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Probabilistic Bayesian framework for infrared face recognition

Moulay A. Akhloufi, and Abdelhakim Bendada

***Abstract*—**Face recognition in the infrared spectrum has attracted a lot of interest in recent years. Many of the techniques used in infrared are based on their visible counterpart, especially linear techniques like PCA and LDA. In this work, we introduce a probabilistic Bayesian framework for face recognition in the infrared spectrum. In the infrared spectrum, variations can occur between face images of the same individual due to pose, metabolic, time changes, etc. Bayesian approaches permit to reduce intrapersonal variation, thus making them very interesting for infrared face recognition. This framework is compared with classical linear techniques. Non linear techniques we developed recently for infrared face recognition are also presented and compared to the Bayesian face recognition framework. A new approach for infrared face extraction based on SVM is introduced. Experimental results show that the Bayesian technique is promising and lead to interesting results in the infrared spectrum when a sufficient number of face images is used in an intrapersonal learning process.

***Keywords*—**Face recognition, biometrics, probabilistic image processing, infrared imaging.

I. INTRODUCTION

FACE recognition is an area of computer vision that has attracted a lot of interest from the research community. A growing demand for robust face recognition software in security applications has driven the development of interesting approaches in this field.

A large quantity of research in face recognition deals with visible face images [1], [2]. In the visible spectrum the illumination changes represent a significant challenge for the recognition system. Illumination change introduces a lot of errors during the recognition phase. Another challenge for face recognition in the visible spectrum involves the changes in facial expressions. Facial expression can lead to a poor performance of the face recognition system in visible images. To avoid these problems, researchers propose the use of 3D face recognition [3] and infrared face recognition [4], [5]. Infrared face recognition is a growing area of research. Many of the techniques used in infrared face recognition are inspired from their visible counterparts. Known techniques used in visible face image recognition are also used with infrared images, like Eigenfaces or Fisherfaces [4], [5]. More recently in [6], [7] and [8] physiological information extracted from high temperature regions in thermal face images were used in infrared face recognition.

The vast majority of infrared face recognition techniques are based on linear approaches used in visible face recognition. Recent work has been conducted using non linear dimensionality reduction techniques for infrared face recognition with promising results [9].

In this work we introduce a probabilistic Bayesian framework for face recognition in the infrared spectrum. Different Bayesian techniques were proposed for visible face recognition [10], [11]. Bayesian techniques can reduce intrapersonal variation which makes them suitable for face recognition. In the infrared spectrum, variations can occur between face images of the same individual due to pose, metabolic, time changes, etc. The proposed approach adapt to these changes in the learning step thus reducing possible errors during the recognition process.

Tests were conducted using two infrared face databases: Equinox multimodal face database [12] and a new infrared multispectral face database we have developed recently in order to evaluate infrared face recognition techniques in a close to real world situations. This new database is briefly introduced in the following section.

In this work we used the popular Equinox database and a new multispectral database we developed for infrared face recognition tests.

II. INFRARED FACE DATABASES

In this work we used the popular Equinox database and a new multispectral database we developed for infrared face recognition tests.

A. Equinox database

The Equinox database [12] is a large collection of face images. These images were acquired using a special setup formed by visible and infrared cameras and a controlled lighting system (frontal, left and right lights). The following modalities are available:

- Visible (0.4-0.7 microns);
- Short-wave (SWIR, 0.9-1.7 microns);
- Long-wave infrared (LWIR, 8-12 microns);
- Mid-wave infrared (MWIR, 3-5 microns).

M. A. Akhloufi is Vision Systems Laboratory, Laval University, Quebec, QC G1V0A6 and with Centre de Robotique et Vision Industrielles, Levis, QC G6V 6Z9 Canada (phone: 418-833-1965 x3275; fax: 418-833-8726; e-mail: akhloufi@gel.ulaval.ca, moulay.akhloufi@crvi.ca).

A. Bendada is with Vision Systems Laboratory, Laval University, Quebec, QC G1V0A6 Canada (e-mail: Bendada@gel.ulaval.ca).

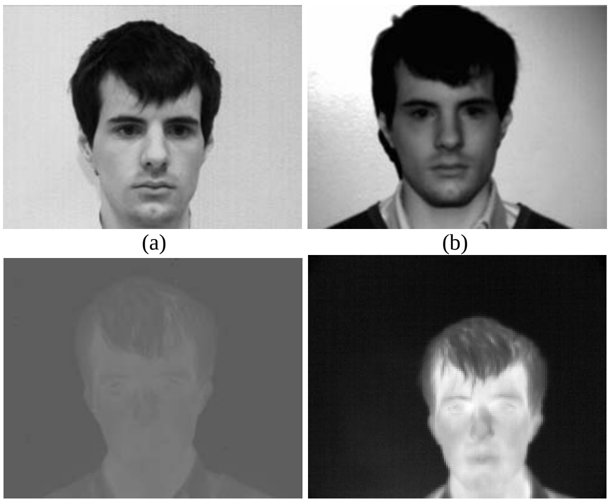
The image acquisition was conducted under controlled conditions. Multiple facial expressions, illumination changes and facial images with and without eyeglasses are available.

B. Laval University multispectral face database

A new multispectral face database was developed in order to evaluate the performance of infrared face recognition techniques. This database has the following spectrums (Fig. 1):

- Visible (0.4-0.7 microns);
- Near infrared (NIR, 0.8-0.9 microns).
- Long-wave infrared (LWIR, 8-12 microns);
- Mid-wave infrared (MWIR, 3-5 microns).

The images have a higher resolution than equinox (640x480 for visible and NIR images and 640x512 for MWIR images). Image acquisition was conducted in a less controlled environment compared to Equinox. The database contains multiple facial expressions, changes over time, metabolic variations (after temperature change due to exercise) and presence of eyeglasses.



(a) (b) (c) (d)

Fig. 1 Images from the new multispectral database: (a) visible, (b) near infrared, (c) mid-wave infrared and (d) long-wave infrared.

III. FACE EXTRACTION

For face learning and recognition, we extract face regions for further processing. In the visible, NIR and SWIR spectrums, face images are extracted using the alignment technique proposed in [11] (Fig. 2).

Fig. 2 Face extraction in the visible spectrum.

For MWIR and LWIR face images, learned thermal data is used in order to segment the face region. First, the face image intensities are normalized using a histogram stretching technique.

A set of randomly selected thermal face images is used in the learning process. Face and non face regions are extracted and feed to an SVM classifier. This classifier is further used to classify face and non face regions. The result of this classification is sent to the Bayesian face recognition framework. Figure 3 show an example of the obtained segmentation in a MWIR face image

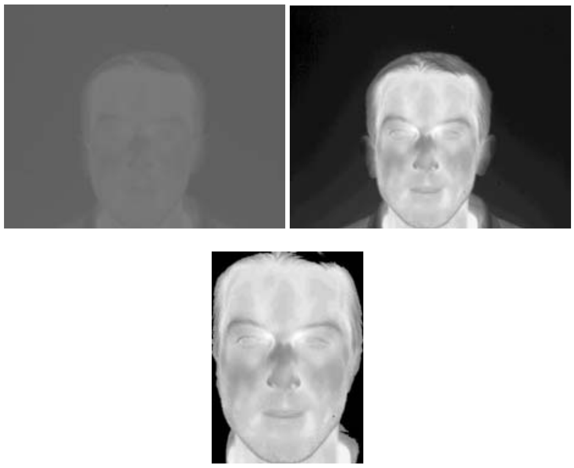


Fig. 3 MWIR face normalization and segmentation using learned thermal data.

IV. BAYESIAN FRAMEWORK

The proposed Bayesian approach is based on the work described in [11]. A combination of PCA technique and a Bayesian Maximum Likelihood (ML) is used in order to classify the face image.

The Bayesian approach uses a probabilistic measure of similarity based on a Bayesian Maximum Likelihood (ML) analysis of image differences [10], [11]. The PCA is used for the projection of differenced images in two subspaces: intrapersonal and extrapersonal.

An intrapersonal subspace are learned from face images of the same person using the PCA face recognition approach, while extrapersonal subspaces is learned from faces of multiple individuals as in the standard eigenfaces technique (PCA).

The projection in the two sets of learned eigenfaces is used to compute and compare the likelihoods $P(\Delta|\Omega_I)$ and $P(\Delta|\Omega_E)$.

The image is considered to belong to the same person if $P(\Delta|\Omega_I) > P(\Delta|\Omega_E)$ (Ω_I and Ω_E represent respectively the intrapersonal and extrapersonal eigenfaces. Δ is the difference image).

V. Non linear techniques

Dimensionality reduction techniques are a set of mathematical techniques used for representing available data in a low dimensional space. The obtained representation is a compressed version of the original data with the most important characteristics preserved for further processing. Dimensionality reduction seek to represent a set of data as a *p*-dimensional manifold embedded in an *m*-dimensional space (with $p<m$) [13].

Dimensionality reduction techniques can be classified in three types [13]:

• Linear/nonlinear: based on the type of transformation applied to the data (mapping).

• Local/global: based on the properties the transformation does preserve (in most nonlinear methods, there is a compromise between the preservation of local topological relationships and the global structure of the data).

• Euclidean/geodesic: based on the distance function used to estimate whether two data points are close to each other before and after the mapping.

In face recognition, dimensionality reduction techniques are used for subspace learning and recognition of data extracted from face images. In infrared face recognition most of the techniques used are linear techniques. In this work we used nonlinear techniques we have developed for multispectral face recognition. For this purpose, the following techniques were developed: global non linear techniques (Kernel-PCA, Kernel-LDA) and local non linear techniques (Local Linear Embedding, Locality Preserving Projection).

A. Global techniques

Kernel based subspace learning techniques [14], [15] have been used in order to overcome the limitations of classical linear mapping. Kernel-PCA and Kernel-LDA are tested in this work. The kernel trick is used to map original data in a non linear space prior to dimensionality reduction using PCA and LDA. In our experiments we used the following Gaussian kernel function:

$$k(x,y) = \exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right) \qquad (1)$$

B. Local techniques

In our work, two local non linear techniques are used for multispectral face recognition: Local Linear Embedding (LLE) and Locality Preserving Projection (LPP).

1) Local Linear Embedding (LLE)

LLE is a non-linear dimensionality reduction technique based on the assumption that that each data point and its neighbors lie on or close to a locally linear patch of the manifold [16].

Given $X \in R^n$ a *DxN* matrix of the data and $Y \in R^n$ a *dxN* matrix of the data in the new subspace with *N* the number of data and *D* and *d* the dimensions in the original space and the new subspace. In order to compute LLE, three steps are needed:

1) Create the adjacency graph containing the information from K nearest neighbors of each data point.
2) Compute the reconstruction weights *Wij*. Choose the weights to minimize the following cost function:

$$J(W) = \sum_{i=1}^{N} \left\| x_i - \sum_{j=1}^{K} W_{ij} x_j \right\|^2 \qquad (2)$$

3) Compute the new coordinates Y using the weights W:
   a. Compute the matrix: $M = (I-W)(I-W)^T$;
   b. keep the *d* eigenvectors u_i associated with the bottom *d* non zero eigenvalues.

2) Locality Preserving Projection (LPP)

LPP finds an embedding that preserves local information. LPP shares some properties with LLE, such as locality preserving character [17]. It aims to represent the data in a lower dimensional subspace while preserving the local structure of the original image space. LPP is obtained by finding the optimal linear approximations to the eigenfunctions of the Laplace Beltrami operator or an approximation to Laplacian eigenmaps [18].

The first step is similar to LLE in finding adjacent K nearest neighbors.

The second step permits the computation of a weight matrix *Wij*. The matrix values can be computed using a kernel function of the following form:

$$W_{ij} = e^{\frac{\|x_i - x_j\|^2}{t}} \qquad (3)$$

Where t is a real.

The last step permits the computation of the eigenvectors using the Laplacian by solving the following system:

$$XLX^tA = \lambda XDX^tA \qquad (4)$$

Where D is a diagonal matrix with $D_{ii} = \sum_j W_{ij}$ and $L = D - W$ is the Laplacian matrix.

The new representation Y in the new subspace: $x_i \to y_i = A^t x_i$ where $A = (a_0; a_1; \ldots; a_{d-1})$ and a_i are the eigenvectors obtained by solving equation (8).

VI. Experimental results

Experimental tests were conducted using two infrared face databases: the Equinox multimodal face database and a new infrared multispectral face database. Table I show the obtained results for Equinox database and Table II show the obtained results using the new face database.

TABLE I
FACE RECOGNITION RESULTS IN EQUINOX DATABASE

	Visible	SWIR	MWIR	LWIR
PCA	**95%**	**89%**	**92%**	93%
LDA	**95%**	88%	**92%**	**95%**
KPCA	0%	5%	3%	3%
KLDA	2%	5%	4%	4%
LLE	86%	85%	89%	89%
LPP	88%	**89%**	89%	90%
Bayesian	50%	71%	74%	72%

Bayesian face recognition in the infrared spectrum of Equinox database performs better than its visible counterpart (Table I). Mid-wave infrared gives the best performance closely followed by long-wave and short-wave spectrums. The best results are however obtained using linear dimensionality reduction algorithms: PCA for visible, SWIR and MWIR and LDA for visible, MWIR and LWIR. Also, a non linear technique LPP gives good results in the SWIR spectrum.

TABLE II
FACE RECOGNITION RESULTS IN LAVAL UNIV. DATABASE

	Visible	NIR	MWIR	LWIR
PCA	85%	12%	11%	10%
LDA	59%	**78%**	11%	10%
KPCA	20%	26%	11%	10%
KLDA	0%	11%	11%	9%
LLE	86%	24%	11%	10%
LPP	**88%**	24%	13%	13%
Bayesian	**88%**	70%	**86%**	**70%**

The results of Bayesian face recognition using the new database shows that a better performance is obtained with the visible spectrum (Table II). This result contradicts the Equinox database result. However, the visible images in this last database have a higher resolution and the availability of more images for intrapersonal learning can explain this increase in performance. The visible spectrum results are closely followed with the mid-wave face recognition results. In the other hand, the poor results of near infrared Bayesian face recognition can be explained by the low number of intrapersonal images available for the Bayesian learning process. LDA gives the best results in the NIR spectrum. LWIR results are due the low resolution of the image. However, overall the Bayesian approach gave the best results for this database.

In this work, experimental results show that the Bayesian framework for face recognition is an interesting approach for processing infrared face images taken in a non controlled environment. This approach integrates the intrapersonal variations during the learning process thus leading to an increase in recognition performances. Comparison between the results obtained with Equinox database and the new database indicate that the number of intrapersonal faces used during the learning process is very important in the recognition performance. This will be explored furthermore in future work.

VII. CONCLUSION

In this work we introduced a new approach based on a probabilistic Bayesian framework for face recognition in the infrared spectrum. In the infrared spectrum, variations can occur between the face images of the same individual due to pose, metabolic, time changes, etc. Bayesian approaches permit to reduce intrapersonal variation, thus making them very interesting for infrared face recognition.

Tests were conducted using a popular Equinox multimodal face database and a new infrared multispectral face database developed recently. This new database is built in a less controlled environment in order to permit an evaluation of multispectral face recognition techniques in a close to real world situations.

The obtained results are promising and show that a Bayesian approach is an interesting solution to intrapersonal variations occurring in thermal face images.

Work is being conducted to adapt Bayesian infrared face recognition techniques in a multimodal fusion scheme for robust face recognition.

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