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Composite Feature Based Face Recognition using Machine Learning and Neural Network Algorithm

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Abstract-

The demand for face recognition technology is clearly articulated due to its extensive use in various industrial applications for achieving diverse objectives. As these applications become more integrated into daily life, the accuracy of individual identity verification becomes crucial. Face recognition, boasting distinct advantages over alternative commercial algorithms, continues to evolve with improved algorithms and reduced computational costs.

However, despite the seemingly straightforward nature of recognizing faces through human eyes, artificial intelligence has yet to fully replicate this process. Faces, being the typical source of identification, present a multitude of complexities and variations in images, including noise, rotation, and more. Numerous techniques employ various algorithms to establish similarity between a face model and a test image, often achieving commendable levels of accuracy. Nevertheless, due to the broad range of applications and image sources, a one-size-fits-all algorithm is unfeasible, necessitating continual improvements to face recognition techniques. This research undertakes a two-fold approach: initially, it employs conventional recognition algorithms, followed by hybrid methods to address their limitations. The research commences with the computation of global face features using techniques such as Principal Component Analysis (PCA), Discrete Wavelet Transform (DWT), and Independent Component Analysis (ICA). Standard classifiers like Neural Network (NN) and Support Vector Machine (SVM) are used. An observation made is that higher learning rates in machine learning enhance system accuracy but escalate the area and cost overhead.

To surmount this training limitation, a Fusion-based approach is proposed. This approach combines Harris corner, Speed Up Robust Features (SURF), and DWT+PCA system model. By utilizing only 10% of training samples from the Essex database, an accuracy of 99.45% is achieved. However, creating the Fusion rule requires some trial-and-error methods, which might not be universally applicable to every database. Further overcoming this limitation, an efficient Hybrid method is proposed. It elaborates on local features like Linear Binary Pattern (LBP), Histogram Oriented Gradients (HOG), Gabor wavelet, and global features (DWT, PCA) of the face. These features are then trained using a Neural Network classifier, resulting in enhanced accuracy of nearly 99.40%, even with training from a single image per class.

Keywords— DWT, PCA, ICA, LBP

1. INTRODUCTION

Face recognition is a task that humans perform effortlessly in their everyday lives. The prevalence of powerful computing systems, both standalone and embedded, has sparked significant interest in automatically processing digital images and videos across a range of applications. Among these, automatic face recognition stands out as a critical and intriguing task within computer vision and biometrics. It involves using theoretical techniques and software to identify individuals based on their facial images. This interdisciplinary research area has a substantial history, dating back to the 1980s [1].

The significance of face recognition stems from its numerous applications across diverse domains. These include security, surveillance in public spaces, forensic investigations, person identification in image or video databases, human-machine interaction, smart cards, and the biometric passport (E-Passport) [2]. This field draws on a multitude of disciplines, such as image processing, applied mathematics, pattern recognition, machine learning, visual perception, psychophysics, and neuroscience.

Face recognition offers distinct advantages over other biometric technologies: it's natural, non-intrusive, and user-friendly. Ideally, a facial recognition system should autonomously identify faces within images or videos.

Most face recognition algorithms rely on vector or matrix data models. However, these operations can disrupt the data structure, leading to reduced performance and robustness across various applications. To address this, adapting conventional methods to these new multidimensional configurations is essential. Enter multilinear algebra [3, 4], which enables leveraging this data while preserving its inherent structure. The data is represented as multidimensional arrays known as tensors [5]. Recently, these techniques have been extended to facial biometric data as well. Nonetheless, transitioning from processing facial data in conventional vector or matrix forms to tensor-based approaches presents challenges. Several researchers have demonstrated the development of tensor-based face verification systems to tackle issues like varying illuminations, expressions, and poses [6]

2. FACE RECOGNITION USING DWT-PCA-NN ALGORITHM

The steps in proposed model for face recognition using DWT-PCA-NN:
Pre-processing:

1. Take image I1 and I2 as an input.
2. Resize both images for 160×160 matrix.
3. Apply RGB to Gray value conversion.
4. Histogram Equalization is performed on the gray image for Image enhancement.

Feature Extraction:

1. After pre-processing, all the images are saved into database.
2. Convolve the images with the LPF and HPF filters
3. The images are decomposed into low frequency and high frequency components.
4. The low frequency components are down sampled by the factor of 2 in order to get the approximation coefficients as its output. Select the window with even indexed columns.
5. The high frequency components are down-sampled by the factor of 2 in order to get detailed coefficients as its output. Select the window with even indexed rows.
6. To obtain Level-2 decomposed coefficients, the rows and the columns of entry are further convolved with the filter. And the horizontal, vertical, diagonal features are extracted.
7. Compute the mean value of four coefficients (LL, LH, HL, HH) for the selected window
8. LL sub-band co-ordinates is again considered for reference by PCA measurement for each sub-window
9. Each sub-window is changed into a row vector Vi (i =1, 2….n)
10. The standard deviation σ and mean μ of vector components (W) is computed
11. Find 'A', the average shifted version of W.
12. PCA matrix coefficient is computed by PCA measurement on A
13. The decomposed coefficients of image I1 and I2 are fused on the basis of PCA algorithm by extracting Eigen value and Eigen vectors.
14. I-DWT is applied in order to achieve final fused image 'F'
15. The performance matrix is evaluated using reference image 'I1' and fused image 'F'

Face Recognition Using DWT-PCA-ICA-NN Algorithm Following are the steps included in DWT-PCA-ICA-NN Algorithm: Pre-processing:
1. Take image I1 and I2 as an input.
2. Resize both images for 160×160 matrix.
3. Apply RGB to Gray value conversion.
4. Histogram Equalization is performed on the gray image for Image enhancement.

Feature Extraction:
1. After pre-processing, all the images are saved into database.
2. Convolve the images with the LPF and HPF filters
3. The images are decomposed into low frequency and high frequency components.
4. The low frequency components are down sampled by the factor of 2 in order to keep the even indexed columns. We get the approximation coefficients as its output
5. The high frequency components are down sampled by the factor of 2 in order to keep the even indexed rows. We get the detailed coefficients as its output
6. To obtain Level-2 decomposed coefficients, the rows and the columns of entry are further convolved with the filter. And the horizontal, vertical, diagonal features are extracted.
7. Compute the mean value of four coefficients (LL, LH, HL, HH) for the selected window
8. LL sub-band co-ordinates is again considered for reference by PCA measurement for each sub-window
9. Each sub-window is changed into a row vector Vi (i =1, 2 …..n)
10. The standard deviation σ and mean μ of vector components (W) is computed
11. Find 'A', the average shifted version of W
12. PCA matrix coefficient is computed by PCA measurement on A

13. The decomposed coefficients of image I1 and I2 are fused on the basis of PCA algorithm by extracting Eigen value and Eigen vectors.
14. From Eigen values and Eigen Vectors, independent component analysis (ICA) is calculated with the help of whitening and learning.
15. Calculate centre for test images with database.
16. Multiply centred information of test image to Eigen vector of database,
17. Perform whitening on output.
18. Calculate cosine distance between the feature of reference and features of test image
19. Threshold is given by cosine distance and finally result is taken out.
20. I-DWT is applied in order to achieve final fused image ‘F’
21. The performance matrix is evaluated using reference image ‘I1’ and fused image ‘F’

3. Result and Discussion

The initial test case involves utilizing a dataset of 160 images from an Indian women dataset. This dataset includes frontal and tilted face images. The Indian dataset consists of a total of 11 distinct images for each of the 40 individual subjects. In certain cases, additional photographs have been included for specific subjects. These image databases are in JPEG format and have dimensions of 640×480 pixels per image, with each pixel having 256 gray levels.

Test images and the recognition results for some of these images are presented below. Additionally, the Principal Component Analysis (PCA) and Independent Component Analysis (ICA) components are provided in Table 1 for the Indian female dataset after conducting simulations..

Table 1: PCA& ICA components for Indian women datasets

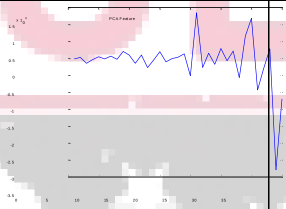
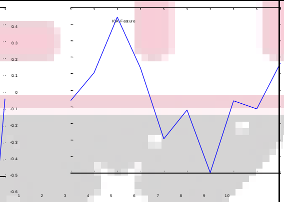
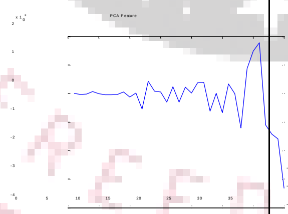
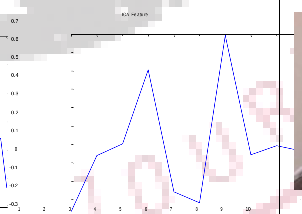
Query Image	Principle Components	Independent Components	Recognized Image
			
			

Table 2: Recognition rates according to training rate for Indian women datasets

Technique	1/160	2/160	3/160	4/160	5/160	6/160
DWT-PCA-ICA-SVM	**45.1**	**71.7**	**84.3**	**89.6**	**90.6**	**92.12**
DWT-NN	56	76.8	89.7	92.6	95.5	96.3

PCA-NN	52.4	72.9	88.3	92.1	93.5	97.9
DWT-PCA-ICA-NN	**68.9**	**79.3**	**92.3**	**94.5**	**96.17**	**98.78**

In Table 2, the recognition rates for face images within the training set are displayed. When using only 1 image for training, the recognition rate was notably low, specifically 45.1%. However, as the number of images in the training set increased, the recognition rates of the system displayed improvement. Notably, the proposed hybrid approach, which combines DWT-PCA-ICA-NN, achieved an accuracy of approximately 68.9% even when using a single image for training..

TABLE 3: RECOGNITION RATE OF INDIAN FEMALE DATABASE USING 6 IMAGES AS TRAINING

Using NN	Using SVM
98.78%	92.12%

When assessing the results in comparison to previous studies, Support Vector Machine (SVM) demonstrates promising outcomes for face recognition. Specifically, the combination of wavelet-SVM yields superior results in comparison to PCA-ICA-DWT-SVM. However, in terms of overall performance, Neural Network (NN) outperforms SVM significantly. NN achieves a recognition rate of 98.78% (as shown in Table 3), whereas the proposed SVM or previous implementations of wavelet SVM achieved recognition rates of 92.12%. Consequently, the overall performance of the proposed system surpasses existing outcomes.

5.1 INDIAN MALE DATA BASE

The second test case comprises 40 images extracted from an Indian Male dataset, encompassing both frontal and tilted face images. Below, you'll find test images along with their corresponding recognition outputs for a subset of these images. Additionally, Table 5.10 provides PCA and ICA components for the Indian male dataset following the simulation.

Table 4: Recognition rate comparison for proposed method with training set

Technique	1/160	2/160	3/160	4/160	5/160	6/160
DWT-PCA-ICA-SVM	47.4	67.9	74.3	85.6	90.6	92.6
DWT-NN	62.4	68.9	78.9	89.6	93.5	94.7
PCA-NN	59.4	64.5	77.5	87.1	91.6	93.9
DWT-PCA-ICA-NN	63.4	69.7	79.9	92.5	94.07	95.9

Table 4 presents the recognition rates of face images in training set. When only 1 image was selected, the recognition rate was quite low i.e. 47.4 %. However, with increase in training sets, the recognition rates of system improved. The proposed one with hybrid of DWT-PCA-ICA-NN gives approximately 63.4 % accuracy when single image has been considered.

TABLE 5: RECOGNITION RATE OF INDIAN FEMALE DATABASE USING 6 IMAGES AS TRAINING

Using NN	Using SVM
95.9%	92.6%

In comparison to previous research, Support Vector Machine (SVM) demonstrates favorable outcomes in the context of face recognition. Notably, the combination of wavelet-SVM yields superior results when contrasted with PCA-ICA-DWT SVM. Nevertheless, when evaluating the overall efficacy of SVM against Neural Network (NN), the latter exhibits substantially greater recognition rates than SVM. Specifically, the neural network attains a recognition rate of 95.9% (as outlined in Table 5), surpassing the 92.6% of the proposed SVM or prior implementations involving wavelet SVM. As a result, the proposed system's comprehensive performance excels beyond established benchmarks.

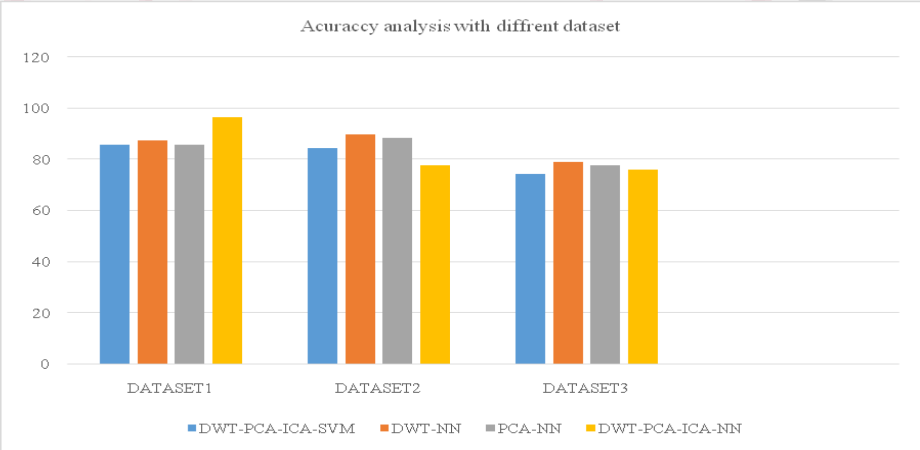


FIGURE 6: ACCURACY ESTIMATION WITH CHANGE IN DATASETS

Figure 6 elaborates the accuracy estimation with change in the dataset. Where 3 images are taken as training data for each class. Dataset 1 represents ORL dataset and DWT-PCA-ICA-NN gives better accuracy compare to others. Dataset 2 represents the Indian female dataset, where DWT-NN outperforms compare to other methods. Dataset 3 represents the Indian male dataset, where all the hybrid methods yield nearly similar results in terms of accuracy.

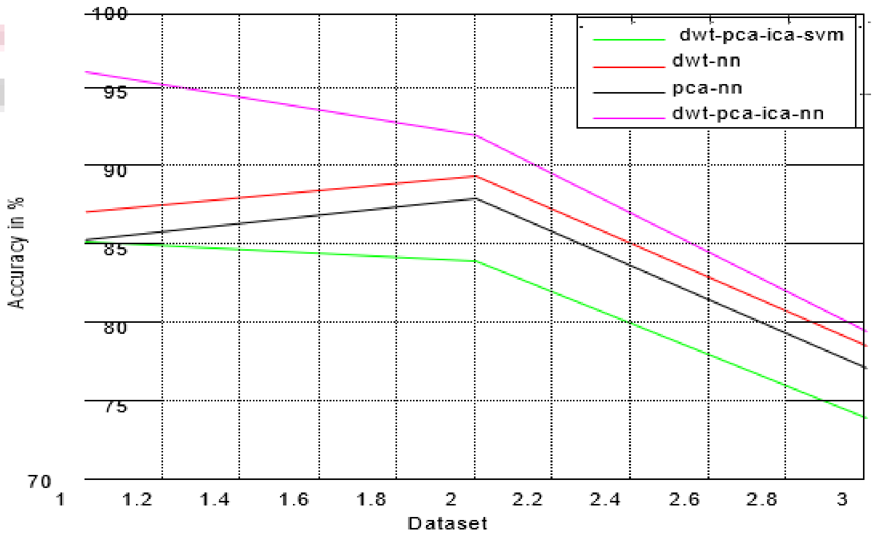


FIGURE 7: COMPARISON OF ACCURACY AMONG HYBRID METHODS

Figure 7 shows the dataset v/s accuracy with different dataset (ORL, Indian dataset female and Indian dataset male) .

TABLE 6: RECOGNITION RATE COMPARISON WITH DIFFERENT DATA SETS WITH REFERENCETO PROPOSED METHOD.

Methods	Dataset	Accuracy
PCA +NN[28]	ORL	88.86 %
ICA +NN[28]	ORL	88.86 %
PCA + SVM [28]	FERET	85.2 %
2DPCA + SVM [28]	FERET	95 %
Common Eigen Value [33]	YALE B, FERET	97.5 %, 98%
PCA[31]	ORL	88.67 %
PCA [31]	YALE	93.25 %
DWT [29]	YALE	83.3 %
DWT [29]	ORL	92.5 %
DWT+PCA [29]	YALE	84 %
DWT +PCA [29]	YALE	94.5 %
DWT-PCA-ICA-SVM	**ORL**	**88.7%**
DWT-NN	ORL	91.6%
PCA-NN	ORL	90.1%
DWT-PCA-ICA-NN	**ORL**	**97.14%**
DWT-PCA-ICA-SVM	**YALE**	**82.7%**
DWT-NN	YALE	90.3%
PCA-NN	YALE	92.1%
DWT-PCA-ICA-NN	**YALE**	**96.23%**

From the above Table 6, it shows that stiff changes in accuracy when dataset has been changed. DWT_PCA_ICA_NN yields better results in all datasets compare to other hybrid method respectively.

4. CONCLUSION

The field of automatic face recognition has seen active research efforts spanning the last four decades. Face recognition carries significant implications across various domains, including biometric identification, surveillance, human-computer interaction, and multimedia data management. Facial biometrics has notably contributed to bolstering security measures by curbing criminal activity, preventing fraud, and aiding in the search for missing individuals. This thesis centers on the theme of biometric recognition through a hybrid fusion of 2D facial features and machine learning.

The presented approach has demonstrated its superiority over both state-of-the-art and baseline algorithms, underscoring the resilience of the proposed techniques against challenges posed by variations in articulation, lighting conditions, and more. The effectiveness of these techniques has the potential to stimulate fresh perspectives and innovative strategies for addressing face recognition complexities.

The process of feature extraction is undertaken through three distinct stages: PCA, ICA, and DWT. PCA yields global features in the second stage, which are subsequently refined by ICA to provide locally diminished spatial features. For a more nuanced analysis, DWT is integrated following ICA to further extract features, culminating in the final set of features used for face recognition. In the recognition phase, two parallel experiments are conducted: one utilizing SVM and the other involving Neural Network. The simulation outcomes are meticulously compared with existing methodologies, including PCA, DWT, SVM, and other techniques, to provide a comprehensive analysis of the proposed system. It has been observed that the system's performance was not optimal with SVM. In contrast, Neural Network exhibited exceptional performance, yielding recognition rates of up to 96%.

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