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Objective Evaluation of Seam Pucker on Textiles by Using Self-Organizing Map

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Abstract—**Evaluation of seam puckers is one of the most important aspects for quality control in garments manufacturing industry. Seam puckers lead to garments aesthetically unacceptable and may also cause inconvenience in wear. At present, seam pucker evaluation is mainly carried out by human inspectors, which is subjective, unreliable and time-consuming. Instead of manual evaluation, this paper presents an objective method by using image analysis and pattern recognition technologies. The evaluation system consists of image acquisition, image normalization, feature extraction and self organizing map classifier. Textural features of seam puckers are studied with a widely used statistical method, the co-occurrence matrix approach. After training, the self organizing map classifier can grade unidentified seam puckers and the experiments results demonstrate the effectiveness and efficiency of the proposed approach.**

Index Terms—**Pattern recognition, Image analysis, Seam puckers, Self organizing map.**

I. Introduction

In the garment manufacturing industry, manufacturers are faced with increased pressure to remain competitive in the worldwide global markets. The ability to compete mainly depends on productivity and quality. With the advances in electronic technologies, much can be done to improve productivity and quality by using automation as an integral part of manufacturing systems. However, automated vision-based inspection of textile products has been developing at a relative slow pace, and has not been widely studied in the research literature.

Seam pucker, identified as a sewability problem about seventy years ago, has been regarded as one of the most important parameter of quality control in garment manufacturing industries. As defined in Oxford Dictionary [1], seam pucker is “a ridge, wrinkle, or corrugation of the material or a number of small wrinkles running across and into one another, which appear in sewing together two pieces of cloth.” It is usually caused by improper selection of sewing parameters and material properties, which results in unevenness on fabrics being stitched together, thus impairing their aesthetic values. In severe cases, seam pucker could appear like a wave front, originating from the seam, and extending to the entire piece of garment, e.g., when the seam is the cent ridge linking the two pieces of fabrics in the back of a man’s suit. In less severe cases, the wave formation is less pronounced, but nevertheless discernible. Indeed, garments exhibiting pronounced seam puckers are certainly unwelcome by customers.

It has been well recognized that elimination of seam pucker entirely is almost impossible, and the common practice is to accept a small amount of pucker as normal. Hence, it is essential to be able to grade puckered seams as objectively as possible. For this purpose, a set of photographic standards (Fig. 1) has been produced by the American Association of Textiles Chemists and Colorists (AATCC) which shows five standard classes in descending order of severity, from class 5 (no pucker) to class 1 (the most severe pucker). Using this method, observers compare each seam sample with the standard photographs and classify the sample as similar in pucker severity to one of the standard classes. However, this human inspection process is known to be subjective, unreliable and inconsistent. Since quality control plays a prominent role in garment manufacturing, the ability to evaluate seam puckers and to solve the seam pucker problem in the manufacturing process becomes vital. An objective method for seam pucker evaluation, which results in high quality products, is therefore highly desired.

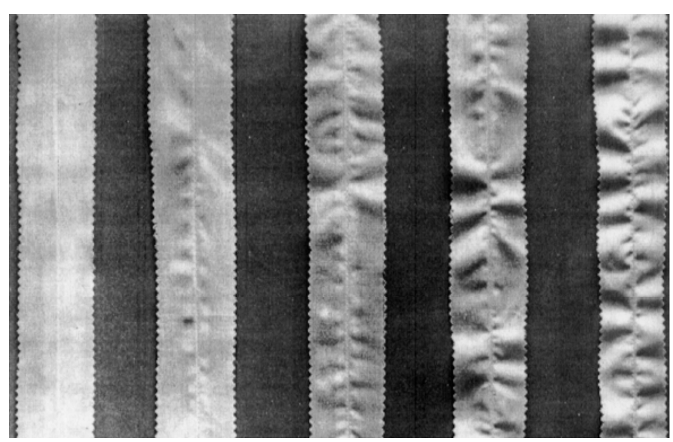

Fig. 1. Photographic standards for subjective pucker inspection by the AATCC method [2].

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Over the years, various objective methods have been developed for the evaluation of seam pucker. In the earlier works, instruments using photo or displacement sensors were developed to assess seam pucker, such as the “Wrinklemeter” [3], the “Sivim Wrinklemeter” [4] and the “SAWTRI Puckermeter” [5]. However, these methods were suspected for the problems of reproducibility and accuracy. A quantitative evaluation technique for seam pucker was reported by Inui et al. [6], and in [7] a device for seam pucker evaluation was introduced, where a laser scanner was used to record the surface profiles of seams. Similar works have been carried out by using laser scanner in [8-10]. Stylios and his colleagues [11-13] studied the severity prediction of seam pucker with the images obtained by a CCD camera. In [2] [14] the seam pucker images were also acquired by CCD camera and artificial intelligent algorithms were used to rate seam pucker. Although these research facilitate the realization of automatic seam pucker evaluation, the economical and accurate method is still absent. In this paper, an objective evaluation method based on the technique of artificial neural networks is presented to grade seam pucker with a high accuracy rate. The system consists of a suitable image acquisition setup, an algorithm for locating the seam, a feature extraction stage and a neural network of self-organizing map type for features classification.

The rest of this paper is organized as follows: part II gives a brief introduction of the self organizing map, and part III describes the proposed procedure for seam pucker evaluation in detail, from image acquisition to neural network classifier selection. The experiments results are shown in part IV, which demonstrates the proposed approach has a high accordance with the judgments of human experts. Part V gives a summary of this study.

II. THE NUERAL NETWORK

Subjective evaluation of seam pucker by humans is performed by firstly collecting huge amount of information visually and then using the human brain to process such information. Since visual evaluation is synthetic and complex, it is not sufficient to simulate visual evaluation by a linear evaluation system. Therefore artificial neural network, a kind of nonlinear system that has been widely used as a useful approach to facilitate automatic inspection, seems suitable for objective seam pucker evaluation.

Artificial neural network is a method of computation and information processing. With their remarkable ability to derive meaning from complicated or imprecise data, neural networks can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information that is being analyzed. This expert can then be used to provide projections given new situations of interest and answer "what if" questions. Other advantages include adaptive learning, self-organization, real time operation and fault tolerance via redundant information coding [15].

The Self Organizing Map (SOM) neural network algorithm formulated by Teuvo Kohonen [16] is a good solution to classification problems. SOM is naturally an unsupervised learning approach (without teacher signals). However, if class labels are known, it can be used as a classifier. In a SOM classifier, each neuron is assigned a class label based on the maximum class frequency or some other principles, and is classified by a nearest neighbor strategy.

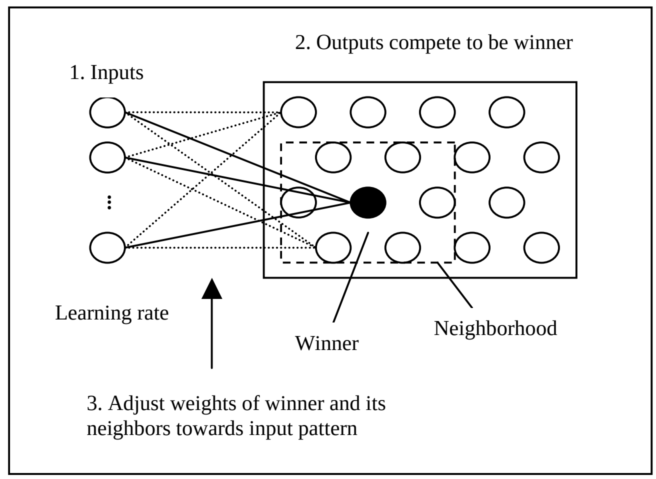


Fig. 2. Self organizing map

A SOM consists of two layers as shown in Fig. 2. One is an input layer into which input feature vectors will be fed and the other layer is a 2D competitive layer which orders the neurons’ responses spatially. SOM stores prototypes m_i of the input vectors x (t) at time t. At each iteration, the neuron that stores the closest prototype to the new input vector (according to the Euclidean metric for instance) is chosen as the winner, denoted as c.

$$\|x - m_c\| = \min_i \{\|x - m_i\|\} \tag{1}$$

The winner neuron updates its prototype vector, making it more sensitive for latter presentation of that type of input. This allows different neurons to be trained for different types of data. To achieve a topological mapping, the neighbors of the winner neuron can adjust their prototype vector towards the input vector as well, but in a lesser degree, depending on how far away they are from the winner. Usually a radial symmetric Gaussian neighborhood function $h_{i,c(j)}$ is used for this purpose:

$$m_i(t+1) = m_i(t) + \alpha(t) \cdot h_{i,c(j)}(t) \cdot (x(t) - m_i(t)) \tag{2}$$

where $c(j)$ is the winner of the input vector x_j. The learning rate

α and the neighborhood function $h_{i,c(j)}$ decrease as the value of t, the time that was spend in the current context, increases. Different neurons on the output layer will become more sensitive to different types of input as more input vectors are presented. Neurons that are closer in the map tend to respond to input that are closer in the input space. In classification, the SOM works as a vector quantizer, that is, an unknown pattern is classified according to the weight vector closest to it.

III. PROCEDURE

The procedure of our classification system for seam pucker is shown in Fig. 3. The images of seam puckers are acquired with a CCD camera system, and then are mapped onto grey-level images. Next, an algorithm for detecting the seam lines is applied. Based on the defined seam lines the grey-level images are normalized (include transforming and truncating). The normalized images are then divided into two sets, template images are employed for classifier training and the other set of unidentified images can used as testing data to verify the accuracy and effectiveness of the trained classifier.

The learning process uses the training sets to develop an identification system for seam puck grading, and the steps are described as follows:

1. Feature Selection. Sets of appropriate features extracted from training images are selected, which must be able to code the useful contour information of the seam puckers.
2. Training. Construct the neural network and train it in order to make it have the ability of classification with the sets of selected features representing those template pucker images.

After training, the neural network can serve as a seam pucker classifier instead of human inspectors. For each unidentified image repeat the following steps:

1. Feature Extraction. The set of features for a given image are calculated. Collect these features into a feature vector F as the representation of a seam pucker sample in neural network classifier.
2. Classification. Input F to the SOM classifier and find the best matching unit c. The label of c is then assigned to the seam pucker image as the grade number.

In the following, each part in the process of the objective evaluation of seam puckers will be introduced in detail.

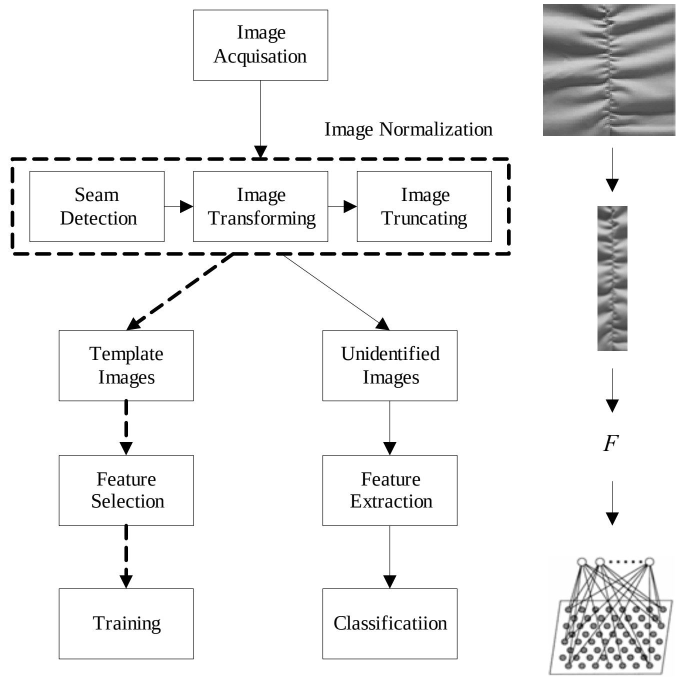


Fig. 3. Block diagram of the classification system.

A. *Image acquisition*

The first problem faced is to acquire surface contours of the seam pucker samples. Two main instruments of information acquisition of seam pucker are CCD camera and laser scanner. Laser scanners have been used in [8-10] to obtain geometrical profile of puckers by measuring surface height variation. However the cost of laser scanner makes it too expensive for industrial applications. CCD camera system is a convenient and low-cost way for image acquisition, which can yield good resolution images besides more similar to human's judge measure. Moreover, images acquisition by CCD camera has much less restrictions than that by laser scanner. Using a laser scanner, the measuring area on either side of the seam line should be equivalent for a reliable classification result, this is a burden for surface profiles acquisition of seam pucker samples. Whereas in CCD camera system, as long as no area coding the contour information on the fabric are missed in the seam pucker images acquired, an image normalization algorithm can be applied to find the useful pucker image area for the subsequent evaluation process. The methods to acquire information with laser scanner also require the laser probe move parallel with the direction of the seam line. This is not easy to realize because quality control measurements of seam puckers are normally done on completed garments where the garments are usually hanged up.

To capture high quality images, illumination equipment is necessary. Halogen-tungsten lamp is inexpensive and durable, and after setting a light filter paper the brightness is very homogeneous, therefore it is used as the lighting source in this study. The relative positions of Halogen-tungsten lamp, CCD camera and the seam pucker samples are fixed to acquire images in the same condition.

600 seam pucker samples in uniform color are made with 120 samples for each grade. All the sample images acquired by the CCD camera are 210mm long and 158mm wide with a resolution of 640×480 pixels. The grades of the seam samples are evaluated by human inspectors first according to the AATCC standards.

B. Image normalization

In order to increase the accuracy of seam pucker evaluation, the same areas should be investigated for classification in both sides of the seam lines of different samples. However in practice it is very difficult to acquire all the images with the seam lines in the same positions. Moreover since the area far from the seam line provides little useful information for seam pucker evaluation we only care about the area close to the seam line. Consequently an image normalizing (seam detection, image transforming and image truncating) algorithm is implemented, which is able to define the position of seam lines and obtain the partial images we really interested in.

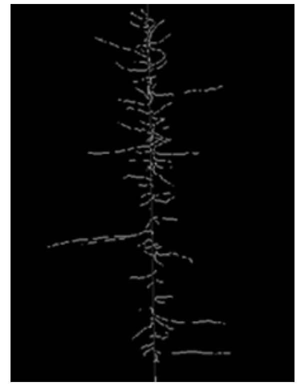
The Canny edge detection algorithm is known to many as the optimal edge detector and is always among the best performers in various edge operation evaluation experiments [17]. Thereby canny edged detector is used to calculate the binary edge images of original seam pucker images. Afterward the seam line is found by Hough transformation [18], which has been recognized as one of the most popular methods for the detection of line segments having good stability and robustness when working on images where noise is present. The idea of Hough transform is to describe a certain line shape (straight lines, circles, ellipses, etc.) globally in a parameter space – the Hough transform domain. In the Hough space straight lines can be specified by:

$$\rho = x\cos\theta + y\sin\theta \tag{3}$$

where ρ is the perpendicular distance from the origin and θ is the angle with the normal. Collinear points (x_i, y_i), with $i = 1, 2. \ldots, N,$ are transformed into N sinusoidal curves $\rho = x_i\cos\theta + y_i\sin\theta$ in the Hough plane, which intersect in the point (ρ, θ). The value of a function in Hough space gives the point density along a line in the input space. A straight line can be defined in the input space if there is a peak point in Hough space and it is the cumulative value of all the sinusoids. In this work, the point with the maximum density in the Hough space is considered as the seam line.

According to the parameters of the seam line acquired in Hough transform the rotation and translation can be applied to transform the seam line to the vertical center of the image. To eliminate redundant and reduce data processing time, an area of 610 × 122 pixels is obtained after truncating corresponds to 200mm long and 40mm wide. The process of image normalization is shown in Fig. 4.

(a) Primary Image



(b) Edge image with seam line

(c) Image after rotation

(d) Objective image

Fig. 4. Seam detection, image transforming and truncating. (a) is the primary gray-level image acquired by a CCD camera system, and (b) is the image after canny edge detection with the seam line positioned by Hough transform. In (c) and (d) are the images after rotation and truncating, respectively.

C. Feature Extraction

The most important task in the classification of seam puckers is to extract features which can characterize the roughness degree of various grades. In this research feature extractions are based on three main aspects considered in the process of inspection by humans, they are density, depth and thickness of the seam puckers. The process of feature extraction is showed in Fig. 5.

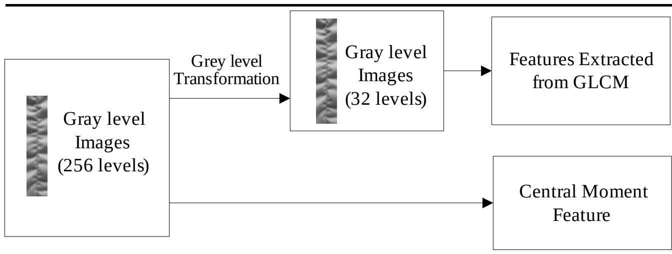


Fig. 5. Process of feature extraction

Images of seam puckers can be considered as a kind of textures, hence the co-occurrence matrix, also known as the spatial gray-level dependence matrix, is used for the texture analysis. A grey-level co-occurrence matrix (GLCM) is a second-order statistical measure of gray-level variation whose entries are transitions between all pairs of two gray-levels [19]. Let $P(i, j; d, \theta)$ be the transition probability from gray-level i to gray-level j, which is defined using the following relation:

$$P(i,j;d,\theta) = \frac{\#\left\{ \begin{array}{l} ((k,l),(m,n)) \in (L_x \times L_y) \times (L_x \times L_y) : \angle(k,l)(m,n) = \theta, \|(k,l)-(m,n)\| = d, \\ I(k,l) = i, I(m,n) = j \end{array} \right\}}{N(d,\theta)} \quad (4)$$

where $\angle$ denotes the angle between (k, l) and (m, n), $\|(k, l) - (m, n)\| = d$ indicates that (k, l) and (m, n) are d-pixel apart, # stands for the function "number of", L_x and L_y are the horizontal and vertical spatial domains, $I(x, y)$ is the image intensity at point (x, y), and $N(d, \theta)$ is the total number of pixel pairs in the image having angel θ with d-pixel apart.

GLCM is a two dimensional matrix with the same size as the number of grey-levels in an image. In this study, the images have 256 distinct grey levels; therefore the GLCM will be a matrix of size 256 × 256. In order to reduce calculation time, the gray-level range is transformed from [0, 255] to [0, 31] by coarseness technique results in 32×32 GLCM, which is used for evaluating the textural features of each seam pucker sample. The new images with fewer gray-levels are almost the same as the original ones visually, but the calculation time is reduced enormously.

To generate a suitable co-occurrence matrix, the relative distance d plays a major role whose value is always 1, 2, 3 or 4. The classification of fine textures usually requires small values of d, whereas coarse textures require large values of d. Here d = 4 is selected and two angels ($\theta = 0$, $\theta = 90$) are considered for evaluation. In this way, two GLCM are calculated for each of the seam pucker samples.

Haralick [19] proposed 14 feature measures derived from the GLCM for image texture analysis, and each represents certain image properties such as coarseness, contrast, homogeneity and texture complexity. In the present study, three of the features: Contrast (CON), Inverse Difference Moment (IDM) and Entropy (ENT) are used for classifying the seam puckers because they are found to show better discrimination than the other features. They are described as below.

1. Contrast:

$$\text{CON} = \sum_i \sum_j (i-j)^2 p(i,j \mid d,\theta) \quad (5)$$

Contrast is a measure of the image contrast or the amount of local variations present in an image, in which a zero-value denotes no contrast while larger values corresponds to an increase in contrast or coarseness.

2. Inverse difference moment:

$$\text{IDM} = \sum_i \sum_j \frac{1}{1+(i-j)^2} p(i,j \mid d,\theta) \quad (6)$$

Inverse Difference Moment is a measure of lack of local variability. A large value indicates few varieties among different areas of an image and a flat pixel distribution in local area.

3. Entropy:

$$\text{ENT} = -\sum_i \sum_j p(i,j \mid d,\theta) \log(p(i,j \mid d,\theta)) \quad (7)$$

Entropy determines the degree of randomness or lack of information contained in the co-occurrence matrix. When the value of Entropy is zero, no information is attributed to the matrix. As the magnitude increases more uncertainty is associated with the image region.

In Equations (5)-(7), i and j are the rows and columns of the co-occurrence matrix. For two directions ($\theta = 0$, $\theta = 90$) are considered there are totally six features extracted from GLCM.

In general, it is not easy for humans to tell depth information from an image. Since variance (a kind of central moment feature) reflects the amplitude of an image, it can be used as the depth feature of images.

$$DEP = \sum_{i=0}^{255} (k-\mu)^2 \times p(k) \quad (8)$$

where $p(k)$ is the probability of gray-level value k in the histogram of an image derived from $p(k) = n_k / n$ (n_k is the number of pixels with the gray-level k and n is the total number of pixels) and μ is the mean of the grey-level image matrix.

Using these seven features, an inspected region of seam pucker image is characterized by a seven-dimensional feature vector $F = (CON_0, IDM_0, ENT_0, CON_{90}, IDM_{90}, ENT_{90}, DEP)'$. The subscript 0 means the feature is calculated from the 0 degree GLCM and 90 is from 90 degree GLCM. In this way, N feature vectors are produced from a set of N samples and such feature vectors will be fed to a classifier to classify these samples into different grades.

D. Constructing and training the neural network

The map size (number of output neurons) of the SOM is critical for the performance of classification. If the map size is too small, it might not explain some important differences that should be detected, whereas if the map is too large, the differences will be too small. The type of input data affects the size of the SOM. If the inspected data are complex and the features have no ability to discriminate them correctly, a larger SOM is required.

The main aspects considered in designing the SOM classifier are the following:

1. Accuracy, and
2. Speed of operation.

The evaluation accuracy is characterized by classification error E, which is defined by:

$$E = \sqrt{\frac{\sum_{i=1}^{N}(G_h(i) - G_s(i))^2}{N}} \tag{9}$$

Where $G_h(i)$ and $G_s(i)$ are grades determined by the human inspectors and by the SOM classifier, respectively. N is the number of testing samples.

In general when constructing SOM, two quality indices are considered, i.e. quantization error and topographic error. The quantization error is the average distance between each input vector and its BMU (Best Matching Unit) and is used to measure map resolution [16]. The topographic error represents the accuracy of the map in preserving topology; the error value is calculated from the proportion of all data vectors for which first and second BMUs are not adjacent for measuring topology preservation [20]. These two indices serve as a criterion in our research to choose a suitable map.

In order to compare the performance of SOMs in different map sizes, the 600 seam pucker samples are randomly divided into two even sets, one for training and the other for testing. The random division is performed four times. For each training and testing set experiments are done with nine different maps of sizes from 5 × 1 neurons to 16 × 16 neurons. Other parameters needed in training are chosen properly so that they have a minimum impact on the performance results. For example, the number of training steps should be larger for bigger maps. Also the radius of neighborhood kernel should change with the training going on. During the first round, it is large enough to ensure the global ordering of the map. The radius also has an impact at the second round, since a larger radius provides a more homogeneous map, while a smaller one provides more accurate discrimination between feature vectors as the map adapts more tightly to the training material. For each map size, the average quantization error and average topographic error of the four sets of classification results are shown in Table 1, and the average classification error E is shown in Fig. 6 with a trendline for clarity.

Table 1
Changes of average quantization error (AQE) and average topographic error (ATE) of different SOM map sizes

Map Size	5×1	3×3	4×4	6x6	8×8	10×10	12×12	14×14	16×16
AQE	0.723	0.883	0.368	0.201	0.159	0.135	0.114	0.101	0.086
ATE	0.000	0.000	0.024	0.092	0.129	0.156	0.145	0.139	0.133

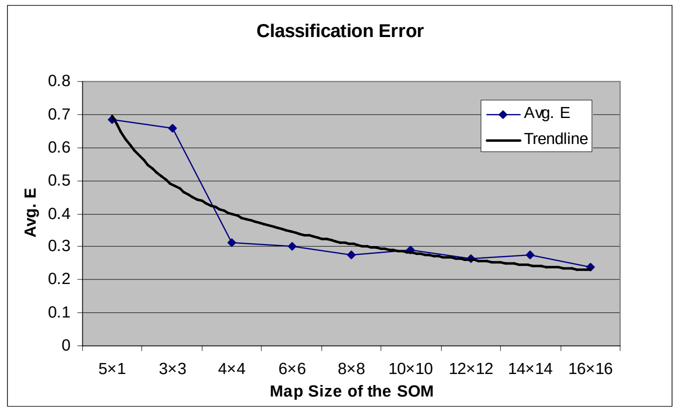


Fig. 6. Average classification error in function of map size of SOMs

As can be seen from Fig. 6, even the largest realistically sized SOM improves classification accuracy only by a small degree compared to rather small ones, such as the SOM with 8 × 8 neurons. Furthermore, although larger maps slightly increase the classification accuracy, the effect on computation speed is the opposite. For each sample, the times of comparisons required equal to the number of neurons in the output layer, and the cost of each comparison depends on the number of features there used. For example, using a SOM with 8 × 8 neurons instead of 16 × 16 neurons saves 75% of computational effort.

Considering classification accuracy, speed and quality indices of SOM synthetically a map size of 8 × 8 neurons is selected since it does not need much computation effort and only slightly less accurate than larger ones.

The SOM training algorithm that we implemented is the Batch training algorithm [9]. The whole training set is gone through at once and only after this the weight vectors are updated with the net effect of all the samples. Actually, the updating is done by simply replacing the prototype vector with a weighted average over the samples, where the weighting factors are the neighborhood function values.

$$m_i(t+1) = \frac{\sum_{j=1}^{n} h_{ic(j)}(t) x_j}{\sum_{j=1}^{n} h_{ic(j)}(t)} \tag{10}$$

where $c(j)$ is the BMU of sample x_j, $h_{i,c(j)}$ is a non-increasing neighborhood function (the weighting factor) around the BMU $c(j)$, and n is the number of input samples.

Training the SOM classifier, whose map size is 8 × 8, is carried out in two stages: rough training and fine-tuning. The aim of the first stage of the training is to roughly order the weight vectors of each neuron in the input vector space with large (initial) neighborhood radius and large (initial) learning rate. During the fine-tuning stage of the training, approximately ordered neurons are fine-tuned. In this stage, because all neurons are already ordered approximately, weight vectors of neurons need not be modified significantly. Therefore, neighborhood radius and learning rate are smaller than rough training stage. The SOM network structure and training characteristics are summarized in Table 2.

Table 2
SOM network structure and training characteristics

Neurons	64
Structure	Two-dimensional (8 × 8)
Neighborhood function	Gaussian
Distance metric	Euclidean
Weight initialization	Linear
Input feature values	7
Training mode	Batch
Training patterns	300
Test patterns	300
Training	
Rough	
Epochs	10
Initial learning rate	0.5
Initial radius	2
Final radius	1
Fine	
Epochs	40
Initial learning rate	0.05
Initial radius	1
Final radius	0

After the learning stage has finished the neurons need to be labeled, then the network can be used as a classifier. Three methods of labeling are used, they are listed as below.

Majority voting: Every neuron is assigned five counters, one counter for each class. Samples of equal number from each class are offered to the SOM classifier. With the training samples input successively, the counters of the winner neurons for the corresponding classes are incremented. At last each neuron is given a label according to the class for which its counter is the highest. Neurons that never win, or for which the above method leads to ambiguities (e.g., as often winner for two classes) can be labeled according to the labels of their neighbors using majority voting.

Minimum Average Distance: As in majority voting method, five class counters are also used for each neuron. However in minimum average distance method, with the samples offered to the network, the corresponding class counters for all neurons are not simply incremented but are increased by that lateral distance of the neuron to the winner. After all samples have been presented, the average distances are calculated by dividing each class counter by the number of samples for that class. The class with the smallest average lateral distance to the winner forms the label of the neuron.

Minimum Average Difference: This method is very similar to the labeling by minimum average distance, only the differences between the presented samples and the neuron's feature vector for each neuron are accumulated instead of accumulating the lateral distances to the winning neurons.

It is found that labeling by minimum average difference outperforms other methods in this study, so the experiments results in part IV are based on this method. Once the neurons have been labeled, an unknown sample can be offered to the network, and the classifier output is based on a winner-take-all method, that is the label of the winning neuron serves to grade the unknown pattern.

IV. Results

The 600 samples are divided into two even sets, 300 samples (consist of different seam pucker grades that has been graded by human experts) each for training and testing. After training the network gains the ability to determine seam quality, new samples not presented for training thus can be used to test the performance of the trained SOM classifier. The results are compared to the grades given by human experts. Classification results of the SOM classifier are displayed by a confusion matrix in Table 3, where H represents the grades given by human experts and S denotes SOM network outputs. In the confusion matrix, each cell contains the number of samples classified for the corresponding combination of desired and actual network outputs. The value of cell (i, j) represents the number of classifications of a seam in class j into class i. If all the entries located along the main diagonal, it means that the classification results of neural networks are totally accord with that of human experts. It can be observed that the error of all the samples being misclassified is only one grade.

Table 3

Classification confusion matrix of SOM classifier.

H/S	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5
Grade 1	49	11	0	0	0
Grade 2	6	51	3	0	0
Grade 3	0	6	50	4	0
Grade 4	0	0	3	56	1
Grade 5	0	0	0	2	58

The 600 seam pucker samples are randomly divided 100 times into two even sets. With different sets of samples the training and testing processes are performed 100 times, and the average classification accuracy rate is 88.3%. The classification accuracy of each grade is show in Fig. 7, which is defined as the percentage ratio of the number of samples correctly classified to the total number of samples considered for classification.

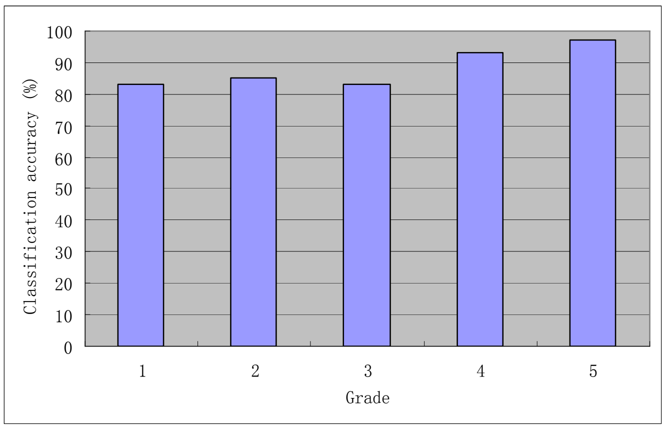


Fig. 7. Classification accuracy in each grade.

V. Conclusions

In this research, objective evaluation of seam pucker is achieved by using image analysis and pattern recognition instead of the traditional subjective method. The system consists of image acquisition, image normalization, feature extraction and self organizing map classifier. Each part is implemented with efficient algorithms (such as co-occurrence matrix features and the self organizing map). The experimental results indicate a good performance of texture analysis and ANN-based classifier in characterization of seam pucker, which show a high accordance with the judgments of human experts. This system will have a significant impact on garment factories in alleviating problems in the evaluation the surface quality of garments, a difficult yet important quality control process, and assist garment manufacturers to remain competitive in the worldwide global market.

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