Kinship Verification based on Local Binary Pattern features coding in different color space

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***Abstract*—Kinship verification is one of the interesting and challenging topics which is related to face analysis. Most of existing methods have been trying to find out the relevant information between two persons (edge nose, lip, eyes) to increase the verification rate. In this paper, we propose to apply the Local Binary Pattern for Kinship on different color space. Then the features are computed by χ^2 distance and apply feature selection to reduce the noisy and irrelevant features. The Support Vector Machine is used to train and predict the model. We analyze the effectiveness of our method by carrying out experiments on two popular databases such as KinFaceW-I and KinFaceW-II.**

Keywords*—*color space, LBP, feature selection, kinship verification, face analysis.

I. Introduction

Computer vision has many applications for real life such as face recognition, age estimation, gender classification, face analysis, object detection, defect inspection. Among them, face analysis receives more attention because it is widely applied. One of the related problems is kinship verification. This process allows to determine the relationship kin or non-kin between two persons quickly. This is a relatively young topic and has still challenging problems because most of the facial images are selected from varied sources and affected by aging, skin color, illumination. Moreover, some people who are related by blood seem like different when they grow up. Thus, kinship verification by computer vision can help people identify and find lost children, determine the kinship or not kinship quickly instead of ADN testing, which take more times.

Many methods have been proposed to improve performance and algorithm for kinship verification in the state-of-the-art. Lu et al. proposed a new model, namely Neighborhood Repulsed Metric Learning (NRML) which aims to learn distance metric. NRML method pulls image pairs without kin relations as far as possible and closes the distance between image pairs with kin relations [1]. Patel et al. proposed use Block-based Neighborhood Repulsed Metric Learning (BNRML) method [2]. This is an extension from NRML which learn multiple local distances metric from different blocks of the image. Furthermore, color space has been intensive which aims to improve the face recognition task [3]–[5]. Lu et al. show how color space effective to recognize face images when using different color space instead of *RGB* space or gray-scale [6]. Liu et al. propose new color Generalized InCs (GInCs) framework for kinship verification which based on InCs automatically derived by trading off the criterion of minimizing the kinship pairs and the criterion of maximizing the non-kinship pairs [7]. Yang et al. proposed a new color model - the $g1g2g3$ model based on the log chromaticity color space, which preserves the relationship between three components of the *RGB* color space in the model [8]. Moujahid and Dormika propose Pyramid Multi-level (PML) to use multi-block with multi-channel color space for extracting images to enhance the histogram [9].

Besides that, Local Binary Pattern (LBP) is one of the most successful descriptors because of fast and simple computation among the local and global descriptors proposed in the literature. In this paper, instead of extracting the LBP features from facial images globally, we propose to divide the image into small blocks. It can be expected some regions contain important information than others (such as eyes, cheeks, nose, lips). The feature selection approach is applied to determine the relevant information.

The remain of this paper is organized as follow. Section 2 presents related works. Next, we propose a face descriptor based on LBP feature coding in different color space in section 3. The experimental results and conclusion can be found in section 4 and 5.

II. Background

In this section, we briefly review the definition of LBP, the family of color spaces and the extension of feature selection for kinship verification.

A. Local binary pattern

The $\text{LBP}_{\mathcal{P},\mathcal{R}}(x_c, y_c)$ code of each pixel (x_c, y_c) is computed by comparing the gray value g_c of the central pixel with the gray values $\{g_i\}_{i=0}^{\mathcal{P}-1}$ of its $\mathcal{P}$ neighbors , as follows:

$$\text{LBP}_{\mathcal{P},\mathcal{R}} = \sum_{p=0}^{\mathcal{P}-1} s(g_p - g_c)2^p \tag{1}$$

where g_c is the gray value of central, g_p is the gray value of $\mathcal{P}$ and $s(g_p - g_c)$ is defined as

$$s(g_p - g_c) = \begin{cases} 1 & if (g_p - g_c) \geq 0, \\ 0 & otherwise. \end{cases} \tag{2}$$

LBP has many variants for different application and purpose. One of the first extension of LBP is LBP "uniform patterns" [10]. LBP was called uniform if the binary pattern contains at most two bitwise transitions from 1 to 0 or 0 to 1. Example of uniform patterns 00000000 (0 transition) and 01110000 (2 transitions) are uniforms but 10011011 (4 transitions) are not. LBP uniforms are coded by only 59 histograms compared with 256 by the original LBP. Moreover, LBP uniform can detect the important local textures such as the like spots, the line ends, edges and corners.

B. Color space

Color images are usually acquired by devices that code the colors information on the *RGB* space. However, there are many color spaces with different properties in the literature and the appropriate space depends on the specific application [11]. So, color spaces can be grouped into four families as follow [12]:

- **primary spaces** like the *RGB*, *rgb*, *xyz* space;
- **luminance-chrominance spaces** like the *YUV*, *YIQ*, YC_bC_r, $b_wr_gb_y$ space;
- **independent axis spaces** like the $I_1I_2I_3$ space;
- **perceptual spaces** the *HSV*, *HLS*, *HSI* space.

C. Feature selection

In order to extract the features of the facial images from multi-block, this tends to produce high dimensional feature vectors. It is clear that all the features contribute unequally in the recognition task and it leads to the performance of classification and increasing computational efficiency. Various approaches are proposed to obtain more discriminative, robust LBP features with reduced feature dimensionality. Among of them, feature selection aims to find the adequate subsets of features by keeping some original features and therefore maintains the physical meanings of the features.

Recently, Moujahid and Dormika proposed an extension of Fisher score for kinship verification [9]. Fisher score is a supervised approach which identifies the relevant feature by using class labels. The Fisher score of the r_{th} features for kinship verification is defined as follow:

$$F_r = \frac{N_P(\mu_{r,P} - \mu_r)^2 + N_N(\mu_{r,N} - \mu_r)^2}{N_P\sigma^2_{r,P} + N_N\sigma^2_{r,N}} \tag{3}$$

where N_P and N_N are the numbers of positive and negative pairs of images. $\mu_{r,P}$ and $\sigma^2_{r,P}$ refer to the mean and variance of the r^{th} feature of the positive class, $\mu_{r,N}$ and $\sigma^2_{r,N}$ refer to the mean and variance of the r^{th} feature of the negative class. The last μ_r is a global mean of r^{th} feature.

III. THE PROPOSED APPROACH

We divide an image into non-overlapping blocks before extracting the features in the proposed approach. Therefore, several researchers had successfully proposed to divide an image into many blocks for face recognition task [13], [14]. It is well known that this method has an advantage since some blocks contain relevant information than the others(such as edges, nose, spots). Given an image I with the size $N \times N$ pixels and the number of l levels. The total number of blocks of all levels are defined as follows:

$$B = \sum_{i=1}^{l} 2^{2(l-1)} \tag{4}$$

with the size of square blocks at level is $b \times b$, where, $b = \frac{N}{2^{2(l-1)}}$ pixels.

The image I is then represented by l levels which is an array $L_1, \dots, L_l$. Each L_i is defined by:

$$L_i = \{B_{i,1}, ..., B_{i,n_i}\} \tag{5}$$

where $i = 1, \dots, l$ and $n_i = 2^{2(l-1)}$. For each B_{i,n_i} block the local descriptor f_i is extracted. So, the image I are combined with l levels, $I = \{L_1, L_2, ..., L_l\}$. Figure 1 illustrates the feature extraction from blocks in multi-level.

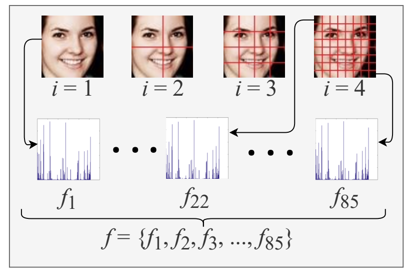

Fig. 1: An illustration of feature extraction from blocks in multi-level

The image is coded in different color space and then is calculated by the Chi-Square distance to find out correlate information between parents image and children image. There are two reasons for using this distance. Firstly, Chi-Square distance gives a better result than others by LBP based features on multi-block [15]. Secondly, the feature vectors are high dimensional space which contains redundant and irrelevant information. The χ^2 statistic is defined as:

$$\chi^2(P, C) = \frac{1}{2}\sum_{i=1}^{N_P} \frac{(P_i - C_i)^2}{P_i + C_i} \tag{6}$$

where, P and C represent parents and children pairs of images. Finally, a subset of features selected is processed by SVM to determine the kinship relation. The schema of the proposed approach is illustrated in figure 2.

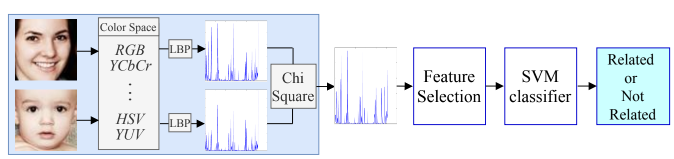

Fig. 2: The schema of the proposed approach on a pair of relation

The following section presents the experimental results.

IV. EXPERIMENTAL RESULTS

A. Data setup

In this paper, we use two benchmark kinship datasets namely KinFaceW-I and KinFaceW-II [1]. The number of images of KinFaceW-I is 1066 images which are divided into 533 pairs. The KinFaceW-II dataset has 2000 images which are divided into 1000 pairs. They are analyzed in table I. We can observe that the proportion of Asian people in these two datasets is different and imbalanced. The images of KinFaceW-I dataset is extracted from different images while the images of KinFaceW-II dataset is obtained by decomposed from one image.

	KinFaceW-I	KinFaceW-II
Image	1066 images – 533 pairs	2000 images – 1000 pairs
Asian people	64.40%	8%
Not Asian people	35.60%	92%
Source Image	Many images	One image
Image Size	64×64 pixel	64×64 pixel

TABLE I: The analysis of two kinship databases.

Each dataset has four relations such as Father-Daughter (FD), Father-Son (FS), Mother-Daughter (MD) and Mother-Son (MS) for. The detailed analysis of each dataset is illustrated in table II. Each fold contains positive pairs and negative pairs of images. The cross-validation is applied into five folds in the experiments. The $(k-1)$ fold is used for training data and the rest one is used for testing.

	KinFaceW-I				KinFaceW-II			
Class	**FD**	**FS**	**MD**	**MS**	**FD**	**FS**	**MD**	**MS**
Pairs of images	134	156	127	116	250	250	250	250
Asian people (%)	61.9	63.5	55.1	78.4	6	7.2	7.6	11.2
Not Asian people (%)	38.1	36.5	44.9	21.6	94	92.8	92.4	88.8

TABLE II: Summary of KinFaceW-I and KinFaceW-II databases

B. Results

We first compare the performance of different color space (see section II-B) for kinship verification. Fourteen spaces have been investigated to code the image. Figure 3 and 4 compare the performance of different color space on 4 levels of extracting features. The results of each level (from 1 to 4) is the average performance of 4 relations verification.

By analyzing those tables, two top color spaces (*YUV* and *bwrgby*) which have the best result is selected. In order to enhance the discriminant information, the LBP features extracted from these spaces are concatenated. We might think that we can remove irrelevant, noisy and redundant features by the feature selection approach.

Table III and IV compare the results obtained by our proposed approach and several selected works in the state-of-the-art on KinFaceW-I and KinFaceW-II dataset, respectively. The first column presents the reference and the year of publication. The second, third and fourth present the method, classifier used and characterized feature for verification. The five last columns represent the results obtained of verification on four relations (FS, FD, MS, MD) and the mean results. By analyzing these tables, we see that the proposed approach is

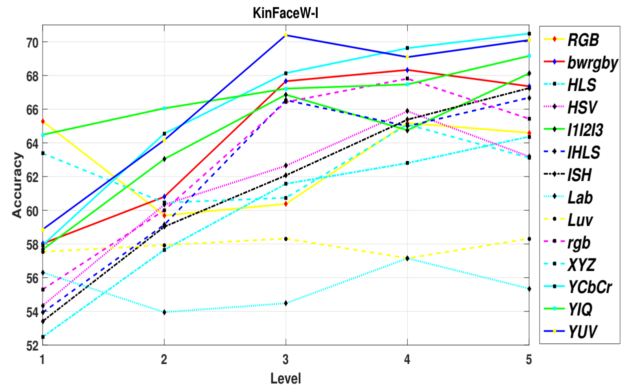

Fig. 3: The performance of verification on KinFaceW-I dataset in different color space. Four levels of features extraction have been considered such as 64×64, 32×32, 16×16 and 8×8 pixels.

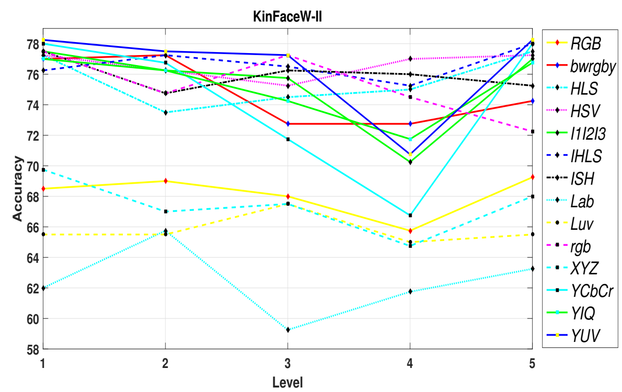

Fig. 4: The performance of verification on KinFaceW-II dataset in different color space. Four levels of features extraction have been considered such as 64×64, 32×32, 16×16 and 8×8 pixels.

shown to outperform the other methods on the two benchmark dataset.

There are several works proposed to concatenate multiple features to enhance the discriminant information for KinFaceW-I [1], [20], [22] and KinFaceW-II [1], [20], [22], [33]. We combine LBP features extracted from two color spaces and this gives better results. For example, Jiwen et al. use LBP + TPLBP + SIFT + LE on the KinFaceW-I dataset [1] (see table III). It gives the mean accuracy by 69.9% while our approach reaches the accuracy as 72.6%. Similarly, on the KinFaceW-II dataset, the proposed approach gives accuracy by 81.8% and improves 1.8%. The results can be explained that the feature selection approach allows to remove the irrelevant and noisy features by the extension of the Fisher score for kinship verification. Furthermore, the mean of our proposition is better than DMML by 0.3%, 4.2% of Deep & Shallow and is equal to QMCBP$_p$ 72.6%.

Locally, among the kin relation in KinFaceW-I dataset, our

TABLE III: Mean verification accuracy (%) of difference features on KinFaceW-I

Reference and publication year	Method	Classifier	Feature	FS	FD	MS	MD	Mean
[16], (2015)	LGM	-	SPLE	66.1	62.2	64.3	70.0	**65.7**
[17], (2017)	NRCML	SVM	LE	66.1	61.1	66.9	73.0	**66.3**
[18], (2011)	FIUUC	SVM	SPLE	63.5	61.5	72.5	73.5	**67.8**
[19], (2018)	Deep & Shallow	SVM	-	68.8	68.8	70.5	65.5	**68.4**
[1], (2014)	MNRML	SVM	LBP + TPLBP + SIFT + LE	72.5	66.5	66.2	72.0	**69.9**
[20], (2015)	MPDFL	SVM	LBP + SPLE + SIFT	73.5	67.5	66.1	73.1	**70.1**
[21], (2015)	FS	-	LPQ	75.4	63.8	69.9	74.6	**70.9**
[22], (2014)	DMML	SVM	LBP + SPLE + SIFT	74.5	69.5	69.5	75.5	**72.3**
[23], (2016)	QMCBP$_p$	-	-	74.4	69.6	68.8	77.8	**72.6**
Our approach		**SVM**	**LBP**	**78.1**	**69.2**	**70.8**	**72.2**	**72.6**

TABLE IV: Mean verification accuracy (%) of difference features on KinFaceW-II

Reference and publication year	Method	Classifier	Feature	FS	FD	MS	MD	Mean
[19], (2018)	Deep + Shallow	SVM	-	66.5	68.5	65.4	65.4	**66.5**
[24], (2012)	GGOP	SVM	-	65.5	65.5	73.5	74.5	**69.8**
[25], (2015)	SILD	SVM	HOG	79.6	71.6	73.3	69.6	**73.5**
[26], (2017)	R-K^{2}ISSME	-	LBP	75.6	78.4	68.6	73.2	**74.0**
[9], (2018)	PML	SVM	LBP	-	-	-	-	**74.7**
[16], (2015)	LGM	-	SPLE	74.9	71.0	76.9	76.4	**74.8**
[27], (2017)	SPML - PN	-	HOG	81.4	71.2	74.8	73.0	**75.1**
[23], (2016)	QMCBP$_q$	-	-	77.2	71.6	79.0	73.4	**75.3**
[28], (2018)	MHSL	SVM	-	-	-	-	-	**75.4**
[29], (2016)	ESL	-	HOG	81.2	73.0	75.6	73.0	**75.7**
[1], (2014)	MNRML	SVM	LBP + TPLBP + SIFT + LE	76.9	74.3	77.4	77.6	**76.5**
[30], (2017)	QIWD	-	-	77.4	73.6	78.4	76.8	**76.6**
[20], (2015)	MPDFL	SVM	LBP + SPLE + SIFT	77.3	74.7	77.8	78.0	**77.0**
[31], (2016)	OSL-A	-	HOG	82.0	77.2	75.6	73.6	**77.1**
[21], (2015)	FS	-	LBP	82.4	76.2	76.6	73.2	**77.1**
[32], (2016)	MMTL	-	-	-	-	-	-	**77.2**
[22], (2014)	DMML	SVM	LBP + SPLE + SIFT	78.5	76.5	78.5	79.5	**78.3**
[33], (2015)	LM^{3}L	-	LBP + TPLBP + SIFT + LE	82.4	74.2	79.6	78.7	**78.7**
[17], (2017)	NRCML	SVM	LE	79.8	76.1	79.8	80.0	**78.7**
[34], (2015)	NBDFDL	-	HOG	86.2	77.2	78.6	75.0	**79.3**
[35], (2018)	L^{2}M^{3}L	-	LBP + TPLBP + SIFT + LE	82.4	78.2	78.8	80.4	**80.0**
[36], (2017)	EHRMFS	-	-	84.4	80.6	84.4	77.6	**80.2**
[37], (2016)	SSML	-	HOG	85.0	77.0	80.4	78.4	**80.2**
[38], (2018)	MvDML	-	LBP + TPLBP + SIFT + LE	80.4	79.8	78.8	81.8	**80.2**
[2], (2017)	BNRML	-	LTP	84.0	79.0	79.2	80.0	**80.6**
[39], (2015)	SC	SVM	-	82.6	73.8	82.8	84.0	**80.8**
[7], (2016)	GInCS	SVM	SIFT	85.4	77.0	81.6	81.6	**81.4**
[40], (2015)	GATC	SVM	LID - WLD - ANGLES - RATIOS - SEGS	82.7	76.9	82.3	83.9	**81.5**
[41], (2015)	IFVF	-	SIFT	85.6	75.4	82.8	82.6	**81.6**
Our approach		**SVM**	**LBP**	**87.0**	**82.0**	**71.0**	**87.0**	**81.8**

approach gives the best result on FS. Similarly, we give the best results on FS, FD and MD kin relation on KinFaceW-II dataset.

V. Conclusion

We presented the kinship verification problem based on LBP features coding in different color space. We first compare the performance of several color spaces and then extract the features of the two selected spaces. The extension of Fisher score is applied to find out relevant features before using SVM to verify the relationship. The experimental results on two well-known benchmark datasets (KinFaceW-I and KinFaceW-II) show the efficiency of the proposed approach. This work is now continuing by comparing various feature selection approaches for kinship verification.

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