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BOOSTING STEERABLE FEATURES FOR 2D FACE RECOGNITION ON IV² DATABASE

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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 IV² 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 IV² 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 IV² 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 IV² project. Section 4 describes the proposed method and reports experimental results in comparison to five other algorithms submitted in the first IV² evaluation campaign (Mellakh, 2009). Finally, section 5 ends up with conclusions and perspectives for future work.

2 BACKGROUND CONCEPTS

This section introduces the basical 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 $(x_1, y_1)\ldots(x_n, y_n)$ with y_i in $\{+1, -1\}$ is the class label for the positive or negative sample x_i; where $i = 1,\ldots,n$. 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 $t = 1,\ldots,T$:

1. For each filter Φ_j, compute the best weak classifier h_j, that uses Φ_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 α and β 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 :

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

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.

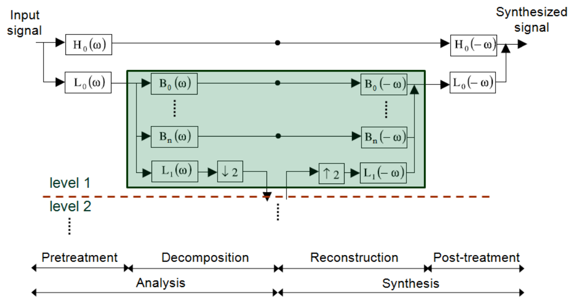

Figure 1: First level of the diagram system of a steerable pyramid.

The block diagram of a steerable pyramid (Kasaridis, 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 $B_0, B_1,\ldots, B_n$ 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.

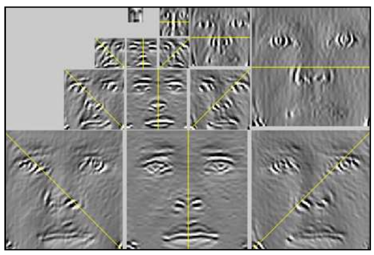

Figure 2: Face image decomposition using a 3-level steerable pyramid with 4 orientations.

Figure 2 illustrates a three level steerable pyramid decomposition of a face image, with *4* orientations *(n=3)*. Shown are the four orientated bandpasss 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 IV² 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 IV² 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 IV² 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.

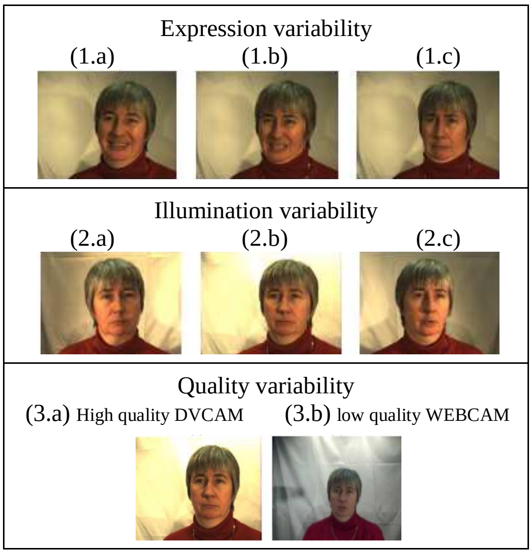

Figure.3. Examples of variability related to (1.a-c) expression, (2.a-c) illumination and (3.a-b) quality.

3.1 Database description

The publicly available IV² 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 IV² 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 IV² 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 IV² 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 *(64x64).*

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 (8x8)* 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 *(8x8)* 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 *(64x64)* 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 IV² 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 IV² 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.

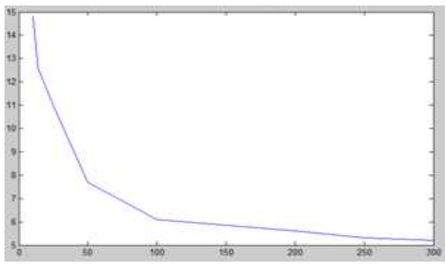

Figure.4. Equal Error Rate vursus number of iterations in Adaboost model.

It is obvious from EERs in table 3 (Test3.a) that allying adaboost to SP, is much better than applying Adaboost or SP separately. The results are almost acceptable, when compared to the IV² 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 took 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.

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

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

and 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 (Chaari 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. Despites, 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.

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Table 3: Comparative results between proposed algorithms (blue and green) and IV² 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 IV²		PCA1	6.7 (±0.8)	20.7 (±1.3)	20.1 (±1.6)	22.2 (±1.6)
		PCA2	7.3 (±0.8)	21.6 (±1.4)	13.6 (±1.4)	16.3 (±1.4)
		mod PCA	5.3 (±0.7)	20.7 (±1.4)	19.5 (±1.6)	20.5 (±1.5)
		LDA	**3.7 (±0.6)**	22.5 (±1.4)	21.7 (±1.7)	19.7 (±1.5)
		LDA/Gabor	4.2 (±0.6)	**12.0** (±1.1)	**8.3** (±1.1)	**11.3** (±1.2)
1		Adaboost	**3.7(±0.6)**	22.7(±1.4)	44.3(±2.0)	28.6(±1.8)
2		SP	11.0 (±1.0)	23.0 (±1.4)	20.1 (±1.6)	23.9 (±1.7)
3.a	400(total_SP)	Ada/SP	5.0(±0.7)	19.5(±1.3)	14.1(±1.4)	22.9(±1.6)
3.b	400(8*50)s	Ada/SP	4.4(±0.7)	18.8(±1.3)	13.7(±1.4)	22.4(±1.6)
	800(8*100)s	Ada/SP	4.6(±0.7)	18.6(±1.3)	13.7(±1.4)	21.3(±1.6)
3.c	400(rate)s	Ada/SP	4.5(±0.7)	18.6(±1.3)	13.0(±1.3)	21.8(±1.6)
	800(rate)s	Ada/SP	4.7(±0.7)	18.2(±1.3)	12.9(±1.3)	20.9(±1.6)
3.d	400(8*50) ws	Ada/SP	**3.7(±0.6)**	18.7(±1.3)	13.5(±1.3)	22.4(±1.6)
	800(8*100)ws	Ada/SP	3.9(±0.6)	18.5(±1.3)	12.9(±1.3)	21 .0(±1.6)
3 .e	400(rate) ws	Ada/SP	4.1(±0.6)	18.6(±1.3)	13.0(±1.3)	21.7(±1.6)
	800(rate) ws	Ada/SP	4.1(±0.7)	**18.1(±1.3)**	**12.9(±1.3)**	**20.4(±1.6)**