Neural Network Prediction of Human Psychological Perceptions of Fabric Hand
C.L. Hui, T.W. Lau, S.F. Ng and K.C.C. Chan
DOI: 10.1177/004051750407400501

The online version of this article can be found at:
http://trj.sagepub.com/cgi/content/abstract/74/5/375
Neural Network Prediction of Human Psychological Perceptions of Fabric Hand

C. L. HUI, T. W. LAU, AND S. F. NG

Institute of Textiles and Clothing, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong

K. C. C. CHAN

Department of Computing, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong

ABSTRACT

Fabric hand is commonly adopted for assessing fabric quality and prospective performance in a particular end use. In general, fabric hand is primarily assessed subjectively. Subjective assessments treat fabric hand as a psychological reaction obtained from the sense of touch, based on the experience and sensitivity of humans. It is very difficult to predict such psychological perceptions of hand based on fabric properties. In this paper, we identify reliable sensory fabric hand attributes with correlated attributes of fabric properties, and we attempt a novel approach for predicting sensory hand based on fabric properties using a resilient back-propagation neural network. In this study, we assess forty woven fabrics to determine twelve significant fabric properties and fourteen reliable attributes of sensory hand. Our proposed system performs at a very low mean square error after fine tuning. Five extra woven fabrics are used to show that the performance of such a prediction system closely agrees with subjective test results. Our proposed system can allow field practitioners to evaluate their fabrics more closely to match with customers’ expectations.

Fabric hand is a generic term for the tactile sensations associated with fabrics that influence consumer preferences [12]. It is basically a reflection of overall quality, consisting of a number of individual physical properties [24], and is the human response to touching, squeezing, rubbing, or otherwise handling a fabric [16]. It is commonly adopted for assessing fabric quality and prospective performance in a particular end use.

In general, fabric hand can be assessed by subjective and objective methods. Subjective assessments treat fabric hand as a psychological reaction obtained by the sense of touch. It is a primary descriptive method based on the experience and sensitivity of human beings. Objective assessments attempt to predict fabric hand using instrumental data and sensory-instrumental relationships.

Theoretical approaches to subjective fabric hand sensory assessments have recently aroused great interest in the area of clothing and textiles, and many researchers have looked for "world-famous" methodologies to transform subjective hand properties to objective measurements [38]. The motivation behind these works is due to the different fabric sensory perceptions of individuals. Brand [2] is one of several researchers who commented on differences between vocabularies of experts and untrained judges of textile hand. Wauer [36] concluded that these differences are great enough to interfere with communications between experts and consumers. They may use the same adjective, say, “harsh,” to describe a hand that differs among individuals. Moreover, Brand [2] stated that, "Aesthetic concepts are basically people’s preferences and should be evaluated subjectively by people." This differentiation has initiated much research focused on how to model subjective fabric hand objectively. Although many older techniques for evaluating fabric hand did not use standards or proper psychological methods, more recent approaches certainly do use standard scales and measures. For example, the Spectrum Method of Descriptive Hand Evaluation (Civille and Dus) [5] is based on a set of fifteen-point intensity scales for twenty-one different attributes of fabric hand. Each of these intensity scales is anchored at several points by specific fabric standards, i.e., physical references, so that
subjective evaluations of fabrics can be made with reference to physical standards with defined values along the measurement dimension. This technique has been used successfully in a number of applications for assessing the subjective hand of woven and nonwoven products and for determining the relationships between instrumental measures of physical properties of fabrics and their subjective hand values [31]. However, evaluators must first train very thoroughly before using such methods, so they may not be appropriate for consumer use.

Many researchers have justified objective methods by stating that the stimuli in fabrics that lead to subjective hand assessment can be described by specific fabric properties [19–21, 26, 34, 37]. Numerous methods have been used for predicting objective fabric hand, for example, a linear regression model [18], Weber-Fechner’s law, Steven’s power law, rank correlation [33], multiple factor analysis [1, 17], and weighted euclidean distance [26]. All these methods require tedious computations and are thus inappropriate for providing quick responses to consumers. Although recent works such as Rachel and Liu [30] and Park et al. [27] have used fuzzy comprehension evaluation and neural networks to predict fabric hand, these works were concerned only with total hand evaluation and could not predict each individual hand attribute for a particular fabric. Wong et al. [41] used a neural network to predict human psychological perceptions of clothing sensory comfort but did not specifically treat sensory fabric hand. This has led to our motivation for tackling such problems by using the artificial neural network approach, so that objective fabric hand assessments can cater to the consumers’ preferences.

In this paper, we determine reliable and significant attributes of fabric properties for assessing the sensory hand of woven fabrics in our first experiment. We then use an artificial neural network (ANN) to build a model to predict the sensory measures of hand from fabric properties in the second experiment. Finally, we evaluate our proposed ANN scheme with some design parameters and users validate it in our last experiment. We conclude with a discussion of our results.

The Three Experiments

EXPERIMENT 1: DETERMINING SIGNIFICANT ATTRIBUTES OF FABRIC PROPERTIES FOR ASSESSING A RELIABLE ATTRIBUTE OF SENSORY FABRIC HAND

Before we start to develop the neural network to predict sensory hand ratings from fabric properties, we need to establish the reliable attributes of evaluating sensory fabric hand and then determine the significant attributes of fabric properties for assessing these reliable hand attributes.

Experimental

Thirty general university students (twenty females, ten males) were selected as panelists based on interest, availability, and successful completion of a screening test to establish minimum tactile sensitivity. The latter was necessary because tactile sensitivity has been shown to vary significantly as a function of age, degree of skin hydration/wettedness, dermatitis, and other factors.

The research of Winakor and Kim [38], Kim and Piromthamsiri [21], and Mahar et al. [25] revealed that there are fourteen significant bipolar pairs of sensory attributes of fabric hand. Definitions and English word descriptors of each bipolar pair are given in Table I. Panelists trained to understand the definitions of these sensory attributes prior to evaluation.

In order to assess the reliability of the fourteen significant bipolar pairs of sensory attributes of fabric hand, we conducted a test-retest reliability study at the completion of the panelists’ training. We selected forty wo-

| Table I. Definitions and English word descriptors of 14 bipolar pairs of sensory fabric hand attributes. |
|---|---|---|---|
| Definition | Descriptor | Definition | Descriptor |
| Flat | smooth and level | Textured | having a certain kind of texture |
| Not bulky | slim size, shape, mass, or quantity | Bulky | great size, shape, mass, or quantity |
| Light | easy to be seen in; bright | Heavy | having a certain weight |
| Thin | small distance between opposite surfaces | Thick | large distance between opposite surface |
| Silky | like silk; soft, smooth, or shiny | Scratchy | spoilt by scratches |
| Smooth | even surface; not rough | Rough | uneven surface; not smooth |
| Fine | very thin | Coarse | not fine or smooth, rough |
| Limp | lacking strength or stiffness | Crisp | firm, fresh |
| Flexible | can be bent easily | Stiff | not easily bent |
| Soft | not firm against pressure | Hard | firm and stiff, not easily broken or bent |
| Firm | strong, solid, hard | Flimsy | not strong, light and thin |
| Compact | pressed, joined together, or united firmly and closely | Loose | not fastened or tied together |
| High drape | easy to hang or stretch out loosely and carelessly | Low Drape | difficult to hang or stretch out loosely and carelessly |
| Cool | neither warm or cold; pleasantly cold | Warm | having or giving off a pleasant feeling of heat |
ven fabrics consisting of 100% cotton, 100% polyester, 100% wool, 100% nylon, 100% acetate, 50% nylon/50% acetate, and 65% polyester/35% cotton for evaluation to represent a range of tactile attributes that might be encountered in testing and to include both similar and dissimilar fabrics. All these fabrics were evaluated by the panelists on two different occasions (i.e., morning and afternoon sessions), separated by a two-week interval. In addition, five of the test fabrics were selected again six months later to assess long-term reliability.

All evaluations were conducted in a textile conditioning room at a temperature of 20+/-2°C and 65%+/-1.5 RH. Panelists evaluated test samples independently and in random order. All fabric specimens were laundered five times to remove nondurable sewing lubricants and softeners that could affect tactile characteristics. The launderings were in accordance with American Association of Textile Chemists and Colorists test method no. 96, test condition IIIc, tumble dry (option A). After laundering, the fabrics were cut into 25 x 25 cm swatches, with edges parallel to the fabric warp and filling directions, and all edges were serrated to prevent raveling.

Each panelist was asked to assess forty fabric specimens, each 25 x 25 cm, by placing their hands into a 30 x 30 cm black box through a hole to eliminate the effect of subjective color preference on hand rating. Panelists were asked to rate fabric specimens using a 99-point scale for the fourteen bipolar adjectives as the output data. The use of 99-point scale is supported by Warren [35], who stated that moderately well educated persons can respond rapidly and reliably to this scale. Responses to the semantic differential scale were transformed from the 99-point scale to normal deviates by the computing method of Wolins and Dickinson [40]. A score of 1 on the certainty scale was transformed to -2.33, 50 to 0, and 99 to +2.33. Transformed data were used for the training data set in the neural network. Judgements were repeated twice, and the mean and variance of the transformed ratings for each fabric specimen were then calculated.

Meanwhile, all fabric specimens were measured by physical instrumentation, the KES-F system and the FAST system, to determine their physical and mechanical properties. The selection of physical and mechanical fabric properties that affect hand is based on an analysis of the essence of handling. Hand is a sensory feedback of fabric macroscopic deformation during handling if thermal character is ignored. Of the four possible methods of deformation (tensile, compression, bending, and shear properties), all happen easily when handling a fabric. Another significant attribute is wrinkle recovery. The effect of wrinkle recovery on hand is similar to flexural rigidity, which reflects a smaller reacting force on the human hand during slack holding, whereas wrinkle recovery reflects a greater reacting force when a fabric is tightly held. As for fabric surface characteristics, the frictional coefficient is one of the most important properties affecting hand, but a standard method or instrument for measuring this property is not available. Thus, we selected surface roughness as a measuring attribute instead of the frictional coefficient. Fabric weight and thickness are two exceptional physical properties whose affect on hand cannot be substituted by other mechanical properties [19-21, 26, 34, 37]. Before the measurements, all fabric specimens were conditioned in the laboratory at a temperature of 20+/-2°C and 65%+/-1.5 RH for 24 hours.

Results and Discussion

Pearson correlation coefficients were calculated across mean ratings of the fourteen sensory hand attributes for each fabric rated on different test days. The correlation coefficients of panel ratings for the same fabrics tested two weeks apart ranged from 0.91-0.98, depending on the attribute examined. For the five fabrics tested again six months later, the correlation coefficients between each of the first two sessions and the third ranged from 0.84-0.94, indicating a minor drop in test-retest reliability over the six-month period. From these findings, we concluded that the fourteen bipolar pairs of sensory hand attributes listed in Table I, in conjunction with the panel training program, resulted in a sensory hand evaluation method that is highly reliable over extended time periods.

We also calculated Pearson correlation coefficients for all pairs of fourteen bipolar adjectives of sensory fabric hands and twenty-one fabric properties (294 coefficients). Of these 294 pairings, 168 had coefficients greater than 0.40. We found that the following fabric properties correlated with the fourteen bipolar pairs of sensory hand attributes were significant at the 0.01 level (two-tailed): formability in the warp direction (F1), formability in the filling direction (F2), bending rigidity in the warp direction (B1), bending rigidity in the filling direction (B2), bending length in the warp direction (C1), bending length in the weft direction (C2), fabric thickness at 2gf/cm² (T2), shear rigidity (G), fabric weight (W), coefficient of friction (MIU), mean deviation of coefficient of friction (MMD), and mean of geometric roughness (SMD). From these data, we concluded that twelve fabric properties are significantly correlated with the fourteen bipolar sensory fabric hand attributes in a highly reliable way over extended periods of time.

© 2004 SAGE Publications. All rights reserved. Not for commercial use or unauthorized distribution.
EXPERIMENT 2: ESTABLISHING AN ARTIFICIAL NEURAL NETWORK TO PREDICT SENSORY FABRIC HAND BASED ON INPUTS OF FABRIC PROPERTIES

Experimental

Neural networks are widely used in artificial intelligence research [4, 13]. The basic element in an artificial neural network is the neuron, which has nonlinear input-output characteristics similar to real neurons. We show the typical characteristics of an artificial neuron in Figure 1.

An artificial neuron has multiple inputs from others. Each input connection has a weight \( w_{ij} \) that indicates the strength of the connection. The products of input values \( x_j \) and weights \( w_{ij} \) are summed and fed into a nonlinear element \( F \) to yield an output \( y_i \). Sometimes, a threshold \( \theta_i \) is added before the nonlinear operation. This can bias the neuron's output to a certain value when all inputs are disconnected.

In this study, we chose a multilayer feed-forward artificial neural network [11]. The structure of this network is shown in Figure 2. It consists of an input layer, two hidden layers, and an output layer. Twelve fabric properties are fed into the input layer. From there, they propagate forward through two hidden layers and then fourteen bipolar pairs of sensory fabric hand attributes arrive at the output layer. During this propagation, the mapping from fabric properties to subjective fabric hand ratings takes place.

Proposed Architecture of an Artificial Neural Network for Predicting Sensory Fabric Hand

The proposed neural network in this study consists of two parts, shown in Figure 3. The core of the architecture is a four-layer resilient back-propagation neural network, shown in Figure 2. The auxiliaries are the fine-tuning mechanism for tuning the network's input strength to reduce the generalization error.

The core of the proposed network contains an input layer, two hidden layers, and an output layer. Before fine tuning, twelve physical properties extracted from fabric specimens are fed into twelve input nodes. Fourteen normalized bipolar fabric hand ratings are produced by fourteen neurons in the output layer. The output is normalized to \([0, 1]\) because the log sigmoid activation function, shown in Figure 1, is used on each layer, and the range of this function is \([0, 1]\). Another reason to use the log sigmoid is that the back-propagation learning algorithm requires a continuous activation function to ensure the existence of the derivative of cost function with respect to the weights among neurons. In our proposed system, two hidden layers are designed for the interaction of inputs with output neurons. The reason behind is that Cybenko [6] proved that two hidden layer networks are enough to approximate any multidimensional function with any desired degree of accuracy.

However, Cybenko [6] did not conclude how many neurons are necessary and/or sufficient for the hidden

![FIGURE 1. Input-output characteristic of an artificial neuron (threshold = \( \theta_i \)).](image)

![FIGURE 2. Framework of the four layer back propagation neural net.](image)

![Outputs:](image)

layers of the network, because this depends on different situations. It may grow exponentially with the number of inputs in the case of a decision-based neural network [9] or a Boolean function network [15] for example. In our case, we conducted a simple experiment to find the optimal number of neurons in the hidden layers in terms of training performance. An optimal network size in terms of relative training time is around 100 x 100 in hidden layers.

After the network architecture was defined and training examples prepared, we trained the network core by the resilient back-propagation algorithm (RBP) [11, 13]. The objective of training the network is to train the weight \( w_i(l) \) and the threshold \( \theta_i(l) \) for \( l = [1, 2, 3] \), so as to minimize the cost function, specifically the mean square error (MSE), between the target \( t_i(m) \) and the actual response \( a_i(m) \) [3]. That is,

\[
MSE : E = \frac{1}{40 \times 14} \sum_{m=1}^{40} \sum_{i=1}^{14} [t_i(m) - a_i(m)]^2 ,
\]

where \( m \) is the running index for the number of training fabrics, and \( i \) is the running index for the dimension of the output space.

Reducing the Generalization Error of the Proposed Network with an Early Stopping Methodology

The second training parameter to be designed is the MSE training target. In general, the MSE target is set to 1e-8, which is obviously too tight for good generalization. The trained networks have already memorized the training targets. To avoid network over-fitting, we have used an early stopping methodology in this study to reduce the generalization error of the network.

To apply Larsen's early stopping [22] methodology during training, we first divide the forty input-output pairs into two groups, a training set \( D_{\text{train}} \) containing \( N_{\text{train}} \) data pairs, and a validation set \( D_{\text{validate}} \) containing \( N_{\text{validate}} \) data pairs. \( D_{\text{train}} \oplus D_{\text{validate}} = D \) and \( N_{\text{train}} + N_{\text{validate}} = N \). There is no definite rule for how to divide the data; any reasonable choice is acceptable. In this study, we chose \( N_{\text{train}}/N_{\text{validate}} = 30/10 \) for \( N = 40 \). However, the choice of the validation set should be a careful one. If the validation set can represent only a few data points in the training set, the stopping criterion will not be general and the network will not be optimal. Therefore, by analyzing the characteristics of our data set, we can assign the training set and validation set as shown in Table II.

The assignment is based on the distribution of different fabric categories in our data set. The largest fabric category in our data set is pure cotton, followed by pure polyester and then blended polyester/cotton. We have designed half of the validation data set from the pure cotton category and the remaining half from pure polyester and blended polyester/cotton. The data from other categories are not selected because the number of samples is relatively low compared with the entire data set.

After dividing the samples into the training set and validation set, we apply a resilient back-propagation algorithm to the training set to train the network. The gradient of the MSE is calculated and the weights and the bias are changed to reduce the error. The validation set will not change the network. However, in each training iteration, the MSE\(_{\text{validate}}\) for the validation set is calculated by

\[
MSE_{\text{validate}} : E_{\text{validate}} = \frac{1}{10 \times 14} \sum_{m=1}^{10} \sum_{i=1}^{14} [t_{\text{validate}, i}(m) - a_{\text{validate}, i}(m)]^2 ,
\]

TABLE II. Fabric categories in training set and validation set.

<table>
<thead>
<tr>
<th>Fabric categories</th>
<th>100% Cotton</th>
<th>100% Polyester</th>
<th>100% Wool</th>
<th>100% Nylon</th>
<th>100% Acetate</th>
<th>50% Nylon-50% Acetate</th>
<th>65% Polyester-35% Cotton</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of samples in training set</td>
<td>11</td>
<td>7</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>No. of samples in validation set</td>
<td>5</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Total no. of samples</td>
<td>(3, 9, 10, 12, 16)</td>
<td>(20, 21)</td>
<td>(37, 38, 39)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
where \((p_{\text{validate}}^{(m)}; t_{\text{validate}}^{(m)})\) are the input-output data pairs in \(D_{\text{validate}}\) and \(d_{\text{validate}}^{(m)}\) \((3)\) is the network output with validation set inputs.

The MSE on the validation set is monitored during the training process. This error will normally decrease during the initial training phase, as does the training set error. However, when the network starts over-fitting the data, the error on the validation set will begin to rise. When the error increases for a specified number of iterations, say, ten in this study, the training is stopped, and the weights and biases at the minimum of the validation error are returned.

**Results and Discussion**

In this section, we analyze the performance of our proposed neural networks for predicting sensory fabric hand. We test the network with 100 hidden units in the first and second hidden layers and apply the early stopping algorithm to the training processes. We also conduct a transient and correlation analysis of the proposed networks before and after fine tuning, and we present their comparisons in this section.

**Transient Performance**

By collecting the computed MSE in each training step, we can plot a transient performance diagram, shown in Figure 4, for the fine-tuned network and the network without fine tuning.

These two networks show a similar transient performance for training iterations. The mean square error (MSE) for the training set decreases rapidly in the first twenty iterations and decreases slowly in next 200 iterations. The MSE for the validation set also follows the training set in the first phase. However, when the network is saturated, it starts to memorize the training data set, and the error for the validation set begins to increase. This phenomenon happens quickly so the network is not fine tuned. The network starts to be over-fitted at around the fortieth iteration, which is shown in line a. However, the fine-tuned network, which is shown in line c, has a better validation performance, and the network is saturated much later. Finally, we have found that the MSE for the training set in the fine-tuned network improves 56%, with 21% improvement for the validation set.

**Correlation Analysis**

The minimum MSE obtained after training yields only the overall network performance. It is often useful to investigate the network response for each output. One option is to perform a correlation analysis. Network outputs are compared with their corresponding training targets. Correlation coefficients \((R\) values\) for each output are calculated. In a normal situation, \(R > 0.85\) should be considered as a good match to the targets. The correlation coefficients for each output variable are listed in Table III. We have found that all the output variables have a good match with the training target in the fine-tuned model. The \(R\)-values are almost greater than 0.9.

**EXPERIMENT 3: VALIDATING PROPOSED NEURAL NETWORKS FOR PREDICTING SENSORY FABRIC HAND**

**Experimental**

We selected five sets of woven fabrics (comprising 100% linen and 100% silk) that were different from the training and validation data sets. We also invited five general university students (three males and two females) to train to understand the definition of the four-
TABLE III. Correlation coefficients between the network's outputs and the target values.

<table>
<thead>
<tr>
<th>Output variable (bipolar pairs of sensory fabric hand attributes)</th>
<th>Correlation between output and target value after fine tuning</th>
<th>Correlation between output and target value before fine tuning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flat → textured (S1)</td>
<td>0.915</td>
<td>0.752</td>
</tr>
<tr>
<td>Not bulky → bulky (S2)</td>
<td>0.979</td>
<td>0.894</td>
</tr>
<tr>
<td>Light → heavy (S3)</td>
<td>0.982</td>
<td>0.903</td>
</tr>
<tr>
<td>Thin → thick (S4)</td>
<td>0.968</td>
<td>0.903</td>
</tr>
<tr>
<td>Silky → scratchy (S5)</td>
<td>0.942</td>
<td>0.727</td>
</tr>
<tr>
<td>Smoothness → roughness (S6)</td>
<td>0.936</td>
<td>0.763</td>
</tr>
<tr>
<td>Fine → coarse (S7)</td>
<td>0.910</td>
<td>0.745</td>
</tr>
<tr>
<td>Lamp → crisp (S8)</td>
<td>0.959</td>
<td>0.875</td>
</tr>
<tr>
<td>Flexible → stiff (S9)</td>
<td>0.974</td>
<td>0.860</td>
</tr>
<tr>
<td>Soft → hard (S10)</td>
<td>0.970</td>
<td>0.926</td>
</tr>
<tr>
<td>Flimsy → firm (S11)</td>
<td>0.946</td>
<td>0.764</td>
</tr>
<tr>
<td>Compact → loose (S12)</td>
<td>0.893</td>
<td>0.552</td>
</tr>
<tr>
<td>High drape → low drape (S13)</td>
<td>0.954</td>
<td>0.856</td>
</tr>
<tr>
<td>Cool → warm (S14)</td>
<td>0.963</td>
<td>0.837</td>
</tr>
</tbody>
</table>

teen bipolar attributes of sensory fabric hand. The method for assessing the ratings was the same as in the previous section.

Meanwhile, the five selected fabric specimens were tested to assess twelve significant fabric properties determined in the previous section by the KES-F and FAST systems. Before the measurements, all fabric specimens were conditioned in the laboratory at a temperature of 20±2°C and 65±1.5 RH for 24 hours.

Results and Discussion

Figures 5a–e show the comparison of the mean ratings of each attribute assessed by humans and the value of each attribute predicted by the proposed neural networks for all five fabric specimens (100% linen and 100% silk). The results show a good correlation between predicted and actual sensory fabric hand ratings with a significance of p < 0.001 for all five specimens. From this finding, we can conclude that the sensory hand ratings predicted by the proposed neural network closely agree with those assessed by human subjects.

General Discussion and Conclusions

In this paper, we have identified reliable sensory fabric hand attributes with correlated attributes of fabric properties and proposed a novel approach for predicting sensory hand based on measurable properties using a resilient back-propagation neural network. Twelve fabric properties are fed into the network to predict fourteen sensory ratings of fabric hand. Our proposed system improves the prediction of consumers' sensory hand ratings rather than the existing total hand value. Taking such an approach, industries can more closely evaluate their fabrics to match customers' expectations.

We have implemented a fuzzy fabric predictor to predict customers' favorable reactions using the...
input of fourteen subjective hand ratings. Our future work includes the integration of our proposed scheme with this fuzzy predictor, so as to be able to construct a hybrid fuzzy-neural system for fabric selection to allow more effective selections in business-to-consumer e-commerce applications.

Literature Cited

31. Robinson, K. J., Chambers, E., and Gatewood, B. M., Influence of Pattern Design and Fabric Type on the Hand
The Residual Electrostatic Voltage of Laminated Nonwovens with Different Surface Patterns

C. H. LEI,1 J. H. LIN, AND C. H. CHANG

Laboratory of Fiber Application and Manufacturing, Graduate Institute of Textile Engineering, Feng Chia University, Taichung 407, Taiwan, Republic of China

ABSTRACT

We have laminated polyamide nonwovens with different surface patterns and polypropylene nonwovens of varying thicknesses and charge them in by a high voltage discharger. We then measure and analyze the remaining surface electrostatic voltage. Our results show that the patterns of nylon nonwovens can affect the residual electrostatic voltage, which increases with the thickness of the nonwovens. The increased surface area in the laminated nonwovens enhances their efficiency in dispersing electrons. These nonwovens can be used in general demands for anti-electrostatic usage.

Nowadays, the development of composites has progressed rapidly. The first generation of composites needed to be light weight with high strength and high toughness. Thereafter, composites were expected to have more functional applications such as recycling, electromagnetic interference (EMI) [3, 7], tissue engineering, and so on.

Ordinary polymer materials are electrically nonconductive. The surface electrical resistance of these mate-

---

1 Email address: chlei@fcu.edu.tw