Applied Mathematics & Information Sciences
An International Journal

Emotional Cellular-Based Multi- Class Fuzzy Support Vector Machines on Product's KANSEI Extraction

Fuqian Shi[1] *and Jiang Xu*[2]

[1] Department of Information and Engineering, Wenzhou Medical College, 325035 Wenzhou, China
[2] School of Mechanical Engineering, Southeast University, 211189, Nanjing, China

Received: May 22, 2011; Revised September 21, 2011; Accepted October 02, 2011
Published online: 1 January 2012

Abstract: It is an important methodology to extract product's overall KANSEI images by evaluating Critical Form Features (CFF). In this paper, Multi-class Fuzzy Support Vector Machines (MF-SVM) employing Emotional Cellular (EC) model was presented to extract KANSEI images of product's CFF. EC is a very special kind of semantics cell, which is defined on two-dimensional (Valence-Arousal) emotional space. The shell of EC covers the areas of the boundary of each emotional word that reflects its uncertainty, in common, a density function was employed to reflect this uncertainty. Firstly, product from features was mapped into an N- dimensional vector. Secondly, the norm of vector space and the fuzzy membership of each element are calculated by using probability density function of EC including Single Gaussian Model (SGM) and Gaussian Mixture Model (GMM). Finally, One-Versus-Rest (OVR) for multi-class SVMs was addressed to deal with multi-dimensional KANSEI images. For new products, system will specify all CFFs by using MF-SVMs. A case study of mobile phone design is given to demonstrate the effectiveness of the proposed methodology.

Keywords: Emotional Cellular, Gaussian Density Function, Multi-class Fuzzy Support Vector Machines, KANSEI Image

1. Introduction

The relationship between preference (KASNEI image) and physical design elements, such as product form was reported in our previous works [1][2]. KANSEI image is a persistent awareness, assessment and behavioral tendencies on product including cognitive component, affective component and behavioral component [3]. Normally, KANSEI Engineering in product form design includes at least five steps: collecting product pictures and KANSEI image, refining samples, building the relationships between product pictures and KANSEI image, analyzing product form and synthesizing product form. In this paper, MF-SVM was applied to solve the problem of product KANSEI recognition. Firstly, CFFs from products evaluation data that produced by effective survey system will be mapped into a point (vector) on Valence-Arousal emotional space. Secondly, fuzzy membership of conceptual model was defined by the probability density of emotional cellular on Valence-Arousal space. And for multiple KANEI images, multi-class SVM will resolve this situation and One-against-Rest was adopted this research.

Emotional Cellular (EC) [4] was applied to express CFF's KANSEI image. Kernel forms of Emotional Cellular (EC) have three forms: single point type, plat type and circular type for that the density function of each EC also appears multi- modular features, such as Single Gaussian Model (SGM) and Gaussian Mixed Model (GMM). Based on the works of Olvi Mangasarian and Wang [5][6], we developed a GMM density function to measure the EC's sensibility that how a point belongs to an EC. The different Kernel of EC must be defined separately; and boundary computing problems will also be introduced according to different kernel types and density functions. EC's boundary computing will play an important role for the exact classification of product's implicit calculation.

Support Vector Machines, (SVMs) firstly introduced by V. Vapnik [7], whose basic idea is to look for a suitable Hyper-Plane to split the set of points on the space (Universe), and give the boundary division (Margin). This is a widely used method for classification and regression, and it obtains the classification model from training data; the model can be used to predict the classification of new data sets including two formals: Binary Support Vector

* Corresponding author: e-mail: sfq@wzmc.edu.cn

Machines (B-SVMs) and Multi-Class Support Vector Machines (M-SVMs). The advantage of SVM theory is that it can better solve the small sample on machine learning problems; the low-dimensional vector is transformed into high-dimensional space to overcome the classification problems and finally to improve the generalization performance; for non-separated linear space, it also can be assigned a nonlinear transformation to a linear separated in high-dimensional space that is particularly suitable for nonlinear cognitive aspects and avoiding the neural network structure selection and Partial Minimum Point (PMP) problem [8].

Currently, the support vector machine main application areas are pattern recognition, density estimation, handwriting recognition, biological information processing, posture classification, network intrusion detection and vehicle classification, etc [9][10][11][12][13]. In the field of industrial design, Meng-Dar Shieh [14] introduced a features regression method applying SVMs and extracted CFFs subset from the case of mobile phone research and illustrated the effectiveness of this method.

2. Preliminaries

2.1. Label Semantic

Label Semantic (LS), introduced by Lawry [15][16] in 2006, used two appropriateness measures to describe the inexactness of object, one is a finite set-LA, and another is Label Expression-*LE*. For $\forall L_i \in LA$, L_i is a KANSEI word, and *LE* is a complex logical connection of LA; for example, sentence can be generated by words to express our feelings; however, Natural Language (NL) can not be quantified them exactly; therefore, it needs a rough granular operation process, such as Linguistic Variables (LV) , introduced by Zadeh in 1965. The LA can generate an expression to describe the object. Thus, the use of LA for describing objects overcomes the singularity problem regarding to traditional KANSEI Engineering (KE), and also weaken the complexity of NL processing. The main theoretical system is constructed as follows:

Definition 1 for a finite set LA, LE has the following properties:

(1) $LA \subset LE$; i.e. $\forall L \in LA$, $L \in LE$;

(2) LE is a complete set; if $\theta, \varphi \in LE$, then $\neg\theta, \theta \wedge \varphi, \theta \vee \varphi \in LE$, obviously, $\neg\theta \wedge \varphi, \theta \vee \neg\varphi \in LE$.

Definition 2 for $\forall x \in \Omega$, Mass Function $m_x : 2^{LA} \rightarrow [0,1]$, satisfying:

$$\sum\nolimits_{F \subseteq LA} m_x(F) = 1 \tag{1}$$

Definition 3 λ-Mapping: $\lambda : LE \rightarrow 2^{2^{LA}}$, satisfying:

(1) $\forall L_i \in LA, \lambda(L_i) = \{F \subseteq LA | L_i \in F\}$

(2) $\lambda(\theta \wedge \varphi) = \lambda(\theta) \cap \lambda(\varphi)$

(3) $\lambda(\theta \vee \varphi) = \lambda(\theta) \cup \lambda(\varphi)$

(4) $\lambda(\neg\theta) = \lambda(\theta)^c$

$\theta \in LE$ is a description of an instance x on Universe Ω, denoted by $\mu_\theta(x)$, then we have that:

Definition 4 Appropriate Measurement: $\mu : LA \times \Omega \rightarrow [0,1]$, satisfying:

$$If \forall\theta \in LE, \forall x \in \Omega, then \mu_\theta(x) = \sum_{F \in \lambda(\theta)} m_x(F) \tag{2}$$

$\mu_\theta(x)$ have the following properties:

(1) If θ is a synonymous expressions, then $\mu_\theta(x) = 1$

(2) If θ is contradictory, then $\mu_\theta(x) = 0$

(3) If $\theta \wedge \varphi$ is contradictory, then $\forall x \in \Omega, \mu_{\theta\vee\varphi}(x) = \mu_\theta(x) + \mu_\varphi(x)$

(4) $\forall x \in \Omega, \mu_{\neg\theta}(x) = 1 - \mu_\theta(x)$

(5) For $F \subseteq LA$, let $\theta_F = (\wedge_{L_i \in F} L_i) \wedge (\wedge_{L_i \notin F} L_i)$, then $m_x(F) = \mu_{\theta_F}(x)$

For single point description L_i, we have that:

$$\mu_{L_i}(x) = \sum_{F \subseteq LA : L_i \in F} m_x(F), \forall x \in \Omega, L_i \in LA \tag{3}$$

And $\mu_{L_i}(x)$ have the following properties:

(1) For $\mu_{L_i}(x), i = 1, 2..., n$, and $\mu_{L_i}(x) \geq \mu_{L_{i+1}}(x)$, then $m_x(\{L_1, L_2, ..., L_n\}) = \mu_{L_n}(x)$, furthermore, we have that:

$$m_x(\{L_1, L_2, ..., L_i\}) = \mu_{L_i}(x) - \mu_{L_{i+1}}(x), \quad m_x(\phi) = 1 - \mu_{L_1}(x) \tag{4}$$

(2) For $\forall F \subseteq LA$, we have that:

$$m_x(F) = \prod_{L_i \in F} \mu_{L_i}(x) \times \prod_{L_i \notin F} (1 - \mu_{L_i}(x)) \tag{5}$$

Definitions mentioned above implicated an inexactly description of object in mathematical formalization, but in fact, the distribution status of mass function is difficult to be obtained. LS theory proved the reasonability of expression method that generated by emotional vocabulary that will make contribution to EC modeling. In the semantic space, LS theory although gave the formal definition of the expression, but its ultimate goal is to obtain an independent semantic concept, and to use this concept of the semantic content on fuzzy boundary computing to determine the inherent emotional element of product. Further, Lawry and Tang proposed the Prototype Theory (PT) [17][18][19], which developed a calculation method based on neighborhood of the concept for establishing a model of semantic extraction, and illustrated its effectiveness in rule-based knowledge reasoning.

2.2. Prototype Theory

For $\forall L_i \in LA$, Label L_i is a conception which can formalized as " $AboutP_i$ ", where P_i is a prototype of conception L_i. $AboutP_i$ can describe the conception L_i exactly, if LA is an n-dimensional Euclidean space, d is an Euclidean distance, then there exists a unknown boundary $\varepsilon > 0$ that all elements in a neighborhood of P_i will describe L_i more exactly.

Definition 5 for $\forall L_i \in LA$, $\varepsilon > 0$, neighborhood is defined by:

$$N^{\varepsilon}_{L_i} = \{x : d(x, P_i) \leq \varepsilon\} \tag{6}$$

where $d(x, P_i) = \{\inf\{d(x, y) : y \in P_i\}$

Definition 6 $\forall \varepsilon > 0, \theta, \varphi \in LE$, $N^{\varepsilon}_{L_i}$ have the following properties:

(1) Single Point: $N^{\varepsilon}_{\theta} = N^{\varepsilon}_{L_i}$, if $\theta = L_i \in LA$
(2) $N^{\varepsilon}_{\theta\wedge\varphi} = N^{\varepsilon}_{\theta} \cap N^{\varepsilon}_{\varphi}$
(3) $N^{\varepsilon}_{\theta\vee\varphi} = N^{\varepsilon}_{\theta} \cup N^{\varepsilon}_{\varphi}$
(4) $N^{\varepsilon}_{\neg\theta} = (N^{\varepsilon}_{\theta})^c$

Definition 7 $\forall \theta \in LE, \forall x \in \Omega$, the probability of x belongs to the random neighborhood of θ is:

$$\mu_\theta(x) = \delta(\{\varepsilon : x \in N^{\varepsilon}_{\theta}\} \tag{7}$$

$\mu_\theta(x)$ have the following properties:

(1) If $AboutP_i$ is the exactly description of L_i, then $\mu_{L_i}(x) = d(x, P_i)$
(2) $\mu_{\theta\wedge\varphi}(x) = \mu_\theta(x) \cap \mu_\theta(x)$
(3) $\mu_{\theta\vee\varphi}(x) = \mu_\theta(x) \cup \mu_\theta(x)$
(4) $\mu_{\neg\theta}(x) = \mu_\theta(x)^c$

EC's formalized definition will founded based on the prototype theory as mentioned above.

2.3. Emotional Cellular Theory

2.3.1. Kernel of Emotional Cellular

Definition 8 For $\forall P \in \Omega$, P is a point belongs to the universe $\Omega = \{(E_1, E_2, ..., E_n) : E_i \in P\}$. Particularly, in Valence-Arousal emotional space $P = (Valence, Arousal) = (v, a)$, $\Omega = \{(v, a)|v, a \in R\}$

Definition 9 Distance $d = \|\cdot\|$ in Valence-Arousal emotional space, satisfied by the condition as follows:

$$d(P, P) = \|P\| = \sqrt{(v^2 + a^2)} \tag{8}$$

$$\begin{aligned} d(P \pm Q) &= \|P \pm Q\| \\ &= \sqrt{((v_P \pm v_Q)^2 + (a_P \pm a_Q)^2)}, \\ \forall P, Q \in \Omega \end{aligned} \tag{9}$$

$\forall \alpha, \beta \in R, P, Q \in \Omega$, we have that:

$$\begin{aligned} d(\alpha P \pm \beta Q) &= \|\alpha P \pm \beta Q\| \\ &= \sqrt{(\alpha v_P \pm \beta v_Q)^2 + (\alpha a_P \pm \beta a_Q)^2} \end{aligned} \tag{10}$$

Furthermore, we have that:

$$d(\alpha P + \beta Q) \leq |\alpha| \cdot d(P) + |\beta| \cdot |d(Q) \tag{11}$$

Definition 10 for $\forall P \in \Omega$, there exists a neighborhood N^{ε}_P:

$$N^{\varepsilon}_P = \{X| \, \|P - X\| < \varepsilon, X \in \Omega\} \tag{12}$$

Definition 11 Single point kernel is defined by:

$$\{P_K\}, P_K = \frac{1}{\|K\|} \sum_{P_i \in K} P_i \rho(P_i) \tag{13}$$

where K is KASNEI adjectives set and $\rho(P_i)$ is the density of P_i.

Definition 12 Circular kernel is defined by:

$$\{P_j | P_j \in N^{\varepsilon}_{P_K}\} \tag{14}$$

where $P_K = \frac{1}{\|K'\|} \sum\limits_{P_i \in K'} P_i \rho(Pi), K' \subset K$ and $K' = \{P_i | \rho(P_j) \leq \rho_T\}$, ρ_T is a given const to limit the scale of kernel.

Definition 13 Flat kernel is defined by:

$$\{\bigcup_i P_K\} \tag{15}$$

where P_K subject to Def. 12.

2.3.2. The shell of Emotional Cellular

The shell of EC gives the scale of neighborhood of all emotional elements that is uncertainty- we called "soft membrane" which was defined by:

Definition 14 Upper Approximation Shell (UAS): $UP_B = \{P_l | P_l \in N^{\varepsilon_u}_{P_K}\}$, Lower Approximation Shell (LAS): $LP_B = \{P_l | P_l \in N^{\varepsilon_l}_{P_K}\}$, then shell of EC is:

$$P_B = UP_B \backslash LP_B = N(u, v) \tag{16}$$

where u, v are related to the density function.

2.3.3. Probability density of Emotion Cellular under SGM and GMM

For single point and circular type kernel of EC, Single Gaussian Model (SGM) was applied to describe the density of these points, which was defined as:

$$\rho(P; \mu, \Delta) = \frac{1}{\sqrt{(2\pi)^3 |\Delta|}} e^{-\frac{1}{2}(P-\mu)^T \Delta^{-1} (P-\mu)} \tag{17}$$

where Δ is a covariance matrix, μ is the central point of density function, the density function's properties are conducted by (Δ, μ), so, this is a Parameter Estimation (PE) problem.

And for plat type kernel of EC, multi SGMs will be addressed to resolve this problem.

$$G(P) = \sum_i \alpha_i \rho(P; \mu_i, \Delta_i), i = 1, 2, \cdots n \tag{18}$$

Where $\sum\limits_i \alpha_i = 1$, $G(P)$ is a Gaussian Mixture Model (GMM).

3. Multi-Class Fuzzy Support Vector Machines Based Emotional Cellular

3.1. Definitions

Definition 15 For $\forall X_i \in \Re^N$, $0 < s_i \leq 1$, $Y_i \in \{1, -1\}, i = 1, 2, \cdots, k$ is classification labels, noted by $\{(Y_i, X_i, s_i)|i = 1, 2, \cdots, k\}$. Let Y_i be the label of X_i's classification. If there exits a plane $f(x) =< w, x > -b$ that all points ($Y_i = -1$) are in the side of $f(x) < 0$, and other points ($Y_i = 1$) are in side of $f(x) > 0$, then $f(x)$ is a Separating Hyper-Plane (HP)(shown in Fig 1).

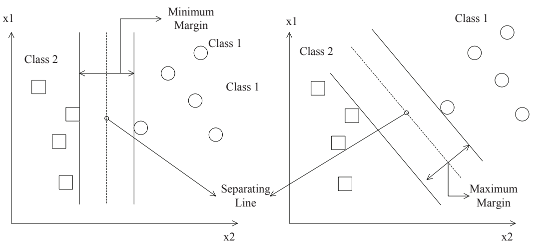

Figure 1 Separating Hyper-Plane in Support Vector Machine

Definition 16 Let SHP be $< X, W > +b = 0$, the distance between point X and SHP is:

$$D = \frac{|(WX_q) \pm b|}{\|W\|} = \frac{|\sum_{i=1}^{n} w_i x_{iq} \pm b|}{\sqrt{w_1^2 + w_1^2 + \cdots + w_n^2}} \quad (19)$$

where W is weight, B is bias.

Definition 17 Support Hyper-Plane is parallel with SHP and the closest to the data group, which is denoted by: $< w, x >= b + \delta$ and $< w, x >= b - \delta$

Definition 18 Let d be the distance between Support Hyper-Plane and Optimal Separating Hype-plane (OSH), which is calculated by: $d = \frac{1}{\|w\|}$, where $\|w\| =< w^T, w >$ is the norm of vector.

Definition 19 The objective of SVM is to resolve the minimum of $\frac{1}{2}\|w\|^2$ subject to $y_i(< w^T, x_i > -b) - 1 \geq 0$.

From Def. 19, by using Lagrange Multiplier Methods (LMM), we have that:

$$L = (w, b, a) = \frac{1}{2}\|w\|^2 - \sum_{i=1}^{n} \alpha_i [y_i(w^T x_i - b) - 1] \quad (20)$$

The objective is transformed to resolve the minimum of L. Partial deferential on Eq. (20) by w, b respectively, we have that:

$$\frac{\partial L}{\partial w} = w - \sum_{i=1}^{n} \alpha_i y_i x_i = 0, \quad \frac{\partial L}{\partial b} = \sum_{i=1}^{n} \alpha_i y_i = 0 \quad (21)$$

then we have that:

$$Max\{L\} = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{ij} \alpha_i \alpha_j y_i y_j {x_i}^T x_j \quad (22)$$

where $\sum_{i=1}^{n} \alpha_i y_i = 0, \forall \alpha_i \geq 0$

Karash-Kuth-Tuchwe terms:

$$\begin{aligned} &\frac{\partial L}{\partial w} = w - \sum_{i=1}^{n} \alpha_i y_i x_i = 0 \\ &\frac{\partial L}{\partial b} = \sum_{i=1}^{n} \alpha_i y_i = 0 \\ &y_i(w^T x_i - b) \geq 1 \\ &\alpha_i \geq 0 \\ &\alpha_i[y_i(w^T x_i - b) - 1] = 0 \end{aligned} \quad (23)$$

While training data was subjected to KKT and all these points are on support Hyper-Plane, we call these points as Support Vectors (SV), which are applied to classify new point. For SV x_i, $b^* = \sum_j \alpha_j y_j {x_j}^T x_i - b^*$, the new point will be classified by the positive and negative of $f(x) = w^{*T} x - b^* = \sum_i \alpha_i y_i {x_i}^T x - b^*$.

High dimensional mapping to resolve non-separating situation: Kernel Mapping Φ.

(1) Linear Kernel: $k(x_i, x_j) = {x_i}^T x_j$

(2) Polynomial Kernel: $k(x_i, x_j) = (\gamma x_i^T x_j + r)^p$, $\gamma > 0$

(3) Radial basis function: $k(x_i, x_j) = e^{(-\gamma \|x_i - x_j\|^2)}$, $\gamma > 0$

(4) S -type: $k(x_i, x_j) = \tanh(\gamma x_i^T x_j + r)$

If there is not exist an OSH, we need to set a error variable ξ to deal with the margin overlap, let

$$\begin{aligned} &w^T x_i - b \leq -1 + \xi_i, \forall y_i = -1 \\ &w^T x_i - b \geq 1 - \xi_i, \forall y_i = +1 \end{aligned} \quad (24)$$

Let penalty function for error variable ξ be $C(\sum_i \xi_i)^k$, where C is weight, then the objective function is converted to:

$$Min\{\frac{1}{2}\|w\|^2 + C \sum_i \xi_i\} \quad (25)$$

subject to $y_i(w^T x_i - b) - 1 + \xi_i \geq 0, \xi_i \geq 0$.

The new objective is:

$$L(w, b, \xi, \alpha, \mu) = \frac{1}{2}\|w\|^2 + c \sum_i \xi_i - \sum_{i=1}^{n} \alpha_i [y_i(w^T x_i - b) - 1 + \xi_i] - \sum_{i=1}^{n} \mu_i \xi_i \quad (26)$$

We can update KKT terms as:

$$\begin{array}{l} \frac{\partial L}{\partial w} = 0 \\ \frac{\partial L}{\partial b} = 0 \\ \frac{\partial L}{\partial \xi} = 0, y_i(w^T x_i - b) - 1 + \xi_i \geq 0, \\ \alpha_i \geq 0, \mu_i \geq 0 \\ Slackness : \alpha_i(y_i[w^T x_i - b) - 1 + \xi_i] = 0 \\ Slackness : \mu_i \xi_i = 0 \end{array} \tag{27}$$

3.2. Multi-class SVM

SVM is a binary classifier, for multi-classification, it can be combined in two methods as bellow:

(1) One-Versus-Rest (OVR): the two-class SVM was used as a component in these multi-class classifications algorithms. The i -th SVM can separate the j -th classification and the rest, so it is also regarded as a binary SVM [20].

(2) One -Versus-One (OVO), to construct $\frac{n(n-1)}{2}$ SVMs for each 2 SVMs [21][22][23].

OVR was applied in this paper.

3.3. Fuzzy SVM

To improve the performance of SVM, C. Lin proposed [24] fuzzy support vector machines (FSVMs), and gave the fuzzy membership functions that applied widely in industrial design fields [25][26][27]. In FSVMs, it is very difficult to assign the membership for every element. In this paper, for KANSEI extraction problem, we'll re-define the fuzzy membership.

Given a large enough C to make the margin small enough that will be under less misclassification. For $(y_i, x_i, s_i), 0 < s_i \leq 1$, $s_i\xi_i$ is the indicator of error, let

$$\begin{array}{l} \xi = \{\xi_i | i = 1, 2, \cdots N\}, \\ s = \{s_i | i = 1, 2, \cdots N\} \end{array} \tag{28}$$

Then we have that:

$$Min\{\phi(w, \xi, s)\} = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N} s_i\xi_i \tag{29}$$

subject to $y_i(w^T\phi(x_i) + b) \geq 1 - \xi_i, \xi_i \geq 0, i = 1, 2, \cdots, N$, where $w = (w_1, w_2, \cdots, w_N)^T$, by using LMM, we have that:

$$L(w, \alpha, \beta) = f(w) - \sum_{i=1}^{k} \alpha_i g_i(w)$$

$$- \sum_{j=1}^{m} \beta_j h_j(w) = \alpha^t g(w) - \beta^t h(w) \tag{30}$$

$$L(w, b, \xi, \alpha, \beta) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N} \xi_i s_i$$

$$- \sum_{i=1}^{N} \alpha_i(y_i(w^T\varphi(x_i) + b)$$

$$-1 + \xi_i) - \sum_{j=1}^{N} \beta_j\xi_j \tag{31}$$

We have that:

$$Max\ \ w(x) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} \alpha_i\alpha_j y_i y_j k(x_i, x_j) \tag{32}$$

where $\sum_{i=1}^{l} y_i\alpha_i = 0$, $0 \leq \alpha_i \leq s_iC$, $i = 1, 2, \cdots, N$. In FSVMs, if $s_i = 0, \forall i$ then it means the minimum misclassification. Membership of SVMs includes distance - base and density-base [28][29]. Distance-based membership was introduced as bellows:

Definition 20 Let $\mu > 0$ be the minimum of membership and $s_i = f(t_i) > 0$, $t_1 < t_2 < \cdots < t_N$, $s_1 = f(t_1) = \mu$, $s_N = f(t_N) = 1$ we have that:

$$s_i = \frac{1 - \mu}{t_N - t_1} t_i + \frac{t_N\mu - t_1}{t_N - t_1} \tag{33}$$

or

$$s_i = (1 - \mu)(\frac{t_i - t_1}{t_N - t_1})^2 + \mu \tag{34}$$

Definition 21 Let X^+, N^+, be average and count of points $(y_i = +1)$, X^-, N^- be the same of points $(y_i = -1)$, then we have $X^+ = \frac{1}{N^+}\sum_{y_i=+1} x_i$, $X^- = \frac{1}{N^-}\sum_{y_i=-1} x_i$. And the distance between X^+ and X^- is: $r = \|X^+ - X^-\|$.

Definition 22 Let $U^+ = \underset{y_i=+1}{Max}\|X^+ - x_i\|$, $L^+ = \underset{y_j=-1}{Max}\|x_j - X^-\|$, then the radius of class (+1), $r^+_{Min} = L^+$, $r^+_{Max} = Max\{r, U^+\}$. If $\exists\|x_j - X^+\| = r^+_{Max}$, then its membership is $\mu(\mu > 0)$, if $\|x_j - X^+\| > r^+_{Max}$ then its membership is 0, and furthermore we have that:

$$s_j = (1 - \frac{\|x_j - X^+\|}{r^+_{Max} + \mu}) \times \frac{r^+_{Max} + \mu}{r^+_{Max} + \mu - L^+} \tag{35}$$

We can also define $U^- = \underset{y_i=-1}{Max}\|X^- - x_i\|$, $L^- = \underset{y_j=+1}{Min}\|x_j - X^-\|$, $r^-_{Min} = L^-$, and $r^-_{Max} = Max\{r, U^-\}$ to get:

$$s_i = (1 - \frac{\|x_i - X^-\|}{r^-_{Max} + \mu}) \times \frac{r^-_{Max} + \mu}{r^-_{Max} + \mu - L^-} \tag{36}$$

But, the fuzzy membership solely measuring by the absolute distance will make the class not to be under a true reflection of the degree of aggregation. In this paper, the perceptual image representative of the typical product form features under different degree of dispersion will need to be employed the density method to construct fuzzy membership degree, while the density is the probability density function (decided by (σ, c)) of product form features in Valence-Arousal emotional space.

Definition 23 Let $\rho(x_i) = \rho(\sigma_i, c_i)$ be the probability density function of form $F_i = x_i$ in Valence-Arousal emotional space, where σ is the standard deviation of relative EC's Valence-Arousal. c is an average value. If the kernel of EC is plat-type, then $\rho(x_i) = \sum_{k=1}^{3} \rho(\sigma_i^k, c_i^k)$, we have that:

$$\rho(x_i) = \sum_{k=1}^{3} \rho(\sigma_k, c_k) = \sum_{k=1}^{3} \frac{1}{\sqrt{2\pi}\sigma_k} e^{-\frac{1}{2}\left(\frac{VA(x_i)-c}{\sigma_k}\right)^2} \quad (37)$$

where $VA(F_{ij})$ denotes the form- F_{ij} 's single dimensional date ν_{ij} or a_{ij} in Valence-Arousal emotional space. For points x_i, $y_i = \{-1, +1\}$ are classification labels, we can construct MF-SVMs. To calculate the similarity of two points, the similarity formula must be given as:

Definition 24 Let N^+, N^- be the count of points $y_i = +1$ and $y_i = -1$, let

$$D^+ = \frac{2}{N^+(N^+ - 1)} \sum_{i,jy_i=y_j=1} \|x_i\rho(x_i) - x_j\rho(x_j)\| \quad (38)$$

$$D^- = \frac{2}{N^-(N^- - 1)} \sum_{i,jy_i=y_j=-1} \|x_i\rho(x_i) - x_j\rho(x_j)\| \quad (39)$$

And let

$$D^+_{Max} = Max\{\sum_{i,jy_i=y_j=+1} \|x_i\rho(x_i) - x_j\rho(x_j)\|\} \quad (40)$$

$$D^-_{Max} = Max\{\sum_{i,jy_i=y_j=-1} \|x_i\rho(x_i) - x_j\rho(x_j)\|\} \quad (41)$$

$$D^+_{Min} = Min\{\sum_{i,jy_i=y_j=+1} \|x_i\rho(x_i) - x_j\rho(x_j)\|\} \quad (42)$$

$$D^-_{Min} = Min\{\sum_{i,jy_i=y_j=-1} \|x_i\rho(x_i) - x_j\rho(x_j)\|\} \quad (43)$$

Let $\eta = |D^+ - D^-|$, then

$$\eta_{Max} = Max\{\left|D^+_{Max} - D^-_{Min}\right|, \left|D^+_{Min} - D^-_{Max}\right|\} \quad (44)$$

$$\eta_{Min} = \left|D^+_{Min} - D^-_{Min}\right| \quad (45)$$

The fuzzy membership of point was calculated by:

$$s_i = (1 - \frac{\left\|x_i\rho(x_i) - D^+_{Min}\right\|}{\eta_{Max} + \mu}) \times \frac{\eta_{Max} + \mu}{\eta_{Max} + \mu - D^+_{Min}} \times \frac{1}{D^+} \quad (46)$$

or

$$s_i = (1 - \frac{\left\|x_i\rho(x_i) - D^-_{Min}\right\|}{\eta_{Max} + \mu}) \times \frac{\eta_{Min} + \mu}{\eta_{Min} + \mu - D^-_{Min}} \times \frac{1}{D^-} \quad (47)$$

4. Kasnei Extraction Employing MF-SVM And Emotional Cellular Model

4.1. Probability Density- based Fuzzy KANSEI Representation

By morphological analysis, product form can be decomposed into a number of features, let $P = \{P_1, P_2, \cdots, P_l\}$, $P_i, 1 \le i \le l, P_i \in \{a_{i1}, a_{i2}, \cdots, a_{ik_i}\}, a_{ij}, 1 \le i \le l, 1 \le j \le k_i$ is the attribute set relative to P_i and each product P was mapped into a point in n -dimensional space which denoted by $P = \{a_{1t_1}, a_{2t_2}, \cdots, a_{nt_n}\}$, where form element a_{ij} is a vector of Valence-Arousal emotional space whose measurement is defined by EC and its probability density function. For each product form, a Valence-Arousal space will be defined subsequently. And we need to give the fuzzy similarity computing methods for two products. Given two products P and Q, if their evaluation is similar, then:

$$Sim = \sum_{i=1}^{n} \|E(P_i)\rho(P_i) - E(Q_i)\rho(Q_i)\| < \delta \quad (48)$$

where $E(P_i)$ is the evaluation on the i -th form noted by (v, a) and $\rho(P_i)$ is the Gaussian density function. δ is the given threshold. For each product P, its KASNEI images will be formalized as $K = \{K_1, K_2, \cdots, K_t\}$. The kernel's probability function of KASNEI image K_i is ρ, hence, the fuzzy evaluation is presented by $\{\frac{K_1}{\rho(K_1)} + \frac{K_2}{\rho(K_2)} + \cdots + \frac{K_t}{\rho(K_t)}\}$; furthermore, it can be transform to standard presentation through a standardization operator Γ, which mapped each $\rho(K_i)$ into $[0, 1]$, we have that:

$$E = \{\frac{K_1}{\Gamma(\rho(K_1))} + \frac{K_2}{\Gamma(\rho(K_2))} + \cdots + \frac{K_t}{\Gamma(\rho(K_t))}\} \quad (49)$$

Applying K -class SVM, product form's KASNEI image will be evaluated by $\{K_i\}$. So, we need to classify under t -dimension. For K_1, binary SVMs was applied to classify the first dimension data from K and in n -dimension space, a hyper-plane will be constructed to separate the space into K_1 and not K_1, and let $y = \{K_1, \neg K_1\}$, $K_1 = \{x_i, y_i, s_i\}$, where x_i is the evaluation data on K_1 which belongs to n - dimensional space, let $y_i = \{+1, -1\}$, where $+1$ denotes K_1 and -1 denotes $\neg K_1$, s_i is calculated by (Eq. 46). All points are belonging to R^n. However, due to multi-dimensional description of KANSEI image, the data must be under high - dimensional mapping manipulation and linear kernel was adopted in this paper.

4.2. Case Study

In case study, we illustrated how the proposed method applied in product KANSE image prediction. First, mobile phones pictures were collected widely, and the product's features were divided into form features and non-form features through morphological analysis. Then, we applied the proposed MF-SVMs process to extract KANSEI images from these CFFs. The framework of this work was illustrated in Fig 2. Each product (mobile phone) was evaluated by using Staple scale (shown in Fig 3.) and the critical form features were listed in Fig 4.

Second, the KASNEI adjectives were also collected widely and selection evaluation experiment will be conducted to select suitable adjectives to describe the semantics of the style. Table 1 illustrated the computing result applying the proposed methods where density membership S relatives to classification label Y and each form features $X1 - X9$, if Xi is a CFF, then $Y = +1$, or else $Y = -1$.

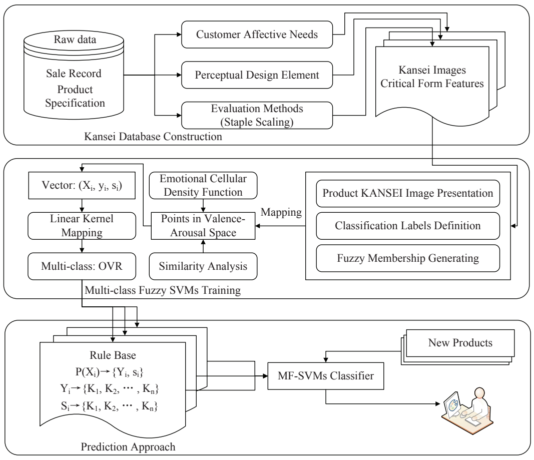

Figure 2 The framework of EC based MF-SVM in Product KASNEI Extraction

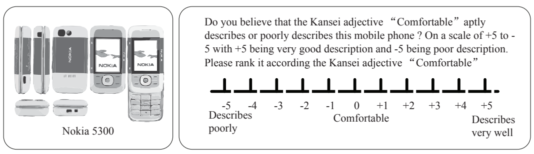

Figure 3 Staple Scale Evaluation on Mobile Phone's KANSEI Image

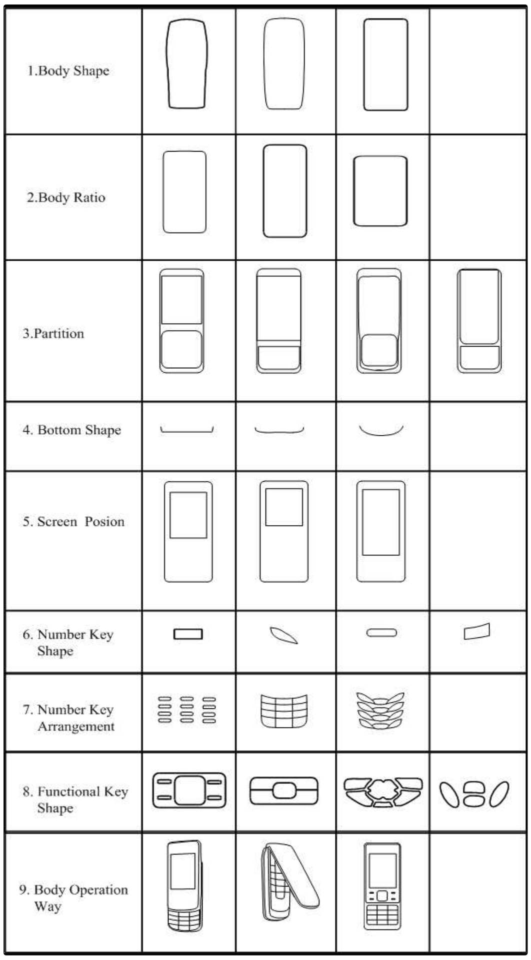

Figure 4 Critical Form Features of Mobile Phone

Table 4.1: Product classified by EC and its fuzzy membership

n	Product: $X = (x1, x2, \cdots, x9)$ Classification labels on Kansei adjectives: $Y = (y1, y2, \cdots, y15)$ Relative membership: $S = (s1, s2, \cdots, s15)$
1	X=(1 2 4 1 2 3 2 4 1) Y=(+1 -1 -1 +1 -1 +1 -1 -1 -1 +1 +1 -1 +1 -1 +1) S=(0.55, 0.75, 0.58, 0.32, 0.75, 0.76, 0.87, 0.75, 0.59, 0.69, 0.47, 0.58, 0.68, 0.43, 0.57)
2	X=(2 1 1 2 2 4 3 4 2) Y=(-1 -1 +1 -1 +1 -1 -1 -1 -1 +1 -1 1 +1 +1 -1) S=(0.35, 0.73, 0.35, 0.63, 0.80, 0.66, 0.82, 0.55, 0.54, 0.68, 0.28, 0.37, 0.57, 0.55, 0.56)
3	X=(1 1 4 2 3 1 3 3 1) Y=(+1 +1 +1 -1 +1-1 -1 +1 +1 -1 +1 +1 -1 +1 +1) S=(0.57, 0.56, 0.34, 0.62, 0.52, 0.34, 0. 73, 0.52,0.43, 0.69, 0.50, 0.52, 0.35, 0.67, 0.35)
4	X=(2 2 1 1 2 1 2 4 2) Y=(-1 -1 +1 -1 +1 +1 -1 -1 -1 +1 -1 -1 +1 -1 -1) S=(0.72, 0.35, 0.45, 0.45, 0.45, 0.26, 0. 67, 0.76, 0.66, 0.54, 0.54, 0.56, 0.72, 0.38, 0.72)
5	X=(1 2 4 3 1 4 2 4 1) Y=(+1 +1 +1 -1 -1 -1 +1 -1 -1 +1 -1 -1 +1 -1 -1) S=(0.82, 0.7,0 0.75, 0.78, 0.39, 0.82, 0. 47, 0.37, 0.49, 0.58, 0.72, 0.56, 0.78, 0.82, 0.82)
6	X=(2 1 2 2 3 4 1 3 1) Y=(+1 -1 +1 +1 -1 -1 +1 +1 -1 +1 -1 -1 +1 -1 -1) S=(0.67, 0.76, 0.56, 0.82, 0.42, 0.64, 0. 65, 0.33, 0.37, 0.21, 0.65, 0.82, 0.36, 0.64, 0.52)
7	X=(1 1 3 1 1 2 2 4 3) Y=(+1 +1 -1 -1 -1 +1 -1 -1 -1 +1 +1 -1 +1 +1 +1) S=(0.45, 0.73, 0.56, 0.59, 0.50, 0.39, 0. 69, 0.37, 0.65, 0.29, 0.62, 0.91, 0.75, 0.54, 0.65)
8	X=(1 2 1 1 2 3 3 1 1) Y=(+1 -1 +1 -1 -1 -1 -1 +1 +1 -1 +1 -1 -1 -1 -1) S=(0.34, 0.64, 0.76, 0.68, 0.30, 0.52, 0. 72, 0.27, 0.72, 0.37, 0.53, 0.89, 0.82, 0.53, 0.70)
9	X=(2 1 3 1 3 2 2 1 2) Y=(+1 -1 -1 -1 +1 -1 +1 -1 -1 +1 +1 +1+1 -1 +1) S=(0.59, 0.30, 0.43, 0.62, 0.61, 0.73, 0. 77, 0.53, 0.68, 0.78, 0.61, 0.37, 0.49, 0.63, 0.20)
10	X=(2 1 4 3 3 1 1 2 3) Y=(-1 -1 -1 +1 -1 +1 -1 -1 +1 -1 -1-1 +1 -1 -1) S=(0.62, 0.32, 0.42, 0.51, 0.81, 0.68, 0. 52, 0.76, 0.62, 0.65, 0.27, 0.65, 0.72, 0.69, 0.43)

According to the results of Table 4.1, the typical samples- (V, A) will be calculated and then they were classified into appropriate emotional cellular kernels. According to the center samples of emotional cellular set and Gaussian density parameters, we can calculate the average density of the kernel. Table 4.2 shows the result. The kernel density by standardization operation (center samples of Table 4.2.) is the fuzzy membership of corresponding KANSEI image. it will be easy to calculate the fuzzy similarity of any products by parameters (σ, c).

Table 4.2: EC presentation and Typical Products

KANSEI Image	Central Sample (C)	Kernel Density	Parameters
Portable	(123123121)	0.752	0.35 I, c=(2.35,4.59)
Sturdy	(224223131)	0.680	1.25 I, c=(3.23,3.45)
Freehand	(112221322)	0.598	1.03 I, c=(2.88,5.37)
Dignified	(113124121)	0.764	1.25 I, c=(1.65,6.25)
Happy	(223123323)	0.357	1.34 I, c=(4.57,3.41)
Nature	(322113121)	0.342	2.01 I, c=(3.57,3.23)
Happy	(124133111)	0.674	1.65 I, c=(5.58,5.37)
Stimulation	(131123141)	0.298	1.57 I, c=(5.77,4.21)
Comfort	(323123122)	0.566	1.74 I, c=(4.17,1.40)
Shine	(221123121)	0.872	1.29 I, c=(2.90,6.34)
Mature	(222123121)	0.651	1.65 I, c=(5.12,1.37)
Fashion	(212134122)	0.731	0.87 I, c=(4.45,6.98)
Friendship	(223123121)	0.776	2.48 I, c=(2.17,5.26)
Cute	(124123321)	0.438	1.92 I, c=(6.23,1.55)
Future	(334124113)	0.442	1.77 I, c=(1.28,1.97)

5. Concluding remarks

In this paper, we proposed multi-classification fuzzy support vector machines employing emotional cellular model and developed its applications in KANSEI engineering. First of all, the basic concepts of support vector machines was discussed, as reference to product's multiple KANSEI images expression, a multi-class support vector machine was applied in KANSEI extraction system and emotional cellular model relative to Valence-Arousal space was applied to express implicit emotional of products. Evaluation on product is no longer appearing purely and single KANSEI, and Valence-Arousal will directly be used to evaluate the product form features. According to ratings data, the relationship between product and EC including the typical product set with the Gaussian density function can be discovered. By multi-class support vector machine model, the emotional cellular and its Gaussian density function were used to classify each KANSEI. Case study shows that the emotional cellular model combining MF-SVMs technology was suitable to extract KANSEI of products. The proposed methods and its application research also show that KANSEI is presented more exactly by comparing with traditional methodology. Otherwise, the EC based multi-class fuzzy support vector machines integrated to KANSEI Engineering is still under development, perceptual evaluation on product and efficient algorithms also depend on the further improvement of the accuracy and mathematical formalization of emotion, especially Valence-Arousal space was also directly affects the extraction process of product form features.

Acknowledgment: This work is funded by Natural Science Foundation of Zhejiang Province under Grant No.(Y1110322).

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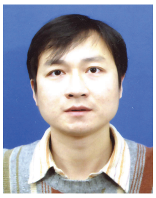
Fuqian Shi, IEEE Membership (90648136), now is an associate professor of department of information and engineering of Wenzhou Medical College, he received his Ph.D degree from Modern Industrial Design Institute of Zhejiang University, China, and his research interest includes fuzzy set, semantic networks and KNASEI engineering.



Jiang Xu is a lecturer in School of Mechanical Engineering at the Southeast University of China. He received his Ph.D in college of computer science and technology of the Zhejiang University, China. His research interests focus on KANSEI Engineering and tools and methods to improve creative design, emotional design, and decision support for product60c¯s life cycle, the approach is multidisciplinary, including computer science, engineering, and psychology.