Analyzing Kansei from Facial Expressions by CSRBF Mapping

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Abstract: This paper describes an application where a new Kansei/Affective Engineering (KAE) system was applied to define the properties of the facial images perceived as *Iyashi*. *Iyashi* is a Japanese word used to describe a peculiar phenomenon that is mentally soothing, but is yet to be clearly defined. Instead of analyzing facial expressions of an individual to determine his emotional state, the proposed system introduces a fuzzy-quantized holographic neural network (FQHNN) to find the rules involved in the Kansei evaluation provided by the subjects about the limited dataset of 20 facial images.

In order to validate and gain a clear insight into the rules involved in the Kansei evaluation process, Procrustes analysis and Compactly-Supported Radial Basis Functions (CSRBF) are combined to generate new facial images. Procrustes analysis is used to find the minimal dissimilarity measure between two facial images with opposite classification (i.e. Iyashi and Non-Iyashi). CSRBFs are proposed for tuning of 17 facial parameters and mapping between facial images within opposite classes. The experiments with two subjects demonstrate that if only two from the five most important parameters of the face are changed then the Kansei evaluation can change to the opposite class. This paper shows that a continuous and efficient tuning of the design space can be achieved by introducing CSRBF mapping into the new KAE system.

Keywords: Kansei evaluation, Iyashi expressions, neuro-fuzzy classifiers, radial basis functions.

1. INTRODUCTION

In an attempt to understand what motivates people to buy consumer products product manufacturers often rely on questionnaires and polls to investigate the consumers preferences and why they purchase or avoid certain items (Sandhusen 2000, Fitzsimons et al 2002). The major problem with this approach is that, as shown by a variety of studies (e.g. Sandhusen 2000), consumer attitudes and behaviors are frequently formed and influenced by non-conscious emotional and cognitive processing (Fitzsimons et al 2002), which is not subject to detection via traditional survey or interview methods. Here KAE systems (Nagamachi 2011) assume that product-related stimuli (e.g. paintings or photographs) are shown as questionnaires to the consumers and at the same time a machine automatically recognizes and analyzes interactive signals while consumers evaluate what they felt about products in photographs. Then, using simple (e.g. "yes/no") answers to evaluate Kansei words, a comprehensive analysis of those results could play an important role during analysis of consumer state of mind (cognitive and emotional reaction, both conscious and un-conscious) at the time of review, selection or use of a product or product-related stimuli.

1.1. How to measure subject's emotional response to a picture?

Psychological researchers use diverse methods to investigate emotions (Bradley et al 1994, Lang et al 2008, Mikels et al 2005). These procedures range from imagery inductions to film clips and static pictures. One of the most widely used stimulus sets is the International Affective Picture System (IAPS, Lang et al 2008), a set of static images based on a dimensional model of emotion (Russel 1999). The image set contains various pictures depicting mutilations, snakes, insects, attack scenes, accidents, contamination, illness, loss, pollution, puppies, babies, and landscape scenes, among others. However, while many samples are desirable for estimating the response of a person more accurately (e.g. how much the person likes a product), in a real world situation, only a small number of samples needs to be obtained because of the efforts required for the persons to provide their responses from many samples. Hence in this paper as in our previous works (Diago et al 2011) we use a small dataset of portraits to teach the machine to classify the facial images in the same way that people perceive them.

1.2. Why faces?

Facial expressions are our primary means of communicating emotion (Ekman 1978, Russel 1999, Scherer 1992), and that is why the majority of efforts in affective computing concern automatic analysis of facial displays (Pantic et al 2008, Fasel et al 2003, Tian et al 2005). Instead of analyzing facial expressions of an individual to determine their emotional state, using a database of portraits, (Diago et al 2011) showed that machines are also capable of perceiving faces as they relate to the social impressions they make on people. A new method for the quantification of qualitative judgments and evaluations of facial expressions was proposed in order to gain a clear insight into the reasoning made by nonlinear prediction models, such as holographic neural networks (HNN).

1.3. What type of facial expressions?

In previous works (Kitaoka et al 2008), the term "*Iyashi*[1] expressions" was defined to study facial expressions related with the peculiar phenomenon of Iyashi. In Japan, Iyashi is a popular buzzword today, referring to anything that is physically or mentally soothing (Kitaoka et al 2008, Matsui 2008). Iyashi goods -- books, music, pictures, incense and aromas, bath salts, and plants -- abound, offering to heal the physical and psychological stress of the workplace and of daily life in

[1] We use the word *Iyashi* as the stimulus given to a person that changes its internal condition to a better physical or emotional state (see Kitaoka et al 2008 for details).

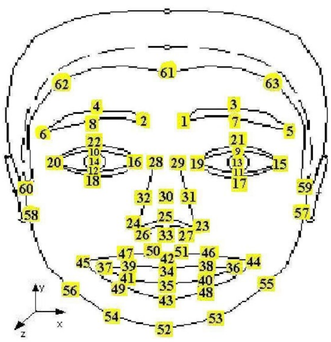
general. In society the expression Iyashi-kei is frequently used to describe laypersons that simply help people to relax. However, the word Iyashi (like other such as pleasure, well-being or satisfaction) does not have a consensus among people. Therefore a KAE system was developed to explain human decision-making by extracting fuzzy rules from the computational models.

In this paper procrustes analysis and CSRBF are combined to validate the extracted rules making a continuous and efficient tuning of the design space. Related KAE sytems are reviewed in section 2. The proposed FQHNN is presented in section 3. The combination of procrustes analysis with CSRBF is introduced in section 4. The experimental results with two subjects are shown in section 5. Finally, conclusions and future works are presented in section 6.

2. RELATED KAE SYSTEMS

Various KAE Systems have been developed to automatically support the design process (M. Nagamachi et al 2011). In this section we do not intend to do a thorough analysis on existing KAE systems but mention some of the methods or systems including similar applications. For example, Benitez et al, 2013 developed a KAE system for Gigakuman Character Design. The system generates different facial expressions of Gigakuman in order to represent an abstract concept. Ohira et al 2010 also use a rough set approach to extract painting composition rules and synthesize drawing and painting from the identification of salient features within images to produce an abstract composition. A more sophisticated system was proposed by (Ando & Hagiwara 2009) to create 3D characters using interactive genetic algorithm and a rule extraction method based on the comparison between attributes of user's evaluated characters. Recently the generation of Kansei rules trends to include parameters from physiological measurements (see e.g. Okuhara et al 2011) but we will not cover this topic here.

Fuzzy Logics, Neural Networks, Genetic Algorithm, Rough-Set Analysis, and Partial Least Square Analysis are used within KAE systems to analyze Kansei (see details in Nagamachi et al 2011). A neuro-fuzzy approach is used in the proposed KAE system (Diago et al 2011). Twenty images represented by seventeen parameters were evaluated by one hundred and fourteen subjects between 15 and 70 years old (102 Japanese and 12 non-Japanese, 47 females and 67 males) and were used to train different neuro-fuzzy classifiers. The participants rated each stimulus on the scale '0'-NO, '1'-DON'T KNOW , '2'-YES to express whether or not they feel an Iyashi-stimulus. Figure 1 shows 63 feature points used to compute the set of parameters describing 20 portrait images.



Face parameters		
Area parameters: $\mathbf{p_1}$ (right eye), $\mathbf{p_2}$ (left eye), $\mathbf{p_3}$ (nose), $\mathbf{p_4}$ (mouth), $\mathbf{p_5}$ (face), $\mathbf{p_6}$ (right eyebrow), $\mathbf{p_7}$ (left eyebrow). Distance/size parameters: $\mathbf{p_8}$ (face height), $\mathbf{p_9}$ (face width), $\mathbf{p_{10}}$ (forehead height), $\mathbf{p_{11}}$ (forehead width), $\mathbf{p_{12}}$ (eye-eye), $\mathbf{p_{13}}$ (left eye-eyebrow), $\mathbf{p_{14}}$ (right eye-eyebrow), $\mathbf{p_{15}}$ (eye-nose), $\mathbf{p_{16}}$ (nose height), $\mathbf{p_{17}}$ (nose width), $\mathbf{p_{18}}$ (eye-mouth), $\mathbf{p_{19}}$ (mouth height),$\mathbf{p_{20}}$ (mouth width)		
Normalization		
$x_1 = p_1/p_5$	$x_7 = p_{12}/p_9$	$x_{13} = p_{14}/p_8$
$x_2 = p_2/p_5$	$x_8 = p_{15}/p_8$	$x_{14} = p_{19}/p_8$
$x_3 = p_3/p_5$	$x_9 = p_{18}/p_8$	$x_{15} = p_{20}/p_9$
$x_4 = p_4/p_5$	$x_{10} = p_{10}/p_8$	$x_{16} = p_{16}/p_8$
$x_5 = p_6/p_5$	$x_{11} = p_{11}/p_9$	$x_{17} = p_{17}/p_9$
$x_6 = p_7/p_5$	$x_{12} = p_{13}/p_8$	

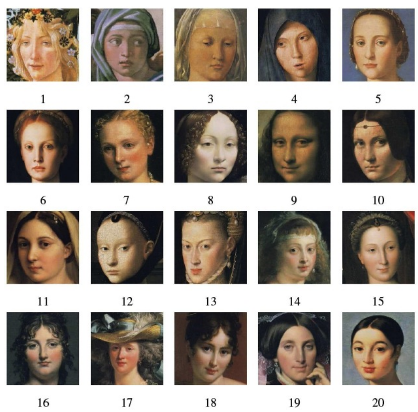


Figure 1: Feature points, Face Parameters and Portrait images

3. FUZZY-QUANTIZED HOLOGRAPHIC NEURAL NETWORKS

Figure 2 shows the architecture of the proposed fuzzy-quantized holographic neural network (FQHNN). The HNN module (upper part) is combined with the FQ module (lower part) to increase HNN interpretability. HNN module is proposed to select the most important parameters of the face from the complex values stored in the holographic memory (**H**). FQ module is proposed to build the membership functions (MFs) describing facial parameters ($\mu_{11} \ldots \mu_{kli}$) and the groups of subject evaluations ($\mu_{G1} \ldots \mu_{Gm}$) without solving a generalize eigenvalue problem ($\mathbf{Ac}=\eta^2\mathbf{Bc}$). Later, the fuzzy reasoning is used to provide transparency to HNN models extracting linguistic rules (see details in Diago et al 2011).

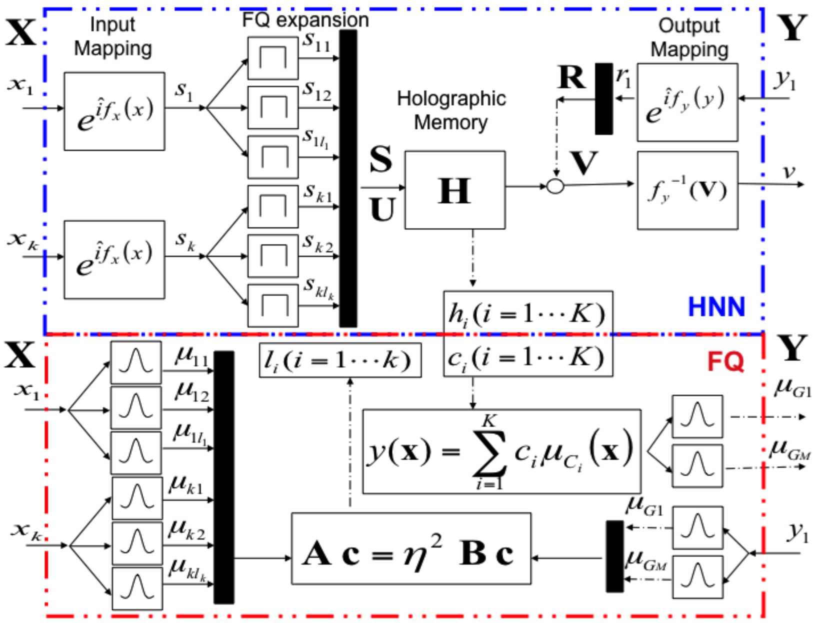


Figure 2: Architecture of the proposed Fuzzy-Quantized Holographic Neural Network (FQHNN).

An initial knowledge base of 35 rules was created from the trained FQHNN representing the evaluations of N=87 subjects reported in Diago et al 2011. Table 1 shows eleven parameters (x_1, x_3, x_5, x_6, x_8, x_{10}, x_{11}, x_{13}, x_{14}, x_{15}, x_{17}) used to explain the meaning of subjects evaluations from the set of 21 rules extracted from N=41 subjects using a single parameter in the antecedent. The first row displays the category (S = Small, M = Medium, L = Large) of each parameter in the rules. The second row shows the number of classes involved in each parameter. The class is specified between parentheses in case of a single class ('0 '-NO, 1 "-DON'T KNOW, '2'-YES). The third and fourth rows show the number of rules and the number of subjects in which each parameter defined the evaluation.

Table 1: Eleven parameters used to explain the meaning of subjects evaluations of Iyashi-expressions

	x_1	x_3	x_5	x_6	x_8	x_{10}	x_{11}	x_{13}	x_{14}	x_{15}	x_{17}
Categories	M	S	**S,M**	**M,L**	M	M	**S,M**	**M**	S	M	**S,M**
No. of Classes	1(1)	1(0)	**3**	**2**	1(1)	1(0)	**1(0)**	**2**	1(0)	1(2)	**2**
No. of Rules	1	1	**5**	**3**	1	1	**2**	**2**	1	1	**3**
No. of Subjects	1	1	**11**	**8**	1	2	**2**	**7**	1	2	**3**

Table 2 shows fuzzy rules corresponding to the 5 parameters (x_5, x_6, x_{11}, x_{13}, x_{17}) influencing the evaluation of many subjects (~80%). Each row represents a rule. Columns 3 and 5 represent the antecedents and consequences of each rule respectively. Column 6 shows the number of subjects in which the rule defined the evaluation. According to the number of subjects (11), x_5 is the most influential parameter. However, the rules are contradictory. The same applies to x_6 and x_{17}. In over 80% of cases S or M values of the parameters x_{11} and x_{13} do not produce Iyashi i.e. Class (Iyashi) = NO. In the next section changing the parameters x_6 and x_{17} new expressions are generated in order to validate the extracted rules.

Table 2: Fuzzy rules to classify Iyashi-expressions

No.		Parameter		Class (Iyashi)	No. of Subjects	
1	IF	X_5 is S	THEN	NO	4	11
2		X_5 is M		NO	1	
3		X_5 is M		DON'T KNOW	2	
4		X_5 is S		YES	2	
5		X_5 is M		YES	2	
6	IF	X_6 is M	THEN	NO	5	8
7		X_6 is M		YES	1	
8		X_6 is L		YES	2	
9	IF	X_{11} is S	THEN	NO	2	4
10		X_{11} is M		NO	2	
11	IF	X_{13} is M	THEN	NO	5	7
12		X_{13} is M		DON'T KNOW	2	
13	IF	X_{17} is S	THEN	NO	1	3
14		X_{17} is S		YES	1	
15		X_{17} is M		YES	1	

4. COMPACTLY-SUPPORTED RADIAL BASIS FUNCTIONS

Compactly Supported Radial Basis Functions (CSRBFs), firstly introduced by Wendland in 1995, are used for tuning facial parameters and mapping between facial images within opposite classes. Firstly, procrustes analysis determines a linear coordinates transformation (translation, reflection, orthogonal rotation, and scaling) of the feature points in the original image to best conform them to the feature points coordinates in the target image. The goodness-of-fit criterion is the sum of squared errors. The procrustes analysis also returns the minimized value of this dissimilarity measure and the transformed coordinates of the feature points from original image. The coordinates of the transformed images are used to compute the movement of the original feature points and to generate the requested expression by CSRBF-based image warping.

In general, from given two data sets in $\mathbf{R}^3$,$\boldsymbol{s}_i$ ={ x_s^i, y_s^i, z_s^i },for a non-deformed object, and $\boldsymbol{d}_i$ = { x_d^i , y_d^i , z_d^i }, for the deformed object, we construct a space mapping F : $\mathbf{R}^3 \rightarrow \mathbf{R}^3$ which is a CSRBF interpolation of form (1) in each of its components.

$$F(\bullet) = p(\bullet) + \sum_{i=1}^{N} a_i \phi(\| \bullet - s_i \|) \tag{1}$$

Here p is a low degree polynomial, ϕ is a positive definite and compactly supported radial function in the form (2) and a_i and s_i are the coefficients and centers of the RBFs respectively. The r_0 is the support radius.

$$\phi(r) = \begin{cases} (1 - r / r_0)^2{}_+ & 0 \le r \le r_0 \\ 0 & otherwise \end{cases} \tag{2}$$

A system of linear algebraic equations (SLAE) is solved from the displacements of the two data sets to compute RBF coefficients and the coefficients of the low degree polynomial p. The warped images are generated from equation (1) and reevaluated by two subjects in the experimental section.

Figure 3 shows the face profiles derived from the 63 feature points marked on each portrait and the dissimilarity measure between face profiles computed by procrustes analysis. The 20x20 matrix is shown as image and each pixel of the image indicates the minimized value of the dissimilarity measure between the feature points in the firth image and the transformed coordinates of the feature points in the second image. Note that the dissimilarity distance between images is very small. The highest value is shown between pictures 10 and 14 (D = 0.09125). However evaluations of subjects may not match with these values.

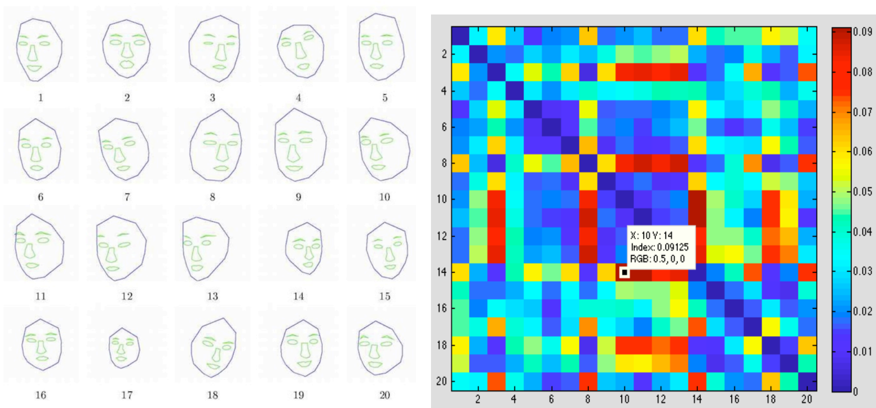


Figure 3: Face profiles and dissimilarity matrix for 20 portrait images.

5. EXPERIMENTAL RESULTS

For the experimental section, the warped images from the 20 portraits were prepared beforehand. As in the previous work, the participants rated each stimulus on the scale '0'- NO, '1'- DON'T KNOW, '2'- YES to express whether or not they feel the emotion in question. The time for evaluating each stimulus was set to a maximum of 10 seconds. In each trial, stimulus were selected at random from the set of 20 images and presented for five seconds. The total time for evaluation of each image was also recorded. If the time exceeds 10 s, the image is returned to the set of images in order to be presented one more time. The images evaluated within the maximum time interval of 10s are removed from the set. After storing evaluations of each user, the FQHNN was used to learn which are the facial expressions that induce Iyashi on each user. Table 3 shows an example of evaluations made by two subjects.

Table 3: Evaluation of 20 portrait images by two subjects

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Subject 1	2	1	0	1	2	1	2	0	2	1	2	0	0	1	1	2	1	2	1	2
Subject 2	2	0	1	0	2	0	2	0	2	0	2	0	0	2	2	2	2	2	2	2

After FQHNN learning is finished, the system selects which of the rules is closer to user evaluations. Then, it selects one of the images evaluated as 2 and begins to select modified images according to the values of the parameters in the antecedents of the selected rule. For example, in the case of subject 1, the rule number eight in table 2 i.e. IF (x_6 is L) THEN Class(Iyashi) = YES covered about 60% of the evaluations in the class. So, the parameter x_6 was modified to change the evaluation of the subject to the opposite class by using the same image. The image number 5(x_6 =0.0041) was selected. Figure 4 shows the set of warped images from image 5 (left) and image 6 (right). The following sequence of warped images was presented to the subject for evaluation: Image 15 (x_6 =0.0029), Image 10 (x_6 =0.0028), Image 8 (x_6 =0.0018). After image 8 was shown the subject evaluated that the image do not produce Iyashi i.e. Class (Iyashi) = NO as it was expected.

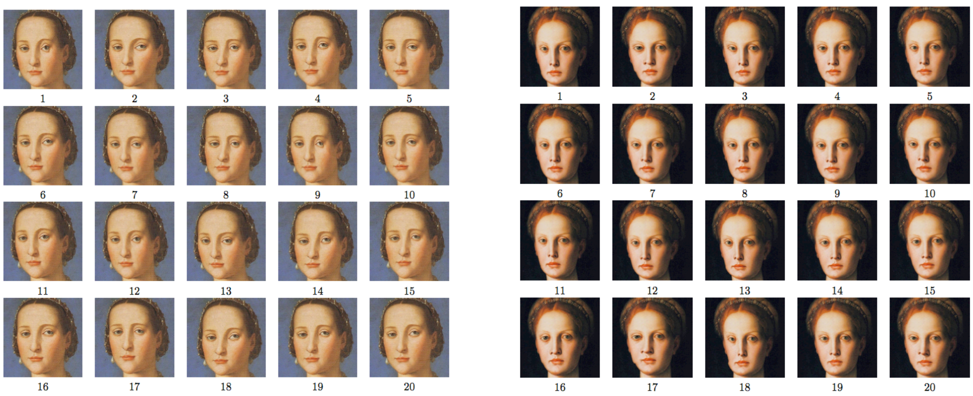


Figure 4: Warped images used to evaluate the rules generated from the evaluations of subject 1.

The rule No.13 in table 2 i.e. IF (x_{17} is S) THEN Class(Iyashi) = NO covered more than 50% of the evaluations in the class. So, the parameter x_{17} was modified to change the evaluation of the subject to the opposite class by using image number 6(x_{17} =0.2339). The following sequence of images was presented to the subject for evaluation: Image 3 (x_{17} =0.2383), Image 16 (x_{17} =0.2463). After image 16 was shown, the subject evaluated that the image produced Iyashi i.e. Class (Iyashi) = YES as it was expected. In both cases, the starting image is selected randomly. The experiments have been repeated several times for both subjects using different starting images but similar results are obtained (results not shown).

6. CONCLUSIONS AND FUTUR WORKS

This paper is a continuation of our previous works in which a knowledge base of 35 rules was created from the trained fuzzy-quantized holographic neural network (FQHNN) representing the evaluations of N=87 subjects. In order to validate the extracted rules, the parameters influencing the evaluation of 80% the subjects were selected from the set of rules. Changing only two of the selected parameters (i.e. normalized area of the right eyebrow and the nose) new warped images were generated and evaluated by two subjects. The experimental results showed that although the dissimilarity distance between images is very small, the evaluation of the subjects could be modified to the opposite classification (i.e. Iyashi and Non-Iyashi) by warping original images with Compactly Supported Radial Basis Functions (CSRBF).

In this work we have explored only single parameters influencing subjects evaluations separately. However, we could employ genetic algorithms to explore combinations of parameters and increase the % coverage of the rules to explore. An active learning technique to explore the design space is also under development.

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BIOGRAPHY

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