# Method for Face Identification with Facial Action Coding System: FACS Based on Eigen Value Decomposition

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***Abstract*—Method for face identification based on eigen value decomposition together with tracing trajectories in the eigen space after the eigen value decomposition is proposed. The proposed method allows person to person differences due to faces in the different emotions. By using the well known action unit approach, the proposed method admits the faces in the different emotions. Experimental results show that recognition performance depends on the number of targeted peoples. The face identification rate is 80% for four peoples of targeted number while 100% is achieved for the number of targeted number of peoples is two.**

***Keywords-face recognition; action unit; face identification.***

## I. INTRODUCTION

In order to keep information system security, face identification is getting more important. Face identification has to be robust against illumination conditions, user's attitude, user's emotion etc. Influences due to illumination conditions, user's movement as well as attitude changes have been overcome. It is still difficult to overcome the influence due to user's emotion changes in face identification. Even users change their emotion, face has to be identified. There is the proposed method for representation of user's emotion based on Face Action Coding System FACS utilizing Action Unit: AU1. FACS is a system to taxonomize human facial expressions [1]. Also users' faces can be classified in accordance with their emotions2 based FACS AU [2], [3].

The conventional face identification methods extract features of the face such as two ends of mouth, two ends of eyebrows, two ends of eyes, tip of nose, etc. Then the faces can be distinguished using the distance between feature vectors of the users in concern. One of the problems of the conventional method is poor distinguish performance due to the fact that the distance between the different feature vectors is not so long results in poor separability between two different faces.

The face identification method proposed here is based on eigen value decomposition [4]. The different AU of which user's face representing emotions can be projected in the eigen space. By project the AU in eigen space not the feature space, the distance between different AU is getting much longer rather than the distance between feature vectors in the feature space. Using the distance between users, the different persons' faces can be distinguished. In other words, difference of features is enhanced by using AU. Namely, face feature changes by emotion changes can be used for improving distinguishing performance. Face feature changes due to emotion changes are different by person by person. Furthermore, distinguish performance is also improved through projection of AU onto eigen space.

The following section describes proposed method followed by some experiments with two to four people's cases. Then conclusion with some discussions is described.

## II. PROPOSED METHOD

### A. Outline and Procedure of the Proposed Method

When the authorized person is passing through an entrance gate, cameras acquire person's face. The acquired face image is compared to the facial images in the authorized persons' facial image database. There are some problems for the aforementioned conventional face identification systems such as influence due to illumination condition changes; users' head pose changes, etc. More importantly, persons' faces are changed in accordance with their emotion. Face identification has to be robust against persons' face changes.

The face identification method proposed here is based on eigen value decomposition. The different AU of which user's face representing emotions can be projected onto the eigen space. By project the AU onto eigen space not the feature space, the distance between different AU is getting much longer rather than the distance between feature vectors in the feature space. Using the distance between users, the different persons' faces can be distinguished. In other words, difference of features is enhanced by using AU. Namely, face feature changes by emotion changes can be used for improving distinguishing performance. Face feature changes due to emotion changes are different by person by person. Furthermore, distinguish performance is also improved through projection of AU onto eigen space.

### B. Face Action Coding System: FACS and Action Unit: AU Concept

Based on FACS, all of emotional faces can be represented as a combination of AU. Table 1 shows the 49 of AU while

[1] http://www.cs.cmu.edu/~face/facs.htm
[2]http://journals2.scholarsportal.info.myaccess.library.utoronto.ca/tmp/14963947897443139832.pdf.

Table 2 shows weighting coefficients for each AU of linear combination function for representation of emotional faces and relations between emotional faces and combination of AU.

TABLE I. ALL ABOUT THE ACTION UNITS

| AU Number | FACS Name | Muscular Basis |
|---|---|---|
| 0 | Neutral Face | |
| 1 | Inner Brow Raiser | frontalis (pars medialis) |
| 2 | Outer Brow Raiser | frontalis (pars lateralis) |
| 4 | Brow Lowerer | depressor glabellae, depressor supercilii, corrugator supercilii |
| 5 | Upper Lid Raiser | levatorpalpebraesuperioris |
| 6 | Cheek Raiser | orbicularis oculi (pars orbitalis) |
| 7 | Lid Tightener | orbicularis oculi (pars palpebralis) |
| 8 | Lips Toward Each Other | orbicularis oris |
| 9 | Nose Wrinkler | levatorlabiisuperiorisalaequenasi |
| 10 | Upper Lip Raiser | levatorlabiisuperioris, caput infraorbitalis |
| 11 | Nasolabial Deepener | zygomaticus minor |
| 12 | Lip Corner Puller | zygomaticus major |
| 13 | Sharp Lip Puller | levatoranguliorис (also known as caninus) |
| 14 | Dimpler | buccinator |
| 15 | Lip Corner Depressor | depressor anguliorис (also known as triangularis) |
| 16 | Lower Lip Depressor | depressor labiiinferioris |
| 17 | Chin Raiser | mentalis |
| 18 | Lip Pucker | incisiviilabiisuperioris and incisiviilabiiinferioris |
| 19 | Tongue Show | |
| 20 | Lip Stretcher | risorius w/ platysma |
| 21 | Neck Tightener | platysma |
| 22 | Lip Funneler | orbicularis oris |
| 23 | Lip Tightener | orbicularis oris |
| 24 | Lip Pressor | orbicularis oris |
| 25 | Lips Part | depressor labiiinferioris, or relaxation of mentalis or orbicularis oris |
| 26 | Jaw Drop | masseter; relaxed temporalis and internal pterygoid |
| 27 | Mouth Stretch | pterygoids, digastric |
| 28 | Lip Suck | orbicularis oris |
| 29 | Jaw Thrust | |
| 30 | Jaw Sideways | |
| 31 | Jaw Clencher | masseter |
| 32 | [Lip] Bite | |
| 33 | [Cheek] Blow | |
| 34 | [Cheek] Puff | |
| 35 | [Cheek] Suck | |
| 36 | [Tongue] Bulge | |
| 37 | Lip Wipe | |
| 38 | Nostril Dilator | nasalis (pars alaris) |
| 39 | Nostril Compressor | nasalis (pars transversa) and depressor septinasi |
| 41 | Glabella Lowerer | Separate Strand of AU 4: depressor glabellae (aka procerus) |
| 42 | Inner Eyebrow Lowerer | Separate Strand of AU 4: depressor supercilii |
| 43 | Eyes Closed | Relaxation of levatorpalpebraesuperioris |
| 44 | Eyebrow Gatherer | Separate Strand of AU 4: corrugator supercilli |
| 45 | Blink | Relaxation of levatorpalpebraesuperioris; contraction of orbicularis oculi (pars palpebralis) |
| 46 | Wink | orbicularis oculi |

TABLE II. EMOTIONS AND THE CORRESPONDING AU COBINATIONS

| | **Weighting Coefficients** | | | |
|---|---|---|---|---|
| **AU No.** | ***Angrily*** | ***Pleasantly*** | ***Sadness*** | ***Surprisingly*** |
| 1 | 0 | 60 | 100 | 100 |
| 2 | 70 | 0 | 0 | 40 |
| 4 | 100 | 0 | 100 | 0 |
| 5 | 0 | 0 | 0 | 100 |
| 6 | 0 | 60 | 0 | 0 |
| 7 | 60 | 0 | 80 | 0 |
| 9 | 100 | 0 | 40 | 0 |
| 10 | 100 | 100 | 0 | 70 |
| 12 | 40 | 50 | 0 | 40 |
| 15 | 50 | 0 | 50 | 0 |
| 16 | 0 | 0 | 0 | 100 |
| 17 | 0 | 0 | 40 | 0 |
| 20 | 0 | 40 | 0 | 0 |
| 23 | 0 | 0 | 100 | 0 |
| 25 | 0 | 40 | 0 | 0 |
| 26 | 60 | 0 | 0 | 100 |

I selected 16 of AU out of 49 AU to represent emotional faces, angrily, pleasantly, sad, and surprising faces. Based on Table 2, all kinds of emotional faces can be created when 16 of AU faces are available to use. Also, it is possible to create all kinds of emotional faces with only one original face image in a clam and normal condition. All AU of facial images can be created with Computer Graphics: CG software. Then all the emotional faces are created accordingly.

### C. Facial Image Acquisition in a Calm Status

The first thing we have to do is acquisition of user's facial image in a clam status for the security system with face identification proposed here. Then feature points are extracted from the facial image. Figure 1 shows an example of feature points extracted from the acquired facial image. There are 19 of feature points as shown in Figure 1. These 19 feature points can be used for identifying AU followed by emotion classification. Therefore, only one facial is required to create all 16 of AU images and then users' emotional faces can be created and recognized.

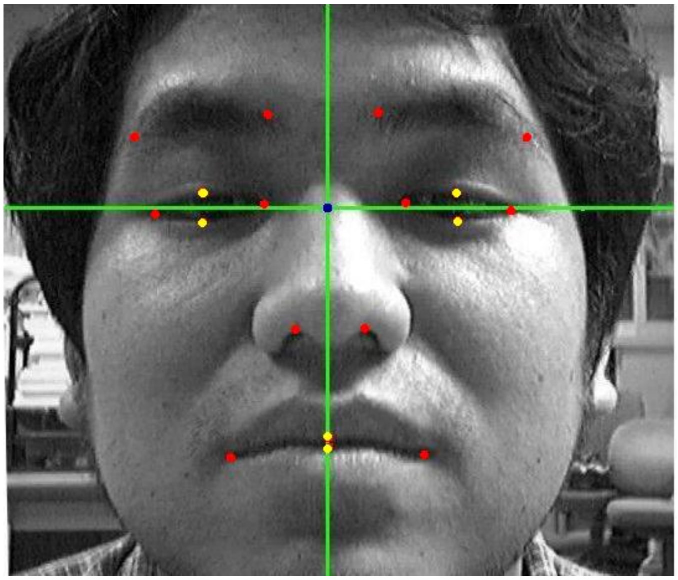


Figure 1. Example of feature points extracted from the acquired facial image

### D. Eigen Space Method

Feature space can be expressed with equation (1).

$$X = [x_1, x_2, \Lambda\ x_n] \quad (x_i \in R^M) \tag{1}$$

Eigen values of covariance matrix, $XX^T$ can be represented with equation (2).

$$\lambda_1 \geq \lambda_2 \geq \Lambda\ \lambda_p (p \leq M) \tag{2}$$

Also eigen vector for each eigen values are expressed with equation (3).

$$v_k = \{v_{1k}, v_{2k}, \Lambda\ v_{nk}\} \tag{3}$$

Then k-th principal component, $f_k$ can be represented with equation (4)

$$f_k = v_{1k}x_1 + v_{2k}x_2 + \Lambda + v_{nk}x_n \tag{4}$$

### E. Plot the Four Emotional Faces onto Eigen Space

Using the acquired face image in calm status, 16 of AU images can be created. Then four emotional images are also created followed by. All the feature vectors which are derived from four emotional images are plotted in the feature space, E as shown in Figure 2. The plots are different by person by person. Furthermore, four emotional image derived feature vectors are much different in comparison to the feature vectors derived from only one person's facial image. Therefore, face identification performance is improved.

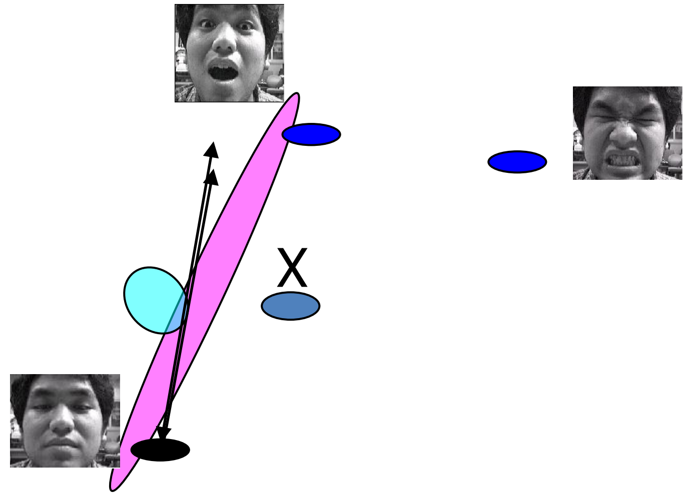



Figure 2. Plotted feature vectors which are derived from four emotional faces in the feature space.

### F. Minimum Distance Classification Method Based on Euclidian Distance

Distance between the unknown feature vector and known vectors A, and B is shown in Figure 3 and is expressed with equation (5).

$$L = (AX + BX) - AB \tag{5}$$

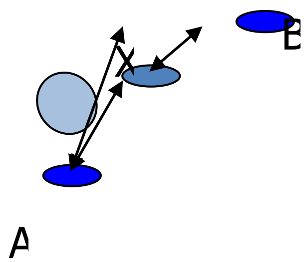



Figure 3. Distance between the features vectors, A, B, and the unknown vector, X

Then face identification can be done with equation (6) with the Euclidian distance.

$$L' = \min_{A,B \in E} L \tag{6}$$

where E denotes eigen space A denotes the vector in the feature space for the face of which the people is in a calm status, normal emotion.

In order to define representative of each emotional image derived feature, mean vector of the features derived from 16 AU feature vectors. Then distance between mean feature vector of calm status and that of each emotional image is calculated. Thus training samples are collected. Persons' facial images have to be acquired at least five times. Through the aforementioned manner, Euclidian distance is calculated as training sets as shown in Figure 4.

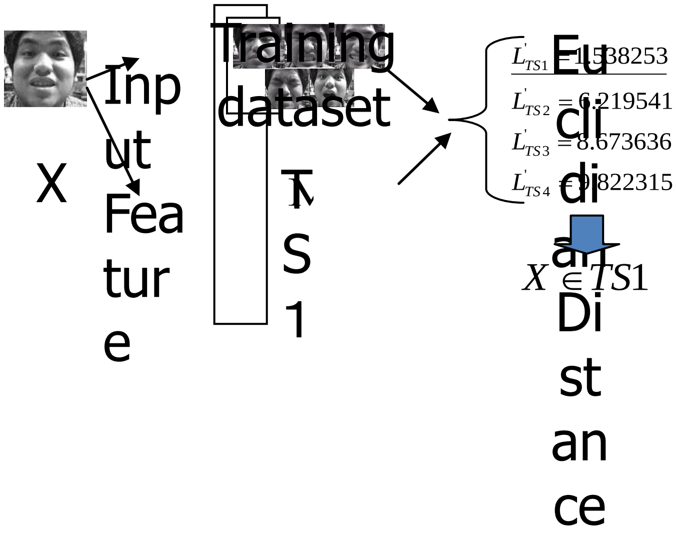



Figure 4. Training datasets of feature vectors derived from each emotional image for each person.

Then unknown feature vector, X derived from person's facial image comes in the eigen space of feature. After that, the distance between X and the other feature vector in the training dataset are calculated. Then the unknown feature vector is classified to one of the class of each person with the minimum distance between features basis.

## III. Experiments

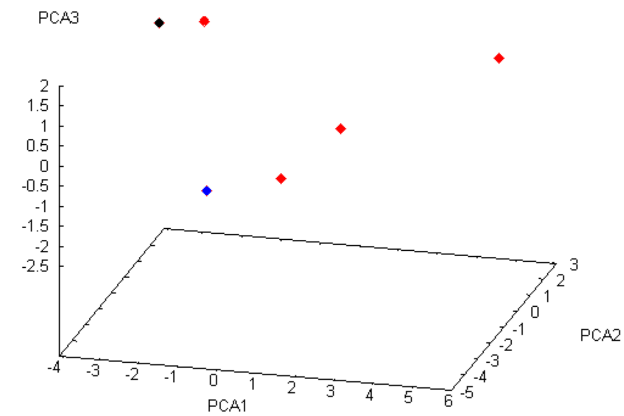
### A. Training Dataset

Four persons participated to the experiments. 640 by 480 pixels of persons' facial images in calm status are acquired for more than five times from the front of person's face. Then training dataset is created for each person. After that, feature vector is converted to eigen space. Figure 5 shows the feature vectors for each person in the space which is composed with first to third eigen vectors, PC1, PC2, and PC3.

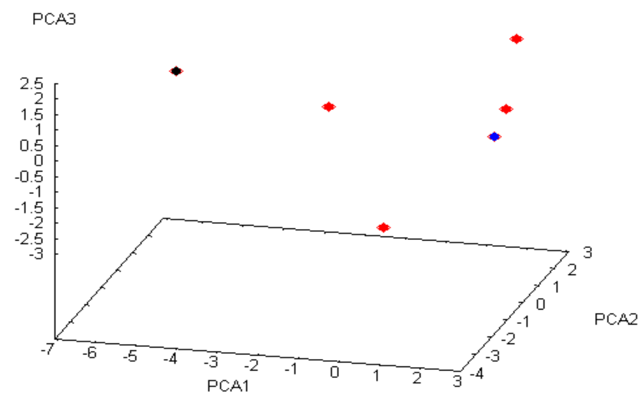
Red circles shows feature vectors derived from the four emotional facial images. Blue circle shows feature vector derived from the facial image in calm status while black circle shows example of the unknown feature vector. Example of the facial images and distance between unknown feature vector and the feature vectors derived from the four emotional facial images is shown in Figure 6.

### B. Face Idintification Accuracy

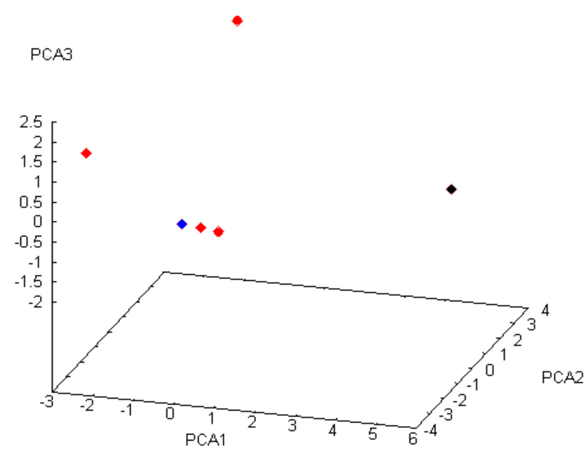
Face identification performance is evaluated with the following three cases, (1) Two persons, (2) Three persons, and (3) Four persons. For each case, 10 of unknown feature vectors derived from the 10 different person's facial images are used for evaluation. Therefore, there are 10 different input facial images and five of the training feature vectors derived from each emotion.



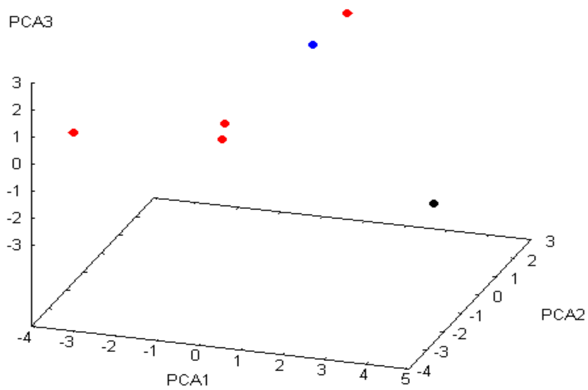

(a)Person #1




(b)Person #2




(c)Person #3




(d)Person #4

Figure 5. Feature vector derived from person's facial image


Un-known feature vector


D=1.538


D=6.220


D=8.674


D=9.822


D=12.182

Figure 6. Example of Training dataset with ficial image and the distance between unknown feature vector and the training data of feature vectors

In the case of the number of persons is four, face identification accuracy is 80 (%). If the number of persons in concern is reduced at three, then we could achieved 90 (%) of face identification accuracy. Furthermore, if the number of persons in concern is reduced at two, then we could achieved 100 (%) of face identification accuracy. On the other hand, if we do not use the four emotional face images of feature vectors, then face identification accuracy get worth at 80 (%) for two persons case. Therefore, the effect of using four emotional face images is around 20 (%) improvements.

TABLE III. FACE IDENDITIFICATION PERFORMANCE

| **Number of Person** | ***Percent Correct Identification (%)*** |
|---|---|
| 2 | 100.0 |
| 3 | 90.0 |
| 4 | 80.0 |

In accordance with decreasing of the number of training samples, face identification accuracy is getting poor drastically. Therefore, we would better to increase the number of training samples. Five of training samples in this paper is marginal, though.

## I. Conclusion

Method for face identification based on eigen value decomposition together with tracing trajectories in the eigen space after the eigen value decomposition is proposed. The proposed method allows person to person differences due to faces in the different emotions.

By using the well known action unit approach, the proposed method admits the faces in the different emotions. Experimental results show that recognition performance depends on the number of peoples in concern. The face identification rate is 80% for four peoples in concern number while 100% is achieved for the number of targeted number of peoples is two.

Further investigation is required for improvement of face identification accuracy by using a plenty of training dataset as much as we could.

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**Kohei Arai**, He received BS, MS and PhD degrees in 1972, 1974 and 1982, respectively. He was with The Institute for Industrial Science and Technology of the University of Tokyo from April 1974 to December 1978 also was with National Space Development Agency of Japan from January, 1979 to March, 1990. During from 1985 to 1987, he was with Canada Centre for Remote Sensing as a Post Doctoral Fellow of National Science and Engineering Research Council of Canada. He moved to Saga University as a Professor in Department of Information Science on April 1990. He was a councilor for the Aeronautics and Space related to the Technology Committee of the Ministry of Science and Technology during from 1998 to 2000. He was a councilor of Saga University for 2002 and 2003. He also was an executive councilor for the Remote Sensing Society of Japan for 2003 to 2005. He is an Adjunct Professor of University of Arizona, USA since 1998. He also is Vice Chairman of the Commission "A" of ICSU/COSPAR since 2008. He wrote 30 books and published 322 journal papers.