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Min DONG[ab†], Xianyi ZENG[ba†], Ludovic KOEHL[b] and Junjie ZHANG[a]

[a]Research Center of Nonlinear Science, Engineering Research Centre of Hubei Province for Clothing Information, Mathematics & Computer Institute, Wuhan Textile University, Wuhan, China

[b]Laboratoire Génie et Matériaux Textile (GEMTEX), the ENSAIT Textile Institute, Centrale Lille, F-59000 Lille, France

[†]E-mail: dongmin_min@126.com, xianyi.zeng@ensait.fr

Abstract: In this paper, we originally propose a new predicting model to the fashion features of fabrics. It enables to select fabrics satisfying fashion demand according to a small amount of technical parameters which is easy to be measured. For this, we set up three mathematical models. By using fuzzy technique, we first define several fuzzy sets to express measured technical parameters and sensory properties of fabrics. Then, we set up the relational model between the technical parameters and sensory properties by using the rough set method. Next, we set up the relational model between the fashion themes (to express the fashion features of fabrics) and sensory properties by using fuzzy technique. Combine with the two models, we establish the relational model between fashion themes and technical parameters. The proposed model has been validated through a number of successful real design cases.

Keywords: Fashion theme; Technical parameter; Sensory property; Fuzzy technique; Rough set theory

1. Introduction

Fabric is one of the important factors for expressing fashion themes. During garment design, it should be considered to select fabric according to the features of fabric materials and design requirements. fabric materials should satisfy both designers' requirements and expectations in terms of appearance, fit and comfort, and garment manufacturers' technical requirements and functionally restrictions. Therefore, it is necessary to characterize fabrics in terms of physical, mechanical, aesthetic and sensory properties.

In the researches on fabric selection, scholars have done a lot of work. For example, Piotr Karwaczynski [1] proposed a synergistic proximity neighbor

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selection method for fabric, through which fabric enables an overlay to optimize its topology at runtime in an adaptive manner. Liu [2] set up a hierarchical model for the optimum selection of fabrics according to the hand, formability, brightness of fabrics by Analytic Hierarchy Process(AHP). Lu [3] developed a fuzzy multi-criteria group decision support system for textile material fabric-hand evaluation. Yu [4] developed an intelligent prediction system for prediction of fabric specimens based on the fabric hand descriptors with fuzzy neural network. Han [5] realized the optimum choice of fabric according to the technical parameters of fabrics Based on Analytic Hierarchy Process. McCann [6] focused on the selection of fabrics for the functional clothing layering system for use in the outdoor environment. Shankar Chakraborty [7] researched cotton fabric selection using a grey fuzzy relational analysis approach. Xue [8] developed an intelligent model to predict tactile properties from visual features of textile products.

In the existing work, most researchers focus on the fabric selection according to the sensory properties or mechanical features of fabrics. In fact, an experienced designer can select suitable fabric according to fabric hand, visual or mechanical features. To an unexperienced young designer, however, it is difficult to give a choice according to the above ones. He/She would rather select fabric based on the fashion demand for a garment product. In addition, the incomplete data cannot be analyzed by these existing methods. Therefore, we propose a new method to select fabric by predicting the fashion features of fabrics from technical parameters based on design experts' sensory experience.

2. Relevant concepts and notations

This paper aims at predicting the fashion features of fabrics for garment design. In garment design, we express the fashion features of fabrics by using the fashion themes of garments.

(1) Fashion theme of garment

Generally, fashion theme of a garment is the value orientation, intrinsic character and artistic characteristics shown from the form and content of the garment. In the important fashion events, fashion themes are often communicated to general public through fashion forecasting reports or seminars [9]. Different fabrics can express different fashion themes, and they can be described by relevant semantic words, such as “Elegant”, “Wild”, “Traditional”, “Modern”, and so on. For describing the fashion features of fabrics simply and accurately, synonyms and near-synonyms of the words are combined and then regrouped with opposite semanteme into pairs, such as “Elegant-Wild”, “Traditional-Modern”, and so on. During this procedure, the unpaired words are removed. According to the semantic differential method [10], these pairs of fashion features are expressed by the 7-points scales. Let $T = \{T_1, T_2, \dots, T_t\}$ be the set of all the t fashion themes.

(2) Technical parameters of fabrics

The technical parameters cover Fiber-Composition (Cotton, Polyester, Viscose, Spandex, Lyocell, etc.), Gram-Weight, Thickness, Warp-Density, Weft-Density, Warp Breaking-Strength, Weft Breaking-Strength, Warp Elongation, Weft Elongation, Water-Permeability, Air-Permeability, and so on.

Let $F = \{f_1, f_2, \dots, f_n\}$ be the set of all the n representative fabrics.

Let $TP = \{tp_1, tp_2, \dots, tp_m\}$ be the set of all the m technical parameters of fabrics. The m technical parameter values of all the n fabrics in F constitute a matrix, denoted as $\text{TPM} = (p_{ij})_{n\times m} = (p_1, p_2, \dots, p_m)$, with $i = 1, 2, \dots, n$, $j = 1, 2, \dots, m$, and $p_1, p_2, \dots, p_m$ is the column vectors of the matrix TPM.

(3) Sensory properties of fabrics

Sensory properties of fabrics can be obtained by visual and tactile perception, including softness, roughness, warmness, and draping, wrinkle-resistance, and so on. They are represented by these semantically opposite keyword pairs: “soft-hard”, “smooth-rough”, “cool-warm” and “draped-non draped”, “wrinkle resistance-crumply”, each with seven evaluation levels.

Let $SP = \{sp_1, sp_2, \dots, sp_l\}$ be the set of all the l sensory properties of fabrics. The l sensory property values of all the n fabrics in F constitute a matrix, denoted as $\text{SPM} = (q_{ij})_{n\times l} = (q_1, q_2, \dots, q_l)$, with $i = 1, 2, \dots, n$, $j = 1, 2, \dots, l$, and $q_1, q_2, \dots, q_l$ is the column vectors of the matrix SPM.

3. Prediction model to the fashion features of fabrics

In this section, we set up the prediction model to fashion features of fabrics by using fuzzy method and rough set theory.

3.1. *Modeling the relationship between technical parameters and sensory properties of fabrics*

We set up a decision system for modeling the relationship between technical parameters and sensory properties of fabrics.

(1) Fuzzification of technical parameters

Let tp_1 be Fiber-Composition, $tp_1^{(1)}, tp_1^{(2)}, \dots, tp_1^{(K)}$ be the K kinds of various familiar fibers, such as Cotton, Polyester, Viscose, Spandex, Lyocell, and so on, and $tp_2 \sim tp_m$ be the other numerical parameters.

Let the value of the Fiber-Composition $tp_1^{(1)}, tp_1^{(2)}, \dots, tp_1^{(K)}$ of the i-th fabric f_i in the fabrics set F be respectively $x_{i1},\ x_{i2}, \dots, x_{iK}$ $(i = 1,2, \dots, n)$.

Let the value of the technical parameter $tp_2, tp_3, \dots, tp_m$ of the fabric f_i be respectively $x_{i,K+1},\ x_{i,K+1}, \dots, x_{i,K+m-1}$ $(i = 1,2, \dots, n)$.

We use five fuzzy sets $\tilde{C}_k$ $(k \in \{1, \dots ,5\})$ to express each technical parameter, where $\tilde{C}_1$="very small(VS)", $\tilde{C}_2$= "small(S), $\tilde{C}_3$= "middle(M)", $\tilde{C}_4$= "large(L)", $\tilde{C}_5$= "very large (VL)". The membership degree of the index value x_{ij} to the fuzzy set $\tilde{C}_k$ is denoted as $\mu_{ij}^{(k)}(i = 1, \dots, n; j = 1,2, \dots, K + m - 1; k = 1,2, \dots ,5)$. For obtaining these five fuzzy sets, we denote the following five numerical values as Eq. (1) and The membership functions is as Figure 1.

$$X_1^{(j)} = \min_{1 \le i \le n}\{x_{ij}\},\ X_3^{(j)} = \underset{1 \le i \le n}{median}\{x_{ij}\}, X_5^{(j)} = \max_{1 \le i \le n}\{x_{ij}\},$$
$$X_2^{(j)} = (X_1^{(j)} + X_3^{(j)})/2,\ X_4^{(j)} = (X_3^{(j)} + X_5^{(j)})/2 \tag{1}$$

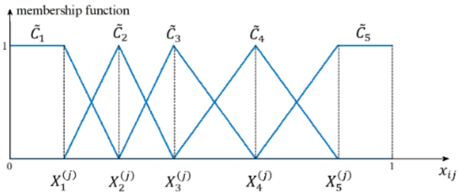

Fig. 1. Fuzzy membership functions of technical parameters

According to the Maximal Membership Principle, x_{ij} is affected to $\tilde{C}_{k^*}$ if $\mu_{ij}^{(k^*)} = \vee_{k=1}^{m}\{\mu_{ij}^{(k)}\}$ $(i = 1, \dots, n; j = 1,2, \dots, K + m - 1)$. The five fuzzy sets $\tilde{C}_1, \tilde{C}_2, \tilde{C}_3, \tilde{C}_4, \tilde{C}_5$ constitute the standard models base of the technical parameters. The technical parameter tp_1 is a K-dimensional vector of different (from 1 to K) fiber compositions and any other parameters of tp_2, …, tp_m is just a one-dimensional numerical value. For tp_1, it can be represented by a vector of multiple fuzzy sets and each component is expressed by $tp_1^{(k)}(\tilde{C}_i)$ $(i = 0,1,2, \dots ,5; k = 1,2, \dots, K)$, which means that the composition of the k-th kind of fiber in a specific fabric corresponds to $\tilde{C}_i$ $(i \in \{1,2, \dots ,5\})$ with $\tilde{C}_i$=$\tilde{C}_0$ $(i = 0)$ if there is no this kind of fiber composition in the fabric.

Assume the fuzzy vector or fuzzy set corresponding to the technical parameter tp_j of fabric f_i be denoted by p_{ij} with $i \in \{1,2, \dots, n\}$ and $j \in \{1,2, \dots, m\}$. i.e.

$$p_{ij} = \left(\left(tp_1^{(1)}(\tilde{C}_{i_1}), tp_1^{(2)}(\tilde{C}_{i_2}), \dots, tp_1^{(K)}(\tilde{C}_{i_K})\right), \tilde{C}_{i_{K+1}}, \tilde{C}_{i_{K+2}}, \dots, \tilde{C}_{i_{K+m-1}}\right) \tag{2}$$

(2) Identification of the sensory properties

The evaluation scores of each sensory property of all the n fabrics come from the set of seven linguistic levels of the sensory property, respectively expressed by seven fuzzy sets $\tilde{F}_1, \tilde{F}_2, \tilde{F}_3, \tilde{F}_4, \tilde{F}_5, \tilde{F}_6, \tilde{F}_7$, whose membership functions are expressed by the triangular functions defined on interval [-3, 3] as Fig. 2. These seven fuzzy sets can be regarded as the standard evaluation levels.

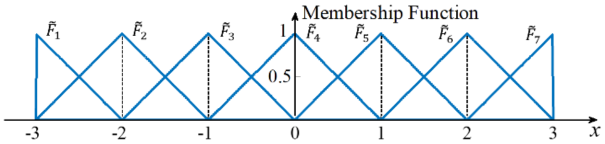

Fig.2. The membership functions of evaluation scores

We assume that $r_{ij}^{(k)}$ represents the number of people among the r panelists who give the evaluation score k ($k \in \{-3, -2, -1, 0, 1, 2, 3\}$) on the sensory property $sp_j(j \in \{1, \dots, v\})$ of the fabric f_i ($i \in \{1, \dots, n\}$). The evaluation results of all the panelists can be expressed by a fuzzy distribution:

$$\mu_{\tilde{F}_{ij}}(x) = \left(r_{ij}^{(-3)}/r, r_{ij}^{(-2)}/r, r_{ij}^{(-1)}/r, r_{ij}^{(0)}/r, r_{ij}^{(1)}/r, r_{ij}^{(2)}/r, r_{ij}^{(3)}/r\right) \tag{3}$$

We define the *Close Degree* $r\left(\tilde{F}_{ij}, \tilde{F}_k\right)$ of $\tilde{F}_{ij}$ to the standard evaluation level (score) $\tilde{F}_k$ as Eq. (4).

$$r\left(\tilde{F}_{ij}, \tilde{F}_k\right) = \frac{\int_{-3}^{3}\left[\mu_{\tilde{E}_{ij}}(x)\ \wedge \mu_{\tilde{F}_k}(x)\right] dx}{\int_{-3}^{3}\left[\mu_{\tilde{E}_{ij}}(x) \vee \mu_{\tilde{F}_k}(x)\right] dx} \tag{4}$$

The final evaluation score $\tilde{F}_{k^*}$ is computed from the maximum of the distribution of the close degrees for all the 7 levels, i.e. $r\left(\tilde{F}_{ij}, \tilde{F}_{k^*}\right) = \bigvee_{k=1}^{7} r\left(\tilde{F}_{ij}, \tilde{F}_k\right)$.

(3) Relational model

If the data of all the fabric technical parameters $tp_1 \sim tp_m$ and the sensory property sp_k are known, we can set up a decision system (complete or incomplete). Then, we can obtain a generalized decision rule as follows.

$\mathbf{RULE\ 1}$: $\mathbf{IF}$ $tp_1 = \left(tp_1^{(1)}\left(\tilde{C}_{i_1}\right), tp_1^{(2)}\left(\tilde{C}_{i_2}\right), \dots, tp_1^{(K)}\left(\tilde{C}_{i_K}\right)\right)$ AND $\left(tp_2 = \tilde{C}_{j_2}\right)$ AND … AND $\left(tp_m = \tilde{C}_{j_m}\right)$, $\mathbf{THEN}$ $sp_k = \tilde{F}_k$.

3.2. *Modeling the relationship between fashion themes and sensory properties of fabrics*

For each evaluator, we obtain a judgment (relevant or irrelevant) on the relation between each sensory property level and each fashion theme level. For each sensory property and each fashion, their levels are all expressed by seven fuzzy sets $\tilde{F}_1, \tilde{F}_2, \tilde{F}_3, \tilde{F}_4, \tilde{F}_5, \tilde{F}_6, \tilde{F}_7$ (see Section 3.1).

We assume that $r_{kg}^{(lj)}$ represents the number of people among r panelists who consider that the k-th level of the sensory property sp_l ($k \in \{1, \dots, 7\}, l \in \{1, \dots, v\}$) is relevant to the g-th level of the fashion theme T_j ($j \in \{1, \dots, t\}$).

Denote $\mu_{kg}^{(lj)} = r_{kg}^{(lj)}/r$, and the relevancy of the k-th level $sp_l^{(k)}$ of the sensory property sp_l to the fashion theme T_j can be expressed by a fuzzy distribution on the set of $\{\tilde{F}_1, \tilde{F}_2, \tilde{F}_3, \tilde{F}_4, \tilde{F}_5, \tilde{F}_6, \tilde{F}_7\}$ as follows.

$$R\left(sp_l^{(k)}, T_j\right) = \left(\mu_{k1}^{(lj)},\ \mu_{k2}^{(lj)}, \dots,\ \mu_{k7}^{(lj)}\right) \tag{5}$$

Thus, the relevancy of the sensory property sp_l to the fashion theme T_j can be expressed by a (7×7)-dimensional fuzzy relational matrix as follows.

$$\begin{aligned} FRM\left(sp_l, T_j\right) &= \left(R\left(sp_l^{(1)}, T_j\right)^T,\ R\left(sp_l^{(2)}, T_j\right)^T, \dots,\ R\left(sp_l^{(7)}, T_j\right)^T\right)^T \\ &= \left(\mu_{ik}^{(lj)}\right)_{7\times 7} \qquad (l \in \{1, \dots, u_2\}, j \in \{1, \dots, t\}) \end{aligned} \tag{6}$$

3.3. *Modeling the relationship between fashion themes and technical parameters of fabrics*

Assume the aggregated evaluation score (level) of a specific fabric f on the sensory property sp_l, provided by all the evaluators, is $\tilde{F}_{k_l}$ ($k_l \in \{1,2, \dots ,7\}$ with $l = 1,2, \dots , v$).

We define M_j, i.e. the relevancy distribution of all the sensory properties related to the fashion theme T_j in the fabric f, as Eq. (7).

$$\begin{aligned} M_j = \frac{1}{v}\sum_{l=1}^{v} R\left(sp_l^{(k_l)}, T_j\right) &= \left(\frac{1}{v}\sum_{l=1}^{v}\mu_{k_l 1}^{(lj)},\ \frac{1}{v}\sum_{l=1}^{v}\mu_{k_l 2}^{(lj)}, \dots,\ \frac{1}{v}\sum_{l=1}^{v}\mu_{k_l 7}^{(lj)}\right) \\ &\triangleq \left(m_1^{(j)},\ m_2^{(j)}, \dots,\ m_7^{(j)}\right) \end{aligned} \tag{7}$$

According the Fuzzy Selecting Near Principle, for any fabric, it corresponds to the g^*-th evaluation level of the fashion theme T_j if $m_{g^*}^{(j)} = \bigvee_{g=1}^{7}\{m_g^{(j)}\}$.

From this, we obtain the following decision rules.

RULE 2: **IF** $\left(sp_1 = \tilde{F}_{k_1}\right)$AND $\cdots$ AND $\left(sp_{u_2} = \tilde{F}_{k_{u_2}}\right)$, **THEN** $T_j = \tilde{F}_{g^*}$.

Combining the Rule 1 and Rule 2, we obtain the decision rules on the relationship between the technical parameters of fabrics and the fashion theme T_j as follows.

RULE 3: **IF** $tp_1 = \left(tp_1^{(1)}\left(\tilde{C}_{i_1}\right), tp_1^{(2)}\left(\tilde{C}_{i_2}\right), \dots, tp_1^{(K)}\left(\tilde{C}_{i_K}\right)\right)$ AND $\left(tp_2 = \tilde{C}_{j_2}\right)$ AND $\left(tp_3 = \tilde{C}_{j_3}\right)$AND ... AND $\left(tp_u = \tilde{C}_{j_u}\right)$, **THEN** $T_j = \tilde{F}_{g^*}$.

Using the above decision rules, we can classify all the fabric samples into the 7 evaluation levels of each fashion theme without making any ranking inside each evaluation level. For any given fashion requirement such as “Rather Elegant”, we can always find all the fabrics corresponding to this level. In some cases, several fabrics can correspond to the same fashion theme level and the final choice will be done by the concerned designer according to his/her personal preference and other criteria.

4. An illustrative example

We give a predicting example of fashion feature of denim fabrics related to the fashion theme $T =$“Elegant-Wild”.

(1) Predicting the fashion feature of denim fabrics

Taking the denim fabrics as the sample, we select 11 technical parameters of 50 various denim fabrics, including "Fiber-Composition (tp_1)", "Gram-Weight(tp_2)", "Thickness(tp_3)", "Warp-Density(tp_4)", "Weft-Density(tp_5)", "Warp Breaking-Strength (tp_6)", "Weft Breaking-Strength (tp_7)", "Warp Elongation(tp_8)", "Weft Elongation(tp_9)", "Water-Permeability(tp_{10})", and "Air-Permeability(tp_{11})". The fiber compositions of these samples are mainly composed of 5 types including Cotton ($tp_1^{(1)}$, denoted by *C*), Polyester ($tp_1^{(2)}$, denoted by *P*), Viscose ($tp_1^{(3)}$, denoted by *V*), Spandex ($tp_1^{(4)}$, denoted by *S*), Lyocell ($tp_1^{(5)}$, denoted by L).

For obtaining more effective decision rules, we first reduce the number of attributes in this decision system and obtain the reduction $\{tp_1, tp_2, tp_3, tp_4, tp_5\}$.

In addition, after discussion with fashion designers, we identify five sensory properties related to denim fabrics: "softness", "roughness", "wrinkle-resistance", "warmness", and "draping". They are represented by 5 semantically opposite keyword pairs: "soft-hard(sp_1)", "smooth-rough(sp_2)", "wrinkle resistance-crumply(sp_3)", "cool-warm" (sp_4) and "draped-non draped(sp_5)", each with seven evaluation levels expressed by seven-points scales.

For the selected subset of attributes (fabric technical parameters), by using the **RULE 1**, we obtain 12 "**IF-THEN**" rules.

(rule 1) **IF** $tp_1 = \left(C(\tilde{C}_4), P(\tilde{C}_2), V(\tilde{C}_0), S(\tilde{C}_1), L(\tilde{C}_0)\right)$ AND $tp_2 = \tilde{C}_5$ AND $tp_3 = \tilde{C}_5$ AND $tp_4 = \tilde{C}_2$ AND $tp_5 = \tilde{C}_3$,
THEN $sp_1 = \tilde{F}_5$ AND $sp_2 = \tilde{F}_6$ AND $sp_3 = \tilde{F}_3$ AND $sp_4 = \tilde{F}_5$ AND $sp_5 = \tilde{F}_6$.

…

Next, we collect the responses of $r(= 15)$ evaluators for the fashion theme and 5 sensory properties. The final results can be found in the following fuzzy relational matrices:

$$FRM(sp_1, T_2) = \begin{array}{c} \begin{array}{ccccccc} \tilde{F}_1 & \tilde{F}_2 & \tilde{F}_3 & \tilde{F}_4 & \tilde{F}_5 & \tilde{F}_6 & \tilde{F}_7 \end{array} \\ \begin{pmatrix} 0 & 0.1 & 0.2 & 0.5 & 0.2 & 0 & 0 \\ 0 & 0.1 & 0.3 & 0.4 & 0.2 & 0 & 0 \\ 0 & 0.3 & 0.3 & 0 & 0.2 & 0.2 & 0 \\ 0.2 & 0.3 & 0.4 & 0.1 & 0 & 0 & 0 \\ 0.3 & 0.2 & 0.1 & 0.1 & 0.3 & 0 & 0 \\ 0 & 0.2 & 0 & 0.2 & 0.2 & 0.2 & 0.2 \\ 0 & 0.2 & 0.1 & 0.1 & 0.1 & 0.3 & 0.2 \end{pmatrix} \end{array} \begin{array}{c} \text{extreme soft} \\ \text{soft} \\ \text{a little soft} \\ \text{neutral} \\ \text{a little hard} \\ \text{hard} \\ \text{extreme hard} \end{array} \quad sp_1$$

…

From these results, we can obtain the most relevant level to each fabric for the specific fashion theme. Then, combining the rules obtain the corresponding decision rules as follows.

(rule 1') **IF** $tp_1 = \left(C(\tilde{C}_4), P(\tilde{C}_2), V(\tilde{C}_0), S(\tilde{C}_1), L(\tilde{C}_0)\right)$ AND $tp_2 = \tilde{C}_5$ AND $tp_3 = \tilde{C}_5$ AND $tp_4 = \tilde{C}_2$ AND $tp_5 = \tilde{C}_3$, **THEN** $T_2 = \tilde{F}_5$ (A little Wild).

…

Finally, we can find that the most of these fabrics are relevant to the levels of “neutral” and “wild” for the fashion theme “”Elegant”. This conclusion generally conforms to the nature of denim fabrics.

5. Conclusion

In this paper, we present a predicting method to the fashion features of fabric and set up the predicting model for fabric selection. By testing to the performance of this model, the predicting error is 8.57%. It indicates that the proposed method is validated. The designers, especially young designers, can quickly select the suitable fabric according to the fashion demand in garment design. The proposed model will be expected to be used for establishing the intelligent recommender system to garment design.

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