Study of Visible Face Recognition Methods Applied to Infrared Spectrum

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***Abstract*—The face recognition methods originally implemented in the visible spectrum show that the recognition rate will not be necessarily the same as in the infrared spectrum. Such is the case of many visible methods for instance Local Derivative Pattern (LDP), Local Binary Pattern (LBP), Histogram of Oriented Gradients (HOG), Gabor Jet Descriptor (GJD) which obtains high performance in visible spectrum but they have not been studied in thermal domain. For that reason the aim of this article is to show the performance of such methods in both spectra using a comparative analysis of current methods for face recognition. In addition, this work shows characteristics in each spectrum indicating their advantages as robustness to illumination and changes in expressions for infrared spectrum and weaknesses as the major use of the face when articulating gestures for the visible spectrum.**

Index Terms*—*face recognition; visible spectrum; infrared spectrum;

I. Introduction

Since the beginning of computer vision analysis, methods for people and face recognition have been created for the use of visible spectrum. Progress in the infrared spectrum cameras have been made to improve quality, lower the prices and simplify the use, which makes accessibility easier to studies in this spectrum. Infrared studies have raised their popularity primarily because of their robustness to illumination changes and pose variations [1]. In the recent years, methods made for visible spectrum have been used in the infrared spectrum. Thus, this work is intended to perform a comparison and a study of the behavior of the current methods designed for the visible spectrum but in the thermal domain.

The visible spectrum is a well-known field of research in face recognition, where this area has grown stronger for security purposes and applications, such as access permissions or even identity control, however its dependency on illumination and pose, makes it hard to find and create robust methods with acceptable performance in these conditions. That is why the infrared spectrum offers a good choice for face recognition, because this spectrum does not depend on these factors. However, the infrared spectrum has undesirable variations, for example depends on changes in ambient temperatures, and it is affected by modifications in metabolic processes. In addition, the thermal camera sensors vary when the camera is working for long periods of time [2] [3].

In [4] a comparative study of visible methods applied to thermal domain is presented. This study incorporates current methods such as Local Binary Pattern (LBP) [2], Weber Law Descriptor (WLD) [10], PCA [5] [17], ICA [4] [17], SIFT [6], SURF [7] and Gabor Jet Descriptor (GJD) [6]. The results show high performance in local descriptors such as LBP and WLD for Equinox database. For this reason, the aim of this article is to study and analyze of the new visible methods for face recognition in both spectrums: visible and infrared. We have chosen four methods for this article: the Local Derivative Patterns (LDP) [3], LBP [2], HOG [8] and GJD [6], because they have high performance in visible spectrum [3] [5] [6].

These methods are evaluated using Equinox database [1], [12]. The database consists in face images in the visible, long-wave infrared (LWIR), mid-wave infrared (MWIR) and near-wave infrared (NWIR) spectra. For this study only the Visible and LWIR are used with 6 sets used as Gallery and 9 sets used as Test sets in both spectra.

This paper is structured as follows: The methods under analyses are described in section II. In section III the comparative analysis and experiments of the methods are presented. Finally, the main conclusions of this work are given in section IV.

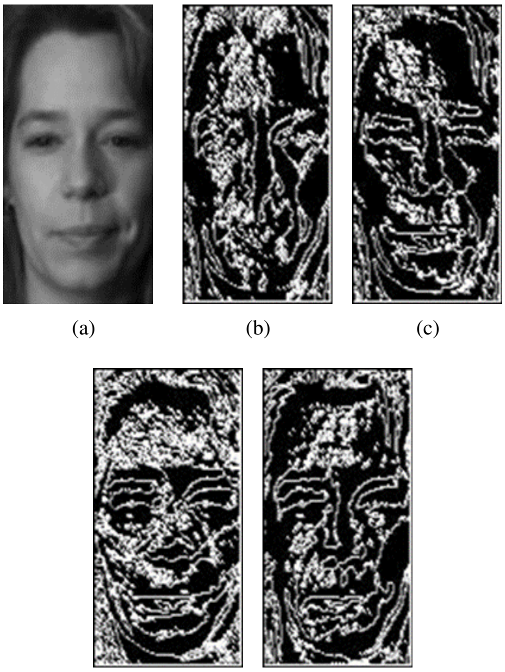
II. Methods Under Comparison

As mentioned above, the methods under comparison were selected considering the high performance and their requirements such as real time, just one image per person and their performance in related comparative studies.

A. LDP Histograms

Local Derivative Pattern of nth order was first proposed in [9] and it is a method that uses micropatterns which at the same time uses the information contained in directional derivatives of (n-1)th order of the original image. The directions used are 0°, 45°, 90° and 135° only, since 180°, 225°, 270° and 315° are implicitly contained in the used directions. In Fig. 1, an example of LDP of order 2 of the original image in the visible spectrum (a) is represented as a set of images for viewing purposes, through the first derivative with direction 0° (b), direction 45° (c), direction 90° (d) and direction 135° (e).

The micropatterns are obtained using a neighborhood of 8 pixels around a central pixel, taking from the derivative image in α direction for extracting the information. These micropatterns are used to obtain region-based histograms with 256 bins each to give a holistic feature to this method. The information taken from all the directions for every region are



(a) (b) (c)

(d) (e)

Fig. 1: 2^{nd} order LDP representation of an Equinox Database Image: (a) Visible image (b) 2^{nd} order LDP in 0° direction (c) 2^{nd} order LDP in 45° direction (d) 2^{nd} order LDP in 90° direction (e) 2^{nd} order LDP in 135° direction.

concatenated for the final LDP descriptor of order n of the original image.

B. LBP Histograms

Local Binary Pattern was originally proposed in [13]. The method compares the information contained in a neighborhood around a central pixel and then obtains a region-based histograms with 256 bins, which are used to give a holistic feature to this method. The histogram of each region is concatenated to obtain the final LBP descriptor of the original image. In Fig. 2, an image in the infrared spectrum is shown, displaying the original image in (a) and the LBP representation of the image in (b).

C. HOG histograms

Histograms of Oriented Gradients, proposed in [8], uses the information contained in both magnitude and direction of the gradients presented in the original image. The face image is divided in a given number of regions and then the histograms are calculated with 9 bins. These histograms are concatenated to obtain the final HOG descriptor of the original image, taking half of the precedent region in both directions to overlapping the face information.

D. Gabor Jet Descriptor (GJD)

Gabor filters are used in face recognition because of their similitude to the cells behavior involved in visual perception and their robustness to change in illumination. The

(a) (b)

Fig. 2: LBP representation of an infrared image of the Equinox Database: (a) Infrared Image (b) LBP image.

implementation for this work was based on [6], these filters extract characteristics by means of selection of frequency, orientation and scale. The jets are calculated in different points in a grid and then the Borda count method [11] is applied to obtain a ranking and thus generate the recognition.

To sum up, local descriptors are based on the information contained in the neighbors of a central pixel, such as LBP, LDP and HOG. With these methods, a division of the image is performed to give them a holistic feature in partitions of 20x4 taken from [4], 8x4 and 16x16 regions. Then, a histogram is calculated for each region of the image and the fit is performed with Euclidian Distance (EU), Histogram Intersection (HI) and Xi Square (X2). For the case of Gabor Jets, the image is used as a whole, and the Borda Count is used to match the images.

III. Experiments

The experiments are performed with the Equinox Database, which consider visible and thermal images with different illumination conditions and different face expressions. This section is divided in three points. A explains the description of Equinox database. B shows the detailed procedure of experiment, and C explains the notations of the methods.

A. Equinox Database Description

The Equinox Database [1] [7] has already been used in several studies to validate face recognition methods. Thus, it allows the direct comparison between methods previously performed such as PCA [14], ICA [4], LBP [4], WLD [4], GJD [4], KPCA [14] and KFLD [14].

The database consists in various set of frontal images taken from both visible and infrared spectra at the same time, which reach 18629 pictures for each spectrum in total with gray scale with a size of 240x320 pixels. 40 $frames$ were taken when the subject was speaking. Of these $frames$, 3 were chosen to be labeled as $vowelframes$ and frames with expressions "smile", "frown" and "surprise" were chosen to be labeled as $expression\ frames$. Also, 3 different setups of illumination were performed with frontal, left and right lights to obtain $frontal$ and $lateral\ frames$. Finally, the subjects

TABLE I: NAMES AND DESCRIPTIONS OF GALLERY AND TEST SETS, WITH V FOR VOWEL, E FOR EXPRESSION, A FOR ALL ILLUMINATION, F FOR FRONTAL ILLUMINATION, L FOR LATERAL ILLIMUNATION, G FOR GLASSES, AND RR FOR RANDOM.

Name	Description	Characteristics	Illumination	Image quantity (gallery)	Image quantity (test)
VA	Vocals	All Subjects	All directions	81	729
EA	Expressions	All subjects	All directions	81	729
VF	Vocals	All subjects	Frontal	81	243
EF	Expressions	All subjects	Frontal	81	243
VL	Vocals	All subjects	Lateral	81	486
EL	Expressions	All subjects	Lateral	81	486
VG	Vocals	Using glasses	All directions	-	324
EG	Expressions	Using glasses	All directions	-	324
RR	Vocals and expres- sions	Random	All directions	-	500

were suggested to wear glasses to make $glasses\ frames$. The images were processed to have 150 pixels height and 81 pixels width, with eyes aligned and showing only the face of the subjects (see Fig. 1 a and Fig. 2 a).

For the evaluation of the methods under study, 15 sets of images were established with the following criteria. All subjects must have frames in every set; for gallery sets only one image per subject; in a given set a visible image must have its counterpart in the infrared set and subjects have multiple images in test sets. In this mode, 6 gallery sets are established (VA, EA, VF, EF, VL, EL) and 9 test sets (VA, EA, VF, EF, VL, EL, VG, EG, RR) as detailed in Table 1.

B. Experiment Description

The experiment consists in comparing a test set containing frontal images with different expressions and different kind of illumination against the gallery sets. The recognition experiments were performed following the Equinox Methodology [15] [16] and for each gallery versus test set experiments, the top-1 recognition rate is computed. Finally, visible galleries are not compared against infrared spectrum and vice versa. To obtain the method and variant performance, the average of every result for all the gallery sets is calculated.

C. Notations and Variants

The following notation is used to name every method and variation: A_B_C; (i) A Describes the name of the method (LBP, HOG, Gabor descriptors, LDP of order 2 as LDP2, LDP of order 3 as LDP3 or LDP of order 4 as LDP4); (ii) B shows the similarity measure (EU, HI or X2); (iii) C denotes the number of regions used (80 for 20x4, 32 for 8x4 and 256 for 16x16).

In the case of GJD, only the Borda Count is used, and the image is used as a whole, so its notation is simply Gabor.

TABLE II: RESULTS OBTAINED IN BOTH VISIBLE AND INFRARED SPECTRA. THE BEST RATE OF RECOGNITION FOR THE GIVEN METHOD ARE IN BOLD. NUMBER OF REGIONS ARE 20X4 (80), 8X4 (32) AND 16X16 (256). GABOR DOES NOT USE IMAGE DIVISIONS AS A PARAMETER.

Methods	Visible Spectrum (%)			Infrared Spectrum (%)		
	80	32	256	80	32	256
LBP_EU	74.15	71.65	74.55	84.94	88.20	82.83
LBP_HI	**81.60**	80.11	80.82	93.89	**95.32**	93.03
LBP_X2	81.59	80.38	80.14	93.72	94.89	92.87
LDP2_EU	72.85	68.71	76.41	81.47	80.25	81.86
LDP2_HI	82.23	82.34	81.57	87.78	87.67	86.04
LDP2_X2	81.91	**83.12**	80.36	86.91	**88.98**	83.60
LDP3_EU	76.90	73.04	80.66	45.10	46.56	45.76
LDP3_HI	86.36	85.22	**88.20**	69.77	70.05	61.10
LDP3_X2	86.63	85.93	87.61	68.59	**73.30**	50.50
LDP4_EU	75.92	72.43	80.09	23.94	24.61	23.30
LDP4_HI	85.25	83.82	88.59	47.58	47.87	41.23
LDP4_X2	85.46	84.30	**88.60**	47.87	**51.06**	36.51
HOG_EU	62.46	60.18	72.60	77.10	74.93	92.84
HOG_HI	58.79	55.21	72.42	75.87	72.80	89.52
HOG_X2	63.78	61.78	**73.59**	80.10	77.58	**94.03**
Gabor	**85.35**			**70.07**		

IV. RESULTS

Recognition rates obtained from each experiment are computed from gallery and test sets in a confusion matrix. From these results, the average of every face recognition rates was performed to obtain a unique recognition rate criterion. The performance of all variants of the methods under study in both spectra, including different number of regions are summarized in Table 2, where the average of every test set against all the galleries is displayed, where bold numbers represent the best variant of every method, and in the case of LDP, the best result of each order. In general terms, it can be said that according to Table 2, infrared results are better than visible by almost 7 %, comparing the best visible recognition rate with the best infrared variant. The best results in visible spectrum are obtained with LDP of higher order (LDP4_X2_256 with 88.60 %, LDP4_HI_256 with 88.59 % and LDP3_X2_256 with 88.20 %). That equals the results obtained in [9] where it states that LDP of high order presents better results than LBP. GJD with 85.35 % has better recognition rate than LDP of order 2, but lower than LDP of order 3. LBP has a lower recognition rate than GJD and LDP of order 2, reaching 81.60 %. Finally, HOG places last between the 4 methods compared with only 73.59 %.

Results obtained with LDP with small size regions (16x16 divisions) are explained because of the use of derivatives that includes information carried from neighbor pixels with every derivative around the region taken into account.

In the infrared spectrum, best results are obtained with LBP method (95.32 %), closely followed by HOG (94.02 %), and, opposed to the case with the visible spectrum, LDP

TABLE III: BEST RESULTS FOR EVERY METHOD IN VISIBLE AND INFRARED SPECTRA. COMPARISON OF RECOGNITION RATES OF BEST VARIANTS IN BOTH SPECTRA.

Variant	Visible Spectrum (%)	Infrared Spectrum (%)
LBP_HI_80	**81.60**	93.89
LBP_HI_32	80.11	**95.32**
LDP2_X2_32	**83.12**	**88.98**
LDP3_HI_256	**88.20**	61.10
LDP3_X2_32	85.22	**73.30**
LDP4_X2_256	**88.60**	36.51
LDP4_X2_32	84.30	**51.06**
HOG_X2_256	**73.59**	**94.03**
Gabor	**85.35**	**70.07**

degrades with higher order. This can be explained because of the inclusion of more noise with each derivative that is inherently present in an infrared image.

The best results obtained by each method and variant do not repeat as the best variant for a specific method for both spectra, except for LDP2_X2_32, HOG_X2_256 and Gabor, as this method only has one variant. This is resumed in Table 3, where bold numbers indicate the value as the best variant in a specific spectrum.

From Table 3, comparing results for each method and variant, it is seen that the behavior between visible and infrared spectra is not the same in each case. With LBP, the recognition rate in infrared spectrum with 95.32 % is almost 14 % greater than visible with 81.60 %. In the case of LDP, in the visible spectrum, a greater order of this method increases significantly the recognition rate, but in the case of infrared spectrum, this has the opposite effect. Further increasing the order of LDP is not advised in [9] since greater derivatives include more noise. With LDP of order 2, in the visible spectrum the performance of the recognition rate with 83.12 % is almost 6 % lower than infrared with 88.98 %, however with LDP of order 3 the visible spectrum performance with 88.20 % is better than its counterpart in the infrared with 73.30 % by almost 15 %. With LDP of order 4, the difference grows to 37 % with a recognition rate of 88.60 %, being the infrared results worse with 51.60 %. It can be noted that LDP4 recognition rate is just 0.40 % greater than LDP3. In the case of HOG, the recognition rate in infrared spectrum is almost 21 % more, making an outstanding 94.03 % against 73.59 % in the visible spectrum. With GJD, the performance lowers significantly in the infrared spectrum, since in visible spectrum makes 85.35 %, but in infrared it reaches 70.07 %.

Considering robust behavior of the methods in both spectra, LBP_HI_80 has the best performance in both visible and infrared, considering it has the lowest difference between spectra (5.86 %) with 83.12 % visible and 88.98 % infrared. In this way, the worst result is achieved by LDP4_X2_256 with a difference of 51.91 % between spectra.

In order to analyze the behavior of the methodologies when different factors as illuminations and expression are applied we have computed the recognition rate of different tests (different illumination/expression/glass/random conditions) versus the entire gallery. The results are shown in Fig. 3 and Fig. 4, for visible and thermal case respectively.

It can be seen in Fig. 3, the kind of illumination takes an important role in recognition efficiency for visible face recognition, due to the frontal illumination has better rates of recognition with LBP and HOG but not with LDP of order 3 and 4 and GJD. As stated in [11], GJD is almost immune to changes in illuminations as it can be seen when comparing results with test sets VF with VL and EF with EL. The changes in expression degrade the recognition rate in comparison with vocal gestures, as they use a greater portion of the face. Also, the use of glasses means the worst degradation to the recognition rate in this study. Best results were obtained with frontal illumination and vocal gestures.

When analyzing the results obtained with the infrared spectrum in Fig. 4, the illuminations changes do not matter in this spectrum. That means the infrared spectrum is invariable to illuminations in any direction. In the same way as the visible spectrum, all methods degrade their performance with glasses test sets (EG and VG) because they are opaque to infrared and hides a portion of the subject. The expressions gestures that involve all the face, as opposed to the visible spectrum, do not lower the efficiency of the methods. In fact, it can be said that infrared spectrum recognition methods are invariable to expressions and gestures of vocals. In fact, it demonstrates the robustness to expressions in the infrared spectrum, even if all the face is involved.

V. Conclusions

Three local descriptor methods (LBP, LDP of 2^{nd}, 3^{rd} and 4^{th} order and HOG) and one global descriptor (GJD) were analyzed, with a region based histogram to give a holistic feature to LBP, LDP of order 2, 3 and 4 and finally HOG. Every method was evaluated with the Equinox Database with Visible and Infrared spectra, divided into 6 gallery sets and 9 test sets with the top-1 recognition performance.

The Equinox Database presents images with frontal and lateral illumination of the subject and every subject has an image representation in both visible and infrared spectra which were taken in the same session. Also, the test sets consisted in a given number of images of the same subject with different expressions and pronunciation of vocals and with different illumination directions.

With these, it can be concluded that a method working with a certain rate of success in the visible spectrum, will not necessarily work in the same way and with the same rates in the infrared spectrum. In fact, taking HOG for example, that has poor rates in the visible spectrum (73.59 % for HOG_X2_256), has good grades in the infrared spectrum (94.03 % for HOG_X2_256).

Results obtained with HOG in the infrared spectrum are notorious, taking into account that it had a poor performance in the visible spectrum (73.59 %). However, it is highly dependent in the number of regions, since it had 80.10 %

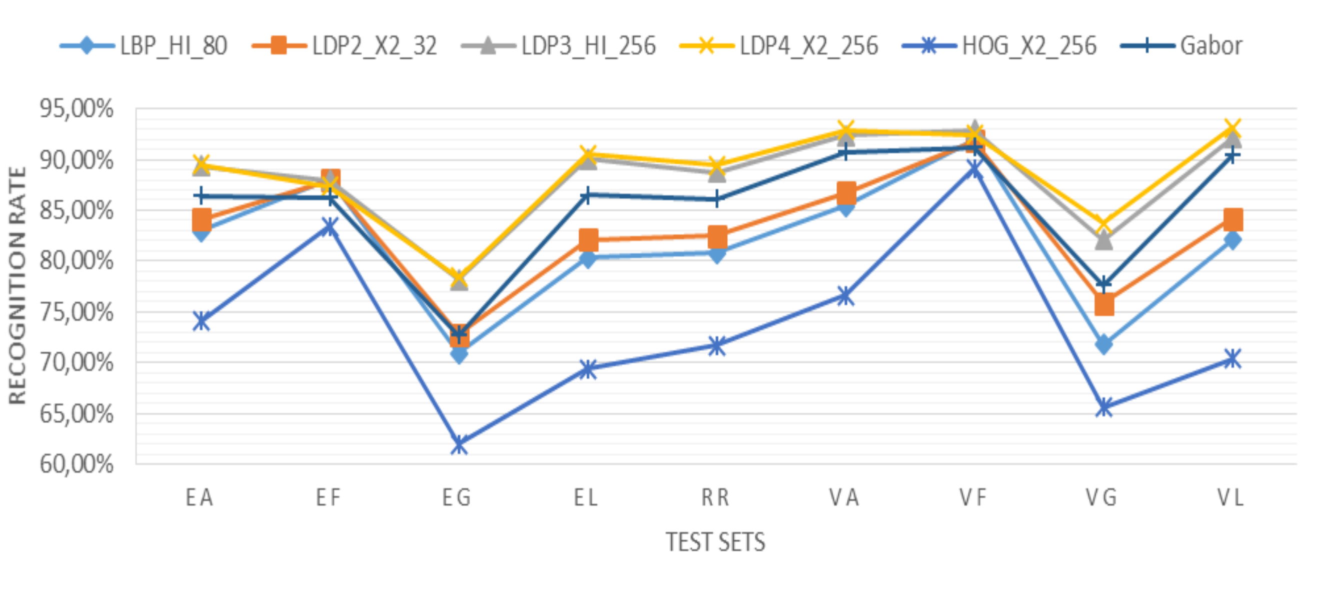


Fig. 3: Behavior of every method compared against each other in the visible spectrum for each test set EA. EF. EG, EL, RR, VA, VF, VG and VL. General behavior of the methods across test sets are displayed, where a method is evaluated with every test set against all gallery set.

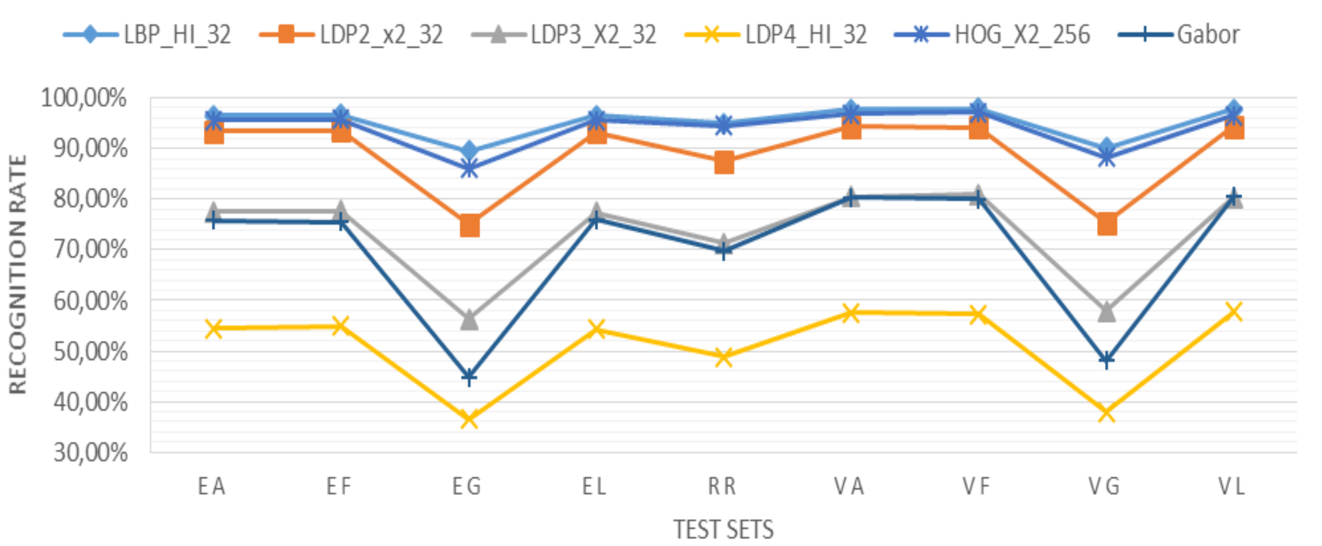


Fig. 4: Behavior of every method compared against each other in the infrared spectrum for each test set EA. EF. EG, EL, RR, VA, VF, VG and VL. General behavior of the method across test sets are displayed, where a method is evaluated with each test set against all gallery set.

for 80 regions, 77.58 % for 32 regions and 94.03 % for 256 regions.

The presence of noise in the infrared images explain the poor performance of LDP, since with higher derivatives, more noise appears in the image. Also, LDP works better with the presence of textures which present high variations on local derivative directions. Still, LDP of order 2 with 88.98 % (LDP2_X2_32) had better rates than GJD (70.07 %).

LBP results are notorious, since it has a better performance than Gabor. LBP, as a local descriptor, demonstrates to be more appropriate than Gabor to represent an infrared image, because in this spectrum, the textures of the image are smoother, with highly defined contours.

Also, the best method under comparison, is LBP_HI_32, since it has 1.52 % less than the lowest difference method in recognition rates in visible spectrum and 6.34 % higher in infrared spectrum. Also, LBP with its variant LBP_HI_32 has the first place recognition rate in the infrared spectrum.

Results obtained in this work, indicates that a novel method made for the visible spectrum should not be discarded from the experimentation with the infrared spectrum and vice versa, since it may or may not have good performance with the other spectrum.

Further experiments should be executed with newer databases, since progress in thermal cameras have made them more reliable and more robust to noise. Also, more experiments with different size of regions shall be done to reach the optimum size of divisions and not only one database. Finally, the study of fusion methods of images or descriptors is proposed for future work.

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