# Infrared face recognition using texture descriptors

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## ABSTRACT

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. In the visible spectrum the illumination and face expressions changes represent a significant challenge for the recognition system. To avoid these problems, researchers proposed recently the use of 3D and infrared imaging for face recognition.

In this work, we introduce a new framework for infrared face recognition using texture descriptors. This framework exploits linear and non linear dimensionality reduction techniques for face learning and recognition in the texture space. Active and passive infrared imaging modalities are used and comparison with visible face recognition is performed. Two multispectral face recognition databases were used in our experiments: Equinox Database (Visible, SWIR, MWIR, LWIR) and Laval University Multispectral Database (Visible, NIR, MWIR, LWIR).

The obtained results show high increase in recognition performance when texture descriptors like LBP (Local Binary Pattern) and LTP (Local Ternary Pattern) are used. The best result was obtained in the short wave infrared spectrum (SWIR) using non linear dimensionality reduction techniques.

**Keywords:** Face recognition, infrared imaging, biometrics, textures.

## 1. 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 [9] and Bayesian techniques for infrared face recognition with promising results [10].

Texture analysis have been widely studied in the literature. Many methods have been proposed in order to handle machine vision problems where texture features serve as a cue for classification, segmentation and recognition. Various statistical descriptors have been proposed for the measure of image textures [11], [12]. Since its introduction, Local Binary Pattern (LBP) texture descriptor has been successfully used in texture classification [13]. Many work was done using LBP for visible spectrum face recognition [14]-[18].

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In this work we introduce the use of LBP like texture descriptors for efficient multispectral face recognition. The proposed descriptors will be used in active and passive infrared spectrums face recognition. Local Binary Pattern (LBP) and Local Ternary Pattern (LTP) descriptors are used. Also a simple differential LTP descriptor (DLTP) is introduced. The proposed texture space is less sensitive to noise, illumination change and facial expressions. These characteristics make it a good candidate for efficient multispectral face recognition. Linear and non linear dimensionality reduction techniques are used for performance evaluation of multispectral face recognition in the texture space

Tests were conducted using two multispectral infrared face databases: Equinox multimodal face database [19] 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.

## 2. INFRARED FACE DATABASES

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

The Equinox database [19] 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 µm);
- Short-wave (SWIR, 0.9-1.7 µm);
- Mid-wave infrared (MWIR, 3-5 µm);
- Long-wave infrared (LWIR, 8-12 µm).

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

Also, a new multispectral face database [9] was developed in order to evaluate the performance of infrared face recognition techniques and compare it with the visible spectrum face recognition. This database has the following spectrums (Figure 1):

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

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)

Figure 1. Example images with different expressions from Laval University multispectral face database: (a) visible happy, (b) near infrared angry with eyeglasses, (c) mid-wave infrared with glasses and a smile and (d) long-wave infrared neutral.

## 3. TEXTURE DESCRIPTORS

### 3.1 Local Binary Pattern (LBP)

The local binary pattern (LBP) texture analysis operator was introduced in [13]. It is a gray-scale invariant texture measure computed from the analysis of a 3x3 local neighbourhood over a central pixel. The LBP is based on a binary code describing the local texture pattern. This code is built by thresholding a local neighbourhood by the gray value of its center.

The eight neighbours are labelled using a binary code {0, 1} obtained by comparing their values to the central pixel value. If the tested gray value is below the gray value of the central pixel, then it is labelled 0, otherwise it is assigned the value 1:

$$P_i' = \begin{cases} 0 & \text{if } P_i < P_0 \\ 1 & \text{otherwise} \end{cases} \quad (1)$$

$P_i'$ is the obtained binary code, $P_i$ is the original pixel value at position $i$ and $P_0$ is the central pixel value.

With this technique there is 256 ($2^8$) possible patterns (or texture units).The obtained value is then multiplied by weights given to the corresponding pixels. The weight is given by the value $2^{i-1}$. Summing the obtained values gives the measure of the LBP (Figure 2):

$$I_{LBP} = \sum_{i=1}^{8} P_i' \, 2^{i-1} \quad (2)$$

| | | |
|---|---|---|
| 100 | 90 | 40 |
| 212 | 100 | 12 |
| 200 | 75 | 120 |

(a)

| | | |
|---|---|---|
| 1 | 0 | 0 |
| 1 | | 0 |
| 1 | 0 | 1 |

(b)

| | | |
|---|---|---|
| 1 | 2 | 4 |
| 8 | | 16 |
| 32 | 64 | 128 |

(c)

| | | |
|---|---|---|
| 1 | 0 | 0 |
| 8 | | 0 |
| 32 | 0 | 128 |

(d)

LBP = 1+8+32+128 = 169

Figure 2. Computation of LBP; (a) Original image region, (b) Thresholding step of equation (1), (c) Binary mask, (d) Resulting image after using the binary mask.

The central pixel is replaced by the obtained LBP value (169 in the example of figure 2). A new LBP image is constructed by processing each pixel and its 3x3 neighbours in the original image. LBP can be easily extended to include a larger neighbourhood area, leading to a different result.

### 3.2 Local Ternary Pattern (LTP)

LBP has been successfully used by the research community in texture classification. However LBP is sensitive to noise in near uniform regions. In order to solve this problem a new texture descriptor was introduced recently in [18]. This Descriptor is called local ternary pattern (LTP). Like the LBP, it gives an invariant texture measure computed from the analysis of a local neighbourhood over a central pixel.

LTP extends LBP to 3-valued codes, in which local pixels having their gray levels within an interval between a user defined threshold *–t* and *+t* when compared with the central pixel are assigned a value 0. The pixels above *+t* when compared to the central pixel are assigned a value 1 and the ones below *–t* when compared to the central pixel are assigned a value -1. Equation (3) shows how to compute the LTP:

$$P_i^{'} = \begin{cases} 1 & if\ P_i \geq P_0 + t \\ 0 & if\ \left|P_i - P_0\right| < t \\ -1 & if\ P_i \leq P_0 - t \end{cases} \tag{3}$$

*t* is a user defined threshold. This makes the resulting descriptor less sensitive to noise but no longer strictly invariant to graylevel transformations.

Figure 3 shows the result of applying LTP to an image using a threshold $t = 5$.

| | | |
|---|---|---|
| 100 | 90 | 40 |
| 212 | 100 | 12 |
| 200 | 98 | 103 |

(a)

| | | |
|---|---|---|
| 0 | -1 | -1 |
| 1 | | -1 |
| 1 | 0 | 0 |

(b)

Figure 3. Computation of LTP; (a) Original image region, (b) Thresholding step of equation (3).

In order to get rid of the negative part of the LTP, the LTP above is split in two LBP channels. The upper pattern (LTPU) is obtained by replacing the negative values with 0. The lower pattern (LTPL) is obtained by first replacing the 1 with 0 and then changing the negative values to 1. Figure 4 shows the resulting upper and lower patterns (LTPU and LTPL).

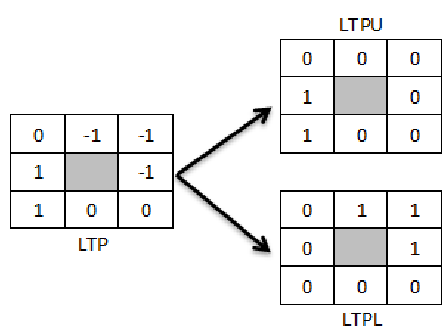


Figure 4. Result of splitting LTP in two LBP channels (LTPU and LTPL).

The resulting pixel is computed as for LBP by multiplying the resulting kernels with the local weights. Figure 5 show how to compute the LTPU and LTPL values. This processing gives two texture images enhancing different characteristics of the image texture.

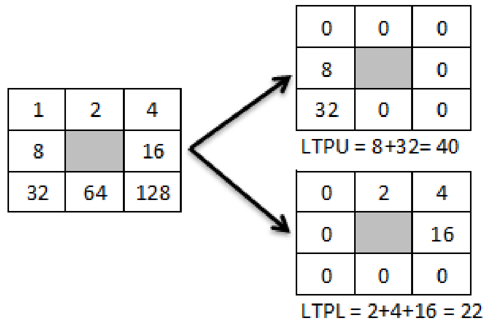


Figure 5. Computation of LTPU, LTPL for the data in figures 3 and 4.

## 4. SUBSPACE LEARNING AND RECOGNITION

Subspace learning 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 $p<m$) [20].

Dimensionality reduction techniques can be classified in three types [20]:

- 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 present nonlinear techniques we developed for multispectral face recognition. Global and local dimensionality reduction techniques are used and their performances compared to classical linear dimensionality reduction techniques. 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).

### 4.1 Linear techniques

The most popular techniques in infrared face recognition are linear based techniques. The most used is by far the Eigenfaces (PCA) technique [5],[9] followed by Fisherfaces (LDA) technique [5],[9]. These techniques serve as a reference for performance comparison with other techniques.

**Principal Component Analysis (PCA)**

The PCA or Eigenfaces technique permit a dimensionality reduction by subspace representation of faces. Average face image is constructed from the training set and used to derive the eigenvectors representing the face space approximation.

Given an $m$-dimensional vector representation for a face image, the PCA can be used to find a subspace with maximum variance basis directions in the original space. Let $F$ represent the linear transformation mapping the original $m$-dimensional space onto a $n$-dimensional subspace with $n<<m$. The new vector is defined by: $y_i = F x_i$. The columns of $F$ are the eigenvectors obtained by solving $\lambda_i v_i = Q v_i$, where $Q$ is the covariance matrix.

Under the assumption that the training set is a good representation of possible face images, the selected vectors are a good approximation of all possible faces. By selecting the eigenvectors corresponding to high eigenvalues we construct a low dimensional projection space of face images. More details about this technique can be found in the work of Turk *et al.*[21].

**Linear Discriminant Analysis (LDA)**

The second most popular technique in infrared face recognition is LDA, also known as Fisherfaces technique. Like PCA, this technique permits a dimensionality reduction by subspace representation of faces. Instead of principal components decomposition, in LDA the data are separated linearly in the Eigenspace using Singular Value Decomposition (SVD) [5],[9].

LDA searches for vectors that best discriminate between classes. Given a number of features representing the data, LDA creates a linear combination of these features in order to get the largest mean differences between the desired classes. The LDA defines two measures [9]:

Within-class scatter matrix: $$S_w = \sum_{j=1}^{c}\sum_{i=1}^{N_j}(x_i^j - \mu_j)(x_i^j - \mu_j)^T \quad (4)$$

Between-class scatter matrix: $$S_b = \sum_{j=1}^{c}(\mu_j - \mu)(\mu_j - \mu)^T \quad (5)$$

Where: $x_i^j$ is the $i^{th}$ sample of class $j$, $\mu_j$ is the mean of class $j$, $c$ is the number of classes, $N_j$ is the number of samples in class $j$, $\mu_j$ is the mean of all classes.

With LDA we try to maximize between-class measure while minimizing within-class measure. We look for a linear subspace $W$ maximizing the discrimination criteria:

$$J(W) = \frac{\left|W^T S_b W\right|}{\left|W^T S_w W\right|} \quad (6)$$

## 4.2 Global kernel based non linear techniques

Kernel based subspace learning techniques [9] have been used in order to overcome the limitations of 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 use a Gaussian kernel function:

$$k(x, y) = \exp(-\frac{\|x - y\|^2}{2\sigma^2}) \quad (7)$$

## 4.3 Local non linear techniques

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

**Local Linear Embedding (LLE)**

LLE is a non-linear dimensionality reduction technique. The assumption is that that each data point and its neighbors lie on or close to a locally linear patch of the manifold [9],[20].

Given $X \in R^n$ a $D$x$N$ matrix of the data and $Y \in R^n$ a $d$x$N$ 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, the following steps are needed:

1. Create the adjacency graph containing the information from K nearest neighbors of each data point.
2. Compute the reconstruction weights $W_{ij}$. Choose the weights to minimize the following cost function:

$$J(W)=\sum_{i=1}^{N}\left\|x_i-\sum_{j=1}^{K}W_{ij}x_j\right\|^2 \qquad (8)$$

3. Compute the new coordinates $Y$ using the weights $W$ :

   a. compute $M=(I-W)(I-W)^T$ ;

   b. keep the $d$ eigenvectors $u_i$ associated with the bottom $d$ non zero eigenvalues:

$$Y=[y_1\ldots y_N]=\begin{bmatrix}u_1\\ \vdots\\ u_d\end{bmatrix}_{d\times N} \qquad (9)$$

**Locality Preserving Projection (LPP)**

LPP finds an embedding that preserves local information. LPP shares some properties with LLE, such as locality preserving character [9],[20]. 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 [9],[20].

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

The second step permits the computation of a weight matrix $W_{\text{ij}}$. The matrix values can be computed using a kernel function of the following form:

$$W_{ij}=e^{\frac{\|x_i-x_j\|^2}{t}} \qquad (10)$$

Where $t$ is a real.

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

$$XLX^tA=\lambda XDX^tA \qquad (11)$$

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: $x_i\rightarrow y_i=A^t x_i$ where $A=(a_0;a_1;\ldots;a_{d-1})$ and $a_i$ are the eigenvectors obtained from solving equation (11).

## 5. EXPERIMENTAL RESULTS

Experiments were conducted on normalized images from the multispectral databases presented above. A face region was extracted based on the detected eyes and mouth positions. This region was then aligned and normalized using an affine transform in a 128x128 pixels image. The obtained images were processed using LBP and LTP. The face images contain variations like: facial expressions, pose, eyeglasses, facial hair, etc. For LTP processing we tested different thresholds, and the best results were obtained for a threshold value equal to 5 (Only the best results are presented in the tables below). Figures 6 and 7 show two examples of different texture processing techniques on the extracted infrared face images.

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

Figure 6. Processed images in the MWIR spectrum : (a) Extracted MWIR face image, (b) LBP texture image, (c) LTPL texture image, (d) LTPU texture image and (e) Differential LTP texture image.

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

Figure 7. Processed images in the LWIR spectrum : (a) Extracted LWIR face image, (b) LBP texture image, (c) LTPL texture image, (d) LTPU texture image and (e) Differential LTP texture image.

Subspace learning was conducted for each algorithm and for all the spectrums. For each recognition algorithm, 10 tests with 100 randomly chosen images for recognition were conducted (overall 1000 tests were done).

The obtained results are given in tables 1 and 2, they show the obtained success rate for each algorithm in different spectrums and with different texture processing. The result with the original image without texture processing is also presented.

We can see that the results are very interesting. Texture descriptors also increase the recognition performance, particularly in the infrared spectrums (LBP and LPTH are the best performing texture descriptors techniques). Recognition in the visible spectrum for Equinox is also increased by texture processing. Non linear techniques are also the best performing in Equinox database. For Laval University database LDA gives overall the best results. The performance of LDA in University Laval database is explained by the availability of more face images for each individual in the intrapersonal learning process. Overall the best results were obtained for Equinox SWIR images when using non linear dimensionality reduction techniques.

Table 1. Results for Equinox Database.

| | **Visible** | | | | **SWIR** | | | | **MWIR** | | | | **LWIR** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Orig** | **LBP** | **LTPH** | **LTPL** | **Orig** | **LBP** | **LTPH** | **LTPL** | **Orig** | **LBP** | **LTPH** | **LTPL** | **Orig** | **LBP** | **LTPH** | **LTPL** |
| **PCA** | 16% | 87% | 87% | 83% | 29% | 71% | 88% | 94% | 32% | 72% | 61% | 77% | 25% | 57% | 65% | 67% |
| **KPCA** | 0% | 4% | 4% | 2% | 6% | 17% | 0% | 6% | 3% | 3% | 11% | 0% | 7% | 0% | 2% | 3% |
| **LDA** | 2% | 7% | 9% | 10% | 76% | 16% | 17% | 18% | 0% | 12% | 2% | 18% | 5% | 8% | 12% | 5% |
| **KDA** | 0% | 2% | 3% | 3% | 5% | 5% | 5% | 6% | 0% | 3% | 2% | 3% | 0% | 3% | 2% | 2% |
| **LPP** | 67% | 69% | 89% | 82% | 66% | 95% | 95% | 94% | 18% | 79% | 74% | 76% | 18% | 62% | 73% | 67% |
| **LLE** | 75% | 86% | 79% | 78% | 68% | 96% | 93% | 94% | 40% | 81% | 74% | 73% | 46% | 40% | 48% | 47% |

Table 2. Results for Laval University Database.

| | Visible | | | | NIR | | | | MWIR | | | | LWIR | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Orig | LBP | LTPH | LTPL | Orig | LBP | LTPH | LTPL | Orig | LBP | LTPH | LTPL | Orig | LBP | LTPH | LTPL |
| **PCA** | 39% | 76% | 87% | 76% | 10% | 41% | 66% | 70% | 35% | 80% | 79% | 82% | 42% | 71% | 75% | 69% |
| **KPCA** | 3% | 0% | 1% | 3% | 5% | 3% | 4% | 4% | 5% | 7% | 1% | 3% | 5% | 2% | 2% | 8% |
| **LDA** | 86% | 80% | 89% | 92% | 60% | 68% | 80% | 75% | 65% | 86% | 82% | 84% | 54% | 79% | 81% | 82% |
| **KDA** | 2% | 3% | 1% | 0% | 4% | 4% | 0% | 2% | 2% | 3% | 2% | 2% | 2% | 0% | 0% | 1% |
| **LPP** | 66% | 69% | 60% | 68% | 31% | 42% | 62% | 50% | 52% | 71% | 81% | 65% | 44% | 62% | 52% | 65% |
| **LLE** | 94% | 67% | 66% | 72% | 37% | 39% | 42% | 43% | 55% | 50% | 57% | 55% | 45% | 50% | 46% | 52% |

# 6. CONCLUSION

In this work we introduced the use of LBP like texture descriptors for efficient multispectral face recognition. The recognition algorithms in texture space outperformed the success rate obtained for non transformed images particularly in the infrared spectrum.

The obtained results are promising and show that texture descriptors are interesting solutions for a better multispectral face recognition system. The proposed texture space is less sensitive to noise, illumination change and facial expressions.

Work is being conducted to adapt the above texture descriptors to a multispectral fusion scheme in order to build a robust face recognition system.

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