Recognition of Facial Action Units with Action Unit Classifiers and An Association Network

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Abstract. Most previous work of facial action recognition focused only on verifying whether a certain facial action unit appeared or not on a face image. In this paper, we report our investigation on the semantic relationships of facial action units and introduce a novel method for facial action unit recognition based on action unit classifiers and a Bayes network called Facial Action Unit Association Network (FAUAN). Compared with other methods, the proposed method attempts to identify a set of facial action units of a face image simultaneously. We achieve this goal by three steps. At first, the histogram of oriented gradients (HOG) is extracted as features and after that, a Multi-Layer Perceptron (MLP) is trained for the preliminary detection of each individual facial action unit. At last, FAUAN fuses the responses of all the facial action unit classifiers to determine a best set of facial action units. The proposed method achieves a promising performance on the extended Cohn-Kanade Dataset. Experimental results also show that when the individual unit classifiers are not so good, the performance could improve by nearly 10% in some cases when FAUAN is used.

1 Introduction

Facial expression is a very powerful and important nonverbal way for people to transmit message in daily life. Facial expression recognition has attracted an increasing attention in the past decade. Facial expressions are caused by facial muscle movements. These facial muscle movements are called facial action units. Ekman et al. [1] developed the Facial Action Coding System which was used for describing facial expressions by action units (AUs). In the 44 AUs defined, 30 AUs are anatomically related to the contractions of specific facial muscles: 12 are for upper face, and 18 are for lower face [2]. Although the number of action units is relative small, more than 7000 different AU combinations have been observed [3]. Facial action units provide an important cue for facial expression recognition.

We have witnessed much progress about facial action unit recognition. Two mainstream approaches, appearance based and geometry based [4], are widely employed to handle this problem. Bartlett et al. [5] proposed an automatic spontaneous facial action units recognition system based on Gabor filters, AdaBoost and Support Vector Machine (SVM) classifiers. They applied the AdaBoost to select Gabor filters and the outputs of the selected Gabor filters were employed to train a SVM. Valstar et al. [6] combined SVMs and hidden Markov models to model facial action temporal dynamics. In their system, a set of carefully selected geometrical features were used to separate a facial action unit into several temporal phases. They utilized an SVM and the hybrid SVM / Hidden Markov Model (HMM) as the classifiers, respectively. Senechal et al. [7] computed the Local Gabor Binary Pattern (LGBP) histograms of the neutral and expressive faces. The differences between the two histograms were used as features to train an SVM with a Histogram Difference Intersection (HDI) kernel. Simon et al. [8] introduced a segment-based SVM to detect action units. They explored two widely used models: static modeling, typically evaluated each video frame independently, and temporal modeling, typically modeling action units with a variant of dynamic Bayesian networks and integrated the benefits of the two models. The system beats state-of-the-art static methods for AU detection. Lucey et al. [9] described an active appearance model (AAM)-based system that can automatically detect the frames in videos, in which a patient is in pain. They defined the AU combinations as the pain emotion. The pain emotion was predicted through detecting the related Action Units. Tong et al. [10] analyzed the semantic relationships among AUs and proposed a novel method to handle Action Units recognition. A Dynamic Bayes network (DBN) was employed to model the relationships among different AUs. Experiments illustrated that the integration of AU relationships and AU dynamics with AU measurements could improve the performance of AU recognition. Chu et al. [11] considered that most existing Automatic Facial Action (AFA) unit detection methods neglected individual differences in target persons. They introduced a transductive learning method called Selective Transfer Machine (STM), to personalize a generic classifier by attenuating person-specific biases. The STM could learn a classifier and re-weight the training samples that were most relevant to the test subject.

However, most previous works mentioned above focused on single facial action unit recognition. In fact, facial action unit combination is very important for facial expression analysis. Each of most facial expressions consists of several facial action units. Compare with the methods which recognize facial expressions directly, facial action unit combination provides another meaningful way for facial expression recognition. Instead of verifying a single facial action unit on a face image, in this paper, we propose a method to identify the facial action unit combination of a face image. We achieve this goal through three steps, feature extraction, single AU detection and AU combination recognition. We conduct the experiments on the extend Cohn-Kanade Dataset [12] and achieve a good performance.

The rest of the paper is organized as follows. In Section 2, we describe our proposed AU combination recognition system. We report and analyze experimental results in Section 3. The paper is included in Section 4.

2 An AU Combination Recognition System

The system includes three parts. At first, the Viola-Jones face detector [13] is employed to detect the face and Histogram Oriented Gradients (HOG) are used to encode the face. After that, we train a Multi-Layer Perceptron (MLP) for each facial action unit detection. At last, on the basis of the semantic relationships of facial action units, we construct a Bayes network called Facial Action Units Association Network (FAUAN) to combine the responses of all individual facial action unit classifiers. Figure 1 shows our proposed system.

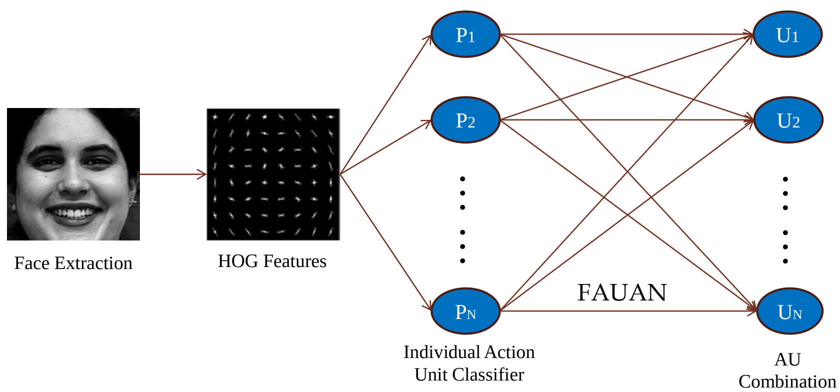


Fig. 1. Our proposed system for AU combination recognition.

2.1 Feature Extraction

Facial action units are caused by the corresponding facial muscle movements. These movements are subtle and transient. How to capture and represent these muscle movements is a long standing problem in facial expression analysis. Many different features like SIFT [14], Gabor filters [15], Local Binary Pattern (LBP) [16], Histogram Oriented Gradients (HOG) [17] and Local Phase Quantization (LPQ) [18] have been proposed for facial expression analysis. Gabor filters and LBP have been widely used for facial expression analysis. In this paper, we adopt the HOG to represent the facial images. HOG was first introduced by Dalal and Triggs in 2005 [17]. It is very popular in computer vision community and widely used in many object detection applications, especially in pedestrian detection. HOG calculates the occurrences of gradient orientations in a local patch of an image. The distribution of the local gradient intensities and orientations can describe the local object appearance and shape.

HOG is very sensitive to object deformations. After analyzing facial action units, we find that these facial action units could regard as some sorts of deformations. For example, there are several facial action units related to the lip. Such as lip stretcher, lip tightener and lip pressor etc. These facial action units are different distortions of the lip. Compared with the other feature descriptors, HOG can better characterize these facial actions. In our study, we divide the detected face regions into many overlapped small blocks. Each block includes 2×2 cells. The cell size is set to 8×8. The bin size is set to 9. There are two orientation ranges used, 0°-360° and 0°-180°. We set the orientation range to 0°-180° in our study.

2.2 Individual Facial Action Unit Classifiers

In this step, we build a visual classifier for each facial action unit. It is used to detect whether a face image containing a certain action unit.

For computer vision and pattern recognition, SVM [19] and Multilayer Perceptron(MLP) [20] are two commonly adopted classifiers and have been successfully used in many applications. In this paper, MLPs are trained as facial action unit classifiers. An MLP maps inputs to appropriate outputs through hidden layers and transform functions. In general, a supervised learning technique called back propagation [22] is utilized to train the MLP. With the hidden layer and nonlinear activition functions, MLP can discriminate the data which could not be separately linearly.

2.3 Facial Action Unit Association Network

Besides the visual features are related to facial action units, we also find that some facial action units appear together on face images. A study reported in [9] and [12] has shown that some universal expressions like happy, angry, and surprise etc. have specific sets of facial action units. It indicates that some facial action units have strong correlations. These correlations can help to recognize facial action units in groups. In [23], Fu et al. proposed a Concept Association Network (CAN) for image annotation. The CAN utilized the correlations of the concepts. Inspired by their work, we construct a Bayes network called Facial Actin Unit Association Network (FAUAN) for the recognition of facial action units in groups. Suppose that we have facial action units in the FAUAN, the appearances of action units are denoted by

$$F = (f_1, ..., f_i, ..., f_N) \tag{1}$$

where f_i denotes the number of occurrences of facial action unit i, the relationship between each pair of facial action units are defined by

$$\mathbf{W} = \{w_{ij}\}, i, j = 1, ...N \tag{2}$$

where w_{ij} is the number of co-occurrences of action unit i and j appear together on face image. With the Bayes rule, we can obtain the co-occurrence matrix among facial action units as:

$$M = \{m_{ij}, i \neq j\} = \{\frac{w_{ij}}{\sum_{k \neq j} w_{kj}}\}, i, j, k = 1, ...N \tag{3}$$

where m_{ij} denotes the occurrence frequency (an estimation of probability) of action unit i when action unit j appears.

2.4 Facial Action Unit Group Recognition with FAUAN

The FAUAN can combine the responses of individual action unit classifiers to identify which facial action unit group appears on a face image. Given a test face image, the pre-trained action unit classifiers can give a likelihood of the face image including a certain action unit:

$$\mathbf{P} = \{P_1, ...P_t, ...P_N\} \tag{4}$$

where subscript t is the index of the facial action unit, for example, P_1 means the probability of a test face image including action unit (AU)1. Because there are correlations among facial action units, when we consider an action unit in a face image, it is necessary to consider the appearance of the other action units. Based on the outputs of individual action unit classifiers and the FAUAN, we define

$$\mathbf{U} = \{U_1, ...U_k, ...U_N\} \tag{5}$$

$$U_k = P_k + \sum_{j \neq k} P_j m_{jk} \tag{6}$$

where k is the index of action unit, P is the output of individual action unit classifiers and m is the correlation coefficient of each pair of action units, defined in Eq. (3). U is the final output. Using Eq. (6), we can obtain the output for each facial action unit.

$$\begin{aligned} U_1 &= P_1 + \sum_{j \neq 1} P_j m_{1j} \\ U_2 &= P_2 + \sum_{j \neq 2} P_j m_{2j} \\ &\vdots \\ U_N &= P_N + \sum_{j \neq N} P_j m_{Nj} \end{aligned} \tag{7}$$

Eq. (7) can be rewritten as:

$$\begin{bmatrix} U_1 \\ U_2 \\ \vdots \\ \vdots \\ U_N \end{bmatrix} = \begin{bmatrix} 1 & m_{12} & m_{13} & \cdots & m_{1N} \\ m_{21} & 1 & m_{23} & \cdots & m_{2N} \\ m_{31} & m_{32} & 1 & \cdots & m_{3N} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ m_{N1} & m_{N2} & \cdots & m_{NN-1} & 1 \end{bmatrix} \begin{bmatrix} P_1 \\ P_2 \\ \vdots \\ \vdots \\ P_N \end{bmatrix} \tag{8}$$

From Eq. (8), given a test face image, we can obtain the response of the image to each facial action unit. Each individual action unit classifier at first computes the likelihood. All the likelihoods go through the FAUAN and the response of each action unit is determined. And the facial action units which have the largest responses will be selected with the face image labeled accordingly.

3 Experimental Results and Discussions

In order to evaluate our method, we conduct the experiments on the extend Cohn-Kanade Dataset [12]. This dataset consists of 123 subjects between the age of 18 to 50 years, of which 69% female, 81% Euro-American, 13% Afro-American, and 6% other groups. There are 593 image sequences from 123 subjects. The peak frame of each sequence has been labeled by FACS [24]. It means that there are 593 face images including facial action unit labels. For our experiment, we pick out all the peak frames and divide them into two groups. We randomly select 60 face images as the test set and the remaining 533 face images are used for training.

For the feature extraction, we apply the Viola-Jones face detector [13] to detect the face and resize the face to the 64×64 from the original image size of 640×490, the final HOG features for each face is a 1764×1 vector.

There are 30 different action units (AUs) in the dataset. We select 15 AUs which are universal and appear in the dataset with a high frequency. The indexes and names of 15 AUs are shown in Table 1. From Table 1, we could find that most action units are related with the lip. This may due to that among all the facial components (nose, eye, lip, brow etc.); the lip is the most flexible. It could generate many different actions. There are three action units (AU1, AU2 and AU4) related to the brow. Each of the other facial components (nose and cheek) has one action unit.

For individual facial action unit classification, we employed a 3-layer MLP. The input is a 1764×1 vector, followed by a hidden layer with 100 nodes and the output with two nodes. The target output (1,0) represents a positive sample and (0,1) means a negative sample. During training, the face images which include the specific action unit are positive samples and the other face images are negative samples.

Table 1. The indexes and names of the selected 15 AUs.

AU	Name	AU	Name	AU	Name
1	Inner Brow Raiser	7	Lid Tightener	20	Lip Stretcher
2	Outer Brow Raiser	9	Nose Wrinkler	23	Lip Tightener
4	Brow Lowerer	12	Lip Corner Puller	24	Lip Pressor
5	Upper Lip Raiser	15	Lip Corner Depressor	25	Lips Part
6	Cheek Raiser	17	Chin Raiser	27	Mouth Stretch

Table 2. The distribution of the action unit pairs in the training set.

AU	1	2	4	5	6	7	9	12	15	17	20	23	24	25	27
1	157	102	64	76	8	16	0	7	34	46	42	7	3	110	62
2	102	102	18	70	1	1	0	3	11	16	17	2	3	87	62
4	64	18	178	23	32	89	44	8	37	116	48	41	34	54	2
5	76	70	23	90	3	6	1	3	2	11	19	6	0	81	54
6	8	1	32	3	113	44	23	74	1	21	16	8	5	78	0
7	16	1	89	6	44	112	44	11	6	64	26	31	30	38	0
9	0	0	44	1	23	44	66	4	4	46	2	9	10	11	0
12	7	3	8	3	74	11	4	120	0	2	9	0	2	84	2
15	34	11	37	2	1	6	4	0	88	86	1	9	8	1	0
17	46	16	116	11	21	64	46	2	86	186	6	44	41	8	0
20	42	17	48	19	16	26	2	9	1	6	72	1	0	69	1
23	7	2	41	6	8	31	9	0	9	44	1	55	32	0	0
24	3	3	34	0	5	30	10	2	8	41	0	32	53	0	0
25	110	87	54	81	78	38	11	84	1	8	69	0	0	285	70
27	62	62	2	54	0	0	0	2	0	0	1	0	0	70	70

In order to compute the co-occurrence matrix, we count the co-appearances of each action unit pair based on the training set first. The frequency distribution of action unit pairs in the training set is shown in Table 2.

A diagonal value in Table 2 is the number of appearances of an action unit in the training set. From Table 2, we can see some pairs have a large value and some pairs have a small value. It indicates that the pairs with a large value have a strong correlation and the pairs with a small value have a weak correlation. There are some zeros in Table 2, indicating that some action units do not appear together. They have litte correlations. Applying Eq. (3) we can get the co-occurrence matrix as is shown in Table 3.

We determine a set of action units using two methods. One way is to obtain the output from the individual action unit classifiers directly without the FAUAN. It means that the results totally depend on the performance of individual action unit classifiers. Another way is our proposed method. We employ the FAUAN to fine tune the results. The classification rate of each individual action unit classifier is shown in Figure 2.

In order to compare the performance of the two methods, we fix the number of outputs (AUs) and compute the F1-score, recall and precision respectively.The definitions of the three metrics are given as follows [25]:

$$precision = \frac{TP}{TP+FP}, recall = \frac{TP}{TP+FN}, F1 = \frac{2TP}{2TP+FP+FN} \quad (9)$$

where TP is the true positive, in our experiment, it means that an action unit predicted actually appears in the test face image. FP is the false positive. In our experiment, an FP occurs when an action unit predicted does not appear in

Table 3. The co-occurrence matrix.

AU	1	2	4	5	6	7	9	12	15	17	20	23	24	25	27
1	1.00	0.26	0.10	0.21	0.03	0.04	0.00	0.03	0.17	0.09	0.16	0.04	0.02	0.16	0.25
2	0.18	1.00	0.03	0.20	0.00	0.00	0.00	0.01	0.06	0.03	0.06	0.01	0.02	0.13	0.25
4	0.11	0.05	1.00	0.06	0.10	0.22	0.22	0.04	0.19	0.23	0.19	0.22	0.20	0.08	0.01
5	0.13	0.18	0.04	1.00	0.01	0.01	0.01	0.01	0.01	0.02	0.07	0.03	0.00	0.12	0.21
6	0.01	0.00	0.05	0.01	1.00	0.11	0.12	0.35	0.01	0.04	0.06	0.04	0.03	0.11	0.00
7	0.03	0.00	0.15	0.02	0.14	1.00	0.22	0.05	0.03	0.13	0.10	0.16	0.18	0.06	0.00
9	0.00	0.00	0.07	0.00	0.07	0.11	1.00	0.02	0.02	0.09	0.01	0.05	0.06	0.02	0.00
12	0.01	0.01	0.01	0.01	0.24	0.03	0.02	1.00	0.00	0.00	0.04	0.00	0.01	0.12	0.01
15	0.06	0.03	0.06	0.01	0.00	0.01	0.02	0.00	1.00	0.17	0.00	0.05	0.05	0.00	0.00
17	0.08	0.04	0.19	0.03	0.07	0.16	0.23	0.01	0.43	1.00	0.02	0.23	0.24	0.01	0.00
20	0.07	0.04	0.07	0.05	0.05	0.06	0.01	0.04	0.01	0.01	1.00	0.01	0.00	0.10	0.40
23	0.01	0.01	0.07	0.02	0.03	0.08	0.05	0.00	0.05	0.09	0.00	1.00	0.19	0.00	0.00
24	0.01	0.01	0.06	0.00	0.02	0.07	0.05	0.01	0.04	0.09	0.00	0.17	1.00	0.00	0.00
25	0.19	0.22	0.09	0.23	0.25	0.09	0.06	0.40	0.01	0.02	0.27	0.00	0.00	1.00	0.28
27	0.12	0.16	0.00	0.15	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.10	1.00

Table 4. The F1-score, recall and precision of the two methods tested (the final classifiers).

	With FAUAN			Without FAUAN		
Outputs/N	F1	Recall	Precision	F1	Recall	Precision
3	0.6361	0.6178	0.6556	0.6146	0.5969	0.6333
4	0.6636	0.7487	0.5958	0.6404	0.7225	0.5750
5	0.6640	0.8534	0.5433	0.6354	0.8168	0.5200
6	0.6352	0.9162	0.4861	0.6134	0.8848	0.4694
7	0.5892	0.9424	0.4286	0.5728	0.9162	0.4167
Avg.	0.6376	0.8157	0.5419	0.6153	0.7874	0.5229

the test face image. FN is the false negative, which occurs when an action unit appears in the test face image but it is missed in the prediction. Table 4 shows the F1-score, recall and precision with or without FAUAN.

We can see that through the FAUAN, the F1-score, recall and precision all become higher, meaning that the performance is improved with the FAUAN. And we also draw the ROC curve and compute the area under the ROC curve. Figure 5(a) shows the ROC of the two methods. The area under curve with FAUAN is 0.9291 and without FAUAN is 0.9160 respectively.

Intuitively, it is easy to foresee that the performance of individual action unit classifiers would influence the final results. We want to explore whether or not the FAUAN could improve the performance when individual action unit classifiers is not so good. We set the number of iterations for training to control the classification rate of each action unit classifier and to evaluate the AU detection performance with and without FAUAN.

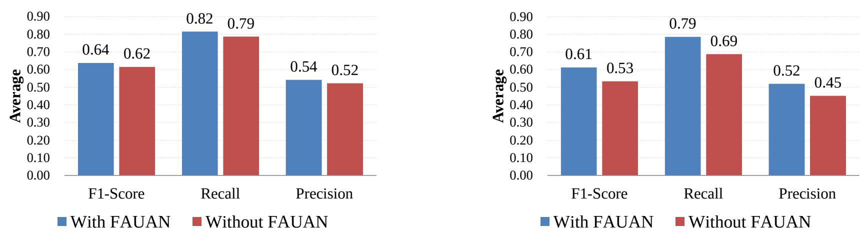
Fig. 2. The classification rate of each individual action unit classifier (the final classifiers).

Fig. 3. The classification rate of each individual action unit classifier (the classifiers trained with 5 iterations).

Figure 3 shows the classification rate of each individual action unit classifier when the iteration is set to 5. Compared with Figures 3 and 2, we can see that the classification rates in Figure 3 are smaller than those in Figure 2. The F1-score, recall and precision with or without FAUAN are shown in Table 5. The average F1-score, recall and precision of the two test methods are shown in Figure 4. From Table 5, we can see that when the classification rate of each individual action unit classifier becomes lower, the improvement with FAUAN is more obvious. The F1-score, recall and precision all improve by about 10% when the numbers of outputs are 3, 4 and 5, respectively. Figure 5(b) shows the ROC of the two methods. The area under curve with FAUAN is 0.9038 and without FAUAN is 0.8452.

Table 5. The F1-score, recall and precision of the two methods (the classifiers trained with 5 iterations).

	With FAUAN			Without FAUAN		
Outputs/N	F1	Recall	Precision	F1	Recall	Precision
3	0.5984	0.5812	0.6167	0.5013	0.4869	0.5167
4	0.6311	0.7120	0.5667	0.5383	0.6073	0.4833
5	0.6395	0.8220	0.5233	0.5499	0.7068	0.4500
6	0.6098	0.8796	0.4667	0.5554	0.8010	0.4250
7	0.5827	0.9319	0.4238	0.5237	0.8377	0.3810
Avg.	0.6123	0.7853	0.5194	0.5337	0.6879	0.4512



(a) (b)

Fig. 4. The average F1-score, recall and precision of the two methods tested. (a) the final classifiers. (b) the classifiers trained with only 5 iterations.

4 Conclusion

Facial expression recognition is still a challenge problem in computer vision. Facial action units provide an important cue to solve this probelm. We can detect the facial action units in groups and then recognize the facial expressions from the facial action units. In this paper, we explore the correlations among facial action units and propose a Facial Action Unit Association Network (FAUAN) for the recognition of facial action units in groups. To evaluate our proposed method, we conduct the experiments on the extended Cohn-Kanade Dataset. Experimental results show that the FAUAN can improve the AU detection results. When the classification rates of individual action unit classifiers are poor, the improvement with FAUAN is more obvious. The future work will include the application of the proposed method to facial expression recognition.

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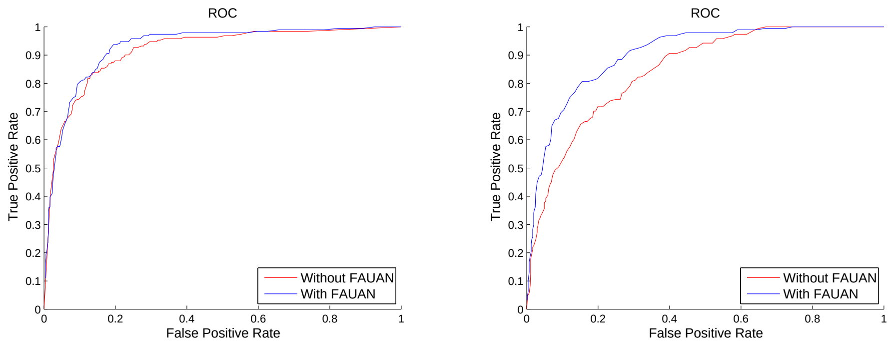

(a) (b)

Fig. 5. The ROCs of the two methods tested. In (a), the area under curve with FAUAN is 0.9291 and that without FAUAN is 0.9160. In (b), the area under curve with FAUAN is 0.9038 and that without FAUAN is 0.8452.

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