Thermal Face Recognition Using Local Patterns

Gabriel Hermosilla[1], Gonzalo Farias[1], Hector Vargas[1],
Francisco Gallardo[1], and Cesar San-Martin[2]

[1] Escuela de Ingeniería Eléctrica,
Pontificia Universidad Católica de Valparaíso,
Valparaíso, Chile
[2] Department of Electrical Engineering,
University of La Frontera, Temuco, Chile
{gabriel.hermosilla,gonzalo.farias,hector.vargas}@ucv.cl,
gallardo.silva@gmail.com,
cesar.sanmartin@ufrontera.cl

Abstract. The aim of this article is to compare the performance of well-known visible recognition methods but using the thermal spectrum. Specifically, the work considers two local-matching based methods for face recognition commonly used in visible spectrum: Local Binary Pattern (LBP) and Local Derivative Pattern (LDP). The methods are evaluated and compared using the UCHThermalFace database, which includes evaluation methodology that considers real-world conditions. The comparative study results shown that, contrary to what happens in the visible spectrum, the LBP method obtains the best results from the thermal face recognition. On the other hand, LDP results show that it is not an appropriate descriptor for face recognition systems in the thermal spectrum.

Keywords: Face Recognition, Thermal Face Recognition, Local Binary Pattern, Local Derivative Pattern.

1 Introduction

The past decade has experienced a steady increase of research and development in a wide variety of security surveillance applications which has been studied primarily in the visible spectrum. Among others these includes: automatic safety monitoring, access control and biometrics applications such as face recognition. Face recognition allows us to recognize the identity of a subject which is stored in a database in order to perform, for example, a video monitoring or access control. However, most of these systems operate in the visible spectrum, which involves some issues such as dependency on light conditions and variations in pose.

Several studies have shown that the use of thermal images can solve limitations of visible-spectrum face recognition, such as invariance to illumination and robustness to variations in pose [1][2]. This is due to the physical properties of thermal technology, located in the long-wave infrared spectrum (8-12 μm). Furthermore, in recent years, the price of thermal cameras has decreased significantly, and their technology has

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been improved, obtaining better resolution and quality (e.g., non-uniformity correction techniques have eliminated the fixed pattern noise that was produced by old thermal cameras [3]).

Nevertheless, thermal face images still have undesirable variations due to different factors: (i) changes in ambient temperature, (ii) modifications of the metabolic processes of the subjects, and (iii) variable sensor response when the camera is working for long periods of times [4][5][6]. These factors make the performance of recognition methods decrease significantly if no corrective action is taken into account or no invariant features are employed. Therefore, methods that improve the performance of thermal face recognition still need to be developed.

In [7] a comparative study of advanced thermal face recognition methods, which considered real-world conditions and unconstrained environments, was presented. The comparison was carried out using the UCHThermalFace database[1]. This database incorporates thermal images acquired in indoor and outdoor setups, with natural variations in illumination, facial expression, pose, accessories, occlusions, and background. The methods considered in the study were: Histograms of Local Binary Pattern (LBP) features [8], Histograms of Weber Linear Descriptors (WLD) [9], Gabor Jet Descriptors (GJD) [10], Scale-Invariant Feature Transform (SIFT) Descriptors [11], and Speeded Up Robust Features (SURF) Descriptors [12]. Best results were obtained by SIFT and WLD. However, all methods showed a very low performance when an indoor gallery set was used with an outdoor test set, or vice versa. In addition, in all cases the performance in outdoors was lower than in indoor setups.

In this general context, the aim of this article is to compare two face recognition algorithms based on local patterns, the Local Derivative Pattern versus the Local Binary Pattern. The Local Derivative Pattern (LDP) is a local feature descriptor, which have been recently used in visible-spectrum face recognition [13]. The Local Binary Pattern (LBP) is a classical texture descriptor used mainly in face recognition applications. Both algorithms are selected to perform this study due to their excellent face recognition results in the visible spectrum [13]. However, the performance of LDP outperforms LBP in the visible spectrum.

The methods are evaluated and compared using exactly the same evaluation methodology performed in [7]. The comparative study is carried out in the thermal spectrum using UCHThermalFace database. The use of the UCHThermalFace database allows evaluating the methods under real-world conditions, which includes natural variations in illumination, indoor/outdoor setup, facial expression, pose, accessories, occlusions, and background. The analyzed methods consider also their suitability for the defined requirements, i.e., real-time operation, just one image per person, fully online (no training), and robust behavior in thermal domain.

This paper is structured as follows. The methods under analysis are described in section 2. In section 3 the comparative analysis of these methods is presented. Finally, the main conclusions of this work are given in section 4.

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[1] The UCHThermalFace database is available for download at `http://vision.die.uchile.cl/UCHThermalFaceDB/`

2 Methods under Comparison

As mentioned above, the methods under comparison were selected considering their fulfillment of the defined requirements (real-time, fully online, just one image per person), and their performance in former comparative studies of face-recognition methods [13][14].

2.1 LBP Histograms

Face recognition using histograms of LBP features was originally proposed in [8], and has been used by many groups since then. In the original approach, three different levels of locality are defined: pixel level, regional level, and holistic level. The first two levels of locality are achieved by dividing the face image into small regions from which LBP features are extracted and histograms are used for efficient texture information representation. The holistic level of locality, i.e. the global description of the face, is obtained by concatenating the regional LBP features. The recognition is performed using a nearest neighbor classifier in the computed feature space, using one of the three following similarity measures: histogram intersection, log-likelihood statistic, and Chi square. We implemented this recognition system, without considering preprocessing (cropping using an elliptical mask and histogram equalization are used in [8]), and by choosing the following parameters: (i) images divided in 32 (4x8) or 80 (4x20) regions, instead of using the original divisions which range from 16 (4x4) to 256 (16x16), and (ii) using the Euclidean distance as the similarity measure, instead of the log-likelihood statistic, in addition to histogram intersection and Chi square.

2.2 LDP Histograms

Local Derivative Pattern was originally proposed in [13]. The high-order LDP encodes micropatterns by using information based on local derivative direction variations in a face region. The algorithms can capture more detailed information than LPB because of the use of high order local derivative direction variations.

The algorithm operates with four directional derivatives of the original image. The image is derived in 0°, 45°, 90° and 135° directions. For a neighborhood of 8 pixels around a central pixel Z0 (see Figure 1), it is obtained the nth set of derivatives (a set of 4 new images) using:

$$I^{n}_{0^\circ}(Z0) = I^{n-1}_{0^\circ}(Z0) - I^{n-1}_{0^\circ}(Z4) \tag{1}$$

$$I^{n}_{45^\circ}(Z0) = I^{n-1}_{45^\circ}(Z0) - I^{n-1}_{45^\circ}(Z3) \tag{2}$$

$$I^{n}_{90^\circ}(Z0) = I^{n-1}_{90^\circ}(Z0) - I^{n-1}_{90^\circ}(Z2) \tag{3}$$

$$I^{n}_{135^\circ}(Z0) = I^{n-1}_{135^\circ}(Z0) - I^{n-1}_{135^\circ}(Z1) \tag{4}$$

being I^{n}_{α} the nth derivative of the original image in α direction (α=0°, 45°, 90°, 135°).

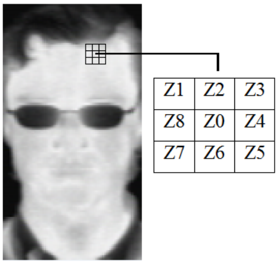


Fig. 1. Example of 8-neighborhood around the central pixel Z0

To calculate the high order nth LDP, it is necessary to describe the gradient in a local region of directional (n-1)th – order derivative images I_α^{n-1}. This is performed using:

$$LDP_\alpha^n = \{f\left(I_\alpha^{n-1}(Z0), I_\alpha^{n-1}(Z1)\right), f\left(I_\alpha^{n-1}(Z0), I_\alpha^{n-1}(Z2)\right)$$

$$\ldots, f\left(I_\alpha^{n-1}(Z0), I_\alpha^{n-1}(Z8)\right)\} \quad (5)$$

where $f(.,.)$ is a binary coding function which determines the types of local patterns transitions, given by:

$$f\left(I_\alpha^{n-1}(Z0), I_\alpha^{n-1}(Zi)\right) = \begin{cases} 0 \; if \; I_\alpha^{n-1}(Z0) \cdot I_\alpha^{n-1}(Zi)) > 0 \\ 1 \; if \; I_\alpha^{n-1}(Z0) \cdot I_\alpha^{n-1}(Zi)) \leq 0 \end{cases}$$

$$i = 1,2,..,8 \quad (6)$$

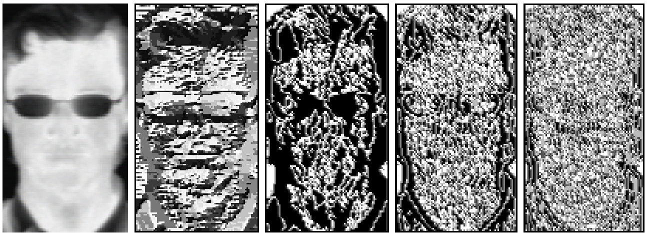
The high-order local patterns provide more detailed texture information than the LBP operator, because the high order nth LDP corresponds to a local pattern string of 32-bit encoding local texture pattern around the pixel. However, it is more sensitive to noise when the order n becomes high.

To perform a face representation, the LDP method is combined by using a spatial histogram. This allows it to be more robust against variations in pose or illuminations. Given a direction α, the LDP image is divided into rectangular regions, the spatial histogram is represent by the concatenation of these regions for each direction α.

We implemented this recognition system using 2nd, 3th and 4th order for LDP histograms, with the use of three similarity measures: Histogram Intersection, Euclidean distance, and Chi Square. Examples of the visualization of LBP and LDP are shown in Figure 2.

2.3 Notation: Methods and Variants

We use the following notation to refer to the methods and their variations: A-B-C. (i) A describes the name of the face-recognition algorithm: LBP (Histogram of LBP features), LDPn (Histogram of n^{th} order LDP features); (ii) B denotes the similarity measure or classification approach: HI (Histogram Intersection), XS (Chi square), EU (Euclidian Distance); (iii) C number of divisions or regions of LBP-based and LDP-based methods.



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

Fig. 2. Different representations of LBP and LDP (α=0°). (a) Original face image. (b) LBP. (c) Second order LDP. (d) Third order LDP. (e) Fourth order LDP.

3 Experiments

The evaluation of the selected methods is analyzed considering real-world conditions that include indoor/outdoor setups and natural variations on facial expression, pose, accessories, occlusions, and background. The analysis is carried out using the UCHThermalFace database, and the experiments defined in [7]. The methods based on local patterns are also compared with the best variant of LBP obtained from [7], the pattern uniform LBP.

3.1 Database Description[2]

The UCHThermalFace database consists of three sets: Rotation, Speech and Expressions. In this work only the Rotation and Speech sets are considered, which consist of indoor and outdoor thermal face images of 53 subjects obtained under different yaw and pitch angles, as well as a set of images captured while the subjects were speaking. The thermal images were acquired using a FLIR 320 TAU Thermal Camera[3] with sensitivity in the range 7.5 -13.5 μm, and a resolution of 324x256 pixels.

The Rotation set contains 22 images per subject, each one corresponding to a different rotation angle acquired in indoor and outdoor sessions. In both cases, the distance from the subject to the thermal camera was fixed at 120 cm, and the thermal camera was situated at different spatial positions (see description in [7]). The Speech

[2] The UCHThermalFace database is described in [7]. Upon request of the readers a more complete description of the database can be provided here.

[3] `http://www.flir.com/cvs/cores/uncooled/products/tau/`

set was captured using the same setup, but with individuals facing the camera and speaking different words. Later on, three frames were randomly selected from the video sequence of each individual in each session (indoor and outdoor).

In summary, for the Rotation and Speech sets, 14 indoor and 14 outdoor subsets are defined in order to carry out face recognition experiments. For the indoor session and the outdoor session, 11 subsets correspond to the different yaw-pitch combinations of the Rotation set (subsets R1 to R11), and 3 to the different images captured in the Speech set (subsets S1 to S3). In each experiment a given subset is used as a test set, and a second one as a gallery set.

3.2 Experiments Description

In order to evaluate the performance of methodologies under comparison, two types of experiments were carried out: (1) parameter's selection experiments that includes the analysis of number of divisions for LDP histograms, and (2) performance analysis in unconstrained conditions experiments which consider partial face occlusions, variations in eye detection accuracy, and indoor versus outdoor galleries (same as in [7]). In all experiments face images are aligned using the annotated eye position; faces are aligned by centering the eyes in the same relative positions, at a fixed distance of 42 pixels between the eyes. All experiments use the best windows size obtained from [7] for the LBP case, 81x150 pixels. Some image examples are showing in Figure 3. The specific experiments are:

Number of Divisions: This experiment examines the effect of the number of division or regions on the recognition performance. This experiment tries to find the optimal number of regions where the performance of LDP histograms is high. For the LBP case, the number of divisions (80 divisions) was obtained from [7].

Partial Face Occlusions: In order to analyze the behavior of the methods in response to partial occlusions of the face area, images were divided into 10 different regions (2 columns and 5 rows), and one of the regions was randomly selected and its pixels set to 0 in order to simulate a partial occlusion.

Eye Detection Accuracy: In order to analyze the sensitivity of the methods on eye position accuracy, we added noise to the position of the annotated eyes in the test images. The noise was added independently to the horizontal and vertical positions of each eye, using the procedure described in [14], which was also used in the experiments reported in [7]. In the different experiments, the noise can take up to 2.5%, 5%, or 10% of the distance between the eyes.

Indoor versus Outdoor Galleries: The performance of face recognition methods depends largely on environmental conditions, particularly of the indoor and outdoor conditions. In these experiments the test and gallery images correspond to images taken from indoor or outdoor session. When the test set corresponds to indoor images, then the gallery images are outdoor images, and vice versa. The outdoor images were captured in summer (with high temperatures up to 30 degrees Celsius), and at that time the faces, as well as the camera, were receiving direct sunlight.

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

Fig. 3. Examples of faces of 81x150 pixels (UCHThermalFace database). (a) Indoor session. (b) Outdoor session. (c) Partial face occlusion. (d) 10% noise in the eyes positions.

3.3 Parameter Selection: Number of Divisions

The dependence of the LDP methodology on number of image divisions is analyzed. In all experiments the indoor rotation subset R6, without any occlusion and without noise in the eye position, is selected as a gallery set because it contains clean frontal views of the faces.

In the experiment the average top-1 recognition rate is computed over all indoor subsets (Rotation and Speech) of the UCHThermalFace database using the already selected face-window size (81x150), and a much larger number of divisions (1x1, 4x4, 4x8, 9x5, 4x20, 9x10, 9x15, 11x22 and 27x10). Figure 4 shows the obtained results. Best performance is obtained when 4x8 and 11x22 regions are used. Since 11x22 regions takes a lot of processing time because it uses a large numbers of divisions, the 4x8 regions (LDP-X-32) is selected to be used in the next experiments.

For the LBP case, the best number of regions is obtained from [7], which corresponds to 4x20 regions (LBP-X-80), however, the experiments include the same number of regions (4x8) used for LDP to perform the comparison.

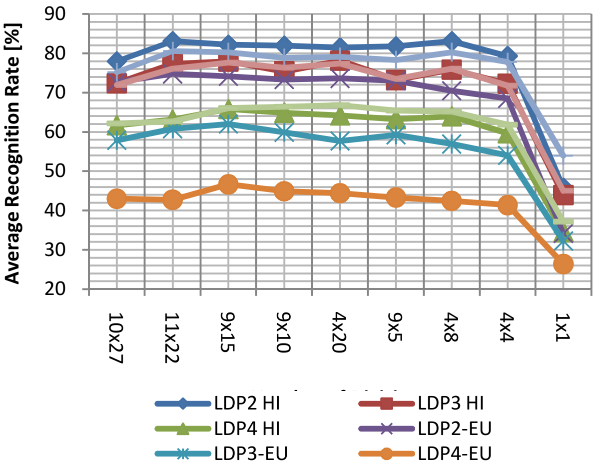


Fig. 4. Average top-1 recognition rate for parameter selection of LDP based methods. The best configuration is for 4x8 regions of the face image for LDP2-HI.

4 Experiments under Unconstrained Conditions

The LDP and LBP based methods are validated using the indoor and outdoor datasets of the UCHThermalFace database. Experiments include partial face occlusions, different eye detection accuracy and the joint use of indoor and outdoor datasets.

The comparison is carried out with the best variants of the LDP and LBP methods, the LDPn-X-32 and the LBP-X-80. Because the number of division are different, the experiment include besides both size of regions, the LDPn-X-80 and LBP-X-32. In addition, the results of LBP-HI-80 pattern uniform obtained from [7] are included.

Table 1 summarizes the recognition rates obtained by the different methods in the experiments. Best results are indicated in bold. In some cases small variations in the results are observed (smaller than 1%) which have no statistical significance and are produced by the statistical nature of the methods.

Preliminary Case: No modifications applied to the database images. Methods are first evaluated without applying any modification to the database images (neither occlusions, nor noise in eyes' positions, etc.), and using a gallery image captured in the same setting as the test set. As shown in table 1, the best results are obtained with LBP-HI-80 for indoor case with 92.5% of recognition rate, and with LBP-HI-32 with 93.1% for outdoor case. It is possible to observe that the LBP variants in the most cases obtain better results than LDPn-X-X methods. The reason about this situation is that LDP operates well when the image is highly detailed, however the thermal image is often more uniform, showing no significant local LDP patterns. The thermal image shows more details when there are variations in the face temperature. In addition, the results of pattern uniform LBP [7], is in third position with 88.5% of recognition rate, being overcome by the original LBP. For LDP case, the results are lower than LBP-variants, the LDP2-HI-32 obtain 83.1% and 83.6% of performance rate for indoor and outdoor respectively. The high order for LDP-variants do not show better rates to perform robust thermal face recognition.

Partial Face Occlusion. From Table 1 shows that the partial face occlusions experiments we observe that LBP variants obtain the best results of performance of recognition, with 90%, decreasing 2.5% percentage points. In the case of the LDP variant, the results are low with 75.1%, the top-1 recognition rate decreases by about 8% with occlusions of 10% of the face area in indoors, and in outdoors decrease 11.9% percentage point. For the LBP pattern uniform the performance decreases from 88.5% to 82.3%, being much better than the original LBP-HI-80. In the outdoor case the performance decreases more than the indoor case.

Eye Detection Accuracy. From Table 1 it can be observed that, as expected, for all methods the recognition rates decreases as the noise in the eye's position increases in indoor and outdoor cases. In the case of the LBP variants, only when the noise is 10%, the performance decreases considerably. The top 1 recognition rate for LBP-HI-32 decreases about 8.3% when the noise is 10%, from 92.1% to 83.8%, while the LBP-HI-80 decreases 10.4%. The LBP pattern uniform decreases from 88.5% to 74.9%. This result is similar to the obtained for the LDP2-HI-32 with 72.3% when the noise is 10%. The high orders LDP are the worst performance of recognition rate. It can be concluded that the original LBP is affected by large changes in alignment, however is most robust to this type of disturbance than LBP pattern uniform and the LDPn variants.

Indoor versus Outdoor Galleries. Same as reported in [7], all methods obtain a very low performance when an indoor gallery set is used with an outdoor test set, or vice versa. The explanation for this poor performance is due to the saturation of outdoor images, produced by the thermal camera exposure to the sun, which varies its operating point [7]. Nevertheless, the best performing method is LBP-HI-32. As the results are lower, neither of the compared methods are robust to this kind of experiments.

In Table 1 is also shown the average performance of the different methods. This value is computed as the average of the results obtained in all indoor and outdoor experiments. It can be observed that the best performance is obtained by LBP-HI-32 with 78.7%, followed by LBP-HI-80 with 75.8%, and by pattern uniform LBP-HI-80 with 73.2% ([7]).

Table 1. Recognition rate (%) of the methods under comparison in the different experiments of the UCHThermalFace database. IN/OUT: Indoor/Outdoor session. AVG: Average. In each case best results are indicated in bold. Variations smaller than 1% are not considered statistically significant.

Method	No variations		Partial Occlusion		2.5% Eye Noise		5% Eye Noise		10% Eye Noise		Gallery Indoor	Gallery Outdoor	AVG
	IN	OUT	IN	OUT	IN	OUT	IN	OUT	IN	OUT	OUT	IN	ALL
LBP-HI-80 [7]	88.5	89.0	82.3	78.7	88.6	87.8	86.9	85.4	74.9	76.5	21.8	18.1	73.2
LBP-EU-80	81.8	71.2	66.1	47.5	81.8	68.8	81.2	67.1	66.8	55.5	8.1	9.3	58.8
LBP-HI-80	**92.5**	90.7	**90.0**	86.6	91.6	90.8	89.3	87.6	82.1	79.2	18.0	11.3	75.8
LBP-XS-80	91.7	90.4	89.6	85.5	91.3	90.5	89.5	87.5	82.6	79.2	16.9	11.8	75.5
LBP-EU-32	79.4	70.8	57.7	37.7	78.9	71.1	77.2	67.6	68.9	60.5	13.0	15.5	58.2
LBP-HI-32	92.1	**93.1**	89.1	**90.0**	**92.2**	**91.4**	**89.7**	**90.7**	**83.8**	**82.9**	**28.6**	**21.1**	**78.7**
LBP-XS-32	91.5	92.9	87.1	87.4	91.2	90.7	88.9	89.4	**83.8**	82.6	28.5	20.6	77.9
LDP2-EU-80	74.7	67.3	51.5	43.6	74.3	64.9	69.0	63.3	58.9	51.3	10.5	14.5	53.6
LDP2-HI-80	81.9	81.9	77.7	69.3	83.2	79.8	79.7	78.4	70.8	66.2	20.5	17.7	67.2
LDP2-XS-80	79.8	79.9	74.7	63.1	79.6	77.0	78.0	75.1	68.0	63.8	17.9	17.2	64.5
LDP2-EU-32	70.5	66.6	42.2	34.3	69.8	65.3	67.1	62.8	58.3	54.3	8.8	11.8	51.0
LDP2-HI-32	83.1	83.6	75.1	71.7	82.8	80.9	80.2	78.9	72.3	70.9	17.4	15.4	67.7
LDP2-XS-32	80.3	81.9	71.7	63.4	79.3	80.3	76.2	77.3	68.8	69.3	16.9	15.3	65.1
LDP3-EU-80	58.8	53.1	26.9	31.8	58.0	53.3	53.6	51.0	45.3	40.6	6.8	10.2	40.8
LDP3-HI-80	79.2	75.4	71.2	59.7	78.2	73.5	74.1	70.8	63.8	62.7	19.8	13.8	61.8
LDP3-XS-80	79.0	75.1	68.1	57.3	77.8	72.4	74.5	71.8	63.9	62.1	17.5	14.1	61.1
LDP3-EU-32	56.9	54.5	19.0	25.3	55.9	52.6	53.6	52.9	45.0	43.1	7.1	8.5	39.6
LDP3-HI-32	75.9	75.0	68.4	59.4	76.4	72.5	73.0	71.9	63.5	64.8	15.5	11.6	60.6
LDP3-XS-32	76.1	74.5	66.0	57.4	76.9	72.4	72.8	70.9	63.8	66.0	13.6	12.6	60.3
LDP4-EU-80	45.4	49.0	19.4	27.6	43.5	44.1	36.6	43.7	31.6	34.5	6.3	8.3	32.5
LDP4-HI-80	65.3	65.9	56.1	53.2	65.3	66.4	62.3	62.4	49.6	53.8	14.8	11.4	52.2
LDP4-XS-80	68.1	67.0	54.2	52.5	68.2	66.1	62.8	60.9	51.4	53.3	14.1	11.0	52.5
LDP4-EU-32	42.5	48.2	14.9	23.1	41.4	46.2	37.1	46.8	31.1	36.0	6.8	7.4	31.8
LDP4-HI-32	64.3	65.8	55.8	51.1	63.0	65.0	58.7	62.4	49.0	54.3	12.5	9.9	51.0
LDP4-XS-32	65.2	67.6	53.8	51.1	66.0	65.6	60.9	63.3	51.1	55.3	12.3	10.8	51.9

For illustrative purposed Table 2 presents in more details the results for the indoor case, by showing the recognition rate of the different methods for the different Rotation test sets as well as for the Speech test set (the last column in Table 2 corresponds to the first column in Table 1). It can be observed the robustness of the different methods to changes in the view angle (yaw and pitch). The most robust methods are LBP-HI-80 and LBP-HI-32. It is included only the best results obtained for each variant methods.

Table 2. Recognition rate (%) of the methods under comparison using the indoor UCHThermalFace database. Rotation and Speech sets for indoor case. AVG: Average. In each case best results are indicated in bold. Variations smaller than 1% are not considered statistically significant.

Method	**Rotation Sets**												**Speech Set**	**AVG**
	R1	**R2**	**R3**	**R4**	**R5**	**R6**	**R7**	**R8**	**R9**	**R10**	**R11**	**AVG**	**AVG**	
LBP-HI-80 [7]	73.6	88.7	73.6	64.2	96.2	**100.0**	96.2	50.9	90.6	**100.0**	**96.2**	84.6	92.5	88.5
LBP-HI-80	**77.3**	**96.2**	**88.6**	66.0	**98.1**	**100.0**	**100.0**	**64.1**	**94.3**	**100.0**	92.4	**88.8**	96.2	**92.5**
LBP-HI-32	**77.3**	**96.2**	83.0	**67.9**	**98.1**	**100.0**	98.1	58.4	90.5	**100.0**	90.6	87.3	**96.9**	92.1
LDP2-HI-80	58.4	83.0	71.7	58.4	94.3	**100.0**	94.3	43.4	90.5	96.2	81.1	80.1	83.6	81.9
LDP2-HI-32	56.6	83.0	64.1	56.6	92.4	**100.0**	90.5	39.6	88.6	94.3	79.2	76.8	89.3	83.1
LDP3-HI-80	56.6	81.1	62.2	43.4	92.4	**100.0**	83.0	33.9	81.1	96.2	75.4	75.3	83.0	79.1
LDP3-HI-32	52.8	81.1	58.4	39.6	86.7	**100.0**	73.5	33.9	81.1	94.3	67.9	69.9	81.7	75.8
LDP4-XS-80	32.0	60.3	41.5	26.4	71.7	**100.0**	67.9	26.4	69.8	86.7	73.5	62.6	73.5	68.1
LDP4-XS-32	35.8	66.0	41.5	26.4	69.8	**100.0**	64.1	20.7	69.8	86.7	56.6	57.9	72.3	65.1

5 Conclusions

In this article a comparison of two local descriptor based methods for thermal face recognition was presented. The methods were evaluated using the UCHThermalFace database and its associated evaluation methodology. The UCHThermalFace database includes thermal images acquired in indoor and outdoor sessions, with natural variations in illumination, facial expression, pose, accessories, and background, as well as occlusions and variations in the face alignment.

First, the effect of the number of regions for LDP variants in the recognition process was analyzed. We selected face regions of 4x8 (32 regions) for LDP and LBP methods. The results obtained from the experiments shown that original LBP with 4x8 regions has the highest performance in almost all of the experiments. The number of divisions 4x8 is considerate better than 4x20, used in [7], for the original LBP case.

For LDP case, the results of the recognition experiments shown that LDP is not an appropriate descriptor for face recognition systems in the thermal spectrum because the thermal image does not show significant variations on local derivative direction variations, which makes the performance descriptor decreases in thermal recognition systems. The third- and fourth-order LDP methods does not show a significant improvement in the performance in the thermal recognition systems, but rather, the performance result is decreased when the order is higher.

We conclude that contrary to the visible spectrum, comparing LDP and LBP based methods, the LBP methods obtains the best results in thermal face recognition.

Future work includes possible improvements in the obtained results, specifically, in the case of combining indoor and outdoor images, results could be enhanced by a better calibration of the camera or by using normalization algorithms [15][16]. In addition, new experiments of thermal-visible images captured in the same time could be perform a direct and more accurate comparison between LDP and LBP methods.

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