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A HIGHLY EFFICIENT SYSTEM BASED ON DCT-TPLBP AND DCT-FPLBP DESCRIPTORS FOR FACE RECOGNITION

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ABSTRACT

In this paper, we describe an application for face recognition that combines local and global descriptors to improve performance. Here's a summary of the approach described in the paper: The performance of these local descriptors is comparatively better than global descriptors that operate on the entire image. To address this, the proposed approach applies local descriptors by dividing the image into blocks. By doing so, they aim to capture both the advantages of global and local methods. The local descriptors are applied in the DCT domain. The DCT is a commonly used transform technique that represents the image in terms of frequency components. By using the DCT domain, the aim is to exploit the frequency characteristics of facial features and capture relevant information for recognition. The proposed approach claims to provide a good compromise between global and local methods in terms of simplifying calculations while maintaining classification performance. This implies that the approach aims to strike a balance between accuracy and computational efficiency. Finally, we compare the results obtained from our approach with other local and global conventional approaches. The specific methods compared and the performance metrics evaluated should be detailed in the paper.

Keywords: *Face Detection, Face Recognition, Discrete Cosine Transforms (DCT), FPLBP, TPLBP.*

1. INTRODUCTION

Face recognition has indeed made significant advancements and gained considerable attention over the past two decades. It has emerged as one of the most successful applications of image analysis. Two main approaches to face recognition are feature-based and appearance-based techniques.

1- Feature-based face recognition relies on

extracting specific geometric facial features, such as the mouth, eyes, brows, nose, etc., and analyzing the geometric relationships between these features. The idea is to capture the unique characteristics and spatial arrangements of these facial features to differentiate individuals. By comparing the extracted features and their relationships, algorithms can determine the identity of a person.

2- Appearance-based face recognition, on the

other hand, focuses on the holistic texture features of a face. It analyzes the overall facial appearance rather than specific facial features. This technique can be applied to the entire face or specific regions within a face image. The algorithms in appearance-based recognition extract and analyze the patterns, textures, and colors present in the facial image to identify individuals.

Both feature-based and appearance-based techniques have their own advantages and limitations. Feature-based methods can be more robust to variations in lighting conditions, pose, and facial expressions since they focus on specific facial landmarks. However, they may struggle with occlusions and variations in feature extraction. Appearance-based methods, on the other hand, can capture global facial information and are effective in dealing with variations in appearance. However, they may be more sensitive to changes in lighting and pose.

It is worth noting that the field of face recognition has seen continuous advancements, and various hybrid approaches that combine both feature-based and appearance-based techniques have been proposed. These hybrid methods aim to leverage the strengths of each approach to improve overall performance and overcome their individual limitations.

The paper aims to address the issue of high computational complexity associated with FPLBP (Full Pixel Local Binary Pattern) and TPLBP (Three-Patch Local Binary Pattern) algorithms, with a focus on reducing response time. To achieve this, the authors propose utilizing the Discrete Cosine Transform (DCT) coefficient vector of the image instead of the original vector image. The study also concentrates on selecting appropriate descriptors and defining a method for recognizing blocks, which will be combined with a Neural Network for classification.

The authors propose a block-based approach, where the face image is divided into regular blocks, and descriptors are computed for each block. This approach is referred to as the "semi-local method" in the paper. The semi-local method will be compared to both global and local methods to evaluate its effectiveness. The comparison involves considering different sizes of the learning set and applying various disturbances to the image database.

By dividing the face image into blocks and calculating descriptors for each block, we aim to achieve a more efficient and faster method for facial recognition. The choice of descriptors and the block recognition method will be critical in improving the overall classification accuracy and reducing computational complexity. The study will also investigate the impact of different learning set sizes and image disturbances on the performance of the proposed method.

The structure of the remaining sections of the paper is outlined as follows:

Section II: In this section, we present an overview of the existing face recognition techniques. Section III: we present and explain the Four-Patch Local Binary Pattern (FPLBP), Three-Patch Local Binary Pattern (TPLBP). Section III: we describe the steps of their proposed approach. Section IV: Neural Network Architecture for Classification. Section V: we present the results obtained from their experiments and provide a detailed discussion and analysis of the findings. Last Section: Conclusion and Future Work In the final section, we summarize the key findings and conclusions of their study.

2. STATE OF FACE RECOGNITION TECHNIQUE

The face recognition literature has indeed grown significantly over the past 30 years. Conventional algorithms such as eigenfaces, Fisher faces, and methods discussed in references [2] and [3] have shown good results in controlled environments. However, when faced with variations in factors like image quality, installation conditions, and lighting, the performance of these algorithms tends to decline significantly. As a result, researchers have been developing new solutions to address these challenges.

In one study mentioned in reference [4], researchers explored the combination of Independent Component Analysis (ICA) and Neural Networks (NN) for face recognition. They claimed that this combination outperformed Principal Component Analysis (PCA) and NN. ICA is a feature extraction technique that can be seen as a generalization of PCA. While PCA seeks a representation of inputs based on uncorrelated variables, ICA provides a representation based on statistically independent variables. The researchers evaluated the performance of the ICA and NN combination on databases like Yale or AR.

It is important to note that the methods presented here are just a few examples of the wide range of approaches in face recognition. In general, face recognition methods can be divided into two groups: global methods and local methods.

Global methods consider the face as a whole and extract features that describe the entire face. These features can include the overall shape, texture, or appearance of the face. Algorithms like eigenfaces and Fisher faces fall into this category, as they analyse the face as a complete entity.

On the other hand, local methods focus on specific facial regions or features. They aim to capture distinctive details such as the eyes, nose, or mouth, which can be more robust to variations. Local methods often utilize techniques like facial landmarks or local image descriptors to extract and match these specific features.

Both global and local methods have their advantages and limitations, and researchers continue to explore and develop new techniques to improve face recognition performance under various conditions.

2.1 Global methods

Global methods in face recognition are indeed based on well-known statistical analysis techniques [1]. These methods do not require the identification of specific facial landmarks, such as the centers of the eyes, nostrils, or mouth, for image normalization [9]. Instead, the face images, represented as matrices of pixel values, are processed as a whole and often transformed into vectors for easier handling. Global methods offer the advantage of relatively straightforward implementation and involve calculations of moderate complexity. However, they are susceptible to variations in illumination, pose, and facial expression.

Among global methods, Principal Component Analysis (PCA) is one of the most popular techniques [9]. PCA aims to find a linear transformation into a lower-dimensional space that maximizes the variance of the projected samples. In 1996, an extension of PCA to a nonlinear version called Kernel Principal Component Analysis (KPCA) was introduced, which incorporates nonlinear kernel functions [10].

Other global techniques include Linear Discriminant Analysis (LDA) and Independent Component Analysis (ICA) [11], [12]. LDA focuses on reducing the dimensionality of the data while maximizing the separability between classes. ICA, on the other hand, aims to extract statistically independent components from the data. These techniques have also been applied to face recognition, with LDA applied to faces as early as 1996 [13].

It's important to note that while global methods have their advantages in terms of simplicity and computational efficiency, they may struggle with variations in illumination, pose, and facial expression. Researchers continue to explore and develop new algorithms and techniques to address these challenges and improve the performance of face recognition systems.

2.2 Local methods

Local methods in face recognition involve detecting points of interest, such as key facial landmarks, and extracting features from these points. The earliest face recognition methods belong to this category. These methods rely on extracting specific geometric characteristics, like head width and eye distance. Classifiers then use this data to identify individuals. However, these methods have certain disadvantages:

1- In some cases, it is challenging to remove

geometric characteristics from the face. This is especially true when dealing with occlusions or variations in pose and expression, which can make accurate detection of characteristic points difficult.

2- Purely relying on geometric characteristics

is not enough to adequately represent a face. Other valuable information, such as the gray level values of the image, remains unutilized. These additional details can provide important cues for face recognition but are not captured by geometric features alone.

To address these limitations, researchers have explored alternative approaches in face recognition that leverage more comprehensive and robust features, such as holistic representations or deep learning-based methods. These techniques aim to capture both geometric and appearance-based information to improve the accuracy and robustness of face recognition systems.

3. DESCRIPTORS

In face recognition methods, the extraction of facial characteristics is a crucial step. Local characteristics have several advantages over global characteristics, which is why newer systems often rely on local facial features [6]. Two successful approaches in face recognition using local characteristics are three-patch Local Binary Patterns (LBP) and four-patch Local Binary Patterns. Local Binary Patterns (LBP) is a widely used texture descriptor in computer vision and face recognition. It captures the local texture information by comparing the intensity values of pixels in a neighbourhood around each pixel. Three-patch LBP and four-patch LBP are variations of this approach.

For each type of feature, there are several ways to utilize them [7]. However, the principal basis of these descriptors is as follows:

1- Three-patch LBP: In this approach, a

circular neighbourhood around each pixel is divided into three patches. The intensity values of the pixels within each patch are compared to the

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intensity value of the centre pixel. The comparisons are encoded into a binary pattern, and the resulting patterns from all pixels are concatenated to form a feature vector representing the face.

2- Four-patch LBP: Similar to three-patch

LBP, four-patch LBP divides the circular neighbourhood around each pixel into four patches. The intensity comparisons are performed within each patch, and the resulting binary patterns are concatenated to form a feature vector.

These local binary patterns capture the local texture variations in different facial regions, providing discriminative information for face recognition. By utilizing these local features, face recognition systems can be more robust to variations in pose, expression, and occlusions.

It's important to note that there are various variations and extensions of local feature extraction methods, including different patch sizes, neighborhood configurations, and encoding schemes. These variations allow for flexibility in adapting the local feature extraction to different face recognition tasks and datasets.

3.1 Three-Patch LBP Codes.

The Three-Patch LBP (TPLBP) code is generated by comparing the values of three patches around each pixel to produce a single bit value in the code assigned to that pixel [7]. The process involves considering a central patch and additional patches distributed uniformly in a ring of radius r around it. Pairs of patches, α-patches apart along the circle, are compared with the central patch to determine the similarity. The resulting code has S bits per pixel. To calculate the Three-Patch LBP code for each pixel, the following formula is applied:

$$TPLBP_{r,S,w,j}(p) = \sum_{i=1}^{S} f(d(C_i; C_p) - d(C_{i+j \bmod s};\ C_p))2^i \quad (1)$$

$$f(x) = \begin{cases} 1 & if \quad x \geq t \\ 0 & if \quad x < t \end{cases} \quad (2)$$

Where:

t value will be used for constancy of uniform areas (i.e. t = 0.01) [18]. CSLBP [17] features like images are encoded and histogram is calculated of every divided grid area by determining every binary code frequency, then normalized and truncated at 0.2 to unit length and merged as single vector.

- S is the number of patches (bits) in the code.
- C_p is the value of the central patch.
- $f(x)$ is a function that returns 1 if $x \geq t$ and 0 if $x < t$.

The comparison between the patches and the central patch determines the similarity, and based on that, the corresponding bit in the code is set. The resulting code captures the local texture variations around each pixel in the image and can be used as a feature descriptor for face recognition.

In this section, the performance of the Three-Patch LBP and Four-Patch LBP extensions as feature descriptors for face recognition is reported. Before performing the matching process, the faces have been normalized using an affine transformation [13].

Face normalization is a common pre-processing step in face recognition systems. It involves applying geometric transformations to align and standardize facial images, reducing the influence of variations in pose, scale, and rotation. Affine transformation is one such technique used for face normalization. It includes translation, rotation, scaling, and shearing operations to bring the facial features into a consistent configuration.

By normalizing the faces using affine transformation, the aim is to enhance the robustness of the face recognition system by reducing the impact of geometric variations across different images of the same individual. This ensures that the extracted local features, such as the Three-Patch LBP and Four-Patch LBP codes, are more comparable and discriminative during the matching process.

The performance evaluation of these feature descriptors, along with the application of face normalization, would typically involve measuring metrics such as recognition accuracy, verification rates, or identification rates on a face dataset or benchmark. These metrics provide insights into the effectiveness of the feature descriptors in capturing facial variations and discriminating between different individuals.

Please note that without specific details or data from the source you mentioned, it is not possible to provide exact performance results or analyse the comparative performance between Three-Patch LBP and Four-Patch LBP extensions in combination with affine normalization.

The Three-Patch LBP (TPLBP) and Four-Patch LBP (FPLBP) descriptors, as illustrated in Figures 1 and 2, exhibit only modest performance differences between them in face recognition [assuming these figures are present in the original source]. While both descriptors capture local texture information around each pixel, their specific configurations and the number of patches used may result in slightly different performance.

However, to further enhance the face recognition system's accuracy and robustness, it is possible to explore fusion techniques that combine the TPLBP descriptor with other approaches. Fusion methods aim to combine multiple descriptors or algorithms to leverage their complementary strengths and improve overall performance.

The methodology for fusion scoring involves integrating the TPLBP descriptor with other face recognition approaches. This fusion can be performed at different stages of the recognition pipeline, such as feature extraction, feature-level fusion, or decision-level fusion. The specific fusion technique would depend on the characteristics of the other approaches and the desired goals of the face recognition system.

Some commonly used fusion techniques include:

1- Feature-level fusion: This involves

concatenating or combining the feature vectors extracted from different descriptors, such as TPLBP and another descriptor, into a single feature representation.

2- Score-level fusion: In this approach, the

similarity scores or distance measures obtained from different recognition algorithms, including TPLBP, are combined using methods like weighted sum, weighted average, or classifier-based fusion.

3- Decision-level fusion: This technique

involves combining the decisions or classification results from multiple recognition algorithms, including TPLBP, using methods such as majority voting, weighted voting, or classifier ensemble techniques.

By fusing the TPLBP descriptor with other approaches, it is possible to leverage the strengths of each method and potentially achieve improved face recognition performance. The choice of the fusion methodology depends on factors such as the nature of the additional approach, the availability of training data, and the specific requirements of the application. It's worth noting that the specific fusion methodology and its effectiveness would need to be evaluated and validated through experimental studies using appropriate datasets and performance metrics.

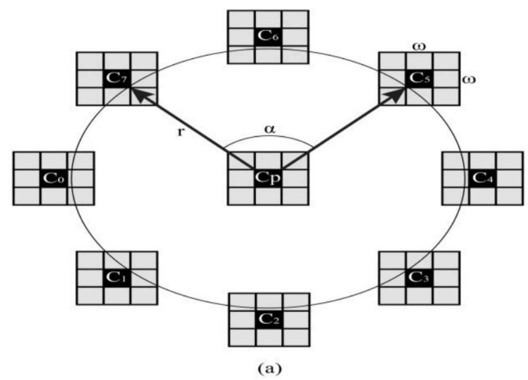

Figure 1. The Three-Patch LBP code with $\alpha = 2$ *and* $S = 8$

3.2 Four-Patch LBP Codes.

The Four-Patch LBP (FPLBP) codes are generated by comparing center symmetric patches in the inner and outer rings around each pixel in the image [9]. The process involves considering two rings of radii r1 and r2 centered on the pixel, and S patches of size w spread evenly on each ring (Fig. 3).

To calculate the FPLBP codes, we compare two center symmetric patches in the inner ring with two center symmetric patches in the outer ring. These patches are positioned α patches away along the circle in a clockwise direction. The comparison determines the similarity between the pairs of patches, and based on that, one bit in each pixel's code is set.

For S patches along each circle, we have S/2 center symmetric pairs, which determine the length of the binary codes produced by the FPLBP descriptor.

The formal definition of the FPLBP code is as follows:

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$$FPLBP_{r_1,r_2;S,w,j}(p) = \sum_{i=1}^{\frac{S}{2}} f(d(C_{1i};C_{2,i+j \bmod S}) - d(C_{1,+i+\frac{S}{2}};C_{2,i+\frac{S}{2}+j \bmod S}))2^i \quad (3)$$

Where:

- FPLBP is the Four-Patch LBP code for the pixel.
- S is the total number of patches (bits) in the code.
- f(x) is a function that returns 1 if $x \geq 0$ and 0 otherwise.

The comparison between the center symmetric patch pairs determines the similarity, and based on that, the corresponding bit in the code is set. The resulting FPLBP code captures the local texture variations around each pixel in the image, providing a feature descriptor for face recognition. As with the Four-Patch LBP descriptor, the values of r1, r2, w, S, and α are parameters that can be adjusted based on the specific requirements of the application and the characteristics of the dataset.

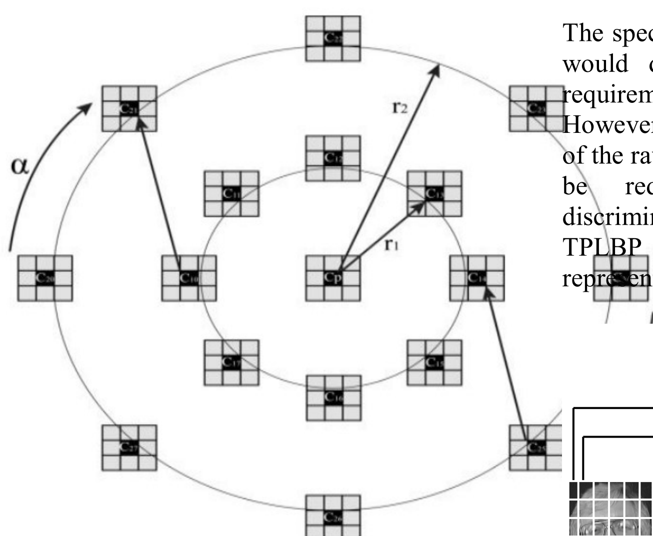

Figure 2. The Four-Patch LBP code

In order to address the computational complexity associated with the Four-Patch LBP (FPLBP) and Three-Patch LBP (TPLBP) descriptors, researchers have considered integrating a step to reduce computation time in face recognition systems. This is particularly important when dealing with high-resolution images and large learning samples, as the computational demands can become significant. The response time of the system is crucial in real-time face recognition applications. One solution to reduce computation time is to utilize the coefficient vector of the 2D-DCT (Two-Dimensional Discrete Cosine Transform) of the image, instead of directly using the image itself [14]. The 2D-DCT transforms the image from the spatial domain to the frequency domain, providing a representation of the image in terms of its frequency components.

By using the coefficient vector of the 2D-DCT, rather than the raw image, the dimensionality of the feature space can be significantly reduced. This reduces the computational complexity required for subsequent processing steps, such as feature extraction and matching. The 2D-DCT coefficients capture the image's frequency content, allowing for efficient representation and computation.

Integrating the 2D-DCT coefficients with the FPLBP or TPLBP descriptors allows for a more efficient and faster face recognition system. The combination of these techniques leverages the advantages of both the local texture information captured by the LBP descriptors and the frequency-based representation of the 2D-DCT.

The specific implementation and integration details would depend on the system design and the requirements of the face recognition application. However, by using the 2D-DCT coefficients instead of the raw image, the computational complexity can be reduced while still maintaining the discriminative power of the combined FPLBP or TPLBP descriptors and the frequency-based representation.

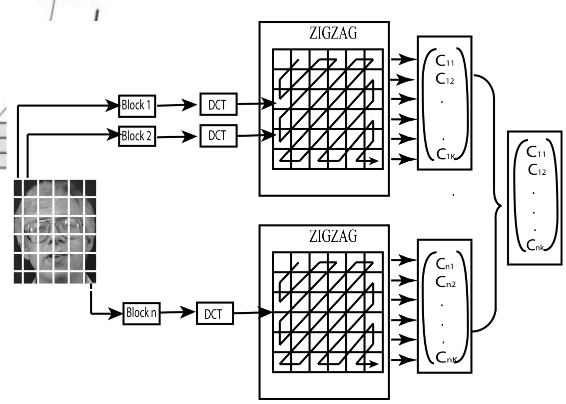

Figure 3. Feature extraction in DCT-TPLBP and DCT-FPLBP.

4. THE PROPOSED APPROACH

The proposed approach for face recognition consists of two main methodologies: DCT-TPLBP (DCT-Three-Patch LBP) and DCT-FPLBP (DCT-Four-Patch LBP). The diagram of the proposed method is shown in Figure 4. The approach involves the following steps:

1- Modelling of faces based on DCT-TPLBP

and DCT-FPLBP: In this step, the faces in the dataset are modeled using the DCT-Three-Patch LBP and DCT-Four-Patch LBP descriptors. These descriptors capture local texture information and are computed based on the 2D-DCT coefficients of the facial images.

2- Calculating distance vectors for all M

faces: The distance vectors for DCT-TPLBP and DCT-FPLBP are calculated for all M faces in the face database. These distance vectors represent the similarity or dissimilarity between the features of the query face and the faces in the database.

3- Standardization of distance vectors: In

order to ensure comparability and uniformity, the

distance vectors of DCT-TPLBP and DCT-FPLBP are standardized. Standardization typically involves subtracting the mean and dividing by the standard deviation of the distance vectors. This step helps in normalizing the values and ensuring that the distances are on a consistent scale.

By following these steps, the proposed approach aims to effectively represent and compare faces using the DCT-TPLBP and DCT-FPLBP descriptors. The distance vectors obtained from these descriptors can be used for subsequent steps in face recognition, such as classification, identification, or verification.

It's important to note that the specific details and parameters of the DCT-TPLBP and DCT-FPLBP descriptors, as well as the distance calculation and standardization methods, would need to be provided in the original source or further elaborated on for a more comprehensive understanding of the proposed approach.

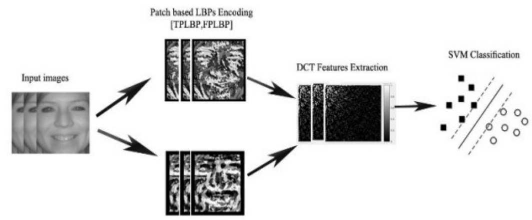

Figure 4. Proposed Technique method.

5. SUPPORT VECTOR MACHINE CLASSIFICATION

The images are encoded in Section III-1 followed by DCT features extraction and merged to form a feature vector classified through SVM. Automatic data arrangement into high or low dimensions is the key role of SVM [6]. In terms of accuracy and efficacy, SVM is best for image classification. The binary classification process evaluates two classes hyperplane separation through neighboring points of classes and hyperplane margin maximization. One vs. rest approach and a specific linear kernel SVM has been used for multi-class problems.

6. RESULTS AND DISCUSSIONS

The simulations and evaluations of the proposed face recognition system were conducted on a computer with an Intel Core i3 processor running at a clock speed of 2.53 GHz and 3GB of RAM. The chosen face database for testing is the Olivetti Research Laboratory (ORL) database.

The ORL database consists of 400 images belonging to 40 different individuals. For each person, there are 10 images, each with a size of 112x92 pixels. It's worth noting that the images were captured at different times, leading to variations in facial expressions and appearances.

Figure 5 displays five sample images from the ORL database, showcasing the variability in facial expressions and appearances within the dataset. These variations pose challenges for face recognition algorithms as they need to account for differences in pose, lighting conditions, and facial expressions to accurately recognize and classify faces.

The chosen ORL database is widely used in the field of face recognition, allowing researchers to benchmark and compare the performance of different approaches. The size and diversity of the database make it suitable for evaluating the

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effectiveness and robustness of the proposed methodology.

The results and discussions section would typically provide an analysis of the performance metrics achieved by the face recognition system using the proposed methodology. This could include accuracy rates, recognition rates, comparison with other approaches, and discussions on the strengths and limitations of the system. Unfortunately, the specific results and discussions for this particular system are not provided in the given information.

Figure 5. Five images of the same person in the ORL database.

In the conducted simulation, a random selection of five individuals was chosen for the learning phase, while the remaining images were used for testing. This resulted in a total of 200 images for both training and testing. The learning recognition rates were calculated for each of the following methods: TPLBP, FPLBP, DCT-TPLBP, and DCT-FPLBP.

Table I presents the recognition rates obtained using the TPLBP, FPLBP, DCT-TPLBP, and DCT-FPLBP methods. It is noted that the DCT methods, namely DCT-TPLBP and DCT-FPLBP, achieve better performance in terms of recognition rates compared to the LBP-based methods.

Table II provides information on the learning and identification times for all four methods. The times were calculated using the developed software in Matlab, and it can be observed that the DCT methods significantly reduce both learning and identification times compared to the LBP-based methods.

Table III displays the recognition rates achieved by the DCT method for different sizes of the training set and different sizes of image (image patches or sub-images). It is emphasized that the recognition rate is influenced by the size of the training set used in the DCT method. This implies that a larger training set can potentially lead to higher recognition rates. It is important to note that without the actual values and specific details provided in the tables, it is not possible to analyses the exact recognition rates, learning and identification times, and the impact of different training set sizes and image sizes on the DCT method's performance. However, based on the information given, it can be concluded that the DCT-based methods outperform the LBP-based methods in terms of recognition rates and reduce learning and identification times. Additionally, the size of the training set influences the recognition rate in the DCT method.

Table 1: Best methods recognition rate: TPLBP, FPLBP, DCT-TPLBP AND DCT-FPLBP in %

Distance	TPLBP	DCT-TPLBP	FPLBP	DCT-FPLBP
L1	93.02	94.23	95.5	97.2
L2	93.78	95.1	96.4	98.1

Table 1: Best methods Learning time and identification.

Time	TPLBP	DCT-TPLBP	FPLBP	DCT-FPLBP
Learning	120 s	10 s	80 s	5 s
Identification	4.8 s	0.8 s	1.7 s	0.5 s

Table 1: Recognition rate of the DCT method for different sizes of the training set and different sizes of images.

Size of the training set	25%	50%	75%
Image 8x8	83.20	89.7	93.4
Image 16x16	85.12	90.1	94.62
Image 32x32	87.1	91.4	95.3
Image 64x64	90.2	93.5	97.4

7. CONCLUSIONS

In this paper, a new procedure for face recognition has been presented, comparing four different approaches. One of the major advantages of using the Discrete Cosine Transform (DCT) is its ability to reduce redundant information and serve as a feature extraction step. This characteristic makes the proposed technique well-suited for real-time applications where efficiency and speed are crucial.

The simulation results in the specific and independent scenarios indicate that DCT-FPLBP convergence is superior to DCT-TPLBP. In the future, we intend to assess the resilience of DCT using different facial databases.

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