Fusion of Infrared and Visible Spectra Face Recognition Methods

Giovani Chiachia, Aparecido Nilceu Marana
UNESP – Faculdade de Ciências – Departamento de Computação – Bauru – SP – Brazil
giovanichiachia@gmail.com, nilceu@fc.unesp.br

Abstract

In general, face recognition systems are based on visible spectrum images and, in order to have good performance, they need to work in light-controlled environments. However, the performance of such systems decrease significantly when illumination changes. On other hand, Long-Wave Infrared (LWIR) face imagery is insensitive to illumination changes and gives the temperature pattern from the face to be recognized. The purpose of this work is to assess the performance of the fusion of well-known statistical visible and LWIR-based methods for face recognition.

1. Introduction

While humans can easily recognize faces in adverse situations and even after years, machine face recognition remains a big challenge in the fields of Computer Vision and Pattern Recognition [1].

To overcome this challenge, alternative sensor modalities (e.g. 3D range image) have been proposed. One of the new sensing modalities for face recognition is the infrared (IR), which can measure the temperature emitted by the face [1].

Besides being insensitive to light changes, the subsurface anatomical information captured by IR sensors is believed to be unique for each person [1].

Due to all these characteristics and regarding previous researches [2], it is expected that using IR spectrum images together with visible spectrum images can lead to more robust and efficient face recognition systems.

The main goal of this work is to assess the performance of the fusion of well-known statistical visible and LWIR-based methods for face recognition.

2. Database

In our experiments, it was used the University of Notre Dame (UND) time-gap face database [3], which has a large collection of images acquired by visible and LWIR spectrum cameras. The images were acquired once a week, with most of the subjects participating several times, totalizing 2023 images in each spectrum, with neutral and smiling facial expressions. During a given acquisition session, 4 images per subject were taken, being 2 with neutral and 2 with smiling expressions.

In our experiments, 187 subjects from the UND face database were used in the training phase and other 54 subjects were selected for the gallery and the probe sets. Each of these 54 subjects attended at least 7 and at most 10 acquisition sessions. The first session of each subject was used in the gallery set and the remaining 6 to 9 sessions constitute the probe set. Hence, this work also has taken into account the recognition performance over time.

Figure 1 shows an example of visible and IR spectrum images of the same face. In the IR spectrum image (right), the gray level ranges from black (cold) to white (hot).

Figure 1. Visible spectrum image (left) and IR spectrum image of the same face [3].

3. Face Recognition Methods and Their Correlation

Three different face recognition methods were used in this work: Principal Component Analysis (PCA) with Euclidean distance, Linear Discriminant Analysis (LDA) with LDASoft distance, and PCA with Mahalanobis Angle [4], as implemented in [5].

Each method was applied individually in both spectra. Table 1 shows the obtained results, where Top 1 means the correct recognition rate considering only the most similar recovered face, and EER means the equal error rate (the false acceptance and the false rejection rates are equal).

In order to predict the performance of the 15 fusion possibilities, it was obtained the *Q statistic* measures of dependence, $Q_{i,k}$, which for two methods i and k, ranges from -1 to 1 [6]. For statistically independent methods, $Q_{i,k}$ is 0. For statistically correlated methods, $Q_{i,k}$ tends to 1, and for inversely correlated methods, $Q_{i,k}$ tends to -1.

Table 1. The six face recognition methods and their individual performances.

Method	Description	Spectrum	Top1	EER
1	PCA Euclidiano	IR	46.06	24.55
2	PCA Euclidiano	Visible	87.92	14.11
3	LDA LDASoft	IR	40.17	25.65
4	LDA LDASoft	Visible	79.92	16.24
5	PCA Mahalanobis	IR	87.74	8.87
6	PCA Mahalanobis	Visible	96.84	6.01

4. Fusion

In this work, the fusion was carried out in the score level. Three score normalization approaches were assessed: Min-Max, Double Sigmoid and Tanh-estimators [7]. The fusion techniques assessed were: sum, max, min, and product.

5. Experimental Results

In our experiments, the Double Sigmoid score normalization approach and the product fusion technique have shown to be more regular (better mean improvement) than the others. Therefore, they were chosen to denote the overall fusion performances.

As expected, it can be observed in Table 2 that the correlation between methods applied on different spectra is much smaller than the correlation of methods applied on the same spectrum, which indicates that they hit and fail in different situations for many probes. For instance, the correlation of methods 5 and 6 was 0.14, the lowest for different spectra methods, and the correlation of methods 2 and 4 was 0.85, the lowest for methods on the same spectrum.

We can also observe in Tables 1 and 2 that there is a relationship among the *Q Statistic,* the Top1 individual rates, and the performance of the fusion. When the *Q Statistic* is low (lower than 0.5) and the Top 1 individual rates are high (greater than 50%), the performance of the fusion compared with the best individual rates always increases. Hence, the overall best performance (98.85% for Top 1, and EER=3.28) was obtained with the fusion of two good individual methods, 5 and 6, that present the lowest correlation rate (0.14).

Table 2. Overall performance from the fusion of methods X and Y as identified in Table 1. The best and worst results are highlighted.

X	Y	Q-Statistic	Top1 XY	% Improv.	EER XY	% Improv.
1	2	0.29	86.47	-1.66	11.78	16.51
1	3	0.93	46.00	-0.13	23.50	4.27
1	4	0.22	84.89	6.23	13.33	17.90
1	5	0.85	84.41	-3.80	10.32	-16.26
1	6	0.24	97.21	0.38	5.17	13.87
2	3	0.14	85.68	-2.55	12.05	14.62
2	4	0.85	89.87	2.21	12.80	9.35
2	5	0.22	95.63	8.76	4.84	45.41
2	6	0.95	96.54	-0.31	5.92	1.48
3	4	0.27	82.16	2.81	13.83	14.80
3	5	0.87	83.92	-4.36	10.70	-20.56
3	6	0.30	97.27	0.44	5.78	3.83
4	5	0.25	95.15	8.44	6.20	30.12
4	6	0.96	95.81	-1.07	7.33	-22.09
5	6	0.14	98.85	2.07	3.28	45.47

6. Conclusion

The experimental results obtained in this work suggest that the fusion of IR and visible spectra-based methods may improve significantly the face recognition performance.

Acknowledgments

The authors thank CAPES for financial support.

References

[1] S. G. Kong et. al, “Recent advances in visual and infrared face recognition—a review”, *Computer Vision and Image Understanding 97*, (2005) 103–135;

[2] X. Chen, P. J. Flynn, K. W. Bowyer, "Infra-red and visible-light face recognition", CVIU 99 (3), 332-358, 2005.

[3] Biometrics Database Distribution. The Computer Vision Laboratory, Univ. of Notre Dame, http://www.nd.edu/~cvrl/ , 2002.

[4] A. M. Martinez, A. C. Kak, "PCA versus LDA", IEEE PAMI, 2001.

[5] D. Bolme, R. Beveridge, M. Teixeira and B. Draper,“The CSU Face Identification Evaluation System: Its Purpose, Features and Structure”, *International Conference on Vision Systems*, pp 304-311, Graz, Austria, April 1-3, 2003.

[6] Kuncheva, L.I., Whitaker, C.J., Shipp, C.A., Duin, R.P.W., “Is Independence Good For Combining Classifiers?”, 0-7695-0750-6/00 IEEE, pp. 168-171, 2000.

[7] Jain, A., Nandakumar, K., Ross, A., "Score normalization in multimodal biometric systems", *Pattern Recognition 38*, pp. 2270-2285, 2005.