Construction of Predictive Model on Fabric and Sewing Thread Optimization

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Received January 14, 2004; Accepted for Publication April 16, 2004

Abstract

Along with the trend of automation in apparel industry, some key parameters are applied to establish a prediction model for the sewing optimization between fabric and thread, which has become an important issue in apparel quality control. Hence, the structural properties of fabric and thread are used in this study to establish the optimized scope and prediction model for the quality of the sewed item. It can be noticed from the research results that the sewing quality and the structural properties of the fabric and the thread are in fact highly correlated. Therefore, neural network method can be applied to establish a neural network model between the two. By testing the neural network model established in this study, it is found that the model has high correlation coefficient and low residuals, indicating that the model has good fitting ability. Besides, the optimized scope of sewing quality can be used as a basis for evaluation of sewing optimization between fabric and thread.

Key words : Sewing quality, Sewing optimization between fabric and thread, Neural network

1. Introduction

Following the evolution of apparel automation along with other critical parameters, statistical methods are used to establish quality assessment standard that is an important apparel industry task [1]. Ready-made garments are assembled from cut fabrics. Factors affecting sewing quality include quality of sewing threads and fabrics, sewing conditions, human factors, etc. These factors are important aspects in academic researches. In 1985, H. Shimizu and others proposed controls for slipping and coming off of sewing threads and seam pucker when wool fabrics endured tensile. They felt the number of sewing thread count was the key pivotal influence [2]. In 1988, I. Ajiki discovered fabric flexibility, sewing thread tension and fabric thickness all influenced sewing thread breakage, and inferred a relation model [3]. In 1989, T. J. Mahar conducted research on influences of fabric physical properties versus sewing thread breakage, deformation and elongation [4]. In 1990, K. Nakano and K. Shimazaki proposed correlation analysis on fabric physical properties versus sewing thread tensile strength and elongation when 2-Thread Chain Stitch was used, and applied statistical methods for analysis [5]. In 1991, J. Gersak and B. Knez proposed influences of sewing thread type, count, breakage strength and elongation, twisting count, etc to the quality of sewing products [6]. In 1985, M. Matsuo probed the relationship between sewing thread types, stitch types, tensile cycle, number of tensile and sewing thread fatigue [7]. In 1999, S.S Lai probed the influence sewing thread count and twisting count had on sewing product tensile fatigue properties [8]. In 2001, S.S Lai probed time effect of sewing angle and sewing product ; influences fabric physical properties had on seam pucker [9-10]. An overview of above showed that many factors

influenced sewing quality, and previous scholars have provided volumes of research results. But researches on optimization of fabric and sewing thread collocation and sewing quality quantification remained lacking. Thus based on correlation analysis, this research hopes to understand fabric and the influence of sewing composition properties and sewing quality. And then use neural network method to establish translation model between fabric and sewing thread composition properties and sewing quality. Finally, assess optimization of fabric and sewing thread collocation.

2. Research Methodology

2.1 Experiment material

This research uses polyester silk, polyester/cotton blend, polyester/rayon blend, cotton and other fabrics sold on market, in combination with cotton/polyester sewing thread as experiment materials. Basic properties of experiment materials see Table 1.

2.2 Fabrication of Samples

First, cut fabric warp sense into rectangles length x width measuring 10.5cm x 5cm, then sew together two cut pieces. Sewing conditions are: # 10 sewing needle, 5 stitches per centimeter, lock stitch, sewing machine speed around 3500rpm. Finished sample size (length x width) should be 20cm x 5 cm.

2.3 Sewing Assessment

2.3.1 Neatness and Handsomeness

First, divide sewed objects into five levels according to

pucker, creases and neatness, and make standard samples. Level one is the worst, and increase progressively with level five being the best. Afterwards, vision is used to compare and observe sewed objects' neatness and handsomeness. Sewed objects are placed in a WINTREE DC-1 Type experimental washing machine, experiment conducted according to JIS L1042 (E method), then compare neatness and handsomeness after wash.

2.3.2 Tensile Properties

Using universal tensile strength tester manufactured by GOTECH Company, conduct tensile experiment in accordance to JIS L1093 standard. Experimental conditions are: constant rate of loading; tensile speed at 100mm/min; temperature and humidity are 25°C (± 3°C), 65%RH (± 5%RH) respectively.

2.3.3 Openness of Stitches after Tensile Cycle Test

Tensile cycle test experiment on sewed objects uses MTS-810 Type universal tensile strength tester. Testing conditions: tensile speed 100 mm/min; fixed stress (30% load at break for samples); rate at 3 min/sequence; cycle sequence is 6 times, clip relax 5 seconds in between each cycle. Samples are observed under microscope, and stitch openings (mm) are recorded (under 100 grams of loading).

Table 1 Details of fabric samples

Details of fabric and thread	Symbols	Minimum	Maximum	Mean	Standard deviation
Fabric thickness (mm)	FTN	0.11	0.74	0.32	0.15
Fabric warp and weft average count (Ne)	FN	17	89	36.21	17.61
Fabric warp and weft average density (n/cm)	FD	27	48	35.83	5.94
Fabric warp and weft average Twisting count (TPI)	FTW	10	28	16.21	5.58
Fabric warp and weft average strength (kgf)	FS	18.68	89	59.18	24.04
Fabric warp and weft average elongation (%)	FE	10.5	35.14	19.43	6.97
Thread count (Ne)	YN	8.05	30.3	15.91	5.52
Thread twisting count (TPI)	YT	13	30	21.5	5.81
Thread strength (kgf)	YS	0.14	1.2	0.87	0.2
Thread elongation (%)	YE	7.2	28.24	19.73	4.26

2.3.4 Total Quality Levels

Take the above four assessment values and through variables transform them into a total grading level.

Calculation formula: $M_t = (M_p + M_{wp} + M_s + M_o)/4$, where, M_t : sewing optimization; M_p : neatness and handsomeness level; M_{wp} : neatness and handsomeness after water wash; M_s : sewing strength level; M_o : stitch opening level. Sewing strength is in ascending order, lowest level being 1. Stitch opening is in descending order, highest being 1. Using above formula, sewing optimization (M_t) levels are between 1 and 5. Of those level 1 is worst optimization, and in ascending order with level 5 being superior.

2.4 Neural Network Model [11]

In this study, neural network was used to establish a predictive model for sewing quality from fabric and sewing thread structure properties. A back-propagation neural network with three layers of input layer, output layer, and hidden layer, was used in this study. The network configuration is shown in Figure 1. Seven structural properties of the fabric and the thread were used as input variable candidates. The input values show Table1. The

sigmoid function, $f(x) = \frac{1}{1 + e^{-x}}$, was used for nonlinear

transformation. The related network conditions are presented in Table 2. For computation of the weight value variation between the hidden layer and output layer, generalized delta learning rules were employed. The learning network was used for reducing the margin between the target value and prediction output. The quality of the learning was evaluated

using the energy function (E), $E = \frac{1}{2} \sum (T_j - Y_j)^2$,

where T_j is the output layer target value and Y_j is the output layer prediction value. In order to minimize the value of the energy function, the steepest gradient descent entry method was employed. The optimal data convergence after network training was obtained under these conditions (see Table 2). In the supervised network learning process, the degree of convergence can be expressed in a root-mean-square error

(RMSE), $RMSE = [\frac{1}{n} \sum (T_j - Y_j)^2]^{1/2}$, where n is the

number of units processed by the output layer. The RMSE were used to evaluate the network learning performance.

Figure 1. Adopted neural network structure

Table 2. Neural network parameters

	Item	Parameter
Input layer	Normalization	Standard
	Number of unit	<10
Hidden layer	Transfer function	Sigmoid
	Number of unit	4
Output layer	Normalization	Standard
	Number of unit	1
Weights	Distribution	Uniform
	Range	0.1-1
Learning rule	Algorithm	Steepest descent
Training stages	Learning coefficient.	0.5
	Momentum coefficient.	0.3
	Max. Record	105
	Max. Update	10000
Stop when	% Correct	
	-Training	95.0
	-Validation	95.0

2.5 Optimal Scope for Total Quality Levels of Sewed Objects

Correlation exists between sewing quality of sewed objects and fabric and fabric structure properties. First, take top 10 out of 120 set of samples with the highest total quality grade levels as optimal samples. Next, standardize sample structure properties. Finally, find maximum and minimum range of each structure properties of samples and define them as optimal scope of sewing quality levels. Using random sampling method, select 5 samples that match structure properties scope in Table 1. Substitute structure properties into model to assess model predictive ability and optimal scope of quality optimization.

3. Conclusions and Discussions

3.1 Correlation Analysis

Table 3 shows correlation coefficient of fabric and sewing thread structure properties and sewing quality. Sewing neatness and handsomeness and fabric warp and weft average count, fabric warp and weft average density show negative dependency. On the other hand, sewing neatness and handsomeness and fabric warp and weft average twisting count show positive dependency. Stitch opening and fabric thickness show positive dependency. On the other hand, stitch opening and fabric warp and weft average elongation, sewing thread strength and elongation show negative dependency. Neatness and handsomeness of sewed objects after water wash and fabric warp and weft average count show negative dependency. On the other hand, neatness and handsomeness after water wash and fabric warp and weft average twisting count show positive dependency. Strength and fabric thickness of sewed objects, fabric warp and weft strength, sewing thread twisting count, sewing thread strength and sewing thread elongation show positive dependency. Total quality level and fabric warp and weft average count, stitch count show negative dependency. Total quality level and fabric warp and weft average twisting

count; fabric warp and weft average strength, sewing thread twisting count, sewing thread strength and sewing thread elongation show positive dependency.

Table 3 Correlation coefficient of fabric and sewing thread structure properties and sewing quality

Symbols	S _P	S _O	S _{WP}	S _S	M _t
FTN	-0.05	0.31***	0.06	0.29**	0.050
FN	-0.37***	-0.17	-0.34**	-0.45***	-0.3***
FD	-0.2*	-0.12	0.09	0.13	0.06
FTW	0.425***	-0.14	0.41**	0.06	0.26**
FS	0.065	-0.14	-0.03	0.3***	0.26**
FE	-0.16	-0.39***	-0.11	-0.26**	0.03
YN	-0.07	0.14	0.12	-0.71***	-0.52***
YT	-0.05	-0.07	-0.15	0.62***	0.41***
YS	0.133	-0.18*	-0.07	0.70***	0.57***
YE	0.149	-0.79***	0.02	0.28**	0.62***

* : P<0.05, ** : P<0.01, *** : P<0.001

3.2 Construction of Predictive Model for Sewing Quality

This chapter attempts to establish a predictive model for sewing quality from fabric and sewing thread structure properties. And hope to understand how to match fabric and sewing thread to create the optimum sewing quality. From Figure 2, it is discovered that neural network RMSE will diminish as number of training increases, and from then on gradually show trend of convergence. When number of training reaches 1100 times, RMSE shows convergence status. Even if number of training is increased, RMSE diminishing margin is limited, thus network training ended. RMSE of the five sets are: Mo, 0.09; Ms, 0.1; Mwp, 0.1; Mp, 0.08; Mt, 0.09. This shows that the five predictive model of sewing quality constructed by this research institute, RMSE converges stably after brief training. RMSE diminishing trend matches normal condition of neural network training, showing traditional convergence trend. Neural network predictive ability is assessed by correlation coefficient of model predictive values and practical values.

Points on each model scatter distribute evenly on the diagonal line, showing little difference between predictive values and practical values, the model has excellent predictive ability (see Figure 3). Points on the scatter of neatness and handsomeness after water wash deviate further away from the diagonal line, showing a lesser predictive ability.

After residual analysis, the mean absolute residual value for the five set models are: neatness and handsomeness at 0.05 level, neatness and handsomeness after water wash at 0.89 level, sewing strength at 0.13 (kgf), stitch opening model at 0.42(mm), and total quality level model at 0.08 level. The difference between each model's practical value and predictive value is small, showing the model has excellent fitting ability. Although neatness and handsomeness after water wash is lesser than others in above assessments, but from the average value of mean absolute residual value, it is discovered that there is only a 0.9 level difference between model predictive value and practical value, showing that it still has fitting ability.

Figure 2 RMSE values

Figure 3 Scatter of predictive values and practical values of the five models

3.3 Optimal Scope of Sewing Total Quality Level

This chapter uses fabric and sewing thread structure properties as parameters to establish optimal scope of sewing total quality level. Optimum structure qualities after standardization of sewing quality samples will arrive scope as in Table 4. Optimal scope of sewing total quality levels is within ± 3 standard deviation. Fabric density and elongation have a greater scope. Scope of fabric warp and weft average count, sewing thread twisting count, elongation and other properties is lesser. Scope of four stitch sewing

thread properties is less than that of six fabric structure properties. A lesser standard deviation scope means that particular structure property within the ten sample sets is less likely to change. Through the optimal scope table in Table 4, it can be used as reference for optimal match of fabrics and sewing threads.

Table 4 Optimal Scope of sewing total quality level

Symbols	Minimum	Maximum
FIN	-1.19	1.59
FN	-1.54	1.83
FD	-1.45	2.02
FTW	-1.49	1.22
FS	-1.81	1.17
FE	-1.17	1.79
YN	-0.71	1.79
YT	-2.07	0.71
YS	-1.64	0.78
YE	-1.09	2.94

Table 5 Model Assessment Result

Symbols	Sample A	Sample B	Sample C
FIN	0.13	0.3	0.43
FN	89.1	33	17.1
FD	29.8	47.2	34.2
FTW	11.01	10.8	28
FS	18.7	80	77.8
FE	23.1	12.1	18.9
YN	21.7	13.2	8.1
YT	13.1	28	28
YS	0.71	0.84	1.2
YE	16.3	17.2	22.4
Mo	2.3	2.5	2
Ms	1.2	19.6	21.2
Mwp	3	3	4
Mp	3	3	4
Mt	2.01	3.25	4.25
M _O *	2.32	2.35	1.98
M _S *	2.3	17.5	22.8
M _{WP} *	2.63	2.82	3.52
M _P *	2.89	3.02	4.02
M _t *	1.85	3.11	4.06
Result	Poor	Good	Excellent
Result*	Poor	Good	Excellent

Note: unit of fabric and sewing thread quality as in Table 1, and *: predictive value.

3.4 Model Assessment

After model assessment, it is discovered that two out of the five sample sets are of poor level: 2 are middle level, and one is superior. Taking one sample set out of poor, middle and superior levels, assessment results are listed in Table 5. Difference of residual is small between the predictive value and practical value of the sewing quality of the three sample sets. Total quality level for sample A, B, C is level 1.85, 3.11 and 4.06 respectively, exactly the poor, middle and superior levels. Thus the predictive model constructed by this research institute has excellent predictive ability.

Figure 4 is a scatter of the three sample sets after property standardization. In sample A, fabric thickness, fabric warp and weft average count, fabric strength, sewing thread twisting count; and thread elongation are all above optimal scope. In sample B, sewing thread elongation property is above optimal scope. In sample C, fabric and sewing thread structure properties are within optimal scope. From this we can see that the sewing quality of sample C is better than sample A and B ; and Sample B is better than sample A. This result proves that selection from optimal scope can be used as assessment basis of fabric and sewing thread matching optimization.

4. Conclusion

Fabric and sewing thread structure properties, including thickness, warp and weft average count, warp and weft density, warp and average twisting count, strength, elongation, sewing thread count, sewing thread strength and elongation, etc, exist a correlation between them and sewing quality level primes. By using the neural network model, quality levels of the predictive model can be established through above-mentioned ten properties. The five models constructed by this research institute, the correlation coefficient between the model predictive value and practical value is above 0.9, mean absolute residual value is small, therefore has excellent fitting ability.

By defining the optimal scope of total quality levels, fashion designers can be provided with optimal selections of sewing threads and fabrics. This research successfully constructed an assessment method for fabric and sewing thread sewing optimization, including considerations for quantification, objectivity and effectiveness, provides actual benefits to apparel quality assessment and automation.

Acknowledgments

Many thanks with sincere gratefulness to Dr. Sang Song Lai for his ardent guidance.

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Figure 4 Scatter of assessment structure properties of sample set A, B, and C