An intelligent system for supporting design of fashion oriented personalized fabric products

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An intelligent system for supporting the design of fashion oriented personalized fabric samples has been proposed. Based on fuzzy logic and semantic network, it permits to model the relationship between fabric parameters and fashion design elements via fashion images. This system can effectively help textile producers and designers to determine parameters of new fabrics to be produced according to fashion requirements of garments and predict garment fashion styles for given fabrics. A sensory evaluation on fabric hand has been used to determine fabric parameters of a collection of samples. Principal component analysis has been used to reduce the complexity of the model. A set of fashion images has been selected in order to extract abstract fashion design elements and identify relationship between fabric samples and fashion design elements. This system is helpful for textile companies to realize mass customization, i.e. design and production of personalized products with very low costs.

**Keywords:** Fabric parameters, Fashion design elements, Fashion images, Fuzzy logic, Mass customization

1 Introduction

In modern textile/apparel industry, mass customization plays a more and more important role. It provides personalized products and services to individual customers at a mass production price. It integrates the design and sales activities before the production stage.

Computer aided design (CAD) systems are powerful tools for realization of mass customization. They can support product design at all stages by characterizing relationship among materials, process parameters, finished products and market elements, and visualizing the performance of new designs via virtual products or virtual prototypes. Development of computerized virtual products can effectively decrease costs related to realization of real prototypes and be easily adapted to personalized requirements of customers by adjusting parameters of products.

Most of existing CAD systems only deal with the concrete technical parameters of products, such as shape and size. However, in textile/apparel industry, fashion styles of finished garments are important elements in design of fabrics, considered as intermediate products in the related supply chain. It is necessary to establish relationship between concrete technical parameters and sensory features (fabric hand, appearance, color, etc.) of fabrics and to abstract fashion design elements of garments in order to predict garment effects for given fabrics and to produce or select new fabric products according to personalized requirements of customers on fashion styles. In the textile/garment industry, fabric quality evaluation is performed in two ways, namely subjective human evaluation and objective evaluation or physical measurements.

In this study, focus is on sensory evaluation or normalized subjective evaluation because it is directly related to consumer’s behavior in textile and garment transactions. Sensory evaluation is performed by a panel of trained personnel using a standard evaluation procedure. They generate a list of exhaustive sensory attributes describing fabric hand and appearance, and then determine relative or absolute scores of fabric samples for each sensory attribute. Some of the existing evaluation procedures for fabric hand have already been reported.

An intelligent system is proposed to model these relationships and to formalize related variables. Fuzzy logic and semantic network have been used in this context.
system, which is constructed based on the following stages. Firstly, a collection of fabric samples with various technical parameters is selected. All data measured and evaluated on these samples constitute the learning base for modeling. Moreover, for simplicity, the influence of sensory features related to appearance and technical parameters on fashion styles can be studied in the same way. In order to characterize abstract fashion design elements and to set up relationships between them and concrete fabric parameters, representative fashion images are collected and a questionnaire is prepared to extract abstract fashion design elements from these images. For each fashion image, a fuzzy model is built for computing the relevancy of any fabric sample related to this image from its sensory attributes. In order to decrease the complexity of each model with respect to very few number of learning data, principal component analysis (PCA) is used for generating two dimensional input space of this model. Finally, a semantic network is set up for relating fashion images to fashion design elements. The software MATLAB- 7 is used for plotting two dimensional curves by PCA and modeling with fuzzy logic. Several papers have been published on sensory properties in the design of fabric products.

2.1 Sensory Evaluation of Fabric Samples

For sensory evaluation, 16 fabric samples (S1-S16) with various technical parameters have been selected and then evaluated by a trained panel of six members (A1, A2, …, A6), specialized in textile and apparel engineering. The evaluation results are used as input data for determining the compatibility of these fabric samples related to a set of fashion images. The sensory terms or attributes (linguistic terms) proposed by these individual panelists are softness, massive feeling, thermal feeling, graininess, breathability, temperature, flexibility, hairiness, drape, glossiness, slipperiness, extensibility, transparency, stiffness, creasing, thickness and smoothness.

Panelists selected ten most relevant terms (softness, massive feeling, thermal feeling, graininess, glossiness, slipperiness, extensibility, transparency, stiffness and creasing) for evaluation of fabric hand and fabric appearance according to their appearing frequencies and defined their normalized meanings and methods of evaluation.

The outside evaluation conditions are also normalized (relative humidity 65±2% and temperature 20±2 °C). Each panelist individually evaluates fabrics on each normalized sensory attribute. Some evaluation techniques used for fabric hand are summarized in Table 1. The corresponding evaluation scores vary from 0 to 16. The averages of evaluation scores for all the panelists are given in Table 2.

2.2 Analysis of Fashion Images

This section describes the extraction of design elements and fashion statements from a collection of fashion images with the help of fashion designers and then computation of compatibility degrees of fabric samples related to these fashion images.

The structure of a fashion image (Fig. 2) is composed of three components, namely concrete...
design elements, abstract design elements and fashion statement. The fashion statement is the unique message or the motivation describing the whole image. The concrete design elements include cutting, silhouette, material, color and accessories, denoting technical details which can be easily manipulated and understood by garment makers and textile producers. However, the abstract design elements cannot be easily understood by them. These include non-technical details, such as type of garment (leisure type, professional type, etc), weather, age and texture, and are more related to fashion styles and outside wearing conditions of garments. In this study, the efforts have been made to extract the abstract design elements and manufacture new fabric products corresponding to a set of specific abstract design elements.

For extracting relevant information of these three components from a fashion image, a questionnaire has been designed so that the fashion designers can give relevant responses to the questions while evaluating the image.

For setting up the model to predict compatibility degree of a new fabric related to a specific fashion image,
data collection from the 16 learning fabric samples and the corresponding images are related. The sensory results obtained constitute the input learning data. The output learning data are the degrees of compatibility of these fabric samples related to the fashion image, as evaluated by designers. During this evaluation, designers divide the 16 learning samples into four groups, namely very compatible, compatible, a little compatible and totally incompatible. The corresponding degrees of compatibility are 0.25, 0.5, 0.75 and 1 respectively.

The degrees of compatibility of the 16 learning fabric samples related to the 10 learning fashion images are given in Table 3. The distances between image 6 and four fabric samples S3, S4, S6, S16 are 1, 0.5, 0.75 and 0.25 respectively. They can be explained as follows. Fabric S16 is very compatible with the image because of its texture and its color conform the trouser of the image. Fabric S4 is also very compatible with the image because of its relevant texture. S6 is less compatible than S16 and S4 because its texture is little different from that of the trouser on the image. The texture of S3 is totally different from that of the image. When designers evaluate degrees of compatibility between fabrics and fashion images, they generally pay more attention to texture and color because the former is related to fabric hand, fabric appearance and nature of materials and the latter adjusts human impression on fabric appearance and fabric hand. Their combination can generate one important part of basic design elements describing fashion styles of finished garments. Having obtained input and output learning data evaluated on the 16 fabric samples, a model characterizing the relationship between fabric samples and a specific fashion image can be set up.

### Table 3—Degrees of compatibility* between fabric samples and fashion images

<table>
<thead>
<tr>
<th>Images no.</th>
<th>Very compatible (0.25)</th>
<th>Compatible (0.5)</th>
<th>A little compatible (0.75)</th>
<th>Totally incompatible (1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>S11</td>
<td>-</td>
<td>-</td>
<td>All other samples</td>
</tr>
<tr>
<td>2</td>
<td>S7</td>
<td>S12</td>
<td>S3</td>
<td>All other samples</td>
</tr>
<tr>
<td>3</td>
<td>S4</td>
<td>S6</td>
<td>-</td>
<td>All other samples</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>S2, S13</td>
<td>S6</td>
<td>All other samples</td>
</tr>
<tr>
<td>5</td>
<td>S16</td>
<td>S4</td>
<td>S6</td>
<td>All other samples</td>
</tr>
<tr>
<td>6</td>
<td></td>
<td>S15</td>
<td>S13</td>
<td>All other samples</td>
</tr>
<tr>
<td>7</td>
<td>S1</td>
<td>S14</td>
<td>-</td>
<td>All other samples</td>
</tr>
<tr>
<td>8</td>
<td></td>
<td>S14</td>
<td>S2</td>
<td>All other samples</td>
</tr>
<tr>
<td>9</td>
<td></td>
<td>S8</td>
<td>S10</td>
<td>All other samples</td>
</tr>
<tr>
<td>10</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

S, denote the i<sup>th</sup> learning fabric sample.

*Sample S9 has no compatibility with any fashion image.

### 2.3 Building a Fashion Image Based Model for Fabric Samples

The data obtained in Table 2 will be used for describing fabric hand of related samples. They constitute the input space for modeling the relationship between fabric parameters and relevancy of fabric samples related to each fashion image. However, the number of input variables or normalized sensory attributes is often too big related to the number of samples because of limited production time. Principal component analysis (PCA) is used to reduce the dimensions of the input space and decrease the complexity of the model.

PCA performs a linear transformation of an input variable vector for representing all original data in a lower-dimensional space with minimal information loss. The q observations in R<sup>n</sup>, corresponding to n input variables, constitute a data distribution characterized by the eigenvectors and the eigen values which can be easily calculated from the variable covariance matrix. PCA aims at searching for the smallest subspace in R<sup>n</sup>, maintaining the shape of this distribution. The first component of the transformed variable vector represents the original variable vector in the direction of its largest eigenvector of the variable covariance matrix, the second component of the transformed variable vector in the direction of the second largest, and so on. In our model, the first two components are taken as input variables. Therefore, we obtain a two input/one output system for each descriptor of subjective evaluation. This system can be easily modeled from a small set of learning data.

### 2.4 Designing of Semantic Network

A semantic network was designed for determining the degree of relevancy of fabric samples for abstract design elements which consists of set of keywords (abstract design element) having links to the images in data base (Fig. 1). The links between keywords and image provide structure for the network. The degree of relevancy of the keyword to an associated image is represented as the weight on each link. This weight can be a numerical value, data structure or data distribution, depending on the available database.

W<sub>i</sub> is the weight associated with the i<sup>th</sup> image and j<sup>th</sup> keyword. The weight W<sub>ij</sub> associated with each link of keyword presents the degree of relevance in which this keyword describes the linked image. To define these weights a questionnaire was prepared. This
A questionnaire is drawn up with an aim of defining what means for abstracted elements of design, and by what they are concretized. This questionnaire was filled up by 9 people and everyone described the three abstract design elements (type of garment, season and age) with different linguistic terms. To avoid the problem of widespread synonymy and polysemy in linguistic terms, these types of words were combined. Table 4 shows the result of the questionnaire for ten fashion images.

In the bracket along with each design element the frequency of the term is defined. For example casual wear (6) implies that 6 person out of 9 defined the image as casual wear. It can be defined as frequency ratio ($\mu_{jk}$). The frequency ratio of $j$th abstract design element for $k$th linguistic term is given as $\mu_{jk}$.

Table 4—Abstract design elements for fashion images

<table>
<thead>
<tr>
<th>Image no.</th>
<th>Garment type</th>
<th>Season</th>
<th>Age</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Casual wear</td>
<td>Winter</td>
<td>20-25 (3), 18-30 (2), 25-40 (3)</td>
</tr>
<tr>
<td>3</td>
<td>Casual wear</td>
<td>Winter</td>
<td>25-60 (4) 20-30 (2)</td>
</tr>
<tr>
<td>4</td>
<td>Casual wear</td>
<td>Summer</td>
<td>18-35 (3), 16-28 (4)</td>
</tr>
<tr>
<td>5</td>
<td>Casual (5)</td>
<td>Summer</td>
<td>20-60(3), 20-30 (2)</td>
</tr>
<tr>
<td>6</td>
<td>Formal (6)</td>
<td>Summer</td>
<td>5-25(6) 6-35 (3)</td>
</tr>
<tr>
<td>7</td>
<td>Formal (8)</td>
<td>Summer</td>
<td>20-50(5) 20-30 (3)</td>
</tr>
<tr>
<td>8</td>
<td>Formal (8)</td>
<td>Summer</td>
<td>16-30 (8)</td>
</tr>
<tr>
<td>9</td>
<td>Casual wear</td>
<td>Winter</td>
<td>32-60(4) 30-80(2)</td>
</tr>
<tr>
<td>10</td>
<td>Casual wear</td>
<td>Winter</td>
<td>18-30 (2) 20-50(4)</td>
</tr>
</tbody>
</table>

Values in the parentheses indicate the no. of persons who related the image with type of garment.

Table 5—Subdivision of abstract design elements

<table>
<thead>
<tr>
<th>Abstract design element</th>
<th>Range of $k$</th>
<th>Subdivisions of element</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type of garment ($j=1$)</td>
<td>$k \in [1,3]$</td>
<td>Casual wear ($k=1$)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Semiformal wear ($k=2$)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Formal wear ($k=3$)</td>
</tr>
<tr>
<td>Season ($j=2$)</td>
<td>$k \in [1,3]$</td>
<td>Winter ($k=1$)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Summer ($k=2$)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Rainy ($k=3$)</td>
</tr>
<tr>
<td>Age ($j=3$)</td>
<td>$k \in [1,3]$</td>
<td>May be different ranges</td>
</tr>
</tbody>
</table>

Table 6—Normalized data for age

<table>
<thead>
<tr>
<th>Image no.</th>
<th>Age</th>
<th>$k \in [1,8]$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5-10(0), 10-15(0), 15-20(0), 20-25(5), 25-30(5), 30-35(3), 35-40(3), &gt;40(0)</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>5-10(0), 10-15(0), 15-20(3), 20-25(3), 25-30(7), 30-35(7), 35-40(4), &gt;40(4)</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>5-10(0), 10-15(0), 15-20(0), 20-25(6), 25-30(6), 30-35(4), 35-40(4), &gt;40(4)</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>5-10(0), 10-15(0), 15-20(7), 20-25(7), 25-30(7), 30-35(3), 35-40(0), &gt;40(0)</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>5-10(0), 10-15(0), 15-20(0), 20-25(5), 25-30(5), 30-35(3), 35-40(3), &gt;40(3)</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>5-10(9), 10-15(9), 15-20(9), 20-25(9), 25-30(3), 30-35(3), 35-40(0), &gt;40(0)</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>5-10(0), 10-15(0), 15-20(0), 20-25(8), 25-30(8), 30-35(5), 35-40(5), &gt;40(5)</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>5-10(0), 10-15(0), 15-20(8), 20-25(8), 25-30(8), 30-35(0), 35-40(0), &gt;40(0)</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>5-10(0), 10-15(0), 15-20(0), 20-25(0), 25-30(0), 30-35(6), 35-40(6), &gt;40(6)</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>5-10(0), 10-15(0), 15-20(2), 20-25(6), 25-30(6), 30-35(4), 35-40(4), &gt;40(4)</td>
<td></td>
</tr>
</tbody>
</table>

The distribution ranges of the age need to be normalized for all the fashion images. Hence, the ranges at the interval of 5 years, i.e. 5-10, 10-15, 15-20, 20-25, 25-30, 30-35, 35-40 and >40 have been selected. The frequency for these ranges is determined by the frequency of ages given in Table 6. For example, the ranges 5-10 and 10-15 are defined as the sum of frequency of 5-10 and 10-15, which gives 15-20 as the new range. The normalized data for age is given in Table 6. Now the weight for fashion image to ages can be defined as:

\[
W_{11} = \begin{pmatrix} 6/9 \\ 0 \end{pmatrix}, \quad W_{12} = \begin{pmatrix} 6/9 \\ 0 \end{pmatrix}, \quad W_{13} = \begin{pmatrix} 3/9 \\ 2/9 \end{pmatrix}
\]
If there are N fabric samples and F fashion images, the relevancy of jth abstract design element related to mth fabric sample \( R_{mj} \) can be given by the following relationship:

\[
R_{mj} = \frac{\sum_{l=1}^{F} (\mu_{jkl} \times S_{ml})}{\sum_{l=1}^{F} S_{ml}} \quad \ldots (3)
\]

where \( S_{ml} \) is the similarity (1-dissimilarity) between mth fabric sample and lth fashion image. It can be determined by the fuzzy logic based model as given in this paper, considering the following two cases:

**Case 1**—For a linguistic term (k) of an abstract design element (j), the frequency ratio weight (\( \mu \)) is maximum, i.e. 1 for all the fashion images and the fabric sample (m) has maximum similarity with all the fashion images, i.e. 1. The relationship is shown below:

\[
\mu_{jkl} = \mu_{jkl} = \ldots = \mu_{jkl} = 1
\]

\[
S_{ml} = S_{ml} = \ldots = S_{ml} = 1
\]

In this case, the degree of relevancy of abstract design element (j for linguistic term k) related to fabric sample (m) will be maximum, i.e. 1.

**Case 2**—For a linguistic term (k) of an abstract design element (j), the frequency ratio weight (\( \mu \)) is minimum, i.e. zero for all the fashion images or the fabric sample (m) has minimum similarity with all the fashion images, i.e. zero. The relationship is shown below:

\[
\mu_{jkl} = \mu_{jkl} = \ldots = \mu_{jkl} = 0
\]

\[
S_{ml} = S_{ml} = \ldots = S_{ml} = 0
\]

In this case, degree of relevancy of abstract design element (j for linguistic term k) related to fabric sample (m) will be minimum, i.e. zero.

### 3 Results and Discussion

The explanation rates of all the components are obtained after applying PCA to the data of Table 2. The explanation rates for components 1-10 are 0.3702(1), 0.3299(2), 0.116(3), 0.0995(4), 0.413(5), 0.0277(6), 0.0243(7), 0.0054(8), 0.0033(9), and 0.0005(10). The reduced two dimensional data for 16 samples can be visualized on a plan (Fig. 3). The relationship of fabric hand between these samples can be qualitatively observed from this plan. In the same way, PCA can also generate the plan describing relations between all the sensory attributes (Fig. 4). On this plan, we can find that var4 (graininess) and var5 (glossiness) are rather closed and the findings are also same for var2 (massive feeling) and var7 (extensibility).

Fuzzy logic is used for modeling the relationship between the two input variable \( V_1, V_2 \) and the output.
variable D (degree of compatibility of fabrics) from the 16 learning data. This is because the values of D are mostly 1 (totally incompatible) but different from 1 only for a very small number of learning data (less than 4).

By applying algorithms of continuous learning such as back propagation algorithm of neural networks, we will obtain many zeros for output variations and then effects of the corresponding input variables cannot be correctly evaluated. In this case, we need to focus the learning rules on the significant data, i.e. values of D are different from 1. According to this idea, various steps of fuzzy modeling procedure are proposed as follows:

Step 1—Used for the fashion image of interest, identifying the number of significant learning data N, i.e. the corresponding values of D are different from 1. These data are denoted as \((v_{11}, v_{12}, D_1), \ldots, (v_{N1}, v_{N2}, D_N)\).

Step 2—Used for the fuzzification of the input and output variables:

The range of \(V_1\) is divided into N fuzzy values centered on \(v_{11}, v_{21}, \ldots, v_{N1}\) respectively. The membership functions of \(v_{11}\) and \(v_{N1}\) are Gaussian shapes because they should cover all values of \(V_1\). The membership functions of \(v_{21}, \ldots, v_{N-1,1}\) are trapezoidal shapes.

The range of \(V_2\) is divided into N fuzzy values centered on \(v_{12}, v_{22}, \ldots, v_{N2}\) respectively. The fuzzy values of \(V_1\) and \(V_2\) divide the whole input space into \(N^2\) fuzzy values. The same procedure is applied to the output variable D.

Step 3—Used for building fuzzy rules from the significant data. We obtain

Rule 1: IF \(V_1\) is \(v_{11}\) AND \(V_2\) is \(v_{12}\) THEN D is \(D_1\)
Rule 2: IF \(V_1\) is \(v_{21}\) AND \(V_2\) is \(v_{22}\) THEN D is \(D_2\)

……

Rule N: IF \(V_1\) is \(v_{N1}\) AND \(V_2\) is \(v_{N2}\) THEN D is \(D_N\)

Membership function of inputs \(V_1\) and \(V_2\) is given in Fig. 5.

Step 4—Used for building fuzzy rules from the non significant data. We obtain \(N^2-N\) rules as follows:

Rule k: IF \(V_1\) is \(v_{i1}\) AND \(V_2\) is \(v_{i2}\) THEN D is 1
with \(i, j=1, \ldots, N, i \neq j\) and \(k=N+1, \ldots, N^2\)

\(N^2\) fuzzy rules can be obtained from all the learning data.

Step 5—The Mandani method is used for aggregating these fuzzy rules and computing output values of D from input values of \(V_1\) and \(V_2\).

One illustrative example is given below for fuzzification of the input variables \(V_1\) and \(V_2\). In this example, five fuzzy values are defined for \(V_1\). We have chosen trapezoidal functions (mf2, mf3, mf4), and only the boundary functions (mf1 and mf5) are chosen Gaussian as it covers all the possible values for input \(V_1\).

In the same way, the input \(V_2\) is also assigned the four membership functions.

The fuzzy values of the output D are independent of learning data because D only has 4 possibilities (0.25, 0.5, 0.75 and 1). Then, 4 trapezoidal membership functions mf2, mf3, mf4 and mf5 are defined for them. Assuming that the range of D is between 0 and 1, an additional fuzzy value mf1 is used to represent the case in which any fabric sample is fully appropriate to the fashion image (Fig. 6).

The angle \(\alpha\) in Fig. 6 shows how well the panel is trained. More the value of \(\alpha\) means panel is well trained. At lower angle of \(\alpha\), the spreading of the membership function will be higher, which implies that there are more chances of getting same output for the different input. Here in this model, 85° \(\alpha\) is chosen for which spreading of each membership function is 0.26, R assuming that the panel is well trained.

3.1 Aggregation of Consequents Across the Rules

Since decisions are based on the testing of all the rules, the rules must be combined in such a manner so
as to make a decision. Aggregation is the process by which the fuzzy sets that represent the outputs of each rule are combined into a single fuzzy set (Fig. 7).

The input for the defuzzification process is a fuzzy set (the aggregate output fuzzy set) and the output is a single number. The defuzzification method we used is the centroid calculation, which returns the centre of area under the curve.

Degree of relevancy of casual wear of winter for 20-25 year age group for fabric samples ($R_{mj}$) is calculated by Eq. (3) (Fig. 8).

It can be concluded that for the required three factors, sample nos S5, S7, S10, S11, S12 show higher degree of relevancy and hence these samples can fulfill the customer requirements in aspect of casual wear for winter season for 20-25 years age group.

4 Conclusions

This paper presents a general method for subjective evaluation of the fabrics. Principal component analysis has been used for analyzing and interpreting subjective evaluation done by the panel. PCA projected original higher dimensional data into a lower dimensional subspace. A fuzzy logic based model is proposed to determine the compatibility of fabric samples with the fashion images. The error for each model is very less, so proposed model can play a critical role in the field of garment industry especially for the mass customization and personalization of the garments.

**Industrial Importance**: This model can work as a tool for online shopping; a customer can first choose a garment and then the web interface can select relevant textiles/fabrics in a database that fits with his demand. It makes the e-shopping easier and efficient in order to fulfill the customer’s requirements. The proposed method permits to set up a link between fabric parameters and fashion design elements.

References

at the conference EUFIT’97, Aachen, Germany, 8-11 September 1997.