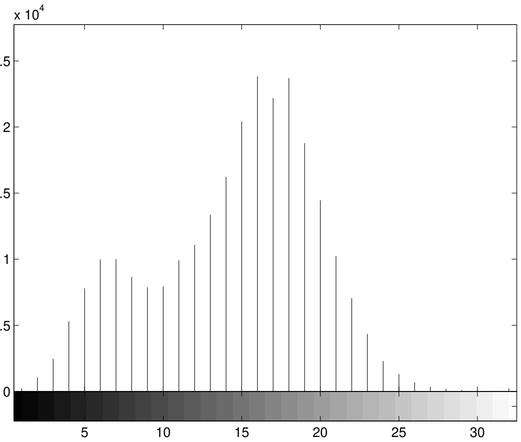
The proposed method is demonstrated by samples of base paper. Finding defects on a base paper is not an easy task. There exist many different kinds of defects, for example holes (clean hole, wire hole etc.), spots (dirt spot, light spot, water spot etc.), wrinkles, and streaks. An uneven formation of paper makes the task more difficult. Defects in base paper may cause the paper web to break when coating material is applied to paper by a coating blade. Web breaks mean losing of production time. Therefore, those defects which are risks to runnability of paper, should be detected and classified reliably. The detection principle of contemporary surface inspection systems is mostly based on classifying defects in holes and spots, and measuring their sizes. The proposed method makes it possible to extract features which also describe the internal structure of defects. This kind of classifying could be useful also for inspection of other web products, e.g. board, nonwoven, and glassfiber.

The size of the base paper images was 512x512 and they were quantized to 32 gray levels (Figure 3). The feature vector consisted of 6 features, namely Energy, Contrast, and Mean, which are calculated from two co-occurrence matrices formed at different displacements, $(2, 0)$ and $(4, 0)$. The different displacements were used to avoid the problem concerning improper spatial resolution [14]. The window size used was 15x5. The size of the map was 9x9 units. The size of the training set was 100000 feature vectors extracted from faulty-free samples. The confidence level d was 99%.

In Figures 4(a)-(b) are the segmentation results with the proposed method with different values of T. Defects are marked with black color. The best result is obtained when using $T = 1$. If a complete match is demanded for a faulty-free sample ($T = 0$), a noisy segmentation is obtained. In Figures 4(c)-(d) are the segmentation results when using gray level thresholding. In Figure 4(c) an iterative optimal threshold algorithm was used [11](pages 118-119). The obtained threshold value was $G = 12$. In Figure 4(d) the threshold was selected by hand according to the histogram in Figure 3(b) ($G = 9$). The pixels having gray level value 32 were also classified to a defect in Figures 4(c)-(d). However, even if the thresholded image is quite good, thresholding is not a very applicable technique in this kind of problem. For discussion of different thresholding techniques and their restrictions, see for example [7], pages 14-28.



(a)



(b)

Figure 3. (a) Base paper image and (b) its histogram.

4. Discussion

The idea of using the Self-Organizing Map to estimate the distribution of faulty-free samples and then to classify an unknown sample as a defect if it differs enough from this

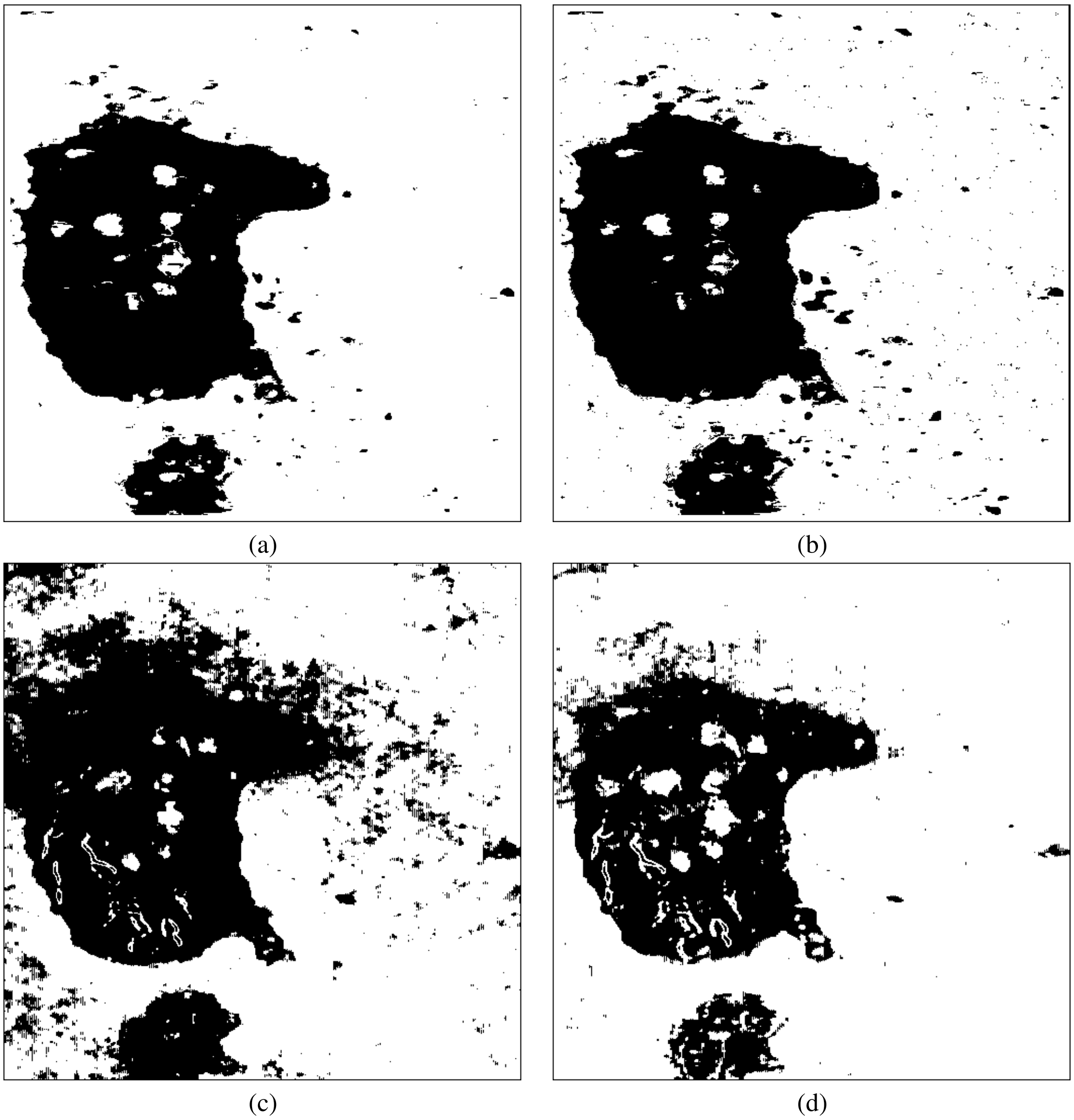


Figure 4. Base paper image after segmentation. Defects are marked with black color. (a) The proposed method ($T = 1$). (b) The proposed method ($T = 0$). (c) Gray level thresholding by an iterative algorithm ($G = 12$). (d) Gray level thresholding by hand ($G = 9$).

estimated distribution, is not a new one [1]. The remaining question has been how much an unknown sample can differ from the best-matching unit of the map before it is classified as a defect. One solution is to determine a threshold value for the distance between a feature vector of the unknown sample and the best-matching map unit. It is not, however, easy to choose such a threshold value, and in fact a common threshold value for all map units may not be enough. Instead, a distinct threshold value for each map unit would be necessary.

The proposed method overcomes the threshold selection problem. It makes use of the Voronoi set of each map unit and defines a new rule for finding the best-matching map unit. For each component plane j of the Voronoi set F_i a confidence interval is defined. When assuming a uniform distribution for a component plane j, which is actually the best possible assumption that can be made, the definition of the confidence interval is straightforward. However, these distributions are not necessary uniform. For example the Parzen estimation procedure could be used to estimate these distributions if more accuracy were needed. Forming the Voronoi tesselation of the feature space with other estimator than the Self-Organizing Map could also be possible. For a recent review of different estimators, see for example [5].

There are two parameters in the proposed scheme that must be given by hand, namely the confidence level d and the limit T. The confidence level d should be near 100% so that the mean of the minimum error e_c would be zero (for faulty-free samples). The determination of the limit T is quite straightforward. First of all, the T is an integer and it takes values between zero and n (n is the dimension of feature vector). Secondly, the value of T depends on the desired accuracy of the segmentation. For large values of T noise is eliminated and only the most evident (or easily detectable) defects are found. On the other hand, for small values of T noise is increased but also the weak (or difficult) defects are found. So the value of T is a compromise between accuracy and noise.

The results of experiments with base paper samples are encouraging. When compared with simple threshold segmentation based on gray level histograms, the proposed scheme has obvious advantages. The method is also general in the sense that it can be applied to fault detection of different types of surfaces. However, it may be necessary to reselect features to take into account the specific properties of the surface type.

Acknowledgment

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

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. Conners and C. Harlow. A Theoretical Comparison of Texture Algorithms. *IEEE Transactions of Pattern Analysis and Machine Intelligence*, PAMI-2(3):204–222, May 1980.

[4] 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.

[5] A. Hämäläinen. *Self-Organizing Map and Reduced Kernel Density Estimation*. PhD thesis, University of Helsinki, Rolf Nevanlinna Institute, Helsinki, 1995.

[6] 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.

[7] R. M. Haralick and L. G. Shapiro. *Computer and Robot Vision*, volume 1. Addison-Wesley, 1992.

[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, 1995.

[10] T. Ojala, M. Pietikäinen, and O. Silven. Texture Measures for Surface Inspection. In *11th International Conference in Pattern Recognition*, volume II, pages 594–598, The Hague, The Netherlands, August 30 - September 3 1992.

[11] M. Sonka, V. Hlavac, and R. Boyle. *Image Processing, Analysis and Machine Vision*. Chapman & Hall Computing, 1993.

[12] 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.

[13] 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.

[14] 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.

[15] 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.

[16] J. S. Weszka, C. Dyer, and A. Rosenfeld. A Comparative Study of Texture Measures for Terrain Classification. *IEEE Transactions on Systems, Man, and Cybernetics*, SMC-6(4):269–285, April 1976.

[17] 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.