An intelligent garment recommendation system based on case-based reasoning technology

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ABSTRACT – REZUMAT

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Garment purchasing through the Internet has become an important trend for consumers. However, various garment e-shopping systems, systematically lack personalized recommendations, like sales advisors in classical shops, to propose the most relevant products to different consumers according to their consumer profiles and successful recommendation cases. In this paper, we propose a consumer-oriented recommendation system by Case-based reasoning techniques and Similarity degree of fuzzy sets, which can be used in a garment online shopping system like a virtual sales advisor. This system has been developed by integrating successful recommendation cases and taking into account consumer profiles. It can effectively help consumers to choose garments from the Internet. Compared with other prediction methods, the proposed method is more robust and interpretable owing to its capacity to treat uncertainty. This paper presents an original method for predicting one or several relevant product profiles from the similarity degree between a specific consumer profile and a successful cases database.

***Keywords**: recommendation system, case-based reasoning, successful cases database, similarity degree*

Un sistem inteligent de recomandare a articolelor de îmbrăcăminte cu tehnologia raționamentului bazat pe caz

Achiziționarea articolelor de îmbrăcăminte prin internet a devenit o tendință importantă pentru consumatori. Cu toate acestea, în diverse sisteme de e-shopping de articole de îmbrăcăminte, lipsesc în mod sistematic recomandările personalizate, cum ar fi consilierii de vânzări în magazinele clasice, pentru a propune produsele cele mai relevante diferiților consumatori în funcție de profilul lor de consumator și de cazurile de recomandare de succes. În această lucrare, este propus un sistem de recomandare orientat spre consumator prin tehnici de raționament bazat pe caz și gradul de similaritate al seturilor fuzzy, care poate fi utilizat într-un sistem de cumpărături online de articole de îmbrăcăminte ca un consilier virtual de vânzări. Acest sistem a fost dezvoltat prin integrarea cazurilor de recomandare de succes și luând în considerare profilul consumatorului. Poate ajuta eficient consumatorii să aleagă articole de îmbrăcăminte de pe internet. În comparație cu alte metode de predicție, metoda propusă este mai robustă și mai interpretabilă datorită capacității sale de a trata incertitudinea. Această lucrare prezintă o metodă originală de predicție a unuia sau mai multor profiluri de produs relevante din gradul de similaritate dintre un anumit profil de consumator și baza de date de cazuri de succes.

***Cuvinte-cheie**: sistem de recomandare, raționament bazat pe caz, baza de date de cazuri de succes, grad de similaritate*

INTRODUCTION

With the rapid development of e-commerce, more and more consumers buy garments via the Internet [1]. For general consumers, the way of consumption is changing considerably. E-shopping is becoming a generally accepted purchasing way due to its economical and convenient features [2]. This situation largely enhances interactions between consumers and shoppers and can help to expand the businesses of fashion brands to all parts of the world with fewer physical restrictions.

A large number of shopping websites already integrate recommendation systems to help their consumers find relevant products to increase their sales [3]. In the developed personalized recommendation systems, data mining techniques, such as association rules mining for offline operations and connection rule excavation for online operations, have been widely used [4]. In practice, to cope with the data explosion on the Internet and retrieve relevant and concise product information out of overflowing advertisements, the methodology of recommending and learning has been used for acquiring the user preference and providing the user with the user adaptive product information.

In the developed personalized recommender systems, intelligent technologies have been used. In this context, we propose in this paper a new consumer-oriented intelligent recommender system. Compared with the existing work which mostly focuses on learning from product data, this system can recommend garments to a specific consumer by exploiting consumer profile.

2nd section describes how to implement of consumer profile with a fuzzy description of height and a fuzzy description of fat-thin. 3rd section gives an introduction to the details of how to implement of successful case recommendation system, including mathematical methods: case-based reasoning and similarity degree of fuzzy sets. 4th section presents the details of the validation of the recommendation system. 5th section concludes the paper and future work.

FORMALISATION OF THE CONCEPTS AND DATA

The proposed recommender system aims at ranking and selecting the most relevant garments for a specific consumer in terms of body shape fitting and fashion style conformity. In this paper, we illustrate the system with a concrete case: online recommendation of jeans for Chinese women whose ages are from 18 to 25 years old. In this system, the specific consumer needs to input her consumer profile, composed of body shapes, style keywords and visual images.

Moreover, the consumer can visualize the virtual try-on effect by using the Clo3D software. If the consumer is not satisfied with the recommended result, she can identify the unsatisfied body parts and the system will recommend a new product repeatedly by another recommendation module until his satisfaction.

Consumer profile

A consumer profile is a way of describing a consumer directly so that they can be grouped for marketing purposes [5]. A consumer profile can be defined in different aspects, including personal preference, cost requirements, brand requirements, lifestyle, range of age, body shape, desired consumption occasion, recycling effects, and so on.

In this paper, for simplicity, I define the consumer profile (figure 1) as the combination of three parts, i.e. body shapes, style keywords and visual images. The cost and brand effects are not considered here.

The body shapes are used to characterize the body data of the consumer. The style keywords are the verbal description of the consumer of the desired product. The visual images are used to describe the ambience associated with the product desired by the consumer, which cannot be directly expressed in language by himself/herself.

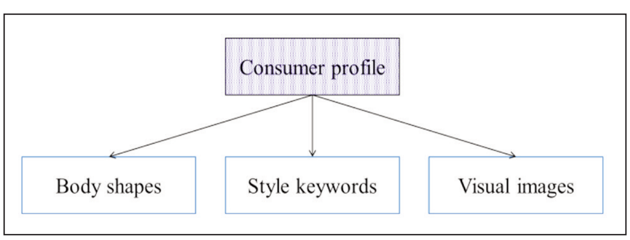

Fig. 1. The proposed consumer profile

Body shapes

Body shapes generally include different body measurements, such as Stature, Chest Circumference, Waist Circumference, Hip Circumference, Neck Circumference, Length of the arm, and Length of the leg. Weight is also considered in some applications.

In my paper, for simplicity, I only consider four parts, i.e. b1: Stature, b2: Chest Circumference, b3: Waist Circumference, and b4: weight. It is easier for general consumers to obtain these data by themselves.

Style keywords

Including a set of emotional keywords used for describing desired fashion styles of garments. The most used style words include: w1: Elegant, w2: Feminine, w3: Young, w4: Sexy, w5: Classic, w6: Romantic, w7: Folk, w8: Sport ($n=8$). To understand each style word, we select one reference picture from several fashion websites and Levis's official website, considered as the most relevant one to this style word.

Visual images

For a non-trained general consumer, style keywords cannot cover all her expectations and preferences. Evaluations with images are relatively more intuitive and closer to her perceptions of garment products. In my paper, for simplicity, I choose 6 pictures of visual images so that each consumer can select the best one according to her expectations: p1, p2, p3, p4, p5 and p6 ($k=6$).

More details about the consumer's profile are given below.

Fuzzy description of height

Normally, we use two indices to describe a human body shape, namely height and fat-thin. However, how to evaluate tall-low and fat-thin is vague. It is for this reason that we use fuzzy sets to express human body shapes [6].

Based on the garment designer's knowledge, tall-low can be expressed by b1, and fat-thin can be expressed by b1 & b4.

According to the Chinese female database of human body shapes, 160A is generally taken as the standard body shape for the Chinese female population, and 145 cm and 175 cm can be considered as the lower and upper bounds of the whole population. We can describe the tall-low as five levels: X1: short, X2: a little short, X3: middle, X4: a little tall, and X5: tall.

The fuzzy function and rules are obtained by uniformly dividing the whole range of the body shapes in height into 5 classes or 5 fuzzy values, denoted as X1, X2, X3, X4, and X5 (figure 2).

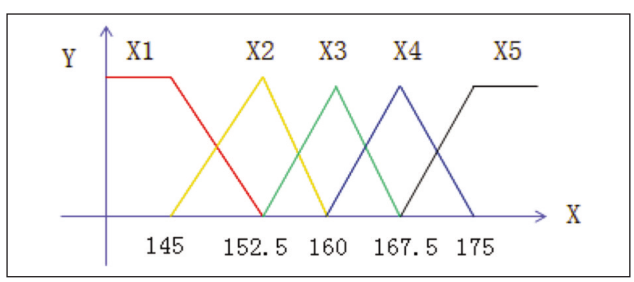

Fig. 2. Fuzzy function (tall-short)

Fuzzy description of fat and thin

BMI (Body Mass Index = Weight in Kilograms / (Height in Meters × Height in Meters)) is a measurement of body fat based on height and weight and applied to both men and women from 18 to 65 years. The WTO regards a BMI of less than 18.5 as being underweight and may indicate malnutrition, an eating disorder, or other health problems, while a BMI equal to or greater than 25 is considered overweight and above 30 is considered obese. The range of BMI values is valid only as statistical categories.

Based on the information, we can define fat-thin as four levels: Y1: underweight, Y2: normal, Y3: overweight, and Y4: obese. Therefore, all kinds of body shapes can be described using one of the 5×4 fuzzy values ($m=20$).

The proposed recommendation system permits to generate of two outputs:

- Fitting of a Garment Style

The fitting of a garment style can be perceived using several frequently used emotional keywords. In this paper, we just extract those from the H&M shopping guide: Skinny, Slim, Straight, Loose. However, for different brands, there are different fashion rules on garment style fitting. To solve this problem, we make a unified neutral description of garment fitting by defining a fuzzy variable of five values: tight, a little tight, moderate, a little loose, and loose ($h=5$).

- Details

Based on the design or shopping experts' knowledge, we take three details: waist, foot and ornamental. And we formalize them according to the same principle as the garment style fitting. The three defined fuzzy variables describing the details are given below.

1. Low-waist, Regular-waist, High-waist
2. Pencil Pants, Regular, Bell-bottom
3. Ornamental, without ornamental

Next, we formalize the proposed system as well as the concerned data:

Category 1: Let $BS = \{bs_1, \dots, bs_m\}$ be a set of m (m = 20) body shapes, representing all the combinations of the 5 standard tall-low types and 4 fat-thin types obtained from the Chinese National Standard GB/T 1335.2-1997, i.e. "X1Y1", "X2Y1", "X3Y1", "X4Y1", "X5Y1", "X1Y2", "X2Y2", "X3Y2", "X4Y2", "X5Y2", "X1Y3", "X2Y3", "X3Y3", "X4Y3", "X5Y3", "X1Y4", "X2Y4", "X3Y4", "X4Y4", "X5Y4".

Category 2: Let $S = \{s_1, \dots, s_n\}$ be a set of n style keywords (n = 8), including "Elegant", "Feminine", "Young", "Sexy", "Classic", "Romantic", "Folk" and "Sport".

Category 3: Let $C = \{c_1, \dots, c_k\}$ be a set of k visual images (k = 6).

Let N be the total number of input variables (Categories 1, 2, and 3). We have $N=m+n+k$ because, for each specific consumer, her body shape (all the body shapes correspond to m inputs), desired style keyword (all the style keywords correspond to n inputs) and visual image (all the visual images correspond to k inputs) constitute the complete consumer profile.

Category 4: Let $I = \{I_1, \dots, I_q\}$ be a set of q weights (q = 3) corresponding to the three input parts BS, S and C. They are obtained by human evaluations using the Fuzzy AHP method [7].

Category 5: Let CP be a profile of a specific consumer including her body shape and desired style keywords and visual images. It is expressed by a N-dimensional weighted vector denoted as

$CP = (I_1 \times bs_1, \dots, I_1 \times bs_m, I_2 \times s_1, \dots, I_2 \times s_n, I_3 \times c_1, \dots, I_3 \times c_k)$.

Category 6: Let $G = \{g_1, \dots, g_h\}$ be a set of h fitting levels (h = 5), including "fitting-loose", "fitting-a little loose", "fitting-moderate", "fitting-a little tight" and "fitting-tight".

Category 7: Let $DW = \{dw_1, \dots, dw_x\}$ be a set of x details of the waist (x = 3), including "waist-high", "waist-moderate", and "waist-low".

Category 8: Let $DF = \{df_1, \dots, df_y\}$ be a set of y details of leg opening (y = 3), including "Bell-bottom", "Regular", and "Pencil Pants".

Category 9: Let $DO = \{do_1, \dots, do_z\}$ be a set of z details of ornamentals (z = 2), including "Ornamental-more", "Ornamental-little".

The above M variables (Categories 6, 7, 8, 9) describing garments constitute the profile of a recommended product with $M = h + x + y + z$.

A real case of consumer profile

A real case is given here to illustrate the performance of the proposed method. For a given consumer whose data include the following three parts:

(1) Body shapes: $b1=163$ cm, $b2=104$ cm, $b3=92$ cm, $b4=50$ kg.

(2) Style keywords: $w1$ (elegant).

(3) Preferred image: $p1$.

We can calculate from the body data the corresponding fuzzy sets describing the criteria of (tall-low) and (fat-thin), i.e. ($X1$, $X2$, $X3$, $X4$, $X5$) = (0,0,0.65,0.35,0) and ($Y1$, $Y2$, $Y3$, $Y4$) = (0,0.98,0.02,0).

Next, we calculate the BS, S and C, based on the three parts of the input data.

(1) BS = {0,0,0,0,0,0,0,0.64,0.34,0, 0,0,0.01,0.01,0, 0,0,0,0,0}, representing m (m = 20) body shapes, formed by the combinations by multiplication of all the elements "XiYj" (i =1, …, 5 and j = 1, …, 4) in "tall-low" and "fat-thin".

(2) S = {0.5,0,0,0.5,0,0,0,0}, representing that the consumer selects the 1st and 4th style elements at the same time from all the n styles keywords ($n=8$). The selected keywords are "Elegant" and "Sexy" respectively. The 1st and 4th elements of S are 0.5 and the others 0 so that the sum of all elements in S is 1. If only "Elegant" is selected, we have S = {1,0,0,0,0,0,0,0}. For simplicity, we just suppose that this consumer selects "Elegant".

The elements of S can be defined by the consumer herself. For example, we can give S = {0.4,0.3,0,0.1, 0,0.2,0,0}, showing that 40% for "Elegant", 30% for "Feminine", 10% for "Sexy" and 20% for "Romantic".

(3) C = {1,0,0,0,0,0}, representing that the consumer selects "Picture 1" from all the k visual images ($k=6$).

The elements of C can be defined by the consumer herself.

As we have $(l_1,l_2,l_3) = (0.48,0.31,0.21)$ by fuzzy AHP, then we can calculate the consumer profile by

$CP = (l_1 \times bs_1, \ldots, l_1 \times bs_m, l_2 \times s_1, \ldots, l_2 \times s_n, l_3 \times c_1, \ldots, l_3 \times c_k)$ = (0,0,0,0,0,0,0,0.31,0.16,0, 0,0,0.005,0.005,0, 0,0,0,0,0, 0.31,0,0,0,0,0,0,0, 0.21,0,0,0,0,0).

SUCCESSFUL CASES RECOMMENDATION SYSTEM

Successful cases are very helpful for increasing the relevancy and accuracy of the recommendation system. After each successful recommendation is satisfied by the consumer, the corresponding couple of <consumer profile, recommended product profile> will be added to the database of successful cases. When a new consumer arrives, her/his profile will be first compared with the existing successful cases. If the similarity of this new consumer profile and an existing consumer's profile is higher than a predefined threshold ε ($\varepsilon \in [0.5,1]$), then this recommendation system will recommend the corresponding successful product to the consumer. The computation of this system is realized using case-based reasoning technology.

Case-based reasoning

Case-based reasoning is the process of solving new problems based on the solutions of similar past problems [8]. For example, a doctor who cures a patient by recalling another patient who exhibited similar symptoms is using case-based reasoning. A lawyer who advocates a particular result in a trial based on legal precedents and a judge who creates case law using case-based reasoning. Case-based reasoning is a prominent kind of analogy-making [9].

Case-based reasoning is not only a powerful way for computer reasoning but also a pervasive behaviour in everyday human problem-solving. More radically, all reasoning is based on past cases personally experienced. This view is related to prototype theory, which is most deeply explored in cognitive science [10].

As shown in figure 3, Case-based reasoning is described using a cyclic process as follows.

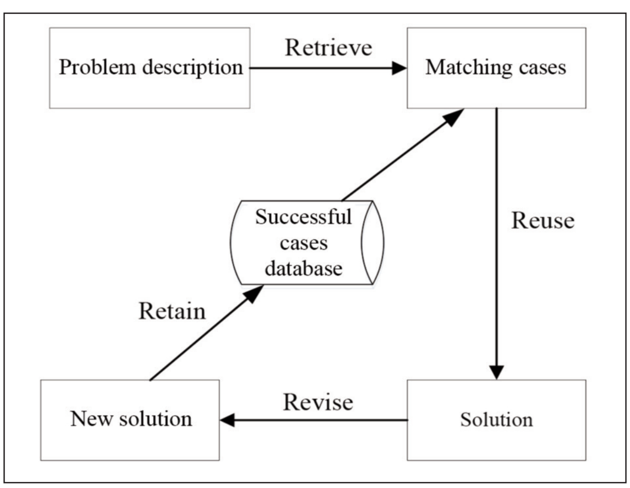

Fig. 3. Cyclic process of Case-based reasoning

(1) Retrieve the most similar cases or cases.
(2) Re-use the knowledge in that case to solve the problem.
(3) Revise the proposed solution.
(4) Retain the experience for the next problem-solving.

Similarity degree of fuzzy sets

The similarity degree of two fuzzy sets can be defined as below.

Let X be the universe.

Let $F(X)$ be the set of all the fuzzy sets on X.

Assuming that A, B, and C are three fuzzy sets defined on $F(X)$, i.e. $\mathbf{A}, \mathbf{B}, \mathbf{C} \in \mathbf{F}(\mathbf{X})$ and N is a mapping function with $\mathbf{F}(\mathbf{X}) \times \mathbf{F}(\mathbf{X}) \rightarrow [\mathbf{0}, \mathbf{1}]$.

$\mathbf{N}(\mathbf{A}, \mathbf{B})$ is called the similarity degree of any two fuzzy sets A and B if the following conditions are satisfied:

① $\mathbf{N}(\mathbf{A}, \mathbf{B}) = \mathbf{N}(\mathbf{B}, \mathbf{A})$

② $\mathbf{N}(\mathbf{A}, \mathbf{A}) = 1$, $\mathbf{N}(\mathbf{X}, \varnothing) = 0$

③ if $\mathbf{A} \subseteq \mathbf{B} \subseteq \mathbf{C}$, then $\mathbf{N}(\mathbf{A}, \mathbf{C}) \leq \mathbf{N}(\mathbf{A}, \mathbf{B}) \wedge \mathbf{N}(\mathbf{B}, \mathbf{C})$

This definition just gives the guidelines for defining a similarity degree, and it can cover several specific definitions given in different contexts. The most used definitions are summarized below.

1. Hamming similarity degree

If $\mathbf{X} = \{x_1, x_2, \ldots, x_n\}$, then

$$N_1(A,B) = 1 - \frac{1}{n}\sum_{i=1}^{n}|A(x_i) - B(x_i)| \qquad (1)$$

If $\mathbf{X} = [a, b] \subseteq R$, then

$$N_1(A,B) = 1 - \frac{1}{b-a}\int_a^b |A(x) - B(x)|\,dx \qquad (2)$$

We give below one example of the Hamming similarity degree of two fuzzy sets A and B. If A = {(x1, 0.4), (x2, 0.8), (x3, 1), (x4, 0)} and B = {(x1, 0.4), (x2, 0.3), (x3, 0), (x4, 0.2)}, the Hamming similarity degree is:

$$N_1(A,B) = 1 - (0 + 0.5 + 1 + 0.2)/4 = 0.575 \qquad (3)$$

2. Euclidean similarity degree

If $\mathbf{X} = \{x_1, x_2, \ldots, x_n\}$, then

$$N_2(A, B) = 1 - \frac{1}{\sqrt{n}}\left(\sum_{i=1}^{n}(A(x_i) - B(x_i))^2\right)^{1/2} \qquad (4)$$

If $\mathbf{X} = [a, b] \subseteq R$, then

$$N_2(A,B) = 1 - \frac{1}{b-a}\left(\int_a^b (A(x) - B(x))^2 dx\right)^{1/2} \qquad (5)$$

For the same fuzzy sets A and B defined previously, the Euclidean similarity degree is

$$N_2(A,B) = 1 - 0.5 \cdot \sqrt{(0 + 0.25 + 1 + 0.04)} = 0.43 \qquad (6)$$

3. Max-min similarity degree

If $\mathbf{X} = \{x_1, x_2, \ldots, x_n\}$, then

$$N_3(A,B) = \frac{\sum_{i=1}^{n}(A(x_i) \wedge B(x_i))}{\sum_{i=1}^{n}(A(x_i) \vee B(x_i))} \qquad (7)$$

For the same fuzzy sets A and B, the max-min similarity degree is

$$N_3(A,B) = 0.4 + 0.3 + 0 + 0/0.4 + 0.8 + 1 + 0.2 = 0.29 \qquad (8)$$

4. Arithmetic averaged similarity degree

$$N_4(A,B) = \frac{2\sum_{i=1}^{n}(A(x_i) \wedge B(x_i))}{\sum_{i=1}^{n}A(x_i) + \sum_{i=1}^{n}B(x_i)} \quad (9)$$

For the same fuzzy sets A and B, the arithmetic averaged similarity degree is

$$N_4(A,B) = 2\cdot(0.4+0.3+0+0)/3.1 = 0.45 \quad (10)$$

Formalization, similarity and reasoning

The database of successful cases *DB_SC* is composed of all the *w* past successful recommended consumer profiles, the corresponding consumer profiles and frequencies of being used.

It is formalised by

$$DB\_SC = \{<CP_i, \{<SRPP_i^{(k)}, T_i^{(k)}> \mid k = 1,\ldots, p(i)\} > \mid i = 1,\ldots, w\} \quad (11)$$

where CP_i is the *i*-th consumer profile in *DB_SC*, and $SRPP_i^{(k)}$ – the *k*-th product profile successfully recommended to CP_i, and $T_i^{(k)}$ – the frequency with which this product profile has been used.

In real shopping experience, several different products may have been accepted by consumers having the same profile.

According to the previous formalization of *CP*, each consumer profile CP_i of *DB_SC* is expressed by a *N*-dimensional weighted vector ($N=m+n+k$), denoted as

$$CP_i = (l_1\times bs_{1i}, \ldots, l_1\times bs_{mi}, l_2\times s_{1i}, \ldots, l_2\times s_{ni}, l_3\times c_{1i}, \ldots, l_3\times c_{ki}) \quad (12)$$

where $bs_{1i},\ldots,bs_{mi}$ are the elements of CP_i corresponding to the *m* ($m=20$) body shapes, $s_{1i},\ldots,s_{ni}$ are the elements of CP_i corresponding to the *n* style keywords ($n=8$), $c_{1i},\ldots,c_{ki}$ are the elements of CP_i corresponding to the *k* visual images ($k=6$).

The similarity degree between a new consumer profile *CP* and the successful cases database *DB_SC*, denoted as *Similarity*(*CP, DB_SC*), is defined as the maximal value of the similarity degrees of *CP* related to all the consumer profiles CP_i ($i=1,\ldots,w$) in the database *DB_SC*. The similarity of *CP* related to CP_i, denoted as *Similarity*(*CP*, CP_i) is defined using the fuzzy sets and Hamming similarity degree. We have

$$Similarity(CP, CP_i) = 1-\frac{1}{2} \times \left[l_1\times\left(\sum_{j=1}^{m}|bs_j - bs_{ji}|\right) + l_2\times\left(\sum_{j=1}^{n}|s_j - s_{ji}|\right) + l_3\times\left(\sum_{j=1}^{k}|c_j - c_{ji}|\right)\right]$$

This similarity degree varies between 0 and 1. The closer the new consumer profile *CP* is to the existing consumer profile CP_i, the closer their similarity degree is to 1.

According to these similarity degrees, we try to select the most relevant product profiles to be recommended to the new consumer *CP* by using the Case-based reasoning method. Case-based reasoning is basically based on the *k*-Nearest Neighbours algorithm. Its reasoning is composed of the three following rules:

Rule 1: If *Similarity*(*CP*, CP_i) $\leq \varepsilon$ for all $i=1,\ldots,w$, then there is no similar consumer profile in the database *DB_SC* and the system will start the other recommendation modules for *CP*.

Rule 2: If there exists only one CP_i ($i\in\{1,2,\ldots,w\}$ so that *Similarity*(*CP*, CP_i) $> \varepsilon$, then we select the product profile $SRPP_i^{k*}$ with $T_i^{k*} = \max\{T_i^{(k)} \mid k=1,\ldots,p(i)\}$ for recommendation to the consumer *CP*. If $SRPP_i^{k*}$ is not accepted by the consumer, the system will successively recommend the other product profiles from $\{SRPP_i^{(k)}\}$ according to the descending order of $T_i^{(k)}$'s.

Rule 3: If there exist several CP_j's ($j=1,2,\ldots,g$ and $1<g\leq w$) so that *Similarity*(*CP*, CP_j) $> \varepsilon$, then we will select a consumer profile CP_i meeting *Similarity*(*CP*, CP_i) = $\max\{Similarity(CP, CP_j) \mid j=1,\ldots,g\}$ and apply Rule 2 for successively recommending relevant product profiles. If the product profiles of CP_i cannot be accepted by the consumer, we will select the consumer profile from $\{CP_j \mid j=1,\ldots,g\}$ corresponding to the second biggest similarity degree and recommend its concerned product profiles, and so on.

VALIDATION OF THE RECOMMENDATION SYSTEM

In this example, we define ε = 0.8. With this threshold, we search for the product profiles corresponding to a new consumer profile from the successful cases database. A garment e-shop is created with two successful cases in the database DB_SC. It is represented by CP_1=(0,0,0,0,0,0,0,0.17,0.3,0, 0,0,0.005, 0.005,0, 0,0,0,0,0, 0.31,0,0,0,0,0,0,0, 0.21,0,0,0,0,0), $SRPP_1^{(1)}$ = (0.8,0.7,0.4,0.4,0.3,0.1,0.2,0.4,0.9,0.5, 0.2,0.8,0.4) and $T_1^{(1)}$ = 1. $SRPP_1^{(2)}$ = (0.1,0.3,0.4,0.7, 0.5,0.1,0.3,0.8,0.5,0.7,0.6,0.1,0.7) and $T_1^{(2)}$ = 3.

A female consumer is visiting the e-shop. Her profile CP is (0,0,0,0,0,0,0,0.28,0.19,0, 0,0,0.005,0.005,0, 0,0,0,0,0, 0.31,0,0,0,0,0,0,0, 0.21,0,0,0,0,0).

From the computation, we find that the similarity degree of *CP* related to CP_1 is 0.89 (> the threshold 0.8). However, the frequency of the recommended product $T_1^{(2)}$ is 3 (larger than $T_1^{(1)}$ = 1). Therefore, this system will recommend the product $SRPP_1^{(2)}$ to the consumer *CP*. From $SRPP_1^{(2)} = (\underset{loose}{0.1}, \underset{a\ little\ loose}{0.3}, \underset{moderate}{0.4}, \underset{a\ little\ tight}{0.7}, \underset{tight}{0.5}, \underset{waist\text{-}high}{0.1}, \underset{waist\text{-}moderate}{0.3}, \underset{waist\text{-}low}{0.8}, \underset{Bell\text{-}bottom}{0.5}, \underset{Regular}{0.7}, \underset{Pencil\ Pants}{0.6}, \underset{Ornamental\text{-}more}{0.1}, \underset{Ornamental\text{-}little}{0.7})$, we can see that the garment fitting level of this product is "a little tight" since 0.7 is the biggest one of the garment fitting levels. In the same way, details of the waist are "low", details of the leg opening are “regular” and details of ornamental are “little”.

The virtual try-on is given in figure 4, and this consume\r is satisfied with the recommendation product. It shows that the database of successful cases is helpful for this consumer.

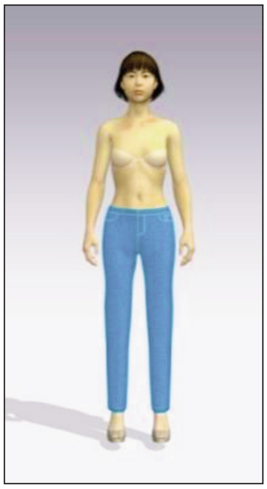

Fig. 4. Virtual fitting effects by the consumer

CONCLUSIONS AND FUTURE WORK

In this garment recommendation system, we use Case-based reasoning technology to recommend relevant garments to each consumer by comparing her consumer profile and the successful cases database. If the similarity value between the consumer profile and the successful cases database is higher than a predefined threshold ε ($\varepsilon \in [0.5,1]$), this recommendation system will be applied to the consumers. Its principle is to use the experience of successfully recommended products for making new recommendations to consumers having similar profiles. In practice, this module will enable to propose more satisfactory products to consumers because it is closer to a successful real shopping experience. In this context, the comparison between the consumer profile and the successful cases database is particularly important.

Compared with other existing methods, the proposed system is more robust and interpretable owing to its capacity to treat human perception. This work can be further extended to support other fashion-oriented products such as suits, dresses, coats and so on.

Due to the time limitation, the current work is still far from being perfect. In future work, more effort should be dedicated to the following aspects:

1. In the future, to obtain more generalized and concrete information about successful recommendation cases, it is imperative to integrate deep learning technology into the system.
2. In the future, fashion trend forecast strategies can be introduced to make the recommendation system more accurate and intelligent.

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