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Hybrid Discrete Wavelet Transform and Local Binary Pattern for Ethnicity Identification from Facial Images algorithm

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Abstract:

Human facial images provide significant amount of demographic information such as ethnicity, age, and gender. Ethnicity identification involves automatic estimation of ethnicity which has many potential applications ranging from forensics to social media. This paper concerns the ethnicity identification from facial images by extracting Local Binary Pattern (LBP) in Discrete Wavelet Transform (DWT) domain. Furthermore, K-Nearest Neighbor (K-NN) classification technique is used to classify the selected feature vector. We shall demonstrate that the proposed approach has significant impact on improving accuracy compared to existing approaches. The performance of the proposed approach has been evaluated via experiments conducted on our collected dataset of 950 facial images. Experimental results illustrate that the proposed approach reaches an accuracy rate of 90.27% of ethnicity identification.

Keywords: Discrete Wavelet Transform (DWT), Local Binary Pattern (LBP), City Block, K Nearest Neighbor (KNN)

الملخص:

صور الوجه للانسان يبين نسبة كبيرة من ملامح الوجه، مثل تنبؤات العمر والجنس و العرق. التعرف على العرق هو التقيم الملامح الذاتية للانسان ، هذا البحث يؤكد على التعرف على العرق بأخذ تفاصل دقيق حول صورة الوجه بأستخدام (Local Binary Pattern(LBP))في (Discrete Wavelet Transform (DWT))ولغرض استحصال نتيجة دقيقه يستخدم K-Nearest Neighbor (K-NN)) لتعرف على العرق (اوروبا ،اورينتال ، افريقا). طبيق كثير من الاختيارات على (٩٥٠) صوره، و من نتائج تتبين لنا ان الطريقة المتبعة في هذا البعث يعطينا نسبة (٩٠,٢٧٪) من النتائج الصحيحة.

پوختە:

وێنەی دەم و چاوی مرۆڤەکان ڕێژەیەکی زۆر گرنگی زانیاری دیمۆگرافیای مرۆڤەکان دابین دەکات وەک دیاری کردنی تەمەن و ڕەگەزو نەتەوە (قەومیەت)ی مرۆڤەکان. ناسینەوەی نەتەوەیی بریتیە لە هەڵسەنگاندنێکی خودکارانە بۆ دیاری کردنی نەتەوەیی مرۆڤەکان. ئەم توێژینەوەیە جەخت دەکاتەوە لەسەر دیاری کردن و ناسینەوەی نەتەوەیی مرۆڤەکان بە وەرگرتنی زانیاری وورد لە وێنەی دەم و چاویان بە بەکار هێنانی ڕێگەی (Local Binary Pattern(LBP)) لە ناو مەودای (Discrete Wavelet Transform (DWT))وە هەروەها بۆ ئەوەی ئەنجامێکی زۆر ووردمان دەست بکەوێت ڕێگەی (K-Nearest Neighbor (K-NN))بەکارهاتووە بۆ باشتر پۆلێنکردن لە نێوان نەتەوەکانی (ئەورووپی و ئۆرێنتاڵ و ئەفەریقی). ڕێژەیەکی زۆر لە تاقی کردنەوە ئەنجام دراوە لەسەر (950) وێنەی دەم و چاو، وە ئەنجامی تاقی کردنەوەکان ڕونی دەکەنەوە کە ڕێگەی پێشنیارکراو ئەنجامێکی ڕاست و ووردمان دەست دەکەوێت کە(90.27%) بۆ ناسینەوەو پۆلێن کردنەکە.

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1. INTRODUCTION

Ethnicity identification from face images refers to the process of recognizing the ethnic group. This can be used in various areas of application. The basic identification process will consist of; selecting and extracting propagate facial features, and searching for similar facial images from a given dataset. Over the past few decades, several approaches have been proposed for ethnicity identification and much progress has been made. However, it is hard to recognize faces belonging to a different race swiftly and accurately under uncontrolled conditions. Despite the fact that humans are able to identify and recognize faces in a scene with little or no effort, getting a computer system to accomplish such objectives is very challenging. The challenges generally come from the large variations in visual stimulus due to facial expressions, viewing directions, poses, occlusions (eye glasses) and illumination conditions [1,2].

In today's world, the importance of biometrics systems has been supported by the need for large scale identity management systems whose functionality relies on the accurate determination of an individual's identity [2]. This has been especially the case in the past ten years, in which terrorist attacks have happened frequently, which have caused people to focus on the importance of security monitoring and control in national defense and public safety. Among those mentioned biometrics systems before, ethnicity identification of facial images is of interest in a wide area of applications related to homeland security, law enforcement, safety, access control, and automatic annotation. Human facial images provide significant amount of demographic information such as ethnicity, age, and gender. Different from face recognition of individuals, ethnicity identification classifies faces according to the common features of a specific ethnic class. Meanwhile, ethnicity identification of face images refers to the process of recognizing the ethnic group to which the individual of a given face image belongs. The identification process includes extracting facial features, searching for similar facial images from a given dataset or construct a classification model, and determining the ethnic group of the query face image [3].

This paper addresses the ethnicity identification problem and focuses on ethnicity classification in three categories (Oriental, European, and African). The main contribution of this paper is developing an approach by extracting Local Binary Pattern (LBP) in the Discrete Wavelet Transform (DWT) domain. The remainder of this paper is organized as follows: In Section 2, the related work is presented. Section 3 presents the proposed approach for the ethnicity identification. The experimental results are shown in Section 4. Section 5 discusses issues arising from our study. Finally, the conclusions are given in Section 6.

2. Related Work

Attempts to design computational models based on psychological studies for automatic demographic estimation started in the 1990s and since then; a significant progress has been made on automatic demographic estimation [4]. Faces express many social indications, including; gender ethnicity, age, expression, and identity. Most of them have drawn thriving attention from various research communities, for instance, neuroscience, computer science and psychology [5]. Facial images based ethnicity identification and classification is relatively a new topic in computer vision [6]. So far, approaches that focused on designing automated ethnicity identification and classification are very limited. Early works dealing with two group situations to make a difference between Asian and non-Asian [3]. Lu et al. used a linear discriminant analysis (LDA) technology

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for facial features extraction to classify the Asians and non-Asians and the K-nearest neighbor method was used for classification [3]. The basic LBP operator, introduced by Ojala et al. [7], is a powerful feature extraction technique which considers both texture and shape information to represent facial. The LBP operator assigns a label to every pixel of an image by thresholding the intensity values in the 3×3-neighborhood of each pixel with the center pixel intensity value and converts the result into a binary number by using equation (1).

$$\boldsymbol{LBP}_{P,R}(x,y) = \sum_{n=0}^{n-1} 2^n \, S\,(i_n - i_c) \qquad (1)$$

$$\boldsymbol{S}\,(\boldsymbol{k}) = \begin{cases} 1 & k \geq 0 \\ 0 & k < 0 \end{cases}$$

Where ic denote the gray level of the central pixel (xc,yc), in denote the gray level of the 8 surrounding pixels, and s(k) is defined as thresholding operation function. The binary result will be obtained by reading the values clockwise, starting from the top left neighbor. The basic LBP operator is illustrated in Figure 1.

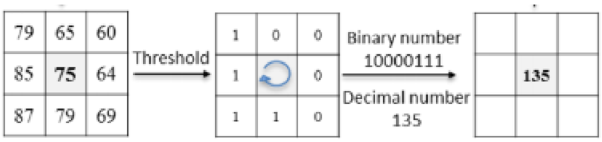

Figure 1: The Basic Local Binary Pattern operator

[8] performed LBP and Weber local descriptors (WLD) for three ethnic classes (Tibetan, Uygur and Zhuang) using local descriptors. The paper proposes the race recognition system from face images based on WLD with City block, Euclidean, and chi-square minimum distance classifiers. Within LBP-based algorithms, most of the face recognition algorithms using LBP follow the approach proposed by Ahonen et al in [9]. In this approach, the face image is divided into a grid of small of non-overlapping regions, where a histogram of the LBP for each region is constructed. The similarity of two images is then computed by summing the similarity of histograms from corresponding regions. Salah et al. portray a combination framework for ethnicity identification to classify the European, Oriental, and African by fusing block-based uniform LBP and Haar Wavelet Transform to combine local and global features [10]. In addition, authors claimed that test results show their scheme gives good accuracy and demonstrate the potential of fusing global and local features, and it reaches around 96% of accuracy. In contrast to the existing approaches that only depend on 2D facial images, Ding et al. proposed a new method for ethnicity classification by combining both boosted local texture and shape features extracted from 3D face images to distinguish Asians from non-Asians [11]. Different from previous reviewed approaches, Du et al. proposed a new scheme of multi-level fusion for ethnicity identification to classify the European, Oriental, and African. This proposal combined texture feature of local areas of a face using LBP with color features using HSV binning [12]. Furthermore, the scheme fused the decision from a k-nearest neighbor classifier and a support vector machine classifier into a final identification decision. The authors claimed that experimental results demonstrate the effectiveness of the combined features with an improvement on the accuracy of identification rate, which is

approximately 95.5% [12]. In this paper, we proposed a new approach for ethnicity identification by extracting LBP in the DWT domain. In the next section, we shall explain the proposed approach in details.

3. roposed Approach

This section explains the developed approach for ethnicity identification in the following steps:

1) Load the face/query image I.
2) Let I'_k be the face image I after Haar Wavelet Transformation is applied on it, where $k \in \{1,2,3,4 \text{ or } 5\}$ since five levels of Haar Wavelet have been considered in our experiments, each time only one level has been tested.
3) Apply LBP feature extractor on LL_k sub-bands, again $k \in \{1 \text{ or } 2\}$, then L is obtained.
4) Finally, KNN technique is used to compare the vector L with the all feature vectors of the database of face images to find the most close ethnicity group of the loaded image I.

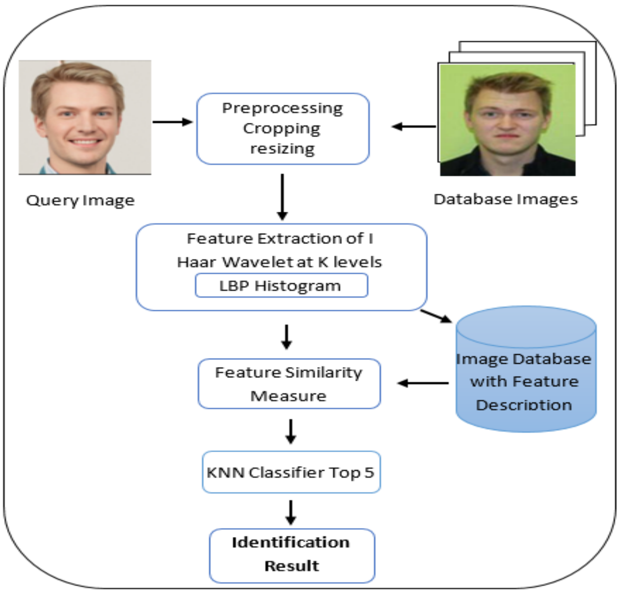

Figure2. Diagram of the proposed Approach.

4. Performance of the Proposed Approach

To test the performance of the proposed approach in terms of accuracy, the collected image dataset explained in Section 4.1 is used, and extensive experiments conducted on that dataset are presented in Section 4.2.

a. Dataset

Currently, there is no benchmark dataset available for ethnicity identification. In contrast, many face datasets exist for face recognition such as the YALE face dataset [13], the GUFD face dataset [14], FERET database [15], the PIE face database [16], and a snapshot dataset. Those existing datasets contain multiple images of the same face in different pose conditions, facial expressions, illumination conditions, with glasses or without, etc. Because of these complications, images in our dataset are manually selected from those different existing dataset sources mentioned before. Furthermore, our dataset contains 950 frontal passport style images of three ethnic groups

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(European, Oriental, and African) which are collected from four different ethnic databases [13-16], and the number of frontal images for each ethnicity is 400, 400 and 150 respectively. These images are cropped with a fixed size of 128 x 128 pixels, and then converted from RGB color space to gray scale. Table 1 represents the sampling details of the final collection of face images.

Table 1. Dataset used for this study

Ethnicity Class	**Image Source**	**No. of Images**	**Total**
European	FERET	110	400
	YALE	84	
	PIE	46	
	GUFD	160	
Oriental	CASIA	180	400
	CUHK	90	
	FERET	100	
	PDA	30	
African	FERET	87	150
	PDA	24	
	OTHER	39	
Total Images		950	

Figure 3. Sample of face images used for the study.

b. Experimental Results

Experiments are conducted extensively and can be classified into the following cases based on feature extraction process:

1- Extracting features from each sub-band of the first level of Haar Wavelet separately after LBP is applied. Meanwhile, first level of the Haar Wavelet is implemented on the whole face image, and then LBP is applied on each sub-band. Table 2 presents the average accuracy for each sub-band separately. Results in Table 2 shows that the accuracy average of LL and LH sub-bands is very close to each other and they are better than other two remaining sub-bands.

Table 2. Accuracy average for each sub-band of the 1st level of Haar Wavelet when LBP is applied

1st Level	European	Oriental	African	Total
LL	88.5	96.25	54	79.583
LH	88.5	77.5	74	80
HL	88.25	77.75	57.333	74.444
HH	89	78.5	57.333	74.944

2- Extracting features from concatenation of two sub-bands of the first level of Haar Wavelet separately after LBP is applied. In other words, first level of the Haar Wavelet is implemented on the whole face image, LBP is applied on each sub-band, then the results of two sub-bands are concatenated at a time based on different probabilities presented in Table 3. Table 3 presents the average accuracy for the concatenated two sub-bands.

Table 3. Accuracy average or the concatenated two sub-bands of the 1st level of Haar Wavelet when LBP is applied

1st Level Concatenated sub-bands	European	Oriental	African	Total
LL+LH	91.25	98	78	89.083
LL+HL	93	97.25	61.333	83.861
LL+HH	92.25	96.75	71.333	86.778
LH+HL	94.5	87	89.333	90.278
LH+HH	91.75	86.5	78	85.416
HL+HH	92.75	86.75	75.333	84.944

The results in Table 3 show that concatenating LH and HL sub-bands provide the better accuracy.

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3- In order to have a better understanding the impact of Haar wavelet features, second level of Haar wavelet is considered to be tested by extracting features from each sub-band of the second level of Haar Wavelet separately after LBP is applied. In other words, second level of the Haar Wavelet is implemented on the whole face image, and then LBP is applied on each sub-band. Table 4 presents the average accuracy for each sub-band separately.

Table 4. Accuracy average for each sub-band of the 2nd level of Haar Wavelet when LBP is applied

1st Level	2nd Level	European	Oriental	African	Total
LL	LL	90.25	95.75	58.67	81.56
	LH	85	76.5	61.33	74.28
	HL	84.5	71.75	53.33	69.86
	HH	67.75	57.25	32	52.33
LH	LL	84.25	78.75	66	76.33
	LH	69	60.75	28.67	52.81
	HL	78.25	59	32	56.42
	HH	65.5	56.75	29.33	50.53
HL	LL	82.75	74.75	50.67	69.39
	LH	79.25	56.75	25.33	53.78
	HL	67.75	65	38.67	57.14
	HH	76.75	52.5	26.67	51.97
HH	LL	78.25	57.75	21.33	52.44
	LH	66.5	57.25	24.67	49.47
	HL	81.25	41.5	24	48.92
	HH	69.5	60.5	30.67	53.56

Results in Table 4 demonstrate that LL of LL sub-band provides better accuracy average out of all other sub-bands.

4- Extracting features from the concatenation of two or more sub-bands of the second level of Haar Wavelet after LBP is applied. In other words, the second level of the Haar Wavelet is implemented on the whole face image, LBP is applied on each sub-band, then the concatenated results of more than one sub-bands based on different probabilities are presented in Table 5. Table 5 presents the average accuracy for the concatenated two sub-bands.

Results in Table 5 shows that the best result gained when LL and LH sub-bans of the LL sub-band are concatenated.

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Table 5. Accuracy average for the concatenated sub-bands of the 2nd level of Haar Wavelet when LBP is applied

1st Level	2nd Level Concatenated sub-bands	European	Oriental	African	Total	1st Level	2nd Level Concatenated sub-bands	European	Oriental	African	Total
LL	LL+LH	92.25	96.25	74.67	87.72	HL	LL+LH	87.25	75.75	45.33	69.44
	LL+HL	88	95.75	68.67	84.14		LL+HL	81.75	75.5	47.33	68.19
	LL+HH	89	93.75	56	79.58		LL+HH	84.75	70	43.33	66.03
	LH+HL	84.75	79.5	66	76.75		LH+HL	77	66.25	30	57.75
	LH+HH	77.5	76	58	70.5		LH+HH	88.5	52	23.33	54.61
	HL+HH	81.75	73.75	52.67	69.39		HL+HH	73.25	57.25	41.33	57.28
	LH+HL+HH	86	79	58.67	74.56		LH+HL+HH	87	57.5	28.67	57.72
	LL+LH+HL+HH	89.75	96	76	87.25		LL+LH+HL+HH	88.75	67.5	46	67.42
	LL+LH+HL	91	96.5	73.33	86.94		LL+LH+HL	81	76	49.33	68.78
	LL+HL+HH	91.75	94	68.67	84.81		LL+LH+HH	91.75	69.25	40	67
	LH+HL+HH	89.75	96.25	64	83.33		LL+HL+HH	83.75	70	49.33	67.69
LH	LL+LH	75.25	78.75	66	73.33		LH+HL+HH	87	57.5	28.67	57.72
	LL+HL	79.75	75.25	58	71		LL+LH	76.75	66.5	27.33	56.86
	LL+HH	80.75	79.5	62.67	74.31		LL+HL	85.5	52.75	22.67	53.64

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LH+HL	80.75	68.5	32.67	60.64		LL+HH	76.75	68.5	20.67	55.31
LH+HH	68.75	70.25	30	56.33		LH+HL	77.5	54.5	29.33	53.78
HL+HH	78	56.5	29.33	54.61		LH+HH	70.75	59.5	24	51.42
LH+HL+HH	76.25	66	32	58.08	**HH**	HL+HH	73.75	62	38.67	58.14
LL+LH+HL+HH	82.25	75	56.67	71.31		LL+LH+HL	79.5	58.75	24	54.08
LL+LH+HL	81.25	78.75	58.67	72.89		LL+LH+HH	77.5	63.75	24.67	55.31
LL+LH+HH	76.25	78.5	54	69.58		LL+HL+HH	81.25	66.75	32	60
LL+HL+HH	84.75	74.75	64	74.5		LH+HL+HH	73.75	62.25	30.67	55.56
LH+HL+HH	76.25	66	32	58.08						

5. Discussion

So far, there is no benchmark dataset available for ethnicity identification that takes into consideration standard environment conditions. This drawback reflects on the difficulty that it is not easy to compare the proposed approach with other recently related works. Comparing the results of the proposed scheme to the results in Ref. 3 is not fair since the scheme deals with binary classification (Asian vs. Non-Asian) situation. The presence of a third class is inevitably having an impact (most likely passively) on accuracy.

6. Conclusion

In this paper the new approach for ethnicity identification has been presented based on LBP feature extractors in DWT domain, to classify facial images into three groups (Oriental, European, and African). K-Nearest Neighbor (KNN) classifier is used to classify the selected feature vector. The proposed approach performs well comparing to the current state-of-art results in ethnicity identification. Test results illustrate the performance of the proposed approach and the average accuracy reached 90.3%.

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