An Adaptive Facial Expression Recognition System Using Fuzzy Neural Network Model and Q-learning

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***ABSTRACT* - This paper proposes Facial Expression Recognition system based on a Gabor Wavelet Neural Network. The proposed system considers only 6 points of face image to extract specific features of facial expression. As an initial learning process, it learns network's weights and Gabor Filters' parameters using the gradient descent method. Through this process, the general parameters are obtained. When continuous unlearned new user's inputs are applied to this system, an adaptation process begins. In this first adaptation process, the system adjust each Gabor filters' parameters using Q-learning to extract more separable features. Secondly, using fuzzy neural network model, the network is self-organized in unsupervised manner.**

It means that the heuristics in the stage of feature extraction can be excluded, and means that the system has adaptation capability with minimum supervisory behavior. Therefore, the features become more separable and the recognition rate increases high only with two-layer network structure. This simplified and integrated Gabor Wavelet Neural Network has good performance and adaptation capability, and enables it to recognize facial expressions efficiently. The result shows that success rate exceeded 90% for general classifier and 93.35% for adapted classifier when two facial expressions considered.

***Keywords:* Facial Expression Recognition, Gabor Wavelet Neural Network, Adaptation, Fuzzy neural network model, Q-learning**

I. Introduction

The researches on human-friendly interface have been proceeded as a means of human-computer interaction (HCI). In a view point of HCI, facial expression recognition can play an important role.

Facial Expression has various characteristics such as multi-resolution, interconnection among each components, vagueness and subjectivity [1]. To consider these characteristics, researchers in the past have used a lot of classification techniques to recognize facial expression. Among them, artificial neural networks-based methods are well-known techniques [4,5,6]. As Support Vector Machine approaches, Salih Burak Gokturk et al. proposed a system extracting 3D information through 3D tracking, and using Support Vector Machine to classify facial expression robustly [4]. Ashish Kapoor et al. proposed a system using Support Vector Machine, which analyzed facial features by PCA [5]. On the other hand, conventional Neural Network-based facial expression recognition systems were developed actively. For example, a local unsupervised processing is integrated into a neural network to recognize facial expressions [6]. The neural network architecture has 4 layers of neurons, and is tested with images from the Yale Faces Database.

As stated above, many researches using various and complex neural network structures have been done to consider various features. However, these are not expectable because the complexity of interconnection increases exponentially as using more features. As one of the solutions for the 'curse of dimensionality' problem, wavelet network-based approaches are focused by some previous works [7,8,9,10,11].

In 1992, Qinghua Zhang [7] proposed wavelet network which was similar to Radial Basis Function Network but had much simpler structure and faster learning time. Since then, various researches have been done related with wavelet neural network [8,9,10,11]. However, at the first stage, a wavelet neural network also has a critical problem, namely 'curse of dimensionality', because the number of hidden nodes is increased exponentially by the number of input nodes [8]. Even though a remedy for the curse of dimensionality problem using multi-scaling functions is proposed [9], it was only fit to function approximation. So it needs additional process of extracting features in facial expression recognition problem. Wang Ting et al. proposed a structure which has hidden neurons as wavelet functions, but this RBF-type structure also needs a feature extraction process additionally [10] as RBF networks does. Recently, Krueger proposed Gabor-Wavelet Network structure in face recognition system [11]. This system only has an image approximation process by complex learning stages, and recognizes each person's face by comparing the distance between approximated network's structures.

In this paper, a Gabor-Wavelet Network is used to solve the above problems. Specially, we integrate the feature extraction process and neural network, and simplify the structure of two-layer network. In addition to that, our proposed system learns network's weights and Gabor wavelet's parameters automatically. Through these two processes, we can obtain not only weights but also parameters of Gabor filters without any heuristics.

On the other side, the problem of variety in personalized service is also considered [13]. This system considers the variety among individuals making performance of recognizer worse, and tries to solve this problem with scheme of pool. Though it allows various people's simultaneous uses, it needs lots of memory.

Therefore, in this paper, we introduced an approach from other point of view – adaptation capability in facial expression recognition system, which deals with how the system can adapt weight for a new user.

In section II, overall learning and adaptation process of proposed network, integrating Section III and IV, is explained. Section III introduces the structure of proposed classifier, Gabor-Wavelet Neural Network, and the methodology of training process. In Section IV, Adaptation stage which tunes Gabor filters using Q-learning, and then performs self-organization using fuzzy neural network model [2,3], is proposed. In section V, the simulation results, which demonstrate superiority of general performance and adaptation capability, are shown with the analysis of feature space.

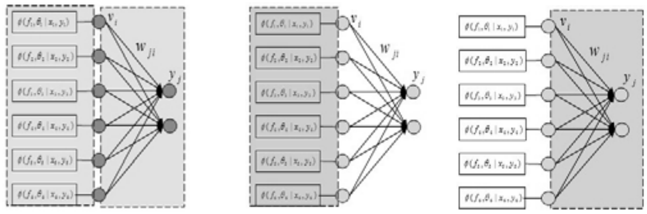
II. PROCESS OF PROPOSED METHOD – FROM INITIAL LEARNING TO ADAPTATION

In this section, we explain overall process integrating the learning of Gabor Wavelet Neural Network in section III and adaptation phases in section IV.

In first stage, as shown in Figure 1-(a), initial learning is carried out based on back-propagation algorithm. The system learns both Gabor filters' parameter and weights to find global solution. The decision of winning neuron is done by multiplication of feature vector by weights. This stage is for finding global solution and assembling network itself, and basically performs supervised and off-line learning.

From this phase, an adaptation process is activated only when unlearned specific user starts to use continuously. In this stage, as shown in Figure 1-(b), the system tunes Gabor nodes' parameters to extract features fitting into the new user's facial expression. This process is similar to that of human's, because Gabor nodes correspond to human's eye. In this Q-learning phase, one of the reinforcement learning technique, is used as explained in section IV-A.

After tuning of Gabor nodes, as shown in figure 1-(b), the system's weights are adapted to perform as an fuzzy neural network model[2,3]. This algorithm converges fastly and shows better classification performance compared with Self-Organized Feature Map [14], and needs no randomized initialization. During organizing clusters, it uses the same learning data already used in Q-learning. This adaptation process is completed after converging within some error bound. In this process, the on-line adaptation is performed.



(a) Initial Learning (b) Adaptation (I) (c) Adaptation (II)

Fig. 1. Overall process of Gabor Wavelet Neural Network

III. PROPOSED SYSTEM

A. System structure

Our proposed system uses a reduced Gabor-Wavelet Neural Network (GWNN) which contains both Gabor filters and a two layer neural network. The first stage is a feature extracting layer which has the set of Gabor filters, and the second stage is a recognizer which decides a decision boundary in feature space. Figure 2 shows the structure of the system.

When the input image is denoted by I, I_i can be an partial input image which is the same size as i-th Gabor Wavelet. Each Gabor wavelet nodes are applied to 6-facial points, (cx_i, cy_i) i=1,2,…6, defined as facial definition parameters (FDP) in MPEG 4 standard. The choice of 6-feature points utilizes the research [12], which studied the recurrent analysis of FDP points and ranked by the degree of explanation with respect to emotional expression. Therefore, the most descriptive six FDPs, explaining facial expressions best according to [12], are selected as in Figure 3.

Basically, Gabor wavelet nodes are 2-dimensional Gabor Wavelet functions. Gabor wavelet node i is shown as below. f, θ mean the size of filter and the angle of filter each, and r_x, r_y mean rotated coordinates of x,y by θ. σ_x, σ_y indicate variations of each coordinates.

$$\phi^{odd}(x,y) = g^{odd}(x,y) = \exp\{-\frac{1}{2}(\frac{r_x^2}{\sigma_x^2} + \frac{r_y^2}{\sigma_y^2})\}\sin(2\pi r_x f) \quad (1)$$

$$\phi^{even}(x,y) = g^{even}(x,y) = \exp\{-\frac{1}{2}(\frac{r_x^2}{\sigma_x^2} + \frac{r_y^2}{\sigma_y^2})\} \{\cos(2\pi r_x f) - \exp(-\frac{\sigma_x \sigma_y}{2})\} \quad (2)$$

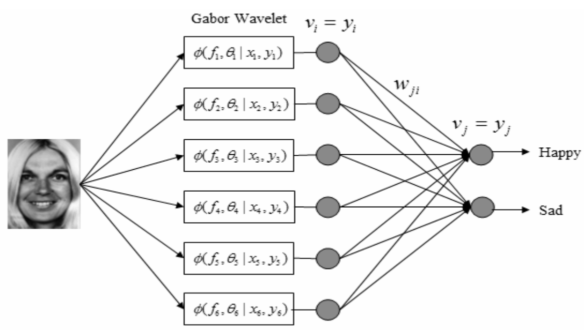


Fig. 2. Gabor Wavelet Neural Network

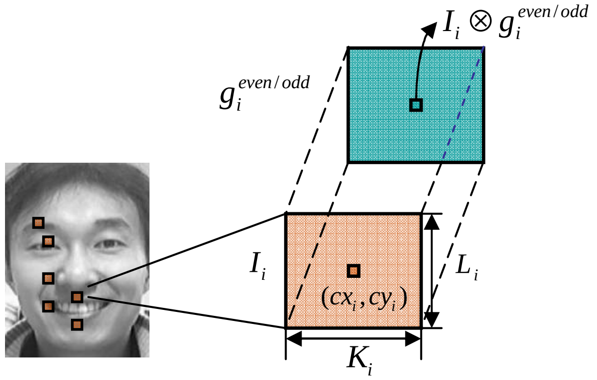


Fig. 3. Six facial points and the process of applying Gabor filter to each points (i=1,2,…6)

At the first step, each odd and even Gabor wavelet filters are applied to each feature points, which become the centers of applied area. The above Gabor wavelets' parameters f, θ are pre-learned in learning process, which will be explained at the next chapter.

Before describing the node i's output, notation $\otimes$ is defined as below.

$$I_i \otimes g_i^{even/odd} = \sum_{k=1}^{K_i} \sum_{l=1}^{L_i} I_i(K_i - k, L_i - l)\, g_i^{even/odd}(k,l)$$

$$(\text{where } i = 1,2,3,4,5,6) \qquad (3)$$

In the equation (3), K_i and L_i denote the size parameters of 2-D Gabor wavelet Filter. I_i is a partial 2D image which is applied to i-th Gabor filter and g is the Gabor filter corresponding to image. It means the summation of the product of the each component of 2D input image and 2D Gabor wavelet. The size of I_i, g are $K_i \times L_i$. This stage is the same as one step of the 2D convolution at the center point of input image.

Then, both even and odd Gabor filters' output can be computed as follows.

$$G_i^{even} = I_i \otimes g_i^{even}, \quad G_i^{odd} = I_i \otimes g_i^{odd} \qquad (4)$$

Using the equation (4), we can get the output of i-th Gabor filter and finally get the output of each i-th Gabor node in normalizing manner.

$$v_i = y_i = \frac{\sqrt{\left|G_i^{even}\right|^2 + \left|G_i^{odd}\right|^2}}{G_i^{MAX}} \qquad (0 \le v_i, y_i \le 1) \qquad (5)$$

In the equation (5), we need the possible maximum value of i-th Gabor filter's output, denoted by G_i^{MAX}, and which can be expressed by root-sum squared of even and odd Gabor filter's maximum output.

$$G_i^{MAX} = \sqrt{\left(Max\left|G_i^{even}\right|\right)^2 + \left(Max\left|G_i^{odd}\right|\right)^2} \qquad (6)$$

Because all input images have real values between 0 and 255, we can calculate the maximum value of each Gabor filter's output after multiplying 255 by positive region of (1), (2) and multiplying 0 by negative region of (1), (2). When multiplying reversely, we can get minimum value of Gabor filter's output. However, it can be maximum value also by squaring. Therefore, the possible maximum value of i-th Gabor filter is defined as follows.

$$Max\left|G_i^{even/odd}\right| \triangleq \max\left\langle \sum_{k=1}^{m_i}\sum_{l=1}^{n_i}\left(255 \times \frac{\left[1+\operatorname{sgn}\left\{g_i^{even/odd}(k,l)\right\}\right]}{2}\right), \sum_{k=1}^{m_i}\sum_{l=1}^{n_i}\left(255 \times \frac{\left[1-\operatorname{sgn}\left\{g_i^{even/odd}(k,l)\right\}\right]}{2}\right)\right\rangle \qquad (7)$$

Through the equations (4)-(7), the calculation of i-th node's output, $v_i = y_i$, is completed. With normalizing process of the equation (6) and the equation (7), Gabor nodes' outputs can represent the degree of intensity which comes under specific frequency and angle, not a Gabor filter's raw output value itself.

In the above calculations, finally each Gabor wavelet is applied to each point. Therefore, the 6-dimensional feature vector can be obtained as follows.

$$\vec{v} = [v_1, v_2, v_3, v_4, v_5, v_6]^T \qquad (8)$$

After applying Gabor wavelets, as the second step, the coefficients of 6 points are multiplied with weights w_{ji}. Since the output nodes are used as linear functions, the $v_j = y_j$ can be obtained by the weighted sum as follows.

$$y_j = \overline{w_j} \bullet \overline{v} = \sum_{i=1}^{6} w_{ji} y_i = \sum_{i=1}^{6} w_{ji} \frac{\sqrt{\left|G_i^{even}\right|^2 + \left|G_i^{odd}\right|^2}}{G_i^{MAX}} \qquad (9)$$

where the index j means output node (j=1,2). Each output node represents each facial expression, happy and sad. In this manner we can expand to the network which classifies more than two facial expressions in the future.

In this second process, 6-dimensional feature vector are classified by decision boundary. If the first layer, Gabor layer, were well-trained, its output vector, 6-dimensional feature vector, can be linearly separable. Therefore, we can say that first layer is devoted to extract good features, and second layer is devoted to classify facial expressions.

In chapter III, this simple 2-layer network without any hidden layer will be used to reconstruct fuzzy neural network model for adaptation.

B. Learning methodology

Basically, gradient descent method is used in learning process. As a first stage, errors of output nodes and total error in batch learning are calculated as follows.

$$e_j(n) = d_j(n) - y_j(n), \quad E(n) = \frac{1}{2}\sum_{j=1}^{2} e_j^2(n)$$

$$\mathrm{E}_{total} = \frac{1}{N}\sum_{n=1}^{N} E(n) = \frac{1}{2N}\sum_{n=1}^{N}\sum_{j=1}^{2} e_j^2(n)$$

where n=1,…,N is pattern index. (10)

Derivatives of (9), (10) and $v_j = y_j$ can be turns into

$$\frac{\partial e_j(n)}{\partial y_j(n)} = -1, \quad \frac{\partial E(n)}{\partial e_j(n)} = e_j(n)$$
$$,\frac{\partial v_j(n)}{\partial w_{ji}(n)} = v_i(n) = y_i(n) \quad ,\frac{\partial y_j}{\partial v_j} = 1 \tag{11}$$

Then we can get the desired partial derivative and the updated weight.

$$\frac{\partial E(n)}{\partial w_{ji}(n)} = \frac{\partial E(n)}{\partial e_j(n)}\frac{\partial e_j(n)}{\partial y_j(n)}\frac{\partial y_j(n)}{\partial v_j(n)}\frac{\partial v_j(n)}{\partial w_{ji}(n)} = -e_j(n)y_i(n)$$
$$\frac{\partial \mathrm{E}_{total}(n)}{\partial w_{ji}(n)} = \frac{\partial \mathrm{E}_{total}(n)}{\partial E(n)}\frac{\partial E(n)}{\partial w_{ji}(n)} \tag{12}$$

$$w_{ji}^{new}(n) = w_{ji}^{old}(n) - \eta\frac{\partial \mathrm{E}_{total}(n)}{\partial w_{ji}(n)} = w_{ji}^{old}(n) - \eta\frac{1}{N}\sum_{n=1}^{N}\frac{\partial E(n)}{\partial w_{ji}(n)}$$
$$= w_{ji}^{old}(n) + \eta\frac{1}{N}\sum_{n=1}^{N} e_j(n)y_i(n) \tag{13}$$

The second learning stage is Updating Gabor Wavelet's parameters f, θ. To calculate updated parameters, we need to solve two kinds of unknown value, $(\partial E/\partial v_i)$ and $(\partial v_i/\partial f, \partial v_i/\partial\theta)$.

First, we get the first layer's derivative,

$$\frac{\partial E(n)}{\partial v_i(n)} = \frac{\partial E(n)}{\partial y_i(n)} = -\sum_{j=1}^{2} e_j(n)w_{ji}(n)$$
$$,\frac{\partial \mathrm{E}_{total}}{\partial v_i(n)} = \frac{\partial \mathrm{E}_{total}}{\partial E(n)}\frac{\partial E(n)}{\partial v_i(n)} \tag{14}$$

Next, three equations were given as follows,

$$G_i^{even}(n) = I_i(n)\otimes g_i^{even}(n), \quad G_i^{odd}(n) = I_i(n)\otimes g_i^{odd}(n)$$
$$v_i(n) = y_i(n) = \sqrt{\left|G_i^{even}(n)\right|^2 + \left|G_i^{odd}(n)\right|^2} / G_i^{MAX}(n)$$

In the above equation (4) and (5), because G_i^{MAX} can be treated as a constant for each Gabor filter, we can consider only a numerator when calculating partial derivative of first node's output, $v_i = y_i$.

Therefore, the desired partial derivative of frequency can be expressed by

$$\frac{\partial v_i(n)}{\partial f_i(n)} = \frac{1}{G_i^{MAX}(n)\sqrt{G_i^{even}(f_i(n),\theta_i(n))^2 + G_i^{odd}(f_i(n),\theta_i(n))^2}}$$
$$\cdot\left\{G_i^{even}(f_i(n),\theta_i(n))\frac{\partial G_i^{even}(f_i(n),\theta_i(n))}{\partial f_i(n)}\right.$$
$$\left. + G_i^{odd}(f_i(n),\theta_i(n))\frac{\partial G_i^{odd}(f_i(n),\theta_i(n))}{\partial f_i(n)}\right\} \tag{15}$$

In the equation (11), we do not obtain the derivatives of $G_i^{even/odd}$. However, because we have predefined and used notation $\otimes$ in the equation (3), we can get

$$\frac{\partial G_i^{even}(f_i(n),\theta_i(n))}{\partial f_i(n)} = \frac{\partial\left\{I_i(n)\otimes g_i^{even}(f_i(n),\theta_i(n))\right\}}{\partial f_i(n)}$$
$$= \frac{\partial}{\partial f_i(n)}\left\{\sum_{k=1}^{K_i(n)}\sum_{l=1}^{L_i(n)} I_i(K_i(n)-k, L_i(n)-l)g_i^{even}(k,l\mid f_i(n),\theta_i(n))\right\}$$
$$= \sum_{k=1}^{K_i(n)}\sum_{l=1}^{L_i(n)} I_i(K_i(n)-k, L_i(n)-l)\frac{\partial g_i^{even}(k,l\mid f_i(n),\theta_i(n))}{\partial f_i(n)}$$
$$= I_i(n)\otimes\frac{\partial g_i^{even}(f_i(n),\theta_i(n))}{\partial f_i(n)} \tag{16}$$

Through similar process, the update of the 'odd' part of Gabor wavelet function can be done easily. The partial derivative of Gabor function, which is the last thing we are to know, also can be obtained by simple derivative of (1) and (2) with respect to f, θ.

Now that we derive all numerical expressions of updating Gabor wavelet's parameters, we can get updated formula of f. In case of θ, all expansions are same.

$$f^{new}(n) = f^{old}(n) - \eta\frac{\partial \mathrm{E}_{total}(n)}{\partial f(n)}$$
$$= f^{old}(n) - \eta\frac{\partial \mathrm{E}_{total}(n)}{\partial E(n)}\frac{\partial E(n)}{\partial f(n)} \tag{17}$$
$$= f^{old}(n) - \frac{\eta}{N}\sum_{n=1}^{N}\frac{\partial E(n)}{\partial f(n)} = f^{old}(n) - \frac{\eta}{N}\sum_{n=1}^{N}\frac{\partial E(n)}{\partial v_i(n)}\frac{\partial v_i(n)}{\partial f(n)}$$

It can be calculated by using the equation (14), (15), (16).

III. ADAPTATION

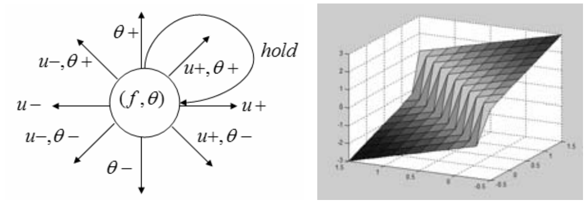
A. Phase I : Q-learning

This stage is for tuning Gabor nodes' parameters to extract features well. This phase, Q-learning, is activated only when new user's data are applied. Whenever user's data are applied, state transition occurs.

Each state has a parameter set f, θ where $u = 1/f$ (pixel), and state transition can be done by total 9 directions including 'hold' transition that means no parameter change. The schematic of state and its transitions is shown as below Figure 4-(a).

The reward consists of two parts. The first part of the reward is a response from the user, denoted by r_h. With only this part, unfortunately, the system cannot have minute adaptation capability. Therefore, we introduce the additional reward from the system itself, denoted by r_c.

Let y_1, y_2 be the values of output nodes and d_1, d_2 be the desired values of them. Then the degree of nearness from the input vector to the hyper plane can be denoted by $|y_1 - y_2|$. When the result of the system satisfies the user's



(a) State & Actions (b) Proposed Reward

Fig. 4. Q-learning

intension, the reward is $+|y_1 - y_2|$. When unsatisfying or being incorrect, the reward is $-|y_1 - y_2|$. Therefore, we can let r_c be $r_c = r_h |y_1 - y_2|$.

Now the combination of two types of reward can be introduced as follows, and showed as Figure 4-(b).

$$r = r_h + r_c = r_h + r_h |y_1 - y_2| \tag{18}$$

With this strategy, the proposed system can learn new user's features by updating Gabor Wavelets' parameters through the continuous usage of the system. However, user must provide correct response to the system during learning.

B. Phase II : Unsupervised Learning [2][3]

After first phase, the output of Q-learning is applied to the classifier that uses the unsupervised learning. In this manner, we used the improved IAFC (Integrated Adaptive Fuzzy Clustering) as the classifier [2,3]. The application to this fuzzy neural network is introduced as following steps.

First, Gabor nodes' outputs are applied to unsupervised neural network. After Input pattern is applied, as a second process, competition among output neurons occurs in a winner-take-all fashion.

$$winning\ \ neuron = \arg\min_j \| v - w_j \| \tag{19}$$

where v is the output vector of Gabor nodes which is identical to the input vector of this algorithm, w_j is weight vector related to the j-th output node.

As a third process, this algorithm, performs the vigilance test according to the vigilance criterion.

$$e^{-\gamma u_i} \| x - v_i \| \le T$$

where $$u_i = \left[\frac{1}{\| x - v_i \|^2} \right]^{\frac{1}{m-1}} \Big/ \sum_{j=1}^{n} \left[\frac{1}{\| x - v_i \|^2} \right]^{\frac{1}{m-1}} \tag{20}$$

In the above equation (20), u_i becomes closer to 1 as x approaches to the weighting of the i-th cluster.

If the winning cluster satisfies the vigilance criterion, the centroids of all clusters are updated regardless of winning or losing. However, if it fails the vigilance test, the input data is registered as the weight of a new cluster. The updating equation is introduced as follows.

$$v_i^{(new)}(n+1) = v_i^{(old)}(n) + f(l) u_i^2(n) \Pi(x, v_i(t), T)(x - v_i^{(old)}) \tag{21}$$

where $f(l) = 1/[k(l-1)+1]$ (k is constant, l is iteration index) , which is the decreasing function as time goes by, and π-function is defined as

$$\Pi(x, v_i(t), T) = \begin{cases} 1 - 2\left(\frac{\| x - v_i \|}{T}\right)^2 & 0 \le \| x - v_i \| \le \frac{T}{2} \\ 2\left(1 - \frac{\| x - v_i \|}{T}\right)^2 & \frac{T}{2} \le \| x - v_i \| \le T \\ 0 & \| x - v_i \| \ge T \end{cases}$$

V. TEST AND RESULTS

We used 30 images of FACS (Facial Action Coding System) DB in learning stage[12]. The learning process is done by using two emotional expressions from FACS DB. To show the system's general performance and adaptation capability, test data from two individuals were used. These data are collected by PC-CAM in realistic circumstance. The specification of each test DBs are listed as Table 1.

In the initial learning stage, 30 facial expressions of EKMAN DB were used. To get generalized performance, training data, EKMAN DB, consist of face images of various people.

Table 2 shows simulation results. In initial learning of GWNN, learning error of training data, EKMAN DB, is 0.07 and recognition rate is 100.0%. When tested other user's data, USER #1, the success rate is 100.0%. Therefore, adaptation process does not necessary. However, for data of USER #2, the success rate is 87.5% (98.3% for 'happy' expression and 76.7% for "sad" expression). In this case, adaptation process is activated, then the system performs Q-learning to tune the Gabor filters' parameter. At the end of Phase I, the success rate is improved to 89.15% (98.3% for 'happy' expression and 80.0% for "sad" expression). In this process, Gabor filters' parameter is slightly tuned, then the recognition rate of "sad" expression is improved. After the last process, Phase II, the recognition rate is more increased to 93.35% (90.0% for 'happy' expression and 96.7% for "sad" expression).

Table 1. Training DB and Test DBs

	EKMAN DB	USER #1	USER #2
Happy	15	53	60
Sad	15	61	60
Total	30	114	120

Table 2. Simulation Results

	Initial learning	Adaptation Process	
		Phase I	Phase II
USER#1 DB	100.0 %		
USER#2 DB	87.5 %	89.15 %	93.35 %

VI. CONCLUSION

A Gabor Wavelet Neural Network-based Facial Expression Recognition system has been presented, and its adaptation process using Q-learning and the improved IAFC has been proposed. Though previous researches considered the each feature and the interconnection among features by using various algorithms and various structures, they did not consider fundamental problem, the stage of feature extraction.

If the system extracts features well regardless of users or the system continues to tune feature extraction process to adapt to user, it will not need to use complex network structure in classifying facial expressions. In this manner, our proposed system has three contributions. First, it integrates the process of extracting features and classifying facial expressions on the basis of Gabor Wavelet Neural network with normalization scheme. Second, because it has simplified the structure of 2-layer network, it can be reorganized to clustering network enabling us to use it in an unsupervised manner. Third, the recognition rate can be improved when unlearned new user continues to use the system using adaptation process. Therefore, it allows us to realize Human-Computer Interaction in a small-sized system, for example, handheld PDA, toy robot and so on. Also, it learns personal user's facial expressions without any supervised learning method.

To verify the usability of the proposed system, classification of two facial expressions ('happy' and 'sad') were considered in this paper. This system, however, was designed as a general way to classify various facial expressions more than two expressions. Therefore, no matter how many expressions we classify, the only thing to do is increasing the number of feature points and the number of output nodes which represents facial emotional expressions.

VII. ACKNOWLEDGEMENT

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