Feature Extraction Based on GRFs for Facial Expression Recognition

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요 약 본 논문에서는 화상자료의 특성인 이웃 화소간의 종속성을 표현하는데 적합한 깁스분포를 바탕으로 얼굴 표정을 인식을 위한 특징벡터를 추출하는 새로운 방법을 제안하였다. 추출된 특징벡터는 얼굴 이미지의 크기, 위치, 회전에 대하여 불변한 특성을 갖는다. 얼굴 표정을 인식하기 위한 알고리즘은 특징벡터 추출하는 과정과 패턴을 인식하는 두 과정으로 나뉘어진다. 특징벡터는 얼굴 화상에 대하여 추정된 깁스분포를 바탕으로 수정된 2-D 조건부 모멘트로 구성된다. 얼굴 표정인식 과정에서는 패턴인식에 널리 사용되는 이산형 HMM를 사용한다. 제안된 방법에 대한 성능평가를 위하여 4가지의 얼굴 표정 인식 실험을 Workstation에서 실험한 결과, 제안된 얼굴 표정 인식 방법이 95% 이상의 성능을 보여주었다.

Abstract In this paper we propose a new feature vector for recognition of the facial expression based on Gibbs distributions which are well suited for representing the spatial continuity. The extracted feature vectors are invariant under translation, rotation, and scale of an facial expression image. The Algorithm for recognition of a facial expression contains two parts: the extraction of feature vector and the recognition process. The extraction of feature vector are comprised of modified 2-D conditional moments based on estimated Gibbs distribution for an facial image. In the facial expression recognition phase, we use discrete left-right HMM which is widely used in pattern recognition. In order to evaluate the performance of the proposed scheme, experiments for recognition of four universal expressions (anger, fear, happiness, surprise) was conducted with facial image sequences on Workstation. Experiment results reveal that the proposed scheme has high recognition rate over 95%.

1. Introduction

Human-computer interaction will be much more effective if a computer know the emotional state of human. The facial expression recognition has been studied in a wide range of fields such as engineering, psychology, anthropology, cosmetology, making it one of the important multi-disciplinary research topic [1]. But it is difficult to categorize facial expression due to the fact that the face exhibits identity of its owner and facial expression is related to one's emotion.

Many researchers have attempted to recognize facial expression problem using variety techniques in order to raise the recognition rate. Facial expressions are reflected by the deformation and displacement of facial features and facial skin.

Mase[2] used optical flow to estimate the facial skin movements. Yacoob and Davis[3] developed a system based on Mase's work. Mase attained an accuracy of nearly 80% to recognize four expressions: happiness, anger, disgust, surprise. Yacoob and Davis achieved an accuracy of 88% to recognize the six universal facial expressions: anger, disgust, happiness, surprise, fear and sadness.

Rabiner *et al.*[4] completed the theories of speech recognition using HMM. Sakaguchi[5] first experienced the effectiveness of employing discrete HMM in facial expression recognition according to image sequences. The feature they used is the

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average power from a distinct frequency band obtained by applying the Wavelet transformation. They obtained 87% recognition rate in user independent mode using 46 image sequences. Tian *et al.*[6] recently proposed a feature- based method using geometric facial features. The extracted facial regions(mouth, eyes, brows and cheeks) are represented with geometric parameters which are then fed into a neural network for recognition. However, their performance for recognizing facial expression is poor since the features did not included spatial continuity(or causality) which is the dependence of the pixel value at a lattice point on the those of its neighbors.

The success of facial expression recognition in given application depends on how good the extracted features fits the characteristics of an facial expression image. An essential issue in the field of facial expression recognition is to find features regardless of their positions, size, and orientations. Moments are invariant under scaling, shifting, and rotation. Finding efficient invariant features is the key to solving this problem. In other words, selection of "good" features is a crucial step in the process. "Good" features are those satisfying the following requirements: (i)small interclass invariance, and (ii) large interclass separation. These features (or shape descriptors) may be divided into five groups as follows[7,8]: moment invariants, transform coefficient features, visual features, algebraic features and differential invariant features.

Moments and functions of moments have been extensively employed as the invariant global features of an image in pattern recognition, image classification, target identification, and scene analysis[9, 10, 11, 12]. Generally, these features are invariant under image translation, rotation, scale change, and rotation only when they are computed from the original non- distorted analog two dimensional image.

In order to overcome the drawback of their facial expression recognition, we propose a new feature vector for recognition of the facial expression based on Gibbs distributions which are well suited for representing the spatial continuity. The extracted feature vectors are comprised of 2-D conditional moments which are invariant under translation, rotation, and scale of an facial expression image. The Algorithm for recognition of a facial expression contains two parts: the extraction of feature vector and the recognition process. In our method, LBG (Linde Buzo and Gray) algorithm is employed for vector quantization and Discrete HMM for recognition. We have tested the recognition effectiveness of original moment invariants with four universal expressions which is anger, fear, happiness and surprise shown in Figure 1.

Anger Fear Happiness Surprise

Figure 1. Different expressions used in recognition.

2. Gibbs Distribution for Facial Expression Image

In this section, we present a particular class of Gibbs distribution(GD) which is suited for describing a facial expression image. We focus our attention on discrete 2-D random fields defined over a finite $N_1 \times N_2$ rectangular lattice of points as $L = \{(x, y) : 1 \leq x \leq N_1,\ 1 \leq y \leq N_2\}$.

Suppose $Q = \{q_{xy}\}$ represents a facial image, where q_{xy} measures the grey-level(or intensity) of the pixel in the x^{th} row and y^{th} column. Let η be neighborhood system defined over the finite L. A random field $Q = \{Q_{xy}\}$ on L has Gibbs distribution or equivalently is a Gibbs Random Field(GRF) with respect to η if and only if its joint distribution is of the form[13, 14]

$$P(Q=q) = \frac{\exp\{-Energy\ function\}}{\{Partition\ function\}} = \frac{\Sigma_q \exp\{-E(q)\}}{\exp\{-\Sigma_{c \in C} V_c(q)\}} \quad (1)$$

where c is a clique, and C is the set of all cliques of a lattice-neighborhood pair (L, η); and $V_c(q)$ is the potential associated with clique c, arbitrary except for the fact that it depends only on the restriction of q to c. Let η^m be the mth order neighborhood system. The GD characterization in some applications provides a more workable spatial model. We assume that the random field Q consists of binary-valued discrete random variables $\{Q_{xy}\}$ taking values in $\Omega = \{\omega_1, \omega_2\}$.

To define GD it suffices to specify the neighborhood system η, the associated cliques, and the clique potentials $V_c(q)$'s. Assume that the random field is homogeneous.

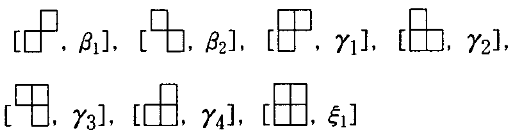

Figure 2. The parameters associated with clique types.

The distribution is specified in terms of the second order neighborhood system η^2. Figure 2 shows the parameters associated with clique types, except for the single pixel clique. The clique potentials associated with η^2 are defined as follows

$$V_c(q_{xy}) = \begin{cases} -\zeta & \text{if all } q_{xy}\text{'s in c are equal} \\ \zeta & \text{otherwise} \end{cases} \quad (2)$$

where ζ is the parameter specified for the clique type c. For the single pixel cliques, the clique potential is defined as

$$V_c(q_{xy}) = \alpha_k \text{ for } q_{xy} = \omega_k. \quad (3)$$

The parameters α_k control the percentage of pixels in each site, that is the marginal distribution of the single random variables Q_{xy}'s, while the other parameters control the size and direction of clustering.

3. Estimation and 2-D Conditional Moment

In this section, we describe a method for estimating parameter of Gibbs distributed facial image. And then we extract feature vector which consists of the calculated 2-D conditional moments. These feature vectors are invariant under image translation, rotation, size, and rotation for an facial expression image.

3.1 Parameter Estimation

Our aim is to estimate the parameters of Gibbs distribution of a facial image. The most commonly used parameter estimation method to date is the so-called "coding method," first presented by Besag[15]. It requires the solution of a set of nonlinear equations. Therefore, it is cumbersome and difficult to use reliably. In view of the practical difficulties involved in using the coding method [10, 16], we describe an alternative parameter estimation scheme for finite range space GRF.

Suppose Q is a GD with a discrete range space of $\Omega = \{\omega_1, \omega_2\}$. . A realization q of this random field is available to be used in estimating the parameters of the distribution. For convenience of notation, let s represent q_{xy} and t' represent the vector of the neighboring values of q_{xy}, that is, $t' = [u_1, u_2, u_3, u_4, v_1, v_2, v_3, v_4]^T$, where the location of u_i's and v_i's with respect to s are shown in Figure 3.

v_1	u_2	v_2
u_1	s	u_3
v_4	u_4	v_3

Figure 3. q_{xy} and η_{xy}.

We define indicator functions

$$I(z_1, z_2, \ldots, z_k) = \begin{cases} -1 & \text{if } z_1 = z_2 = \cdots = z_k \\ 1 & \text{otherwise} \end{cases} \quad (4)$$

and

$$J_m(s) = \begin{cases} -1 & s = \omega_m \\ 0 & \text{otherwise.} \end{cases} \quad (5)$$

We can express the potential functions of the GD in terms of these quantities. Let $V(s,\ t',\ \theta)$ be the sum of the potential functions of all the cliques that contain (x, y), the site of s. That is $V(s, t', \theta) = \Sigma_{c s \in C} V_c(q)$ where θ is the parameter vector $\theta = (\alpha_1, \alpha_2, \beta_1, \beta_2, \quad \gamma_1, \gamma_2, \gamma_3, \gamma_4, \xi_1)$. Using the clique potentials for this class of GD we can write $V(s, t', \theta)$ as $V(s, t', \theta) = \rho^T\ (s, t')\theta$ where

$$
\begin{aligned}
\rho(s,t) = [&J_1(s), J_2(s), \\
&(I(s, v_2) + I(s, v_4)), (I(s, v_1) + I(s, v_3)), \\
&(I(s, u_2, v_2) + I(s, u_4, u_3) + I(s, u_1, v_4)), \\
&(I(s, u_4, u_3) + I(s, u_2, u_3) + I(s, u_1, v_1)), \\
&(I(s, u_2, v_1) + I(s, u_1, u_4) + I(s, u_3, v_3)), \\
&(I(s, u_1, u_2) + I(s, u_4, v_4) + I(s, u_3, v_2)), \\
&(I(s, u_1, v_1, u_2) + I(s, u_2, v_3, u_3) \\
&+ I(s, u_3, v_3, u_4) + I(s, u_4, v_4, u_1))]^T.
\end{aligned} \tag{6}
$$

Now Suppose $P(s|t')$ is the joint distribution of the random variables on the 3×3 window centered at (x, y) and $P(t')$ is the joint distribution of the random variables on η_{xy} only. Then the conditional distribution $P(s|t')$ is given by the ratio of $P(s, t')$ to $P(t')$. It follows from the GRF-MRF equivalence and the resulting local characteristic that

$$
\frac{e^{-V(s, t', \theta)}}{P(s, t')} = \frac{Z(t', \theta)}{P(t')} \tag{7}
$$

where $Z(t', \theta)$ is the appropriate normalizing constant.. Note that the right-hand side of (7) is independent of s. Considering the left-hand side of (7) for any two distinct values of s, e.g., $s = j$ and $s = k$, we have

$$
(\rho(k, t') - \rho(j, t'))^T \theta = \ln \frac{P(j, t')}{P(k, t')} \tag{8}
$$

where $\rho^T(k,\ t')\theta = V(k,\ t', \theta)$. Consideration of all possible triplets (j, k, t'), $j < k$, generates from equation (8) a large set of linear equations, which may be solved for θ by least squares procedures. The question that remains to be answered, now, is how to determine or estimate $P(s, t')$ for all (s, t') combinations using a single or a few realizations. We will calculate the probability $P(s, t')$ using histogram techniques.

3.2 Calculation of 2-D Conditional Moments

The basic and classical moment, a regular 2-D moment of order $(k+l)$ is defined by[7, 14]

$$
m_{kl} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^k\ y^l\ f(x, y), \tag{9}
$$

where $f(x, y)$ is the intensity at a point (x, y) in the image and $k,\ l = 0, 1, 2, \cdots$. The moments proposed by many researchers[12, 14, 16, 17, 18] have not included spatial information which is the characteristic of most facial images. Two dimensional $(p+q)th$ order central moment of a density distributed function $f(x, y)$ is defined as follows:

$$
\mu_{kl} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \bar{x})^k\ (y - \bar{y})^l\ f(x, y) dx dy \tag{10}
$$

where $\bar{x} = m_{10}/m_{00}$, $\bar{y} = m_{01}/m_{00}$. Central moments and their function are invariant under shifting. Here the details of deriving moment invariants will not be discussed. The moment invariants we have used in our facial expression recognition system are given by Hu[16]:

$$
\begin{aligned}
I_1 &= (\mu_{20}\mu_{02} - \mu_{11})^2 / \mu_{00}^3 \\
I_2 &= \frac{[(\mu_{30}\mu_{03} - \mu_{21}\mu_{12})^2 - 4(\mu_{30}\mu_{12} - \mu_{21}^2)(\mu_{21}\mu_{03} - \mu_{12})^2]}{\mu_{00}^7} \\
I_3 &= \frac{\mu_{20}(\mu_{21}\mu_{03} - \mu_{12})^2 - \mu_{11}(\mu_{30}\mu_{03} - \mu_{21}\mu_{12})}{\mu_{00}^5} \\
&\quad + \frac{\mu_{02}(\mu_{30}\mu_{12} - \mu_{21}^2)}{\mu_{00}^5} \\
I_4 &= [\mu_{30}^2\mu_{02}^3 - 6\mu_{30}\mu_{21}\mu_{11}\mu_{02}^2 + 6\mu_{30}\mu_{12}\mu_{02}(2\mu_{11}^2 - \mu_{20}\mu_{02}) \\
&\quad + \mu_{30}\mu_{03}(6\mu_{20}\mu_{11}\mu_{02} - 8\mu_{02}^2) + 9\mu_{21}^2\mu_{20}\mu_{02}^2 \\
&\quad - 18\mu_{21}\mu_{12}\mu_{20}\mu_{11}\mu_{02} + 6\mu_{21}\mu_{03}\mu_{20}(2\mu_{11}^2 - \mu_{20}\mu_{02})^2 \\
&\quad + 9\mu_{12}^2\mu_{20}^2\mu_{02} - 6\mu_{12}\mu_{03}\mu_{11}\mu_{20}^2 + \mu_{03}^2\mu_{20}^3] / \mu_{00}^7
\end{aligned} \tag{11}
$$

An an alternative to cope in the lack of spatial continuity the above ordinary moments, we propose a method for calculating 2-D conditional moments which include spatial information by using the estimated conditional Gibbs distribution. The corresponding 2-D conditional moments are given by the following steps.

● Step 1) Calculate the centroids $\bar{x}, \bar{y}$ of the considered shape as follows.

$$\bar{x} = \Sigma_{x=1}^{N_1} \Sigma_{y=1}^{N_2} x \cdot \hat{P}(Q_{xy} = q_{xy} | \eta_{xy})$$
$$\bar{y} = \Sigma_{y=1}^{N_2} \Sigma_{x=1}^{N_1} y \cdot \hat{P}(Q_{xy} = q_{xy} | \eta_{xy}) \quad (12)$$

where $\hat{P}(Q_{xy} = q_{xy} | \eta_{xy})$ is estimated conditional probability of the site (x, y).

● Step2) Calculate the standard deviation σ_x and σ_y.

$$\sigma_x = \sqrt{\{\Sigma_{x=1}^{N_1} \Sigma_{y=1}^{N_2} (x - \bar{x})^2 \hat{P}(Q_{xy} = q_{xy} | \eta_{xy})\}}$$
$$\sigma_y = \sqrt{\{\Sigma_{y=1}^{N_2} \Sigma_{x=1}^{N_1} (y - \bar{y})^2 \hat{P}(Q_{xy} = q_{xy} | \eta_{xy})\}} \quad (13)$$

● Step3) Calculate and Store the 2-D conditional moments for (k, l)

$$S_{kl} = \Sigma_{x=1}^{N_1} \Sigma_{y=1}^{N_2} \left(\frac{x - \bar{x}}{\sigma_x}\right)^k \left(\frac{y - \bar{y}}{\sigma_y}\right)^l \hat{P}(Q_{xy} = q_{xy} | \eta_{xy}) \quad (14)$$

The above moments are invariant under translation, magnification, and rotation of the image, but not under rotation. It is desired feature vectors do not change under scaling, shifting and rotation. In order to use them as feature vector in the facial expression recognition phase, we have to normalize respect to the rotation. The normalization is a simple operation, $s_{kl} \cdot e^{-j\phi}$, where ϕ is the rotation change of the facial image.

Facial expressions are caused by facial muscle action. The actions of facial muscles change not only the shape of facial features but also their relative positions. So, displacement information in facial expression recognition, such as the relative position of brow and eye and left and right mouth corner, benefits distinguishing between different facial expressions. In order to utilize the relative position change between facial features, we replace central moments in the formula of moment invariants with ordinary moments, thereby modifying the feature vectors. The elements of modified feature vector are as follows:

$$\pi_1 = (S_{20} S_{02} - S_{11})^2 / S_{00}^3$$
$$\pi_2 = \frac{[(S_{30} S_{03} - S_{21} S_{12})^2 - 4(S_{30} S_{12} - S_{21}^2)(S_{21} S_{03} - S_{12})^2]}{S_{00}^7} \quad (15)$$
$$\pi_3 = \frac{[S_{20}(S_{21} S_{03} - S_{12})^2 - S_{11}(S_{30} S_{03} - S_{21} S_{12})}{S_{00}^5} + \frac{S_{02}(S_{30} S_{12} - S_{21}^2)]}{S_{00}^5}$$
$$\pi_4 = [S_{30}^2 S_{02}^3 - 6 S_{30} S_{21} S_{11} S_{02}^2 + 6 S_{30} S_{12} S_{02}(2 S_{11}^2 - S_{20} S_{02}) + S_{30} S_{03}(6 S_{20} S_{11} S_{02} - 8 S_{02}^2) + 9 S_{21}^2 S_{20} S_{02}^2 - 18 S_{21} S_{12} S_{20} S_{11} S_{02} + 6 S_{21} S_{03} S_{20}(2 S_{11}^2 - S_{20} S_{02})^2 + 9 S_{12}^2 S_{20}^2 S_{02} - 6 S_{12} S_{03} S_{11} S_{20}^2 + S_{03}^2 S_{20}^3] / S_{00}^7$$

4. Feature Extraction and Classification

We construct a feature vector for recognition of facial expression and briefly review HMM as facial expression recognition method in this section.

We define seven areas on the face for feature extraction. They are left brow, left eye, right brow, right eye, upper mouth, lower mouth and the area between two eyes. Each area we define is of rectangular shape. We denote left brow, left eye, right brow, right eye, upper mouth, lower mouth and the area between two eyes as area 1, 2, 3, 4, 5, 6, and 7 respectively. The sizes and centers of the rectangulars are adjusted so that each rectangular shape can exactly enclose the whole facial features in every frame of a sequence. The definition of feature extraction areas is shown in Figure 4. The feature vectors are as follows:

$$V_1 = [I_{ij}], \quad 1 \le i \le 7, \quad j = 1, 2, 3, 4$$
$$V_2 = [\pi_{ij}], \quad 1 \le i \le 7, \quad j = 1, 2, 3, 4 \quad (16)$$

where i is the number of the area, j is the number of moment invariants.

Figure 4. Definition of feature extraction areas.

When calculating moment invariants, selection of coordinate origins does not influence the results. While calculating the proposed modified feature vectors, the results vary with the change of origins. In the case of the sequences we have the relative positions of two pupils keep in the same place on the face if the subject doesn't move them deliberately. Therefore, we choose the centers of pupils as reference. We define them as the origins for calculating ordinary moments of brow areas and eye areas.

They can reflect not only the deformation of brows and eyes but also the relative position change of brows and eyes. In order to represent the deformation of upper mouth and lower mouth most efficiently, the middle of the line connecting left mouth corner and right mouth corner is selected as the origin for calculating ordinary moments of left mouth corner area

and right mouth corner area For nose area, according to the experiment results, we choose the middle of lower bound of the area as origin.

we use a scaling factor α to balance the values of I_1, I_2, I_3, I_4 and $\pi_1, \pi_2, \pi_3, \pi_4$ since the differences of the ranges of I_1, I_2, I_3, I_4 and $\pi_1, \pi_2, \pi_3, \pi_4$ are large. The definition of α is, $\alpha = [\alpha_i]$, $1 \le i \le k$, where i is the number of elements of the feature vector. Every element of the feature vector is divided by the corresponding element of α. We also improve the VQ and recognition results by adjusting α The feature vector of each frame subtracted from that of the first frame which is of neutral state. The resultant feature vector reflects the deformation and displacement of facial features. They are used in the recognition system. The sample of a surprise sequence and a happiness sequence are shown in Figure 5.

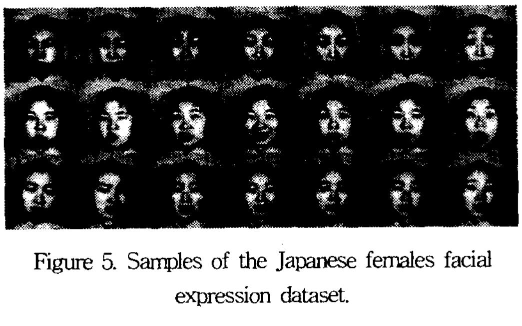

Figure 5. Samples of the Japanese females facial expression dataset.

We use discrete left-right HMM for recognition. The HMM having 3 states and 32 symbols has best recognition accuracy. The structure of the HMM is shown in Figure 6.

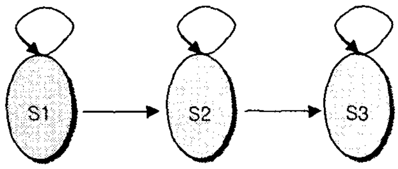

Figure 6. Structure of HMM used for facial expression recognition.

LBG algorithm is employed for VQ. The techniques of applying HMM introduced by L. R. Rabiner *et al.*[4] are used for training HMM and recognition.

5. Experimental Results

In order to illustrate the performance of the proposed a new scheme for recognizing facial expression, we carried out the following experiments was carried out.

The database of the facial expression has 310 image sequences taken from 10 subjects. They are 50 of anger, 70 of fear, 90 of happy and 100 surprise. We use 20 anger, 40 fear, 40 happy and 50 surprise to train the HMM.

The experiments are done under the following training HMM and recognition. The experiments are done under the following conditions: (a) Only the frontal view of the facial image sequences are analysed throughout the whole sequence. (b) The head motion between two consecutive frames is considered small. (c) The subjects are not speaking during image capturing. (d) The subjects do not have facial hair and they are not wearing glasses. The overall block diagram of the proposed method for recognizing facial expression are shown in Figure 7.

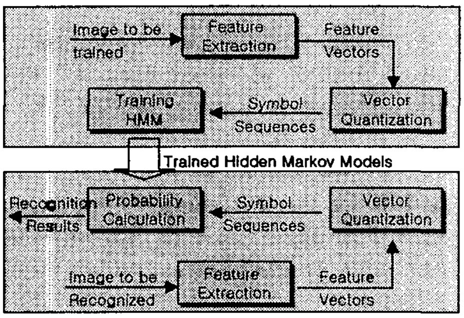

Figure 7. Overview of the proposed scheme for recognizing the facial expression.

The training sequences of each facial expression are composed of half males' and half females'. Our experiments include three parts: (a) Using ordinary moment invariants as feature vector, (b) Using 2-D conditional moment invariants as feature vector, (c) Combining ordinary moment invariants and modified moment invariants as feature vector. The recognition results of using ordinary moment invariants and modified moment invariants are shown in Table 1 and Table 2 respectively. From the results, we can see that the performance of facial expression recognition using the modified moment invariants was shown to be superior to that using ordinary moment invariants.

<Table 1> Recognition results with ordinary moment

	Anger	Fear	Happy	Surprise	Total
Anger	22	2	0	0	24
Fear	8	24	1	4	31
Happy	0	4	45	0	59
Surprise	0	0	4	46	46
Total	30	30	50	50	160

<Table 2> Recognition results with modified moment

	Anger	Fear	Happy	Surprise	Total
Anger	29	2	0	0	31
Fear	1	28	0	1	30
Happy	0	0	48	0	48
Surprise	0	0	2	49	51
Total	30	30	50	50	160

Experiment results reveal that the proposed scheme has high classification rate over 95%. In order to reduce the dimension of feature vector, we have also tested by using π_1, π_2, π_4 or π_1, π_3, π_4 as elements of our feature vector. The same recognition rate as that of using $\pi_1, \pi_2, \pi_3, \pi_4$ was attained. For further reducing the dimension of feature vector, we have tested using just two of the original four elements. The best combination is π_1, π_4. The recognition results are shown Table 3.

<Table 3> Recognition results only using π_1, π_4.

	Anger	Fear	Happy	Surprise	Total
Anger	28	1	0	0	29
Fear	0	29	0	1	30
Happy	0	0	48	0	48
Surprise	2	0	2	49	53
Total	30	30	50	50	160

Ordinary moment invariants can take the only deformation of facial features into account, while modified moment invariants can take both the deformation and displacement of facial features into account. We have tried a simple method to separate the deformations and displacements of facial features, $I_1, I_4, (\pi_1 - I_1), (\pi_4 - I_4)$, subtracting original moment invariants from modified moment invariants. We obtained the same results as those shown in Table 2.

5. Concluding Remarks

In this paper we propose a new feature vector for recognition of the facial expression based on Gibbs distributions which are well suited for representing the spatial continuity. Moment invariants proposed by Hu *et al.* can reflect the deformation of facial features but can not provide sufficient information of displacement of facial features, while the 2-D conditional feature vector reflects deformations and relative displacements of facial features. As a experimental results, we can see that the performance of facial expression recognition using the modified moment invariants was shown to be superior to that using ordinary moment invariants. That demonstrates only using deformation information of facial features is not enough for facial expression recognition. To reduce the dimension of feature vector, we have experimented just using three and two of the four modified moment invariants. We have found that using π_1, π_2, π_4 or π_1, π_3, π_4 recognition rate as high as that of using all the four can be obtained.

In the future, we will add automatic feature tracking techniques to the proposed scheme in order to get highest accuracy.

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