# Symmetric Feature Extraction for Pose Neutralization

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**Abstract.** This paper proposes a method to neutralize the pose of facial databases. *Efficient use of the feature extractors* and its properties leads to the pose neutralization. Feature extractors discussed here are few transforms like Discrete Cosine Transform (DCT) and Discrete Fourier Transform (DFT). *Symmetric behavior* of transforms is the basis of the proposed method. *Modulo* based approach in extracting the features was found to provide better results than the conventional techniques for pose neutralization. Experiments are conducted on various benchmark facial databases mainly pose variant FERET and FEI which show the promising performance of the proposed method in neutralizing pose.

## 1 Introduction

Face Recognition (FR) is a vast and challenging domain. Identification or verification of the person from the digital image is face recognition. FR finds many applications in several fields such as security, authentication systems and surveillance. Extensive research work is going on due the large number of applications of this field.

Two important stages of FR system is training and testing. Training stage involves the learning of the faces of various personalities. Learning involves preprocessing, feature extraction and feature selection. Recognition stage involves all those processes of training stage and in addition it has classification stage.

All the practical FR systems are affected by the variance in illumination, pose, expression and background [1]. There are algorithms which specifically target few of the above mentioned variables [2], [3], [4], [5], [6]. Pose is the most challenging discrepancy in FR. View-specific eigenface [7], [8] analysis as extraction method and neural network to recognize the personality was used by Fu Jie Huang in an attempt to neutralize pose[9]. Pose variant FR was also done by using a single example view by creating virtual views by MIT labs [10]. Facial symmetry [11] was used to neutralize pose in 2D FR [12]. Local regression was an effective solution to develop frontal pose from non-frontal pose and this method also tried to neutralize pose[13]. Texture based pose invariant techniques is discussed in Ref. [14].

Research in the field of FR is going on in both 2D and 3D field [15]. Spatial domain feature extraction, template matching is one of the very efficient methods for recognition [16]. There are many works in the principal component analysis method [17]. The extraction [18], [19], [20] methodology used is not so efficient to extract the required features. We try to improve the research gap here by effectively utilizing the available extractors. This paper proposes a novel method of extracting the features utilizing the *symmetric property* of the extractors.

The rest of the paper is organized as follows. In Section 2, we explain the problem and the proposed solution in brief. In Section 3, we discuss in detail analysis of the proposed extraction. Section 4 completely deals with the experiments conducted and analysis concluded. Section 5 summarizes about limitations of the proposed methodology of extraction and the future work to be done. The paper is concluded in Section 6.

## 2 Problem Definition and Solution

Pose neutralization is a challenging task in Face recognition. System must be able to recognize the person given his different poses. Pose variant FR is tackled using proposed methodology as mentioned below.

### 2.1 Symmetric Extractors for pose neutralization

The *symmetric properties* of the extractors is used so as the pose is neutralized. Face has vertical symmetry by its nature, the feature extractors which follow the principle of symmetry are capable of extracting the facial features more efficiently. *Modelling the transforms so as to make them symmetric is the proposed methodology. Modulo technique avails in achieving the symmetry.*

## 3 Proposed Extraction Technique

The extractors that we use here are few transforms like DCT and DFT. These two transforms are modelled so as to exhibit the symmetry property. We analyze DCT in first subsection and then DFT in second subsection. Symmetry behavior of these transforms can be seen when the proposed modulo technique is used. We discuss both in depth analysis and as well as a general proof for both the transforms.

### 3.1 DCT as symmetric extractor

Discrete Cosine Transforms [21], [22], [23] respond in a peculiar fashion for the symmetric input data. This peculiar behavior is very useful and is the basis of this paper. DCT is analyzed for an assumed particular set of data and as well as a general approach is given so as to figure out this property. The complete analysis of DCT equations are discussed in this section.

DCT is given by Eqn. 1. This is for two dimensional approach. We are trying to find out a method which can make system invariant to original and mirrored sequences (symmetrical sequences). Symmetry property is exhibited by 1D DCT also and is given by Eqn. 2, it is just a modification of the Eqn. 1. The whole symmetry property of DCT is due to *cosine function* and is proved below.

$$B_{pq} = \alpha_p \alpha_q \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} A_{mn} \cos \frac{\pi(2m+1)p}{2M} \cos \frac{\pi(2n+1)q}{2N} \tag{1}$$

$$0 \le p \le M-1 \ \ and \ \ 0 \le q \le N-1$$

$$\alpha_p = \begin{Bmatrix} \frac{1}{\sqrt{M}} & p=0 \\ \sqrt{\frac{2}{M}} & 1 \le p \le M-1 \end{Bmatrix} \quad and \quad \alpha_q = \begin{Bmatrix} \frac{1}{\sqrt{N}} & q=0 \\ \sqrt{\frac{2}{N}} & 1 \le q \le N-1 \end{Bmatrix}$$

$$M : number\ of\ elements\ in\ the\ sequence\ counted\ \ column\ wise$$

$$N : \ number\ of\ elements\ in\ the\ sequence\ counted\ row\ wise$$

$$A_{mn} : \ Value\ of\ the\ element\ at\ the\ m^{th}\ column,\ n^{th}\ row.$$

$$B_{p0} = \alpha_p \sum_{m=0}^{M-1} A_{m0} \cos \left[ \frac{\pi(2m+1)p}{2M} \right] \tag{2}$$

**General Proof** The whole analysis for various cases is performed mathematically to explain how DCT behaves to mirrored input and normal sequence and is solved completely in supplementary material. Let us prove it generally using the main DCT expression given by Eqn. 3.

$$\underset{(original)}{B_{p0}} = \alpha_p \sum_{j=0}^{M-1} x(j) cos \left[ \frac{\pi(2j+1)p}{2M} \right] \tag{3}$$

$$\begin{aligned}
\underset{(mirror)}{B_{p0}} &= \alpha_p \sum_{j=0}^{M-1} z(j) cos \left[ \frac{\pi(2j+1)p}{2M} \right] \\
&= \alpha_p \sum_{j=0}^{M-1} x(M-j-1) cos \left[ \frac{\pi(2j+1)p}{2M} \right] \\
& Substituting \ \ s = M-j-1 \\
\underset{(mirror)}{B_{p0}} &= \alpha_p \sum_{s=M-1}^{0} x(s) cos \left[ \frac{\pi(2(M-s-1)+1)p}{2M} \right] \\
&= \alpha_p \sum_{s=M-1}^{0} x(s) cos \left[ \frac{\pi(2M-2s-2+1)p}{2M} \right] \\
&= \alpha_p \sum_{s=0}^{M-1} x(s) cos \left[ p\pi - \frac{\pi(2s+1)p}{2M} \right]
\end{aligned}$$

$$= \alpha_p \sum_{j=0}^{j-1} x(j) cos \left[ p\pi - \frac{\pi(2j+1)p}{2M} \right]$$

$$\underset{(mirror)}{B_{p0}} = \begin{Bmatrix} +\alpha_p \sum_{j=0}^{j-1} x(j) cos \left[ \frac{\pi(2j+1)p}{2M} \right] & p = even \\ -\alpha_p \sum_{j=0}^{j-1} x(j) cos \left[ \frac{\pi(2j+1)p}{2M} \right] & p = odd \end{Bmatrix}$$

$$\underset{(mirror)}{B_{p0}} = \begin{Bmatrix} + \underset{(original)}{B_{p0}} & p = even \\ - \underset{(original)}{B_{p0}} & p = odd \end{Bmatrix} \tag{4}$$

Important conclusion drawn from the above general proof is stated as in Eqn. 4 and we can say this exists because of *cosine function*.

$$\therefore \left| \underset{mirror}{B_{p0}} \right| = \left| \underset{original}{B_{p0}} \right| \tag{5}$$

*Eqn. 5 shows that using the modulo operation, the DCT output of original and mirrored sequence can be same. This proposed method to make the system blind to the original and mirrored sequence helps in pose invariance. System using the proposed methodology cannot differentiate between 2 different poses of the same person.*

### 3.2 DFT as symmetric extractor

Discrete Fourier Transform [23], [24] can also aid in pose invariance by exhibiting property of symmetry. Here also a general approach and the in depth analysis is done. Our aim is to prove that using some methodology the DFT output of original and mirrored sequence can be made equal. DFT is given by Eqn. 6.

$$X(k) = \sum_{j=1}^{M} x(j) \omega_M^{(j-1)(k-1)} \tag{6}$$

$$Twiddle\ Factor = \omega_M = e^{(-2\pi i)/M} \quad and \quad 1 \le k \le M$$

**General Proof** Various cases are considered and are analyzed mathematically in supplementary material. Here we generalize to draw an important conclusion. Eqn. 7 represents DFT expression for original sequence where as the next equation is for the mirrored sequence.

$$\underset{original}{X(k)} = \sum_{j=1}^{M} x(j) \left| \underline{\left( \frac{-2\pi i(j-1)(k-1)}{M} \right)} \right. \tag{7}$$

$$\underset{mirror}{X(k)} = \sum_{j=1}^{M} z(j) \underline{\left| \left( \frac{-2\pi i(j-1)(k-1)}{M} \right) \right.}$$

$$= \left\{ \sum_{j=1}^{M} z(j) \underline{\left| \left( \frac{-2\pi i(j-1)(k-1)}{M} \right) - \left( \frac{-2\pi i(M-1)(k-1)}{M} \right) \right.} \right\}$$

$$\times \underline{\left| \left( \frac{-2\pi i(M-1)(k-1)}{M} \right) \right.}$$

$$= \left\{ \sum_{j=1}^{M} z(j) \underline{\left| \frac{2\pi i(k-1)}{M}(M-j) \right.} \right\} \times \underline{\left| \left( \frac{-2\pi i(M-1)(k-1)}{M} \right) \right.}$$

$$= \left\{ \sum_{j=1}^{M} x(M-j+1) \underline{\left| \frac{2\pi i(k-1)}{M}(M-j) \right.} \right\} \times \underline{\left| \left( \frac{-2\pi i(M-1)(k-1)}{M} \right) \right.}$$

$$Substituting \quad q = M - j + 1$$

$$\underset{mirror}{X(k)} = \left\{ \sum_{q=M}^{1} x(q) \underline{\left| \frac{2\pi i(k-1)}{M}(M-(M-q+1)) \right.} \right\} \times \underline{\left| \left( \frac{-2\pi i(M-1)(k-1)}{M} \right) \right.}$$

$$= \left\{ \sum_{q=1}^{M} x(q) \underline{\left| \frac{2\pi i(k-1)}{M}(q-1) \right.} \right\} \times \underline{\left| \left( \frac{-2\pi i(M-1)(k-1)}{M} \right) \right.}$$

$$= \left\{ \sum_{j=1}^{M} x(j) \underline{\left| \frac{2\pi i(k-1)(j-1)}{M} \right.} \right\} \times \underline{\left| \left( \frac{-2\pi i(M-1)(k-1)}{M} \right) \right.}$$

$$\left| \underset{mirror}{X(k)} \right| = \left| \sum_{j=1}^{M} x(j) \underline{\left| \frac{2\pi i(k-1)(j-1)}{M} \right.} \right|$$

$$\left| \underset{original}{X(k)} \right| = \left| \sum_{j=1}^{M} x(j) \underline{\left| \frac{-2\pi i(k-1)(j-1)}{M} \right.} \right|$$

$$\therefore \left| \underset{mirror}{X(k)} \right| = \left| \underset{original}{X(k)} \right| \tag{8}$$

$$Since \quad \left| \frac{2\pi i(k-1)(j-1)}{M} \right| = \left| \frac{-2\pi i(k-1)(j-1)}{M} \right|$$

Thus it is proved that the modulo value of both the DFT outputs of original and mirrored sequences are equal and is shown in Eqn. 8 . This symmetry property is due to the exponential term which is varied with '$j$ '.

*This method of applying the modulo over the DFT resultant matrix is the proposed method which makes the system invariant to normal and mirror sequences.*

## 4 Experiments

This section we shall look at in depth analysis and behavior of DCT and DFT. We here in this paper emphasize only on showing variance of Recognition rate by use of symmetry property of transforms, so we didn't try to add any other morphological techniques or classifiers. We also apply this to few benchmark datasets and prove that the proposed method is working as explained.

### 4.1 Analysis Of Proposed Technique

An input data sequence and its mirror sequence is used and the extraction techniques are applied. The results due to DCT and DFT are discussed in following two subsections.

**DCT as extractor** Input sequence details and the corresponding output values are tabulated in Table. 1. Graphs are plotted showing the symmetry of the DCT output (Fig. 1). We just assume a sequence of 10 elements (numbers). DCT is applied to the original sequence and the results are tabulated.

The proposed method result is also tabulated in the same Table 1. On careful observation of the two results, we see that system by using the proposed method becomes invariant to the mirrored and original sequence.

**DFT as extractor** Input sequence details and the corresponding output values are tabulated in Table. 2. This is the same input taken to analyse DCT also. Graphs are plotted showing the symmetry of the DFT output (Fig. 2). *We prefer to express solution in modulo and angle form since expressing it in complex coordinate form doesn't show the symmetry.*

**Table 1.** This explains numerically how proposed technique is suitable for flipping invariance. Original data, its DCT result, DCT result of the mirrored sequence input and also final optimal proposed solution can be seen here. Taking modulo for the results obtained, we make the proposed solution optimal for flipping invariance. The related graphs are shown in Fig. 1.

| Original Data | DCT Result Original | DCT Result Mirrored | **Proposed Method** |
|---|---|---|---|
| 12 | 217.88 | 217.88 | **21.88** |
| 25 | -113.82 | 113.82 | **113.82** |
| 40 | 3.14 | 3.14 | **3.14** |
| 48 | -17.80 | 17.80 | **17.80** |
| 62 | 6.99 | 6.99 | **6.99** |
| 77 | -12.96 | 12.96 | **12.96** |
| 88 | 2.53 | 2.53 | **2.53** |
| 92 | -0.69 | 0.69 | **0.69** |
| 110 | 0.51 | 0.51 | **0.51** |
| 135 | 1.52 | -1.52 | **1.52** |

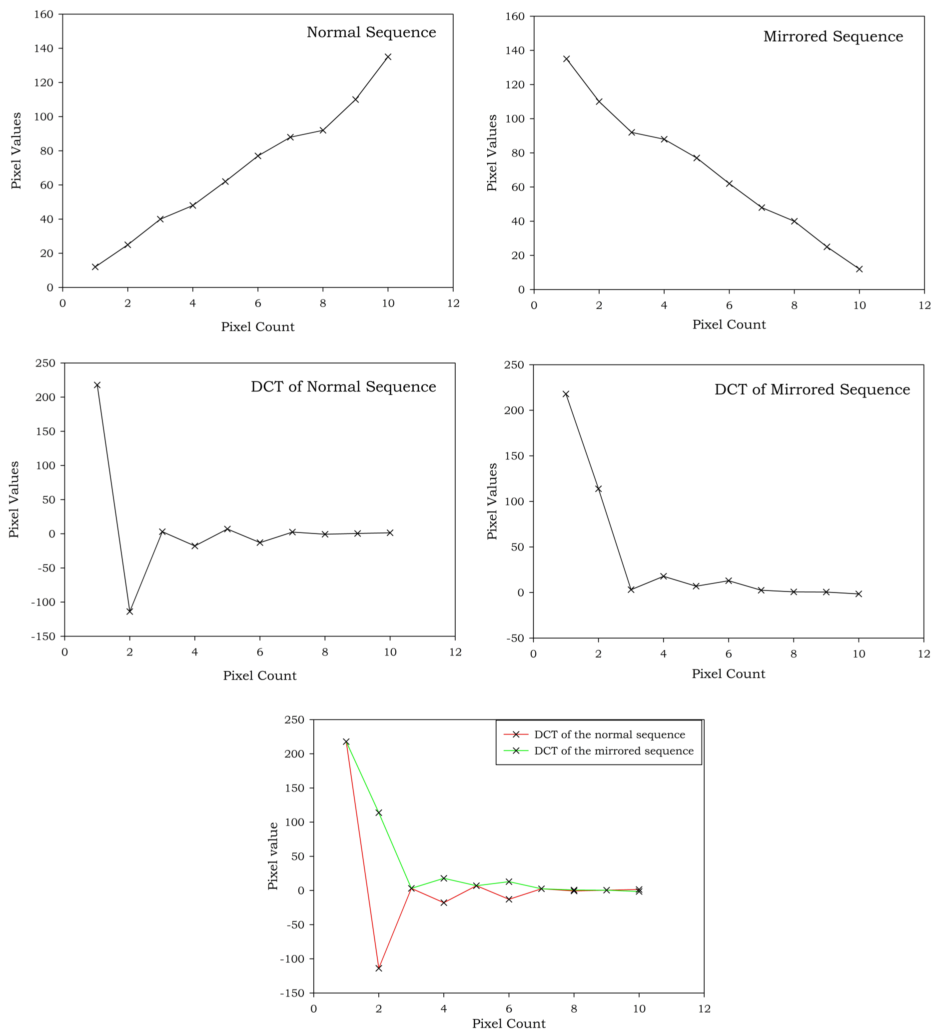


**Fig. 1.** Figure depicts the response of DCT to original and mirrored sequence. The original (normal) sequence and its corresponding mirrored sequence is seen in first row. DCT output results of normal and mirrored sequence is shown in second row. We cannot make out the symmetry by looking at 2 different output plots, therefore we have plotted both the DCT results in a single figure in third row. Considering the zero pixel value line as base we can see the symmetry of the plots, which is exploited here and is the proposed method. The Pixel values of all the graphs are tabulated in Table. 1.

The proposed method result is also tabulated in Table. 2. System by using the proposed method becomes invariant to the mirrored and original sequence as shown in Table. 2.

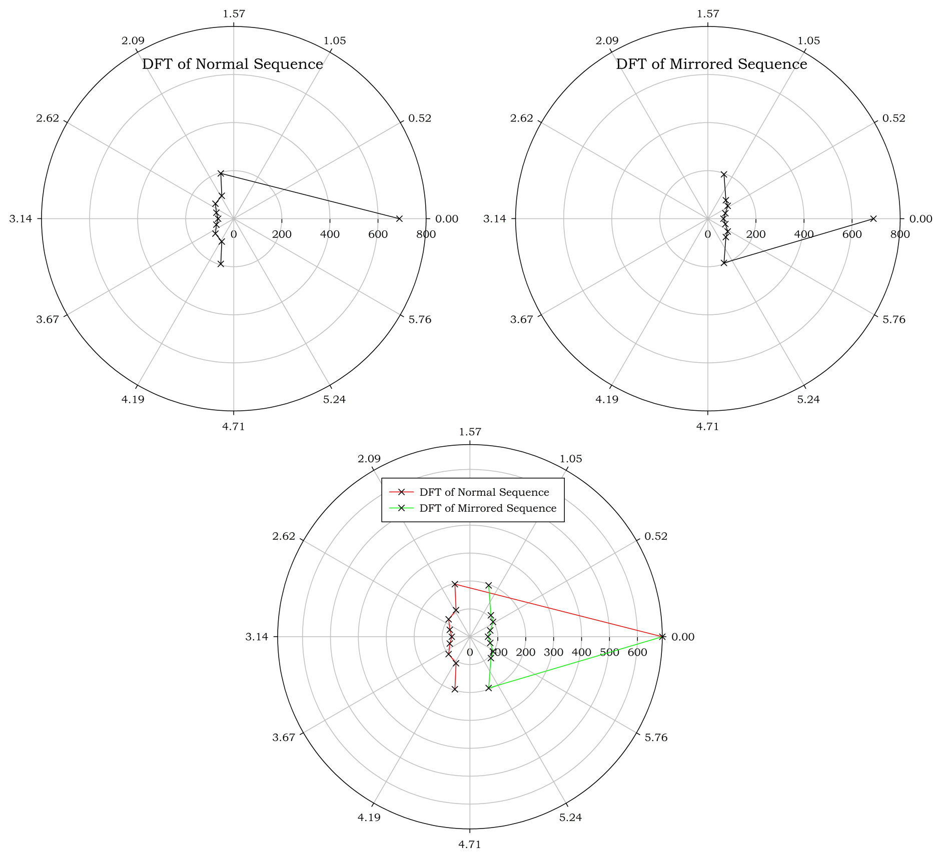


**Fig. 2.** The input sequence of Table. 2 is applied with DFT. The result obtained from DFT for original and mirrored sequence are complex and we use polar plots to show symmetry. First row shows these results. To make out the symmetry in the result obtained, we combine both plots into a single plot and is shown in second row. One can see that all the corresponding points of both the output sequences lie on the same radius circle (modulo circle). This is the proposed method where we choose the radius or the modulo which makes the system flip data invariant.

### 4.2 Face Recognition as an Application

Experiments have been performed on various standard benchmark databases to exemplify the robustness of the proposed methodologies. The proposed FR system is designed to handle various pose present in the benchmark database. If the total number of test images including all classes is 'b', and if 'a' number of images are correctly identified, then the Recognition Rate (RR) is calculated as defined in Eqn. 9.

$$Recognition\ Rate = \frac{a}{b} \tag{9}$$

**Table 2.** This explains numerically how proposed technique is suitable for flipping invariance for DFT. Neglecting the angle and only choosing the magnitude, we make the proposed solution optimal for flipping invariance. The graphs are in Fig. 2.

| | DFT Output Mirrored | | DFT Output Original | | **Proposed Method** |
|---|---|---|---|---|---|
| Original | Modulo | Angle (radians) | Modulo | Angle (radians) | **Modulo** |
| 12 | 689.00 | 0 | 689.00 | 0 | **689.00** |
| 25 | 195.89 | -1.22 | 195.89 | 1.84 | **195.89** |
| 40 | 107.42 | -0.79 | 107.42 | 2.05 | **107.42** |
| 48 | 98.43 | -0.57 | 98.43 | 2.46 | **98.43** |
| 62 | 76.27 | -0.29 | 76.27 | 2.81 | **76.27** |
| 77 | 65.00 | 0 | 65.00 | 3.14 | **65.00** |
| 88 | 76.27 | 0.29 | 76.27 | -2.81 | **76.27** |
| 92 | 98.43 | 0.57 | 98.43 | -2.46 | **98.43** |
| 110 | 107.42 | 0.79 | 107.42 | -2.05 | **107.42** |
| 135 | 195.89 | 1.22 | 195.89 | -1.85 | **195.89** |

The RR is used as a metric to demonstrate the performance of the experiments performed. We have made use of 4 benchmark face databases. These databases are: ORL, FERET, Head Pose and FEI. Experiments on ORL and Head Pose dataset is included in supplementary material.

Customized databases are created for each of the databases for the following four reasons. First, it covers almost all the expected changes such as pose, expression and illumination variations. Second, to reduce the burden of resource utilization. Large number of images may not be required as many images are redundant, in the sense that the customized database contains the variations possessed by all those images. Third, the various databases contain different

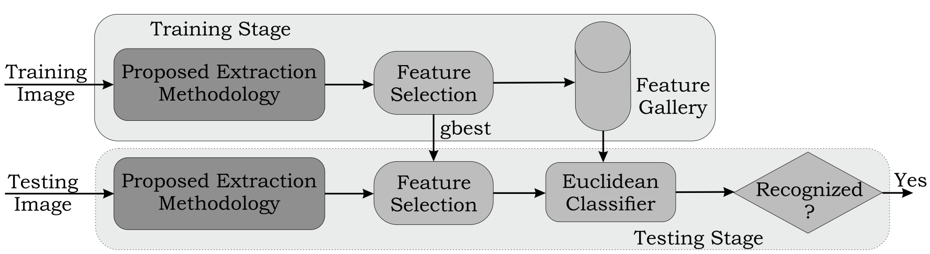


**Fig. 3.** Block diagram of proposed FR system. Our aim is to show the pose invariance, so we start directly with extraction. Extraction by DCT and DFT. Here we use both conventional method and proposed method to obtain the RR. After extraction its feature selection using BPSO. Finally the classification. Our main intention is to show the proposed methodology is better than the conventional for pose invariance,hence the image intensity correction, normalisation and all other precursors are left out.

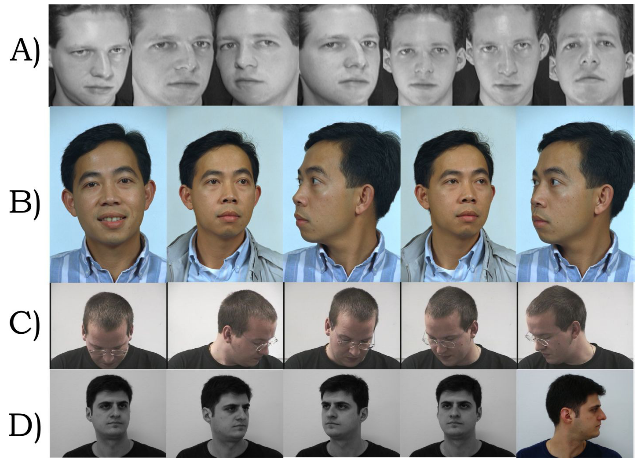


**Fig. 4.** Sample images of A) ORL dataset B) FERET dataset C) HP dataset D) FEI dataset .

number of images per subject, so it will be tedious job to fix the training set in order to have uniform contribution of RR from each subject. Fourth, to compare our results with the standard proven results.

All the experiments have been performed on a computer with specifications Intel Core$^{TM}$i7 2.2 GHz CPU and 8 GB RAM on MATLAB® 2012b[25]. Let the total number of subjects in the customized database be $T_{sub}$ and total images per subject be $T_{img}$. Let the total number of *random* images taken for training be $T_{tr}$ per subject. Then the total number of testing images are all the remaining ones given by $T_{img} - T_{tr}$ per subject. Each experiment is conducted for 20 trials and the results are averaged to *reduce the randomness introduced due to different training sets.*

**Color FERET database** FERET database[26], [27], [28], [29] which stands for Facial Recognition Technology database mainly accounts for pose, scale and costume variations. This is the challenging database to illustrate various poses. Images in this database consists of different sizes. We have chosen the 'smaller' type images whose size is 256×384. The customized database consists of total of 35 classes and 20 images per each class, accounting a total of 700 images. Each class includes 2 sets of fa, fb, pl, hl, pr, hr, qr, ql images and 4 random images totalling 20 images [30].

This experiment is performed to explain the importance of the proposed FR system using proposed methodology. The image is converted to gray scale. This image is reduced by a factor of 2 using Gaussian reduction technique. This converts the image from original size of 256×384 to 64×96. Now extraction is carried out using conventional DCT, DFT (next time the extraction is via proposed DCT, DFT techniques). The feature matrix is then reshaped to one

**Table 3.** Comparison of RR for different ratios of FERET.

| Ratio | DCT + DFT [30] | Proposed DCT method | Proposed DFT method |
|---|---|---|---|
| 8:12 | 80.23 | **83.55** | **83.97** |
| 12:8 | 88.07 | **90.04** | **89.96** |

dimension using raster scan [31]. Then the feature vector is sent to well known evolutionary algorithm Binary Particle Swarm Optimisation (BPSO) [31], [32], [33], [34], [35], [36], [37] and [38] for feature selection (to reduce the number of features in computation). The number of selected features after this stage comes out to be around 60 % of the input features. This is stored in feature gallery. Then the feature vector of the testing image is extracted in the same way as that of the training images. The extracted testing gallery is multiplied with the $g_{best}$ of the BPSO (obtained during the training time). This becomes the test image gallery. A simple Euclidean distance is used for the classification. This process is clearly shown in Fig. 3.

The whole process is repeated but this time using the proposed methodology of extraction. Here we choose the modulus value of the extracted vector before it moves on to next pipelines.

Fig. 5 and Fig. 6 show the proposed techniques. The image and its conventional DCT is shown and further due to proposed methodology, the new plot of only positive values are shown. DFT gives both radius and angle, but due to selection of radius Fig. 6 is obtained.

*Proposed application of modulus to the outputs of DCT and DFT has made the system invariant to the symmetric poses (if one pose is considered as original image, then other is its mirrored image). The above proved concept of modulo application is thus the reason for the pose neutralisation.*

Consider cross correlation as a metric to measure the factor of pose neutralization. Cross-correlation is taken between feature vectors of symmetric poses of the same personality. This cross correlation is measured for the extracted vectors from conventional and proposed methods for both DFT and DCT. These are tabulated in Table. 4. From this table it is very much clear that the proposed technique increases the correlation between the symmetric poses and proposed

**Table 4.** Cross correlation for two extreme poses is noted for conventional and proposed method. Higher cross-correlation is better. This experiment is done using 2 extreme profiles of FERET.

| Method | Cross-Correlation Value |
|---|---|
| Conventional DCT | 0.8723 |
| Conventional DFT real part | 0.9564 |
| Conventional DFT imaginary part | -0.0106 |
| **Proposed Modulo DCT** | **0.9798** |
| **Proposed Modulo DFT** | **0.9851** |

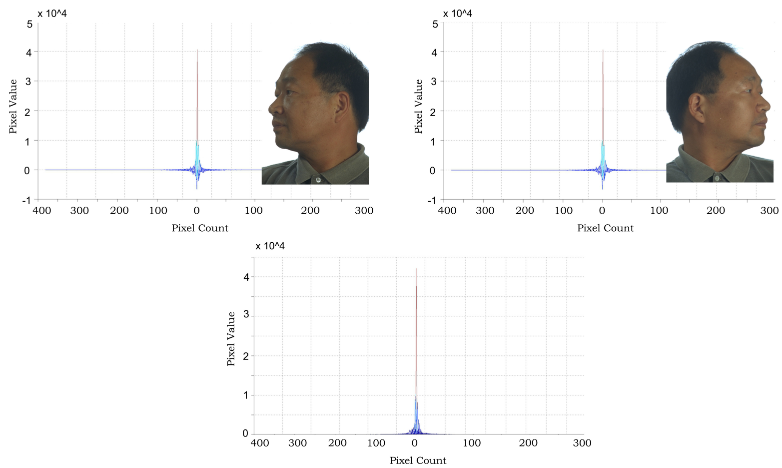


**Fig. 5.** Conventional DCT outputs of 2 extreme poses is shown in first row. This will have both negative and positive components along pixel values. Proposed modulo technique produces only the positive part which is exactly same for both the profile images and shown in second row. This means that for two different symmetric poses the system produces same features indicating pose invariance.

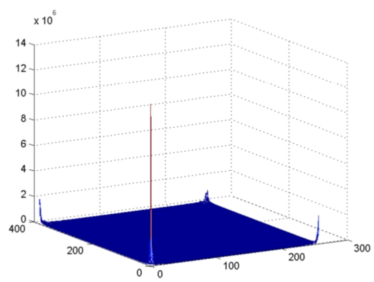


**Fig. 6.** Proposed DFT Output for an facial image of FERET dataset. The value on ‘y’ axis strats from zero indicating we have chosen only magnitude i.e., modulo radius and neglected the angle. DFT basically gives the frequency spectrum as shown in this figure.

method is the possible explanation for pose invariance. Final result is ‘0.9851’ not ‘1’. ‘One’ would have been the result if only mirror images are fed. Cross correlation between the full frontal pose and extreme left profile image will increase from 0.6236 to 0.8942. This shows that not only mirror images are recognized but also other poses. The similar center line features are enhanced.

Comparison of RR of FERET with others is done and is shown in Table. 3.

**Table 5.** Results for different ratio for all the databases. This includes RR from common conventional approach and the proposed approach. Both DFT, DCT results are tabulated in a single table so as it is very easy to compare.

| | DCT based | | DFT based | |
|---|---|---|---|---|
| **FERET** | Normal | **Proposed Method** | Normal | **Proposed Method** |
| Ratio | Avg. RR (%) | Avg.RR (%) | Avg. RR (%) | Avg.RR (%) |
| 4:16 | 56.91 | **65.78** | 22.58 | **69.72** |
| 6:14 | 67.83 | **76.14** | 25.67 | **78.43** |
| 8:12 | 75.47 | **83.55** | 27.07 | **83.97** |
| 10:10 | 78.85 | **85.89** | 29.80 | **86.43** |
| 12:8 | 84.53 | **90.04** | 31.79 | **89.96** |

| | DCT based | | DFT based | |
|---|---|---|---|---|
| **FEI** | Normal | **Proposed Method** | Normal | **Proposed Method** |
| Ratio | Avg. RR (%) | Avg.RR (%) | Avg. RR (%) | Avg.RR (%) |
| 4:6 | 84.72 | **88.57** | 35.00 | **84.81** |
| 5:5 | 88.40 | **91.83** | 34.46 | **87.89** |
| 6:4 | 91.50 | **92.29** | 38.79 | **90.15** |
| 7:3 | 92.67 | **95.14** | 40.28 | **92.24** |
| 8:2 | 92.15 | **95.15** | 39.43 | **92.29** |
| 9:1 | 92.86 | **97.15** | 38.57 | **93.72** |

**FEI database** FEI dataset [39] is also one of the benchmark facial database with pose variance like FERET database. This dataset contains 10 different pose of facial images. We have about 35 subjects in this class. As this has pose variant images, the proposed methodology increases RR which is as shown in Table. 5. The size of the image initially is 640×480. We apply three stages of Gaussian reduction to decrease the size and then the process as shown in Fig. 3.

## 5 Limitations and Future Work

This paper studies the symmetric property which helps for pose neutralization. There can be various properties of the extractors which has to be explored for various applications. We only discussed two transforms here, study has to be done on *various extractors and their properties.*

We have not concentrated on the initial pre-processing steps which will increase the recognition rates, as our concern was to prove the efficiency of the proposed method. Various pre-processing can be applied to obtain high recognition rates.

Future work is in extending this algorithm for various databases and real-time video applications. There are various properties like this symmetry property which can help in eliminating various discrepancies. *Efficient use of properties has to be done to improve the productivity of extractors.*

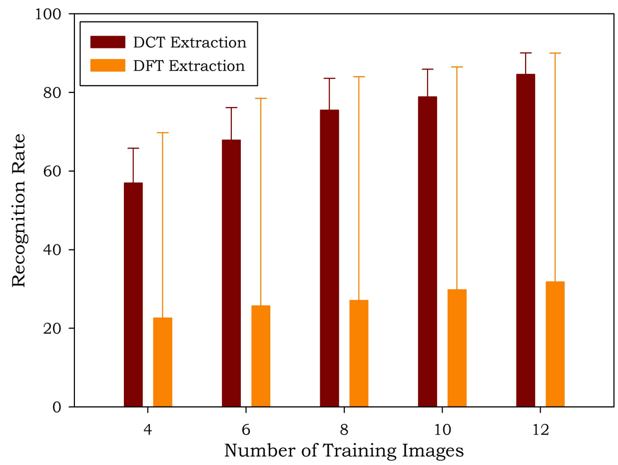


**Fig. 7.** The variation of use of proposed method over conventional method for FERET dataset is seen. The filled bars are the RR obtained for the conventional methods. The line extension is the increase provided by the proposed method. Proposed method increases RR to a greater extent when DFT is used.

## 6 Conclusion

Symmetry behavior of DCT and DFT are analyzed. General approach and specific approach both has been dealt here. We model the symmetric behavior of DCT and DFT for pose neutralization application.

High recognition rates are achieved for pose variant FERET and FEI dataset by using the proposed methodology and these results outperform the conventional methods.

Efficient use of properties DCT and DFT is achieved here. Application of *modulus* over DCT and DFT outputs proved to neutralize pose.

We here try to fill the research gap in the applications of various properties of feature extractors for efficient extraction.

## References

1. P.P.W. Zhao, R. Chellappa, A. Rosenfeld, "Face recognition: A literature survey", ACM Computing Surveys 35 (2003) 399–458.
2. X. Zhang, Y. Gao, "Face recognition across pose: A review", Pattern Recognition 42, 2009, 2876–2896.
3. O. De Vel and S. Aeberhard, "Line-based face recognition under varying pose", Pattern Analysis and Machine Intelligence, IEEE Transactions 21, (1999), 1081–1088.
4. P. N. Belhumeur, J. P. Hespanha, D. J. Kriegman, "Eigenfaces vs. fisherfaces: Recognition using class specific linear projection", Pattern Analysis and Machine Intelligence, IEEE Transactions 19, (1997), 711–720.

5. M. S. Bartlett, J. R. Movellan, T. J. Sejnowski, “Face recognition by independent component analysis”, Neural Networks, IEEE Transactions 13, (2002), 1450–1464.
6. L. Wiskott, J.-M. Fellous, N. Kuiger, and C. Von Der Malsburg, “Face recognition by elastic bunch graph matching”, Pattern Analysis and Machine Intelligence, IEEE Transactions 19, (1997), 775–779.
7. Turk, Matthew, Alex Pentland, “Eigenfaces for recognition”, Journal of cognitive neuroscience 3.1 (1991), 71–86.
8. N.J.M Agarwal, H. Agrawal, M. Kumar, “Face recognition using principle component analysis, eigenface and neural network”, in: Proceedings of the 2010 International Conference on Signal Acquisition and Processing, ICSAP ’10, IEEE Computer Society, 2010, 310–314.
9. Huang, Fu Jie, “Pose invariant face recognition”, Automatic Face and Gesture Recognition, Fourth IEEE International Conference (2000).
10. Beymer, David, Tomaso Poggio, “Face recognition from one example view.”, Computer Vision, Fifth International Conference, (1995).
11. Troje, Nikolaus F, Heinrich H. Blthoff, “How is bilateral symmetry of human faces used for recognition of novel views?.”, Vision Research 38.1 , (1998), 79-89.
12. Gonzlez-Jimnez, Daniel, Jos Luis Alba-Castro, “Toward pose-invariant 2-d face recognition through point distribution models and facial symmetry.”, Information Forensics and Security, IEEE Transactions on 2.3 , (2007), 413-429.
13. Gonzlez-Jimnez, Daniel, Jos Luis Alba-Castro, “Locally linear regression for pose-invariant face recognition.”, Image Processing, IEEE Transactions on 16.7 , (2007), 1716-1725.
14. Troje, Nikolaus F, Heinrich H. Blthoff, “Face recognition under varying poses: The role of texture and shape.”, Vision research 36.12 , (1996), 1761-1771.
15. A.F. Abate, M. Nappi, D. Riccio, G. Sabatino, “2D and 3D face recognition: A survey”, Pattern Recognition Letters 28, (2007), 1885–1906.
16. R. Brunelli, T. Poggio, “Face recognition: Features versus templates”, IEEE Transactions on Pattern Analysis and Machine Intelligence 15 (1993) 1042–1052.
17. S. Chen, Y. Zhu, “Subpattern-based principal component analysis”, Pattern Recognition 37 (2004) 1081–1083.
18. M. Nixon, A.S. Aquado, “Feature Extraction & Image Processing”, Second Edition, Academic Press, 2nd edition, 2008.
19. S. Chen, D. Zhang, Z.H. Zhou, “Enhanced (pc) 2 a for face recognition with one training image per person”, Pattern Recognition Letters 25 (2004a) 1173–1181.
20. S. Chen, J. Liu, Z.H. Zhou, “Making flda applicable to face recognition with one sample per person”, Pattern Recognition 37 (2004b) 1553–1555.
21. W.L. Scott II, “Block-level discrete cosine transform coefficients for autonomic face recognition”, Ph.D. thesis, 2003.
22. Z. M. Hafed, M. D. Levine, “Face recognition using the discrete cosine transform”, International Journal of Computer Vision 43, (2001), 167–188.
23. A.S. Samra, S.E.T.G. Allah, R.M. Ibrahim, “Face recognition using wavelet transform, fast fourier transform and discrete cosine transform”, Proceedings 46th IEEE International Midwest Symposium Circuits and Systems (MWSCAS’03) 1 (2003) 272–275.
24. Bracewell, Ronald Newbold, R. N. Bracewell, in: “The Fourier transform and its applications.”, New York: McGraw-Hill, 1986,
25. MATLAB, www.mathworks.com.
26. Color FERET, http://www.nist.gov/itl/iad/ig/colorferet.cfm.

27. P.J. Phillips, H. Moon, S.A. Rizvi, P.J. Rauss, "The feret evaluation methodology for face-recognition algorithms", IEEE Transactions on Pattern Analysis and Machine Intelligence 22 (2000) 1090–1104.
28. P.J. Phillips, H. Wechslerb, J. Huang, P.J. Rauss, "The feret database and evaluation procedure for face recognition algorithms", Image and Vision Computing (1998) 295–306.
29. Y. Zhu, J. Liu , S. Chen "Semi-random subspace method for face recognition", Image and Vision Computing 27, (2009), 1358–1370.
30. G. Deepa, R. Keerthi, N. Meghana, and K. Manikantan "Face recognition using spectrum-based feature extraction", Applied Soft Computing 12, (2012), 2913–2923.
31. R. M. Ramadan, R. F. Abdel-Kader, "Face recognition using particle swarm optimization-based selected features", International Journal of Signal Processing, Image Processing and Pattern Recognition 2, (2009), 51–65.
32. A. P. Engelbrecht, in: "Fundamentals of computational swarm intelligence.", Wiley Chichester, 2005
33. X. Fan, B. Verma, "Face recognition: a new feature selection and classification technique", Proc. 7th Asia-Pacific Conference on Complex Systems (2004).
34. H.R. Kanan, K. Faez , M. Hosseinzadeh, "Face recognition system using ant colony optimization-based selected features", Proceedings IEEE Symposium Computational Intelligence in Security and Defense Applications (CISDA 2007) (2007) 57–62.
35. R. Eberhart, J. Kennedy, "A new optimizer using particles swarm theory", Proceedings 6th International Symposium Micro Machine and Human Science (1995) 39–43.
36. J. Kennedy, R. Eberhart, "A discrete binary version of the particle swarm algorithm", Proceedings IEEE International Conference on Systems, Man, and Cybernetics 5 (1997) 4104–4108.
37. C. Liu, H. Wechsler, "Evolutionary pursuit and its application to face recognition", IEEE Transactions on Pattern Analysis and Machine Intelligence 22 (2000) 570–582.
38. P. Narendra, K. Fukunage, "A branch and bound algorithm for feature subset selection", IEEE Transactions Computers 6 (1977) 917–922.
39. FEI Database, http://fei.edu.br/~cet/facedatabase.html.