Adjectives Grouping in a Dimensionality Affective Clustering Model for Fuzzy Perceptual Evaluation

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Abstract

More and more products are no longer limited to the satisfaction of the basic needs, but reflect the emotional interaction between people and environment. The characteristics of user emotions and their evaluation scales are relatively simple. This paper proposes a three-dimensional space model valence-arousal-dominance (VAD) based on the theory of psychological dimensional emotions. It studies the clustering and evaluation of emotional phrases, called VAdC (VAD-dimensional clustering), which is a kind of the affective computing technology. Firstly, a Gaussian Mixture Model (GMM) based information presentation system was introduced, including the type of the presentation, such as single point, plain, and sphere. Subsequently, the border of the presentation was defined. To increase the ability of the proposed algorithm to handle a high dimensional affective space, the distance and inference mechanics were addressed to avoid lacking of local measurement by using fuzzy perceptual evaluation. By comparing the performance of the proposed method with fuzzy c-mean (FCM), k-mean, hard -c-mean (HCM), extra fuzzy c-mean (EFCM), the proposed VADdC performs high effectiveness in fitness, inter-distance, intra-distance, and accuracy. The results were based on the dataset created from a questionnaire on products of the Ming style chairs online evaluation system.

Keywords

Affective Computing, Product Evaluation, Fuzzy Set, Clustering, Valence-Arousal-Dominance.

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I. Introduction

Perceptual engineering is a new branch of engineering which combines the perceptual and engineering technologies. It mainly designs products by analyzing human sensibility and manufactures products according to human preference [1]-[2]. The sensibility of perceptual engineering is a dynamic process, which changes fashion, trend and individual timely. It is difficult to grasp and quantify the perceptual issues, but they can be measured, quantified, and analyzed by modern technology, and their rules still can be grasped [3]. Some uncertain inference with evaluations was widely applied in the industrial design field, especially, for the products preference evaluation [4]-[6]. Researchers from Hiroshima University were the first to introduce perceptual analysis into the field of engineering research. In 1970, with the beginning of the comprehensive consideration of the emotions and desires of occupants in residential design, the study of how to embody the sensibility of occupants into engineering technology in residential design was originally called "emotional engineering" [7].

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The customer's emotional evaluation of the product exists in its natural language description, while the vocabulary in natural language is often inaccurate and vague [8]-[11]. The difficulty in dealing with natural language also complicates the study of implicit emotions in products. The traditional fuzzy set theory coarse-grained natural language and the formation of linguistic variables [12] reduce the computational complexity, which brings a feasible direction to language processing under weakening conditions [13]-[15]. Osgood's semantic difference work is composed of three-dimensional indicators [16]-[18]. One important dimension is the range of "Valence" from pleasant to unpleasant; the other dimension is "Arousal", which measures of calm to excited; and "dominance" means the perceived degree of control in a (social) situation, so-called VAD model. Mehrabian and Russell used 150 words for experiments, and Bellezza *et al*. used 450 words for experiments; Bradley & Lang launched the psychological quantity calibration experiment to launch an emotional rating data set of about 1000 words, and more than 1000 words were divided into 56 groups, each group consisted of 14 lines of 4 words per line for the subject to rate [19]-[20]. The corresponding vocabulary of the 56 vocabularies is subjected to the three-dimensional sentiment rating of VAD, which is set to a discrete scale [21].

By statistically calculating the data, the VAD emotional space mean and its standard deviation (SD) of each vocabulary are calculated separately. Since the words of the emotional vocabulary are not all suitable for product and perceptual evaluation, some of the vocabularies need to be selected to reflect the product. Emotional elements are carried; therefore, perceptual engineering classifies and merges certain words using grouping, and forms about 25 representative words (perceptual vocabulary groups) through group computing of perceptual vocabulary. This work conducted an emotional rating experiment based on 25 vocabularies and modified the Self-Assessment Manikin (SAM) and Affective Norms for English Words (ANEW) accordingly. Because the traditional SAM-based class experiments use pure manual methods, they face the problem of inefficient data collection, which also imposes constraints on the design of SAM sentiment rating experiments [8]. For example, a discrete scale design is mainly to consider statistical convenience. In this experiment, the expression scale of SAM is still used, but when setting the number of rating points, the continuous point method is adopted, which is also in line with Osgood's theory of "continuous psychological quantity".

In this study, a SAM continuous-scale sentiment rating system was proposed. The data points are implemented using scroll bars, so that the acquired VAD sentiment spatial data is no longer restricted to the discrete distribution of [0-8]. This will be beneficial to discover the microscopic mode of the VAD space; where, the point set distribution form in the VAD space. The purpose of our experiment is to find the relationship between the perceptual vocabulary and the corresponding VAD space, and the distribution of each perceptual vocabulary and VAD emotional space point set, and to find the consistency degree of the emotional vocabulary from the analysis of the distribution state of the point set [22]-[25]. Specifically, the feelings of the user are relatively consistent; these are all expected to be obtained in the experimental data and later analysis. Similarly, in the specific application, the feature set image of the product can be used to perform the same VAD rating experiment to obtain the VAD data of a certain product feature, so that the product's characteristics and emotional elements pass the VAD emotion.

Visually it reproduces the VAD sentiment data of 25 vocabularies; thus, the rating data of the single dimension is drawn separately. The results established that each dimension data has an aggregation effect, which means only from a single dimension (Valence, Arousal or Dominance) (K= Control), the rating data has certain stability; and from the two-dimensional data point distribution observation (K=Elegant), the data still shows a certain aggregation effect. As the number of data increases, people's ratings are not only stable, but also related to Valence, Arousal and Dominance. However, they cannot be generalized by linear regression. The traditional method is to use cluster analysis to select representative point sets for classification, but the results of clustering still make each emotional element become an isolated point [26]-[27].

In this research, the VAD emotional space was constructed by using the modeling proposed in Section II. Two clustering algorithms were applied for emotion clustering and presented the ANEW system words in VAD space, the 3-dimensional emotion space that was potentially applied in an industrial design product evaluation by using a fuzzy inference system. Section III deployed the results and discussions, while Section IV concluded the proposed methods effectively in some applications. The framework of the research is illustrated in Fig. 1.

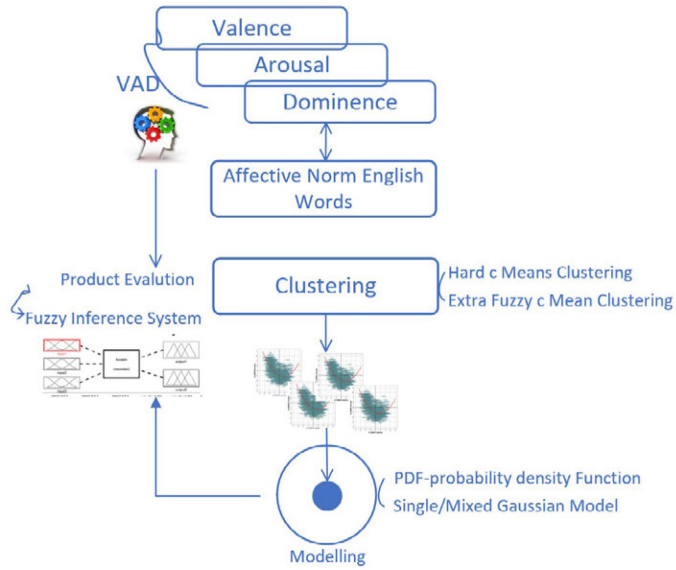


Fig. 1. The framework of VAD emotional model for evaluation by using dimensional clustering methods.

II. Modeling

The emotional evaluation by using a perceptual vocabulary is more concentrated and the emotional meta-core can be defined as a single -point set. The center is the average of the three-dimensional coordinates of the point set. The standard deviation is the domain radius. The point set distribution has a certain range, which can be calculated by its standard deviation. This kind of data distribution can set the kernel of the emotional element as an ellipsoid set indicating that the VAD identity of the emotional element is general. The VAD point set data is a distributed approximation on a plane indicating the VAD identity of the emotional element, such as a specific 25-word VAD point set topology. The content is to carry out the artificial psychological quantity labeling experiment based on the VAD emotional space, and the system design is carried out according to the method of ANEW experimental design. Due to the traditional manual labeling method, it is not conducive to large-scale data acquisition, and there are statistical difficulties. The continuous scale method (VAD emotion rating)does no longer adopt the 9-point rating system through the online survey system. VAD labeling experiments can be performed on a large scale to collect more data. The VAD labeling of the product and the VAD labeling of the relevant sensible vocabulary can establish a kind of mapping of the product feature set to the corresponding sensible vocabulary while it is not a one-to-one correspondence function.

The VAD sentimental spatial point set of each perceptual vocabulary shows that the distribution state of VAD spatial point sets of different perceptual vocabularies is different, which can be roughly divided into three categories: single point set (indicating that the emotional evaluation has a strong one), plane set (indicating that the sentiment evaluation is poorly consistent), and ellipsoid set (indicating that the sentiment evaluation has a medium consistency). Through the different spatial geometric topologies of the point set distribution, these emotions need to be defined separately. The emotional cell metamodel is a very special semantic cell model whose domain is a three-dimensional VAD emotional space. As a special semantic cell, it is composed of two parts: the semantic kernel and the semantic shell. The semantic kernel is a set of VAD values, which represent the typical VAD values of all emotional cell elements. The emotional cell element shell represents the boundary of the field covered by the perceptual vocabulary, which is essentially uncertain, so a distance density function is used to represent this uncertainty. For the kernel of emotional cell elements, there are many forms, such as single point set, and sphere set. For the outer shell of the emotional cell elements, there are also many forms of the density function, such as the Gaussian Mixture Model (GMM).

A. Adjectives Space Construction

$\forall P \in \Omega$ is of $\Omega = \{(E_1, E_2, ..., E_n) : E_i \in P.\ i = 1, 2, ..., n$ where n is the number evaluations. Particularly, in the valence-arousal-dominent dimentinality space, P is described as $P = (Valence, Arousal, Dominance)$ and simplified as $P = (v,\ a,\ d)$, where $\Omega = \{(v, a, d) \mid v, a, d \in R\}$. A given metric $d = \|\cdot\|$ in VAD dimentionality can be defined as [26]:

$$d(P, P) = \|P\| = \sqrt{(v^2 + a^2 + d^2)} \tag{1}$$

$\forall P, Q \in \Omega$, we have that,

$$d(P \pm Q) = \sqrt{((v_P \pm v_Q)^2 + (a_P \pm a_Q)^2 + (d_P \pm d_Q)^2)} \tag{2}$$

Besides, $\forall \alpha, \beta \in R, P, Q \in \Omega$, d can be given by:

$$d(\alpha P \pm \beta Q) = \sqrt{(\alpha v_P \pm \beta v_Q)^2 + (\alpha a_P \pm \beta a_Q)^2 + (\alpha d_P \pm \beta d_Q)^2} \tag{3}$$

Thus, the following expression is applied:

$$d(\alpha P + \beta Q) \leq |\alpha| \cdot d(P) + |\beta| \cdot |d(Q)| \tag{4}$$

Definition 1: $\forall P \in \Omega$, there exists a neighbor of P which is defined as:

$$N_P^{\varepsilon} = \{X \mid \|P - X\| < \varepsilon, X \in \Omega\} \tag{5}$$

Definition 2: For adjectives K, if the VAD values belong to a single point kernel, then the kernel is defined by:

$$\{P_K \mid P_K = \frac{1}{\|K\|} \sum_{P_i \in K} P_i(\rho(P_i))\} \tag{6}$$

where, $\rho(P_i)$ is the probability density function (PDF) of P_i.

Definition 3: The sphere kernel is defined as:

$$\{P_j \mid P_j \in N_{P_K}^{\varepsilon}\} \tag{7}$$

where, $P_K = \frac{1}{\|K'\|} \sum_{P_i \in K'} P_i(\rho(Pi)), K' \subset K$,

and $K' = \{P_i \mid \rho(P_j) \leq \rho_T\}$, ρ_T is a given constant to limit the size of the kernel.

Definition 4: The plain kernel is defined as a union of sphere kernels $\{\bigcup_i P_K\}$, where P_K is subject to Definition 2 and 3.

Definition 5: The border of the kernel is defined by upper and lower sets, which are respectively given by:

$$UP_B = \{P_l \mid P_l \in N_{P_K}^{\varepsilon_u}\} \tag{8}$$

$$LP_B = \{P_l \mid P_l \in N_{P_K}^{\varepsilon_l}\} \tag{9}$$

Then, the border is given by:

$$P_B = UP_B \setminus LP_B \tag{10}$$

B. Metric Function Acquisition

1. Linear Based Function

The density calculation of a point set is a relatively complicated process, and a linear function can be used to simplify the calculation. As the constant function $\rho_i(x) = a_i$, it is clear that when the density function is linear, it will reflect the uniform distribution state of the point set. Fig. 2 shows the grouping of the adjective, where (a) control, and (b) modern in the perceptual space of emotions in the VAD model.

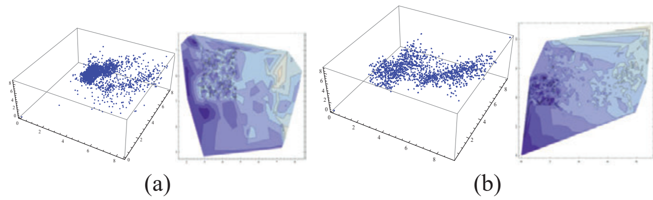


Fig. 2. The density distribution (middle) and contour map (right) of the linear density function of the VAD spatial point, where (a) K=control, and (b) K=modern.

2. Gaussian Based Metric

In the point set topology type of the VAD emotion space, both the single point set and the spheroid set are considered to be approximately spherical. In this case, the Simple Gaussian Model (SGM) is used to describe the probability density of these points, which is defined as follows:

$$\rho(P; \mu, \Delta) = \frac{1}{\sqrt{(2\pi)^3 |\Delta|}} e^{-\frac{1}{2}(P-\mu)^T \Delta^{-1} (P-\mu)} \tag{11}$$

where Δ is the covariance matrix, and μ is the center point of the density function. The characteristics of the density function are determined by (Δ, μ). Then, to achieve the best description of the point set to feature, the parameter p of (Δ, μ) should be estimated. For any $P_i \in \Omega$ of the VAD space, the density probability is $\rho(P_i, \mu, \Delta)$, for any adjective K, each point $P_i \in K$ is independent, then probability density of K can be calculated by:

$$\rho_K = \rho(K; \mu, \Delta) = \prod_i \rho(P_i; \mu, \Delta) \tag{12}$$

By using the maximum likelihood estimation (MLE), the estimating parameter pairs of (Δ, μ) to be applied for the maximization are calculated using the following formula, in which O is an estimation on (μ, Δ) [26] :

$$\begin{aligned} O(\mu, \Delta) &= \ln(\prod_i \rho(P_i; \mu, \Delta)) \\ &= \sum_i \ln(\rho(P_i; \mu, \Delta)) \\ &= \sum_i [-\frac{3}{2}\ln(2\pi) - \frac{1}{2}\ln|\Delta| + \frac{1}{2}(P_i - \mu)^T \Delta^{-1} (P_i - \mu) \\ &= -\frac{3n}{2}\ln(2\pi) - \frac{n}{2}\ln|\Delta| - \frac{1}{2}\sum_i [P_i - \mu)^T \Delta^{-1} (P_i - \mu)] \end{aligned} \tag{13}$$

To get μ, continuously, equate the differentiation of Eq(13) by the variable μ by 0 as follows:

$$\begin{aligned} \partial_\mu (O(\mu, \Delta)) &= -\frac{1}{2}\sum_i [-2\Delta^{-1}(P_i - \mu)] \\ &= \Delta^{-1} \sum_i [(P_i - \mu)] \\ &= \Delta^{-1} \sum_i P_i - n\mu = 0 \end{aligned} \tag{14}$$

Also, the estimated μ and Δ are given by:,

$$\hat{\mu}=\frac{1}{n}\sum_i P_i \tag{15}$$

$$\hat{\Delta}=\frac{1}{n-1}\sum_i (P_i-\hat{\mu})(P_i-\hat{\mu})^T \tag{16}$$

Any density of the point in the kernel can be presented formally as $\rho(P;\hat{\mu},\hat{\Delta})$. The definition of VAD and the center point's parameter estimation μ can be rewritten as:

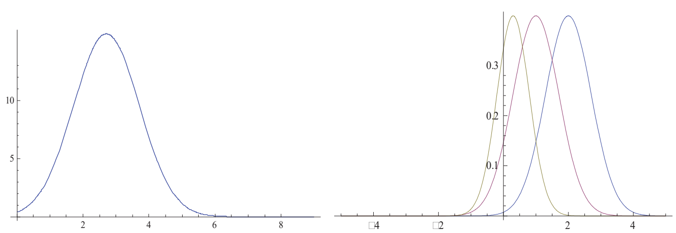
$$\hat{\mu}=\left(\frac{1}{n}\sum_i v_i,\frac{1}{n}\sum_i a_i,\frac{1}{n}\sum_i d_i\right) \tag{17}$$

The parameter estimation of covariance $\hat{\Delta}$ can be rewritten as:

$$\hat{\Delta}=\frac{1}{n-1}\sum_i [v_i-\hat{\mu}_1, a_i-\hat{\mu}_2, d_i-\hat{\mu}_3]\begin{bmatrix} v_i-\hat{\mu}_1 \\ a_i-\hat{\mu}_2 \\ d_i-\hat{\mu}_3 \end{bmatrix}$$

$$=\frac{1}{n-1}\sum_i [(v_i-\hat{\mu}_1)^2+(a_i-\hat{\mu}_2)^2+(d_i-\hat{\mu}_3)^2] \tag{18}$$

where $n = 2^P$, i.e. the number of elements of the set; where the discreet scale can be used if the VAD is in one-dimensional space, where the mode visualization is shown in Fig. 3.



(a) (b)

Fig. 3. One dimensional affective SGM model.

By using K=Elegant in the VAD dataset, after SGM, we have μ = (2.71, 4.79, 5.75), Δ = 2.07I, which is visualized in Fig. 4, where

$$\rho(P_{Elegant})=(2\pi)^{-\frac{3}{2}}e^{-\frac{1}{2}((x-2.71)^2+(y-4.79)^2)} \tag{19}$$

$$\rho(P_{Elegant})=(2\pi)^{-\frac{3}{2}}e^{-\frac{1}{2}((x-1.70)^2+(y-2.45)^2)} \tag{20}$$

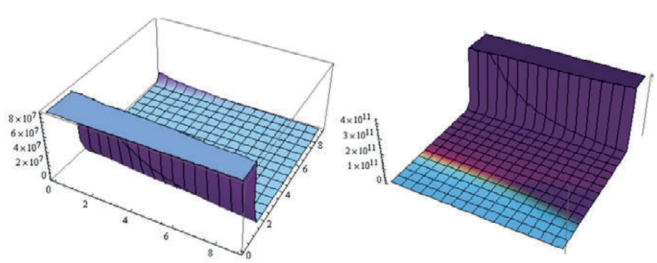


Fig. 4. SGM model in VAD space.

For "P is elegant" in VAD is visualized in Fig. 5, where

$$\rho(P_{Elegant})=(2\pi)^{-\frac{3}{2}}e^{-\frac{1}{2}((x-2.71)^2+(y-4.79)^2+(z-5.75))^2} \tag{21}$$

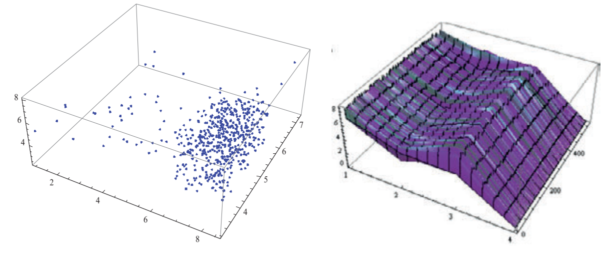
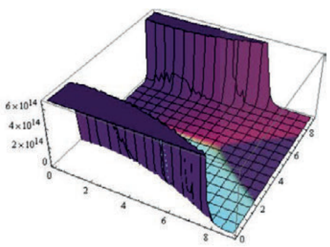


Fig. 5. VAD effective space by using the metric of θ = (2.71, 4.79, 5.75, I) and n =568.

The kernel of the plane set form is formed by the VAD emotional space, which considered that the recognition of the corresponding emotional vocabulary is low. Thus, the GMM describes the characteristics of the VAD emotional space efficiently. To describe the density value distribution corresponding to the equivalent dimension value, the plot of the Valence Arousal dimension is shown in Fig. 6.



$$\rho(P)=(2\pi)^{-\frac{3}{2}}\left(e^{-\frac{1}{2}((x-1.71)^2+(y-2.79)^2)}+e^{-\frac{1}{2}((x-3.05)^2+(y-5.25)^2)}+e^{-\frac{1}{2}((x-1.05)^2+(y-7.25)^2)}\right).$$

Fig. 6. The VAD of the three kernels combination in the SGM distribution.

3. The Density Function of the Single Dimension Affective

For the VAD emotional space, it is not yet possible to accurately obtain the correlation between the three-dimensional emotional data. However, from the medical observation of the brain magnetic resonance imaging data, there is a certain correlation between VAD. Traditional perceptual engineering uses single-dimensional emotional rating data. When the data point set is on the VAD axis, it means that a certain perceptual semantics presents a one-dimensional emotion. For theoretical completeness, this section gives a method for estimating the density of single-dimensional emotions in a single point set [28]-[32]. The point set of the coordinate axes (v, 0, 0), (0, a, 0), and (0, 0, d) can be used to estimate the three- dimensional variables separately. For the VAD point set (v_i, 0, 0) the Parzen-Borel kernel estimation is used, which is given by:

$$f_n(x)=\frac{1}{nh_n}\sum_{i=1}^{n}K\left(\frac{x-v_i}{h_n}\right) \tag{22}$$

Kernel estimation is a type of the nonparametric statistical methods to determine $K(u)$, which is a uniform density distribution function on [−1,1]. Thus, the kernel estimate in Eq.(22) is degenerated into an average, where $K(u)$ is usually used with the forms of $K=\frac{1}{2}$, Epanechikov kernel of $\frac{3}{4}(1-t^2), t\in[-1,1]$, $\frac{5}{16}(1-t^2)^2,\ t\in[-1,1]$, and Gaussian of $\frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}t^2}$. The best distribution of the function is Gaussian as shown in Fig. 7.

Through the definition of the kernel and the outer shell of the perceptual concept, the definition of the neighborhood-based method is used for the point set of different forms. At the same time, the outer layer of the emotional cell element is represented by the approximate set to express the characteristics of the soft film. Secondly, in the definition of the density function part, if the cell element of the VAD sentiment space has a single point set form, a single Gaussian density function is used. Also, for the planar form, the Gaussian mixture model is used. Through the iterative method, the parameters to be determined can be estimated to describe the distribution of the point set of the VAD emotion space [33].

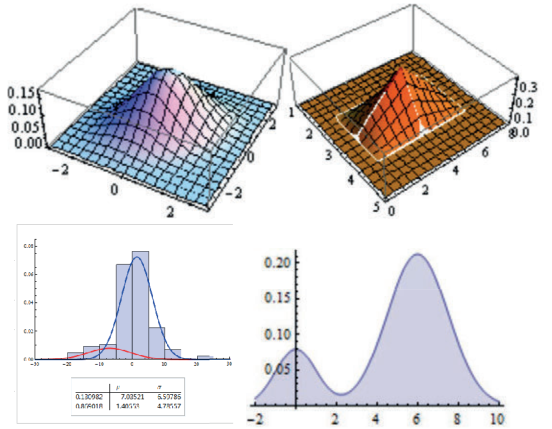


Fig. 7. An example of Gaussian distribution for the dimensional adjectives grouping model.

C. Fuzzy Perceptual Inference Using the VAD Model for Clustering Evaluation

1. Fuzzy Evaluation Process

When using fuzzy inference rules, the conditional statement "IF x is A, THEN y is B" is converted into fuzzy relations rules. The Linguistic Variable (LV) was subsequently introduced for translating the natural language to a membership of fuzzy set as shown in Fig. 8.

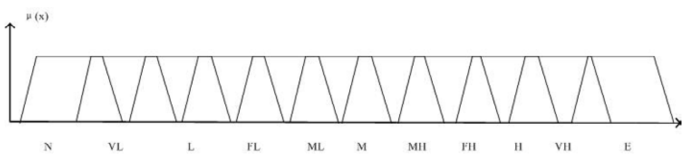


Fig. 8. Linguistic variables and their membership functions.

The fuzzy sets have been studied following fuzzy systems development rapidly. The selection of implication operators and fuzzy reasoning is closely related to the effect associated to the triangular norms. Besides, the implication operators study the fuzzy reasoning and fuzzy logic combined [34]-[35]. Therefore, the purpose is to accompany each other based on the triangular norms and implication operators to establish a new form of fuzzy propositional calculus system [36]. In the basic form of the production $P \rightarrow Q$ or "IF P THEN Q", P is a prerequisite for production(front piece), which gives the possibility to use a production prerequisite based on a logical combination to form; Q is a conclusion or operation (post-production pieces). By using the Gaussian fusion as the density functions, the Fuzzy Inference System (FIS) rules fusion operation is of two "IF-THEN" rules integration. Supposed that,

RULE: IF "x is A", THEN "y is B", the assertion "x is A" satisfies the Gaussian distribution, which is given by:

$$f(P,A,\sigma)=\frac{1}{\sqrt{2\pi}\sigma_A}e^{-\frac{1}{2}[\frac{(P-A)^2}{\sigma_A^2}]} \tag{23}$$

Such as by Mamndini (Fig. 9), it is found that:

$$Mamndini_{FIS}=Min(\frac{1}{\sqrt{2\pi}\sigma_A}e^{-\frac{1}{2}[\frac{(P-A)^2}{\sigma_A^2}]},\frac{1}{\sqrt{2\pi}\sigma_B}e^{-\frac{1}{2}[\frac{(P-B)^2}{\sigma_B^2}]}) \tag{24}$$

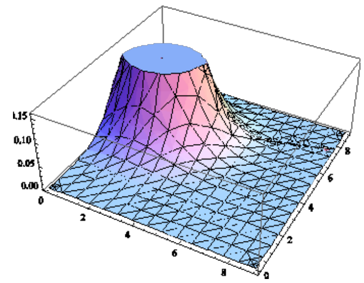


Fig. 9. IF-THEN rule by Mamndini Gaussian implication.

2. FIS for Fusion and Decision Making

Suppose that the m knowledge rules in v_k under Gaussian model (see formula (12)) conclude a particular assertion at the δ_k level, thus, we have that:

$$\text{IF } x_1 \text{ is } v_1 \text{ and } x_2 \text{ is } v_2 \text{ and ..., and } x_m \text{ is } v_m \text{ THEN } I_O \text{ is } V_O, \varpi \tag{25}$$

where ω is the result, this can be simplified to the following rules:

$$\text{IF } v_1 \text{ and } v_2 \text{ and, ..., and } v_m \text{ THEN } \varpi\,(v_1, v_2, ..., v_m) \tag{26}$$

$$\text{IF } x_1 \text{ and } x_2 \text{ and, ..., and } x_m \text{ THEN } x_1 \wedge x_2 \wedge ... x_m \tag{27}$$

$$\text{IF } d_1 \text{ and } d_2 \text{ and, ..., and } d_m \text{ THEN } d_1 \wedge d_2 \wedge ... d_m \tag{28}$$

$$\text{IF } \rho_1 \text{ and } \rho_2 \text{ and, ..., and } \rho_m \text{ THEN } \varpi\,(\rho_1, \rho_2, ..., \rho_m) \tag{29}$$

Consider the density function δ_k in FIS and by letting $\Delta=[\delta_1, \delta_2, ..., \delta_n]$, it is found that:

$$\text{IF } \Delta \text{ THEN } \varpi\,(\Delta) \tag{30}$$

Since $\varpi\,(\Delta)$ is a Gaussian density function, the rule is re-labeled as "IF X THEN $f(X)$", and for this rule set, we have that:

$$R_i\text{: IF X THEN } f_i(X) \tag{31}$$

However, as $f(X)$ is a nonlinear function, it is difficult to find its minimum point under the Mamdani model, so we need to linearize $f(X)$ and use the nonlinear conjugate gradient algorithm to optimize the parameters of $f(X)$. To conduct sub-dataset indexing by some indices using fuzzy transformation, it is necessary to use the fuzzy factor analyst on a matrix type dataset [37].

3. Proposed Model for Affective Clustering

Basic hard c-means: First, the initial cluster centers are given, and all elements are assigned to each cluster according to the closest assignment principle to the cluster center. Afterward, to solve the new cluster center (element centroid) for each cluster, these steps are repeated until the centroid is no longer significantly changed, then the clustering is completed. The distance used depends on the nature of the data or project requirements; and the classification of distance can refer to the A-star algorithm overview and the Manhattan distance, diagonal distance and Euclidean distance can be considered. It is equivalent to solve the minimum problem of a global state function, which is the sum of the distances of each element to the nearest cluster center. The characteristics of this algorithm are, firstly, it does not necessary obtain a global optimal solution; while the initial cluster center does not meet the requirements, only locally optimal solution may be obtained [38]. For globally optimal solution, the algorithm changes the method name to k-means; secondly, the influence of noise points on clustering cannot be ruled out. Thirdly, the cluster shape is required to be nearly circular. The algorithm can be described as follows [39]:

Algorithm 1: Hard c-means
Required: Number of clusters, epsilon [threshold]
Outputs: Clusters
a. Set cluster number's value k.
b. Choose the k cluster center randomly
c. **WHILE** center is not empty DO
    Compute the mean or center of each cluster
    Compute the distance of pixels and cluster's center
    IF |distance – center| < epsilon THEN
        Move points to the cluster.
    ELSE:
        Move points to the next cluster
    ENDIF
    Re-estimate the center
ENDWHILE
e. Output clusters

Extra fuzzy-c-mean: EFCM is a clustering algorithm based on a fuzzy number evaluation system that is also an improvement of the fuzzy c- mean (FCM) algorithm. The EFCM clustering model includes initialization, loop and output; firstly, the method is used to determine the initial clustering center to ensure the optimal solution, while the second step is to determine the degree of membership $U(i, j)$ of each point to each cluster center. In which, $C^{(k)}$ is a weighted index. Thirdly, the system needs to determine the new cluster center and mark the change track of the cluster center to determine whether the changing amplitude of the cluster center is less than the given error limit. If not, it returns to the previous steps, otherwise it exits the loop. Finally, the system outputs the cluster center trajectory and clustering results. The characteristics of this algorithm are similar to ordinary k-means clustering. Full clustering is required, and noisy points cannot be distinguished. The center of clustering is more consistent, but the calculation efficiency is relatively low. The concepts of smoothing parameters and membership are adopted so that the points are not directly attached to a single cluster center. Algorithm 2 shows the process of the model [40]-[43].

Algorithm 2: Extra fuzzy c means clustering
Require: Epsilon [threshold], X [points]
Outputs: Centers, clusters
a. Initializing a segment matrix U
b. Compute $C^{(k)} = [c_j]$ with $U^{(k)}$

$$c(j) = \sum_{m=1}^{n} u(i,j)^m \cdot p(j) \Big/ \sum_{m=1}^{n} u(i,j)^m$$

c. Update $U^{(k)}$ and $U^{(k+1)}$

$$u(i,j) = \left(\sum_{k=1}^{m-1} | p(j) - c(k) | \Big/ | p(j) - c(i) | \right)^{-\frac{2}{m-1}}$$

d. **IF** $|U^{(k+1)} - U^{(k)}|$ < epsilon THEN
    STOP
ELSE:
    GOTO Step b
ENDIF
e. Output clusters

VAD-dimensional clustering: The Valence-Arousal-Dominance dimensional Clustering (VADdC) model was deployed based on hard c-mean and extra fuzzy c-mean. Each element in the initial state is a cluster, and the cluster with the smallest distance between clusters is merged each time until the number of clusters meets the requirements or merges more than 90%. Similar to the Huffman tree algorithm, the union set also needs to be checked. For normal c-mean algorithms (HCM or EFCM), there are also several classifications of the distance definitions: including the minimum distance between cluster elements, the maximum distance between cluster elements, and the centroid distance of clusters. The characteristics of this algorithm are as follows.

a) The storage space consumed by the agglomeration clustering is higher than several other methods. The interference of the noise points can be eliminated, noise points may be divided into a cluster. Suitable for cases with irregular shapes and when complete clustering is not required.
b) The merging operation must have a merging limit ratio, otherwise excessive merging may cause all classification centers to aggregate, causing clustering failure.

Similar to the decision trees, the advantage of hierarchical clustering is that the entire tree can be obtained at one time, and the control of certain conditions, whether depth or width, is controllable. Several problems may occur, such as calculation on the division is determined and cannot be changed; and the cohesion/divisions combined is not "optimal" every time. However, the proposed VADdC algorithm is easy for local optimization and can be performed by appropriate random operations. It uses balanced iterative reducing and clustering. It first divides neighboring sample points into micro-clusters and then uses the c-means algorithm for these micro-clusters (**Algorithm** 3).

Algorithm 3: VADdC-valence arousal dominance dimensional clustering
Required: POINTS, points with index group, cluster numbers
Outputs: Groups, POINTS (clusters, centers)
a. POINTS ← [v, a, d] ## for each point in required VAD space
b. Number of Groups ← index ## from 1 to index in range of length of POINTS
c. **FOR** index, point in POINTS:
    IF type of point is required THEN
        FOR index of the point in POINTS of group index
            ITERATE number of groups with point group
            DELETE number of groups with points of
                index of point of the group
            MERGE the groups with points and POINTS with
                index of point
        ENDFOR
    ELSE IF type of point is not required:
        CALCULATE core point of group index with type
            of POINTS
        COUNT the number of groups with core point
            group index
        DELETE the number of groups with point group
        The group of point ← core point with group index
    ENDIF
    COUNT number of groups with sorted iterations using
        key ← lambda
    FOR key in several groups:
        INCREASE c ## c=c+1
        FOR point in POINTS:
            IF group of the point is key*c THEN
                CONTINUE
            ENDIF
        ENDFOR
        IF c >= cluster number THEN
            BREAK ## exit the loop
        ENDIF
    ENDFOR
EDNFOR
d. Outputs POINTS, group ## clusters and centers

III. Results and Discussion

A. Questionnaire System and Data Acquisition

We developed a questionnaire system for data acquisition to be applied for evaluation. Chair styles are selected from an online shopping website, and the style has a list with values: glam, farmhouse, traditional, eclectic, bohemian, modern, global-inspired, coastal, American traditional, ornate glam, beachy, posh luxe, modern farmhouse, rustic, French country, industrial, ornate traditional, modern rustic, Scandinavian, sleek chic modern, mid-central modern, Asian-inspired, bold eclectic modern, cabin lodge, cottage Americana, nautical, tropical, and Victorian. The questionnaire system for the Ming-style chairs for fuzzy perceptual evaluation was proposed by using (1-9) fuzzy numbers. An ancient furniture system in industrial design fields was evaluated. The relative dataset of results has been employed for clustering by using the VADdC model (shown in Table I).

TABLE I. Shape Classification and Their Sub-shape Code in the Questionnaire System

Shape Category	Sub-shape			
Top Rail (C1)	C11	C12	C13	C14
	Scroll	Luoguo	Bow	Round
Seat-Back (C2)	C21	C22	C23	C24
	Screen	Comb-Teeth	Relief	Slatted
Armrest (C3)	C31	C32	C33	C34
	Square	Round	Openwork	Relief
Foot (C4)	C41	C42	C43	C44
	Carved Foot	Horseshoe	Square	Circle-Center

B. Fuzzy Perceptual Evaluation using VADdC

The adjective evaluation data is illustrated in Fig. 10 and 11, which show the result after grouping by using the VADdC algorithm. Fuzzy perceptual evaluation by using fuzzy number [1,3,5,7,9] is applied on the shape of the Ming style chairs. Performance by using a fuzzy perceptual evaluation system is designed using 3 inputs, and 2 outputs basic Mamdani inference model based on the rule system as demonstrated in Fig. 12.

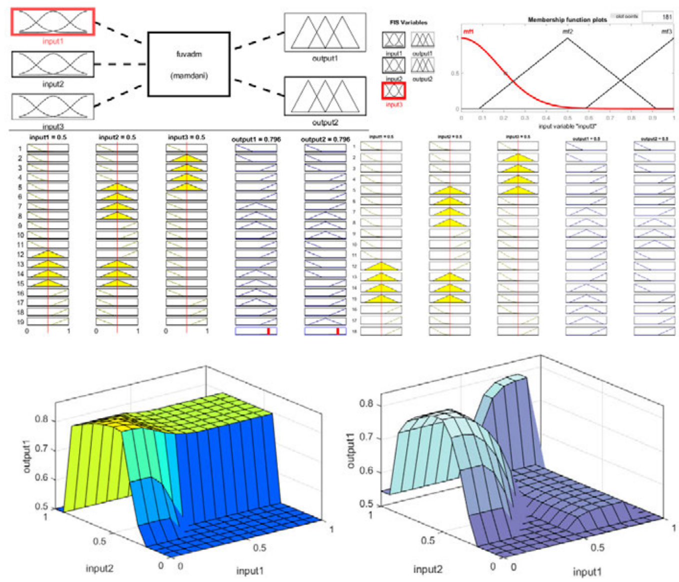


Fig. 12. 3-inputs 2-outputs basic fuzzy Mamdani inference model and rules.

Adjectives		functional	free	friendly	fresh	neat	individuality	artistic	traditional	gum texture	valuable	modern	classic	elegant	unique	technical	professional	arrogant	confident	fun	future	authoritative	strong	reliable
		k1	k2	k3	k4	k5	k6	k7	k8	k9	k10	k11	k12	k13	k14	k15	k16	k17	k18	k19	k20	k21	k22	k23
functional	k1																							
free	k2	3																						
friendly	k3	5	5																					
fresh	k4	3	5	1																				
neat	k5	3	1	1	3																			
individuality	k6	7	5	3	3	9																		
artistic	k7	1	5	3	3	3	3																	
traditional	k8	5	1	3	2	3	7	1																
gum texture	k9	3	7	3	3	1	9	3	3															
valuable	k10	1	5	3	3	1	1	3	3	3														
modern	k11	9	5	3	1	3	3	5	1	3	3													
classic	k12	3	5	1	3	3	9	3	3	3	1	1												
elegant	k13	1	1	5	3	3	3	3	3	5	3	1	1											
unique	k14	5	5	0	1	3	1	3	5	3	5	3	3	5										
technical	k15	3	1	7	3	3	3	1	3	1	3	3	9	3	3									
professional	k16	1	5	7	1	3	9	3	5	1	3	1	7	5	5	3								
arrogant	k17	1	3	7	1	1	3	1	3	1	1	3	7	1	9	1	7							
confident	k18	1	3	3	1	3	5	1	1	1	3	5	3	3	5	1	1	0						
fun	k19	1	1	5	1	1	1	3	2	3	3	3	3	1	3	3	3	3	5					
future	k20	1	3	9	1	3	3	1	3	7	1	1	1	1	1	9	7	0	1	5				
authoritative	k21	1	1	3	1	5	3	1	3	3	3	5	3	5	3	3	1	0	3	5	5			
strong	k22	9	1	1	3	3	1	1	5	7	1	1	5	1	3	1	7	1	1	1	0	5		
reliable	k23	1	1	1	1	3	3	1	1	1	1	1	3	3	1	1	3	1	1	1	1	7	1	

Fig. 10. Adjectives fuzzy perceptual evaluation before grouping.

Adjectives		functional	friendly	technical	reliable	valuable	confident	arrogant	traditional	individuality	professional	authoritative	free	fresh	neat	artistic	gum texture	modern	classic	elegant	unique	fun	future	strong
		k1	k3	k15	k23	k10	k18	k17	k8	k6	k16	k21	k2	k4	k5	k7	k9	k11	k12	k13	k14	k19	k20	k22
functional	k1																							
friendly	k3	0.654																						
technical	k15	0.688	0.576																					
reliable	k23	0.699	0.701	0.723																				
valuable	k10	0.678	0.665	0.675	0.596																			
confident	k18	0	0	0	0	0																		
arrogant	k17	0	0	0	0	0	0																	
traditional	k8	0	0	0	0	0	0	0.569																
individuality	k6	0	0	0	0	0	0	0.678	0.665															
professional	k16	0	0	0	0	0	0	0.824	0.871	0.842														
authoritative	k21	0	0	0	0	0	0	0.794	0.814	0.796	0.786													
free	k2	0	0	0	0	0	0	0	0	0	0	0												
fresh	k4	0	0	0	0	0	0	0	0	0	0	0	0											
neat	k5	0	0	0	0	0	0	0	0	0	0	0	0	0										
artistic	k7	0	0	0	0	0	0	0	0	0	0	0	0	0	0.911									
gum texture	k9	0	0	0	0	0	0	0	0	0	0	0	0	0	0.651	0.861								
modern	k11	0	0	0	0	0	0	0	0	0	0	0	0	0	0.947	0.914	0.921							
classic	k12	0	0	0	0	0	0	0	0	0	0	0	0	0	0.896	0.852	0.451	0.963						
elegant	k13	0	0	0	0	0	0	0	0	0	0	0	0	0	0.796	0.863	0.953	0.971	0.893					
unique	k14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
fun	k19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.991			
future	k20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.985	0.941		
strong	k22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.963	1	0.963	

Fig. 11. Grouping adjectives by using clustering operators.

TABLE II. Selected Adjectives Grouping and their Value Standard Deviation in VAD Dimensional Space

Adjectives	V	V-SD	A	A-SD	D	D-SD	P
Functional	4.65	2.22	5.43	2.10	3.98	1.23	single
Free	5.22	2.54	3.78	3.02	7.32	2.43	plain
Easy To Use	8.42	1.12	5.33	2.50	5.32	2.13	plain
Fresh	7.24	1.09	5.35	2.13	4.97	1.43	sphere
Neat	3.56	3.02	7.23	2.21	3.29	1.67	single
Individuality	5.77	2.24	5.52	1.75	6.76	1.90	plain
Artistic	4.33	2.87	4.39	2.45	6.54	3.87	plain
Traditional	2.98	2.43	8.43	1.65	5.33	3.29	single
Gum Texture	4.39	2.56	7.32	2.08	8.12	1.98	sphere
Valuable	8.22	3.10	5.44	2.34	1.56	2.32	sphere
Modern	7.34	1.65	6.32	3.89	1.75	2.21	plain
Classic	5.55	2.04	5.52	1.65	6.76	3.01	sphere
Elegant	7.65	1.13	4.39	2.55	6.13	2.01	sphere
Unique	7.66	2.04	5.52	2.18	2.55	2.29	plain
Technical	4.56	2.04	5.52	2.09	1.65	2.29	plain
Professional	5.76	2.04	5.52	2.72	4.57	2.29	plain
Arrogant	5.15	1.68	5.83	2.33	5.59	2.40	sphere
Confident	6.68	1.29	6.22	2.41	7.68	1.94	single
Fun	8.12	1.11	7.22	2.01	6.80	1.85	single
Future	7.77	2.04	5.52	2.72	6.76	2.29	sphere
Authoritative	6.03	2.09	5.76	2.04	6.98	2.20	single
Strong	7.58	2.04	5.52	2.72	6.76	2.29	plain
Reliable	6.89	1.87	4.90	2.33	5.98	3.20	single

Table II shows the norms with VAD values from affective norm English Words (ANEW). Table III shows the comparing results of the VADdC model with FCM, K-mean, self-organization mapping network clustering (SOM), HCM, and EFCM. The VADdC performs 91.37% overall accuracy. Due to the superiority of the proposed method, different clustering and machine learning methods can be integrated with the proposed method to solve other applications as in [44]-[51].

TABLE III. Comparing Analysis of HCM, EFCM and VADdC

Clustering Algorithms	Fitness value	Inter-cluster Distance	Intra-cluster Distance	Elapse time	Accuracy (%)
FCM	57.60	8.36	85.36	0.2865	79.68
K-mean	47.23	7.56	76.37	0.3638	79.75
SOM	59.62	10.36	122.35	0.4212	89.56
HCM	60.89	8.566	89.32	0.3568	89.34
EFCM	68.65	8.698	158.37	0.4251	90.07
VADdC	17.53	9.210	126.36	0.4352	91.37

IV. Conclusion

In classical research, word vectors of features (terms, including words, words, phrases, etc.) are often used to build text vectors, and cluster analysis is performed based on the similarity between text vectors. To evaluate the clustering quality of the unsupervised clustering algorithm even in the case of the overlapping cluster centers, a VAD vector space model data was constructed for clustering analysis by studying the principle of clustering algorithms and applying clustering algorithms. For clustering a given set of objects, there can be multiple meaningful divisions due to the distance (or similarity) between objects, which has multiple implicit definitions. The present work constructed a VAD based model including distance, borders and type of centers. It also developed a rule-based inference system using fuzzy perceptual evaluation and introduced dimensional affective based VAD clustering called VADdC, taking successfully application on a dataset that has been acquired from an online questionnaire system.

The comparing analysis reported that the performance of the proposed method is better than others in the fitness of 17.53, elapse time of 0.4352 and 91.37% accuracy finally. In future work, high-dimensional data can be involved, where the data distribution in a high-dimensional space may be very sparse, and highly skewed. In practical applications, it may be necessary to perform clustering under various conditions. Data grouping with clustering characteristics is very challenging. The most difficult question here is how to identify the "specific constraints" implicit in the problem we are trying to solve, and what algorithms should be used to best "fit" these constraints.

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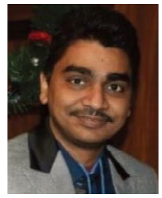

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