Feature Fusion for Kinship Verification based on Face Image Analysis

Fatima Zekrini, Hassiba Nemmour, Youcef Chibani

Laboratory d'Ingénierie des Systèmes Intelligents et Communicants (LISIC), Faculty of Electronic and Computer Sciences, University of Sciences and Technology Houari Boumediene (USTHB), Bab Ezzouar El-Alia BP. 32, Algiers 16111, Algeria

{azekrini, hnemmour, ychibani}@usthb.dz

Abstract. This paper proposes the fusion of two new features for improving kinship verification based on face image analysis. Combined features are the Gradient Local Binary Patterns (GLBP), which associates gradient and textural information. The second descriptor is the Histogram Of Templates (HOT), which is a shape descriptor. These features are utilized with the support vector machines classifier to develop the kinship verification. Experiments are carried out on Cornell and Kinface W-II datasets. Results obtained highlight the effectiveness of the proposed system which provide competitive and sometimes better performance than the state of the art.

Key word. Kinship Verification, GLBP, HOT, SVM

1. Introduction

Automatic Kinship Verification from face imagesconsists of determining whether a kin relation exists for a given pair of facial images. This task is useful in various applications such as finding missing children, WEB images annotation, and social media analysis. The underlying idea is that people from the same family share similar face features that cannot vary according to the age or the sex. Therefore, a Kin verification system is founded on comparing features of two image faces through simple dissimilarity metrics or by using dissimilarity learning techniques. Recall that in facial image analysis, we are usually able to extract multiple feature representations where various kinds of textural, gradient, and shape features are currently used with a notable success. So, compared to face recognition or verification, that are widely used in biometrics, the kin verification is considered as a new application, that derives from biometrical face analysis.

Recently, there has been a lot of efforts in developing methods of kinship verification systems. Mainly, proposed methods can be categorized into two classes that are feature-based methods and model-based methods [1,2]. In the first approach, methods aim to extract discriminative information to preserve stable kin-related characteristics. Representative methods in this category include the Histogram Of Gradient (HOG) [1, 3], Salient Part [4], Self-Similarity [5], and Dynamic Spatio-Temporal Descriptor [6]. In this respect, features are directly compared through distance measure to decide about the kin relation.

In the second approach, methods can be divided into two classes: Methods using metric learning and Methods using deep learning. The aim of metric learning methods consists of extracting more pertinent kin decision that can reduce the distance between positive pairs (images representing a real kin relation), while enlarging the distance between negative pairs (images representing a fake kin relation). In this respect, several supervised classifiers were used in the state of the art such as the large margin nearest neighbor [8], information theoretic metric learning [9], metric embedding [10], pairwise constrained component analysis [11], and Support Vector Machines (SVM) [12]. Note that SVM stills one of the most effective classifiers and stills being the most commonly used.

Furthermore, with the huge performance of deep learning techniques, Convolutional Neural Networks (CNN) were used as a deep learning kin models [13-14]. However, the CNN is commonly effective when handling the face images, while for kin verification, it should learn distance measures. For this reason, the verification scores derived from various CNN models are medium [15]. Therefore, the use of handcrafted features associated with machine learning techniques still remain an effective technique to develop kinship verification systems

In this work, we propose the combination of two new features for improving the kinship verification. the first descriptor is the Gradient Local Binary Pattern (GLBP), which takes advantage from gradient and textural traits [16], and the Histogram Of Templates (HOT) [17], which is a shape descriptor. Both features were originally introduced for human detection, but they show satisfactory performance for other applications such as handwritten signature verification and document analysis [18, 19]. Presently, these descriptors are used to extract face features. The verification step is achieved by a SVM classifier that is trained to separate positive face image pairs from the negative ones. Experiments are conducted on two public datasets.

The rest of the paper is organized as follows: Section 2 details the proposed kinship verification system. Section 3 presents and discusses the experimental results, while Section 4 discusses. Section 5 concludes the paper.

2. Proposed Kinship Verification System

Commonly, a kinship verification system is composed of two main steps that are feature generation and distance metric learning (See figure 1). Given a set of training face images, we first extract features for each face image and consider couples of real and fake child-parent features, by using the difference between feature vectors. These features are then, trained by a classifier that decides whether there is a kinship relationship or not between the two face images. In this work, we propose to reinforce face features by combining two new descriptors. Precisely, we propose the Histogram Of Template (HOT), which is a shape descriptor, with the Gradient Local Binary Patterns (GLBP) that associates gradient and texture information. The distance metric learning is achieved by a SVM classifier.

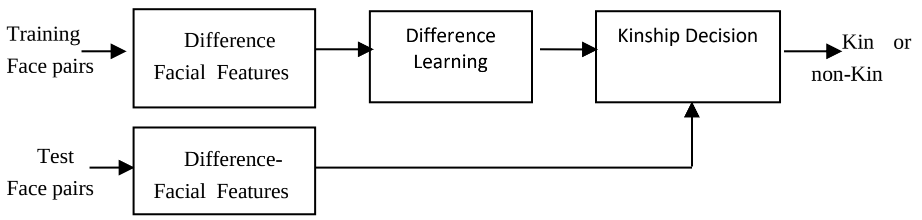

Fig. 1. Framework of kinship verification based on facial image analysis

2.1. Proposed features

In order to get robust facial features, we propose to combine two descriptors that characterize different trait properties. Precisely, we use the Histogram Of Template (HOT) which is designed to highlight local shape features, while the second descriptor is the Gradient Local Binary Patterns (GLBP) that associates gradient and textural information. For each face image both features are independently computed and concatenated to form the face feature vector.

2.1.1. Gradient Local Binary Patterns

GLBP(Local gradient binary Patterns) was introduced for human detection [20]. Its basic principle is to calculated the gradient information at one to zero (or zero to one) transitions of the local binary patterns code. Recall that LBP aim to characterize the distribution of grey levels in the pixel surrounding by comparing the value of the grey level of a central pixel with the neighboring grey levels. For each pixel in the face image, GLBP is calculated according to the following steps:

1. Calculate LBP code
2. Calculation of width and angle such as:
   - The width value: corresponds to the number of “1” in the uniform LBP code and this number of “1” can vary from 1 to 7.
   - The angle value: corresponds to the freeman direction of the medium pixelin the one value area of the uniform LBP (See figure 2).
3. The width and angle values define the position in the GLBP matrix that is filled by the accumulation of gradient values calculated at one to zero (or zero to one) transition such as :

$$G = \sqrt{(I(X+1,Y) - I(X+1,Y-1))^2 + (I(X,Y+1) - I(X-1,Y+1))^2} \quad (1)$$

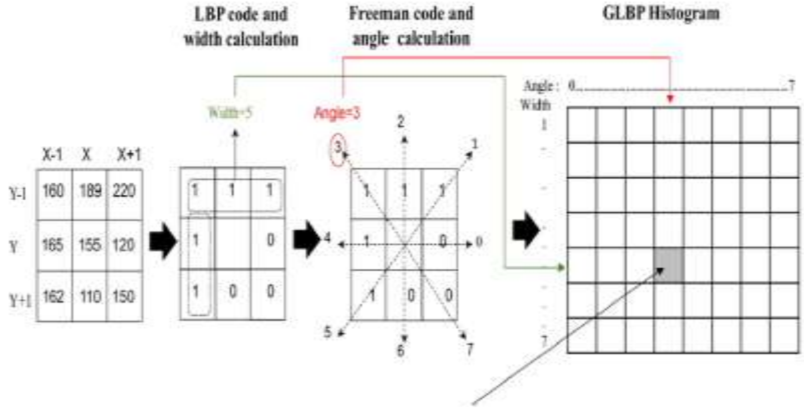

Fig.2. GLBP calculation for a given pixel [20]

2.1.2. Histogram Of Templates

HOT (Histogram Of Templates) was initially introduced to improve local shapes in human detection applications [21]. afterwards it was successfully employed in various handwritten recognition tasks [22]. Roughly, HOT considers local shape orientations through relationships between pixels and their neighbors. This description is done using a set of 20 templates representing all possible orientations of a triplet of pixels (See Figure 3).

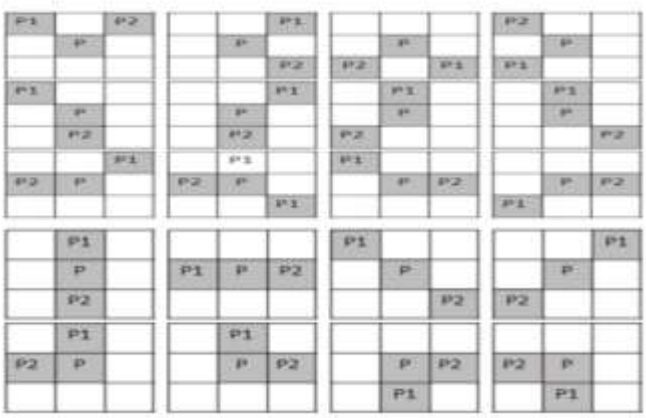

Fig3. Models used in the HOT calculation [21]

The generation of HOT characteristics consists in applying each template to all pixels of the face image. A pixel is said to fit a template if it verifies the following condition :

$$I(P) > I(P_1) \&\& I(P) > I(P_2) \quad (2)$$

I(P) : Gradient intensity calculated by Sobel filtering.

Then, the histogram of templatescontains the number of pixels that fit to each Template.

2.2. SVM-based Kinship verification

To develop the kinship verificatory, training face images are grouped into two classes. The first class is composed of truth child-parent image couples, while the second class contains the same number of false child-parent couples. Each couple is represented by the absolute difference vector calculated between the face features (that are generated by using HOT and GLBP), as described in the following equation:

$$Z_i = |A_i - B_i| \tag{3}$$

Where i=1: N, and N is the size of feature vectors.

Then, a SVM classifier is trained on difference features. Recall that the training of SVM aims to find the optimal hyper-plane separating two classes. After the training, we get the following decision function:
[1]

$$f(A) = sign\left(\sum_{j=1}^{S_v} \alpha_j y_j K\left(A, B_j\right) + b\right) \tag{4}$$

y_j : Class label {+1, -1}.
S_v: Is the number of support vectors that represent training data for:
$0 \leq \alpha \leq C_j$ The bias b is a scalar while C is the cost parameter.

K is the SVM kernel. Presently, we employ the RBF (Radial Basis Function) kernel because of its proven performance in handwritten recognition [16]. This kernel is expressed as:

$$\left(K(A, B_i) = exp(-\gamma \|A - B_i\|^2)\right) \tag{5}$$

γ : user defined parameter

3. Experimental results

To evaluate the effectiveness of our proposed kinship verification system, we conduct experiments on two widely used datasets that are, KinFaceWII, Cornell KinFace. Fig. 1 presents some sample kin pairs from the KinFaceW-II and Cornell KinFace datasets. These datasets are composed of four kin relations classes that are: Father-Son (F-S), Father-Daughter (F-D), Mother-Son (M-S), Mother-Daughter (M-D). The KinFaceW-

[1] https://www.ranksays.com/siteinfo/kinfacew.com
2https://www.ranksays.com/siteinfo/Cornell kinface.com

II contains 250 pairs for each category, while the Cornell set contains 150 pairs per category. In our experiments, 2/3 pairs for each category were used in the training stage, and the remaining pairs were used for performance assessment. Fig. 4 presents some sample kin pairs from the two datasets.

(a) (b)

Fig.4.Some samples from the adopted datasets:
(a) KinFace-WII [19], (b) Cornell dataset [6]

The SVM-based kinship verification is developed by using the RBF kernel. User-defined parameters were experimentally tuning by considering cross-validation. Tables 1 and 2 summarize the verification accuracies obtained for the two datasets. Roughly, the verification accuracies are better on the Cornell dataset which contains a smaller amount of data. For both sets, the most complicated task is the Father-Son verification, which is achieved by medium performance compared to the Father-Daughter kinship. Furthermore, the two proposed features provide approximately similar performance, where the difference in the average precision is 1% for the Kinface dataset and 1.42% for the Cornell corpus. Nevertheless, the proposed combination allows a significant improvement of the verification scores. Specifically, for the Kinface-WII dataset, the combination provides a gain of 5.16% in the average precision. For Cornell dataset set, for which individual features provide higher scores, the gain is about 2.51%. These outcomes highlight the complementarity between the two features, despite of having close individual precisions.

Table. 1. Kinship results obtained for the Kinface-WII Dataset (%)

Features	F-D	F-S	M-D	M-S	Average Precision
GLBP	81.33	62.66	70	73.33	71.83
HOT	74.66	62	72.66	74	70.83
GLBP+HOT	84.66	70	75.33	78	76.99

Table. 2. Kinship results obtained for the Cornell dataset (%)

Features	F-D	F-S	M-D	M-S	Average Precisions
GLBP	87.5	80	88.88	90	86.56
HOT	87.5	80	94.44	90	87.98
GLBP+HOT	92.5	85	94.44	90	90.49

Furthermore, table 3 reports some published results obtained on adopted datasets. As can be seen, our proposed system based on the GLBP and HOT fusion provides a competitive performance, since it outperforms several state-of-the-art systems. More precisely, the hierarchical representation learning proposed by Kohli et al. [34] achieved the best accuracy performance so far on several benchmark datasets. Nevertheless, our system achieves the second-best accuracy performance while being simpler to elaborate.

Table 3. Kinship results published in the state of the art (%)

Reference	Cornell	Kinface-WII
[24]	71.60	74.70
[25]	71.10	76.00
[26]	71.70	76.30
[27]	73.70	78.30
[28]	71.90	77.00
[29]	76.70	80.40
[30]	73.00	75.70
[31]	75.80	79.30
[32]	74.00	76.70
[33]	79.00	81.80
[34]	89.50	96.20
Our system	90.49	76.99

4. Conclusion

In this paper, proposed the combination of two descriptors to perform a robust kinship verification. The first descriptor is the Gradient Local Binary Patterns (GLBP) that associates the gradient and textural information, while the second descriptor is the Histogram Of Templates (HOT) which highlights local shapes. These features are concatenated to characterize the kinship relations in face images. The verification step is achieved by SVM classifier. Experiments conducted on two benchmark datasets, confirm the effectiveness of the proposed combination, which offers similar and sometimes higher performance than the state of the art. To improve again the verification scores, as a future work, we plan to associate other kinds of features such as CNN-based features, and use strength fusion rules such as the fuzzy integral combiners.

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