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EFFECTS OF DIFFERENT DISTANCE MEASURES ON ETHNICITY IDENTIFICATION

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Abstract:

Facial recognition becomes an active research area of computer vision which provides the demographic information such as gender, age, and ethnicity. The feature extraction and classification technique(s) used to recognize facial images play an important role in achieving high identification rate for a recognition system. The present study is a comparative analysis of two feature extraction techniques: Discrete Wavelet Transform and Discrete Cosine Transform with k-Nearest Neighbor classifiers. It uses 9 different distance functions: City Block, Euclidean, Minkowski, Chebyshev, Standard Euclidean, Cosine, Correlation, Spearman, and Mahalanobis to find the similarity measure between face images. The performance is evaluated in term of the identification accuracy rate and identification time. A series of experimentations is performed on 1200 face images are collected from different standard databases. Experimental outcomes demonstrate that for DWT and DCT feature extraction, city block distance and Euclidean distance metrics produce highly accurate identification rate than other distance metrics.

Keywords: Ethnicity Identification; Color Space; Features Extraction; k-Nearest Neighbors; Distance Metrics

الملخص:

التعرف على وجه الانسان احد الحقول المهمة للبحث في انظمة الحاسوب الذي يمكن فيها جمع ادق المعلومات عن الأنسان مثل الجنس و العمر و العرق.جمع المعلومات مع بعض تقنيات التصنيف يشكل برنامج للحاسوب للتعرف على صورة وجه الأنسان.في هذا البحث يتم تحليل دقيق بأستخدام تقنيتين لأخراج و جمع المعلومات من الصور وهما:(Discrete Wavelet Transform) و (Discrete Cosine Transform) و من بعده يتم التصنيف بأستخدام (k- nearest neighbor classifier) . و في المرحلة الأخيرة استخدم (٩) طرق مختلفة لتميز الصور و نسبة التشابه بين الصورة و مجموعة الصور الموجودة في قاعدة البيانات.

(City Block, Euclidean, Minkowski, Chebyshev, Standard Euclidean, Cosine, Correlation, Spearman, Mahalanobis) يتم مقارنة اداء و كفائة التعرف على الصور من جهتين و هما: معدل دقة التعرف و الوقت اللازم للتعرف.وقد طبق سلسلة من الأختيارات على (١٢٠٠) صورة للوجه الذي جمع من عدد من قواعد البيانات القياسيةمن الأختبارات التي اجريت اكتشف و ثبت ان بأستخدام جمع المعلومات من خلال (DCT,DWT) و تشخيص معدل التشابه بأستخدام (City Block Distance) و (Euclidean Distance) سجل معدل عالي و دقة في التعرف مقارنة بالطرق الأخرى.

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پوختە:

ناسینەوەی دەم و چاوی مرۆڤەکان یەکێکە لە بوارە گرنگەکانی بواری توێژینەوە کە بە سیستمی کۆمپیوتەری ئەنجام دەدرێت کە تێیدا دەتوانرێت زانیاری وورد لەسەر مرۆڤەکان بەدەست بهێنرێت لەوانە ڕەگەز و تەمەن و دیاریکردنی نەتەوە.وەرگرتنی زانیارییەکان لەگەڵ کۆمەڵێک تەکنیك ڕێگای پۆلێن کردن دەکرێن بە بەرنامەیەکی کۆمپیوتەری بۆ ناسینەوەی وێنەی دەم و چاوی مرۆڤەکان.لەم توێژینەوەیەدا شیکارییەکی ووردکراوە بەبەکارهێنانی دوو تەکنیک بۆ دەرهێنان و وەرگرتنی زانیارییەکان لە وێنەکاندا ئەوانیش (Discrete Wavelete Transform) لەگەڵ (Discrete Cosine Transform) پاشان پۆلێن کردنیان بە بەکارهێنانی (K - Nearest Neighbor).

لە هەنگاوی کۆتاییدا (٩) نۆ ڕێگای جیاواز بەکارهێنراوە بۆ جیاکردنەوەی وێنەکان ڕێژەی لێکچووی وێنەی دراو بەو وێنانەی کە لە داتابەیسەکەدا هەن.

[City Block, Euclidean, Minkowski, Chebyshev, Standart Euclidean, Cosine, Correlation, Spearman, and Mahalanobis]

هەڵسەنگاندن و توانای ناسینەوەی وێنەکان لە دوو ڕووەوە وەرگیراوە ئەوانیش دیاریکردنی ڕێژەی ووردی ناسینەوەیە لەگەڵ کاتی پێویست بۆ ناسینەوە.

زنجیرەیەکی زۆر تاقیکردنەوەمان ئەنجام داوە لەسەر (١٢٠٠) وێنەی دەم و چاو کە کۆمان کردووەتەوە لە چەند داتابەیسێکی پێوانەیی.لە کۆتایی تاقیکردنەوەکەماندا بۆمان دەرکەوتووە و سەلمێنراوە کە بەبەکارهێنان و وەرگرتنی زانیاری ناو وێنەکان بە ڕێگای (DWT) و (DCT) و دیاریکردنی ڕێژەی لێکچوون بە بەکارهێنانی (city block distance) و (Euclidean distance) ئاستێکی زۆر بەرز و وورد لە ناسینەوەمان دەست دەکەوێت لە چاو ڕێگاکانی تردا.

1- Introduction:

Ethnicity identification refers to the process of recognizing the ethnic group and can be used in numerous areas of application. Historically speaking, several methods are suggested for ethnicity identification and much progress is made. Conversely, it is hard to recognize faces belonging to a different race efficiently and accurately under the uncontrolled situation. The challenges come from the large variations in visual stimulus due to facial expressions, viewing directions, poses occlusions (eye glasses) and illumination conditions. In literature, the algorithms used to represent the face images for ethnicity identification are categorized mostly into two groups: global feature extraction and local feature extraction algorithms [1]. Recently, a lot of extraction approaches has been done in this regard.

Mamatha and Srikantamurthy [2] study a variety of feature extraction methods and classification approaches which are used in numerous optical character recognition applications; these are designed to recognize handwritten numerals of Kannada script. Collins and Kazunori [3] present a systematic comparison of various plug-in (dis-)similarity measures for M-CBIR with a standard bag-of-words feature method. The Author in [4] gives different output with various distance metrics used in algorithm. They also represent computational issues in identifying nearest neighbors and mechanisms for reducing the dimension of the data. Abhijeet, et al [5] state that COREL Database is used for an exhaustive study of numerous distance metrics on different color spaces. Euclidean distance, Manhattan distance, Histogram Intersection and Vector Cosine Angle distances are used to compare histograms in both RGB and HSV color spaces. Kittipong et al [6] focus on the performance of k-nearest neighbor classification by applying different distance similarity measurements. In this study,

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distance metrics including Euclidean, Standardized Euclidean, Mahalanobis, City block, Minkowski, Chebychev, Cosine, Correlation, Hamming, Jaccard, and Spearman are implemented. Meenakshi and Anjali [7] compare six different distance metrics, e.g., Euclidean, Manhattan, Canberra, Bray-Curtis, Square chord, Square chi-squared distances to find the best kindred attribute measure for image retrieval. Ahmed and Tamazouzt [8] evaluate the performance of different distances that can be used in the K-NN algorithm. Also, we analyze this distance by using different values of the parameter "k" and by using several rules of classification that performed on the WBCD database. Mahfuzahet compare between K-Nearest Neighbor (KNN) and Artificial Neural Network (ANN) algorithm for classifying the spectrogram images in brain balancing has been presented [9]. The present study analyzes two different extraction techniques and several distance metrics. The performance is evaluated in terms of identification accuracy rate and classification time. This experimentation is conducted on 1200 collected face images divided into three categories. The paper is organized as follows. Section 2 presents related work on the feature extraction techniques includes DWT and DCT techniques, classification algorithm (KNN), and distance metrics. The empirical study methodology is presented in section 3. Experimental and results are given in section 4, and the conclusion is presented in section 5.

2. Related Work

2.1 Feature Extraction:

Feature extraction methods are helpful in numerous image processing applications. Furthermore, they are computed to get features that are useful in classification and recognition of facial images. Features define the behavior of region of interest in an image. In order to study and analyze the effect of different distance metrics on ethnicity identification, the current study applies Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) as two different feature extraction techniques to extract texture features from the images.

2.1.1 Discrete Wavelet Transform (DWT):

The DWT is the most popular transformation technique in digital image processing, especially in multi-resolution representation. The 2-D Haar Discrete Wavelet Transform decomposes the image into two parts: approximation and detailed parts. Approximation part includes one low frequency LL subband and detailed parts include three high frequency subbands: LH, HL, and HH. The LL subband includes low frequency information of original image from vertical and horizontal wavelet convolutions. The LH subband includes low frequency image information from the horizontal wavelet convolution and high frequency image information from the vertical wavelet convolution. The HL subband includes high frequency information from the horizontal wavelet convolution and low frequency image information from the vertical wavelet convolution. The HH subband includes high frequency information from the vertical and horizontal wavelet convolutions. The present study chooses all coefficient of LL subband as feature vector to train KNN classifier with different distance metrics because the LL subband contains most of original image information [10].

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2.1.2 Discrete Cosine Transform (DCT):

The two-dimensional Discrete-Cosine-Transform is a popular transform that converts an image from spatial domain to frequency domain that is widely used for feature extraction in image processing. DCT reduces the amount of bits needed to represent the information in an image, by eliminating the redundancy between neighboring pixel values [11]. The DCT of an image basically involves different frequency bands low frequency, middle frequency and high frequency sub bands. Each sub band contains some details in an image. The low frequency sub band generally contains the average intensity of an image which is the most intended in feature extraction [12,13]. In this work, the original image is divided into small blocks of pixels (8×8 pixels), then discrete cosine transform is performed over each block independently and result can be 64 transformed coefficients. The outcomes of a 64-element DCT transform are 1 DC coefficient and 63 AC coefficients. The low frequency DC coefficient that are located in the upper left corner represent the average energy of cells that contain the most of information. Therefore, the low frequency DCT coefficients is used for selecting more effective subset of features for the classification process.

2.2 Classification Algorithms

In this paper, the k-Nearest Neighbor (kNN) classifier is implemented to classify face images using a leave-one-out validation strategy. k-nearest neighbor algorithm [7, 8] is a method for classifying objects based on closest training examples in the feature space that consists of two phases of processing: training and testing feature vectors [12, 13]. In the training phase the image feature vectors are isolated then in testing phase the feature vectors are used for identification of images. Typically, an image is classified based on the labels of its kNN by majority vote. In kNN algorithm, there are two parameters to be varied: k variable and distance metric. At first, the k variable is varied and the distance is fixed. Then the distance is varied and k variable is fixed. In this study, the k variable is varied from 2 to 15 and nine different distance metrics used for classification process to provide the best combination of selected parameters to extract the best results from kNN algorithm.

2.3 Distance Metrics

Distance metrics is a technique to measure similarity between two images. In this paper, nine distances metrics are used as a similar rule; they are City block, Euclidean, Minkowski, Chebychev, Standard Euclidean, Cosine, Correlation, Spearman, and Mahalanobis[6]. The nine distance metrics are used for kNN classifiers are explained as follows:

2.3.1 City Block Distance

The City Block, is also known as the Manhattan distance, estimates distance between two points x, y with k dimensions as the sum of the absolute difference of Cartesian coordinates, defined by Eq. (1).

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$$D(x,y) = \sum_{i=0}^{k-1} |x_i - y_i| \qquad (1)$$

2.3.2 Euclidean Distance

The Euclidean distance is the square root of the sum of squared differences between corresponding elements of the two vectors x_i and y_i. According to the Euclidean distance formula, the distance between two points in the plane is determined by Eq. (2):

$$D(x,y) = \sqrt{\sum_{i=0}^{k-1} (x_i - y_i)^2} \qquad (2)$$

2.3.3 Minkowski Distance

The Minkowski distance is a metric on Euclidean space which is considered as more general comparing with the city block and Euclidean distances. The Minkowski distance of order *k* is between two points *x*, *y* as defined by Eq. (3).

$$D(x,y) = \sqrt[\lambda]{\sum_{i=0}^{k-1} |x_i - y_i|^\lambda} \qquad (3)$$

Special cases:

- When λ =1, the distance is known as the city block distance.
- When λ =2, the distance is known as the Euclidean distance.
- When λ =∞, the distance is known as the Chebyshev distance.

2.3.4 Chebyshev Distance

The Chebyshev distance is also called maximum value distance [6]. This metric is a special case of the Minkowski distance with λ = ∞. The Chebyshev distance between two vectors *x* and *y* with standard coordinates x_i and y_i, is given by Eq. (4).

$$D(x,y) = \lim_{\lambda\to\infty}\left(\sqrt[\lambda]{\sum_{i=0}^{k-1} |x_i - y_i|^\lambda}\right) = max_i(|x_i - y_i|) \qquad (4)$$

2.3.5 Standard Euclidean distance

The standardized Euclidean distance between two vectors x_i and y_i, can be defined by Eq. (5):

$$D(x,y) = \sqrt{\frac{\sum_{i=0}^{k-1}(x_i - y_i)^2}{s_i^2}} \tag{5}$$

Where s_i is the sample standard deviation of the x_i and y_i over the sample set.

2.3.6 Cosine Distance

Cosine distance defines vector similarity in terms of the angle separating two vectors. The cosine of two vectors can be derived by using the Euclidean dot product formula [7] and the distance can be written by Eq. (6):

$$D(x,y) = \frac{x \cdot y}{\|x\| \, \|y\|} = \frac{\sum_{i=0}^{k-1} x_i \, y_i}{\sqrt{\sum_{i=0}^{k-1}(x_i)^2} \, \sqrt{\sum_{i=0}^{k-1}(y_i)^2}} \tag{6}$$

2.3.7 Correlation Distance

The distance correlation of two vectors can be obtained by dividing their distance covariance by the product of their distance standard deviations [7]. The correlation distance can be defined as in Eq. (7)

$$D(x,y) = \frac{\sum_{i=0}^{k-1}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=0}^{k-1}(x_i - \overline{x})^2} \, \sqrt{\sum_{i=0}^{k-1}(y_i - \overline{y})^2}} \tag{7}$$

2.3.8 Spearman Distance

Spearman distance is a square of Euclidean distance between two feature vectors x_i and y_i with k dimensions, computed as:

$$D(x,y) = \sum_{i=0}^{k-1}(x_i - y_i)^2 \tag{8}$$

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2.3.9 Mahalanobis Distance

The Mahalanobis distance is a metric used to compare a feature vector to a multivariate normal distribution with a given mean feature vector and its covariance matrix [8]. Mahalanobis distances are calculated as Eq. 9.

$$D(x, y) = \sqrt{(x-y)^T\, C^{-1}\, (x-y)} \tag{9}$$

Where:
x : Feature vector of data.
y : Feature vector of mean values.
C^{-1} : Inverse covariance matrix.
T : Indicate feature vector should be transposed.

3. Empirical Study Methodology:

The framework is demonstrated as a block diagram in Figure 1. It consists of three stages: pre-processing, feature extraction and classification. In the first stage, pre-processing techniques are applied to the images before the feature extraction phase, data preprocessing is necessary to get better quality of the actual data and decreases the computational time for classification. In this stage, a color image is first converted into YUV color space. Color data (U, V) is not very important that it is sub-sampled, then the image is cropped, and probably resized depending on the image size. In this work, the image size is fixed into 128x128 pixels.

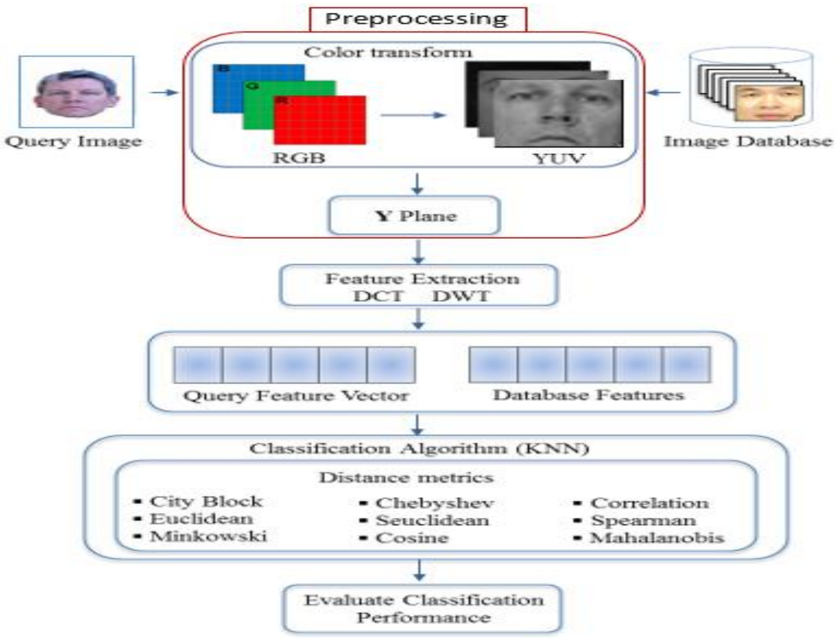

Figure 1: Block Diagram of Proposed System

In feature extraction stage, the spatial domain data is transformed in to frequency domain coefficients using two popular feature extraction techniques separately: discrete wavelet transform

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and discrete cosine transform. In DWT feature extraction method, Haar wavelet transform at level 4 to the whole image is applied, because it is conceptually simple, fast and memory efficient and then selecting the coefficients of the LL subband as features vector to train KNN classifier in the next stage. In DCT feature extraction method, the face image is divided into blocks of 8 x 8 pixel then two-dimensional DCT of each block is performed to convert each 8 × 8 block to a frequency-domain representation. The DCT coefficients are quantized and ordered using zigzag scanning. Then the low frequency DCT coefficients is utilized to be selected features vector for training process with KNN classifier.In classification stage, feature vector for query sample compared with database feature vector by computing the k-Nearest Neighbor method with different distance metrics and different values of the parameter of k for making the classification. Finally, the performance of classification is analyzed and evaluated through applying different distance metrics and different values of the parameter of k that is used in K-NN algorithm.

4. Experiments and Results:

4.1 Dataset:

The dataset is basic requirement for any research work. Currently, a large number of face image datasets such as FERET dataset, the GUFD face dataset, and YALE face dataset. is available to researchers for face recognition [13, 14]. Most of the face datasets contain a set of face images collected in different pose condition facial expressions, illumination conditions. An internal dataset of color face images (frontal face) for 1200 persons of different ethnicity, gender, illumination, pose, expression and lightning (500 European, 500 Oriental, and 200 African) are collected manually from different dataset source for classification task (Figure 2).

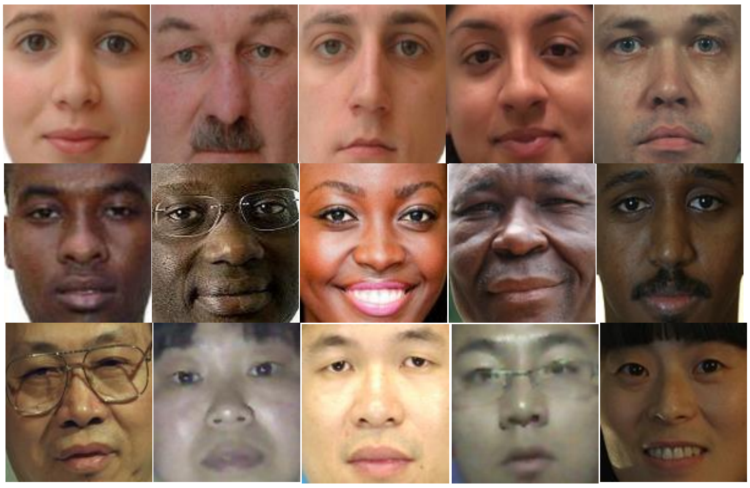

Figure 2: Sample Face Images from the Dataset

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4.2 Results and Conclusion:

All experiments are performed on an Intel (R) Core (TM) i5-4570S CPU@ 2.90 GHz with 4 GB RAM. The implementation of the program is developed on Windows 10 operation system with MATLAB R2014b. The study uses k-Nearest Neighbors which are experimented with several variants of distance metrics and different values of k parameter for the choice of nearest neighbors. The database for the experiment purpose consists of 1200 collected face images divided in three categories (see 4.1). For feature extraction, two different feature sets are used: DCT and DWT. In order to demonstrate the effectiveness of numerous distance metrics, the study calculates identification accuracy rate and efficiency by using the k-nearest neighbors with City block, Euclidean, Minkowski, Chebychev, Standard Euclidean, Cosine, Correlation, Spearman, and Mahalanobis distance; while the optimal value k is estimated by cross-validation.

Figure 3 demonstrates the result of classification accuracy rate based on DCT by using the 9 similarity measurements. It can be clearly seen that the high average classification accuracy rate, 97.11%, is recorded by the algorithm that uses Cityblock distance with a value of K=5. From the figure, it is found that the Euclidian and Minkowski give the same classification accuracy with 96.25% while, Mahalanobis gives the lowest accuracy rate of 86.97%.

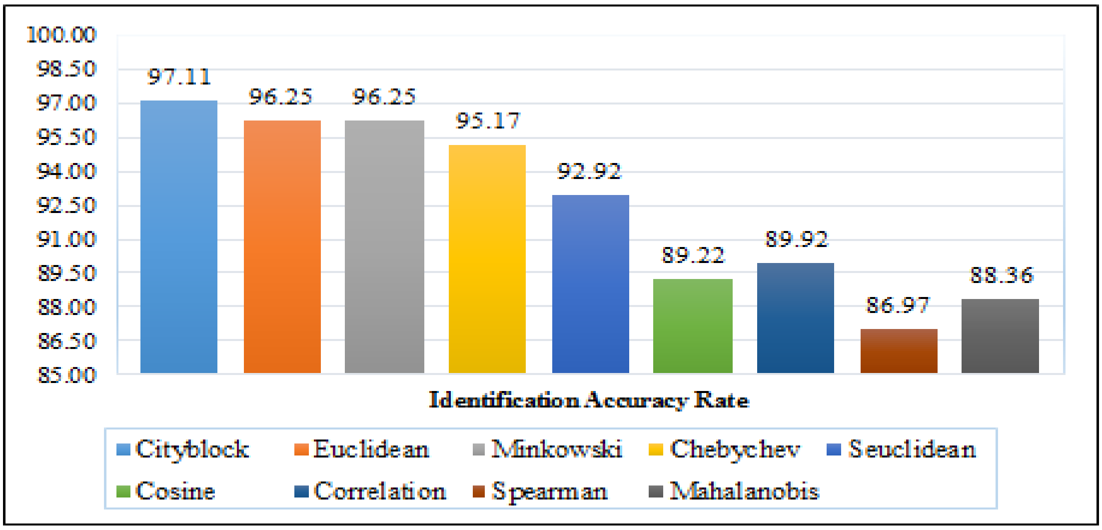

Figure 3: Average accuracy rate using DCT with different distance metrics on identification accuracy

The accuracy rate resulted in varying distances in KNN algorithms based on DWT algorithm is presented in Figure 4. As it shows, Euclidean distance and Minkowsk distance give the same highest accuracy rate of 96.72% among the other distance metrics. The same algorithm used with Cityblock distance and Correlation distance give good accuracy rate of 96.19, 96.11% respectively. Finally, using Mahalanobis distance achieves the lowest classification accuracy rate of 74.50%.

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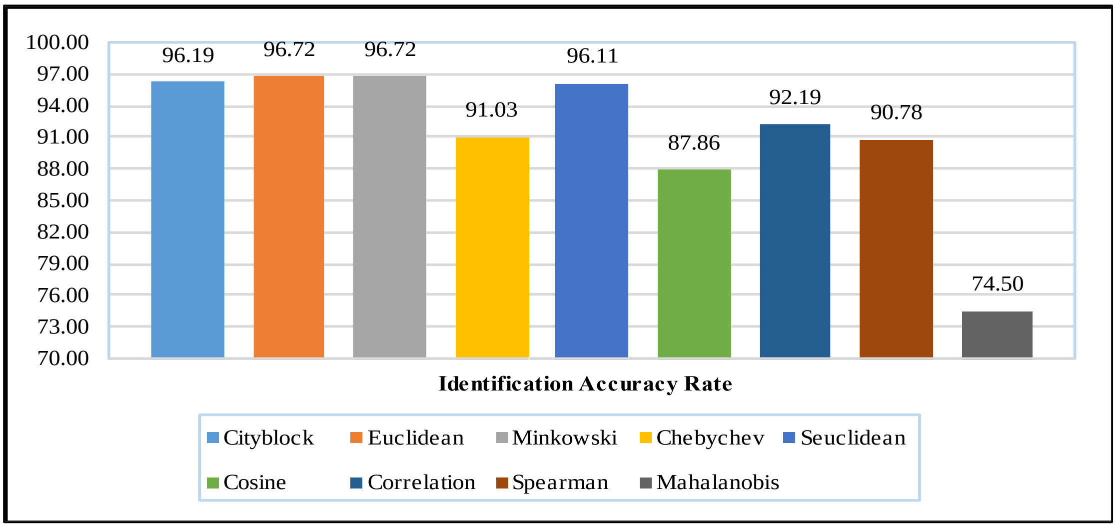

Figure 4: Average accuracy rate using DWT with different distance metrics on identification accuracy

In order to have a better understanding about the effect of varying distance metrics, the current study collects the accuracy rates and classification time results together for DCT and DWT algorithm separately with KNN using 9 different distance metrics. Table 1 summarizes the experiment results for the average accuracy rate and classification time at different distance metrics based on DCT algorithm. The table also clarifies that the minimum time of classification is recorded for Correlation, Cityblock, recording 78, 93 millisecond (ms) respectively. However, the time of classification with Cosine distance and Seuclidean remains stable recording 95 millisecond. Meanwhile, the Mahalanobis distance records highest classification time (961ms) with lowest identification average accuracy rate (88.36%).

Table 1: Identification Average Accuracy Rate Using DCT with Different Distance Metrics

Distance	Ethnic Groups			Aver Accu	Time (ms) 10^{-2})
	European	Oriental	African		
Cityblock	99.00	99.00	93.33	97.11	0.93
Euclidean	98.00	98.75	92.00	96.25	1.22
Minkowski	98.00	98.75	92.00	96.25	1.07
Chebychev	97.00	96.50	92.00	95.17	1.18
Seuclidean	95.75	99.00	84.00	92.92	0.95
Cosine	93.00	98.00	76.67	89.22	0.95
Correlation	93.75	98.00	78.00	89.92	0.78
Spearman	91.25	89.00	80.67	86.97	4.14
Mahalanobis	94.75	97.00	73.33	88.36	9.61

In DWT algorithm the minimum classification time is recorded for Cosine, Cityblock, and Correlation, recording 210,214, and 215 millisecond (ms), respectively. Whereas, Mahalanobis distance record highest classification time with lowest accuracy rate; these result are illustrated in Table 2. In summary, in both DCT and DWT algorithm KNN classifier with Cityblock and Euclidean distance metrics provide good performance in term of classification time and accuracy rate, while Mahalanobis distance gives bad result for ethnicity identification.

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Table 2: Identification Average Accuracy Rate Using DWT with Different Distance Metrics

Distance	Ethnic Groups			Aver Accu	Time (ms) $.0^{-2}$)
	European	Oriental	African		
Cityblock	98.75	98.50	91.33	96.19	2.14
Euclidean	98.75	98.75	92.67	96.72	2.49
Minkowski	98.75	98.75	92.67	96.72	2.36
Chebychev	96.50	97.25	79.33	91.03	4.01
Seuclidean	98.25	98.75	91.33	96.11	2.86
Cosine	95.00	99.25	69.33	87.86	2.10
Correlation	96.00	99.25	81.33	92.19	2.15
Spearman	93.75	99.25	79.33	90.78	5.45
Mahalanobis	88.75	88.75	46.00	74.5	12.1 56

Conclusion:

Reasonable work has been done on ethnicity identification, but search for improved ethnicity identification performance is still going on. In this study, issues of ethnicity identification from face images are examined. The implementation is estimated in terms of the classifying accuracy rate and time classification. A sequence of experimentations is executed on 1200 face images collected from different standard datasets. Experimental results prove that for both DWT and DCT feature extractors, city block and Euclidean distance metrics produce highly accurate identification rate than other distance metrics.

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