

# Candidate narrowing for Face Identification Using Facial Expression

Lifeng Zhang<sup>1</sup> Lin Zhao<sup>2</sup> Keisuke Korekoda<sup>3</sup> and Hiroshi Kondo<sup>4</sup>

<sup>1,2,4</sup>Department of Electrical, Electronic and Computer Engineering Kyushu Institute of Technology,  
1-1 sensui-cho Tobata-ku Kitakyushu city, Fukuoka 804-8550, Japan.

Tel : +81-93-884-3272, Fax : +81-93-884-3203

Email: <sup>1</sup>zhang@elcs.kyutech.ac.jp, <sup>2</sup>linlin@mars.ele.kyutech.ac.jp, <sup>4</sup>kondou@ele.kyutech.ac.jp

<sup>3</sup>ZENRIN Co., Ltd.

1-1-1 Muro-machi, Kokurakita-ku, Kitakyusyu city, Fukuoka 803-8630, Japan.

<sup>3</sup>Email: korekoda@gmail.com

**Abstract:** Recently, face authentication becomes a hot topic not only in security system but also in home entertainment field. Since face identification is of non-contact and little psychological resistance one, it can be easily accept by user side. And also we know it is difficult to perform a perfect authentication with and only with a face, so in fact the identification is combined with other authentication method (Ex. password, finger print, voice, etc.), this makes a complex algorithm, and different sensor will increase the cost. So use one CCD camera do candidate narrowing and identification is a good idea. On the other hand, to read the feelings state of human being, the computer recognition of facial expression is researched from long before, and also many fruitful results were achieved. However, the relation between face identification and expression recognition has been hardly examined up to now though these two researches use the same objects(face). This paper has aimed to unite these two researches, and to find a new approach to narrow candidate for face identification.

## 1. Introduction

On application side of expression recognition, we can classify the method of *limiting individual* or *non-limiting individual*. Limiting individual means the registration data can be used only for the person whose recognition data is made from. The data is not only a expression one but also with a personalized index embedded. Non-limiting individual means the registration data can be used for arbitrary person; it is a pure expression data. This is important point here. Because we use the expression recognition for face identification, the class of non-limiting individual method cannot be used obviously. So we have to find a limiting individual method on purpose [2], and then Show an approach to narrow candidate for face authentication.

## 2. facial expression recognition

In this Research, we use a front view face image as input, and assume the light condition is stable.

### 2.1 Eyes and eyebrow area extractions

To recognize person's expression, we need to analyze the change of face organ by the expression. Therefore, wanting three rectangular areas in the left-eye/left-eyebrow area,

the right-eye/right-eyebrow area, and the mouth area (These three areas are called a feature area at the following). Such areas have remarkable change intent to face organ by the expression, so they are used in this research. Feature area is cut out from each five expressions of Neutral, Anger, Happiness, Sadness, and Surprise. As an example, the standard of the feature area's selection is shown in Figure 1 and Figure 2 for Neutral. Moreover, there are three color component of RGB in the image, we assuming use them to detect the position of face parts(eyes, mouth etc.) in future, but in this research area cutting is done by hand, Therefore, the only brightness component Y with 256 levels is used. Figure 3 shows the one that the feature area was converted into brightness component Y.



Figure 1. Input image

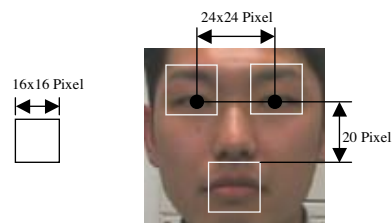


Figure 2. Example for area cutting



Figure 3. Y component of feature area

## 2.2 Making of feature vector

In order to make the feature vector, 2D-DCT transform of  $16 \times 16$  pixel is applied to the three feature area for each expression. Then get the difference value between the each expression 2D-DCT coefficients that we get above and a neutral expression's 2D-DCT coefficient respectively. Each expression feature vector is extracted based on this difference coefficient.

As we known, for DCT transform of a natural image, most of the energy concentrated on the low frequency area where the noise influence are little, so we try to divide the area such as Figure 4(a) (e) at here. And then select the best performance one.

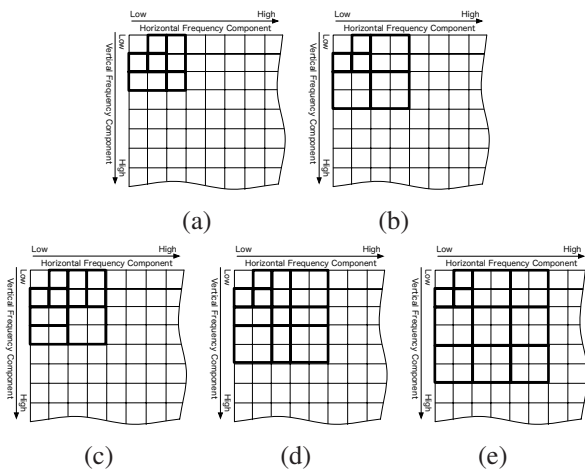


Figure 4. Feature vector consist method

The bands that we used is shown in a black heavy line, in the lowest frequency region, use one coefficient characterizes one band, and in the following region, the average of 2 or 4 coefficients is characterized to one band. The DC element was disregarded to show the feature of the image because of the irrelevance. Therefore, two areas of eyes and the eyebrow areas and one mouth area use the feature of each 6 ~ 11 band in total three areas. That is, the energy change in each 18 ~ 33 band will be obtained with each expression. We use the mean value of each band to make a feature vector.

## 3. Study and recognition with neural net work

The expressions that are recognized and identified are five expressions (expressionless, pleasure, anger, the surprise, and sadness) in total, The neural net work used has three layer structure, the input layer makes 18 ~ 33 unit corresponding to feature vector calculated in the foregoing paragraph, the hidden layer makes 19 units and the output layers five units corresponding to an expression category.

In order to recognize the expression of a specific individual, first of all, ten images are taken in each expression. As a teacher signal, the average of the feature vector is input to the neural network, and it studies. At this time, the output layer ignites only the unit corresponding to each expression. It studied by the BP method, the convergence condition is assumed that the mean error of all study data is less than or

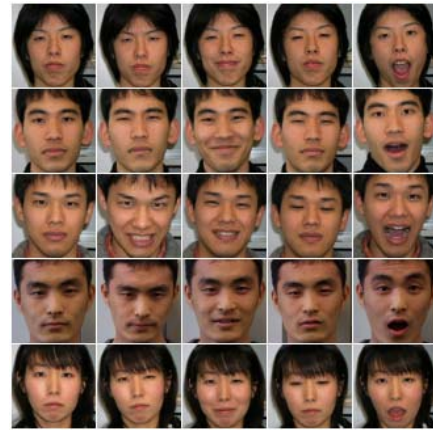


Figure 5. Expressions example, from left to right : Neutral, Anger, Happiness, Sadness, and Surprise

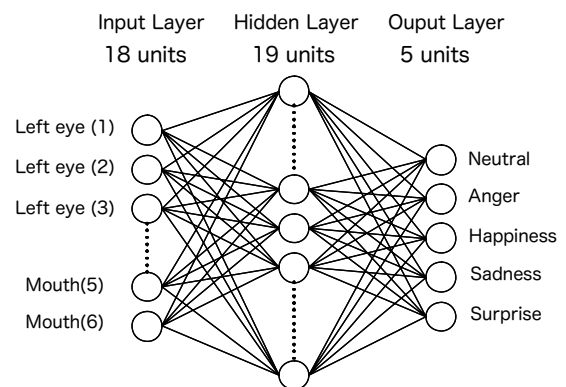


Figure 6. Neural network for expression recognition

equal to  $10^{-5}$ , and the study is about 8000 times. When recognizing it, the feature vector of each area obtained from the image, that is, DCT coefficient is given to the input layer, and the category that shows the largest numerical value that appears to the output unit is assumed to be a recognition result. It is an expression example of the image of making it study by this research in Figure 4(a) ~ Figure 4(e). Figure 6 shows the neural net work when studying by the feature vector of the band of Figure 5(a).

## 4. Experssion Recognition result

Expression recognition is base technology in this research, we need to prove this method can recognize expression well first, and then to show it is a limiting individual one.

### 4.1 Specific individual's expression recognition result

Input five each expression of the person in question to the neural network which studied by himself, the recognition results are shown in Table 1~5. (a)~(e) in each table shows the difference of the recognition performance corresponding to each use band of Figure 5(a)~(e) of section 2.2. "o[n]" is a reactive value of the neural net work, "n" is an expression category, that is 1: Neutral, 2: Anger, 3: Happiness, 4: Sadness and 5: It corresponds to Surprise.

From experiment above, it is understood that the band of

Table 1. Neutral expression recognition result

Neutral		(a)	(b)	(c)	(d)	(e)
1st	a0	0.97199	0.84921	0.87101	0.84352	0.96984
	a1	0.93242	0.92149	0.92149	0.92149	0.92149
	a2	0.93242	0.93242	0.93242	0.93242	0.93242
	a3	0.93242	0.93242	0.93242	0.93242	0.93242
2nd	a0	0.93613	0.84550	0.84647	0.84810	0.96588
	a1	0.93613	0.93613	0.93613	0.93613	0.93613
	a2	0.93613	0.93613	0.93613	0.93613	0.93613
	a3	0.93613	0.93613	0.93613	0.93613	0.93613
3rd	a0	0.91291	0.87905	0.87905	0.87905	0.91291
	a1	0.91291	0.91291	0.91291	0.91291	0.91291
	a2	0.91291	0.91291	0.91291	0.91291	0.91291
	a3	0.91291	0.91291	0.91291	0.91291	0.91291
4th	a0	0.91391	0.81764	0.89279	0.81148	0.93220
	a1	0.91391	0.91391	0.91391	0.91391	0.91391
	a2	0.91391	0.91391	0.91391	0.91391	0.91391
	a3	0.91391	0.91391	0.91391	0.91391	0.91391
5th	a0	0.70292	0.88865	0.85297	0.45989	0.67777
	a1	0.70292	0.70292	0.70292	0.70292	0.70292
	a2	0.70292	0.70292	0.70292	0.70292	0.70292
	a3	0.70292	0.70292	0.70292	0.70292	0.70292

Table 2. Anger expression recognition result

Anger		(a)	(b)	(c)	(d)	(e)
1st	a0	0.28497	0.21640	0.23230	0.15841	0.20501
	a1	0.28497	0.28497	0.28497	0.28497	0.28497
	a2	0.28497	0.28497	0.28497	0.28497	0.28497
	a3	0.28497	0.28497	0.28497	0.28497	0.28497
2nd	a0	0.29651	0.13277	0.07300	0.23909	0.17174
	a1	0.29651	0.29651	0.29651	0.29651	0.29651
	a2	0.29651	0.29651	0.29651	0.29651	0.29651
	a3	0.29651	0.29651	0.29651	0.29651	0.29651
3rd	a0	0.18388	0.10058	0.26273	0.19324	0.07272
	a1	0.18388	0.18388	0.18388	0.18388	0.18388
	a2	0.18388	0.18388	0.18388	0.18388	0.18388
	a3	0.18388	0.18388	0.18388	0.18388	0.18388
4th	a0	0.14495	0.12142	0.26162	0.17498	0.09230
	a1	0.14495	0.14495	0.14495	0.14495	0.14495
	a2	0.14495	0.14495	0.14495	0.14495	0.14495
	a3	0.14495	0.14495	0.14495	0.14495	0.14495
5th	a0	0.03651	0.03817	0.03651	0.03651	0.03651
	a1	0.03651	0.03651	0.03651	0.03651	0.03651
	a2	0.03651	0.03651	0.03651	0.03651	0.03651
	a3	0.03651	0.03651	0.03651	0.03651	0.03651

Table 3. Happiness expression recognition result

Happiness		(a)	(b)	(c)	(d)	(e)
1st	a0	0.64517	0.65662	0.66786	0.63475	0.64112
	a1	0.64517	0.64517	0.64517	0.64517	0.64517
	a2	0.64517	0.64517	0.64517	0.64517	0.64517
	a3	0.64517	0.64517	0.64517	0.64517	0.64517
2nd	a0	0.63510	0.44659	0.63100	0.63991	0.66566
	a1	0.63510	0.63510	0.63510	0.63510	0.63510
	a2	0.63510	0.63510	0.63510	0.63510	0.63510
	a3	0.63510	0.63510	0.63510	0.63510	0.63510
3rd	a0	0.63578	0.43755	0.63263	0.63801	0.65659
	a1	0.63578	0.63578	0.63578	0.63578	0.63578
	a2	0.63578	0.63578	0.63578	0.63578	0.63578
	a3	0.63578	0.63578	0.63578	0.63578	0.63578
4th	a0	0.65018	0.55411	0.63985	0.63529	0.65898
	a1	0.65018	0.65018	0.65018	0.65018	0.65018
	a2	0.65018	0.65018	0.65018	0.65018	0.65018
	a3	0.65018	0.65018	0.65018	0.65018	0.65018
5th	a0	0.63510	0.44457	0.63100	0.63991	0.66566
	a1	0.63510	0.63510	0.63510	0.63510	0.63510
	a2	0.63510	0.63510	0.63510	0.63510	0.63510
	a3	0.63510	0.63510	0.63510	0.63510	0.63510

Table 4. Sadness expression recognition result

Sadness		(a)	(b)	(c)	(d)	(e)
1st	a0	0.66871	0.17902	0.63100	0.69547	0.67208
	a1	0.66871	0.66871	0.66871	0.66871	0.66871
	a2	0.66871	0.66871	0.66871	0.66871	0.66871
	a3	0.66871	0.66871	0.66871	0.66871	0.66871
2nd	a0	0.18847	0.42550	0.29110	0.15209	0.59883
	a1	0.18847	0.18847	0.18847	0.18847	0.18847
	a2	0.18847	0.18847	0.18847	0.18847	0.18847
	a3	0.18847	0.18847	0.18847	0.18847	0.18847
3rd	a0	0.24541	0.33788	0.48862	0.24888	0.22234
	a1	0.24541	0.24541	0.24541	0.24541	0.24541
	a2	0.24541	0.24541	0.24541	0.24541	0.24541
	a3	0.24541	0.24541	0.24541	0.24541	0.24541
4th	a0	0.07018	0.33726	0.09975	0.07133	0.13756
	a1	0.07018	0.07018	0.07018	0.07018	0.07018
	a2	0.07018	0.07018	0.07018	0.07018	0.07018
	a3	0.07018	0.07018	0.07018	0.07018	0.07018
5th	a0	0.68675	0.25579	0.61916	0.67834	0.17051
	a1	0.68675	0.68675	0.68675	0.68675	0.68675
	a2	0.68675	0.68675	0.68675	0.68675	0.68675
	a3	0.68675	0.68675	0.68675	0.68675	0.68675

Table 5. Surprise expression recognition result

Surprise		(a)	(b)	(c)	(d)	(e)
1st	a0	0.10823	0.44544	0.05701	0.09547	0.13129
	a1	0.10823	0.10823	0.10823	0.10823	0.10823
	a2	0.10823	0.10823	0.10823	0.10823	0.10823
	a3	0.10823	0.10823	0.10823	0.10823	0.10823
2nd	a0	0.46288	0.46554	0.03633	0.05523	0.16589
	a1	0.46288	0.46288	0.46288	0.46288	0.46288
	a2	0.46288	0.46288	0.46288	0.46288	0.46288
	a3	0.46288	0.46288	0.46288	0.46288	0.46288
3rd	a0	0.07952	0.17983	0.03911	0.07135	0.06184
	a1	0.07952	0.07952	0.07952	0.07952	0.07952
	a2	0.07952	0.07952	0.07952	0.07952	0.07952
	a3	0.07952	0.07952	0.07952	0.07952	0.07952
4th	a0	0.06163	0.14274	0.06679	0.06668	0.13716
	a1	0.06163	0.06163	0.06163	0.06163	0.06163
	a2	0.06163	0.06163	0.06163	0.06163	0.06163
	a3	0.06163	0.06163	0.06163	0.06163	0.06163
5th	a0	0.41700	0.10834	0.16979	0.20960	0.20967
	a1	0.41700	0.41700	0.41700	0.41700	0.41700
	a2	0.41700	0.41700	0.41700	0.41700	0.41700
	a3	0.41700	0.41700	0.41700	0.41700	0.41700

(b) gives the highest recognition rate when seeing overall. In case of the band of (a), each expression feature cannot be caught completely because the band used is too few, and reversely for (d) and (e), if the similarity of the image between the learning pattern and test pattern is not high enough, it is thought not to be recognized because the band used is much. This means we lost the robustness.

The band area of (b) and (c) are the same, the difference is we divided more bands of (c) than (b), so the feature vector of (c) is longer than (b). We expect more detail more accuracy,

but at the same time the noise come from the position difference of image gives a undesirable result. As a result, the band of Figure 5(b) of section 2.2 which obtain the recognition result with reliability most used in this paper.

## 4.2 Others' expression recognition results

In this research, we want a non-limiting individual method, so correct expression recognition for others is unexpected.

The result when others' expressions are input to the neural network which msde from a specific individual's expression is shown in Table 6~ Table 10. Five arbitrary people A ~ E, each two of five expressions, were input for recognition.

Table 6. Others neutral expression recognition result

		A	B	C	D	E
1	a	0.94121	0.96570	0.93123	0.93634	0.87671
	b	0.93283	0.93283	0.93283	0.93283	0.93283
	c	0.93283	0.93283	0.93283	0.93283	0.93283
	d	0.93283	0.93283	0.93283	0.93283	0.93283
2	a	0.66430	0.65554	0.63152	0.67377	0.65382
	b	0.65554	0.65554	0.65554	0.65554	0.65554
	c	0.65554	0.65554	0.65554	0.65554	0.65554
	d	0.65554	0.65554	0.65554	0.65554	0.65554

Table 7. Others anger expression recognition result

		A	B	C	D	E
1	a	0.38838	0.72226	0.48023	0.38838	0.69029
	b	0.38838	0.38838	0.38838	0.38838	0.38838
	c	0.38838	0.38838	0.38838	0.38838	0.38838
	d	0.38838	0.38838	0.38838	0.38838	0.38838
2	a	0.39890	0.73797	0.47589	0.39892	0.69820
	b	0.39890	0.39890	0.39890	0.39890	0.39890
	c	0.39890	0.39890	0.39890	0.39890	0.39890
	d	0.39890	0.39890	0.39890	0.39890	0.39890

Table 8. Others happiness expression recognition result

		A	B	C	D	E
1	a	0.77689	0.81140	0.81029	0.83229	0.81017
	b	0.77689	0.77689	0.77689	0.77689	0.77689
	c	0.77689	0.77689	0.77689	0.77689	0.77689
	d	0.77689	0.77689	0.77689	0.77689	0.77689
2	a	0.65936	0.33630	0.62538	0.61381	0.68545
	b	0.65936	0.65936	0.65936	0.65936	0.65936
	c	0.65936	0.65936	0.65936	0.65936	0.65936
	d	0.65936	0.65936	0.65936	0.65936	0.65936

Table 9. Others sadness expression recognition result

		A	B	C	D	E
1	a	0.63124	0.22891	0.63124	0.63124	0.63264
	b	0.63124	0.63124	0.63124	0.63124	0.63124
	c	0.63124	0.63124	0.63124	0.63124	0.63124
	d	0.63124	0.63124	0.63124	0.63124	0.63124
2	a	0.61250	0.09792	0.61250	0.61250	0.61710
	b	0.61250	0.61250	0.61250		

## 5. Expression selection for identification

In this research, it has aimed not to ignite in the corresponding expression when only the expression of the person in question that has it study to the neural network is recognized.

To examine whether to distinguish from the original person even if others are what expression, we pay attention to the Happiness reactive value at here, the graph is made when images (five Happiness images of the original person and all expression of five arbitrary people) are inputted, the result shown in Figure 7. In this figure, the straight line in highest position is a reactive value of five Happiness expressions of original person. And the five lower straight lines are five others(A~E) reactive values when input each of five expression into the original one's neural network.

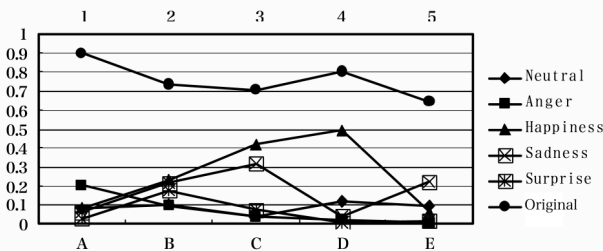


Figure 7. Comparison of person in question's Happiness expression and others' each expression Happiness reaction values

It is understood that there is a difference in Happiness reactive value between Happiness expression of person in question and what expression of others. Through setting a threshold value, the differentiation with person in question and other's expressions can be attempted. Therefore, even if others are what expression, it is not recognized, and it is thought that the individual can be identified with a specified expression. At here the Happiness is selected.

## 6. Simulation

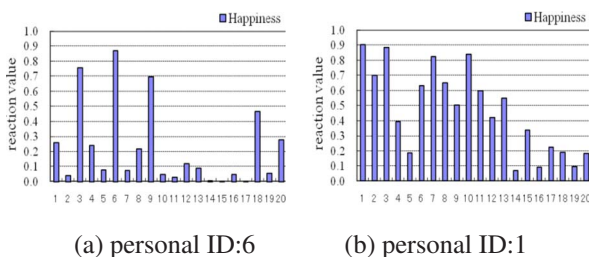


Figure 8. Happiness reaction value with original one's NN

Simulation for candidate narrowing done use 20 person's data. Because the space is limited, we pick up the typical two datas from all and show them in Figure 8, the vertical axis shows the happiness reaction value, and the number of horizontal axis means personal ID. All the input is happiness expression. Figure 8(a) use ID:6 neural network, and (b) use ID:1's one.

In Figure 8(a), we see only the original person's reaction value is larger then 0.8, also it is the Max. value, so we sure

this person's ID is 6. But in Figure 8(b), the reaction value of personal ID:1,3,7,10 are larger than 0.8, although the original person(ID:1) gets the Max. reaction value, we can not sure exactly because the reaction value maybe change slightly every time. But the reaction value of original person keeps in high level every time is observed in our research, so set a threshold value (fixed or dynamic), we can narrow the candidate from amount.

## 7. Conclusions

In this paper, first a limiting individual expression recognition method use 2D-DCT and neural network is developed.

And then a new approach for personal identification using specific expression is proposed. Figure 7 shows a happiness expression obtain a good performance.

Finally, the simulation using 20 persons is executed. From the observation result, for a group less then 10 persons, this method can work alone. And for a group larger than 20 persons, combination with other face identification approach is suggested. And frequency analysis method is recommended cause the same algorithm.

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