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Research Article

Stat LBP Feature Extraction and SIEDA Dimensionality Reduction and Classification for Face-Kin Verification

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Abstract

For man, several types of signals are available to recognize kinship, such as facial resemblance between families. Some studies show that we are able to recognize the kinship between a child's face and a face of a parent. The purpose of our work is to study the face-kin verification by using the Statistical Local Binary Patterns (Stat LBP) descriptor for the extraction of the local characteristics of facial images and the SIEDA (Side-Information based Exponential Discriminant Analysis) for the dimensionality reduction and classification of data. The extensive experimental evaluation carried out on Cornell kinshep database indicates that the proposed approach performs significantly better than state-of-the-art approaches.

Introduction

Biometrics is the technology that measures the characteristics of the living being in order to authenticate it. This technology has used more and more for a decade, especially in the field of security. Biometrics is becoming increasingly necessary in the eyes of states as a security solution. However, the appearance of biometrics is no longer recent; it goes back to the 19th century [1]. At the beginning of its appearance, biometrics was known as anthropometry.

For the recognition of criminals, with recent advances in biometrics, psychology and cognitive science have revealed that the human face is an important indication for measuring the similarity of parents. Children usually resemble their parents more than other adults, because in biology they relate to them in genetics are related biologically. Inspired by this discovery, semantic research has been conducted on the kinship verification by human faces and computer vision. Researchers have developed several advanced computer models to verify human kinship relations through facial image analysis [2] [3]. Although there are many applications for kinship verification, such as searching for missing children and extracting social networks. The difficulty of developing a robust kinship verification system for real applications are: variations on pose, illumination, expression, age on the face image, etc.

Due to its discriminating power and simplicity of computation, the LBP (Local Binary Pattern) [4] has become a very popular approach in various computer vision applications [5-8]. According to [9], LBP is not only regarded as a simple texture operator, but it is the foundation of a new important direction of research for local binary descriptors for image and video. In recent years, different LBP variants have been proposed to improve its robustness and increase its discriminating power and its applicability to different types of problems. We are motivated by the success and widespread use of LBP and its variants in facial recognition; we propose this work for the use of our LBP variant proposed in [10] for 2D and 3D face verification in kinship verification.

Overview of the proposed face-kin verification

Our face-kin verification system as illustrated in figure 1, consists of two phases (learning and testing) and each phase comprises four important stages: pre-processing, feature extraction by Statistical Local Binary Patterns Feature (StatLBP) [10], dimensionality reduction and classification of data by Side-Information Based Exponential Discriminant Analysis (SIEDA) [11] and a comparison by the cosine distance.

The learning phase consists of constructing a general model. Its main purpose in our kinship verification system is to find the projection matrix of SIEDA (Side-Information based Exponential Discriminant Analysis). This projection matrix is used in the test phase to reduce and classify the feature vectors.

Pre-processing

The pre-processing phase makes it possible to prepare the face image in such a way that it can be used in the learning and testing phase.

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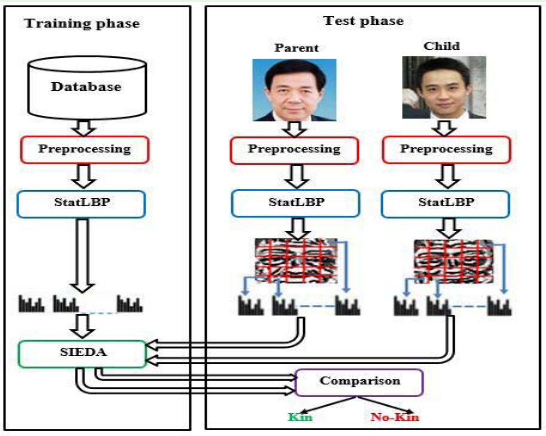

Figure 1 : Our face-kin verification system.

To ensure the proper performance of the kinship verification system, it is important that all images are the same size, scale and colour format (for example, colour images are converted to gray scale).

In our work, we use two phases of pre-processing: the conversion of the color image to gray scale, and the crop the face region to retain the maximum intrinsic variations of the face, and to remove other information like background, hair , collar shirt, ears .... A rectangular window of size (120 × 120), centred on the most stable characteristics related to eyes, eyebrows, nose and mouth, was used. Figure 2 shows the pre-processing steps.

Feature extraction

For feature extraction in our kinship verification, we proposed to use the new method Stat LBP (Statistical Local Binary Patterns feature) proposed in 2017 for 2D and 3D face verification [10]. Our work is the first to use this method in the field of kinship verification. We also use the LBP descriptor for the comparisons.

The goal of the StatLBP descriptor is to increase the accuracy and create a new space of local characteristics characterized by a variation in statistical parameters, which are: mean, median, variance, skewness, kurtosis.

It replaces a pixel i by the calculation of its statistical parameters ($Stat_{P_1,R_1}(i)$) with his neighbour P1of radius R_1. Finally, it calculates the binary code (Stat $LBP_{P1, R1, P2, R2}$(ic)) of the pixel i_c by thresholding its statistical code ($stat_{P1,R1}(i_c)$) with neighbouring statistical codes ($stat_{P1,R1}(i_{P2})$) (Equation 1).

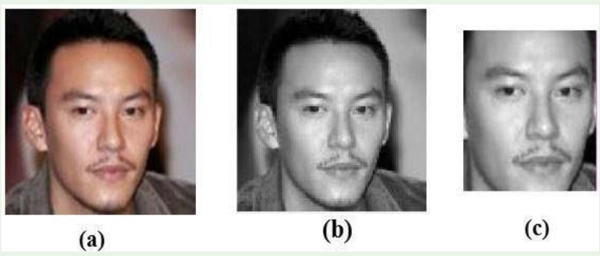

Figure 2: (a) Original image, **(b)** Grayscale images, **(c)** Crop image.

The Stat LBP code of one pixel i_c is given by:

$$StatLBP_{P_1,R_1,P_2,R_2}(i_c)=\sum_{p2=0}^{P_2-1} S(Stat_{P_1,R_1}(i_{p_2})-Stat_{P_1,R_1}(i_c))2^{P_2} \qquad (1)$$

Or: i_c et i_{p_2} are the values of the central pixel and P_2 are the neighbouring pixels in the neighbourhood of the radius circle R_2 (Figure 3). His function $s(x)$ is defined as:

$$s(x)=\begin{cases}1 & if\ x\geq 0\\ 0 & if\ x<0\end{cases} \qquad (2)$$

Stat present: mean, median, variance, skewness, kurtosis which are defined as follows:The mean:

$$mean_{P_1,R_1}(i)=\frac{1}{P_1}\sum_{P_1=0}^{P_1-1} i_{P_1} \qquad (3)$$

Or: i and i_{P_1} are respectively the values of the central pixel and $P_1$the neighbouring pixels belonging to the circle with a radius R_1.

The median:

The median of a pixel i is the numerical value that separates the upper half of i_{P1} pixels, of the lower half.

The variance:

$$Var_{P_1,R_1}(i)=\frac{1}{P_1}\sum_{P1=0}^{P_1-1}(i_{P_1}-mean_{P_1,R_1}(i))^2 \qquad (4)$$

The skewness:

$$skewness_{P_1,R_1}(i)=\frac{\frac{1}{P_1}\sum_{p1=0}^{P1-1}(i_{p1}-mean_{P_1,R_1}(i))^3}{(\sqrt{\frac{1}{P_1}\sum_{p1=0}^{P1-1}(i_{p1}-mean_{P_1,R_1}(i))^2})^{3/2}} \qquad (5)$$

The Kurtosis:

$$kurtosis_{P_1,R_1}(i)=\frac{\frac{1}{P_1}\sum_{P1=0}^{P_1-1}(i_{p1}-mean_{P_1,R_1}(i))^4}{(\frac{1}{P_1}\sum_{P1=0}^{P_1-1}(i_{p1}-mean_{P_1,R_1}(i))^2)^2} \qquad (6)$$

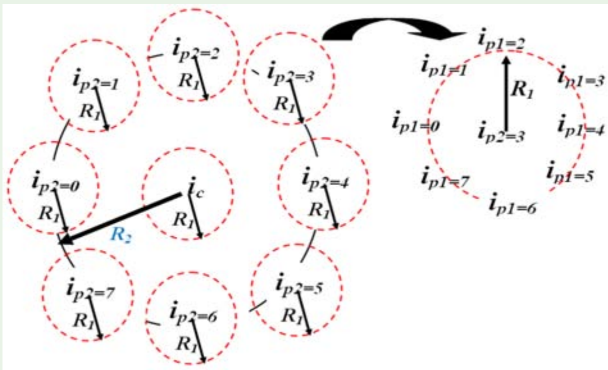

Figure 3: Stat LBP (P_1=8, P_2=8).

The facial image after feature extraction using local descriptors is divided into 25 small blocks. For each block, the local characteristics are summarized by the corresponding histograms. In addition, are concatenated to form a feature vector.

The Stat LBP images are shown in the figure 4 (P_1= 32; R_1= 3; P_2= 8, $R2$ = 2, 4, 6 et 8).

Dimensionality reduction and classification

After the Feature extraction step and the concatenation of the histograms of each block in a vector that forms the characteristics of the faces. We use the SIEDA (Side-Information Based Exponential Discriminant Analysis) [11] method for dimensionality reduction and classification of these characteristic vectors.

In the Linear Discriminant Analysis (LDA), the class label of each sample must be known. With weakly labelled data, LDA does not work because within-class scatter matrix (S_w) and between-class scatter matrix (S_b) cannot be calculated without full label information. To resolve this problem Kan et al. [12] proposed a new definition for S_w et S_b which directly exploit the weak side-information. More precisely, the image pairs of the same class are directly used to compute the within-class scatter matrix and the image pairs of different classes are used to calculate between-class scatter matrix. Let: $S_{class} = \{(x_i, x_j) : l(x_i) = l(x_j)\}$ as a set of same-class image pair and $D_{class} = \{(x_a, x_b) : l(x_a) \neq l(x_b)\}$ as a set of different-class image pairs, $l(x)$ demonstrating the image class label x. Then, the within-class and between-class matrices can be respectively defined as follows:

$$S_w^{sidl} = \sum_{(\chi_i, \chi_j \in S_{class})} (\chi_i - \chi_j)(\chi_i - \chi_j)^T \quad (7)$$

$$S_b^{sidl} = \sum_{(x_a, x_b \in D_{class})} (x_a - x_b)(x_a - x_b)^T \quad (8)$$

As in LDA, the projection matrix in SILD can be achieved by solving the following optimization criteria [11] :

$$W_{opt}^{sild} = \text{argmax}_W \frac{|W^T S_b^{sild} W|}{|W^T S_w^{sild} W|} = \text{argmax}_W \frac{|W^T (V_b^T \Lambda_b V_b) W|}{|W^T (V_W^T \Lambda_W V_W) W|} \quad (9)$$

Where V_w is the eigenvector matrix of S_w^{sild} and represent the corresponding Eigen values of $_{Stat_{P_1,R_1}(i_{p_2})}$. V_b Is the eigenvector matrix of i_{p_2} and $\lambda_b = diag(\lambda_{b_1}, \lambda_{b_2}, \cdots, \lambda_{b_n})$ represent the corresponding Eigen values of S_b^{sild}.

Kan et al proposed a strategy to avoid Sample Small Sample Problem (SSSP) of the LDA. This strategy adopted in two steps, PCA is first used to transform the data space into a smaller dimension space and then apply SILD. By adopting this strategy, the most discriminant information in the null space of S_w^{sild} is lost. To retain the most discriminant information in the null space of S_w^{sild} Ouamane et al. [11] proposed SIEDA method. SIEDA maps the eigenvalues

$(\lambda_{w_i})$of S_w^{sild}, to *exp* $(\lambda_w)$and the eigenvalues (λ_b) of $S_b^{sild}$to exp (λ_b) then:

$$\exp(\lambda_b) = diag(\exp(\lambda_{b_1}), \exp(\lambda_{b_2}), \cdots, \exp(\lambda_{b_n})) \quad (10)$$

$$\exp(\lambda_w) = diag(\exp(\lambda_{w_1}), \exp(\lambda_{w_2}), \cdots, \exp(\lambda_{w_n})) \quad (11)$$

The objective function of the SILD equation ($S_o pt^s ild$) is transformed into:

$$W_{opt}^{sieda} = \text{argmax}_W \frac{|W^T (V_b^T \exp(\Lambda_b) V_b) W|}{|W^T (V_W^T \exp(\Lambda_W) V_W) W|} = \text{argmax}_W \frac{|W^T \exp(S_b^{sild}) W|}{|W^T \exp(S_w^{sild}) W|} \quad (12)$$

The projection matrix W_{opt}^{sieda} then comprises the leading eigenvectors of $(\exp(S_w^{sild}))^{-1} \exp(S_b^{sild})$.

The properties of SIEDA are [11]:

The matrix $\exp(S_w^s ild)$ is a "full" matrix; therefore, discriminant information that was contained in the null space of S_w^{sild} are kept.

The kernel method is used for converting the original nonlinear difficulties into linear difficulties in the transformed feature space. Alike to the kernel method, the exponential function transformed the scatter matrices into a new space.

The objective function for SILD is to maximize the between-class distance and to minimize the within-class distance. These distances can be intended by the trace of the conforming scatter matrices:

$$trace(S_b^{sild}) = \lambda_{b_1} + \lambda_{b_2} + \cdots + \lambda_{b_n}, trace(S_w^{sild}) = \lambda_{w_1} + \lambda_{w_2} + \cdots + \lambda_{w_n} \pm$$

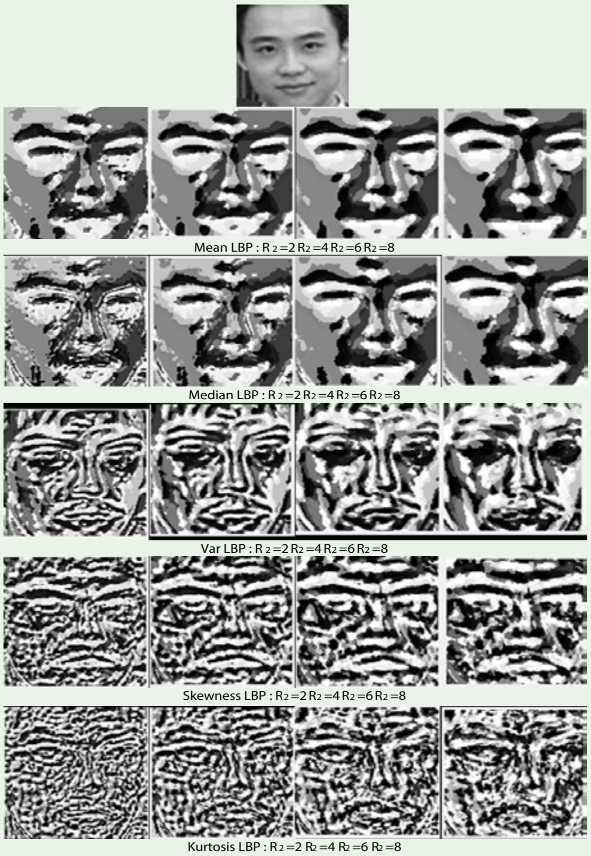

Figure 4 : *StatLBP for face image (R1 = 3; R2 =* 2,4,6,8).

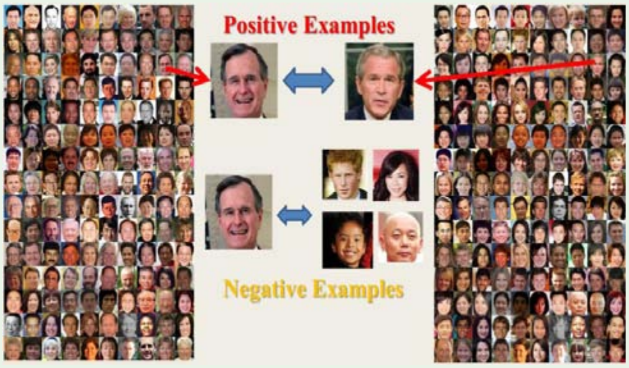

Figure 5 : Examples of images from the Cornell Kinship database.

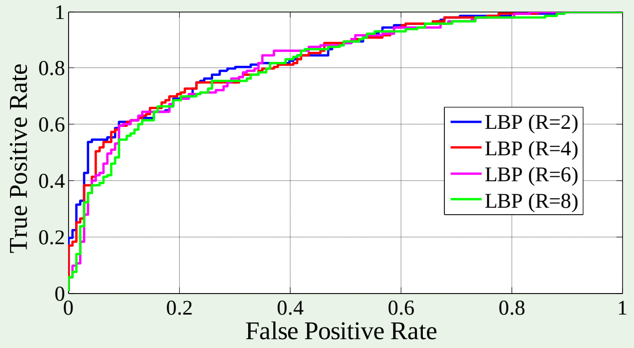

Figure 6 : The ROC curve for the LBP descriptor with the different radius (*R*).

And
$$trace\left(\exp\left(S_b^{sild}\right)\right)=\exp\left(\lambda_{b_1}\right)+\exp\left(\lambda_{b_2}\right)+\cdots+\exp\left(\lambda_{b_n}\right),$$
$$trace\left(\exp\left(S_w^{sild}\right)\right)=\exp\left(\lambda_{w_1}\right)+\exp\left(\lambda_{w_2}\right)+\cdots+\exp\left(\lambda_{w_n}\right),$$

In addition, from the fact that:
$$\exp\left(\lambda_{b_i}\right)\Big/\exp\left(\lambda_{w_i}\right) > \lambda_{b_i}\Big/\lambda_{w_i}$$

This difference in diffusion scale between within and between-class distancesleads to a better separation.

Comparison

We use the cosine similarity [13-15] measure after the dimensionality reduction and classification of feature vectors. The method makes it possible to calculate the cosine score between the two feature vectors $\left(x_1 and x_2\right)$:

$$S_{\cos}\left(x_1,x_2\right)=\frac{\left((W^{SIEDA})^T x_1\right)^T\left((W^{SIEDA})^T x_2\right)}{\|(W^{SIEDA})^T x_1\|\|(W^{SIEDA})^T x_2\|} \qquad (13)$$

Where: W^{SIEDA} the projection matrix of the SIEDA method.

Benchmark Dataset and Experimental Setup

Cornell Kinship Database

Our experiments are performed on frontal face images of the Cornell Kinship Database [16]. There are 143 pairs of parents and children. Cornell Kinship contains facial images collected from the internet representing four classes of family relationships: 40% of the images are father-son pairs, 22% are father-daughter, 13% are mother son, and 26% are mother-daughter. Consequently, it has a extensive spread distribution of facial features which depend on race, gender, age, career, etc. Figure 5 shows examples of images from the Cornell Kinship database.

The number of eigenvectors in the dimensionality reduction phase by SIEDA is set to 180, this value is empirically calculated.

Comparison of local descriptors

LBP: Table 1 presents the face-kin verification of LBP descriptor in terms of classification accuracy. The number of neighborhood pixels is set to $P = 8$ and the radius is varied, $R = \{2,4,6,8\}$. Figure 6 shows the ROC curves of this experiment.

Table 1 shows the classification accuracy changed with the variable radius (*R*). The best accuracy of kinshipverification (79.75%) is obtained by ***R*=6.**

Stat LBP descriptor: For the Stat LBP descriptor, we test the effect of variation of the radius R_1 and R_2 on the kinship verification. Tables 2, 3, 4 and 5 present the classification accuracy as a function of R_1 and R_2 Figures 7, 8, 9 and 10 shows the ROC curves of these experiments.

We can say for the tables 2, 3, 4 and 5 that:

- The classification accuracy changes with the variation of $R_2$of StatLBP descriptor.
- The classification accuracy also changes with the variation of R_2 StatLBP descriptor.
- The two descriptors Mean LBP and Median LBP give month performance as original LBP.
- Variance LBP, Skewness LBP and kurtosis LBP are better than a LBP descriptor for any scale.
- The best result of kinship verification is obtained with the descriptor Kurtosis LBP with an accuracy of **84.92 %** (R_1=3, R_2=2).

Table 1: shows the classification accuracy changed with the variable radius (*R*). The best accuracy of kinship verification (79.75%) is obtained by ***R*=6.**

	R_2= 2	R_2= 4	R_2= 6	R_2= 8
Mean LBP	**77.64%**	*75.83%*	74.40%	73.70%
Median LBP	**77.61%**	*76.93%*	74.81%	75.54%
Variance LBP	81.69%	*80.32%*	81.08%	**82.09%**
Skewness LBP	80.40%	*82.11%*	81.04%	**82.44%**
Kurtosis LBP	**84.92%**	*81.07%*	82.39%	81.14%

Table 2: Classification accuracy for Stat LBP descriptor white R_1=3.

	R_2= 2	$R_{2=}$4	R_2= 6	R_2= 8
Mean LBP	74.78%	**75.85%**	73.36%	72.29%
Median LBP	74.10%	**76.52%**	74.46%	72.28%
Variance LBP	**80.69%**	79.65%	80.61%	80.29%
Skewness LBP	81.71%	81.37%	80.75%	**83.21%**
Kurtosis LBP	81.04%	**84.23%**	82.15%	82.14%

Table 3: Classification accuracy for StatLBP descriptor white R_1=4.

	R_2= 2	R_2=4	R_2= 6	R_2= 8
Mean LBP	74.78%	**75.85%**	73.36%	72.29%
Median LBP	74.10%	**76.52%**	74.46%	72.28%
Variance LBP	**80.69%**	79.65%	80.61%	80.29%
Skewness LBP	81.71%	81.37%	80.75%	**83.21%**
Kurtosis LBP	81.04%	**84.23%**	82.15%	82.14%

Table 4: Classification accuracy for StatLBP descriptor white R_1=5.

	R_2= 2	R_2 =4	R_2= 6	R_2= 8
Mean LBP	74.46%	**75.80%**	74.07%	73.03%
Median LBP	73.70%	74.52%	73.71%	**74.77%**
Variance LBP	**80.98%**	79.96%	80.67%	80.71%
Skewness LBP	**83.47%**	82.14%	80.30%	82.45%
Kurtosis LBP	79.67%	81.37%	**82.20%**	82.14%

Table 5: Classification accuracy for StatLBP descriptor white R_1=6.

Author	**Method**	**Classification accuracy**
Fang et al.	Pictorial structure model	70.67
Turk&Pentland	Discriminative multimetric learning	73.50
Lu et al.	Neighborhood Repulsed Metric Learning	71.60
Yan et al.	Prototype discriminative feature learning	71.90
Our	**LBP (*R*=6) + SIEDA**	**79.00**
Our	**Kurtosis LBP (R_1=3, R_2=2) + SIEDA**	**84.92**

Table 6: Comparisons of classification accuracy of our kinship verification system with different methods on the Cornell Kinship database.

Author	**Method**	**Classification accuracy**
Fang et al.	Pictorial structure model	70.67
Turk&Pentland	Discriminative multimetric learning	73.50
Lu et al.	Neighborhood Repulsed Metric Learning	71.60
Yan et al.	Prototype discriminative feature learning	71.90
Our	**LBP (*R*=6) + SIEDA**	**79.00**
Our	**Kurtosis LBP (R_1=3, R_2=2) + SIEDA**	**84.92**

Comparison against the state of the art

In this section, we presented a comparison of our work with the work of the state of the art of kinship verification in the Cornell database database as a function of classification accuracy. Table 6 shows this experience.

Table 6 shows that our facial kinship verification system with a simple descriptor (LBP) with the SIEDA reduction and classification method gives better accuracy than all the state of the art kinship verification system on the Cornell Kinship database.Our system with Kurtosis LBP (R_1=3, R_2 =2) + SIEDA improves the accuracy with 11.42% compared to the best work of Turk and Pentland [17].

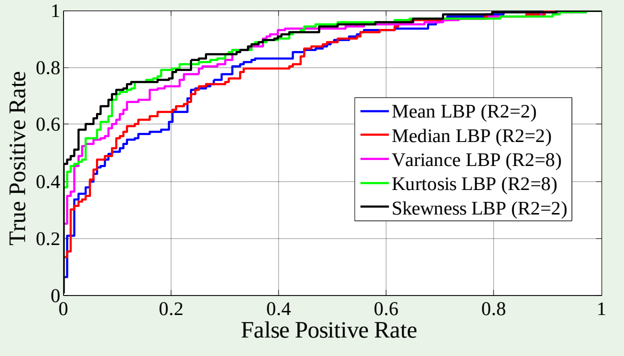

Figure 7: The ROC curve for the StatLBP descriptor white R_1=3.

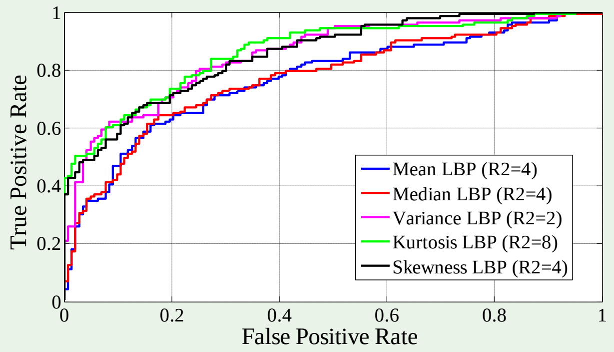

Figure 8 : The ROC curve for the StatLBP descriptor white R_1=4.

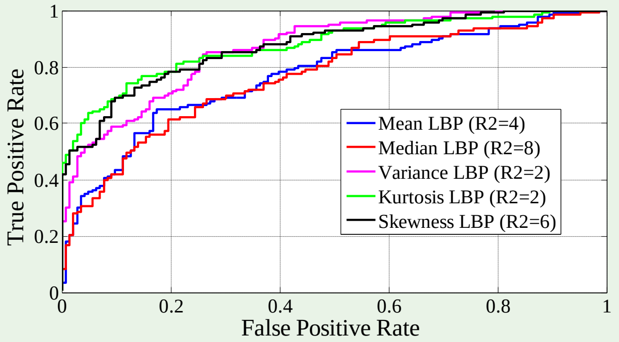

Figure 9: The ROC curve for the StatLBP descriptor white R_1=5.

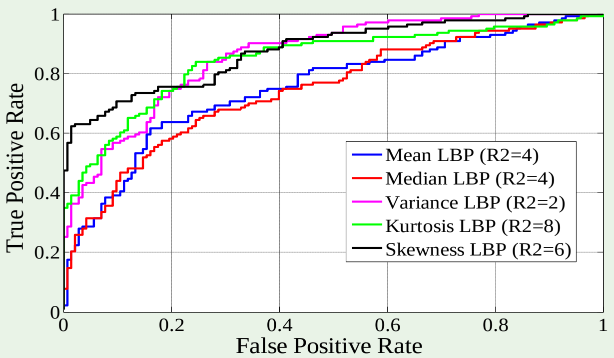

Figure 10: The ROC curve for the Stat LBP descriptor white R_1=6.

Conclusion

In this work, we studied the face-kin verification,which is based on the StatLBP descriptor (Mean LBP, Median LBP, Variance LBP, Skewness LBP and Kurtosis LBP). We used SIEDA (Side-Information based Exponential Discriminant Analysis) for the dimensionality reduction and classification of these descriptors. The scores are calculated by the cosine distance. We validated our proposed system by comparison with existing methods in the state of the art based on a Cornell Kinship database. The results of this work show that. Our system with Kurtosis LBP (R_1=3, R_2=2) + SIEDA better than all the state of the art kinship verification system on the Cornell Kinship database. As a future work, it is interesting to investigate higher tensor orders for Kinship verification.

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