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Human Awareness Support by Changing Values of Hidden Factors of Input Stimuli Dynamically

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***Abstract*—We propose an awareness support system that helps a user to be aware of the reason of his/her evaluations. Based on our proposed definition of human awareness mechanism, we extract hidden factors of input information using an auto-encoder neural networks and implement its decoder part into an awareness support system. The big feature of this system is to let a user change the values of the extracted hidden factors manually and observe the system outputs that change according to the changes of hidden factors. Experimental results using a task of generating facial emotions with 21 human subjects have shown the effectiveness of this approach.**

***Index Terms*—awareness support system, hidden variables, dynamic change, neural networks**

I. INTRODUCTION

When we see paintings or listen to music, we can say how we like them based on our preference. Same evaluation can be done for not only visual or auditory stimuli but also any inputs to our five kinds of sensory organs. However, it does not mean that we can easily explain their reasons. Generally, our explanations for our subjective evaluations come after the evaluations. The reason of this delay would be not only due to the necessity of time for constructing logical explanation linguistically but also our unawareness of the reason of our evaluation itself.

If there are intelligent systems that help us to be aware of the factors of our evaluations or thoughts, we may be able to straighten our thinking, clear up the thoughts, consider complex matters further deeply, and/or make quick decisions for them. If computer provides solutions matching to our preference or helps to arrange our thinking based on the obtained factors of our evaluations or thoughts, affinity between computer and human users must increase through their interaction.

The awareness support systems proposed in this paper is not based on the AI approach that computer acquires human knowledge but the approach that computer lets a user be aware of his/her hidden knowledge. The AI approach models human capabilities, implements it in computers, and aims to realize functions equivalent to humans. On the other hand, our proposed awareness support system can be said as a man-computer symbiosis [3] approach as it cooperatively develops the equivalent functions together with a user.

The first objective of this paper is to propose a method to extract human evaluation factors of which the user himself/herself has not been aware. We proposed to define *awareness* as finding out hidden variables that are included in the information input to a human indirectly and determine his/her evaluations [6]. Based on this unique definition of human awareness, we propose a method letting a user be aware of his/her evaluation factors by extracting hidden variables using an auto-encoder type neural networks (NN) and letting him/her change the variable values dynamically This is the awareness support system proposed in this paper.

The second objective is to evaluate the efficiency of the proposed method. We construct an awareness support system based on the approach of the first objective and experimentally confirm if users become easier to be aware of their evaluation factors.

Following this introduction section, we explain one definition of human awareness mechanism in the Section 2. That is, awareness means finding out of hidden explanatory variables, and awareness support is defined to let users find out the hidden variable. We explain the structure of an awareness support system in the Section 3 and evaluate its effectiveness experimentally in the Section 4, discuss the experimental results in the Section 5, and conclude in the Section 6.

II. CONCEPT OF AWARENESS MECHANISM

A. Awareness in Different Pschological Layers

Information given to a human through five senses is firstly processed at the sensory layer. Loudness and pitch of voice, color and size of goods, and others directly related with physical values are detected here. These pieces of information are combined at the perceptual layer and used for pattern

[1]A part of this work was conducted when he was a Master course student, and he works for Distribution Business Systems Group, SCSK Corporation now.

recognition. Cognitive layer handles the meaning of the recognized patterns. Psychology mainly handles stimuli to humans objectively at these three layers. Since we can give a subjective value to the processed information, such as *I like it*, we can say there is a *KANSEI* layer after these three layers.

Awareness is observed at each layer (Figure 1). For example, *I detected its color* in the sensory layer, *I found a triangle shape* in the perceptual layer, *I got its meaning* in the cognitive layer, and *I realized why I like it* in the KANSEI layer.

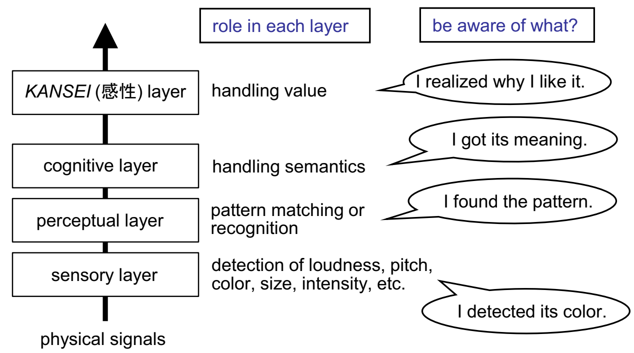

Fig. 1: Awareness in different psychological layers.

B. Modeling of Awareness Mechanism

We proposed a unique definition of human awareness mechanism and an idea of an awareness support system though it was just in the idea level [6]. In this paper, we realize the idea as a system and evaluate it experimentally in the following sections. We summarize the idea proposed in the reference [6] here before we turn into them.

The background of this research was the analysis of interactive evolutionary computation (IEC) user's responses. IEC is an evolutionary optimization method optimizing a target system based on IEC user's subjective evaluations [5]. IEC user evaluates images, sounds, and any other outputs from a target system easily, but it takes time for the IEC user to explain the reason of his/her evaluations. This delay is the process time for human awareness.

We made a hypothesis that a human extracts hidden variables for explanations from inputs and when they are extracted, we feel consciousness of awareness. This extraction process causes the mentioned delay. Based on this hypothesis, we made a model of human awareness mechanism with two steps.

Step 1: Making a human evaluation model.: To make a model of human awareness of the reason for his/her evaluations, we make his/her evaluation model firstly. The i-th outputs $\boldsymbol{x}$ from an IEC target system become inputs to an IEC user, and the user outputs his/her i-th evaluation z_i. It is not difficult to make a model, $z_i = f(\boldsymbol{x}_i)$, using many input-output data. Regression methods, NN, fuzzy systems, and other learning models are used for this user modeling (Figure 2).

When its input-output relation is simple, we can make an awareness model by analyzing the obtained human evaluation

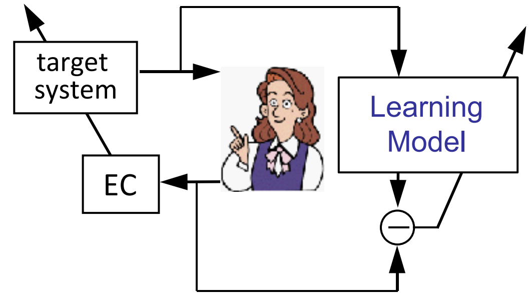

Fig. 2: Step 1: Making an evaluation model of an IEC user.

model. However, when its relation is complicated, we need go to the next step

Step 2: Making a human awareness model extracting hidden factors.: It is difficult for humans to explain the relationship between inputs stimuli to a human and his/her evaluations when this input-output relationship is complicated; inputs may include non-related information to his/her evaluations, and some pieces of inputs information may depend each other.

The mentioned hypothesis is based on the thought that human awareness is to find out hidden meta-factors behind the inputs rather than getting something in input stimuli to humans. Our awareness model is designed using the hidden meta-factors or variables that bridge a gap between inputs and outputs to/from humans (Figure 3). Awareness support system described in the Section III is realized using auto-encoder type NN.

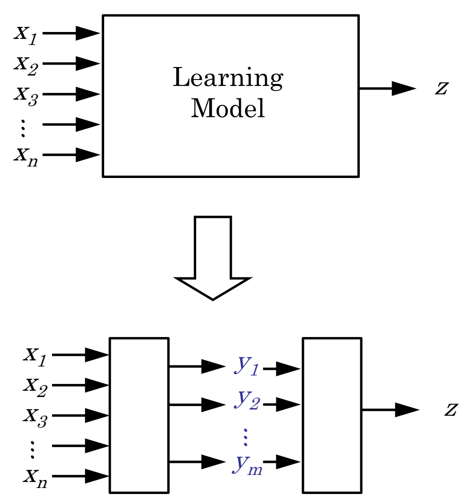

Fig. 3: Step 2: Finding out latent variables $\boldsymbol{y}$ inside the model in the Step 1 that explains the output z from the inputs $\boldsymbol{x}$.

III. Awareness Support System

Our proposed method firstly compresses input information and uses the compressed information as hidden factors and secondly lets a user change the values of the hidden factors manually, let him/her observe the changing outputs synchronized to the changing values of the hidden factors, and helps to be aware of the reason of his/her evaluations for the outputs. We are more sensitive to motion than stasis, and the main appeal point of this paper is to use this feature for awareness support.

The reason why we are more sensitive to motion is that nervous systems of majority of animals have evolved to detect changes, such as approaching predators or escaping preys [4]. Hermann von Helmholtz's hypothesis in 1860 was that vision system becomes tired if eye gaze is kept to the same point and the same motionless stimulus is kept to be given [4]. This is why frog can see only movements. By monitoring brain using functional MRI, it was found that facial emotions, which are used in our experiments, are mainly coded in motion-sensitive areas regardless its emotions are dynamic or static [2]. These physiological facts imply that dynamic changes may help to human awareness.

We use an auto-encoder to extract user's evaluation factors. Auto-encoder is so-called sandglass-type NN from its shape in the Figure 4, and its input layer–hidden layer part works as an encoder, and its hidden layer–output layer works as a decoder. The NN is trained using its inputs as supervised data, i.e. the trained NN shows identity mapping as $\boldsymbol{x} = \mathrm{NN}(\boldsymbol{x})$. Its encoder part can map higher dimensional data to lower ones and works as a principle component analyzer [1], and we use the compressed data at the hidden layer as hidden factors in this paper.

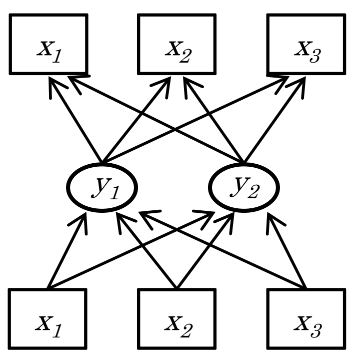

Fig. 4: Auto-encoder type neural networks which supervised data are its input data.

Our awareness support system consists of a decoder part of the trained sandglass-type NN and graphical user interface (GUI). The GUI allows a user to change the values of the inputs to its decoder part, i.e. values of hidden factors, dynamically (Figure 5) and displays the decoder outputs in real time. User observes changes in the outputs synchronized to the manually changed hidden factor values, which helps the user to be aware of the reason of his/her evaluations for the outputs. The point of our awareness support system is to support human awareness by showing dynamic changes in evaluations.

As the hidden factors are compressed results of input information, they do not have concrete meaning and cannot be labeled with explicit semantics. Even we pick up each of

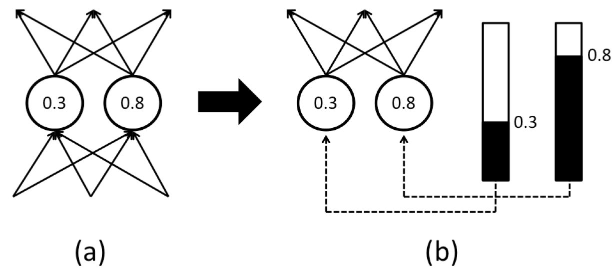

Fig. 5: Decoder part of an auto-encoder type neural networks is implemented in an awareness support system, and values of hidden layer units are expressed by sliding bars. User can change these values using the sliding bars.

hidden factors and analyze their meanings to explain human evaluations, it is hard to say what factor it is because it includes multiple information of inputs. This is why our approach does not take this analytical approach but aims to fully use human awareness capability to know the reason of his/her evaluations.

IV. Experimental Evaluations

A. Experimental System

To evaluate the proposed method, we prepare a parametric face line drawing and evaluate how dynamic change of hidden factors helps us to be aware of facial emotion factors using a five-grade evaluation method. We can recognize *happy*, *sad*, or *angry* emotion as soon as we see their faces. However, it takes time to realize what face parameters decide the emotion. Of course, we have a priori knowledge that the angles of eyebrows and a mouth influence to facial emotions deeply. Even we know it, still there is time delay between time of recognizing facial emotions and time of realizing facial emotion factors. This time delay is due to awareness processing.

A face line drawing used in this experiment have parameters of an eyebrow angle (θ_1), an eye angle (θ_2), a mouth angle (θ_3), and a nose size (s) shown in the Figure 6 and can generate several facial emotions (Figure 7).

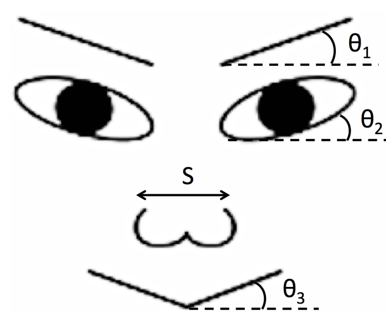

Fig. 6: Facial impression parameters.

Seven facial impression parameters are used to train auto-encoder type NN: angles of eyebrow, eye, and mouth (θ_1, θ_2, and θ_3, respectively), difference angles of eyebrow-eye, eye-mouth, and mouth-eyebrow ($(\theta_1 - \theta_2)$, $(\theta_2 - \theta_3)$, and

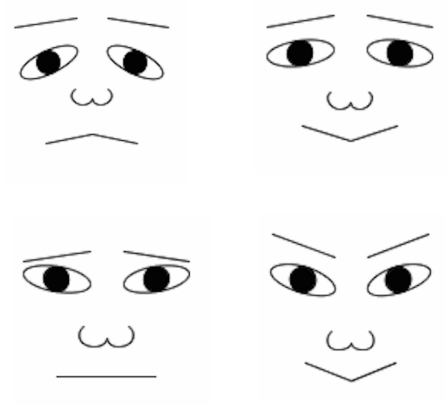

Fig. 7: Line face impressions.

($\theta_3 - \theta_1$), respectively), and a nose size s. Although we know that angles of eyebrow, eye, and mouth are dominant factors of facial emotions as a priori knowledge, we may not have such knowledge of tasks for general human evaluations. Taking account of this fact, we added the mentioned differential angles that somehow related with our knowledge and a nose size that does not seem useful information for recognizing facial emotions and may work as noise for human evaluation.

After we train auto-encoder NN of Figure 8, the decoder part is implemented into our awareness support system. When one face is given to the NN, we can obtain a set of (y_1, y_2, y_3), and the awareness support system displays the same face when the same values (y_1, y_2, y_3) are given to the decoder. The output face impression is changed according to changing the (y_1, y_2, y_3) manually.

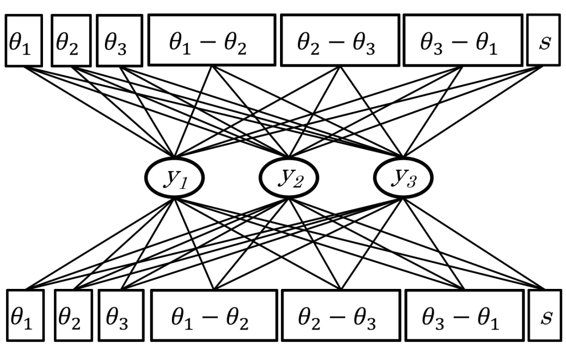

Fig. 8: Auto-encoder type of neural networks used in our experiments. See θ_1, θ_2, θ_3 and s in the Figure 6.

GUI, especially sliding bars, is the key point of our awareness support. As shown in the Figure 5, we introduce sliding bars and allow a user to change the values of hidden factors, i.e. hidden layer nodes of trained auto-encoder NN or inputs to a decoder part of the NN, to help the user to be aware of the reason of his/her evaluations. Since hidden factors are principal components of inputs, each of them does not correspond to a specific facial part but drives multiple facial parts related to the principle component. This is helpful to be aware of anger, for example, when a mouth angle θ_3 moves to negative big and an eyebrow angle θ_1 becomes positive big simultaneously, it becomes easier for a human to be aware of why it looks angry. At the same time, it is also important to realize real-time displays of facial emotions synchronizing with the change of manual changes of hidden factor values using sliding bars.

By changing the values of three hidden factors using sliding bars, several facial emotions can be generated. Figure 9 shows some examples.

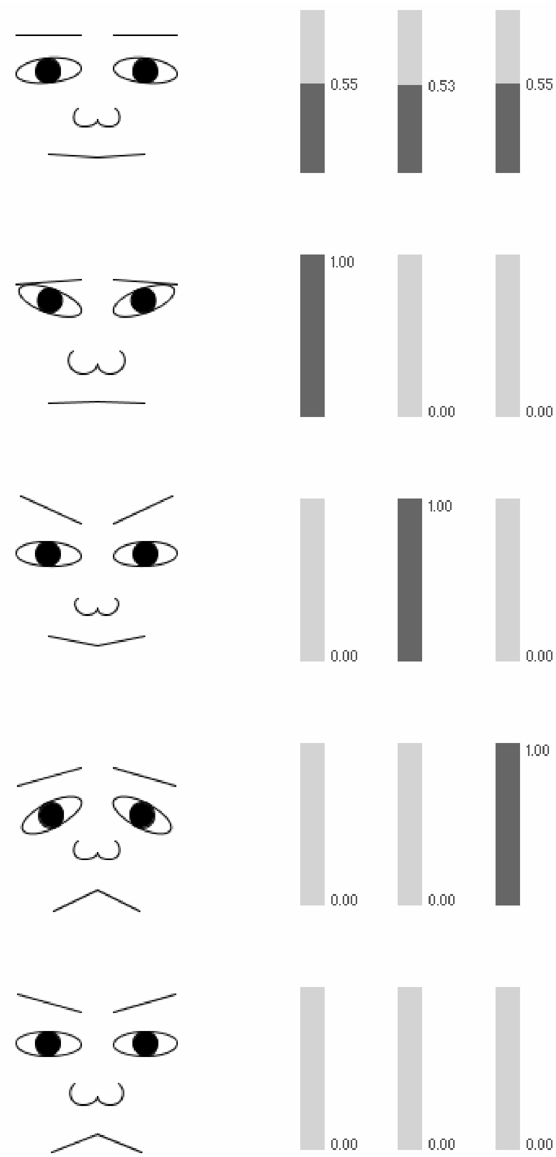

Fig. 9: GUI samples of an awareness support system. Facial emotions as system outputs change (left) according to the manual changes of hidden factors values (right).

B. Experiments and Results

The objective of experiments in this section is to confirm whether dynamical changes of hidden factor values help users to be aware of the reason of their recognition of facial emotions. The number of target facial emotions are three: *happy* face, *angry* face, and *sad* face. We train auto-encoder NN using 20 different faces for each emotion $\times$ 2,000 iterations.

We train four kinds of auto-encoder NN's, and their decoders are implemented into awareness support systems.

- NN_1 Auto-encoder NN trained by 20 kinds of *happy* faces $\times$ 2,000 iterations.
- NN_2 Auto-encoder NN trained by 20 kinds of *angry* faces $\times$ 2,000 iterations.
- NN_3 Auto-encoder NN trained by 20 kinds of *sad* faces $\times$ 2,000 iterations.
- NN_4 Auto-encoder NN trained by (20 *happy* faces + 20 *angry* faces + 20 *sad* faces) $\times$ 2,000 iterations.

Total 21 subjects evaluate how dynamic change using sliding bars of each awareness support system helps them to be aware of the facial factors that mostly influence to their facial emotion recognitions in 5-grade evaluation method. The subjects consist of 11 students of a Japanese university (Group A) and 10 twenties subjects in China (Groups B).

Average scores of 21 subjects are shown in the Table I. All average scores are more than 2.5, and Wilcoxon signed-rank test showed that the number of formative evaluators is significantly biased to the effective side. Especially, it is significant to realize the facial factors of *happiness*.

TABLE I: Average evaluations of 21 subjects for how changing hidden factor values using sliding bars helps their facial awareness in ascending order of 5-grade scores. Wilcoxon signed-rank test for (a) the number of (score 1 + score 2) vs. that of (score 4 + score 5) for the reference score is 3 and (b) the number of (score 1 + score 2 + score 3) vs. that of (score 5) for the reference score is 4. The marks ** and * means there is significant difference with significance levels 1% and 5%, respectively.

decoder extracted from	facial emotions	average score	reference point	
			score 3	score 4
NN_1	happiness	4.55	**	*
NN_2	anger	3.91	*	
NN_3	sadness	4.55	**	*
NN_4	happiness	4.09	*	
	anger	3.55		
	sadness	4.27	**	

V. Discussions

Discussion on Effectiveness:: The number of subjects who felt the effectiveness of our proposed awareness support well, i.e. scores 4 and 5, is significantly more than that of those who felt it slightly, i.e. scores 1 and 2. We can say that the proposed awareness support is effective from this statistical test results. Especially, it was effective to be aware of the features of *happy* faces. On the contrary of *happiness*, it seems difficult to be supported to find out those of *angry* faces.

Discussion on Training Auto-encoders:: Awareness support systems consisting of decoders of NN_1 – NN_3 is more effective than that using decoder of NN_4. It seems to be due to the differences in a changing range of facial emotions when hidden factors values, (y_1, y_2, y_3), are changed using sliding bars. From our observations, facial emotions generated by the decoders of NN_1 – NN_3 that are trained using only one facial emotion changed drastically when hidden factors values are changed, while the changing range of those generated by the decoder of NN_4 that are trained using three kinds of facial emotions was not big. One possible reason might be that NN_4 are trained to be average of three emotions, which resulted less variance of facial emotion changes. This result should be considered when we apply our proposed awareness support system to a variety of applications.

Discussion on the Number of Hidden Factors:: Although we use three hidden factors for facial emotions in our experiments, meaningful changes in facial emotions were not observed when one of three factors' values was changed. It may imply that two factors extracted from seven facial parameters are enough to determine facial emotions. We need to develop a method for determining the best number of hidden factors for a wide variety of applications.

Discussion on Variance of Human Awareness:: To check how the awarer order of facial parts is similar among humans, we asked 10 subjects of the Group B to write down the order among angles of eyebrow, eye, and month (θ_1 - θ_3) and the nose size s. Spearman's rank-order correlation between all pairs among 10 subjects was calculated, and their averages of ${}_{10}\mathrm{C}_2$ are listed in the Table II.

These high correlation values mean that all subjects are aware of the reason of their emotion recognitions similarly. As only four order values are used for this calculations, the correlation values largely change when the order sequence is changed.

TABLE II: Spearman's rank-order correlations for the awarer order of facial parts among 10 subjects.

facial emotion	average coefficient of Spearman's rank correlation
happiness	0.533
anger	0.400
sadness	0.640

VI. Conclusions

We propose to extract hidden factors of input information to a human, let him/her change the values of the hidden factors, and helps to let him/her aware of the reason of his/her evaluations. We conclude that this approach that uses dynamic changes for human awareness support surely helps human awareness through human subjective tests and statistical test.

Once computer has a capability of human awareness support, it must be useful for computer-human interaction or computer-human symbiosis. It is our future work to extend the proposed method from a basic research level in this paper to a practical level.

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