PERGAMON

Pattern Recognition 32 (1999) 1049–1060

PATTERN RECOGNITION
THE JOURNAL OF THE PATTERN RECOGNITION SOCIETY

Artificial Neural Networks for Automated Quality Control of Textile Seams

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Abstract

We present a method for an automated quality control of textile seams, which is aimed to establish a standardized quality measure and to lower costs in manufacturing. The system consists of a suitable image acquisition setup, an algorithm for locating the seam, a feature extraction stage and a neural network of the self-organizing map type for feature classification. A procedure to select an optimized feature set carrying the information relevant for classification is described.

Keywords: *Neural networks; Self-organizing feature maps (SOFM); Textile seams; Quality control; Feature selection*

1. Introduction

Reliable and accurate quality control is an important element in industrial textile manufacturing. For many textile products, a major quality control requirement is judging seam quality. Presently, this is still accomplished by human experts, which is very time consuming and suffers from variability due to human subjectivity. Consequently, investigations about automated seam quality classification and an implementation of an automated seam classificator are highly desireable. Such a system would be useful not just to objectify quality control of textile articles but it can also provide a basis to perform online adjustment of sewing machine parameters to achieve smoother seams.

Previous approaches to automated classification of textile seams were made by Dorrity [1] and Clapp et al.[2]. Using piezoelectric sensors, Dorrity [1] measures the ratio of *thread motion* and a *sewing machine cycle* and compares it to an optimal value. Clapp et al.[2] determine fabric density using beta-rays. From density variation, a quality measure can be derived. However, an optical control method appears to be not only easier to realize from a technical point of view, but also more appropriate, since humans also judge visually.

In this contribution we present a system that can judge seam quality from greyvalue images. An overview of the approach is shown in figure 1. The first stage is an image acquisition system, which can record the structure of the seams and map it onto a greyvalue image (step “a” in the figure, Section 3). As a next step, an algorithm for locating the seam is applied (b, Section 4). This allows to normalize the position of the acquired image. Next, a set of appropriate features is extracted from the normalized seam images, which have to code information about the quality of the respective seam (c, Section 6). We divide the images into two sets: the first (training set) is used to train the neural network to determine seam quality from the chosen input features, using a supervised learning algorithm. The second (test set) is used to test the performance and generalization ability of the trained network (d, Section 5) by computing the error for the test examples (e, Section 5).

Before treating the automated classification system, Section 2 provides a brief overview of the present quality control procedure by textile experts.

2. Seam control by textile experts

2.1. Applications of quality control

Presently, seam quality control is performed visually by human experts. Two main purposes of quality control can be distinguished:

1. The continuous control during manufacturing and the end control of seams in *garments*:
   A direct control of the manufactured products should prevent faulty articles to be sent to sale. If necessary, they have to be resewn or sorted out.
2. The control of *seam specimens*:
   The expert does not inspect the finished article itself, but

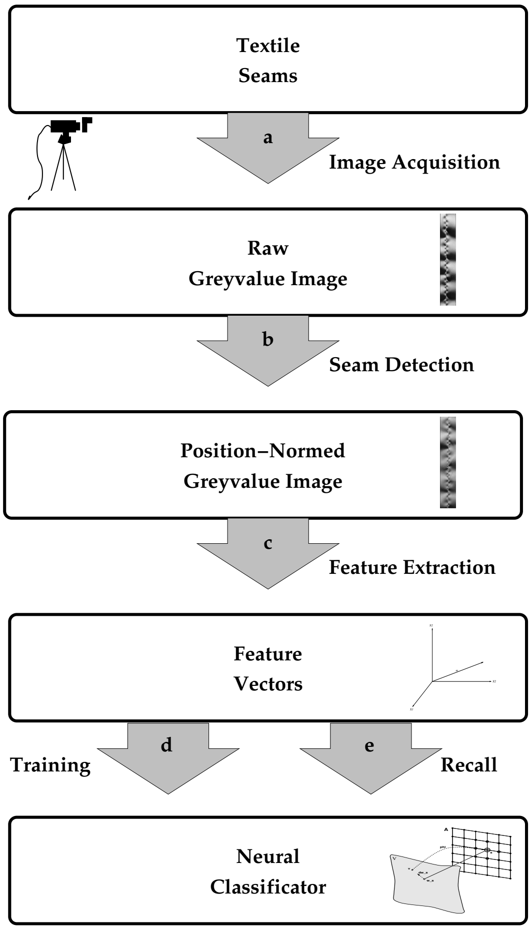


Figure 1: Basis structure of the classification system

so-called seam specimens, which are manufactured especially for the purpose of finding optimal settings for the sewing machine parameters, such as yarn suspension, stitch length, transport type and velocity, etc. In practice the expert sews on a trial basis elongated seam specimens using different settings for the machine parameters. Afterwards he or she inspects the results and re-sets the parameters. Examples of seam specimens are shown in figure 2.

An automated system could be realized for both types of control application. Yet an automatic control of the seam specimens (issue 2) is easier to achieve, because seam specimens are simpler fashioned than complex textile articles.

Thus this paper will focus on seam specimens. Nevertheless the control of ready-sewn garments (issue 1) is left as a future goal.

Within the manifold of fabric textiles (clothing textiles, home textiles, technical textiles) the investigations of this paper are focused on clothing textiles.

2.2. Smoothness as a measure of seam quality

The design of the presented automated quality control system is guided by criterions that human experts use to inspect the seams.

In textile industry, experts use a common standard procedure for the examination of the seam specimens. This procedure considers five different, discrete grades of quality—from grade 5 (best) to grade 1 (worst). The experts judge seam quality by comparing the seam specimen with images of five reference specimens, which define the five grades. The grade of the reference specimen, which is most similar to that one to be judged, defines the grade to be given. Figure 2 shows these reference specimens.

The most important criterion for comparison is the *smoothness* along the seam. In bad sewn specimens the smoothness is disturbed by waves, whereby two main types of waviness can be distinguished: one of high frequency adjacent to the seam center and another one further away with a lower frequency (compare figure 2).

3. Image acquisition

3.1. Geometry of the image acquisition setup

An image acquisition setup that yields greyvalue images preserving the seam features relevant for quality classification (mainly waviness) is crucial for a reliable and accurate judgement. The definition of the image acquisition setup comprises the placing of

- the *specimen*
- the *camera* and
- the *illumination*

Our setup is shown in figure 3. It is similar to a standard setup for specimen judgment used in the textile industry [3]. We will briefly motivate this choice.

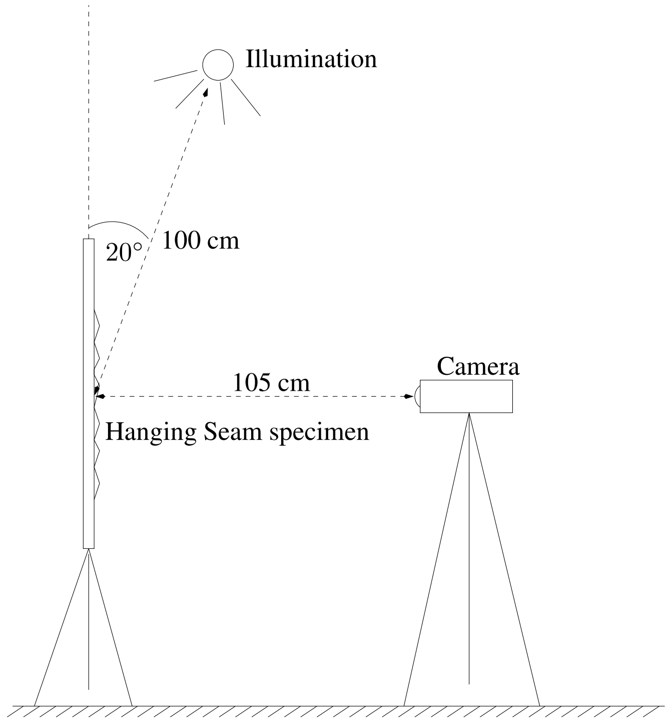


Figure 3: Image acquisition setup

3.1.1. Position of the specimen

Main alternatives for specimen positioning are *horizontally lying* or *vertically hanging*, or a solution between these

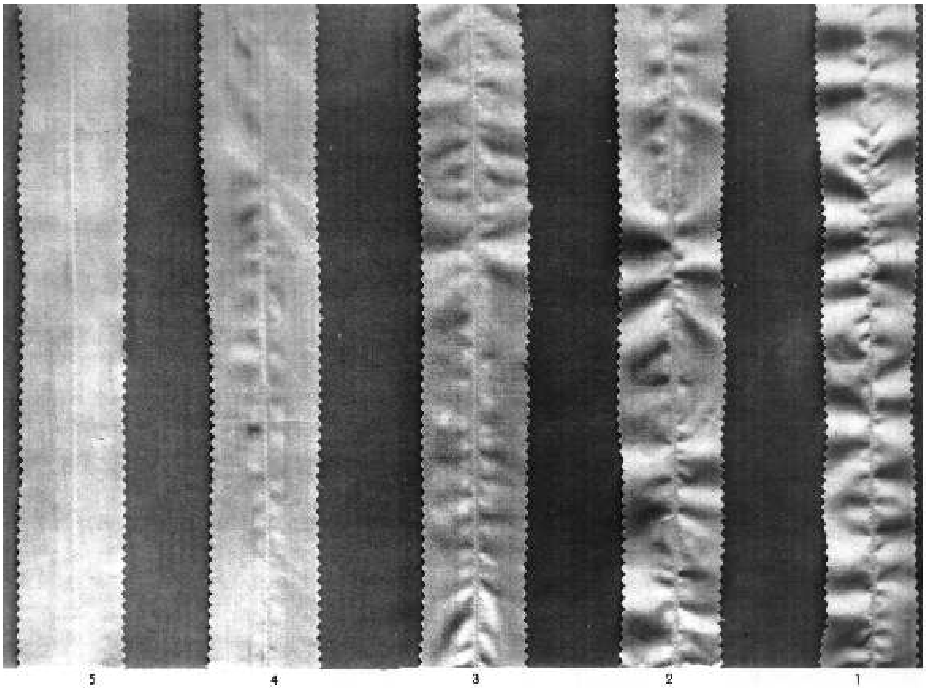


Figure 2: Reference seams for the seam inspection, at the left the grade 5 (best) and at the right the grade 1 (worst). With help of this reference the textile expert accomplishes the seam inspection.

alternatives. Our investigations showed that the appearance of the fabric is independent of its position (hanging or lying). The waviness appears naturally in both cases. This result can be explained by the fact that the weight of the specimen is too small to deform the relatively firm structure of the waves. However, the selection of the vertical position will be preferred, because this position has the benefit that the specimens can be centered along a straight line more easily.

3.1.2. Position of the camera

The most significant camera position parameter is the viewing direction relative to the specimen. Possible settings are a *frontal* direction, a *sidewise* (recording the length profile) direction and an *oblique* direction. Since a sidewise positioning would yield information just about the edge of the seam and an oblique one would complicate the further image processing without gaining any benefits, the frontal direction was preferred.

3.1.3. Placing the illumination

Illumination can be *frontal* or at a *shallow* angle. An advantage of the frontal position is that the fabric would be lighted constantly over the whole area and the image had a homogeneous brightness.

A shallow illumination can map the three-dimensional structure of the specimen onto the two-dimensional image better because the shades of the seam waves code an important piece of information about the frequencies and amplitudes of the waviness, which is the most valuable information about seam quality.

We tested frontal and shallow illumination with different angles, judging success on the basis of the classification results. Images were taken from a set of seam specimens with five different illumination angles and afterwards a test classification was made with each set of seam images. The chosen angles α (= the angle between the illumination axis and the specimen plane)[1] were

$$\alpha_i = 8^\circ,\ 13^\circ,\ 20^\circ,\ 30^\circ,\ 90^\circ.$$

As a preliminary study, the test classifications were realized using a rudimentary set of features, which consisted of the amplitudes of the first 20 Fourier coefficients of one-dimensional image columns extracted at the horizontal position offsets -30, -10, 10, 30 pixels lateral to the seam (for more information about this feature definition see Section 6). The neural nets used for classification were eight Kohonen nets with various grid geometries (5×1, 10×1, 25×1, 100×1, 3×3, 5×2, 5×5, 10×10, more information about the Kohonen net in Section 5). The quality of the classification was measured in terms of the averaged NMSE (normalized mean square error) of 1000 test classification runs with the feature vectors and net geometries mentioned above.

The results of the test classifications are presented in table 1. [2] This table shows that the optimal illumination angle is $\alpha = 20^\circ$, which was used for all further investigations.

3.2. Data acquisition

A set of 126 seam specimens of three different colours and materials was made available from the IFN (INSTITUT FÜR NÄHTECHNIK, AACHEN). Each specimen has uni-

[1]Thus the angle $\alpha = 90^\circ$ corresponds to the frotal illumination.

[2]Note, that the feature vectors were not optimized for classification and only used to find a good illumination angle. So the classification results are much worse than with the features discussed later.

α	8°	13°	20°	30°	90°
NMSE	0.50	0.33	0.25	0.31	0.71

Table 1: The average of 1000 classification errors NMSE using different angles α for the illumination position. For $\alpha = 20°$ the best results are achieved. The feature vectors were not optimized for this preliminary investigation.

form colour. Images are acquired from an area of 4×20 cm with a resolution of 80×512 pixels. [3]

Since colour and brightness of the specimens vary over a wide range, the camera iris has to be individually adjusted in order to achieve the best image quality possible and to norm alike the brightness of the images. This is realized by a gradient-based algorithm described by Kubisch [4], which maximizes the variance of greyvalues of the image.

4. Seam detection

A significant criterion for the seam quality is the waviness on the fabric along the seam, as explained in Section 2. The type of waviness depends on the distance from the seam center. Therefore the examination of the seams requires a precise positioning of some "wave detectors" relative to the seam. For this reason an automatic *image positioning algorithm* was implemented, which is able to

1. detect the seam course and
2. transform (translate/rotate) the detected seam to the vertical center of the image.

The seam detection (1) is implemented in two steps. First, a binary edge image of the original is calculated with a 5x5-Laplace filter and a subsequent threshold operation.

This edge image is used to estimate the seam coarse with help of the *Hough Transform.* The Hough Transform (see e.g. Davies [5] and Bässmann [6]) is a common method for line detection. It transforms the binary edge image from the spatial domain to a "line space", which is defined by the two line parameters "angle θ" and "distance ρ" of the Hessian line equation. The line space is an accumulator space in which the number of points is counted that lie on each line determined by θ and ρ in the binary image. The line parameters (θ_0, ρ_0) that accumulate the most "votes" were taken to describe the location of the seam (figure 4).

With the seam line parameters (θ_0, ρ_0) information about the rotation parameter (angle φ) and the translation parameter (length l) is given and the rotation/translation can be applied.

The described algorithm works very reliably. The seam coarse of any of the 125 seam images of the original data set as well as 10 additional, especially for this purpose obliquely recorded seams were detected and positioned correctly.

[3]The different ratio width/height for acquired area and resolution is explained by the spatial distortion factor 3/4 of the "DataCube" acquisition system.

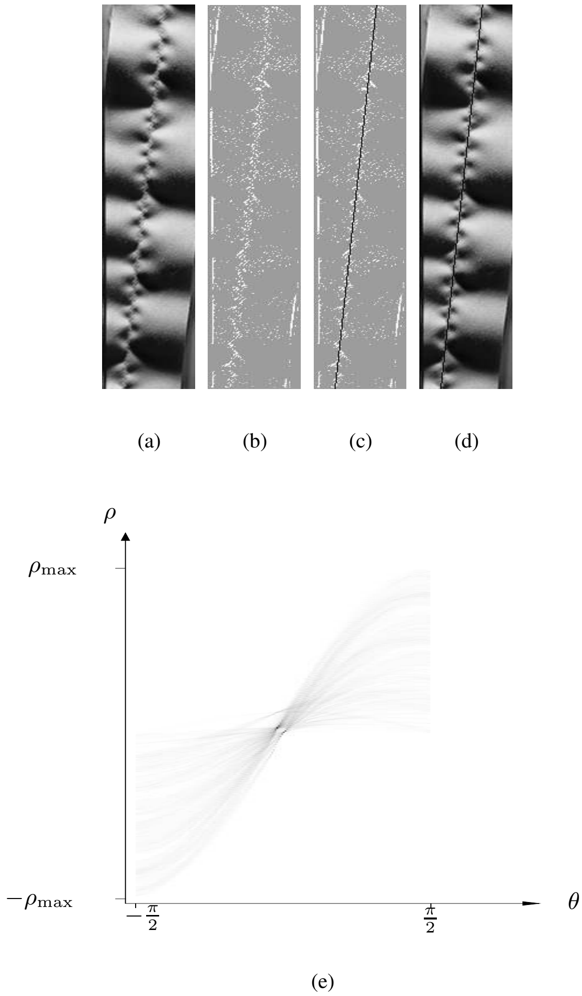


Figure 4: Scheme of seam detection: First from the original image (a) an edge image (b) is computed. The edge image is transformed to the Hough space (e) and the parameters of that straight line (θ_0, ρ_0), that comprises the highest number of edge points, can be determined (in the picture the point with the darkest greyvalue). This line (θ_0, ρ_0) is interpreted as the seam line. In (c) it is sketched into the edge image and in (d) into the original seam image.

5. The Neural Net

5.1. The Kohonen Map

For the classification stage, we employ a self-organizing feature map (SOFM, Kohonen [7], Ritter et al.[8]). This type of network has been used quite successfully in a broad range of applications. In addition to robust and fast convergence, the SOFM offers the possibility to visualize the training process in a way that can provide additional insight about the structure of the training data (see Section 6). This is an important advantage over other adaptive classification approaches, such as the popular MLP– or RBF–networks.

Usually, a SOFM is used to create a dimension-reducing mapping from some data set in a high dimensional space V to a low dimensional map manifold A. This manifold consists of a net of discrete "neurons" or "nodes", between which some topology is defined (commonly a grid or a chain). The nodes of the net are initialized with random values within the data space V and will be adapted to the actual data manifold by a learning rule given below in equation (1). An example is given in figure 5.

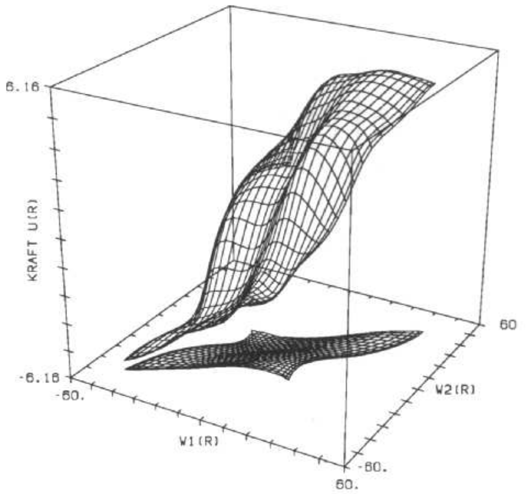


Figure 5: A Kohonen net A in the data space V: For particular points (for the weight vectors $\vec{w}_r \in V$) the corresponding neurons are sketched in; adjacent grid neurons are connected. The adaptation process has developed a Kohonen map, that lays along the stimuli distribution (which is not sketched in) and preserves neighborhood relations, i.e. adjacent neurons (crossing points of two lines) correspond to adjacent positions in V. This figure is an example of a Kohonen map used for solving the pole balancy problem. (from Ritter et al.[8])

In our case, we are additionally interested in obtaining for each input (= feature) vector $\vec{x}$ its associated classification $c(\vec{x})$. Therefore, we teach the SOFM with "augmented" feature vectors

$$\vec{v}^\alpha = \begin{pmatrix} x_1^\alpha \\ \vdots \\ x_f^\alpha \\ c^\alpha \end{pmatrix} \in F \times \Re$$

The $x_1^\alpha \dots x_f^\alpha$ are chosen features that describe data sample α, and $c^\alpha \in [1 \dots 5]$ is the associated classification. F denotes the f dimensional feature space. For the training, we use the standard Kohonen SOFM-algorithm with Euclidean distance measure:

$$d(\vec{a}, \vec{b}) = \sqrt{\sum_j (a_j - b_j)^2}$$

For the case of different variances σ_j^2 in the data distribution for each dimension j the Euclidean metric should be normed by the variances:

$$d(\vec{a}, \vec{b}) = \sqrt{\sum_j \frac{1}{\sigma_j^2} (a_j - b_j)^2},$$

which graphically corresponds to a scaling of the rectangular data distribution to a square one.

If we denote the weight vector of a node at position $\vec{r}$ in the net by $\vec{w}_{\vec{r}}$, an adaptation step for a stimulus $\vec{v}^\alpha$ is defined by

$$\Delta\vec{w}_r = \epsilon h_{\vec{r}\vec{s}}(\vec{v}^\alpha - \vec{w}_{\vec{r}}) \quad \forall \vec{r} \in A, \tag{1}$$

where $\vec{s}$ denotes the location of the "winner node" for which $d\left(\vec{v}^\alpha, \vec{w}_{\vec{r}}\right)$ becomes minimal, and $h_{\vec{r}\vec{s}}$ is the neighborhood function, which is commonly chosen as a Gaussian function of the distance $\vec{r} - \vec{s}$ between nodes at net positions $\vec{r}$ and $\vec{s}$,

$$h_{\vec{r}\vec{s}} = \exp\left(-\frac{(\vec{r} - \vec{s})^2}{\sigma^2}\right) \tag{2}$$

The choice of this shape of function is motivated by the fact that neurons adjacent to the winner neuron should adapt strongly and neurons farther away from the winner neuron weakly. Graphically speaking this corresponds to unfolding an "elastic rubber net" in the feature space, thereby leading to a topology preserving final map.

5.2. Net Parameters

For the Kohonen map, a suitable topology has to be found. In Section 6, we investigate different network topologies of one or two dimensions and various numbers of nodes. It turns out that a two-dimensional 10×10 net topology yields the best results (cf. figure 9).

The chosen grid geometries and the settings for the adaptation step size ϵ (equation (1)), the activation radius for the excitatory function σ (equation (2)), and the number of learn steps n are summarized in table 2.

Net parameter	**Value**
Grid geometry A	$5 \times 1, 10 \times 1, 25 \times 1, 100 \times 1$ $3 \times 3, 5 \times 2, 5 \times 5, 10 \times 10$
Adaptation step size ϵ	$0.8 \rightarrow 0.1$
Activation radius σ	$\frac{1}{3}A_x \rightarrow \frac{1}{10}A_x$
Number of learn steps n	$30A_xA_y$

Table 2: Settings for the net parameters: A Kohonen net was tried with each of the 8 grid sizes A. The terms A_x and A_y indicate the row and column number of the grid A, respectively.

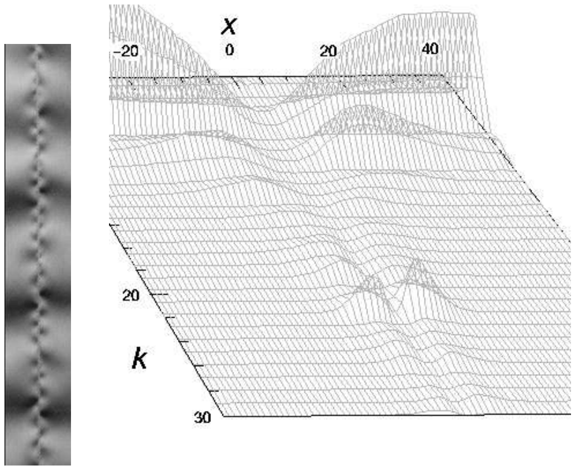
6. Feature Extraction

6.1. One-dimensional Fourier coefficients

As outlined in Section 2.2, the most significant criterion for quality judgement by textile experts is the waviness along the seam.

A well known representation of waviness is the Fourier transform. As the wave vector to be modeled is directed parallel to the seam, we compute the 80 one-dimensional Fourier transforms X of the 80 seam-parallel *columns* of the greyvalue image. Since we are not interested in the location of the waves in this approach, we discard the phase and work with the amplitude $\|X\|$ of the Fourier transform only.

Figure 6 shows a sample seam image (a) and its first 30 Fourier amplitudes (b), which hence depend on the column x, identified by its offset lateral to the seam course, and the wave number k, $\|X\| = \|X(x,k)\|$. In the shown "Fourier transformed seam" there are large values for $\|X\|$ visible at $k \approx 4$ at the edge of the image and for $k \approx 25$ right near the seam course, corresponding to the dominant frequencies found in the seam image.



(a) seam

(b) Fourier spectrum

Figure 6: Fourier spectrum $\|X\|$ of a specimen sample: for each column x of the greyvalue image (a) the amplitude $\|X\|$ of the Fourier transform is computed (column $x = 0$ corresponds to the seam position in the center). (b) shows the Fourier transform as a function of wave number k and the column x. One can see large values for $\|X(x,k)\|$ near $k \approx 4$ at the edge of the image and for $k \approx 25$ right near the seam, corresponding to the dominant frequencies of the specimen. Note that just the first 30 of all 257 wave numbers are shown.

6.2. Determination of suitable regions (x, k) in Fourier space

The "Fourier transformed seam" is still not suitable as a feature vector, since it contains too much redundant information. As a next reduction step we want to find regions (x, k) carrying the relevant information about the seam quality. The Fourier coefficients $\|X(x,k)\|$ of such regions should show high correlation to the quality grade c. A measure of the correlation between $\|X\|$ and c is given by the *correlation coefficient* $\rho_{\|X\|c}$, which is defined as the normalized covariance:

$$\rho_{\|X\|c} = \frac{\mathrm{Cov}\left(\|X\|, c\right)}{\sigma_{\|X\|}\sigma_c}.$$

$\rho_{\|X\|c} = \pm 1$ indicates a maximal correlation or anticorrelation, resp., and $\rho_{\|X\|c} = 0$ no correlation at all. Thus it is desirable for feature formation to find regions (x, k) with high values of $\left\|\rho_{\|X\|c}(x,k)\right\|$.

The correlation coefficient for the given seams is illustrated in figure 7. Correlated regions (bright color $\widehat{=}\ \rho = 0.7$) can be found at $k \approx 4$ and at regions with higher frequencies near the seam course.

6.3. Definition of Features

Our feature set was defined on the basis of the averaged spectrum $\|X\|$ of the high correlated or anti-correlated regions in figure 7. In particular, the one-dimensional Fourier transforms are computed for the almost symmetric offset columns $x = -34, -8, 7, 34$ lateral to the seam, and several wave numbers of the Fourier coefficients are grouped into one interval and averaged within it. For the choice which Fourier coefficients to group together, we were guided by the correlation coefficients depicted in figure 7. Table 3 shows which wave numbers are considered in particular.

Feature Definition				
Column x	-34	-8	7	34
Grouped k-intervals $\{k_m \ldots k_n\}$	3–5	3–5	3–5	3–5
	—	7–9	7–9	—
	—	13–14	12	—
	—	17	15	—
	—	21	22	—

Table 3: The definition of the feature vector: Row 1 denotes the column offset x lateral to the seam for the one-dimensional Fourier transform, rows 2–5 the various wave number intervals, in which the Fourier coefficients are averaged, regarding correlated regions (x, k) in figure 7. The dimensionality of the feature vector is the number of entries in this table, thus 12.

6.4. Classification Results

Classification is accomplished with the feature vector described in Section 6.3 and Kohonen maps with various grid geometries described in Section 5 by presenting training seams to the net for training and different test seams for classification. Training and test seams are described in Section 3.2.

In the following the classification results are documented by three aspects: the classification confusion matrix, the inspection of the NMSE (normalized mean square error), and an investigation of the resulting Kohonen map.

6.4.1. Classification confusion matrix

A specific illustration of the classification results is given by a "summary" of all individual classifications. This information is illustrated in a *classification confusion matrix* in figure 8 for the 10×10–Kohonen map. The columns and rows of this matrix represent the five discrete grades of quality for the expert grade and the net response, resp. The value of element (i, j) denotes the number of the classifications of a class-j-seam into class i. Hence the matrix should have highest entries along the main diagonal $(1,1), (2,2), \ldots, (5,5)$.

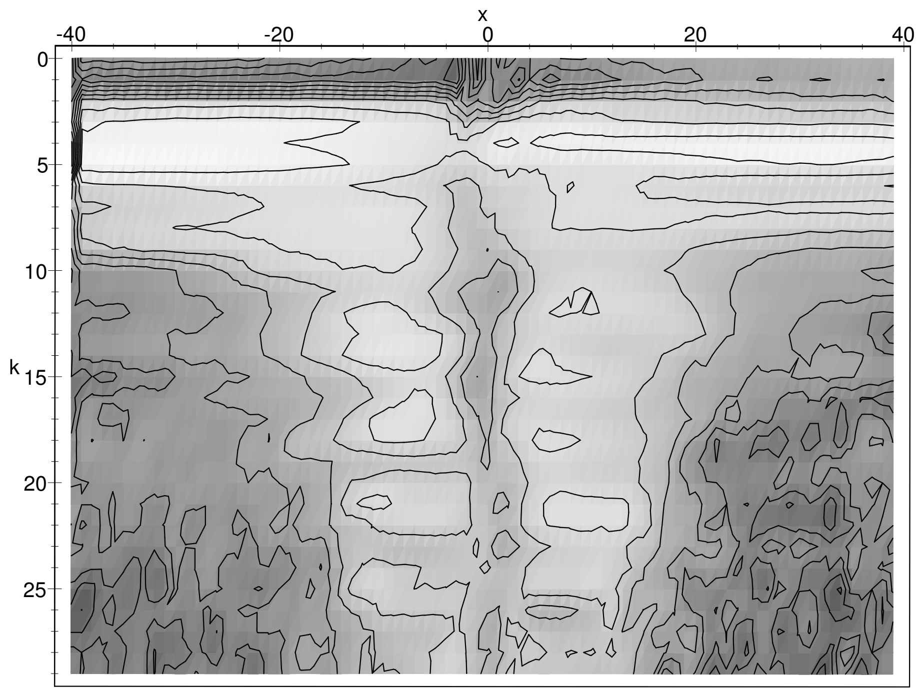


Figure 7: Correlation coefficient $\rho_{\|X\|c}(k, x)$ of Fourier spectrum $\|X(k, x)\|$ and quality grade c dependent on the chosen offset column to transform x and the wave number k of the spectrum. Dark areas denote uncorrelated regions, grey ones a weak anticorrelation ($\rho_{\|X\|c} = -0.2 \ldots -0.4$) and bright ones a stronger anticorrelation ($\rho_{\|X\|c} = -0.4 \ldots -0.7$).

The figure shows that for 79.09 % of all individual classifications the classification is correct. For 20.63 % of all classifications the error is just one grade, only for 0.27 % an error of two grades occurs. This result has been compared to the classification by a committee of three textile experts: the one-class-deviation rate for their classification from the average classification of all three experts is 20.1 %, errors of more grades usually do not occur. Thus from this point of view the artificial system is comparable to human experts.

6.4.2. Normalized mean square error

With the results of the previous section, the achieved NMSE (normalized mean square error) of the best net is 0.21 for assigning integer quality grades 1...5. This compares favourably with the NMSE of the group of three experts, which is about the same value (0.20) on the basis of 126 specimens for this task.

For the purpose of this investigation, the expert team tried to produce evaluations on a finer scale than the standard five integer grades, using in addition grades shifted by ± 0.3. These data were used to train the network, however, the above NMSE-evaluation was based on the rounded values.

In addition, we can make a performance comparison between the network and the expert judgements, using the finer scale that was used for training. Figure 9 shows the resulting accuracy of several different network architectures. As can be seen, with this evaluation scheme the NMSE decreases from 0.2 to 0.13 for the optimal grid topology (10×10).

This is similar for the human experts, however, in their case the decrease is stronger: if evaluated on the basis of the finer grade scale, the NMSE decreases from 0.2 to 0.05. This is significantly better than the average net performance. Still, if we compare the best net architecture (NMSE = 0.13), the quotient of the two error measures is only a factor of 2.6 (or 1.6 if the root mean square errors are considered instead).

6.4.3. Investigation of the adapted Kohonen map

Because of the one- or two-dimensional structure of the Kohonen map the activation of each neuron on the grid can easily be graphically illustrated. This is done in figure 10 (a) for the 10×10–grid. The response of each neuron is sketched at its position.

The regions of the discrete classes 1–5 are additionally distinguished by the separating lines. One can see that adjacent neurons are responsible for similar quality grades, in accordance with the neighbourhood preserving property of the SOFM.

In (b) the expert grades of test samples are sketched at the positions of the "neuron" that they stimulate. Optimally, the expert grade of the stimulus seam should have a similar response to the stimulated neuron. A comparison to (a) shows that this property holds for most stimuli.

Figure (c) again shows the expert grades of the test samples, but this time some additional information is displayed. The rectangular, elliptical and "missing" borders denote the three different fabrics of the test samples. The figure shows that each fabric occupies its own region on the map—especially the "regions with missing borders" are clearly separated from the "rectangular/elliptical regions". This fact indicates a limited generalization ability of this Kohonen map to unknown fabrics.

Though this has to be overcome in future investigations, it has been shown that the Kohonen map is suitable to code

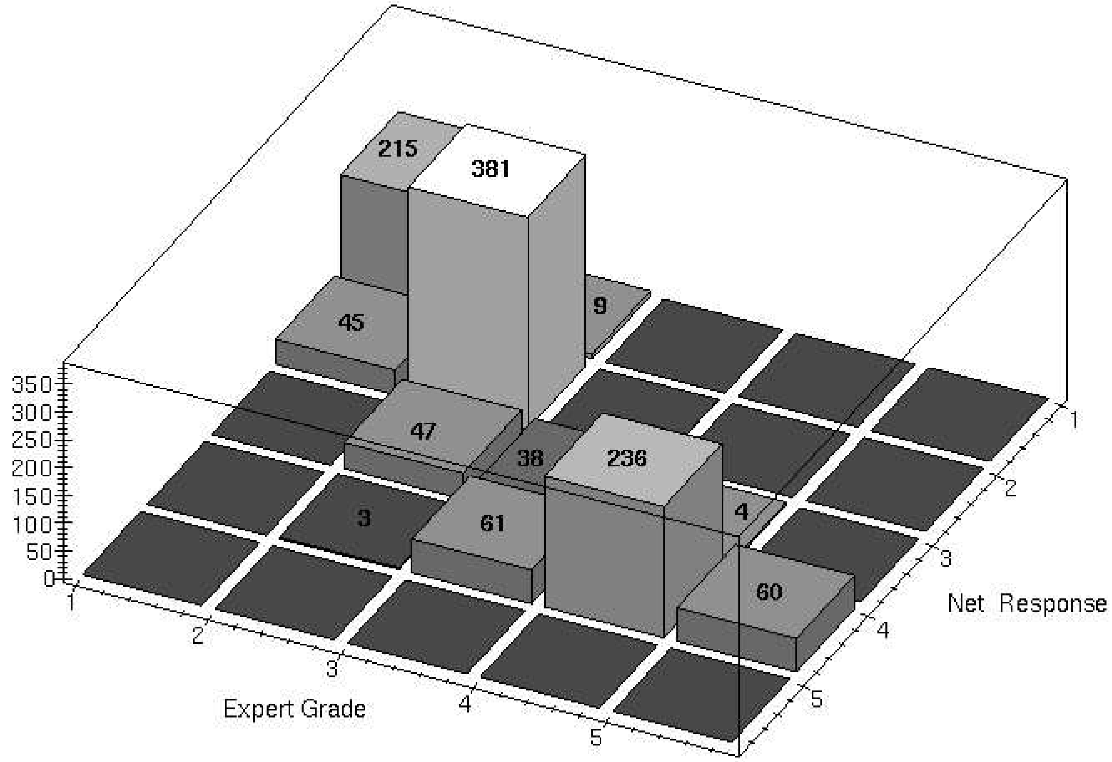


Figure 8: Classification confusion matrix: Columns and rows represent the five grades of quality for the expert grade and the net response, resp. The value of the element (i, j) denotes the number of the classifications of a seam belonging to class j into class i.

the information about the seam waviness.

7. Summary and Outlook

7.1. Summary

This contribution proposed a system for an automated, vision based quality control for textile seams. The developed system consists of

1. a suitable acquisition setup,
2. a seam detection stage, which very reliably transforms obliquely acquired seam images to a normalized position
3. a feature extraction stage, which is based on selected Fourier coefficients of one-dimensional image columns and
4. a self-organizing feature map for classification.

The performance of the system has been evaluated by the classification of so-called seam specimens, which are used in industrial textile manufacturing for the setting of the sewing machine parameters.

The results have shown that even with few, but well-fashioned features good classification results can be obtained. The classification rate amounts to 80 % correct classifications, the rest differs from the correct grade only by one (on a scale of five). We have shown that this result is not worse than the error of human experts, which can be measured by the "disagreement" among a set of different expert judgements.

Time needed for classification is about one second on a standard PC, which is much less than textile experts need for classification ($\approx$ 30 seconds).

7.2. Outlook

Our results show that the approach is a suitable basis for further investigations. Various improvements of the developed system and new challenges for seam quality classification arise from this work:

7.2.1. Improvements for the current control system

- For the improvement of the feature extraction the relevant regions (x, k) in the Fourier space can be selected and grouped automatically by adaptive algorithms.
- The phase information $\angle X$ of the Fourier transform can additionally be used for feature formation.

7.2.2. Further Applications of textile quality control

- For a universal classification system it is necessary to classify also fabrics with a color or structure texture.
- The setting of sewing machine parameters could be automated. An approach for this issue can be implemented by a regulation process, which iterates classifying seam quality and resetting the machine parameters until an appropriate value for quality is obtained.
- The classification system can be extended from inspecting seam specimens to the inspection of garment articles.
- Another useful application of vision based textile control is the control of the correct alignment of patterns when sewing two fabrics with texture.

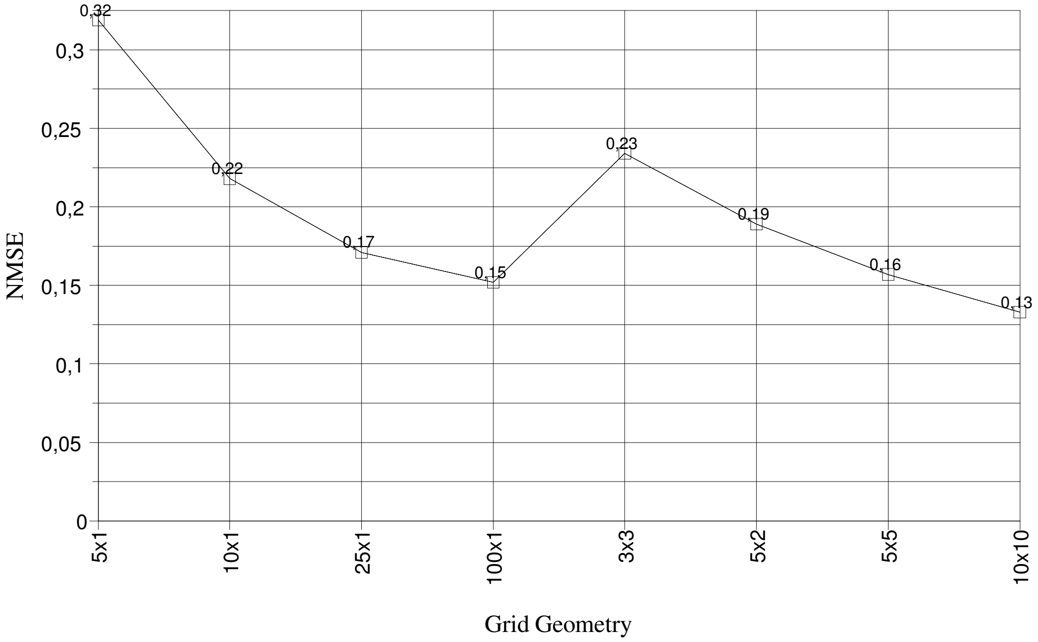


Figure 9: NMSE for various grid geometries. A higher number of neurons yields a smaller NMSE. The two-dimensional neuron grid classifies slightly better than a one-dimensional neuron "chain" with the same number of neurons. The 10×10–grid yields the best classification result (NMSE $= 0.13$).

8. Summary

In this contribution we propose a neural network based approach for an automated, visual quality control of textile seams. We focuse on so-called *seam specimens*, which are used in textile industry to adjust sewing machine parameters. The aim of this work is towards a better and standardized quality measurement in textile examination as well as to enhance the so far expert accomplished and time consuming quality control by an automated system to lower manufacturing costs.

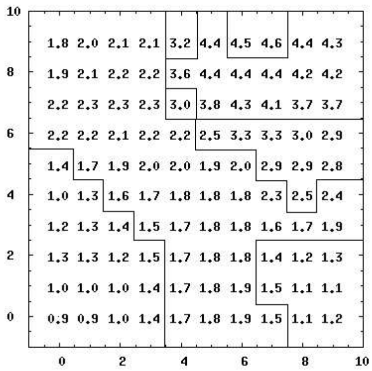
Up to now, classification is based only on human expert knowledge, not on any standardized seam quality measure. Experts judge seam quality by visual inspection of specimen waviness in the vicinity of the seam. Since waviness of the seam is hard to determine even for humans because of strongly varying surface reflectance properties among different fabrics, the inspection by an expert takes about 30 seconds.

Therefore, an automated seam quality control is practically important and atthe same time a challenging task for computer vision. The main problem is to judge the waviness of the specimen (3d-information) from a 2d-image which is inmany cases only of low contrast. However, by a suitable image acquisition setup in combination with an appropriate feature extraction, all information relevant for classification can be extracted.Since there is no explicit model of seam quality, we used an artficial neural network for classification which was trained with samples classified by experts.

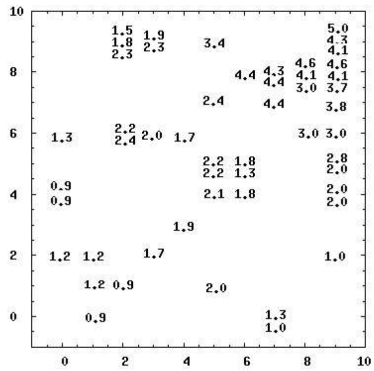
Our approach consists of the following four processing stages:

1. Image acquisition: from an evaluation of different camera positions and lighting conditions we found that a vertically hanging position of the specimens, frontal camera position and a sharp illuminating beam at an angle of $20°$ with the specimen plane led to best results.
2. Seam detection and alignment: we use a Hough-Transform to detect theseam and to translate and rotate the seam image into a normalized position.
3. From the normalized image, features are extracted for quality classification. As textile experts takethe smoothness of the fabric as a quality measure, the feature vector is based on selected Fourier coefficients of image intensity along pixel columnsin several distances parallel to the seam.Appropriate frequencies and column positions of the used Fourier coefficients are selected by analyzing the correlation betweenFourier coefficients and predicted quality.
4. The selected features are classified into five quality categories, using a self-organizing feature map (Kohonen map). We compare classification performance for several different network topologies and find that a 10×10 network performs best.

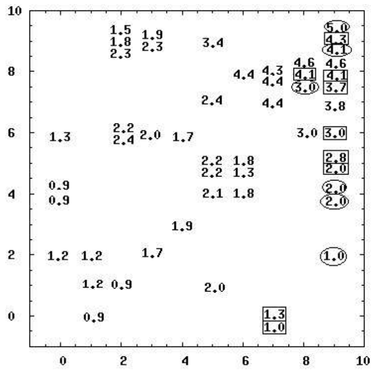
The performance of the system has been evaluated by the classification of 200 seam specimens of varying colour and material. The results show that even with few, but well-chosen features good classification results can be achieved. The classification rate amounts to about 80% absolute correct classifications (as compared to given classifications of human experts), the rest differs from the correct grade only by one (on a scale of five). We compare this result with the error of human experts, which can be measured by the "disagreement" among a committee of several experts, and find



(a) Activation of neurons



(b) Expert grades of stimuli



(c) Expert grades of stimuli with class information

Figure 10: Visualization of a 10×10-Kohonen map: In (a) the corresponding grade of each neuron is entered at the respective grid position. The lines separate the discrete classes 1–5. The neighbourhood preserving topology can nicely be seen. In (b) the expert grades of test samples are sketched at the positions, which correspond to the winner neuron of the respective classification. Optimally they should be mapped to regions corresponding to their class, specified by (a). Regard that for a better readability the position of the entries is moved up- and downwards, if more than one sample stimulate the same neuron. In (c) the test samples are sketched again at the position of their stimulated neurons. This time an additional information is displayed: the rectangular, elliptical and "missing" surroundings denote the three different fabrics of the test samples. This figure shows that samples of different fabric mostly stimulate different regions on the map.

that it achieves about the same accuracy. However, classification time is merely one second on a standard PC, and, therefore, much less than textile experts need.

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