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Comparison of Feature Extraction Techniques for Face Recognition

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ABSTRACT: Face Recognition (FR) is the use of computer to automatically verify/identify faces irrespective of various aspects such as pose, rotation, expression, scale and illumination. It is not possible to perform FR irrespective of above aspects using any single algorithm. The paper presents a comparative study of different algorithms for feature extraction that is very important component in FR. The feature extraction algorithms reduce image dimensionality by extracting significant features from large number of pixels of the face, resulting in reduced time complexity and increased accuracy. There are number of local, global (holistic) and geometrical model based approaches for feature extraction in time and frequency domains. The focus of comparative study is based on local and global features in the time domain as well as frequency domain. The advantages and limitations of various feature extraction algorithms for FR are highlighted. The suitability of using an algorithm for specific above aspects is also mentioned. The comparison is performed based on review of literature as well as implementing algorithms and testing on ORL database. Euclidean distance is applied on extracted features for classification. It is concluded that frequency domain based techniques are more robust to variation in pose and expression as compared to time domain. Also, the Phase components are robust to illumination.

Keywords: Face recognition; Feature extraction; Principal components; Magnitude components; Time & frequency domains and Image classification.

INTRODUCTION: Digital Image Processing (DIP) is a field that describes the use of computer algorithms to analyze digital images. In electromagnetic energy spectrum, there are seven levels from highest to lowest level, namely Gamma rays, X-rays, Ultraviolet, Visible, Infrared, Microwaves and Radio-waves[1]. These images can be used for diagnosis, disease or object recognition and so on. The Visible and Infrared bands images are usually used in face recognition applications. Visible images are very similar to what we see with our eyes and include all the optical and light microscope images. A face recognition system employs image processing techniques to identify/verify faces from digital images. People easily identify faces but automatic face recognition is a big challenge in computer vision applications. The pixels and details of face images can be changed due to variation in pose, expression, illumination, rotation, degradation, etc. Face verification/identification is used in different applications like online attendance, terrorist and criminal identification, monitoring, identification of customers and any other security related applications. However, the FR algorithms can be implemented based on other biometrics such as fingerprint, hand writing, eye recognition systems and so on.

Digital image processing includes low level, middle level and high level processes. The low level processing includes smoothing of images and removing noise. The middle level process involves alignment and segmentation tasks. The high level process focuses on features extraction and object classification. Figure 1 depicts face recognition steps and their algorithms. The first step is to smooth images and remove noise by applying filters on images. The second step is separating faces from an image with many different objects. In the third step, the separated faces should be aligned. There are different techniques for object detection and alignment, such as neural networks[2]. After the alignment, some features should be extracted from faces to represent them in the lower space dimensionality. Extracting significant features from a digital image is an important step in FR, which reduces image dimensionality. Many algorithms have been developed to extract features, including global features, local features and geometrical features. Finding the nearest match for the image can be done by using traditional techniques like Euclidean distance or Chi Square distance[3] or any intelligent technique such as Support Vector Machine (SVM)[4]. These techniques offer many advantages such as the ability to learn and remember over conventional techniques. There is no single algorithm to extract all significant features irrespective of variations in pose, illumination, expression etc. Therefore many researchers are performing and trying to investigate better algorithms to FR that take less time and space dimensionality to achieve accurate recognition. The FR algorithms are covered in the next section.

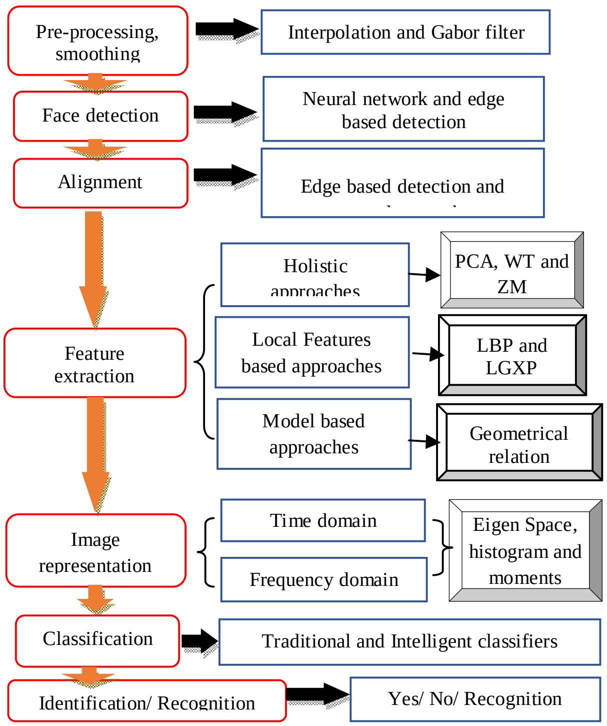

Figure 1: Face recognition steps and algorithms.

Review based on feature extraction for face recognition: Extraction of significant features reduces image dimensionality. This results in the reduction of space and time complexity and improves performance. The features extraction techniques can be categorized into three groups[5] as follows:

A. Holistic approaches are used to extract global features of images to represent images. It is called as Holistic or global features extraction due to features of images which will be extracted from all pixels of image.
B. Local feature based approaches are used to analyze and recognize faces by using local features that are extracted from few pixels in the neighborhoods.
C. Model based approaches are used to extract local and/or global geometrical relationship measurement among special points (mouth, eyes, eyebrows, cheeks, etc.) of the face locally, extract shape, edge, curve or concentration of energy magnitude of whole face as geometrical feature measurement.

There are many well-known FR algorithms which can be used to extract features of images in time or frequency domains. The components of time domain are row pixels value only, whereas, the components of frequency domain include the Phase, energy Magnitude, Amplitude, Real and Imaginary values according to pixels. Images can be converted from time domain into frequency domain by using Fourier transform, Cosine transform and other transformation techniques. Frequency components are robust to pose, expression and degradation variations and provide better recognition rate as compared to time domain applications[6].

a) Review according to holistic approaches: Principal Components and Holistic approach techniques are used to extract significant global features for face identification. Sirovich and Kirby[7] used PCA algorithm to represent extracted features which contained significant characteristics of images. Two directional two dimensional Principal Components Analysis ($(2D)^2$PCA) technique[8] was developed in 2005. It uses column directional two dimensional PCA (c2DPCA) which represents the column details of images and then it is combined with Robust Two-Dimensional Principal Components Analysis (r2DPCA) that uses centralized data with mean of rows. Thus, this algorithm extracts features from both the row and column details of images. However, it is required to compute two scatter matrices according to row and column direction that increases time complexity of the algorithm as compared to 2DPCA algorithm. The PCA algorithm is used in different application areas of image processing, such as, face recognition[8] and handprint identification[9]. However, PCA has the following limitations[10]:

- By selecting only few eigenvectors, some of the image details will be lost.
- The time complexity is high due to large size of covariance (scatter) matrix.

To address the above limitations, the 2DPCA[11] is developed based on two dimensional images. It has less time complexity due to smaller size of covariance matrix. Two dimensional PCA (2DPCA) performs better than PCA for FR under pose and expression variations. It has better recognition rate, when there is single training set image for each individual. Also, it needs less recognition time as compared to PCA technique.

Linear Discriminant Analysis (LDA) algorithm[12] is used to extract linear combination of features and is one of the methods for global feature extraction. PCA algorithm shows better recognition rate whenever there are even a few numbers of samples per class in training set as compared to LDA algorithm. K. Karande and S. Talbar[13] have developed an algorithm based on Independent Components Analysis (ICA) for FR that can identify faces irrespective of illumination and large pose angles variations. The classification of extracted features is performed using Euclidean distance.

Many well-known face recognition algorithms, such as, ICA[13] and Eigen-faces[14] have been developed which work in time domain. However, the images can be converted into frequency domain by using Fourier Transform. There are advantages of using frequency domain for feature extraction irrespective of pose, expression and degradation[15].

Zeytunlu and Ahmad[16], in 2012, applied Fourier transform on ORL database to extract magnitude components of image in frequency domain. Then they extracted principal components of energy magnitudes of images. They applied r2DPCA, c2DPCA, $(2D)^2$PCA and Dia-PCA on Fourier magnitude of the images and compared them with (FM-PCA). They obtained experimental results from (FM-r2DPCA), (FM-c2DPCA), (FM-(2D)2PCA) and (FM-Dia-PCA) algorithms which provide better recognition rate under pose and expression variations as compared to PCA categories in time domain. Computation of Fourier magnitude can be costly due to the need of nested loop computation in Fourier transform[15 & 16].

Singh et al. in 2010[17] compared global features of Complex Zernike moments (CZMs) and Zernike moments (ZMs) for face recognition. The methods were developed in terms of image reconstruction capability and robustness against rotation of images, expression, scale and size. It is observed that phase components extracted useful features for image reconstruction. The Phase information effectively describes the image characteristics and attributes as compared to magnitude of Zernike Moments.

Y. Xiao et al.[18] proved that two dimensional discrete cosine transform (2-D DCT) extracts significant features for variant face expression. They showed that working in frequency domain extracts more significant features irrespective of facial expression. J. Kumar et al.[19] proposed a combination of Wavelet and PCA algorithms for face recognition system which was invariant to pose. In pre-processing step, 2-level of Haar Wavelet decomposition is used to remove the noise and insignificant details from the images. Wavelet transform represents approximate, diagonal, vertical and horizontal details of the images. Only the approximate components (low frequency components) were considered to reduce image dimensionality. Thereafter, PCA algorithm is used to extract features of approximated images.

In 2011, Singh et al.[20] derived rotation invariant features for image classification using complex Zernike moments. The magnitude of ZMs was tested for face and character recognition. The performance of this technique justified that the extracted features of magnitude of ZMs are robust against rotation variation.

A new method for face recognition irrespective of pose and illumination had been proposed based on modular PCA technique[21]. In this method, modular PCA is applied on two dimensional (2-D) and three dimensional (3-D) images of FRAV3D database to extract textual and depth information of faces respectively.

First, they reconstructed 2-D images models from 3-D database. The PCA extracts energy concentration of faces globally. Therefore, its extracted features are not significant for large angle of pose and varying light conditions. On other hand, modular PCA technique divides each image into smaller sub images. Hence this technique extract features of images locally from its sub images. The covariance matrix of modular PCA is computed as follows:

$$Cov = \frac{1}{k.l}\sum_{i=1}^{k}\sum_{j=1}^{l} X_{ij} \cdot X_{ij}^{T} \tag{1}$$

Where k is number of images in database, l refers to the number of sub images according to each image and X is sub images of face database. The proposed multimodal FR system based on modular PCA is compared to PCA, modular PCA on textual and depth features separately. The following classifier based on Euclidean distance has been used to fuse multimodal texture and depth details which are extracted using modular PCA on 2-D as well as 3-D face images.

$$DIS = \sqrt{dt^2 + w * dd^2} \tag{2}$$

Where dt is distance of texture features, dd is distance in depth details and w is weight factor which has been tested with various values to increase the recognition accuracy. Other techniques for compression are classified using Euclidean distance[21].

There are many traditional measurement techniques for object classification, such as Euclidean, Square Euclidean, Murkowski, Canberra and Chi Square distance[22]. However, there are several intelligent classifiers such as Artificial Neural Network (ANN)[23], Fuzzy logic[24] and Support Vector Machine (SVM) which have ability to learn and remember over conventional techniques[25 & 26].

In 2009, J. Gan, and S. He[27] proposed a technique based on 2DLDA and SVM. In this technique, firstly, Wavelet transform (WT) was applied on original image to reduce image dimensionality. Then 2DLDA algorithm was used to extract features of approximate image of WT. Each sample xi is labeled with $yi \in \{-1,$

1}. yi = -1 denotes that sample *xi* belongs to the current class and *yi = 1* denotes that sample *xi* belongs to other class in hyper plane. Thereafter, Polynomial kernel SVM and "one against rest" technique have been employed on projection images. SVM is applied to separate the highest possible fraction of images in same class and maximize distance from either class to the hyper plane. The technique was tested on ORL and Yale face databases. In ORL database, dimensionality of images is reduced using first level decomposition of Wavelet Transform (WT). In Yale database, dimensionality is reduced after two levels of decomposition of WT. FR irrespective of age is a complex process that has effect on shape and textual details of the face[28]. Support Vector Machine (SVM) is one of the techniques which are used against age variation for face recognition[29]. A probabilistic decision based neural network (PDBNN) was proposed by Lin et al[30] for FR under pose and expression variations. However, when the number of persons increased, PDBNN encountered problems. It was not suitable for single model images. Therefore, multiple model images were necessary to train the network.

The recognition rate for face recognition under variant pose and expression depends on different view of poses and expressions in training set[31 & 32] due to the features extracted from intensity resolution of image. This intensity can be changed in any direction of faces, or any expression of face, like anger, disgust, fear, joy, sadness and surprised face. Therefore, the features will be extracted from different views to classify objects, independent of pose and expression variations.

b) Review according to the local based approaches: Local feature-based approaches extract local features by comparing intensity of a pixel with local neighbors. A local binary pattern (LBP) is designed by Ojala et al. in 2002[33] to extract local features, which are based on histogram of image and extracts discriminative features of images. The LBP algorithm is successfully applied in many computer vision applications. The LBP establishes block sequences of image e.g. *3x3* pixel's block, and operates according to a threshold which was defined with central pixel value of associated block and considers the result as a combination of histogram value of each block. Some advantages of LBP include easy implementation, robust to illumination and facial expression and useful for texture analysis. Due to these attributes, LBP can be considered as a useful algorithm for different digital image processing fields.

Feature extraction is an important step of FR systems which results in space dimensional reduction by extracting significant features from faces and represents them into lower space dimensionality. The PCA algorithm extracts linear features from an image whereas kernel-PCA is a nonlinear feature extraction technique. However, kernel-PCA algorithm requires higher dimensional face space to provide accurate performance as compared to PCA algorithm. The polynomial kernel is computed using k(x,y)=(xTy+1)P equation where x and y are the training and test image respectively. P is power of polynomial that can be any value (e.g. 2). The Gaussian kernel, also known as Radial basis kernel, is computed from k(x,y)=exp(||x-y||2/2δ2), where the width δ2 is valuated as one in their experience. The paper compares Gaussian kernel PCA, PCA and kernel PCA algorithms for face recognition independent of pose and expression variations. The Gaussian kernel PCA achieves same recognition rate as compared to PCA algorithm when they implement on ORL database. Kernel PCA provides less recognition rate as compared to PCA and Gaussian kernel PCA algorithms. Kernel PCA requires higher face space dimensionality to achieve accurate recognition as compared to PCA and Gaussian kernel PCA algorithms[34].

S. Xie et al. in 2010[35] developed local XOR pattern technique based on Gabor phase which is called as local Gabor XOR pattern (LGXP) for fusing phase and magnitude components of images. In this method, a two level block-based Fisher's linear discriminant (BFLD) is used for combining the local patterns of Gabor magnitude and phase (LGBP_Mag and LGXP). The basic idea of block-based Fisher's Linear Discriminant (BFLD) is firstly to divide and reduce the high-dimensional LGXP space into multiple feature segments. Thereafter, block-based Fisher's linear discriminants are applied to each block. Finally all the block-wise FLDs were combined together. The technique was tested on FERET and FRGC 2.0 databases which involved images in different illuminations, poses and expressions.

c) Review according to the model based approaches: Model based approaches (geometrical features) are derived from measurement relation among some special points on face. The special points can be detected by using different algorithms such as color features detection[36] and fuzzy logic[37]. These special points of face can be lips, nose, chin point, eye, eyebrow, ear and so on. Also, Shape and curve can be considered as global geometrical features in three dimensional images.

In 2015, Sharma and Patterh[38] developed a hybrid technique for face recognition under pose and expression variations.

Steps of proposed technique are as follows:

i The Viola Jones algorithm is applied on ORL database images to detect faces and its subparts including left eye, right eye, nose and mouth to create training dataset.
ii LBP algorithm has been used to extract histogram of training set images based on 3x3 block pixels neighborhoods which makes 8 bit codes according to central pixel of each block.
iii The histograms of images are reformed into a vector histogram then PCA is applied on training set images including face, eyes, nose and mouth.
iv Euclidean distance which is a well-known neighborhood distance measurement had been used for classification.

The hybrid technique is applied on 170 images of 34 individual which had been selected from ORL database. It provided accurate recognition on selected images as compared to PCA, 2DPCA, LBP, WT+PCA, 2DPCA+DWT and PCA+LBP+SVM techniques. The time complexity of the technique is higher than PCA which is due to apply LBP and PCA algorithms on faces as well as subparts of faces. Also, it is performed on 170 selected images of ORL database instead of complete database. It means that they selected images which provided better recognition as compared to other techniques[38].

Recently, geometrical features have been used for extracting features from 3-D images. F. Al-Osaimi et al.[39] combined local and global geometrical features on 3-D images by using PCA algorithm. In the methodology, faces are uniformed in mesh triangles form. These triangles are used to extract geometrical features of face. They used PCA algorithm to fuse global and local geometrical features. Normalized vectors on neighborhood triangles mesh is applied on faces to extract 11 local ranks zero tensor fields and 3 global ranks zero tensor fields from 3-D geometrical relationship of face as local and global geometrical features, respectively. Rank zero tensor is rigid to pose and rotation variations. In their technique, global geometrical features are used to find similarity of faces where as local geometrical features are used to describe dissimilarity of faces for identification. Global and local geometrical features were considered as vertical and horizontal elements of a histogram respectively. Global geometrical features were computed regarding to energy concentration of whole face. Thus, they were more concise and robust to noise but sensitive to occlusions. Local representations were less sensitive to occlusions but large numbers of them were required to be extracted and matched. Local geometrical features are computationally expensive, more sensitive to noise and can be easily mismatched with each other. Another problem of face recognition algorithm is time complexity of feature extraction and image analysis[40] which can be reduced in model based approaches. The geometrical approaches are usually used for recognizing few images. However, it can be used for recognizing many images according to complexity of their algorithms and techniques. Some of the images are not clear due to illumination, distance of person from camera and spatial resolution of the camera which cause problem in detecting special points of the face. These kinds of images require filtering algorithm for smoothing images before features extraction. Common filters algorithms are Gabor filtering[41] and high and low pass filtering[42]. Interpolation technique is one of the useful algorithms for increasing spatial resolution of images[43]. Image interpolation does tasks such as, zooming, shrinking and geometric correction.

MATERIALS AND METHODS: Approaches based on Eigen-space are important in holistic methods. PCA technique is one of the most popular algorithms that is used to represent linear global features of images[44]. The steps of PCA algorithm are as follows:

Let T be an image matrix and Tj (j=1 to N) denote N different training images.

1) The average image (mean image) $T\ mean$ of training set is calculated as below.

$$T_{mean} = \frac{1}{N}\sum_{j=1}^{N} T_j \tag{3}$$

2) Compute the Covariance (scatter) matrix S as follows:

$$S = \frac{1}{N}\sum_{j=1}^{N}(T_j - T_{mean})^T (T_j - T_{mean}) \tag{4}$$

The Covariance matrix contains attributes of training set.

3) The eigenvalues and eigenvectors for matrix S are computed as below.

$$SV_i = \lambda_i V_i \tag{5}$$

Where; Vi is called eigenvector and λi denotes eigenvalues of the S matrix.

4) From the covariance matrix S, select k higher eigenvalues and extract the corresponding eigenvectors.

$$U = \{V_1, V_2, V_3, \ldots, V_k\} \tag{6}$$

Where; U contains high energy magnitude of the scatter matrix.

5) The represented components of images *Yj* (j=1 to N) are computed using extracted eigenvectors *U* and training set images *Tj* as follows:

$$Y_j = U^T * T_j \tag{7}$$

6) All the test images are represented in Eigen-space using Eq. (7).

7) Image classification: The nearest training image to the test image is selected by computing Euclidean distance.

$$d(Y_j, Y_i) = \sum_{p=1}^{k} \sqrt{(Y_j^{(p)} - Y_i^{(p)})^2} \tag{8}$$

Where; *d(Yj,Yi)* measures the distance between training set *Yj* and test set *Yi* images in face space. Other techniques like neural networks[45] and SVM[46] can also be used in place of Euclidean distance.

The 2DPCA algorithm is applied on two-dimensional image as compared to PCA which is applied on vector images[10-11].

Fourier transform is a mathematical technique which converts the real data to complex data that provides transformation of data between times into frequency domain. Those elements (real and imaginary values) will help to compute the phase, amplitude and magnitude components of the frequency. Fourier transform can be computed as follow[1&15]:

$$F[u,v] = \frac{1}{\sqrt{MN}} \sum_{y=0}^{N-1} \sum_{x=0}^{M-1} f[x,y] e^{-j2\pi(\frac{xu}{M} + \frac{yv}{N})} \tag{9}$$

Where; $M = X/x$ and $N = Y/y$ are contain the number of samples in x and y axis.

And power of the frequency/energy spectrum or Fourier magnitude computes as:

$$Power = \sqrt{R^2 + I^2} \tag{10}$$

Where R and I are Read and Imaginary components of complex number. Power is the magnitude of the frequency domain. The classification had been done using Euclidean distance.

RESULTS AND DISCUSSION: Some of the existing face recognition algorithms including PCA[11], 2DPCA[10 & 11], FMPCA[15 & 16], FM-2DPCA[16] and LBP[33] are implemented and tested on ORL standard face database. The ORL face database contains 40 images from 10 individuals in different poses and expressions, which are resized into 81x81 pixels. The techniques are implemented using MATLAB version 2011. Figure 2 shows sample images of ORL face database. Euclidean distance algorithm is used for classification of objects.

Figure 2: Image samples of ORL face database.

The phase components are robust to illumination variation. It means, two similar images in different illumination conditions are very similar to each other in phase reconstructed image. Figure 3 shows an image sample of ORL face database in different illumination conditions and their phase reconstructed images.

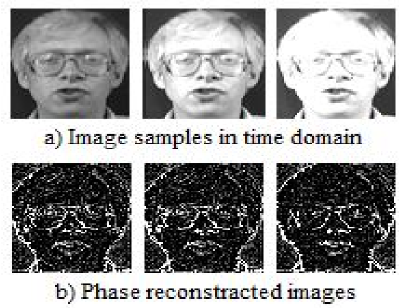

Figure 3: a) Sample image of ORL face database in different illumination condition, b) Phase reconstructed image samples.

Table 1 shows the results of implementation of LBP as well as Principal Components based techniques on ORL database in time and frequency domain. First five images of each individual are considered as training set and remaining images are selected for testing. Each image of ORL database is represented in 324 dimensional Eigen-space. From literature review and experimental results, it is observed that frequency components are more robust to pose and expression as compared to time domain. Also it can be observed that global features provide better face recognition under pose and expression as compared to local extracted features using LBP algorithm.

Table 1: Performance of local features and Holistic based approaches on ORL face database in time and frequency domains.

Algorithm name	Recognition Rate (Percentage)
LBP	83.5
PCA	92.5
2DPCA	93.5
FM-PCA	97.5
FM-2DPCA	95.5

The accuracy, memory and time complexity achieved in FR depends on extracting significant features. The Local features extraction algorithms like LBP and LXP, are robust to illumination and expression variations whereas Holistic approaches, like PCA, 2DPCA, FMPCA and FM-2DPCA are robust to pose and expression variations.

Images can be converted from time domain into frequency domain using different techniques such as Fourier transform (FT) and Discrete Cosine transform (DCT). The frequency domain applications are more time consuming due to nested process loop for domain conversion. However, the components of frequency domain like Fourier magnitudes (FM) and DCT achieve better recognition rate as compared to time domain components. Our experimental results on ORL database confirm that the algorithms based on Principal Components in frequency domain are more robust to pose and expression as compared to time domain.

The literature review focuses on feature extraction techniques for face recognition irrespective of pose, expression, illumination, scale and degradation variations. It is observed from review of literature that most face recognition algorithms are developed for FR irrespective of illumination or pose or expression or rotation or a combination of two or three. The textual details of faces will be changed with pose, expression, illumination and degradation variations. The phase components of image are robust to illumination. In rotation, the coordinates of all pixels will be changed but details of images will remain same.

CONCLUSION: In this paper, extensive review of face recognition techniques and experimental results are included. From literature review it is observed that no single algorithm can perform accurate recognition under all challenges of face recognition system. PCA can be used for face recognition under pose and expression, LBP is independent of illumination and expression. The geometrical features are sensitive to noise and degradation. Therefore, noisy and degraded images should be smoothed by applying some filtering algorithms such as low pass frequency, Gaussian and Gabor filtering on images. Phase components are independent of illumination. From literature review as well as from experiments, it is observed that frequency components like FM-PCA and FM-2DPCA are more robust to pose and expression images as compared to time domain. However, frequency domain algorithms have more time complexity as compared to time domain applications. Extracting significant features from images reduce space dimensionality, time complexity and improve recognition accuracy.

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