AN ADOPTION OF 2D-PCA/ICA BASED POST-PROCESSING
DIMENSIONALITY REDUCTION
ALGORITHM FOR FACIAL RECOGNITION SYSTEM

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Abstract
Face images undergo considerable amount of variations in pose, facial expression
and illumination condition. This large variation in facial appearances of the same
individual makes most Existing Face Recognition Systems (E-FRS) lack strong
discrimination ability and timely inefficient for face representation due to holistic
feature extraction technique used. In this paper, a novel face recognition framework,
which is an extension of the standard (PCA) and (ICA) denoted as two-dimensional
Principal Component Analysis (2D-PCA) and two-dimensional Independent
Component Analysis (2D-ICA) respectively is proposed. The choice of 2D was
advantageous as image covariance matrix can be constructed directly using original
image matrices. The face images used in this study were acquired from the publicly
available ORL and AR Face database. The features belonging to similar class were
grouped and correlation calculated in the same order. Each technique was
decomposed into different components by employing multi-dimensional grouped
empirical mode decomposition using Gaussian function. The nearest neighbor (NN)
classifier is used for classification. The results of evaluation showed that the 2D-PCA
method using ORL database produced RA of 92.5%, PCA produced RA of 75.00%,
ICA produced RA of 77.5%, 2D-ICA produced RA of 96.00%. However, 2D-PCA
methods using AR database produced RA of 73.56%, PCA produced RA of 62.41%,
ICA produced RA of 66.20%, 2D-ICA method produced RA of 77.45%. This study
revealed that the developed face recognition framework algorithm achieves an
improvement of 18.5% and 11.25% for the ORL and AR databases respectively as
against PCA and ICA feature extraction techniques.

Keywords: computer vision, dimensionality reduction techniques, face
recognition, pattern recognition
1.0 Introduction
In recent times, researches in Face recognition and computer vision have dominated the pattern recognition domain. In spite of the successes record so far, there have not been an accurate and robust system developed for face recognition that actually captured both sufficient and discriminating features of facial representation. This is as result of high dimensional recognition of faces which can cause overtraining and high computational load Fernandes S. and Bala J. (2013) In literature, there have been several dimensionality reduction methods proposed, and most successful of them which has been used in solving face recognition problems can be gathered into two, namely: linear and nonlinear Wang W, and Venetsanopoulos A. N. (2016). The Principal Component Analysis and Independent Component-Analysis are the commonly used linear global extraction algorithms.

Extensions of the standard PCA and ICA were proposed, denoted by Fernandes et al., 2013) as 2D-PCA and 2D-ICA respectively. Facial images are complex due to variations in illumination, expression of the face and posture and hence nonlinearity in face recognition may be impossible to be capture by the linear sub-space methods He X., Yan S., Hu Y., Niyogi P., and Zhang H. (2015). As a result, many nonlinear dimensionality reduction algorithms such as Kernel-Principle Component Analysis (KPCA), Kernel Discriminant Analysis (KDA), and Kernel Fisher Analysis (KFA) have been developed (He et al., 2014). In recent times, researchers have demonstrated great interest in manifold learning techniques. Several well-known algorithms are Locality Preserving Projection (LPP), Neighborhood Preserving Embedding (NPE), (Wang, et al., 2016).

To overcome certain problems encountered by using low quality image, the image is subjected to pre-processing methods prior to extracting features from the image. Filtering, image normalization, denoising, histogram equalization, and image cropping are some techniques to enhance the picture quality and to improve the recognition rate of dimensionality-reduction methods Wang et al., (2016) presented a new post processing approach to enhance the recognition accuracy of the Global-based method. Their algorithm can be summarized as follows: first, the discriminant feature vector is mapped into a 2D image; then, a 2D-Gaussian filter is used to blur the discriminant image and filter off noise; lastly, the shaped image is re-mapped to the discriminant vector Punitha P. and Guru D. S. (2018).

In this research, a novel face recognition framework is proposed, which can be adopted as a post processing phase in several dimensionality reduction methods. The Proposed strategy tries to decompose the training template and also testing template into intrinsic mode functions (IMFs) by multi-dimensional ensemble empirical mode decomposition (MEEMD) Zhao W., Chellappa R., Phillips P. J., and Rosenfeld A. (2019). Next, we use a 2D Gaussian filter to correct the features formed as outliers in each component; later, we reconstruct the data of the training
template and testing template. The other part of the research is arranged as follows: Section 2 explains a brief analysis of MEEMD as well as its variations. Section 3 presents the highlight of the proposed post-processing framework. The simulated results and discussion are presented in Section 4. The conclusions are stated in Section 5.

2.0 EMD, EEMD, and MEEMD
Zhao et al., (2019) proposed the Multidimensional-ensemble empirical mode decomposition which is based on empirical-mode decomposition (EMD) and its improved version, ensemble-EMD. Unlike other decomposition methods, EMD is empirical, adaptive and direct with no pre-determined basis functions. The method iteratively decomposes a time series signal into multiple IMFs and a residue. Frequent occurrence of mode mixing serves as the main demerits of the original EMD that is, a single IMF can accommodate signals of varying scales, or one signal scale can reside on multiple IMFs Choudhary K. and Goel N. (2019).

To resolve the problem encountered in EMD, Wang et al., (2015) recently proposed a new method; ensemble-empirical mode decomposition (EEMD) for data analysis. EEMD is built on the hybridization of white noise to the signal prior to the application of EMD. The EEMD algorithm can be simplified as follows: a series of white-noise is combined to the data; next, the data combined with white noise are decomposed into various IMFs using EMD; then, the previous phases are iterated with a several white noise series at a time, and the final resulting IMFs of the decompositions are extracted. A multidimensional EEMD (MEEMD) for multi-dimensional data was proposed by Zhao et al., (2019). This method facilitates the decomposition of multidimensional data using only 1D-EEMD. In the case of an image, the 1D-EEMD is combined to data in one dimension (x-direction), and the data are broken down line-by-line; the sifting process is interrupted after n IMFs, hence, n + 1 intermediate frames are obtained. Then, we broke down each frame; however, this time, the 1D-EEMD is combined in the second dimension (y direction). By hybridizing the appropriate components, several IMFs of the image were obtained. To facilitate the understanding of MEEMD, the strategy of 2DMEEMD is illustrated as an example in Fig. 1. After completing the 1D-EEMD executions for all dimensions, the results obtained for the same scale are added. The final image must satisfy the equation:

\[ C_i(x, y) = \sum_{k=1}^{k} h_i^k(x, y) + \sum_{l=i+1}^{k} h_i^l(x, y) \]

3.0 Proposed Method
This section presents the major steps of the proposed method in detail. Suppose that \( X = [x_1, x_2, \ldots, x_N] \) depicts all the N training samples, and \( Y = [y_1, y_2, \ldots, y_M] \) represents all the testing samples.
3.1. Main Steps of the Proposed approach

Figure 2 represents the block diagram of the proposed face recognition system while the main steps in the proposed approach are as follows Zhao et al., (2019):

1. The dataset is broken into training images, X and testing images, Y. Then, the face images of X and Y become \( \tilde{X} = [\tilde{x}_1, \tilde{x}_2, \ldots, \tilde{x}_N] \) and \( \tilde{Y} = [\tilde{y}_1, \tilde{y}_2, \ldots, \tilde{y}_M] \), where

\[
\tilde{x}_i = \frac{x_i}{\|x_i\|} - x_{\text{mean}}, \quad \tilde{x}_2 = \frac{x_2}{\|x_2\|} - x_{\text{mean}}, \ldots,
\]

\[
\tilde{x}_N = \frac{x_N}{\|x_N\|} - x_{\text{mean}};
\]

\[
\tilde{y}_1 = \frac{y_1}{\|y_1\|} - y_{\text{mean}}, \quad \tilde{y}_2 = \frac{y_2}{\|y_2\|} - y_{\text{mean}}, \ldots,
\]

\[
\tilde{y}_N = \frac{y_N}{\|y_N\|} - y_{\text{mean}};
\]

and \( x_{\text{mean}} = \frac{1}{N} \sum_{i=1}^{N} x_i \) represents the mean image.

2. The projection matrix WT is computed using one of the dimensionality reduction techniques such as PCA or ICA; then, the \( \tilde{X} \) and testing images \( \tilde{Y} \) are projected onto that subspace

\[ P_y = W^T \tilde{X} \quad \text{and} \quad P_y = W^T \tilde{Y}. \] (1)

As shown in Fig. 2, the training and testing templates were subjected to similar condition after projection and only the training templates are used in the remaining steps; furthermore, the same steps are also generalized for the testing templates Zhao et al., (2019).
(3) Multi-dimensional Ensemble Empirical Mode Decomposition (MEEMD) was used to decompose Tsai F. S. (2019)

\[ P_x = \sum_{i=1}^{n} IMF_{x_i} + R_x \]  

where \( IMF_{x_i} \) and \( R_x \) are the \( i \)th IMF and the residue of training templates \( P_x \), respectively.

(4) A 1D Gaussian filter on each IMF to eliminate aberrant or extreme values caused by confounding factors; this step will increase the correlation between the elements of similar class and increase the independence between different classes.

\[ IMF_{x_1}' = IMF_{x_1} \otimes H, \]
\[ IMF_{x_2}' = IMF_{x_2} \otimes H, \]
\[ \ldots \]
\[ IMF_{x_n}' = IMF_{x_n} \otimes H, \]
\[ R_x' = R_x \otimes H, \]
where $IMF_{mx}^i$ and $R_x^i$ are the nth IMF and the residue of training templates filtered by the 1D Gaussian filter, respectively. The operator $\otimes$ represents the convolution operation between the IMFs and the 1D Gaussian filter $H$ is depicted by

$$H(x) = \frac{1}{\sqrt{2\pi}\sigma^2} e^{-\frac{x^2}{2\sigma^2}}$$

(3)

Where $\sigma^2$ is the variance.

(5) The training templates matrix was reconstructed by computing the addition of all the IMFs resulted in step (4). The reconstruction is performed as under:

$$P_x^i = \sum_{i=1}^{n} IMF_{mx}^i + R_x^i$$

(4)

Where $P_x^i$ shows the reconstructed training templates.

![Fig.2: General Block diagram of proposed system](image)

### 3.2. Analysis of Our Approach

This subsection demonstrates the rationale for using the proposed method. First, a facial image is often contaminated by variability in one or more natural factors, e.g., pose, illumination, expression, hair, glasses, or background. Then, the features of facial images continue to retain this information on the use of existing feature extractors, It is difficult to avoid the interference from these factors because they are embedded in the feature vectors, and it is tough to clearly determine which distinguished information in the resulted features can represent...
faces better. Fortunately, most of these variabilities differ with respect to the factor type, e.g., the illumination effect varies slowly, whereas the noise varies rapidly.

Xie Y. (2018). The proposed technique tries to distinguish these variabilities by using MEEMD and removes each variability individually. MEEMD can be broken the facial features into several IMFs. As a result, every mode (IMF) contains information of a specific scale, and if these features of faces are embedded with natural variabilities, they appear as outliers or extreme values in different IMFs. Zhang D. and Zhou Z. (2019).

The second feature of the proposed approach is that it uses a 1D Gaussian filter to adjust the values of features affected by light or by other factors. Figure 3 shows two pseudo-color maps that depict the amount of correlation between various features in a dataset. We chose eight classes extracted from the ORL database; for each class, we used five images of every person as the training set. We grouped the features identified as the same class member and calculated the correlation in the same order. For example, in Fig. 3a, we can observe that the class grouped in tiles 1 to 5 has some grids that correspond to similar class but have low correlation. In Fig. 3b, the grids problem was corrected by using decomposition MEEMD and a Gaussian filter.

4.0 DISCUSSION AND EXPERIMENTAL RESULTS

This section discussed the implementation of our experiments simulated on ORL and AR face databases. First, the experiments were described by using PCA and ICA. Next, we compare our proposed method with state-of-the-art methods. We used two facial databases to evaluate our algorithm. The first database is ORL. This database consists of ten varying images of 40 distinct objects. Variations in these images include facial expression, pose, noise condition and facial details. The dimension of each image is 112 × 92 pixels. In our experiments, we resized each image to 82 × 82 pixels. Figure 4a shows the varying images of one subject from the ORL database.

The second database is AR, which consists of greater than 4000 frontal view images of 126 persons (70 male and 56 female). Each person was represented by 26 varying images taken in two different phases demarcated by a two-week time interval. The first phase contains 13 different images, numbered from 1 to 13 (1–4), different illumination conditions (5–7), and varying occlusions under different illumination changes (8–13). The second session was similar to the first one and was conducted 2 weeks later. The varying images of one subject are shown in Fig. 4b.
In our test, we used the methodology applied by Yang J., Zhang D., and Frangi A. F. (2019). For the ORL database, we tested different approaches for two cases. In case 1, we used the first five images of each person for training and the remaining images for testing. In the second case (Case 2), the first six images of each person were selected to create the training sample set, and the remaining four images were used to create the testing set. Similarly, for the AR facial database, two cases were used to compare the different methods. In the first case (Case 1) we used the first eight images of each person as training images and the remaining eighteen images for testing. In the second case (Case 2), the seven images for each subject from phase 1 were used as training samples, and the seven other images from Session 2 were used as test samples. In MEEMD, three parameters must be set: added white noise, Number of iterations and Number of IMFs. In the following experiments, we choose the noise ratio as $NL = 3$, Number of iterations as $nest = 20$, and Number of IMFs as three IMFs and a residue. Additionally, a Gaussian filter with equal to and a matrix kernel of $[1, w] = [1, 5]$ were used.

4.1 Experiments Using PCA and ICA

The performance of the post-processing framework was explored in this section.
from the description above; we know that our algorithm could be used in any dimensionality reduction method. Because of restrictions on the length of this paper, in our experiments, we choose two well-known subspace methods: PCA and ICA as samples. The nearest neighbor (NN) classifier is used for classification.

The results of evaluation showed that the 2D-PCA method using ORL database in case 1 produced RA of 92.5%, with 117 dimensions, and case 2 produced RA of 90% with 116 dimension, PCA produced RA of 75.00% with 55 dimension in case 1, and RA of 77.5% of 174 dimension in case 2, ICA produced RA of 77.5% with 24 dimension in case 1, and RA of 82.5% with 31 dimension in case 2, 2D-ICA method in case 1 produced RA of 96.00% with 48 dimension, and RA of 97.5% with 35 dimension in case 2. However, 2D-PCA method using AR database in case 1 produced RA of 73.56%, with 439 dimensions, and case 2 produced RA of 73.10% with 199 dimension, PCA produced RA of 62.41% with 339 dimension in case 1, and RA of 64.17% of 239 dimension in case 2, ICA produced RA of 66.20% with 109 dimension in case 1, and RA of 67.26% with 129 dimension in case 2, 2D-ICA method in case 1 produced RA of 77.45% with 109 dimension, and RA of 78.10% with 129 dimension in case 2.

The best recognition accuracy and the resulting number of eigenvectors are given in Tables 1 and 2.

Table 1: Recognition Accuracy for ORL database

<table>
<thead>
<tr>
<th>Methods</th>
<th>Case 1</th>
<th>Case 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Recognition Accuracy (%)</td>
<td>Features Dimensions</td>
</tr>
<tr>
<td>PCA</td>
<td>75.00</td>
<td>55</td>
</tr>
<tr>
<td>2D-PCA</td>
<td>92.50</td>
<td>117</td>
</tr>
<tr>
<td>ICA</td>
<td>77.50</td>
<td>24</td>
</tr>
<tr>
<td>2D-ICA</td>
<td>96.00</td>
<td>48</td>
</tr>
</tbody>
</table>

Table 2: Recognition Accuracy for AR database

<table>
<thead>
<tr>
<th>Methods</th>
<th>Case 1</th>
<th>Case 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Recognition Accuracy (%)</td>
<td>Features Dimensions</td>
</tr>
<tr>
<td>PCA</td>
<td>62.41</td>
<td>339</td>
</tr>
<tr>
<td>2D-PCA</td>
<td>73.56</td>
<td>439</td>
</tr>
<tr>
<td>ICA</td>
<td>66.20</td>
<td>109</td>
</tr>
<tr>
<td>2D-ICA</td>
<td>77.45</td>
<td>109</td>
</tr>
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</table>

1. In all the tables, the dimensionality reduction techniques that integrated our post-processing framework into their existing frameworks yield better accuracy than direct methods in terms of the recognition rate.
2. Our algorithm achieves an improvement of 18.5 and 11.25% for the ORL and AR databases, respectively. The reason for this result is that our method can effectively enhance the recognition accuracy by eliminating some natural
variability embedded in feature vectors. This comparison proves that the proposed approach can achieve greater improvement when the dataset used is not affected simultaneously by several confounding factors. In our experiment, the ORL database is affected by a fewer number of factors than the AR database. The graph of evaluation results showing the comparison between ORL database and AR database is presented in figure 5, 6, 7 and 8.

Table 3: Recognition Accuracy using ORL Database (Case I)

<table>
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<tr>
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<tr>
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<td>2D-ICA</td>
<td>96</td>
<td>48</td>
</tr>
</tbody>
</table>

Fig. 5: Graph of Recognition Accuracy using ORL Database (Case I)

Table 4: Recognition Accuracy using ORL Database (Case II)

<table>
<thead>
<tr>
<th>Methods</th>
<th>Recognition Accuracy (%)</th>
<th>Features Dimensions</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCA</td>
<td>77.5</td>
<td>174</td>
</tr>
<tr>
<td>2D-PCA</td>
<td>90</td>
<td>116</td>
</tr>
<tr>
<td>ICA</td>
<td>82.5</td>
<td>31</td>
</tr>
<tr>
<td>2D-ICA</td>
<td>97.5</td>
<td>35</td>
</tr>
</tbody>
</table>
Fig. 6: Graph of Recognition Accuracy using ORL Database (Case II)

Table 5: Recognition Accuracy using AR Database (Case I)

<table>
<thead>
<tr>
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<th>Features Dimensions</th>
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<tbody>
<tr>
<td>PCA</td>
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<td>339</td>
</tr>
<tr>
<td>2D-PCA</td>
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<td>439</td>
</tr>
<tr>
<td>ICA</td>
<td>66.2</td>
<td>109</td>
</tr>
<tr>
<td>2D-ICA</td>
<td>77.45</td>
<td>109</td>
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</table>

Fig. 7: Graph of Recognition Accuracy using AR Database (Case I)
Table 6: Recognition Accuracy using AR Database (Case II)

<table>
<thead>
<tr>
<th>Methods</th>
<th>Recognition Accuracy (%)</th>
<th>Features Dimensions</th>
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</thead>
<tbody>
<tr>
<td>PCA</td>
<td>64.17</td>
<td>239</td>
</tr>
<tr>
<td>2D-PCA</td>
<td>73.1</td>
<td>199</td>
</tr>
<tr>
<td>ICA</td>
<td>67.26</td>
<td>129</td>
</tr>
<tr>
<td>2D-ICA</td>
<td>78.1</td>
<td>129</td>
</tr>
</tbody>
</table>

From the results presented in Table 1 and 2, we can infer three main observations:

First, different methods reach their peak performance in different subspaces for different datasets. Thus, it is very difficult to predict the optimal subspace because on one hand, each database has its own characteristics and on the other hand, each method has its own ways to extract significant data and eliminate redundant data.

Secondly, we can observe that the recognition rate of different methods varies rapidly for low dimensions; however, when the number of extracted features exceeds a certain value, we observe that most of the methods show stability.

Thirdly and most importantly, the methods with which we have used our post-processing framework outperform the direct methods for all dimensions in all databases; we can clearly observe that the graphs corresponding to the direct methods PCA and ICA are below the graphs of their corresponding post processed versions. Thus, the proposed approach is suitable for any dimensionality reduction.
techniques.

5.0 CONCLUSION AND RECOMMENDATIONS
In this research work, we proposed a novel post-processing framework to enhance the accuracy of face recognition. The core idea of our framework is to detect and correct the outliers embedded in a feature and to maximize the dispersion between classes. In summary, our proposed algorithm has three advantages: First, our method maximizes the correlation and dependency between classes. Second, the features that reflect possible variations in the face are conserved. Third, the dispersion between classes is maximized. Furthermore, the proposed work can be successfully implemented in any dimensionality reduction methods. Several experiments were carried out on the ORL and AR face image databases. The proposed post-processing framework was applied to various Feature Extraction Methods. The results demonstrated that all the methods that embedded our algorithm into their framework achieved an improvement in the recognition rate; in some cases, the improvement was 18.5%. However, each of the approaches has its own merit and disadvantages. The complexity of our post-processing framework increases with an increase in the number of classes. Therefore, this paper focuses on only the recognition rates. In future work, we will try to overcome this limitation using a parallel implementation of MEEMD or by integrating fast

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