# Estimation of Ease Allowance of a Garment using Fuzzy Logic

Y. Chen[1], X. zeng[1], M. Happiette[1], P. Bruniaux[1], R. Ng[2], W. Yu[2]

[1] Ecole Nationale Supérieure des Arts & Industries Textiles,
9 rue de l'Ermitage, Roubaix 59100, France
[2] The Hong Kong Polytechnic University, Hong Kong, China

**Summary.** The ease allowance is an important criterion in garment sales. It is often taken into account in the process of construction of garment patterns. However, the existing pattern generation methods can not provide a suitable estimation of ease allowance, which is strongly related to wearer's body shapes and movements and used fabrics. They can only produce 2D patterns for a fixed standard value of ease allowance. In this chapter, we propose a new method of estimating ease allowance of a garment using fuzzy logic and sensory evaluation. Based on these values of ease allowance, we develop a new method of automatic pattern generation, permitting to improve the wearer's fitting perception of a garment. The effectiveness of our method has been validated in the design of trousers of jean type. It can also be applied for designing other types of garment.

**Key words:** garment design, ease allowance, fuzzy logic, sensory evaluation

## 1 Introduction

A garment is assembled from different cut fabric elements fitting human bodies. Each of these cut fabric elements is reproduced according to a pattern made on paper or card, which constitutes a rigid 2D geometric surface. For example, a classical trouser is composed of cut fabrics corresponding to four patterns: front left pattern, behind left pattern, front right pattern and behind right pattern. A pattern contains some reference lines characterized by dominant points which can be modified.

Of all the classical methods of garment design, draping method is used in the garment design of high level [1]. Using this method, pattern makers drape the fabric directly on the mannequin, fold and pin the fabric onto the mannequin, and trace out the fabric patterns. This method leads to the direct creation of clothing with high accuracy but needs a very long trying time and sophisticated techniques related to personalized experience of

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operators. Therefore, it can not be applied in a massive garment production. Direct drafting method is more quick and more systematic but often less precise [2]. It is generally applied in classical garment industry. Using this method, pattern makers directly draw patterns on paper using a patter construction procedure, implement in a Garment CAD system. This construction procedure does not determine the amount of ease allowance, but instead generates flat patterns for any given value of ease allowance. In practice, it is necessary to find a compromise between these two garment construction methods so that their complementarity can be taken into account in the design of new products.

To each individual corresponds a pattern whose parameters should include his body size and the amount of ease allowance of the garment. In fact, most of fabrics are extensible and can not be well deformed. Moreover, the amount of ease allowance of a garment, defined as the difference in space between the garment and the body, can be taken into account in the pattern by increasing the area along its outline.

In practice, there exist three types of ease allowance: (1) standard ease, (2) dynamic ease and (3) fabric ease.

Standard ease allowance is the difference between maximal and minimal perimeters of wear's body. It is obtained from standard human body shape for the gesture of standing or sitting still. This amount can be easily calculated using a classical drafting method [2], [3].

Dynamic ease allowance provides sufficient spaces to wearers having non standard body shapes (fat, thin, big hip, strong leg, …) and for their movements (walking, jumping, running, etc.).

Fabric ease allowance takes into account the influence of mechanical properties of fabrics of the garment. It is a very important concept for garment fitting.

Existing automatic systems of pattern generation or garment CAD systems can not determine suitable amounts of ease allowance because only standard ease allowance is taken into account. In this case, 2D patterns are generated according to the predefined standard values of ease allowance for any body shapes and any types of fabric.

In this chapter, we propose a new method for improving the system of garment pattern generation by defining the concept of fuzzy ease allowance capable of taking into account two aspects: standard ease and dynamic ease.

This method permits to generate new values of ease allowance using a Fuzzy Logic Controller (FLC), adapted to body measurements and movements of each individual. The corresponding scheme is given in Figure 1.

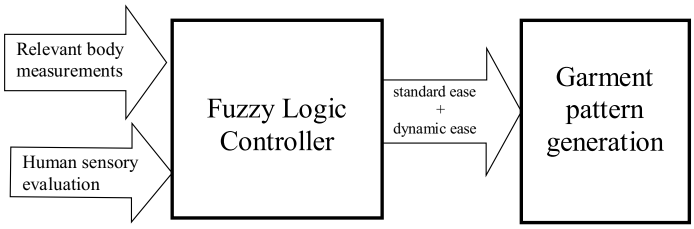



**Fig. 1.** General scheme of the FLC for generating fuzzy ease allowance

For simplicity, we only study the ease allowance for trousers of jean type and the influence of fabric ease related to physical properties of garment materials are not taken into account.

The FLC used for generating fuzzy ease allowance includes an interface of fuzzification, a base of fuzzy rules, an inference mechanism and an interface of defuzzification. It permits to produce the fuzzy ease allowance at each key body position, i.e. the combination of the dynamic ease and the standard ease, from a number of selected relevant measures on wearer's body shapes and comfort sensation of wearers. The amount of fuzzy ease allowance will be further used for generating more suitable patterns.

The construction of this FLC is based on a learning base built from an adjustable garment sample generating different trouser sizes and a group of representative evaluators or wearers (sensory panel). The c-means fuzzy clustering algorithm is used for optimizing the parameters of each fuzzy variable and the method of antecedent validity adaptation (AVA) is used for extracting fuzzy rules.

This chapter is organized as follows. Section 2 gives the basic notations for the elements used in the following sections. These elements include garment samples, garment sensory evaluations of wearers related to garment comfort, body measurements and body parts. Also in this section, we describe the concept of comfort degree obtained from sensory evaluation of wearers. Section 3 presents the method for selecting the most relevant body measurements in order to constitute the input variables of the FLC. In Section 4, we give details of the procedure of fuzzy modeling for estimating values of ease allowance of garments. In Section 5, experimental results and corresponding analysis are given in order to show the effectiveness of our method. A conclusion is included in Section 6.

## 2 Basic Notations and Garment Comfort Degree

In this chapter, the basic notations are formalized as follows.

Given a set of body measurements denoted as $BM_1$, $BM_2$, …, $BM_r$. For example, $BM_1$=waist girth, $BM_2$=hip girth and so on.

Different parts of human body are denoted as $BP_1$, $BP_2$, …, $BP_m$. For example, $BP_1$=lateral abdominal region, $BP_2$=femoral triangle and so on. The comfort degree at each body part can be evaluated subjectively by wearers.

We have produced a special sampling jean whose key body parts can be adjustable in order to generate different values of ease allowance. This sample can be used to simulate jeans of different sizes and different styles. In our project, only the normal size is studied. The corresponding ease allowance at different body parts vary from –1 to 8.

We select a group of n evaluators having different body shapes. These evaluator or wearers are denoted as $WS_1$, $WS_2$, …. ,$WS_n$. The values of the comfort degree at each body part is evaluated by these wearers. For each wearer $WS_i$, the body measurements are denoted as $BM_1(WS_i)$, $BM_2(WS_i)$, …, $BM_r(WS_i)$. In this case, the body measurements for all wearers constitute a (n×r)-dimensional matrix.

In order to take into account the dynamic ease allowance, we ask each wearer to do a series of movements and evaluate the comfort degree at each body part for each movement. These movements include bending leg, bend waist, open legs at sitting and so on and they are denoted as $M_1$, $M_2$, …, $M_h$.

According to the above definitions, the comfort degree can be formalized by $CD(WS_i, BP_j, M_k)$

It is a function of three variables: wearer, body part and movement. It represents the sensory evaluation provided by the wearer $WS_i$ at the body part $BP_j$ (j=1, …, m) when he/she does the movement $M_k$.

In our experiments, we select 20 (n=20) wearers for evaluating comfort degrees at different body parts of the garment sample of normal size. The total number of body movements is 14 (h=14). The values of the comfort degrees given by wearers vary between 0 and 8, in which 0 represents extremely uncomfortable, 2 very uncomfortable, 4 normal, 6 very comfortable and 8 extremely comfortable.

The general comfort degree of the wearer $WS_i$ at the body part $BP_j$ for all movements can be calculated by

$$GCD(WS_i, BP_j)=Min_{k=1...h}\{ CD(WS_i, BP_j, M_k)\}$$

It is the comfort degree corresponding to the movement in which the wearer $WS_i$ feels the least comfortable at the body part $BP_j$ of the trouser sample of normal size. For example, the comfort degree of the wearer n°2 for all movements at the gluteal region can be calculated by

GCD($WS_2$, gluteal region)=

Min{CD($WS_2$, Gluteal region, bending leg), CD($WS_2$, Gluteal region, Bend Waist) , …}

## 3 Selection of the Most Relevant Body Measurements

In garment design, there exist a great number of possibilities for taking body measurements. However, for a specific garment, only a very small set of measurements is relevant to the corresponding comfort degree. Then, we should only take this set of body measurements as input variables. The relevant body measurements can be selected by garment designers using their professional experience. In practice, this personalized knowledge is not normalized and each designer selects his/her own relevant body measurements, different from others. Moreover, for a specific garment, it is possible that some important body measurements are neglected by designers because they have no complete knowledge on all concerned human body parts related to their movements.

In our fuzzy model, the relevant body measurements are first selected using the data sensitivity criterion. Then, these selected variables are validated using the general knowledge of garment design. The principle of the data sensitivity criterion is given as follows.

IF a small variation of a body measurement corresponds to a large variation of the garment comfort, THEN this body measurement is considered as a sensitive variable.

IF a large variation of a body measurement corresponds to a small variation of the garment comfort, THEN this body measurement is considered as an insensitive variable.

Moreover, in practice, body measurements related to uncomfortable feeling of wearers seem to be more important than those related to comfortable feeling. According to this principle, we define, for a specific body part $BP_k$, an importance coefficient $P_{ij}$ in our sensitivity criterion. We have

$$P_{ij} = \rho / (GCD(WS_i, BP_k) + GCD(WS_j, BP_k))$$

where ρ is a constant so that $\sum_{i \neq j} P_{ij} = 1$.

The value of $P_{ij}$ is big if the comfort degrees of the two wearers $WS_i$ and $WS_j$ are low values. In this case, both wearers have uncomfortable feeling at the body part $BP_k$ of the sample of normal size. The value of $P_{ij}$ is small if the comfort degrees of $WS_i$ and $WS_j$ are high values. In this case, both wearers have comfortable feeling at the body part $BP_k$. In any cases, the value of $P_{ij}$ is inversely proportional to the sum of the comfort degrees of $WS_i$ and $WS_j$.

For a specific body part $BP_k$ of the sample of normal size, the sensitivity criterion for selecting the most relevant body measurements is denoted as $S(BM_i, BP_k)$. It is defined by

$$S(BM_i, BP_k) = \sum_{s \neq t} \left( \frac{P_{st} \left| GCD(WS_s, BP_k) - GCD(WS_t, BP_k) \right|}{\left| BM_i(WS_s) - BM_i(WS_t) \right|} \right)$$

where $i \in \{1, \ldots, r\}$, $k \in \{1, \ldots, m\}$, $l \in \{1, 2, 3\}$ and $s,t \in \{1, \ldots, n\}$.

From this definition, we can see that the value of the sensitivity $S$ is big if a small variation of $BM_i$ for different wearers causes a big variation of their comfort feelings (from an uncomfortable level to a comfortable level or from a comfortable level to an uncomfortable level). For any specific body part of the studied trouser sample, all body measurements $BM_1$, $BM_2$, …, $BM_r$ can be ranked according to this criterion and the elements having the highest ranks are considered as the most relevant body measurements, which will be taken as input variables in the fuzzy model.

Using this criterion, for the gluteal region and the trouser of normal size, we obtain 8 body measurements with the highest ranks. These parameters can be classified into two classes as follows.

*Vertical type: Waist to hip, Out leg, Curved front body rise,*

*Girth type : Thigh girth, Waist girth, Half back waist, Hip size, Half back hip*

These body measurements are shown in Figure 2.

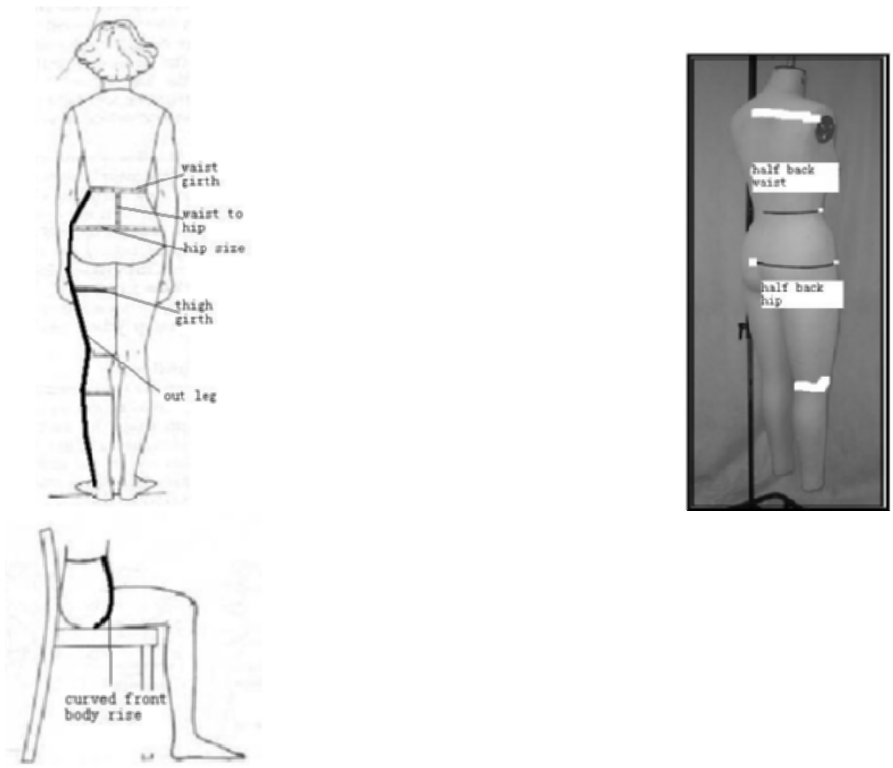



**Fig. 2.** Relevant body measurements related to the gluteal region and the trouser of normal size

## 4 Construction of the Fuzzy Model

In Section 3, we select the 8 most relevant body measurements according to the criterion of data sensitivity. However, in the fuzzy modeling procedure, 8 input variables are still too large related to the number of learning data obtained from 20 wearers. In this case, we apply the Principal Component Analysis (PCA) [4] before the procedure of fuzzy rules extraction in order to further reduce the input space. Its principle is described as follows.

PCA performs a linear transformation of an input variable vector for representing all original data in a lower-dimensional space with minimal information lost.

The $q$ observations in $\Re^n$, corresponding to $n$ input variables, constitute a data distribution characterized by the eigenvectors and the eigenvalues which can be easily calculated from the variable covariance matrix. PCA aims at searching for the smallest subspace in $\Re^n$ 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 this section, we wish to extract two first components from the 8 relevant body measurements selected in Section 3. From the garment design knowledge, we know that there exist a very weak correlation between the parameters of the vertical type and those of girth type. For simplicity, the parameters of each class (vertical type or girth type) are independently projected into two one-dimensional subspaces using PCA. Then, we obtain two extracted variables: the vertical body measurement ($x_1$: VBM) and the girth body measurement ($x_2$: GBM). These two variables as well as the general comfort degree ($x_3$: GCD) obtained from sensory evaluation of wearers are taken as input variables of the fuzzy model. The ease allowance for the corresponding body part, denoted as y, is taken as output variable of the model. Its values are real numbers varying between –1 and 8.

In order to extract significant fuzzy rules, we have to transform measured or evaluated numerical values of the input and output variables into linguistic values. The linguistic values of $x_1$ (VBM), $x_2$ (GBM) and y are: {very small (VS), small (S), normal (N), big (B), very big (VB)}. The linguistic values of GCD are {very uncomfortable (VUC), uncomfortable (UC), normal (N), comfortable (C), very comfortable (VC)}.

The corresponding learning input/output data, measured and evaluated on n different wearers, are denoted by $\{(x_{11}, x_{12}, x_{13}; y_1), \ldots, (x_{n1}, x_{n2}, x_{n3}; y_n)\}$. In our experiments, we have n=20. Mamdani method is used for defuzzification [5]. The fuzzy rules are extracted from these input/output learning. For each input variable $x_i$ (i=1, 2, 3), the parameters of its membership functions are obtained using the fuzzy c-means clustering method [6]. This method permits to classify the learning data $\{x_{1i}, \ldots, x_{ni}\}$ into 5 classes, corresponding to the five fuzzy values of $x_i$. For each learning data $x_{ki}$, we obtain the membership degrees for these five fuzzy values as follows: $\mu_1(x_{ki})$, …, $\mu_5(x_{ki})$. Assuming that the corresponding membership functions take a triangular shape characterized by $Tr(a_{1i}, b_{1i}, c_{1i})$, …, $Tr(a_{5i}, b_{5i}, c_{5i})$, the 15 parameters $a_{1i}$, …, $c_{5i}$ are obtained by minimizing the following criterion:

$$\sum_{j=1}^{5}\sum_{k=1}^{n}\left(Tr(a_{ji},b_{ji},c_{ji})-\mu_j(x_{ki})\right)^2$$

An example of the membership functions optimized by fuzzy c-means method is given in Figure 3. In practice, the fuzzy values obtained by this method lead to more precise results than uniformly partitioned fuzzy values because each fuzzy value generally correspond to one aggregation of learning data.

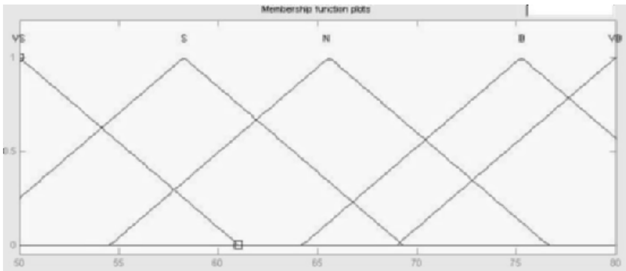



**Fig. 3.** The membership functions for $x_1$ (vertical body measurement) for lumbar

The fuzzy rules of the FLC for estimation of ease allowance are extracted from the learning data $\{(x_{11}, x_{12}, x_{13}; y_1), \ldots, (x_{n1}, x_{n2}, x_{n3}; y_n)\}$ using the method of antecedent validity adaptation (AVA) [7]. It is based on the method of Wang-Mendel [8] but some improvements have been done in it. Its principle is essentially a process by which the antecedent validity of each data, with respect to fuzzy values and fuzzy rules, is evaluated in order to adjust the output consequent. Compared with the other fuzzy extraction methods, the AVA method can effectively resolve the conflicts between different rules and then decrease the information lost by selecting only the most influential rules. In our project, the basic idea of applying the AVA method is briefly presented as follows.

According to the previous discussion, the input variable $x_i$ ($i \in \{1, 2, 3\}$) is partitioned into 5 fuzzy values: $FV_i$={VS, S, N, B, VB}. For each learning data $(x_{k1}, x_{k2}, x_{k3}; y_k)$, we set up the following fuzzy rules by combining all fuzzy values of these three input variables:

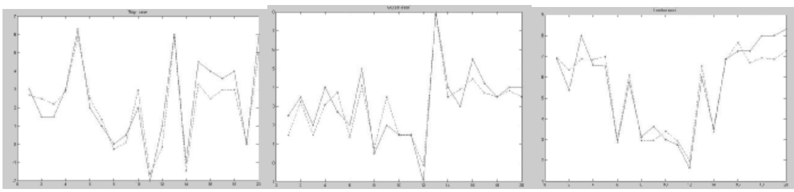
Rule j: IF ($x_1$ is $A_1^j$) AND ($x_2$ is $A_2^j$) AND ($x_3$ is $A_3^j$), THEN (y is $y_k$) with $A_i^j \in FV_i$ and the validity degree of the rule

$$D(rule\ j) = \sum_{i=1}^{3} \mu_{A_i^j}(x_{ki})$$

Given a predefined threshold σ, the rule j is removed from the rule base if the following condition holds: D( rule j)<σ. The value of σ should be carefully selected by taking into account the criteria of precision, complexity, robustness and significance. For big values of σ, the remaining fuzzy rules after this elimination procedure are significant, less complex but probably lead to imprecise results. For small values of σ, the number of fuzzy rules is important and some rules are not significant but lead to more precise results.

## 5 Results and Discussion

To test the effectiveness of the FLC, we carry out the following experiments. Of n learning data (n=20) evaluated and measured on the garment sample, we use n-1 data for learning of the FLC, i.e. construction of membership functions and extraction of fuzzy rules and the remaining one data for comparing the difference between the estimated ease allowance generated by the fuzzy model ($y_m$) and the real value of the ease y. Next, this procedure is repeated by taking another n-1 data for learning. Finally, we obtain the results for 20 permutations (see Figure 4). For three key body parts: lumbar, gluteal and thigh, the averaged errors between $y_m$ and y for all the permutations are 0.62, 0.72 and 0.75 respectively. This means that the difference between the estimated ease allowance and the real ease allowance is very small (<1). The precision condition of the FLC can be satisfied.



*(a) lumbar* *(b) gluteal* *(c) thigh*
*$y_m$: dotted line* *y: solid line*

**Fig. 4.** Comparison between the estimated ease allowance and its real value

Figure 4 shows that the estimated ease allowance for lumbar, gluteal and thigh generated from the fuzzy model can generally track the evolution of the real ease. $y_m$ varies more smoothly than y because there exist an averaging effect in the output of the FLC. The difference between $y_m$ and y is bigger for isolated test data because their behaviors can not be taken into account in the learning data.

Moreover, we obtain 16 fuzzy rules for each key body part. For lumbar, the 2 most important rules are given as follows.

1) *IF GBM=big AND VBM=normal AND GCD=very uncomfortable THEN ease=small( 0.68).*
2) *IF GBM=big AND VBM=normal AND GCD=very comfortable THEN ease=normal (0.62).*

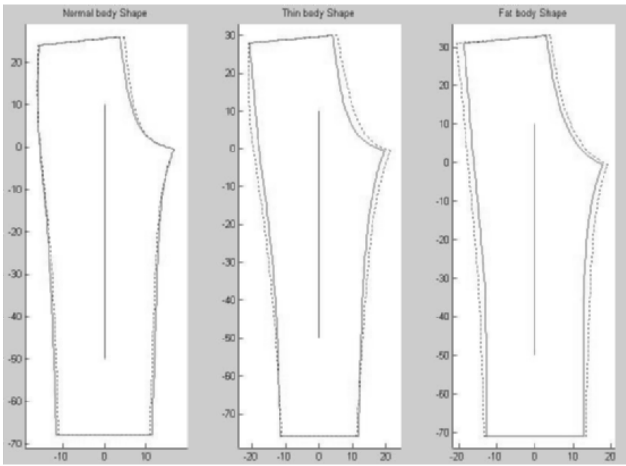
For gluteal, the 2 most important rules are given as follows.

3) *IF GBM=very big AND VBM=small AND GCD=very uncomfortable THEN ease=very small (D=0.85).*
4) *IF GBM=normal AND VBM=normal AND GCD=normal THEN ease=normal (D=0.79).*

For thigh, the 2 most important rules are given as follows.

5) *IF GBM=big AND VBM=normal AND GCD=very uncomfortable THEN ease=very small (D=0.85)*
6) *IF GBM=normal AND VBM=very small AND GCD=normal THEN ease=small (D=0.71).*

For a specific wearer, a fuzzy pattern of his trouser can be generated using the values of ease allowance at three key body parts: lumbar, gluteal and thigh. Next, we compare the patterns obtained using the classical direct drafting method with standard ease allowance and the fuzzy method proposed in this chapter. The results of this comparison are shown in Figure 5.




Fuzzy pattern: dotted line, classical pattern: solid line

**Fig. 5.** Comparison between classical pattern and fuzzy pattern

From Figure 5, we can see that the fuzzy pattern generated using the fuzzy method is very close to that of the classical method for normal body shapes. So, standard ease allowance can be generally taken into account in the proposed fuzzy model. However, there exists some difference between the fuzzy pattern and the classical pattern when human body shapes are abnormal such as fat, thin, strong legs, big hip. The fuzzy pattern is generally more sensitive to variations of human body shapes than the classical method because movements and comfort feeling of wearers have been taken into account in the values of ease allowance generated by the fuzzy model.

## 6 Conclusion

The proposed method combines the experimental data measured on wearer's body shapes and the wearers' sensory perception on garment samples in the construction of the FLC. The FLC has been used for estimating fuzzy ease allowance at three body parts: lumbar, gluteal and thigh. A data sensitivity based criterion has been proposed for selecting the most relevant body measurements. Then, these selected body measurements are separately projected into two one-dimensional subspaces using PCA in order to generate two features: vertical body measurement and girth body measurement. These two features as well as the comfort degree evaluated using sensory evaluation of wearers constitute the input variables of the FLC. Using the method of AVA, we extract the corresponding fuzzy rules from the learning data measured and evaluated on 20 wearers. Using the values of ease allowance related to the key body parts, we generate new garment patterns. The experimental results have shown that the fuzzy patterns are more sensitive to variations of human body shapes than the classical patterns generated using the direct grafting method with standard ease allowance. In this way, the proposed method can effectively improve the quality of garment pattern design.

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