



**HAL**  
open science

## Boosting steerable features for 2D face recognition on IV 2 database

Nefissa Khiari Hili, Sylvie Lelandais, Christophe Montagne, Kamel Hamrouni

► **To cite this version:**

Nefissa Khiari Hili, Sylvie Lelandais, Christophe Montagne, Kamel Hamrouni. Boosting steerable features for 2D face recognition on IV 2 database. International Conference on Bio-Inspired Systems and Signal Processing (BIOSIGNAL 2012), Feb 2012, Vilamoura, Algarve, Portugal. pp.488–493. hal-00744921

**HAL Id: hal-00744921**

**<https://hal.science/hal-00744921>**

Submitted on 1 Feb 2014

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# BOOSTING STEERABLE FEATURES FOR 2D FACE RECOGNITION ON IV<sup>2</sup> DATABASE

Nefissa Khiari Hili<sup>1,2</sup>, Sylvie Lelandais<sup>1</sup>, Christophe Montagne<sup>1</sup>, Kamel Hamrouni<sup>2</sup>

<sup>1</sup>*IBISC Laboratory, University of Evry Val d'Essonne, 40 Rue du Pelvoux, 91020 Evry Cedex, France*

<sup>2</sup>*TSIRF Laboratory, ENIT, University of Tunis El Manar, BP-37 Le Belvédère, 1002 Tunis, Tunisia*

*kh.nefissa@gmail.com, s.lelandais@iut.univ-evry.fr, cmontagne@iup.univ-evry.fr, kamel.hamrouni@enit.rnu.tn*

**Keywords:** 2D face recognition, Feature extraction, Feature selection, Steerable pyramid, Adaboost.

**Abstract:** In this paper, a novel approach for 2D face recognition is proposed, based on local feature extraction through a multi-resolution multi-orientation linear method: Steerable Pyramid (SP) and on a feature selection and classification by means of a non-linear method: Adaboost. Many strategies have been elaborated and tested on IV<sup>2</sup> database including challenging variability such as pose, expression, illumination and quality. To show the robustness of the method, it was compared to five algorithms submitted to the first evaluation campaign on 2D face recognition using IV<sup>2</sup> database. Proposed algorithm is almost among the two best ones.

## 1 INTRODUCTION

In the last two decades, security concerns have deeply increased because of the incessant fraud attempts. Being considered as the ultimate solution, biometrics took part to research works to a great extent, especially, 2D-Face recognition since it is non-invasive and requires less user cooperation.

Despite the considerable efforts in 2D-face recognition, it is still difficult to achieve high accuracy under non-constrained situations. Since most of the existing databases don't offer either enough variabilities or sufficient number of subjects, relevant databases, like the IV<sup>2</sup> one, were recently developed to permit efficient evaluation of the proposed methods. Classical algorithms such as Eigenfaces, Fisherfaces, Gabor (Li, 2005) perform well in controlled environments; however, their performances drastically drop when variability like quality, pose and illumination occur. Therefore, new solutions are being suggested to overcome these challenges. Many of them were based on combining conventional algorithms and brought quite good results. As instance, Mellakh et al. (Mellakh, 2009) proposed a method based on LDA and Gabor; Zhang and Jia (Zhang, 2005) operated an identification by means of SP and LDA and Su et al. (Su., 2009) allied local and global features. With the persuasion of the enhancement a merging strategy could

provide, the 2D face recognition system presented in this paper, was developed by combining a space-scale feature-extraction method: the Steerable Pyramid (SP) to a non-linear feature-selection and classification method: Adaboost. The idea of applying Steerable Pyramids to characterize Face images, emanates from a previous work on iris recognition by Khiari et al. (Khiari, 2008) where good results were reached. The Steerable Pyramid (SP) transform introduced by Simoncelli and Freeman (Simoncelli, 1995) associates multi-scale decompositions with differential measurements, thus able to capture both frequency and orientation information, which perfectly suits this application. On the other hand, AdaBoost method, proposed by Freund and Schapire (Freund, 1995), provides a simple yet effective stage-wise learning approach for feature selection and classification. Therefore, we adopt AdaBoost to select the most discriminant SP features and build a strong classifier.

Through this paper, a promising 2D-face recognition method combining SP and Adaboost is introduced. The following is divided into four sections. Section 2 explains SP and Adaboost formulations. Section 3 illustrates the collection of data and the evaluation protocol elaborated in the IV<sup>2</sup> project. Section 4 describes the proposed method and reports experimental results in comparison to five other algorithms submitted in the first IV<sup>2</sup> evaluation campaign (Mellakh, 2009). Finally,

section 5 ends up with conclusions and perspectives for future work.

## 2 BACKGROUND CONCEPTS

This section introduces the basic concepts of Adaboost and Steerable Pyramids (SP) as being the association that gave birth to proposed approach.

### 2.1 Adaboost

Boosting is a method to combine a collection of weak classification functions (weak learner) to form a stronger classifier. AdaBoost is an adaptive algorithm to boost a sequence of classifiers, in that the weights are updated dynamically according to the errors in previous learning (Viola, 2001).

#### AdaBoost Algorithm :

**Input:**  $n$  training of examples  $(x_i, y_i) \dots (x_n, y_n)$  with  $y_i$  in  $\{+1, -1\}$  is the class label for the positive or negative sample  $x_i$ ; where  $i = 1, \dots, n$ . In our case (face recognition),  $x_i = (I_{1,i}, I_{2,i})$  is a pair of images.

**Initialize:** weights  $D_{1,i} = 1/n$

**Do for**  $t = 1, \dots, T$ :

1. For each filter  $\Phi_j$ , compute the best weak classifier  $h_j$ , that uses  $\Phi_j$ . This amounts to finding the optimum threshold  $t_j$ , minimizing the error  $e_j$  for each possible filter.
2. Choose the classifier  $h_t$  with the lowest error  $e_t$ , according to weighted examples and their labels.
3. Choose  $\alpha$  and  $\beta$  that define the feature  $f_t$ , based on  $e_t$  and the estimated labels  $y_{i,t}$ .
4. Normalize the weights  $D_{t,i}$  so that they are a distribution.

**Output:** The final Strong classifier :

$$F(x) = \text{sign} \left( \sum_{t=1}^T f_t(x) \right) \quad (1)$$

More details about Adaboost algorithm and equations are available at [????].

### 2.1 Steerable Pyramid (SP)

The steerable pyramid, introduced by Simoncelli & Freeman (Simoncelli, 1995), is a linear multi-scale multi-orientation decomposition that provides a front-end to many image-processing applications particularly in texture analysis. The basis functions of a steerable pyramid are directional derivative operators that come in different sizes and orientations. The pyramid can be designed to produce any number of orientation bands. The

representation is translation invariant (it is aliasing free) and rotation invariant (the sub-bands are steerable). More importantly, the transform is a tight-frame, specifically; the same filters used in the decomposition are used for the reconstruction.

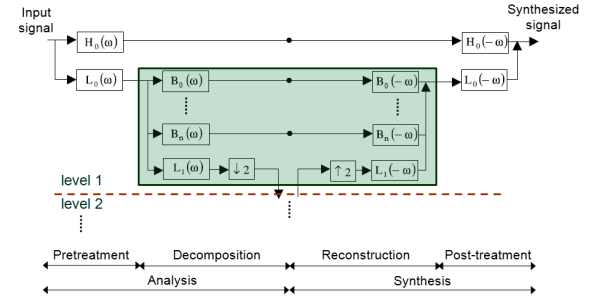


Figure 1: First level of the diagram system of a steerable pyramid.

The block diagram of a steerable pyramid (Kasariadis, 1996) is given in figure 1 for both analysis and synthesis. In the analysis part, the image is decomposed into highpass and lowpass subbands using  $H_0$  and  $L_0$  filters. The lowpass band continues to break down into a collection of oriented  $n+1$  bandpass subbands  $B_0, B_1, \dots, B_n$  and a lower lowpass subband  $L_1$ . The lower lowpass subband is subsampled by a factor of 2 in the  $x$  and  $y$  directions. This process constitutes the first level of decomposition of a steerable pyramid. Repeating the enclosed area on the output of subsampling provides the recursive (pyramid) structure, hence the next levels. In the synthesis part, the reconstructed image is obtained by upsampling the lower lowpass subband by a factor of 2 and adding up the collection of bandpass subbands and the highpass subband.

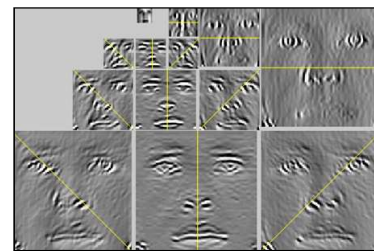


Figure 2: Face image decomposition using a 3-level steerable pyramid with 4 orientations.

Figure 2 illustrates a three level steerable pyramid decomposition of a face image, with 4 orientations ( $n=3$ ). Shown are the four orientated bandpass images at three scales and the final lowpass image. The initial highpass image is not shown.

It is important to point out that only the analysis part of the steerable pyramid diagram system is applied while extracting features from the face texture.

### 3 THE IV<sup>2</sup> DATABASE AND THE EVALUATION PROTOCOL

In biometric studies, it is very crucial to have a big set of data on which the efficiency of proposed algorithms can be evaluated. Some databases are available (Petrovska, 2009) but they don't offer enough data either in number or in variability. The IV<sup>2</sup> database was designed with the aim of proposing multiple test situations to allow evaluation with regard to variability well known to be critical for the biometric systems performance, such as pose, expression, illumination and quality (Figure 3). The IV<sup>2</sup> database has been realized during the Techno Vision program and has been supported by the French Research Ministry in collaboration with the French Ministry of Defence.

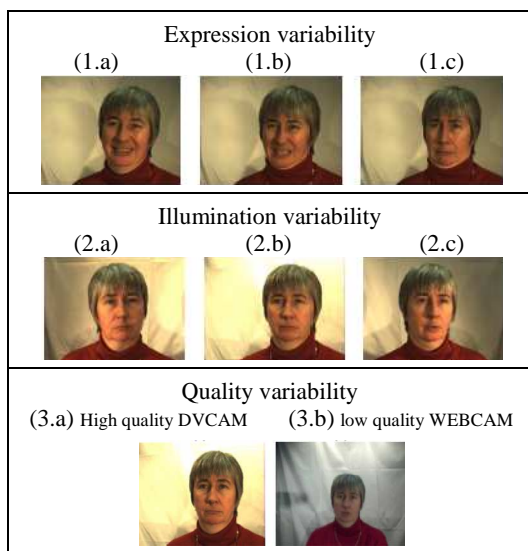


Figure.3. Examples of variability related to (1.a-c) expression, (2.a-c) illumination and (3.a-b) quality.

#### 3.1 Database description

The publicly available IV<sup>2</sup> database allows monomodal and multimodal experiments using face data. It contains 315 subjects with one session data where 77 of them also participated to a second session. From this database, a subset of 52 subjects, distributed as a development set, constitutes also the training set.

The face and sub-face data that are present in the IV<sup>2</sup> database are: 2D audio-video talking face sequences, 2D stereoscopic data acquired with two pairs of synchronized cameras, 3D facial data acquired with a laser scanner, and iris images acquired with an portable infrared camera. This database has been collected in several locations, by many operators. From the totality of the acquired data, are available two disjoint sets for development and evaluation purposes, and also an evaluation package.

#### 3.2 The 2D face evaluation protocol

As a closing stage of the IV<sup>2</sup> project, an evaluation campaign was performed involving iris recognition, 2D and 3D-face recognition and also multimodal recognition. In the 2D-Face evaluation (Mellakh, 2009), the strategy of having "one variability" at a time was adopted in order to evaluate how challenging variability - related to illumination, expression, quality or multi-session images - can be for the biometric systems.

In this evaluation campaign a set of more than 15000 images were divided into four subsets. Table 1 gives a description of the test images according to the corresponding experiment. The protocol was constructed so as to have almost the same number of client and imposters tests. This strategy allows having equivalent FAR (False Acceptance Rate) and FRR (False Rejection Rate).

Table 1: Description for the images used for the 2D-Face experiments (V. = variation and N. = number)

Experiment	Exp1	Exp2	Exp3	Exp4
Sessions	Mono	Mono	Mono	Multi
Quality	High	High	Low	High
Expression V.	Small	No	No	No
Illumination V.	No	Yes	No	No
N. Intraclass	2595	2503	1774	1796
N. Interclass	2454	2364	1713	1796

Each team who proposed an algorithm conducted a list of tests with no indication of their type (intraclass or interclass). Only one still image per subject was used for enrolment and one still image for the test. A set of 156 images from 52 different subjects acquired at the development stage has been as well distributed to each team for the training phase. Five appearance based methods were evaluated on the IV<sup>2</sup> database. Details about the algorithms are given in (Petrovska, 2007) and comparative results are shown in table 3.

## 4 PROPOSED METHOD AND EXPERIMENTAL RESULTS

Beforehand the recognition, normalization process is performed on gray-scale images in order to extract efficiently the region of interest. Normalization is operated so as to deal with pose variations (rotation and scale) taking place at the acquisition step, and get all the images at the same scale and size ( $64 \times 64$ ).

### 4.1 Characterization through Adaboost

First experiments have been conducted only with Adaboost. It has been noticed that the performance increased with the number of iterations of adaboost model. Limited by the computational time, a number of 400 iterations has been kept. It can be seen from table 3 (Test 1) that Adaboost reach very good EER: 3.7%, in Experiment 1. However, performance drastically drops in Experiments 2 to 4 that involve challenges related to illumination, quality and multisession variabilities. This is due to the fact that Adaboost is very dependent on the training set; witch has been acquired, almost under the same conditions as in Experiment 1.

### 4.2 Characterization through SP

Many experiments have been run on how the SP has to be performed. A first experiment constructed the feature vector from the whole information at all orientations and scales provided by the entire filtered image. Another experiment was carried out by composing the feature vector of the 49 ( $8 \times 8$ ) filtered blocs issued from the initial image. A third try was run to build the feature vector with the 49 energy values computed from the ( $8 \times 8$ ) filtered blocs. Other tests have been completed to investigate on how the recognition performance is further enhanced with the increase of the orientations and scales numbers. Specifically an exhaustive set of experimentations has been fulfilled. Optimum parameters were obtained by extracting features from the entire ( $64 \times 64$ ) filtered image by utilizing a four-level fifth derivative steerable pyramid (6 orientations). The feature vector was made of more than  $10^4$  intensity values. Details about EER are given in table 3 (Test 2) where it can be seen that the results obtained by the SP-based algorithm are worse than the  $IV^2$  ones.

As a matter of fact, SP features are over-complete and stand for a high dimensional representation of face images. Straightforward, implementation exhibits a lack of efficiency.

### 4.3 Characterization through Adaboost applied to SP

To make up for the SP and Adaboost shortcomings when operated separately, AdaBoost was adopted as a feature selector and classifier that reduces the SP feature space size in order to keep only relevant characteristics.

In the next, the influence of a non exhaustive list of parameters, related to the application strategy of Adaboost on SP-filtered images, is firstly presented. Then, a comparison with the submitted algorithms at the  $IV^2$  evaluation campaign is brought. The results are reported with the Equal Error Rate percentage.

#### 4.3.1 Applying Adaboost on the whole SP

A first set of tests was carried out by applying Adaboost on the whole steerable features so as to select the more discriminant ones. Increasing the number of iterations related to the Adaboost model (i.e. the number of selected features) improves the recognition rate as shown in figure 4. But, unfortunately, running tests was so time consuming that reaching more than 400 features was not practical.

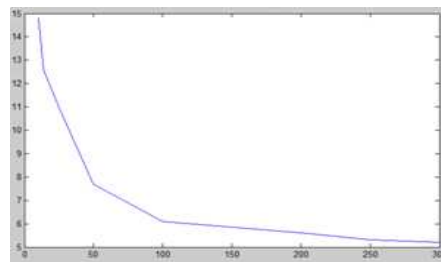


Figure.4. Equal Error Rate versus number of iterations in Adaboost model.

It is obvious from EERs in table 3 (Test3.a) that allaying adaboost to SP, is much better than applying Adaboost or SP separately. The results are almost acceptable, when compared to the  $IV^2$  other tests; but they are still not good enough. The aim to ameliorate the method, and at the same time, encounter the computation time restriction, led to the idea of applying Adaboost per band.

#### 4.3.2 Applying Adaboost on every sub-band of SP

Many strategies of application have been tested:

**Using only one sub-band:** A set of experiments focused on which oriented sub-band of the SP

should be taken into account as an input to Adaboost. Previous works (Khiari, 2011) on SP showed that there is no favourite orientation for all tests. Each one has its own contribution. That's why; the strategy of fusing all sub-bands has been adopted, so as to take advantage of complementarities between different orientations.

**Operating sub-band fusion:** By adopting the alternative of fusion, several parameters had to be fixed. Among them, is the choice of the score fusion rule. Usual operators such as maximum score, scores product and scores sum were tried. Best results were achieved with Sum rule, with an augmentation reaching 4.4% compared to the best band used separately. Another question was about the number of features to keep on every sub-band. Two options were tested:

Same feature number for all sub-bands : Referring to results of Test 3.b in table 3, this kind of fusion is better than applying Adaboost on the whole SP. Moreover, it is much less time consuming, making possible to increase the number of considered features.

Weighting feature number per sub-band : While conducting the test of Adaboost on the entirety of the SP, it has been noticed that the number of selected features was not the same for all sub-bands. Based on this observation, the idea of weighting the number of features for every sub-band (oriented at all scales, high-pass and low-pass) was suggested. Once the total number of features is fixed, the weights were attributed based on feature distribution found in Test 3.a as follows: 2%; 12.75%; 13.5%; 10.25%; 18%; 15.25%; 18.5%; 9.75% respectively for High-pass, oriented band-pass 1 to 6, and low-pass sub-bands. As instance, assuming a total feature number of 800, Adaboost selects respectively: 16, 102, 108, 82, 144, 122, 148 and 78 features from the pre-cited sub-bands. Almost experiments were improved attaining 0.8% of enhancement (table 3, Test 3.c) when compared to taking the same feature number for all sub-bands.

Another possibility was to weight the scores of the different classifiers before the sum fusion:

Weighting scores of classifiers with same number of features : This is equivalent to a weighted sum-rule at the score level while keeping the same number of features for all sub-bands. Assuming that  $E_{sb}$  is the EER of Sub-band  $sb$ , then, the weights  $W_{sb}$  associated to the scores of sub-band  $sb$  are calculated from Equation 2 (Su, 2009).

An improvement reaching 0.7% was denoted (table 3, Test 3.d) when compared to taking the same feature number for all sub-bands.

$$W_{sb} = \frac{1}{E_{sb}}, U = \sum_{sb=1}^{nb\_sb} \frac{1}{W_{sb}}, \quad (2)$$

with  $\sum_{sb=1}^{nb\_sb} W_{sb} = 1$ ,  $0 < W_{sb} < 1$

and  $nb\_sb$  the total number of sub-bands.

Weighting scores of classifiers with weighted feature numbers : A final try, was to proceed by weighting at the characterization level (feature numbers) as well as at the score level (weighted sum rule). This strategy of fusion gave almost best results for the four experiments (table 3, Test 3.e).

To summarize, the method having the optimum configuration was then to filter the entire (64x64) image by a 6-orientation and 3-scale Steerable Pyramid. Then, apply Adaboost on each sub-band (oriented at all scales, high-pass and low-pass) with weighted numbers of features. Afterward, score fusion was operated on classifiers by weighted sum rule.

Table 3 illustrates also the evaluation of the proposed method put side by side with the other ones. It can be seen that combining SP to Adaboost improves considerably the performance of SP and Adaboost applied separately. On another hand, in a comparison to PCA1 (Chari 2009) enhancements are obvious in all experiments.

Regarding PCA2, it has to be underlined that the training set on which the face space has been constructed isn't the same as indicated by the protocol. In fact, it is built using 300 images from BANCA database (30 subjects, 10 images per subject) (Petrovska, 2009) with 3 different quality images. While proposed method strictly followed the protocol using only 156 images of 52 individuals (3 images/person) acquired under quite good conditions, which is not the case of the test subsets where many variations are present. The small number of trained images besides the different acquisition conditions between training and test subsets constitutes an additional challenge, which explains the results obtained in experiment 4 that are better than ours. Despite, proposed method outperforms PCA2 in the first three experiments.

Compared to LDA, except for the first controlled scenario, proposed method achieves higher performance in the other more challenging ones. But it still remains less robust than LDA/Gabor which is a combining approach of a projection-based method (LDA) and a space-scale feature-extraction method (Gabor).

## 5 CONCLUSIONS

Through this work, a combining approach based on Steerable Pyramid and Adaboost has been introduced for 2D-face recognition. It has been proved that joining a non-linear classifier to the SP brought significant enhancements, especially when weighting both sub-bands feature numbers and classifiers scores. Future works are intended to consider Adaboost only as a feature selector, rather than a classifier, on SP outputs, and study the effectiveness of conventional projective classifiers such as PCA and LDA on the Ada-SP-features.

## REFERENCES

- S. Z. Li, A. K. Jain, 2005. *Handbook of Face Recognition*. Springer.
- A. Mellakh, A. Chaari., S. Guerfi & all., 2009. 2D Face Recognition in the IV<sup>2</sup> Evaluation Campaign. In *Conf. on Advanced Concepts for Intelligent Vision Systems (ACIVS)*, Bordeaux, France.
- X. Zhang and Y. Jia, 2005. Face Recognition Based on Steerable Feature and Random Subspace LDA. In *Inter. workshop on Analysis and Modelling of Faces and Gestures (AMFG)*, 3723(2):170-183, Beijing, China.
- Y. Su, S.G. Shan, X.L. Chen, and W. Gao, 2009. Hierarchical ensemble of global and local classifiers for face recognition. In *Journal of IEEE Trans. on Image Processing, IEEE*, 18(8): 1885-1896.
- N. Khiari, H. Mahersia, K. Hamrouni, 2008. Iris Recognition Using Steerable Pyramids. In *1st IEEE Inter. Conf. on Image Processing, Theory, Tools and Applications (IPTA)*, 368-374, Sousse, Tunisia.
- E.P. Simoncelli and W.T. Freeman, 1995. The Steerable Pyramid: A Flexible Architecture For Multi-scale Derivative Computation. In *IEEE Inter. Conf. on Image Processing (ICIP)*, 3(2):444-447, USA.
- Y. Freund and R. E. Schapire, 1995. A decision-theoretic generalization of on-line learning and an application to boosting. In *Computational Learning Theory: Eurocolt '95*, pages 23–37. Springer-Verlag.
- P. Viola and M. Jones, 2001. Rapid Object Detection using a Boosted Cascade of Simple Features. In *Proc of IEEE Comp. Soc. Conf on Computer Vision and Pattern Recognition, 2001. (CVPR)*. I(1):511-518.
- A. Krasaridis and E.P. Simoncelli, 1996. A Filter Design Technique for Steerable Pyramid Image Transforms. In *IEEE, Inter. Conf. on Acoustics, Speech and Signal Processing (ICASSP)*, 4:2387-2390, Atlanta, USA.
- D. Petrovska-Delacrétaz, G. Chollet and B. Dorizzi, 2009. *Guide to Biometric Reference Systems and Performance Evaluation*. Springer.
- D. Petrovska-Delacrétaz, S. Lelandais, J.Colineau & all., 2008. The IV<sup>2</sup> Multimodal Biometric Database (Including Iris, 2D, 3D, Stereoscopic, and Talking Face Data), and the IV2- 2007 Evaluation Campaign. In *2nd IEEE Inter. Conf. on Biometrics: Theory, Applications and Systems (BTAS)*, USA.
- N. Khiari, S. Lelandais, C. Montagne and K. Hamrouni, 2011. 2D Face recognition on IV<sup>2</sup> database by Steerable pyramid and LDA. In *Conf on Traitement et Analyse de l'information, Méthodes et Applications (TAIMA)*, Tunisia.
- A. Chaari, S. Lelandais and M. Ben Ahmed, 2009. A pruning approach improving face identification system. *Advanced Video and Signal Based Surveillance (AVSS)*, Italy.

Table 3: Comparative results between proposed algorithms (blue and green) and IV<sup>2</sup> first evaluation campaign ones (black). 3.a: Adaboost on total SP. 3.a to 3.e: Adaboost on SP bands. Description: feature number; rate = weighting number of features per band; s = sum rule; ws = weighted sum rule.

Numéro test	Description	Participants	Exp1	Exp2	Exp3	Exp4
Previous Tests IV <sup>2</sup>		<b>PCA1</b>	6.7 (±0.8)	20.7 (±1.3)	20.1 (±1.6)	22.2 (±1.6)
		<b>PCA2</b>	7.3 (±0.8)	21.6 (±1.4)	13.6 (±1.4)	16.3 (±1.4)
		<b>mod PCA</b>	5.3 (±0.7)	20.7 (±1.4)	19.5 (±1.6)	20.5 (±1.5)
		<b>LDA</b>	<b>3.7 (±0.6)</b>	22.5 (±1.4)	21.7 (±1.7)	19.7 (±1.5)
		<b>LDA/Gabor</b>	4.2 (±0.6)	<b>12.0 (±1.1)</b>	<b>8.3 (±1.1)</b>	<b>11.3 (±1.2)</b>
<b>1</b>		<b>Adaboost</b>	<b>3.7(±0.6)</b>	22.7(±1.4)	44.3(±2.0)	28.6(±1.8)
<b>2</b>		<b>SP</b>	11.0 (±1.0)	23.0 (±1.4)	20.1 (±1.6)	23.9 (±1.7)
<b>3.a</b>	<b>400(total_SP)</b>	<b>Ada/SP</b>	5.0(±0.7)	19.5(±1.3)	14.1(±1.4)	22.9(±1.6)
<b>3.b</b>	<b>400(8*50)s</b>	<b>Ada/SP</b>	4.4(±0.7)	18.8(±1.3)	13.7(±1.4)	22.4(±1.6)
	<b>800(8*100)s</b>	<b>Ada/SP</b>	4.6(±0.7)	18.6(±1.3)	13.7(±1.4)	21.3(±1.6)
<b>3.c</b>	<b>400(rate)s</b>	<b>Ada/SP</b>	4.5(±0.7)	18.6(±1.3)	13.0(±1.3)	21.8(±1.6)
	<b>800(rate)s</b>	<b>Ada/SP</b>	4.7(±0.7)	18.2(±1.3)	12.9(±1.3)	20.9(±1.6)
<b>3.d</b>	<b>400(8*50) ws</b>	<b>Ada/SP</b>	<b>3.7(±0.6)</b>	18.7(±1.3)	13.5(±1.3)	22.4(±1.6)
	<b>800(8*100)ws</b>	<b>Ada/SP</b>	3.9(±0.6)	18.5(±1.3)	12.9(±1.3)	21.0(±1.6)
<b>3.e</b>	<b>400(rate) ws</b>	<b>Ada/SP</b>	4.1(±0.6)	18.6(±1.3)	13.0(±1.3)	21.7(±1.6)
	<b>800(rate) ws</b>	<b>Ada/SP</b>	4.1(±0.7)	<b>18.1(±1.3)</b>	<b>12.9(±1.3)</b>	<b>20.4(±1.6)</b>