# OBJECTIVE EVALUATION OF SEAM PUCKER USING AN ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

K. L. Mak and Wei Li
*Department of Industrial and Manufacturing System Engineering*
*University of Hong Kong, Pokfulam Road, Hong Kong*

Keywords: Image processing, Pattern recognition, Seam pucker, ANFIS.

Abstract: Seam pucker evaluation plays a very important role in the garments manufacturing industry. At present, seam puckers are usually evaluated by human inspectors, which is subjective, unreliable and time-consuming. With the developments of image processing and pattern recognition technologies, an automatic vision-based seam pucker evaluation system becomes possible. This paper presents a new approach based on adaptive neuro-fuzzy inference system (ANFIS) to establish the relationship between seam pucker grades and textural features of seam pucker images. The evaluation procedure is performed in two stages: features extraction with the co-occurrence matrix approach, and classification with ANFIS. Experimental results demonstrate the validity and effectiveness of the proposed ANFIS-based method.

## 1 INTRODUCTION

Quality control is vital for garments manufacturing industries to increase competitiveness in national and international markets. Seam pucker evaluation is a key requirement of quality control and assessment in garments manufacturing. Seam pucker is defined as the ridges, wrinkles, and corrugations running along the seam line of garments, and has been regarded as one of the most serious faults in garment manufacturing. 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. Due to the importance of seam pucker evaluation, some grading measurements have been developed. The most widely used standards are produced by AATCC (American Association of Textiles Chemists and Colorists). In these standards, a set of photographs (Figure 1) 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 assign a grade according to their similarity. However, this human inspection process is known to be subjective, inefficient and unreliable. 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. Automated vision-based inspection of seam puckers is therefore highly desired.

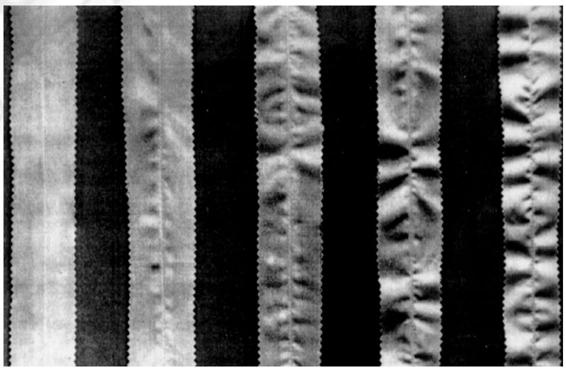


Figure 1: Photographic standards for subjective pucker inspection by the AATCC method (Claus, 1999).

With the development of image processing and pattern recognition technologies, some research (Galuszynski, 1986, Inui, *et.al.*, 1991, Kawabata and Niwa, 1996, Park and Kang, 1997, Fan, *et.al.*, 1999, Claus, 1999, Aibara *et.al.*, 2000) has been conducted over the years to evaluate seam puckers objectively. Nevertheless an economical and accurate method is still absent. In this paper, an objective evaluation method based on the technique of image processing



L. Mak K. and Li W. (2008).
OBJECTIVE EVALUATION OF SEAM PUCKER USING AN ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM.
In *Proceedings of the Third International Conference on Computer Vision Theory and Applications*, pages 234-239
DOI: 10.5220/0001080902340239

and neuro-fuzzy is presented to grade seam puckers with high accuracy.

## 2 ANFIS

The combination of fuzzy logic with architectural design of neural network led to creation of neuro-fuzzy systems which benefit from feed forward calculation of output and back-propagation learning capability of neural networks, while keeping interpretability of a fuzzy system (Jang, *et.al.* 1997). Many neuro-fuzzy structures have been proposed and some were widely used, among which Jang's ANFIS (Adaptive Neuro-Fuzzy Inference System) (Jang, 1993) structure is probably the most famous one. ANFIS has good ability and performance in system identification, pattern recognition and control, and has been applied in many different systems. The ANFIS has the advantage of good applicability as it can be interpreted as local linearization modeling and conventional linear techniques are directly applicable.

To present the ANFIS architecture, two fuzzy if-then rules based on a first-order Sugeno fuzzy model are considered:

Rule 1: If ($x$ is $A_1$) and ($y$ is $B_1$) then ($f_1 = p_1x + q_1y + r_1$)

Rule 2: If ($x$ is $A_2$) and ($y$ is $B_2$) then ($f_2 = p_2x + q_2y + r_2$)

where $x$ and $y$ are the inputs, $A_i$ and $B_i$ are the fuzzy sets, $f_i$ are the outputs within the fuzzy region specified by the fuzzy rule, $p_i$, $q_i$ and $r_i$ are the design parameters that are determined during the training process. The network structure of ANFIS to implement these two rules is shown in Figure 2, in which a square node (adaptive node) has parameters while a circle node (fixed node) has none. The first layer executes a fuzzification process, the second layer executes the fuzzy *AND* of the antecedent part of the fuzzy rules, the third layer normalizes the membership functions, the fourth layer executes the consequent part of the fuzzy rules, and finally the last layer computes the output of fuzzy system by summing up the outputs of layer four.

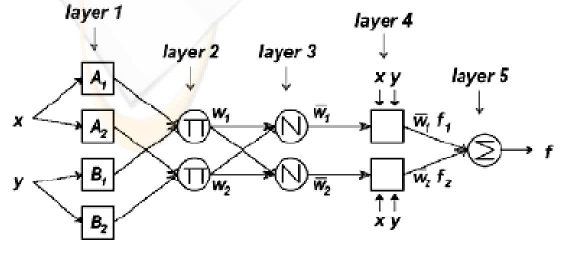



Figure 2: ANFIS architecture (Jang J. R, 1993).

The feed-forward equations of ANFIS with two inputs and two labels for each input which is shown in Figure 2 are as follow:

$$w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), \quad i = 1,2. \tag{1}$$

$$\overline{w_i} = \frac{w_i}{w_1 + w_2}, \quad i = 1,2. \tag{2}$$

$$\left.\begin{aligned} f_1 &= p_1x + q_1y + r_1 \\ f_2 &= p_2x + q_2y + r_2 \end{aligned}\right\} \Rightarrow \\ f = \frac{w_1f_1 + w_2f_2}{w_1 + w_2} = \overline{w_1}f_1 + \overline{w_2}f_2 \tag{3}$$

There are two adaptive layers in this ANFIS architecture, namely the first layer and the fourth layer. In the first layer, the modifiable parameters relating to the input membership functions are the antecedent parameters. In the fourth layer, the modifiable parameters pertaining to the first order polynomial are consequent parameters.

The task of the learning algorithm for ANFIS is to tune all the modifiable parameters, namely antecedent parameters and consequent parameters, to make the ANFIS output match the given training data. The least squares estimate (LSE) method and the gradient descent (GD) method is always combined to solve this problem. The training algorithm is composed of a forward pass and a backward pass. The LSE (forward pass) is used to optimize the consequent parameters with the antecedent parameters fixed. Once the optimal consequent parameters are found, the backward pass starts, always using the gradient descent method, to adjust optimally the antecedent parameters.

## 3 PROCEDURE

Figure 3 shows the procedure of our classification system for seam puckers. The images of seam puckers are acquired with a CCD camera system, and then an algorithm for detecting the seam lines is applied. Based on the defined seam lines the grey-level images are normalized (including transforming and truncating). The normalized images are divided into two sets, one is for training and the other is for testing.

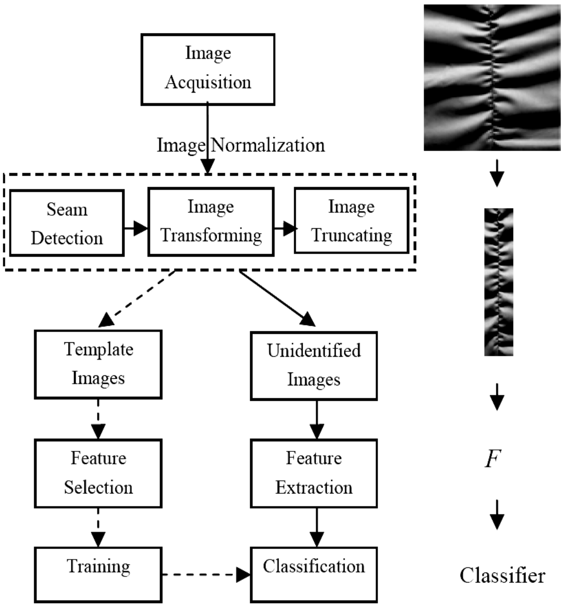



Figure 3: Block diagram of the classification system.

The learning process uses the training sets to develop an identification system for seam puck grading. Finally the trained neural network can serve as the seam pucker classifier instead of human inspectors.

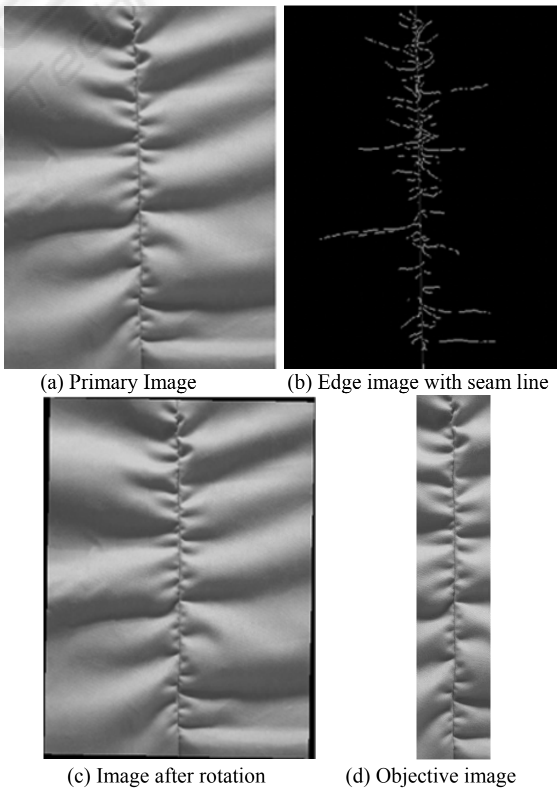
## 3.1 Image Acquisition

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 cameras and laser scanners. Laser scanners have been used (Kawabata and Niwa, 1996, Park and Kang, 1997, Fan, *et.al.*, 1999) to obtain geometrical profile of puckers by measuring surface height variation. However the cost of a laser scanner makes it too expensive for industrial applications. Moreover the methods they used to acquire information with laser scanner require the laser probe move parallel with the direction of the seam. This is not easy to execute for quality control measurements of seam puckers are normally done on completed garments where the garments are usually hanged up. CCD camera system is a convenient and low-cost way for image acquisition, which can yield good resolution images and is more similar to human's judgment measure. 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. The sample images acquired by the CCD camera are 210mm long and 158mm wide with a resolution of 640×480 pixels.

## 3.2 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 position. 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 (positioning, transforming and truncating) algorithm is implemented, which is able to define the position of seam lines and obtain the partial images we really interested in.

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



(a) Primary Image (b) Edge image with seam line

(c) Image after rotation (d) Objective image

Figure 4: Image positioning, transforming and truncating.

## 3.3 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.

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 (Haralick *et.al.*, 1973.). 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:

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

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 angle $\theta$ 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 angles ($\theta = 0$, $\theta = 90$) are considered for evaluation. In this way, two GLCM are calculated for each of the seam pucker samples.

Haralick 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:

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

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:

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

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:

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

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.

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

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 $\mu$ 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.

### 3.4 Evaluate Seam Pucker with ANFIS

600 seam pucker samples in uniform color are made with 120 samples for each grade. The grades of the seam samples are evaluated by observers (human inspectors) according to the AATCC standards. The 600 samples are divided into two even sets, 300 samples (consisting of different seam pucker grades) each for training and testing.

Figure 5 shows the ANFIS model of a seven-input single-output set of seam pucker data. It should be noted that if two linguistic terms are used in each antecedent, which is equivalent to two Gaussian membership functions for each input variable, then there will be $2^7 = 128$ fuzzy rules totally. Fixed number of membership functions will invoke the so-called curse of dimensionality, and causes an explosion of the number of rules when the number of inputs is moderately large, that is, more than four or five. In our work, the input dimension is seven, so an initial ANFIS structure is generated using subtractive clustering (Chiu, 1994).

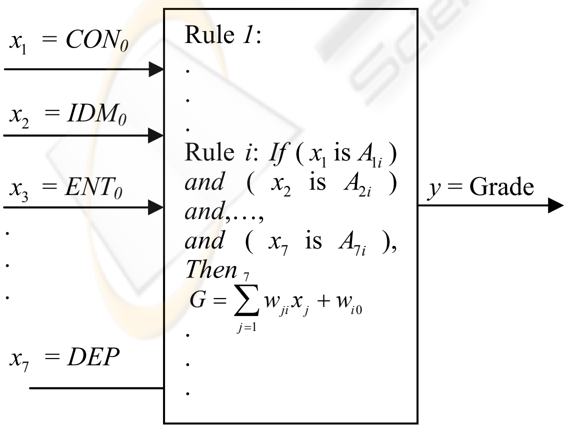



Figure 5: A conceptual ANFIS model of seam pucker evaluation.

Subtractive clustering is a fast and robust method for estimating the number and location of cluster centres for a set of data points. First the subtractive clustering was carried out to obtain the cluster centres which will be used as the basis for the ANFIS to initialize fuzzy rules. The membership functions and other rule parameters were then optimized by the hybrid training algorithm of GD and LSE with respect to the output error criterion, here is the RMSE (root mean square error).

The ANFIS tool in the Fuzzy Logic Toolbox of Matlab 7.0 (The MathWorks, Inc.) was used as a modelling method. A maximum number of 50 epochs for training was applied and the cluster radius for subtractive clustering is set as 0.7.

## 4 RESULTS AND CONCLUSIONS

The trained ANFIS classifier established the relationship between seam pucker grades and texture features of the seam pucker images, thus new samples not presented for training can be evaluated given the texture parameters. The training and testing processes are performed 100 times with seam pucker samples randomly divided 100 times, and the average classification accuracy rate is 89.2%.

This paper proposed an automatic vision-based method to evaluate seam puckers using image analysis and pattern recognition instead of the traditional method. The system consists of image acquisition, image normalization, feature extraction and neuro-fuzzy classifier (ANFIS), which showed good behavior to evaluate the data of seam puckers. The accuracy rate of classifications outperform that of subjective method, which can be measured by the "disagreement" (Claus, 1999) among a set of subjective evaluation grades from an expert group. This system can effectively evaluate seam puckers, and 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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