Pose Robust and Person Independent Facial Expressions Recognition Using AAM Selection

Tomoko Okada
Graduate School of Engineering, Kobe University
1-1 Rokkodai, Nada-ku, Kobe, Hyogo, 657-8501 Japan
Email:pekkle@me.cs.scitec.kobe-u.ac.jp

Tetsuya Takiguchi and Yasuo Ariki
Organization of Advanced Science and Technology, Kobe University
1-1 Rokkodai, Nada-ku, Kobe, Hyogo, 657-8501 Japan
Email:{takigu,ariki}@kobe-u.ac.jp

***Abstract*—Most recent facial expressions recognition systems only work well with frontal face images. However, subjects do not always face front. With this in mind, we propose in this paper a method for pose-robust facial expressions recognition. Active Appearance Models (AAMs) are used for face tracking to extract pose-robust facial feature points. However, AAM has accuracy problems with face tracking when it tracks an unknown face. To solve this problem, a method was already proposed to construct plural AAMs by clustering the training datasets and then selecting one of their AAMs that is similar to the unknown input face based on the Mutual Subspace Method (MSM). In addition to that method, we constructed models based on face direction.The experimental results showed an improvement in the accuracy of facial expressions recognition.**

I. Introduction

facial expressions recognition is vital to the field of man-machine communication to estimate the emotional state of a person. However, most of the studies are limited to frontal face images. Since a person usually moves freely in a real world, in this paper we propose, a method for pose-robust facial expressions recognition using an Active Appearance Model (AAM) [1] to solve this problem. AAM is used in many applications, such as body part tracking. In particular, it is useful for pose-robust face tracking. However, AAM has a problem because person-independent face tracking is difficult due to the fact that, an AAM constructed by training data that includes many subjects loses the individual face characteristics, resulting in inadequate face tracking. To solve this problem, a method [2] was proposed to construct plural AAMs by clustering the training datasets and selecting one of the AAMs that is similar to the unknown input face based on MSM [3]. In this paper, we propose a method to select an AAM based on not only the similarity with the unknown input face but also the similarity of the face direction in order to improve the accuracy of the facial expressions recognition.

II. Overview of the proposed system

Fig. 1 shows the flow of our facial expressions recognition system. At first, exact face regions are extracted from the input face image sequence by AdaBoost based on Haar-like features. Next, the most appropriate AAM (for discrimination, we define it as AAM1), which was constructed in advance by clustering the training data using MSM, is selected for the input facial image sequence based on the degree of similarity in facial features using MSM. The conventional method [2] applied the MSM to the face regions tracked on the input facial image sequence by an AAM which was trained in advance using all the training data. Instead, our system applies the MSM to the face regions extracted by AdaBoost on the input facial image sequence in order to reduce computation time and cluster seledction erros. After this, the most appropriate AAM (for discrimination, we define it as AAM2) is selected based on the face direction computed by tracking the input image sequence using the previously selected AAM1. Next, facial feature points are extracted using the AAM2, and the frontal view facial images were generated by computing the face direction more precisely. View-based AAM [4] is used for generating frontal view face images. Finally, the subject's facial expressions is recognized by the classifier, Support Vector Machines (SVMs).

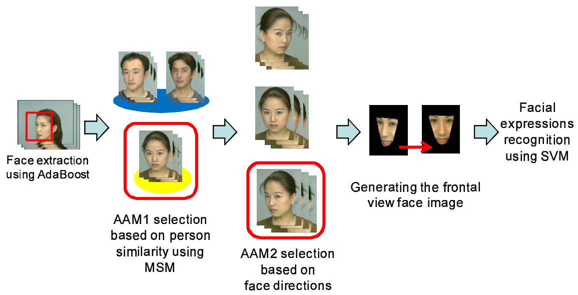

Fig. 1. The flow of the proposed method

III. Generating frontal view face images

Generating frontal view face images makes it possible to recognize facial expressions in any face directions and to reduce the amount of training data. Two characteristics of the model vecter C, which is obtained by AAM, are used. One is that the low component of C contains information about the face direction. The other is that the face direction θ and the model parameters C are highly correlated with each other [4]. This is described as follows:

$$C = C0 + C1 * \theta \quad (1)$$

that $C0$ and $C1$ are constant vectors which are learned from the training data using the least square method. Given a face image with a parameter C', we can estimate the face direction θ' as follows.

$$\theta' = (C' - C0)/C1 \quad (C1 \neq 0) \tag{2}$$

After estimating the face direction θ', the residual vector C_{res} is also estimated:

$$C_{res} = C' - (C0 + C1 * \theta') \tag{3}$$

To generate frontal view face images, the frontal direction namely, θ = 0, is given to the formula (3):

$$C_{front} = C0 + C_{res} \tag{4}$$

Thus, we can generate the frontal view images using the above C_{front}.

IV. Selecting the model

This section describes how to select the most appropiate model (AAM1) based on the degree of facial similarity and the most appropriate model (AAM2) based on face direction. To select the model (AAM1), MSM, which computes the similarity between persons, is used. In advance, all the training images of all the persons included in the database are clustered into k-classes using the k-means method. For each class, the AAM is constructed. The model (AAM1) is selected based on the similarity computed by the MSM between the input face image sequence and the training data of k-classes. In our experiment, we set k to 2. Three directional-AAM models (right, front, and left) are constructed in advance by grouping the face directions from -$45°$ to $45°$ into three classes (right, front, left). The appropriate model (AAM2) is selected according to the face direction estimated by the AAM1. For example, when the estimated face direction is $40°$, we select the right model as the most appropriate model.

V. Experiments

A. Experimental conditions

To evaluate the facial expressions performance of the proposed method, we used the ATR Facial Expression Image Database [5]. Four different facial expressions (neutral, happy, sad and angry) were recognized. Each expression consisted of seven different poses ($\pm 45°$, $\pm 30°$, $\pm 15°$ and front) as shown in Fig. 2. The image size was 320×240 pixcels. The number of subjects was nine persons, and leave-one-out cross-validation was carried out.

B. Experimental results

The results of facial expressions recognition (F value) are shown in Table I and Table II. Table I shows the comparison of the three models; α (result using AAM), β (result using unselected AAM), γ (result using the AAM constructed using all the training data except the subject). Table II shows the results in terms of test images face direction. In the experiments we carried out, the conventional method [2] and the proposed method were compared. The proposed method includes model selection based on the face direction. It can be seen from Table I that model selection based on the face direction is

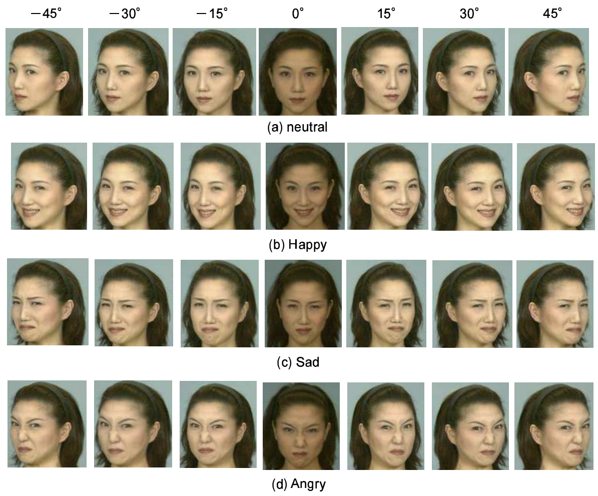

Fig. 2. Examples of the face images

effective, especially in the case ofα using the selected AAM1. Additionally, from Table II, it can be seen that the proposed method is much more effective than the conbentional method for face direction of $\pm 45°$, and showed pose robustness for all of the face directions.

TABLE I
THE RESULT OF THE MODEL COMPARISON (F VALUE)

The type of models	α	β	γ
Conventional method	0.74	0.65	0.70
Proposed method	0.81	0.73	0.74

TABLE II
THE RESULT IN TERMS OF FACE DIRECTION OF TEST IMAGES(F VALUE)

Face direction(○)	-45	-30	-15	0	15	30	45
Conventional method	0.58	0.70	0.75	0.80	0.79	0.80	0.46
Proposed method	0.67	0.75	0.76	0.82	0.80	0.81	0.67

VI. Conclusion

In this paper, we proposed a pose-robust and person-independent facial expressions recognition method that selects a model based on the face direction. As shown by the facial expressions recognition experimental redults, we improved the accuracy compared with the conventional method. In the future, we will study feature value and improve the accuracy of the facial expressions recognition.

References

[1] T. F. Cootes, G. J. Edwards and C. J. Taylor, *Active appearance models*, ECCV, volume 2, pp. 484-498, 1998.

[2] Akihiro Kobayashi, Junji Satake, Takatsugu Hirayama, Hiroaki Kawashima, and Takashi Matsuyama, *Person-Independent Face Tracking Based on Dynamic AAM Selection*, CVIM, No.3, pp. 35-40, 2008.

[3] K. Maeda and S.Watanabe, *A pattern matching method with local structure*, ECCV, volume 2, pp. 484-498, 1998.

[4] T. F. Cootes, K. Walker, C. J. Taylor, *View-based active appearance models*, Image and Vision Computing 20, pp. 227-232, 2002.

[5] ATR-Promotions, *ATR Facial Expression Image Database (DB99) (Contents of License)*.