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An effectual multiscale feature extraction in integer wavelet transform domain for illumination invariable face recognition

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Abstract: Face recognition biometric recognises human faces effectively where their performance is critically affected under deviating light effects. This work presents an efficient illumination invariant feature extraction technique using homomorphic filtering in integer wavelet transform (IWT) domain. The goal of this investigation is to subdue the low frequency components in small-scale extracted features with the simultaneous perpetuation of rugged texture components in face images. The technique exploits homomorphic filtering based illumination normalised (HFIN) images which are then utilised in analysing the low and high pass frequency coefficients. Furthermore, IWT-based multiscale features (MFIWT) over HFIN images are examined with orthogonal and biorthogonal wavelets. The HFIN-MFIWT features are hereafter mapped onto non-correlated lower dimensional subspace using eigenface mechanism. Significant facial features are then classified using K-nearest neighbour. The efficacy of HFIN-MFIWT approach is assessed on Yale, Yale B, CMU-PIE, and extended Yale B databases that evidently authenticate its effectiveness.

Keywords: integer wavelet transform; IWT; illumination invariant; face recognition; homomorphic filtering; wavelet families.

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1 Introduction

Among various biometric automatic systems, face recognition has gained substantial consideration in several real-world applications such as access control, authentication of personal identity, security investigations, law enforcement, etc. (Zhao et al., 2003; Ali et al., 2020). It has been observed that vigorous research is still prevailing in the field of face recognition over other biometric systems, due to high recognition and verification rates that provide accurate identification of an individual. A conventional face recognition approach includes four major steps, namely preprocessing, extraction of facial features, feature selection, and face matching or recognition from digital face images. However, feature extraction is considered to be a vital step as the effectiveness of any modelled face recognition system depends critically on the extracted significant facial features (Yu et al., 2017). Some of the major challenges under which the appearance of a person changes drastically are, pose variations, occlusion, low resolution, unavoidable illumination conditions, etc. (Singh and Prasad, 2018). Consequently, this causes both interpersonal and intrapersonal deviations that make the development of face recognition systems more difficult.

The variations in light effects are one of the major inevitable situations during the acquisition of images, which subsequently reduces the visibility of acquired face images (Chen and Xie, 2020). During biometric scanning, the uncontrolled light beams are projected on face images with varying intensities from different angles of projection (Chen et al., 2015, 2017), which impacts the accuracy of face recognition systems. The intrapersonal differences caused under an uncontrolled illumination environment are higher than that for different persons (Ahmed et al., 2021). The compensation of pixel intensities that abruptly changes under varied environment, is a foremost step for annulling the effects of light deviations incident on images. The role of normalisation techniques is vital in designing the framework for illumination invariant face recognition models. The selection as well as the elimination of significant facial features while normalising the face images, under abrupt illumination changes also affects the recognition rates and computational time immensely (Yadav et al., 2018a). Moreover, illumination effects are prominent in the low frequency component of facial images and while performing the normalisation process, substantial information in low frequency domain may be lost which affects the effectiveness of face recognition systems. Similarly, when efforts are made to preserve the high frequency components in face images, some noise causing artefacts are not discarded successfully and thus affecting the efficacy of face recognition systems. Therefore, an illumination normalisation framework

for face recognition under distinct illumination circumstances must have the capability, to preserve appropriate low frequency components while subduing the illumination effects.

The face recognition models should be able to select the appropriate high frequency components while subduing the low frequency-based facial components (Yadav et al., 2019). Hence, it is desired to propose a feature extraction technique that permits the multiscale feature analysis of face images wherein, the effective examination of both low and high frequency-based facial features is performed effectively. Therefore, in this work, an effectual multiscale feature extraction-based illumination invariable face recognition technique is proposed, that evenly distributes the intensity levels of face images and abates the noise-related information. The proposed multiscale feature extraction technique contributes effectually to accentuating the hidden facial information which is reduced under diverse illumination situations. The objective of designing the proposed illumination invariant face recognition technique is to suppress the noise-related components and to normalise the abruptly changing images in coarse complex light variations while preserving the appropriate multiscale features. The presented approach is based on homomorphic filtering-based illumination normalised images in the integer wavelet transform (IWT) domain. The major contributions of the proposed work are emphasised as:

- Homomorphic filtering-based illumination normalisation (HFIN) for face images under distinct illumination conditions.
- Multiscale feature extraction of HFIN images in the IWT domain (HFIN-MFIWT) with an appropriate selection of facial features.

The presented work is organised as: in Section 2, the existing work related to illumination-normalised face recognition is briefly illustrated. In Section 3, the implementation of the proposed method along with the algorithm description is suitably explained. Section 4 describes the accomplished experimental results. Comparative analysis with other state-of-art techniques is illustrated in Section 5. Finally, Section 6 concludes the proposed work

2 Related work

A lot of work has been proposed in past years related to face recognition for achieving prominent recognition rates under various constraint environments. In this section, a comprehensive review of the recent face recognition methods to overcome the problem of illumination deviations has been presented. It has been seen that the normalisation of illumination effects on face images in previous years has been broadly performed in three different ways: extraction of illumination invariant features; representation of illumination insensitive components, and adjustment of local and global contrast with various preprocessing methods.

Some of the earlier photometric techniques are: logarithmic transformations (Savvides and Kumar, 2003), gamma intensity correction (Shan et al., 2003), self-quotient image (SQI) (Wang et al., 2004), histogram equalisation (Xie and Lam, 2005), single scale retinex (Park et al., 2008), Weber faces (WF) (Wang et al., 2011), generalised Weber faces (GWF) (Wu et al., 2014), etc. (Savvides and Kumar, 2003) has employed a simple preprocessing technique to compensate the varying illumination

effects by transforming the images in the logarithmic domain that maps the pixel intensities nonlinearly. Gamma correction has been proposed by Shan et al. (2003) for discarding the side illuminations on captured images wherein, the brightness is enhanced based on the gamma parameter. Wang et al. (2004) presented a concept of SQIs which computes the ratio of original images with a smoothing mask to sustain the intrinsic facial components.

An improved histogram equalisation technique was proposed by Xie and Lam (2005) which is based on small image blocks to suppress the varying light effects. Park et al. (2008) proposed a face recognition method under moderate illumination situations based on Retinex and an adaptive smoothing filter, convoluted over face images iteratively based on the choice of normalising factor utilised in evaluated conduction function. Another, idea for representing images using Lambertian model is WF, which computes the ratio of pixel intensity and constant background levels (Wang et al., 2011). An enhanced model was proposed by Wu et al. (2014) wherein GWF and weighed generalised Weber faces (wGWF) was implemented based on Gaussian filtered images for the determination of multiresolution information. The stated techniques are based on transforming the pixel intensity values and help in improving the overall contrast of images. However, complex illumination deviations are difficult to analyse using the above-stated methods.

Another category includes illumination invariant feature extraction-based face recognition methods. Ahonen et al. (2006) proposed local binary pattern (LBP) technique, which was robust for monotonic illumination deviations but, was not able to achieve good results under the effects of random noise. Therefore, local directional pattern was presented by Jabid et al. (2010) in which the image is described by a directional local descriptor formed by comparing the response of edges and hence is more robust than LBP technique. Lei et al. (2014) investigated discriminant face descriptor (DFD)-based method for analysing both homogenous and heterogeneous face images based on discriminant kernels. Local vector pattern (LVP)-based feature extraction method was proposed by Fan and Hung (2014) where each pixel was represented as a vector by evaluating the values of referencing and adjacent pixels. In another work, Faraji and Qi (2014) introduced an effective edge enhancer approach based on log function and fractal texture analysis method known as logarithmic fractal dimension (LFD). The performance of face recognition systems was enhanced by Juneja et al. (2015) based on local tetra pattern (LTrP) face descriptor, to extract more detailed information by utilising higher-order derivative neighbourhoods. These stated methods were capable of yielding significant illumination-insensitive facial vectors but, were unable to annul the noise-related components while preserving the substantial facial information.

For resolving the issue of noise effect in face images while retaining significant facial features, various transformation-based methods have been proposed. Petpon and Srisuk (2010), Hu (2011), Emadi et al. (2012) and Vidya et al. (2012) have presented discrete wavelet transform (DWT)-based face recognition techniques. Yuan et al. (2013) introduced a homomorphic wavelet transform-based illumination normalisation (HWIN) technique, based on a difference of Gaussian filter by utilising the approximation facial coefficients. The implementation of DWT-based methods is simple and easy, as the orthogonal wavelet families such as Haar, Symlets, Daubechies, etc., requires only addition and subtraction operations for their forward and inverse transformations. Vishwakarma (2015) presented a fuzzy filter-based face recognition approach in discrete cosine transform (DCT) domain under varying illumination situations. Wang et al. (2018)

proposed an adaptive singular value decomposition in DWT domain to overcome the impact of illumination possession. Ayyavoo and Suseela (2018) investigated an illumination invariant preprocessing approach for frontal faces based on two-dimensional discrete wavelet transform and enhanced contrast limited adaptive histogram equalisation (DWT-E-CLAHE) method. Thamizharasi and Jayasudha (2020) later introduced an enhanced approach based on improved energy of DWT with additional weighting parameters.

A normalisation method based on selective large-scale feature extraction of homomorphic filtering and reflectance ratio images in discrete wavelet transform (HFRIN-SFDWT) domain has been instigated by Yadav et al. (2018a). The reflectance ratio (RR) images are attained by computing the ratio of every pixel intensity to the mean of its considered local neighbourhood of suitable size. Yadav et al. (2018b) also proposed an illumination invariant face recognition technique based on reflectance ratio and contrast stretching (RRCS) preprocessing mechanism in IWT domain for extracting large-scale facial features. Later, Yadav et al. (2019) exploited the concept of RR in the discrete wavelet packet transform (DWPT) domain for normalising the histograms of images, to enhance the performance under low to complex light effects. Recently, Chaudhary and Yadav (2022) presented a method for extracting large-scale facial features based on double density dual tree complex wavelet (DD_DTCWT) transformation, to achieve high frequency facial coefficients in varied directions.

The above-stated transformation-based feature extraction techniques were capable enough in normalising the variable illumination with an investigation of either large-scale or small-scale facial features. To render the illumination deviations in images having heterogeneous wavelengths, Roy and Bhattacharjee (2016) proposed LG-face method that utilises a concept of gravitational local angles, to eliminate the low frequency components effectively. Yu and Wu (2017) presented a deep learning-based two-dimensional principal component analysis (2DPCANet) and histogram computation with an extreme learning machine classifier. A median and Gabor filter along with histogram equalisation has been utilised by Li et al. (2018) in eigensubspace to normalise the lighting variations based on the SVM classifier. Zhang et al. (2019) presented a retina model based on a logarithmic total variation algorithm to overcome the illumination differences by utilising CLAHE to enhance the high frequency features.

It has been observed from the abovementioned techniques, that the existing methods have immensely intricated low frequency details without preserving the high frequency content under varied illumination conditions. Moreover, some approaches have effectively preprocessed the illumination effects but, were unsuccessful in yielding accurate results under extreme lighting effects. While in some methods, the extraction of discriminating features was performed effectually but was unable to eliminate the noise components. The prior approaches in many cases were not efficient in maintaining the evenness of extracted facial features. Hence, the main motivation of the present investigation is to propose an effective multiscale feature analysis method in IWT domain for illumination insensitive face recognition. In this work, the multiscale analysis of homomorphic filtering based illumination normalised (HFIN) images in IWT (HFIN-MFIWT) domain for face recognition is proposed that performs effectually under uncontrolled lighting.

3 Multiscale feature extraction in IWT domain based on HFIN images

This section of the work illustrates the methods utilised for compensating and normalising the illumination effects, on individual face images from varied directions and intensities. Herein, the process of obtaining the homomorphic filtering-based illumination normalised (HFIN) images and the multiscale feature extraction in integer wavelet transform (MFIWT) domain for HFIN images is explained briefly. Thereafter, the implementation of large-scale and small-scale features based on different wavelet families is also described.

3.1 Homomorphic filtering-based illumination normalisation

The homomorphic filtering method utilises an image formation model to efficiently compensate varied illumination pixel intensities and enhance the images (Fan and Zhang, 2011; Xiao et al., 2016). According to the illumination reflectance-based image formation model the intensity function $F(r, s)$ of an image at location (r, s) in spatial domain can be demonstrated as product of illumination $I(r, s)$ and reflectance $R(r, s)$ components as provided in equation (1) as:

$$F(r, s) = I(r, s) * R(r, s) \quad (1)$$

The illumination and reflectance components of an image are thereby segregated by taking a logarithmic transformation of equation (1) which is described in equation (2)

$$\ln[F(r, s)] = Y(r, s) = \ln[I(r, s)] + \ln[R(r, s)] \quad (2)$$

Then, the Fourier transformation of an image is taken as given in equation (3).

$$\begin{aligned} \mathfrak{S}[Y(r, s)] &= \mathfrak{S}[I(r, s)] + \mathfrak{S}[R(r, s)] \\ &= I'(p, q) + R'(p, q) = Y'(p, q) \end{aligned} \quad (3)$$

In the next step, Butterworth high pass filtering function $H(p, q)$ (Shahamat and Pouyan, 2014; Yadav et al., 2018a) is multiplied with transformed image $Y'(p, q)$ to discard the low frequency components as indicated in equation (4). Furthermore, the utilised Butterworth high pass filter function $H(p, q)$ is expressed in equation (5) wherein $\mu\omega$ and \tilde{N} represents the value of threshold frequency and filter order, respectively.

$$\begin{aligned} X(p, q) &= H(p, q) \cdot Y'(p, q) \\ X(p, q) &= H(p, q) \cdot \mathfrak{S}[I(p, q)] + H(p, q) \cdot \mathfrak{S}[R(p, q)] \end{aligned} \quad (4)$$

$$H(p, q) = \left[1 / \left(1 + (\mu\omega / (D(p, q)))^{2\tilde{N}} \right) \right] \quad (5)$$

In this proposed work, the value of threshold frequency ($\mu\omega$) and the order of filter (\tilde{N}), is set empirically as described in Section 4.1. After this, to recuperate the filtered image in spatial domain $X(p, q)$, an inverse Fourier transform is performed on equation (4) as stated in equation (6).

$$\mathfrak{S}^{-1}[X(p, q)] = \mathfrak{S}^{-1}[H(p, q) \cdot \mathfrak{S}[I(p, q)] + H(p, q) \cdot \mathfrak{S}[R(p, q)]] = X(r, s) \quad (6)$$

Finally, an exponential function is applied to get a homomorphic filtering illumination normalised HFIN image as specified in equation (7).

$$c(r, s) = e^{[X(r,s)]} \tag{7}$$

The proposed work has utilised the homomorphic filtering technique to eliminate the artefacts caused due to varying light effects that consequently result in improving the facial features effectively. The critical selection of threshold frequency value $\mu\omega$ for Butterworth high pass filter aids in suppressing the low frequency components while preserving the fine details of a face image. Altogether, the attained homomorphic filtering-based illumination normalised (HFIN) face images have warded off the illumination differences efficiently. The block diagram illustrating the procedure of homomorphic filtering is depicted in Figure 1, and the result of HFIN features under low to extreme lighting variations is illustrated in Figure 2.

Figure 1 Block diagram illustrating the process of homomorphic filtering (see online version for colours)

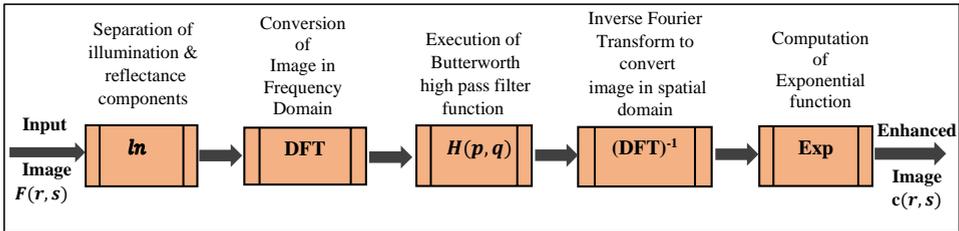
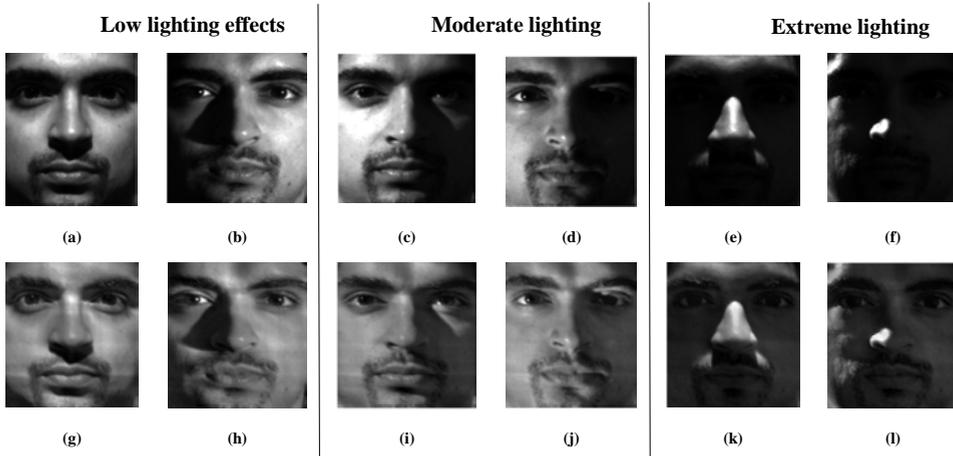


Figure 2 Results of HFIN, (a)–(b) sample face images with low illumination effects (c)–(d) sample face images with moderate illumination deviations (e)–(f) sample face image with extremely high illumination variations, HFIN resulting images, (g)–(h) face image of (a) and (b) (i)–(j) face image of (c) and (d), (k)–(l) face image of (e) and (f)



3.2 Multiscale feature extraction based on integer wavelet transform

As aforementioned, the lighting effects are relatively annulled by employing HFIN. The Butterworth high pass filter is thus utilised in the filtering process, credits in subduing the low frequency components up to an extent while preserving the high frequency components. Hence, this work accomplishes the multispectral analysis of both small-scale and large-scale HFIN facial features, while sustaining significant frequency coefficients for modelling an effective face recognition system. DWT (Shensa, 1992; Du and Ward, 2005) is an effective tool for analysing multiscale frequency coefficients of an image, which is employed in many pattern recognition applications (Nayak et al., 2016; Kovac et al., 2018; Yang et al., 2019; Amin et al., 2020). DWT permits the examination of an image in both time and frequency domain. This technique also provides a multiresolution analysis of face images, by decomposing the considered images into approximation and detailed frequency coefficients, respectively. DWT is desirable for selecting the appropriate facial features that thereby impact the classification techniques utilised in face recognition models. Though DWT has been utilised for multispectral decomposition, however, due to the existence of real-valued DWT-based frequency coefficients, the execution of floating-point operations on such coefficients increases the computational cost and memory requirements, respectively. Hence, the multiscale analysis of face images using a fast and effective lifting scheme is more beneficent.

A second-generation transformation approach based on a lifting scheme mechanism commonly known as IWT was proposed by Sweldens (1996). Unlike DWT, the IWT technique does not involve floating point numbers as the outputs of high and low pass filter operations are rounded off to the nearest integer value (Grangetto et al., 2002). Consequently, this evades the errors that may occur due to rounding of floating-point numbers to approachable integers. So, in this presented HFIN-MFIWT-based face recognition approach, significant facial information is obtained by utilising lifting scheme-based IWT technique. The multispectral analysis of images using lifting scheme in IWT domain, has some inimitable characteristics such as:

- 1 the speed of transformation is faster as only half the number of calculations is required as compared to the classical DWT method that involves convolution operation
- 2 this does not include any extra storage as no auxiliary memory is essential in lifting scheme.

The three major steps of lifting scheme-based IWT transformation are described as:

Step 1 This first step is known as step or lazy wavelet transform includes the division of the complete set of an input image ($h[x]$) into two parts. The first fragment consists of even indices of the input image such as $i_0, i_2, i_4, \dots, i_{2x}$ denoted by $i[x]$ in equation (8) while another part contains the remaining odd indices such as $j_1, j_3, j_5, \dots, j_{2n+1}$ implied by $j[x]$ in equation (9).

$$i[x] = i_0, i_2, i_4, \dots, i_{2x} \tag{8}$$

$$j[x] = j_1, j_3, j_5, \dots, j_{2x+1} \tag{9}$$

Step 2 In this step, dual lifting or predict stage, the odd indexed intensities are predicted from even indexed by computing a predictor operator (Z) as defined in equation (10)

$$j[x] = Z(i[x]) \tag{10}$$

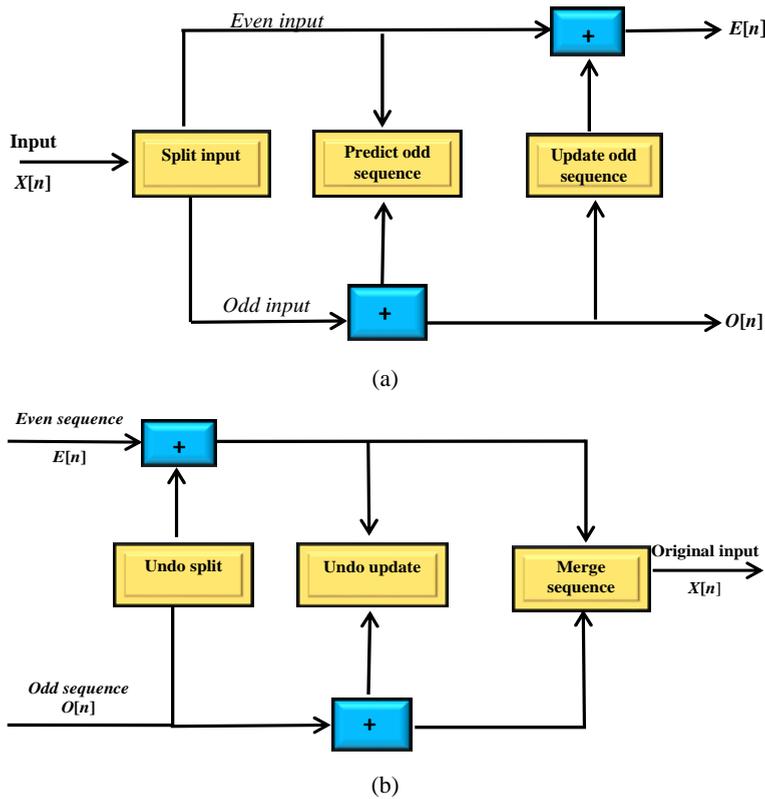
But practically, to exactly predict the value of $j[x]$ from $i[x]$ is unfeasible. Moreover, $i[x]$ is fairly approachable to $j[x]$, hence, $i[x]$ is substituted with the difference between itself and its predicted value as denoted in equation (11):

$$j[x] = i[x] - Z(i[x]) \tag{11}$$

Step 3 This step is commonly known as the *primal lifting* stage in which the odd indexed intensities $i[x]$ are updated based on IWT coefficients $j[x]$ to attain a similar mean value for the approximation coefficient as of original input. The process of updating $i[x]$ is accomplished using the update operator (Y) as denoted in equation (12). The process of decomposition and reconstruction of input signals in IWT domain is illustrated in Figures 3(a) and 3(b), respectively.

$$i[x] = i[x] + Y(j[x]) \tag{12}$$

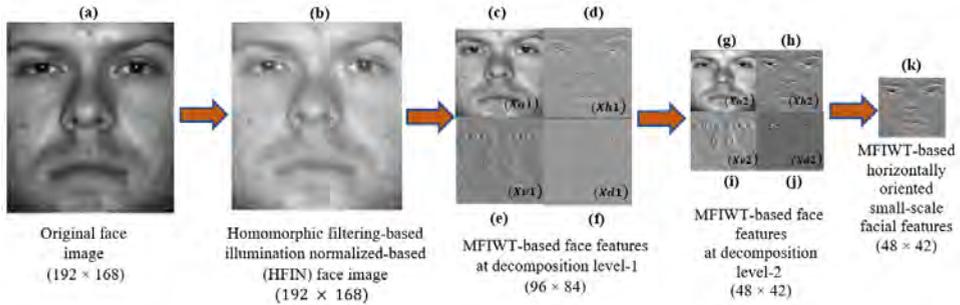
Figure 3 (a) Decomposition of input in IWT domain (b) Reconstruction of decomposed input in IWT domain (see online version for colours)



In this work, HFIN images are transformed in IWT domain for extracting both large-scale and small-scale facial features for multiscale feature analysis. Thereby, the HFIN images are exhaustively examined with different wavelet families at varying levels of decomposition. During the process of accomplishing the MFIWT domain, firstly, IWT-based multiscale facial features are inspected at decomposition level 1 that thereby splitting the HFIN image into large-scale and small-scale features, respectively. Subsequently, the extracted large-scale facial features are selected which are further decomposed into large-scale and small-scale features at the second decomposition level for achieving effective multiscale feature coefficients. Finally, the large-scale facial features are selected from the small-scale features attained at decomposition level 2 for accomplishing prominent recognition rates.

Experiments have been performed exhaustively for IWT-based multiscale features selection based on the suitable selection of wavelets among orthogonal (Daubechies and Symlets), and biorthogonal wavelet families as discussed in Section 4.2. Consequently, the above-mentioned HFIN-MFIWT-based illumination invariable face recognition approach reduces the size of original face images from 192×168 to 48×42 . This reduced-sized facial feature vector space sustains the significant features which are further utilised in the classification phase. The resulting images of MFIWT domain are presented in Figure 4.

Figure 4 Results of multiscale facial feature extraction in integer wavelet transform (MFIWT) domain, (a) original face image (b) HFIN-based face image (c) MFIWT-based large-scale facial features at decomposition level 1 (d)–(f) MFIWT-based small-scale facial features in horizontal, vertical and diagonal directions respectively (g) MFIWT-based large-scale facial features at decomposition level 2 attained by utilising level 1 large-scale face features (h)–(j) small-scale facial features in horizontal, vertical and diagonal directions respectively (k) MFIWT-based horizontally oriented small-scale face features (see online version for colours)



As aforesaid, the choice of suitable wavelet filter can be performed prominently, by selecting them among different existing wavelet families which are broadly classified as orthogonal and biorthogonal wavelets, respectively. The wavelet families vary based on some significant parameters namely, orthogonality, support size, vanishing moments, symmetry, regularity, constructed scaling functions and filter order. Moreover, the complexity and recognition rates of modelled face recognition systems are hereby reliant on the above-stated wavelet criteria. The wavelet filters of both orthogonal and biorthogonal wavelet families are analysed for multiscale feature selection using the lifting scheme-based IWT technique. The orthogonal wavelet family filter structure incorporates a single scaling and wavelet function for both the analysis and synthesis of

images that are not necessarily symmetrical (Prasad and Umamadhuri, 2018). Due to the existence of the orthogonality condition, the orthogonal wavelets are considered to be inflexible, and the complex structure of filter banks also abolishes the linear phase property. As stated in the study (Liu and Wu, 2020), the scaling function sequence must be orthogonal to any number of shifts with only an even number of coefficients.

The orthogonal wavelets such as Haar, Symlets, etc. are compact and have finite support that helps in decomposing an image in fine orthogonal space. The effectiveness of face recognition systems is inversely proportional to the support size of orthogonal wavelets due to which as the wavelets' support size increases the recognition rates decrease that thereby may introduce edge artefacts also. Although, for the examination of complex or fine facial features it is desirable to utilise wavelets with large support sizes. To overcome this drawback, the biorthogonal wavelet family-based wavelet filters are introduced, which utilises one pair of scaling and wavelet function for decomposition and another one for reconstruction (Prasad et al., 2016). The design of symmetric biorthogonal wavelet filters provides a greater number of degrees of freedom, that eventually improves the regularity and smoothness of filter banks. The biorthogonal wavelet family is considered to be more flexible than orthogonal wavelets, as these wavelets are not restrained to exist in the orthogonality condition. Also, it has been stated that the symmetry of wavelets and orthogonality property are incompatible with each other, therefore the biorthogonal wavelets design is symmetrical. The relaxation from orthogonality condition, also allows biorthogonal wavelets to preserve the linear phase characteristic which in turn preserves the phase relationship between input signals.

In biorthogonal wavelets, there can be more than one scaling and wavelet basis function that helps in accomplishing the improved multiresolution analysis of decomposed images. The linear phase property also permits the biorthogonal wavelet family to be considered as a perfect image reconstruction filter bank (Sweldens, 1996). Hence, in this work, the biorthogonal wavelet family when utilised at the appropriate level of decomposition on IWT-based small-scale features yielded prominent results for face recognition. The general notation of biorthogonal wavelets in the MATLAB environment is expressed as *bior* $N_D N_R$, wherein the filter order of decomposition and reconstruction filter is specified by N_D and N_R , respectively. Hence, the extraction of discriminating facial features in computationally efficient IWT domain, improves the accuracy of the proposed multiscale feature extraction technique for recognising facial images.

3.3 Orthogonal linear projection of extracted HFIN-MFIWT features based on eigenspace analysis

The multiscale robust facial features obtained by utilising HFIN, and IWT-based feature extraction using biorthogonal wavelets are hereafter projected onto non-correlated lower dimensional feature vector subspace. This is performed by orthogonal linear transformation based on principal component analysis (PCA) using eigenface mechanism (Turk and Pentland, 1991). This method provides uncorrelated features with maximum variance as best discriminating features in lowered subspace based on orthogonal basis transformations. PCA represents the entire set of images as a face vector matrix, that comprises each image contained in the dataset as a columnar vector. Firstly, the image space for training purpose Y is formulated as expressed in equation (13)

$$Y = y_1, y_2, y_3, \dots, y_N \quad (13)$$

Then, a covariance matrix is computed by utilising equation (14), to provide the reduced dimensional eigensubspace for face matrix Y as:

$$\hat{C} = \frac{1}{N} \sum_{i=1}^N (Y_i - \tilde{Y}) \cdot (Y_i - \tilde{Y})^T \quad (14)$$

Subsequently, eigenvalue and eigenvectors are evaluated for the above-expressed covariance matrix, out of which the best discriminating features with the highest eigenvalues are selected (known as principal components) and the remaining features are rejected. This resulted in a projection matrix over which both train and test feature vectors are mapped. In the proposed work, the large feature vector space of HFIN-MFIWT-based face images is reduced in the lower dimensional eigensubspace, which thereby aids in choosing the appropriate facial features.

3.4 *Classification based on K-nearest neighbour classifier*

In this section, the proposed HFIN-MFIWT approach employs a computationally effective K-nearest neighbour (KNN) method, to accurately recognise the lower dimensional test face image vector. The face matching or recognition phase is considered an imperative phase in face recognition that effectively performs a similarity search by assigning class labels to the uncategorised face images. In this work, KNN-based supervised learning technique has been exploited due to its simplicity and ease in providing better recognition rates over large databases effectively. Moreover, this technique does not require any modelling and tuning of different parameters with certain assumptions as in the case of other complex classification techniques. This technique utilises different distance metrics between the feature datapoint and the considered neighbours (Jose et al., 2012). Hence, the selection of two important criteria over which the KNN classifier provides prominent results are the number of neighbours and the distance metric utilised for calculating the distance between the test and train images. Moreover, the technique assigns the class label of the closest neighbour assessed using the chosen distance measure to the particular test face vectors. The efficacy of the investigated technique is estimated based on a recognition rate, by computing the percentage ratio of matched face images with total images in the testing set.

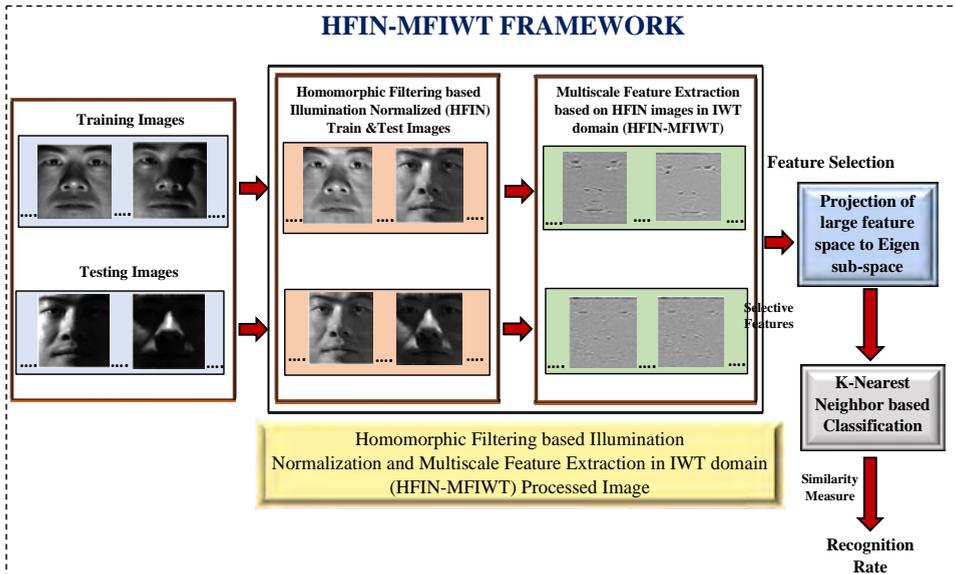
3.5 *Algorithm description of proposed HFIN-MFIWT illumination invariant face recognition technique*

The algorithm description of the presented technique is mentioned below, and the systematic flow diagram of the proposed face recognition technique is illustrated in Figure 5:

- 1 Preserve high frequency coefficients and repudiate the contribution made by low frequency-components by utilising a Butterworth high pass filter in the homomorphic filtering process. An appropriate threshold frequency (μ_0) and filter order (\tilde{N}) are chosen to obtain HFIN-based face images.

- 2 Perform multiscale feature analysis on obtained HFIN images using computationally efficient IWT.
- 3 Investigate a significant feature out of large-scale (X_a) and small-scale (X_h, X_v and X_d facial coefficients) on pertinent decomposition level (varied between 1 to 3) for choosing HFIN-based MFIWT domain.
- 4 Exhaustively examine an appropriate biorthogonal wavelet by assessing the appropriate vanishing moment for reconstruction and decomposition over orthogonal wavelets on HFIN-MFIWT images.
- 5 Apply an elementary PCA method to abate the dimensional space of HFIN-MFIWT-based non-correlated facial features by significantly preserving the selected sub-dimensions in a reduced feature vector matrix.
- 6 Employ a computationally effective KNN method to accurately perform the classification of HFIN-MFIWT-based processed images by utilising a suitable distance measure between the selected test and train feature vectors efficiently.
- 7 Lastly, evaluate the percentage recognition rates for assessing the efficacy of the presented face recognition approach.
- 8 Subsequently, reiterate the aforementioned steps for comprehensive implementation of HFIN-MFIWT-based lighting invariant face recognition.

Figure 5 Systematic flow diagram of proposed HFIN-MFIWT framework for illumination invariable face recognition (see online version for colours)



4 Experimental results

The performance evaluation of the proposed HFIN-MFIWT approach on Yale, Yale B, CMU-PIE, and extended Yale B face databases, with varying low to high lighting effects is presented in this section. Also, the experiments are exhaustively performed on a system with specifications, such as 8 GB RAM, 11th Gen. Intel Core i5 processor with 2.42 GHz CPU speed, and 64-bit operating system. The experimentations are divided into three categories such as:

- a selection of appropriate large-scale and small-scale facial features
- b selection of suitable decomposition level
- c investigation of appropriate wavelet family.

4.1 *Significant selection of appropriate facial features at suitable decomposition level for the proposed HFIN-MFIWT technique*

The determination of suitable multiscale facial feature coefficients and level of decomposition are the two important baselines, for the effective examination of the proposed face recognition approach. Besides, the selection of two other parameters, i.e., threshold frequency ($\mu\omega$) and the filter order (\tilde{N}), thus utilised in HFIN is significant and is determined by analysing results over Yale B and CMU-PIE database. Hence, the experimentation is performed to examine the recognition rates by varying $\mu\omega$ in the range of 50 to 170, at different values of filter order ranging from 1 to 3 as mentioned in Table 1. It has been obvious from the summarised result, that prominent recognition rates are attained at $\mu\omega = 150$ and $\tilde{N} = 2$. Hence, the selected optimal values are utilised further in the presented work to recognise the efficiency of the proposed HFIN-MFIWT approach.

The experiments are now performed on Yale database, by changing the number of train images (per subject) from 1 to 7, and the remaining images are utilised for testing. Correspondingly, the results are obtained on both large-scale or low frequency (X_a) components and small-scale or high pass frequency components of an image by varying the decomposition scale between 1 to 3. It has been perceived that the recognition rate achieved at level 2 is superior to that achieved at level 1, as upsurging the decomposition level although, decreases the feature vector size but significant facial features suitable for illumination invariable face recognition are retained thereafter. However, further increasing the decomposition scale to level 3 resulted in reduced recognition rates as the feature vector space is again reduced and attained diminished features which drop significant facial details. The results on Yale database at different IWT facial frequency coefficients and decomposition levels are summarised in Table 2. It is apparent from the presented results that, accurate recognition rate is attained at decomposition level 2 over large-scale facial coefficients.

Table 1 Evaluation of recognition rates attained based on proposed HFIN-MFIWT face recognition method at varying values of $\mu\sigma$ and \tilde{N} over Yale-B and CMU-PIE, respectively

Threshold frequency ($\mu\sigma$)	Yale-B database									CMU-PIE		
	Subset 3			Subset 4			Subset 5			Test set (20)		
	$\tilde{N}=1$	$\tilde{N}=2$	$\tilde{N}=3$	$\tilde{N}=1$	$\tilde{N}=2$	$\tilde{N}=3$	$\tilde{N}=1$	$\tilde{N}=2$	$\tilde{N}=3$	$\tilde{N}=1$	$\tilde{N}=2$	$\tilde{N}=3$
50	98.33	99.16	97.50	94.28	97.14	94.28	96.84	97.36	96.31	98.93	99.84	98.33
70	97.50	100	97.50	94.28	97.85	94.28	96.84	97.36	96.84	99.09	99.84	98.33
90	98.33	100	97.50	94.28	98.57	94.28	96.84	97.89	96.84	99.09	100	98.40
110	98.33	100	98.33	94.28	99.28	95.00	97.89	98.42	97.36	99.09	100	98.33
130	98.33	100	97.50	95.00	99.28	95.00	98.94	99.47	97.89	99.09	100	98.48
150	99.16	100	99.16	96.42	100	95.71	99.47	100	97.36	99.54	100	98.63
170	99.16	100	99.16	95.00	99.28	95.71	98.94	99.47	97.36	98.33	100	98.71

Table 2 Recognition rates attained on Yale database at different decomposition levels and IWT-based facial frequency coefficients

Level of decomposition	IWT-based low frequency components	IWT-based high frequency components		
	<i>Xa</i>	<i>Xh</i>	<i>Xv</i>	<i>Xd</i>
Level 1	95	93.33	95	75
Level 2	100	88.33	93.33	73.33
Level 3	98.33	95	93.4	81.66

Similarly, the proposed technique is assessed on Yale B and CMU-PIE databases with abrupt illumination effects, for a significant selection of decomposition level and appropriate facial components of an image. The accomplished results on Yale B database are demonstrated in Table 3, for both small-scale and large-scale facial features at varying decomposition levels. As mentioned in Section 4.2.2, Yale B database images include 64 varying illumination conditions which are immensely along the horizontal direction due to which small-scale (*Xh*) facial coefficients eventually resulted in accurate recognition rates over each subset.

Table 3 Recognition rates (%) attained on different subsets of Yale B database at varying decomposition levels and IWT-based facial coefficients

Yale B subsets	Level of decomposition	IWT-based low frequency facial components	IWT-based high frequency facial components		
		<i>Xa</i>	<i>Xh</i>	<i>Xv</i>	<i>Xd</i>
Subset 3	Level 1	97.5	100	98.33	98.91
	Level 2	100	100	100	99.16
	Level 3	98.33	100	100	100
Subset 4	Level 1	56.31	100	80.52	90
	Level 2	52.1	100	70	95.26
	Level 3	46.31	94.73	55.26	81.05
Subset 5	Level 1	56.31	99.16	80.52	90
	Level 2	52.1	100	70	95.26
	Level 3	46.31	94.73	55.26	81.05

Table 4 Recognition rates attained on CMU-PIE database at different levels of decomposition and facial frequency components

Level of decomposition	IWT-based low frequency components	IWT-based high frequency components		
	<i>Xa</i>	<i>Xh</i>	<i>Xv</i>	<i>Xd</i>
Level 1	96.36	100	99.86	99.09
Level 2	95.83	100	99.24	99.92
Level 3	85.53	100	99.24	98.09

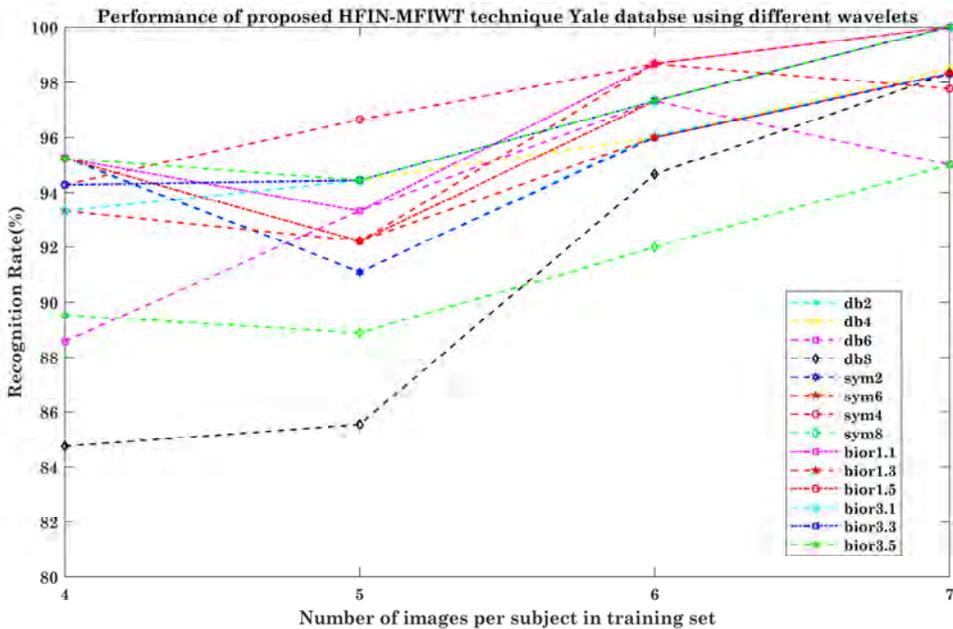
In order to accomplish remarkable results, the said approach has utilised large-scale facial coefficients for Yale database, and small-scale horizontally directed coefficients over Yale B and CMU-PIE databases, respectively. The presented HFIN-MFIWT approach

has effectually examined the multiscale facial features over the varying level of decompositions for investigating the prominent frequency components in IWT domain.

4.2 Experimentations to investigate appropriate wavelet family for implementation of HFIN-MFIWT approach

The selection of appropriate wavelets for the proposed approach under an illumination-constrained environment is significantly performed in this section. As stated in Section 3.2, the biorthogonal wavelet family is considered to be more flexible than orthogonal wavelets as the biorthogonal wavelets are not restrained to exist in the orthogonality condition. Also, it has been specified that the symmetry of wavelets and orthogonality property are incompatible with each other, therefore the biorthogonal wavelets design is symmetrical in nature. The relaxation from the orthogonality condition also allows the biorthogonal wavelets to preserve the linear phase characteristic.

Figure 6 Performance evaluation of proposed approach on Yale database using different wavelet families (see online version for colours)



Thus, extensive experiments are performed for selecting suitable wavelets among orthogonal and biorthogonal wavelet family, to effectively examine the IWT-based multiscale facial features. Among orthogonal wavelet family, Daubechies (db2, db4, db6, db8) and Symlets (sym2, sym4, sym6, sym8) wavelets are utilised over biorthogonal wavelets namely (bior1.1, bior1.3, bior1.5, bior3.1, bior3.3, bior3.5), for assessing the accuracy of the proposed approach. As aforementioned, the second IWT decomposition scale has provided superior outcomes over Yale, Yale B and CMU-PIE databases, respectively. Hence, the choice of wavelet family over the considered databases is performed at the second decomposition level for robust multiscale feature selection. The

results illustrated in the previous section, have shown that the proposed approach when employed over Yale database provides prominent recognition rates over large-scale coefficients in IWT domain, as the images herein possess slight pose and expression deviations with varying illumination.

Furthermore, the investigation of selecting an appropriate wavelet for IWT-based illumination invariant multiscale feature extraction is exploited over orthogonal and biorthogonal wavelets. The evaluation of the proposed technique on Yale database with different wavelet families is illustrated in Table 5. The proposed technique is thereafter examined on each testing subset of Yale B database for appropriate selection of wavelet family. Again, the recognition rates are assessed on different wavelets, and it has been observed, that the stated approach yielded superior results over small-scale (horizontally directed) facial coefficients at the second decomposition level. The results shown in Table 6 clearly revealed that prominent results are attained with biorthogonal wavelet over low to high illumination varying images in subsets (*S3, S4, S5*) of Yale B database.

Table 5 Performance of proposed technique on Yale database with different biorthogonal and orthogonal wavelets

<i>Wavelet family</i>	<i>Wavelet</i>	<i>No. of images per individual for training</i>			
		<i>4</i>	<i>5</i>	<i>6</i>	<i>7</i>
Daubechies	db2	95.23	91.11	96	98.33
	db4	95.23	94.44	96	98.5
	db6	88.57	93.33	97.33	95
	db8	84.76	85.55	94.66	98.33
Symlets	sym2	95.28	91.11	96	98.3
	sym4	93.33	92.22	96	98.33
	sym6	94.28	96.66	98.66	97.77
	sym8	89.52	88.88	92	95
Biorthogonal	bior1.1	95.23	93.33	98.67	100
	bior1.3	95.23	92.22	98.67	100
	bior1.5	95.23	92.22	97.33	100
	bior3.1	93.33	94.44	97.33	100
	bior3.3	94.28	94.44	97.33	100
	bior3.5	95.23	94.44	97.33	100

Likewise, to validate the selection of suitable wavelets for the proposed approach, the results are also examined over CMU-PIE database, based on biorthogonal and orthogonal wavelets respectively as summarised in Table 7. The presented results have clearly depicted that accurate recognition rate is obtained based on biorthogonal wavelet, at the second decomposition level and small-scale (horizontally oriented) facial coefficients, respectively. The performance evaluation graph of the proposed approach on CMU-PIE database, for a significant choice of wavelet among different wavelet families, is represented in Figure 8.

Table 6 Performance evaluation of proposed HFIN-MFIWT approach on Yale B database with different biorthogonal and orthogonal wavelet families

Wavelet family	Wavelets	Yale B subsets		
		Subset 3	Subset 4	Subset 5
Daubechies	db2	100	97.85	97.89
	db4	100	94.28	96.84
	db6	79.16	42.85	35.78
	db8	48.33	30.71	30.1
Symlets	sym2	100	97.85	97.89
	sym4	100	97.14	93.68
	sym6	67.5	51.42	34.73
	sym8	70	48.57	36.31
Biorthogonal	bior1.1	100	100	100
	bior1.3	99.16	96.42	99.47
	bior1.5	100	95	97.89
	bior3.1	100	99.28	100
	bior3.3	99.16	95.71	100
	bior3.5	98.33	89.28	98.94

Figure 7 Percentage recognition rate attained on Yale B database using different wavelets (see online version for colours)

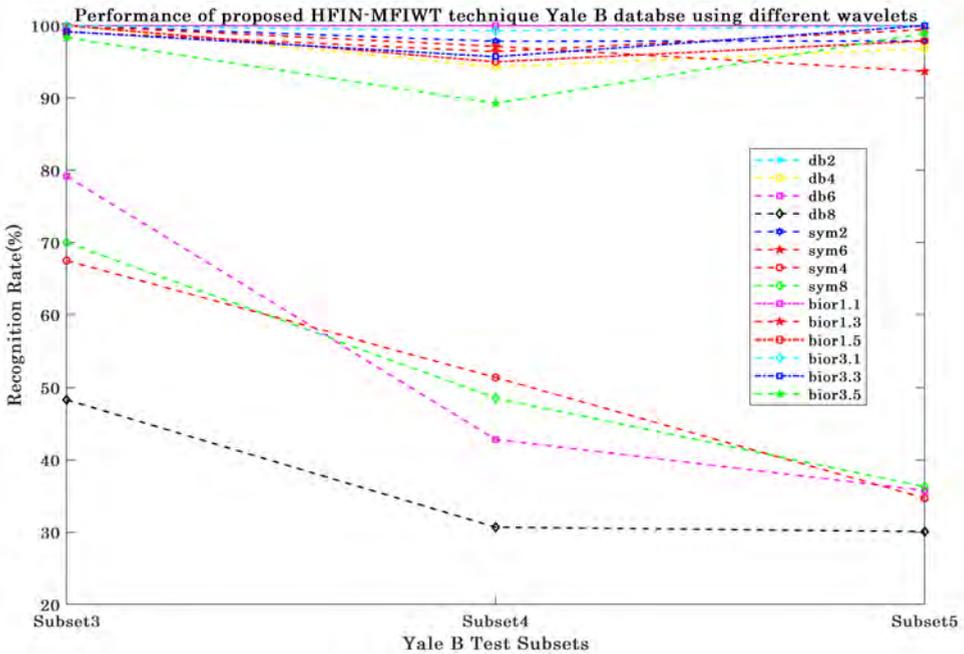
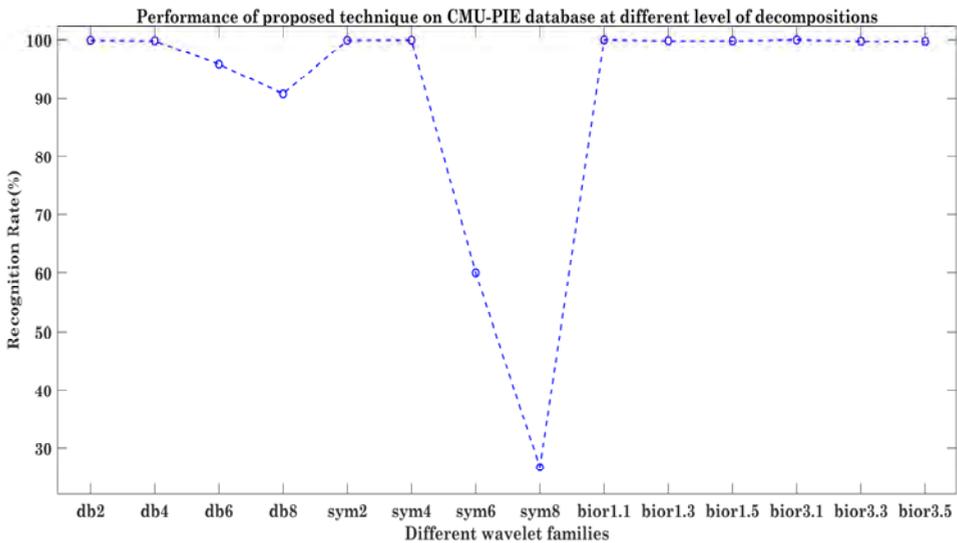


Table 7 Performance evaluation of proposed technique on CMU-PIE database with biorthogonal and orthogonal wavelet families

Wavelet family	Wavelets	$1/20$ (training/testing)
Daubechies	db2	99.92
	db4	99.84
	db6	95.83
	db8	90.75
Symlets	sym2	99.92
	sym4	99.96
	sym6	60
	sym8	26.81
Biorthogonal	bior1.1	100
	bior1.3	99.84
	bior1.5	99.84
	bior3.1	100
	bior1.3	99.77
	bior1.5	99.77

Figure 8 Performance of proposed approach on CMU-PIE database using different wavelet families (see online version for colours)



4.3 Analysis of proposed HFIN-MFIWT technique

This section illustrates the effectiveness of the presented HFIN-MFIWT technique on Yale, Yale B, CMU-PIE, and extended Yale B databases based on the selection of parameters described in Section 4.1 and Section 4.2, respectively.

4.3.1 Experimental results on Yale database

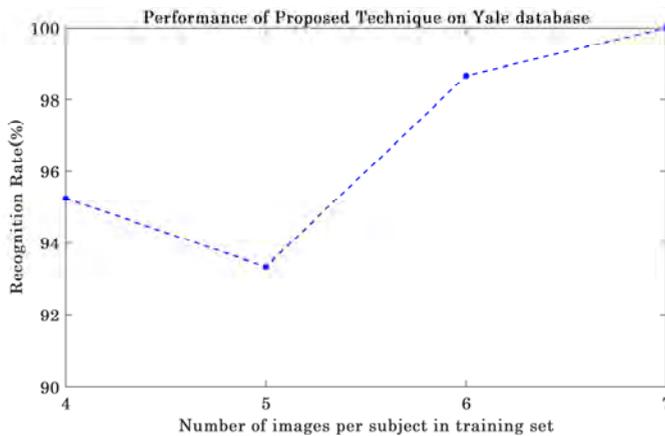
The Yale database comprises of total 165 face images with 15 varying subjects. Distinct subjects of this database consist of 11 face images per individual. In this dataset, three images per subject show varying illumination effects and six of the remaining images depict slight expression deviations such as sad, wink, surprised, etc. The experiments performed in the previous section have demonstrated that biorthogonal wavelet yielded 100% recognition rates, at the second level of decomposition over large-scale facial features on Yale database. The performance of the said approach is assessed by varying the number of training images from 4 to 7 in each subject. The results summarised in Table 8, eventually show that accurate results are achieved on seven training images (per subject) over low frequency facial components with biorthogonal wavelets in IWT domain. HFIN-MFIWT-based multiscale feature selection approach also benefited, in reducing the size of training feature vector space from $38,500 \times 105$ to $2,420 \times 105$ and test feature vector space from $38,500 \times 60$ to $2,420 \times 60$, respectively.

Table 8 Recognition rates attained on Yale database based on proposed HFIN-MFIWT technique

<i>No. of training images per subject</i>	<i>Recognition rate (%)</i>
4	95.23
5	93.33
6	98.67
7	100

For a significant selection of prominent facial features, 70 principal components are chosen for eigenface-based subspace examination which further aids in reducing the size of the train and testing facial feature vector space to 70×105 and 70×60 individually. The performance analysis of the presented technique on Yale database is presented graphically in Figure 9.

Figure 9 Performance of HFIN-MFIWT proposed technique on Yale database (see online version for colours)



4.3.2 Experimental results on Yale B database

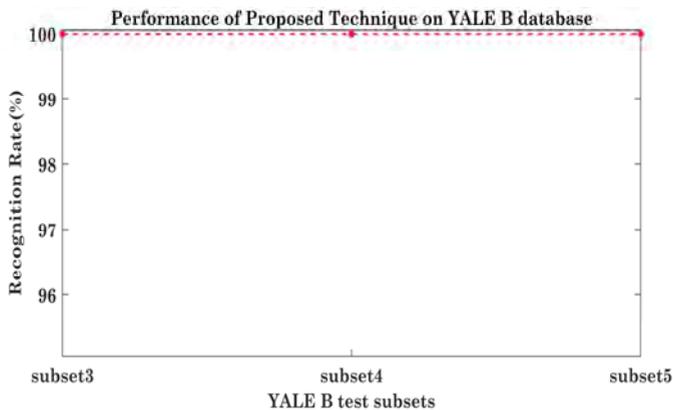
This database contains 5,760 (total) images of ten individuals with 65 light and nine pose varying situations. The proposed work has utilised face images with frontal poses for evaluation. Entirely, the original images are of 640×280 resolution which is categorised into five dissimilar subsets based on illumination intensity deviations and camera axis alliance. The considered 640 fore-face images are clustered into five different subsets. This grouping is done according to the view angle of the camera's dominant (central) axis and the striking direction of source light beam. The segregation is done from subset 1 to subset 5 which contains 70 images as (0° – 12°), 120 images (13° – 25°), another 120 images as (26° – 50°), 140 images as (51° – 77°) and lastly 190 face images (above 77°), respectively. In this work, images of subset 1 (S_1) with low light deviations are utilised in training while images of subset 3 (S_3), subset 4 (S_4) and subset 5 (S_5) are utilised in the testing phase, respectively.

The results described in Section 4.1 and Section 4.2, clearly states that biorthogonal wavelet yielded foremost recognition rates at the second level of decomposition with small-scale features over Yale B database. The presented approach is hereafter examined over different testing subsets of Yale B database and the results thus attained are presented in Table 9. The proposed technique has attained accurate results over all the considered testing subsets with low to high illumination effects effectively, by utilising biorthogonal wavelets over large-scale horizontally directed facial features.

Table 9 Recognition rates attained on different subsets (test) of Yale B based on HFIN-MFIWT approach

<i>Yale B (subsets)</i>	<i>Recognition rate (%)</i>
S_3	100
S_4	100
S_5	100

Figure 10 Performance evaluation of proposed HFIN-MFIWT technique on Yale B database (see online version for colours)



The dimensions of achieved homomorphic filtering-based illumination normalised (HFIN) test and train face feature vector space is $32,256 \times 140$ and $32,256 \times 70$, when decomposed in IWT domain reduces the dimensional space as $3,600 \times 140$ and

$3,600 \times 70$ of testing and training feature vectors, respectively. The test and train feature vector space further reduce to 40×140 and 40×70 when projected on eigenspace. This benefited in reducing the computational complexity of the stated approach. The results illustrated in Table 8 and the performance graph shown in Figure 10 evidently depicted that proposed HFIN-MFIWT technique yielded accurate results on Yale B database also at varying testing subsets.

4.3.3 Experimental results on CMU-PIE database

CMU PIE database includes diverse types of face images that comprise illumination, expression, and pose variations. The database comprises 41,368 images of 68 individuals. The proposed work primarily aims in overcoming the illumination variances hence only illumination deviated images are utilised for experimentation. Hence, the proposed technique is employed over 66 subjects with frontal pose illumination variations, including 21 images per subject. Among these 1,386 face images (66×21), one frontal uniformly illuminated image per subject is utilised in the training phase while the rest 20 images, with variable illumination directions, are utilised for testing. The images are considered in a jpeg file format which is thereby transformed into greyscale images.

Likewise, the efficiency of the proposed homomorphic filtering-based normalised multiscale feature extraction in IWT domain is also exploited on CMU-PIE database with 66 subjects each containing 21 images per individual. Among these 1,386 face images (66×21), one uniformly illuminated front posing image (per subject) is utilised in the training phase while the rest 20 images, with variable illumination effects, are used in testing. The dimensions of achieved homomorphic filtering-based illumination normalised (HFIN) test and train face feature vector space is $16,384 \times 1,320$ and $16,384 \times 66$, which are further decomposed in IWT domain to produce lower dimensional space as $1,024 \times 1,320$ and $1,024 \times 66$ of testing and training feature vectors, respectively. This is further reduced effectively as $65 \times 1,320$ and 65×66 when mapped over eigensubspace, which consequently helps in decreasing the computational complexity of the stated approach. The results illustrated in Table 10 and the performance graph is shown in Figure 11, evidently depict that, proposed HFIN-MFIWT technique yielded accurate results on CMU-PIE database also at varying decomposition levels.

Figure 11 Performance evaluation of proposed technique on CMU-PIE database at varying decomposition levels (see online version for colours)

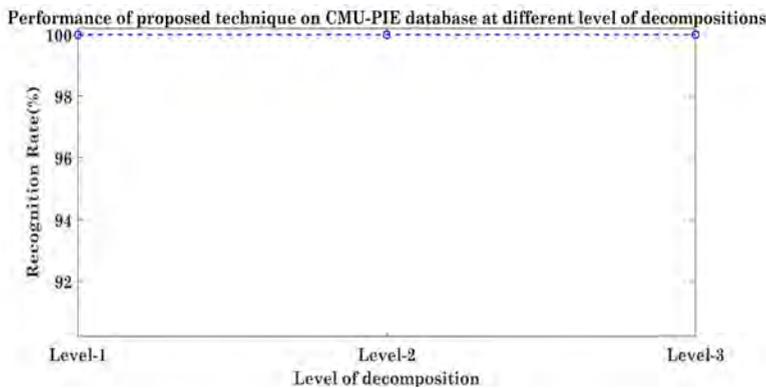


Table 10 Recognition rates attained with proposed HFIN-MFIWT technique on 1 (training set) / 20 (test set) images of CMU-PIE database

<i>Decomposition level</i>	<i>Recognition rate (%)</i>
<i>L1</i>	100
<i>L2</i>	100
<i>L3</i>	100

4.3.4 Experimental results on extended Yale B database

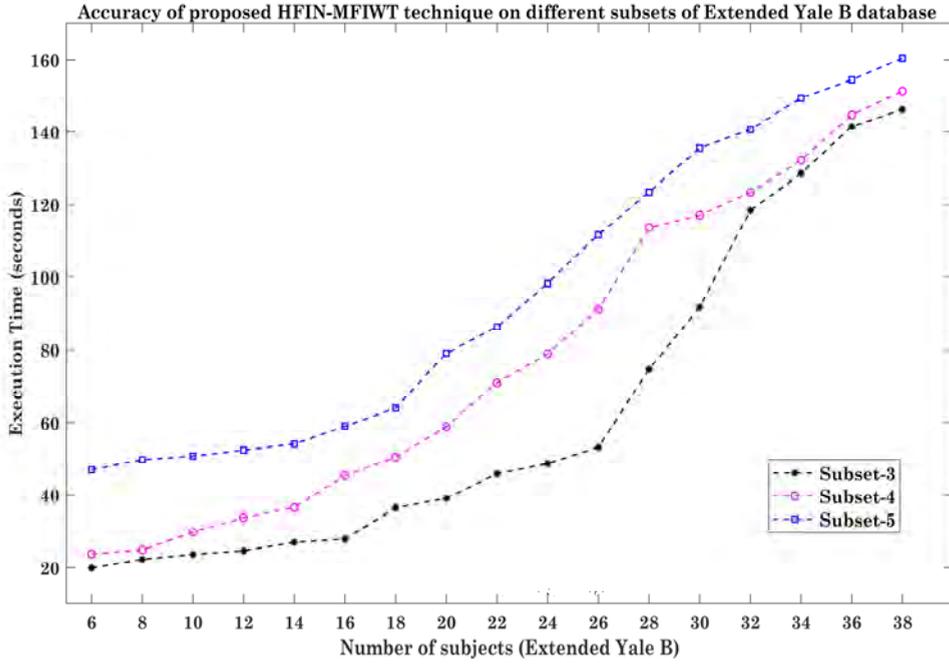
Extended Yale B database includes 16,128 total images with 38 individual subjects. This database is obtained by extending the Yale B database by accumulating 28 additional subjects. The database also has the same number of subsets with the same illumination differences as specified in Section 5.3.2. The grouping of subsets is done in a similar manner as performed in Yale B database based on illumination intensity deviations and camera axis alliance. The work has utilised frontal face images with low to complex light effects to access the performance and complexity of the proposed approach. Alike, Yale B database, in this database also images of subset 1 are utilised for training, and subsets 3 to 5 images are employed for the testing routine. Furthermore, the proposed HFIN-MFIWT-based illumination invariant face recognition approach is analysed and validated on front-posing face images of extended Yale B database with small to very high lighting dissimilarities. Subsequently, experiments are accomplished on this database to validate the effectiveness and complexity of the proposed method, by analysing the recognition rates and evaluating the execution time over a large-size database also. The recognition rates attained over extended Yale B database under low to high light variations are presented in Table 11. The computational complexity of the stated approach is determined in terms of execution time by varying the number of subjects as (6, 8, 10,, 36, 38) in each considered testing subset of extended Yale B database.

Table 11 Recognition rates attained with proposed HFIN-MFIWT technique on varying subsets (test) of extended Yale B database

<i>Extended Yale B (subsets)</i>	<i>Recognition rate (%)</i>
<i>S3</i>	100
<i>S4</i>	94.36
<i>S5</i>	95.56

It is visibly examined that the total execution time of the proposed approach over low illumination deviated images of subset 3, increases linearly from 19.9 seconds to 146.16 seconds, over a varied number of considered subjects as shown in Figure 12. Moreover, the execution time of the investigated HFIN-MFIWT technique also increases linearly $O(n)$ when exploited over subset 4 and 5 face images with average to complex light variations as described in Figure 12. Hence, the above-stated investigation successfully validates the computational efficacy and robustness of the proposed approach in providing prominent results under low to extreme varying illumination circumstances.

Figure 12 Execution time plot of proposed HFIN-MFIWT-based face recognition technique with the increasing number of subjects from (subset 3 to subset 5) in extended Yale B database (see online version for colours)



5 Comparison analysis

The comparative analysis of the proposed approach based on homomorphic filtering-based illumination normalisation and multiscale feature extraction in integer wavelet transform (HFIN-MFIWT), with other prior face recognition approaches is described in this section. The effectiveness of the investigated approach is analysed and validated in terms of achieved recognition rates. As mentioned in Section 4.2.1, the Yale database contains images with slight pose, occlusion, and expression deviations under unrestrained illumination conditions. The results attained on Yale database based on the proposed approach, are compared with DWT-E-CLAHE (Ayyavoo and Suseela, 2018), HE_GLPF_PCA_SVM (Li et al., 2018), GSB2DLPP (Liang et al., 2016), ExtendFace_log (Gao et al., 2019), 2DPCANet (ELM) (Yu and Wu, 2017), DD_DTCWT (Chaudhary and Yadav, 2022) and RRHE-RFDWPT (Yadav et al., 2019). It is certainly observed from the assessment of previous face recognition techniques as presented in Table 12, that the proposed approach outperforms all stated existing approaches. Although, 2DPCANet technique has shown improved performance for illumination invariable face recognition by utilising an efficient extreme learning machine classifier, that biases the efficacy of the method. On the contrary, the performance of proposed HFIN-MFIWT method has been validated based on a simple KNN classifier. Moreover, the recognition rate achieved based on proposed HFIN-MFIWT approach is higher than other described existing approaches under difficult illumination conditions. The accurate

results hereby validate the competence of the proposed approach over slight posing and expression variations under the deviated illumination effects.

Table 12 Performance evaluation of proposed HFIN-MFIWT approach on Yale database with prior state-of-art approaches

<i>Face recognition techniques</i>	<i>Recognition rate (%)</i>
DWT E-CLAHE	99.26
HE_GLPF_Gabor_PCA_SVM	95
GSB2DLPP	92.56
ExtendFace_log	98.33
2DPCANet	99.83
DD_DTCWT-based feature extraction	88.3
RRHE-RFDWPT	98.67
Proposed HFIN-MFIWT	100

Likewise, the proposed technique performance is evaluated on Yale B database with other face recognition techniques such as fMDLRN (Cheng et al., 2017), LFD (Faraji and Qi, 2014), WF (Wang et al., 2011), HWIN + DoG (Yuan et al., 2013), RETINA&TH-LTV-ESRC (Zhang et al., 2019), RRCS-IWT-FLDA (Yadav et al., 2018b) and RRHE-RFDWPT (Yadav et al., 2019). The comparative analysis described in Table 13, clearly analysed that the proposed HFIN-MFIWT approach has provided accurate results on each considered Yale B testing subset, wherein the face images comprise low to extreme illumination variations.

Table 13 Performance evaluation of proposed HFIN-MFIWT approach on Yale B database with prior techniques

<i>Face recognition techniques</i>	<i>Yale B</i>		
	<i>Subset 3</i>	<i>Subset 4</i>	<i>Subset 5</i>
fMDLRN	100	99.34	98.62
Logarithmic fractal dimension (LFD)	93.06	95.67	97.59
Weber face (WF)	100	96.4	96.8
HFRIN-SFDWT	100	99.29	100
HWIN + DoG	97.2	95.9	87.1
RRCS-IWT-FLDA	100	97.85	98.42
RRHE-RFDWPT	100	100	100
Proposed HFIN-MFIWT	100	100	100

This eventually states that the proposed approach is competent in repossessing the significant facial details, under low, moderate, and extensive illumination varying circumstances efficaciously. It has been analysed, that the result of RRHE-RFDWPT (Yadav et al., 2019) technique is comparable with the proposed approach over Yale B face images. Moreover, the said technique was based on the concept of RR images which are attained by computing the ratio of each pixel intensity to the mean of its considered local neighbourhood for illumination normalisation. The significant selection of the neighbourhood size escalates the computational time as compared to the proposed

HFIN-MFIWT approach. Hence, the presented technique is computationally efficient due to IWT-based extraction of facial feature vectors with reduced dimension. Unlike DWT, the IWT technique does not involve floating point numbers as the outputs of high pass and low pass filter operations are rounded off to the nearest integer value. Also, this eliminates the errors that may occur due to rounding of floating-point numbers to approachable integers. So, in this presented work significant facial information is obtained by utilising the lifting scheme-based IWT technique and thus prevents the loss of facial information. Consequently, this helps in attaining superlative recognition rates against other state-of-art techniques with repossession of the prominent facial details.

The results attained over CMU-PIE database based on the proposed HFIN-MFIWT technique, are contrasted with previous face recognition approaches such as, Wang et al. (2011), Faraji and Qi (2014), Roy and Bhattacharjee (2016), Yadav et al. (2018b), Ayyavoo and Suseela (2018), Zhang et al. (2019), Yadav et al. (2019) and Thamizharasi and Jayasudha (2020). The comparative analysis of the proposed approach with other state-of-art techniques over CMU-PIE database is presented in Table 14, which evidently proves its effectiveness in realising remarkable results. Although, DWT E-CLAHE has been capable of achieving high recognition accuracy of 99.84%, but due to the existence of real-valued DWT-based frequency coefficients, the execution of floating-point operations on such coefficients increases the computational cost. Hence, the multiscale analysis of homomorphic filtering-based illumination face images using fast and effective lifting scheme in IWT domain, makes the presented method computationally efficient.

Table 14 Performance evaluation of proposed HFIN-MFIWT approach on CMU-PIE database with prior state-of-art approaches

<i>Face recognition techniques</i>	<i>Recognition rate (%)</i>
DWT E-CLAHE	99.84
Energy enhanced-2D-DWT	99.08
Logarithmic fractal dimension (LFD)	97.86
Weber face (WF)	94.7
HFRIN-SFDWT	100
RRCS-IWT-FLDA	100
LG-face-HFR	97.78
Proposed HFIN-MFIWT	100

It is apparent from Table 14, that HFRIN-SFDWT and RRCS-IWT-FLDA methods have also realised accurate results over CMU-PIE database. However, the computational time of HFRIN-SFDWT is higher due to the extraction of robust illumination invariant feature extraction in DWT domain that provides real-valued facial frequency coefficients. Besides, RRCS-IWT-FLDA method has annulled the illumination differences based on the concept of RR and has achieved remarkable results over CMU-PIE low illumination varied face images. But, the method is incompetent in rendering the intricate light variations in extended Yale B database face images as apparent in Table 15. Also, the complexity of RRCS-IWT-FLDA technique is higher than the proposed method due to locally computed contrast stretched RR images.

The performance efficacy of the proposed method is also validated over extended Yale B database, by comparing the attained results with prior face recognition techniques

as presented in Table 15. The techniques based on the idea of Weber law such as WF (Wang et al., 2011) and GWF (Wu et al., 2014) have provided prominent results on low illumination deviating images of subset 3. However, the techniques were not able to achieve superior recognition rates on subset 4 and subset 5 images, under moderate and extreme light variations, respectively.

Table 15 Performance evaluation of proposed HFIN-MFIWT approach on extended Yale B database with prior state-of-art approaches

<i>Face recognition techniques</i>	<i>Extended Yale B</i>		
	<i>Subset 3</i>	<i>Subset 4</i>	<i>Subset 5</i>
LG-face-HFR	99.54	93.89	93.17
Weber face (WF)	99.78	96.39	90.06
HFRIN-SFDWT	100	98.49	95.66
Generalised Weber face (GWF)	99.78	97.15	92.86
RRCS-IWT-FLDA	100	93.04	93.62
DTCWT-PCA	100	82.89	67.36
Proposed HFIN-MFIWT	100	94.36	95.56

Besides, the comparative analysis of the proposed approach with LG-face-HFR (Roy and Bhattacharjee, 2016), DTCWT-PCA (Selvakumar et al., 2016), and RRCS-IWT-FLDA (Yadav et al., 2018b) face recognition methods respectively, has proved that the presented approach attained prominent recognition rates. The analysis also demonstrated that results attained by utilising HFRIN-SFDWT (Yadav et al., 2018a) technique had achieved better recognition rates over subset 4, while under extreme illumination variations the recognition rates are almost comparable with the recognition rates obtained based on the proposed approach. Also, the computational cost of proposed approach is less than that HFRIN-SFDWT technique, as the result from the low pass and high pass filtering actions performed in IWT are rounded to the nearest integer values.

The aforementioned comparative analysis has empirically established the superiority and efficacy of the proposed HFIN-MFIWT approach, in annulling low to complex varying illumination over different databases. The significant facial features with reduced size are obtained by utilising a computational efficient lifting scheme-based IWT technique while suppressing the illumination deviations and preserving the substantial facial information. The key points about the proposed HFIN-MFIWT-based illumination invariable face recognition approach are stated below:

- A high pass HFIN is utilised for enhancing the low contrast and annulling the noise-related low frequency components with a suitable selection of threshold frequency and order of the filter.
- Multiscale feature extraction of obtained HFIN-based images in IWT (MFIWT) domain is capable of analysing multiscale (both small- and large-scale features) efficiently with analysis of suitable wavelet family. This produced smooth textured HFIN-MFIWT images with simultaneous preservation of hidden high frequency facial details.

- A conventional feature selection technique commonly known as PCA is utilised for reducing the large face vector dimensional space by a selection of prominent features effectively.

6 Conclusions

The visibility of captured face images is severely affected under varied illumination interferences for face recognition. To compensate for such abrupt light deviations, a homomorphic filtering-based illumination normalisation, and analysis of multiscale face features in the integer wavelet transform (HFIN-MFIWT) domain are proposed in this work. The preprocessing is accompanied by Butterworth high pass filter-based homomorphic filtering method, with appropriate selection of threshold value and filter order. In this step, the low frequency components in face images are discarded with the simultaneous preservation of high frequency facial information. Furthermore, the extraction of multiscale facial features in IWT domain is achieved by utilising a significant selection of biorthogonal wavelets over orthogonal wavelet family, based on examination of both small-scale and large-scale facial coefficients to enhance the effectiveness of the proposed technique. The proposed face recognition framework has evidently proven to be outstanding by yielding accurate recognition rates over Yale, Yale B, and CMU-PIE databases, under low to extreme changing illumination effects. Moreover, HFIN-MFIWT technique has attained substantial results over varying subjects of extended Yale B as and when contrasted with existing illumination normalisation-based face recognition techniques. Besides this, the approach is computationally efficient which also preserves the fine information of face images efficiently. In the future, the proposed approach will be exploited with other machine learning techniques for better comparative analysis of large databases with complex illumination states.

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