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Classification of Imagery Data and Face Recognition Techniques

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ABSTRACT
A lot of research work has been done by the researchers in the field of face recognition. These days many innovative issues of research and application in the field of face recognition are still pending and required to be discuss and develop. Different studies on face recognition already have been done and implemented but suffering from a single view point, applications and methods, because of traditional imagery input data. This paper explores and classifies the different input imagery data: traditional images, videos (sequence of images with time interval) and 3D images, considered to develop the face recognition techniques: signal processing, machine learning and multidimensional face recognition. The key feature of this study is to introduce a new era of face recognition system and technology (*input sources*, *effects*, *techniques*, *assessment, limitations etc.)* based on Multidimensional Imagery Data known as Multidimensional Face Recognition System (MFRS).

Keywords
Face Recognition, Sensory Inputs, Manifold learning, Hyperspectral Image.

1. INTRODUCTION
Image processing, Pattern recognition, Computer vision and many more are the different areas in which the face recognition has achieved great popularity. Practically the performance of the face recognition system depends on the several factors such as illumination conditions, viewing directions or poses, facial expression, aging, and disguises. Face recognition is used in various fields such as in commercial, law enforcement, and military, and so on. Face recognition are based on two tasks: verification (one-to-one) and identification (one-to-many). The different applications of face recognition are described in Table 1.

Table 1. Different Applications of Face Recognition

S.No	Areas	Task Performed
1.	Security and Surveillance	• Airport • ATM Machines • Border Cross point • Network security
2.	Indexing of Videos	• Surveillance • Mugshot/ ticket booking • Criminal Justice system
3.	Investigation of Image database	• To find the Missing Children's • Witness face reconstruction • To Manage the driving license
4.	Verification for identity	• Banking field • Electronic Commerce

2. CLASSIFICATION OF INPUT IMAGE FOR FACE RECOGNITION
In the survey, it is found that there can be the different types of input image for the face recognition. The several types of input image for the face recognition are defined as follows:

2.1 Traditional Images
Image-based face recognition methods is categorised into two types i.e. feature-based and holistic methods. In the feature-based face recognition method, geometry-based is one type of face recognition method which is considered as the most popular. The work presented by R.Brunelli [31] is a representative work, in which a vector of 35 geometric features is computed shown in Fig 1, and finally the recognition rate is calculated near to 90%. But again he used the geometry based method named as template-based face recognition, on the same database and found the recognition accuracy near to 100%. Further different geometry based face recognition methods such as filtering and morphological operations, Hough transform methods [1] and deformable templates [2] are proposed. Different authors have applied 30-dimensional feature vector, which were derived from 35 facial features as shown in Fig 2. They calculate the recognition accuracy approximated near to 95% on the database of 685 images. These different facial features are pointed manually and had some constraints on auto recognition in the real face recognition system.

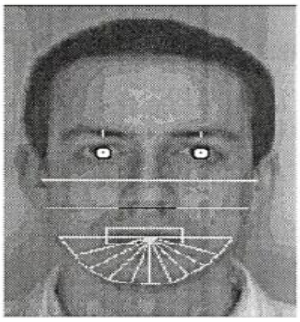

Fig 1: Geometrical Feature Based Face Recognition [31].

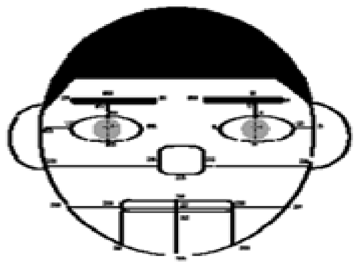

Fig 2: Manually Mark Facial Feature [3].

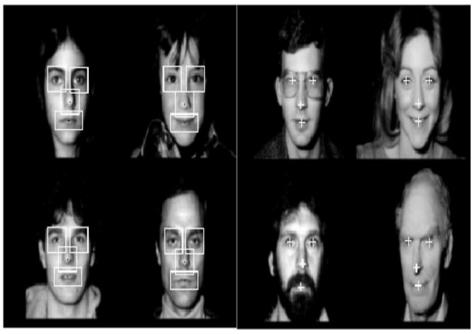

Fig 3: Face Images having Low Resolution [33].

Another method is holistic methods in which the face is identified by using global representations, i.e., the features of entire image is extracted rather than to the local features of the face. The whole face image having low resolution depicting features (salient face features) is shown in Fig 3.

Principal Component Analysis (PCA) has been widely used for the recognition of the face. There are a lot of advances in PCA, used for face recognition. Weighted Modular PCA [4], two-dimensional PCA [5, 6], multi-linear subspace analysis [7], symmetrical PCA [8] are the different PCA based algorithm which were used by different researchers.

2.2 Sequence of Images or Video

Due to the popularity of video surveillance, video based face recognition has been widely implemented in the several areas. Video-based face recognition system typically contains three steps: face detection, face tracking and face recognition [9].In the practical video face recognition system; generally a good frame (sequence of images) is applied to recognize a new face [10]. In video-based face recognition, a sequence of images is generated as shown by the Fig 4 [11].

2.3 3-D Images

Sixteen images which are from front are shown by the Fig 5. The profile photographs were represented as the gray scale images. To avoid the individuals from matching the faces with the hair styles and forehead fringes, the distances of the lowest hair cue in the forehead and the distance of the concave of the nose of all the faces were measured [12].The minimum distance among the faces represents as the standard length for all the faces in the same set.

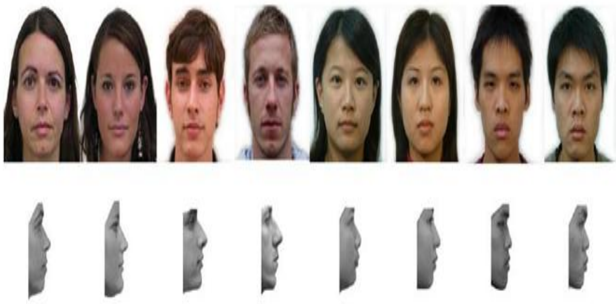

Fig 5: Front Pose with Gray Scale [12].

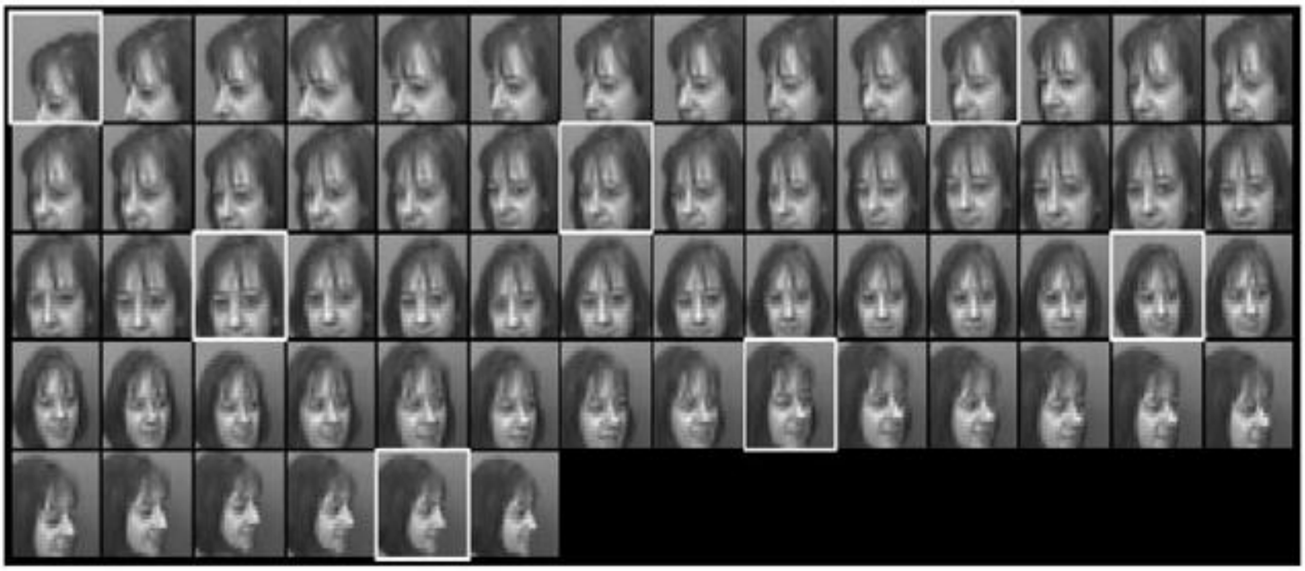

Fig 4: Sequence of the Face Images [11].

2.4 Multi-dimensional Images

There are a number of fields where images of higher dimensionality are analyzed. Good examples of these are medical imaging and biological imaging.

There is also Multispectral and Hyperspectral imaging, which are widely used in environment survey, agriculture, forest and mineral exploration. Multispectral and hyperspectral imaging produces a collection of spatially coregistered images with the contiguous wavelengths. The different applications of Multispectral and hyperspectral imaging are used to different types of biometrics and skin diagnosis, etc. The barrier of limitations of Multispectral images is broken by hyperspectral imaging system, few year back this advance and rigid imaging system is developed, which is coming into the picture as a powerful and versatile means for continues sampling of narrow intervals of the spectrum [26]. In hyperspectral imaging system, hyperspectral camera collect information as a set of 'images layers', called as 3-D data cube. The XY plane represents the spatial information and Z-axis represents the number of bands in an image. In hyperspectral data cube each image is represented by a range of the Electromagnetic spectrum which is also called as a spectral band. These

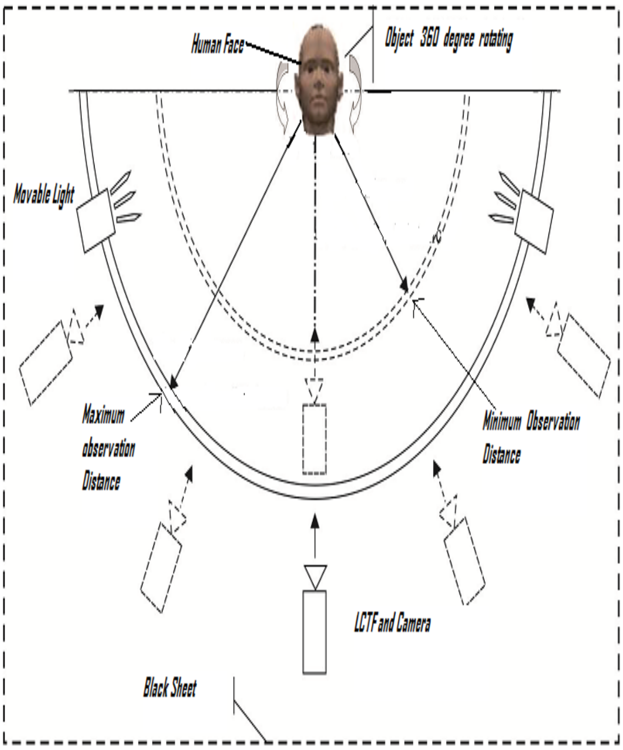

Fig 6: Hyperspectral Imaging System [26]

'images' are combined to make a 3-D hyperspectral data cube which is further used for processing and analysis.

In hyperspectral imaging face recognition, it extracts the spectral information of the human skin at various wavelengths, which represent the information of skin like color, patterns, and spots apparent in the form of reflected, absorbed and emitted electromagnetic energy [30]. The identification pattern of a person can be determined by their molecular composition (water, carbohydrates, lipid, proteins and nucleic acid) that relates to tissue, blood, and structure, etc. Consequently, this leads to the possible application of hyperspectral imaging to face recognition, and has the potential to overcome the difficulties in traditional face recognition, such as the variances of face orientations and expression.

Face recognition has the significant breakthrough due to the development of hyperspectral images and software packages. The hyperspectral imaging system has the ability to analyze the hyperspectral images in an efficient manner. An indoor hyperspectral face acquisition system shown in Fig 6. An example of hyperspectral image of 33 spectra developed by hyperspectral imaging system [26], in the spectral range from 400 to 720 nm is shown in Fig 7.

3. DIFFERENT FACE RECOGNITION TECHNIQUES

The Face Recognition is a computer application for automatically identifying or verifying a person from the input image. The input image can be taken from the different sources such as a video frame from a video source. Face Recognition process passes through the different phases such as pre-processing, feature extraction, recognition and post processing [24].There are different methods for the face recognition.

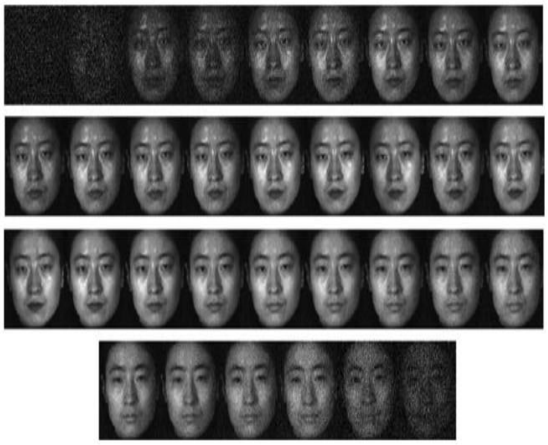

Fig 7: Hyperspectral Images with 33 Spectral Bands in Visible Range (400-720nm) [26].

3.1 Signal Processing Face Recognition

The features of a face image have the great impact in the recognition of a face and based on these features, the new face image can be classified. Generally the feature extraction methods are categorised into two classes i.e. signal processing and statistical learning methods. In signal processing methods, Gabor wavelets are mainly used to represent the face image [13]. This is due to that the kernels of Gabor wavelets are same as the 2-D receptive field profiles of the mammalian cortical simple cells, which is used to acquire the characteristics of spatial localization, selectivity of orientation, and spatial frequency selectivity, which provides help in adjustment of varying in illumination and facial expressions. On the other hand, in the statistical learning based methods, the concepts of method of dimension reduction are mainly used. There are mainly two methods named: PCA and LDA, which are widely used as the dimensionality reduction methods [14]. During the past research, Kernel based feature extraction methods were also used in the face recognition process [15].

In this section the Gabor based method for face recognition is discussed. During the last decades, the image segmentation is performed with the use of Gabor filter sets. These filter sets provides a variety of normal texture features. Inspite of all these, there is some limitations with this method. The first one is that Gabor decomposition represents the processing at the lowest level in the visual system. Another limitations is that Gabor wavelets is generally non orthogonal, so due to this there is always chances that the filtered image represents the redundant information. The Gabor based face recognition method can be categorised into two categories, one is analytical methods and the other is holistic methods.

Analytical methods are based on the selection of the nodes. Graph-matching based, manual detection and enhanced methods falls in this category. Holistic methods works on adequate preprocessing, like face alignment, size normalization and tilt correction. However these methods still face the problem of the dimensionality. So to minimize the dimensionality reduction, the PCA and LDA methods were implemented.

3.2 Machine Learning Face Recognition

Machine learning is the branch of artificial intelligence, which is concern with the designing and study of the system which can learn from the data or can take knowledge from the given data. Machine learning algorithms are also used in the recognition of faces. These algorithms are divided into two categories.

3.2.1. Manifold Learning Based Face Recognition

The important step in data analysis is to extract the feature with the reduction in dimensionality [16]. The dimensional reduction is achieved by two methods named as LDA and PCA. The main objective of LDA is to find the optimal projection matrix with the help of Fisher criterion through considering the class labels. On the other hand, PCA is based on to minimize the mean square error criterion. With PCA the nonlinear curves such as principal curves or principal surfaces are produced which are generally equivalent to self-organizing maps (SOM). With the advancement of SOM i.e. ViSOM which keeps the distance information on the map and produce the nonlinear data [17] called as discrete principal curve. Researchers also developed others manifold algorithm named as Isomap [18], Locally Linear Embedding (LLE) [19] and Locality Preserving Projection (LPP). In recent years Researchers also developed the improved LPP Algorithms. To increase the discriminant power in the low-dimension space, Zheng et al. used the class labels of data points to propose Supervised Locality Preserving Projection (SLPP) for face recognition. Because LPP does not support orthogonality, so it is not possible to reconstruct the data. To avoid this problem, the researchers applied the concept of class information to present a new technique called as Orthogonal Discriminant Locality Preserving Projections (ODLPP) for face recognition. Yu et al. presented constraint which was simple and uncorrelated into the form of objective function, which is called as Uncorrelated Discriminant Locality Preserving Projections (UDLPP). The basic objective to develop UDLPP is to keep geometric structure within a class and maximize the distances between the classes. An alternative of Kernel LPP (KLPP) was developed by Feng et al. called as KPCA+ LPP algorithm. Locality Preserving Projection and its enhanced techniques were used in many fields, such as to recognise an object detection of face and Image analysis. Different researchers proposed 2DLPP technique for the face recognition in which the features are extracted directly from the matrices of image without the transformation of one matrix into the vector [20].

The learning methods are classified into two categories i.e. supervised and unsupervised learning. PCA and LPP methods are the example of unsupervised learning, while LDA method falls under the supervised learning. Another difference between PCA and LPP is based on the global or local property of the image. PCA always contains the global property of image but on the other hand LPP point to the local structure. The locality property characteristics of LPP help LPP to perform better than PCA.

3.2.2. Face Recognition Based on Kernel Learning

In past years for face recognition, many algorithms were developed using the kernel. Some of them are kernel principal component analysis (KPCA), kernel discriminant analysis (KDA) and support vector machine (SVM). In 1998 Scholkopf et al developed KPCA, while KDA was developed by Mika et al. in the year of 1999. A variety of KDA algorithms were developed by different authors. Some of them are Juwei Lu [21], Baudat and Anouar [22] and Yang [23]. The performance of these KDA techniques depends on the geometrical structure of the data in the kernel mapping space. These geometrical structures are computed by the kernel function. To minimize the limitations of KDA, different methods were proposed by different researchers.

3.3 Multidimensional Face Recognition

3.3.1 Multispectral Face Recognition System

Multispectral Face Recognition System (MFRS) have more spectral bands than conventional Face Recognition Systems and reduces color variations in the face due to changes in illumination source type and directions. With all the advantages over the traditional face recognition system, the MFRS has limited number of spectral bands (less than 20) of the EMS. Therefore MFRS is not much capable to provide more accurate, hidden and meaningful information of human face.

3.3.2 Hyperspectral Face Recognition System

The “hyper” in hyperspectral imaging represent “over” as in “too many” and points to the large number of measured wavelength bands [33]. A wavelength band is the range of frequencies in a particular range. Hyperspectral images are spectrally overdetermined, which means that they provide meaningful spectral information to identify and distinguish spectrally unique image. Hyperspectral image is defined by the three dimensions (S_x, S_y, S_z) where S_x and S_y are called as spatial and S_z is called as spectral, shown in the Fig 8.

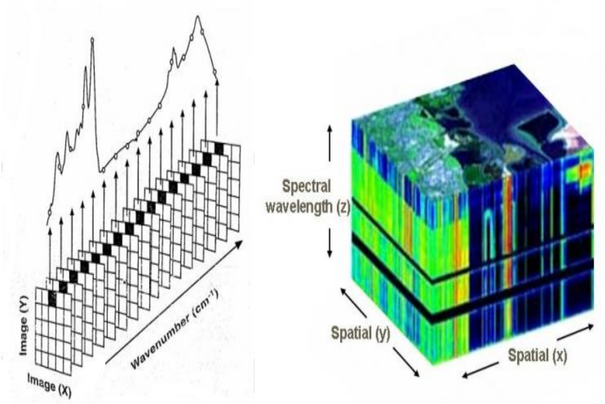

Fig 8: 3-D Representation of Hyperspectral Image [30].

Hyperspectral images also provide help in remote sensing applications to extract the more detailed features called as spectral information [32]. Different methods have been proposed by different researchers for the hyperspectral face recognition system. The brief details are provided as follows.

In 2011, T.J Roper and M. Andrews developed a hyperspectral imaging system, using Hyperspectral Human Skin Database (HHSD) of 79 participants (subjects), covering a wide range of scope like age, ethnicities, skin tones and gender, in Visible (400nm)-NIR (1100nm) electromagnetic spectrum with 10nm/spectral bandwidth. A custom-designed image spectrometer; based on Electromagnetic Tunable Filter (ETF) technology and MySQL Server, were used in data acquisition and data implementation tasks. The custom-built support platform was used to overcome the discontinuities in the spectral dimension of the data cube due to participant movement during the acquisition process. These data, along with the relevant metadata such as participant information, calibration data, etc., have been stored in a MySQL Server. The purpose of this study was to develop a HHSD to aid into hyperspectral face recognition applications, such as skin detection and colour modelling [35].

In 2012, Dong-Lin Li and Mukesh Prasad developed an appearance-based face recognition technique called as Nonparametric-Weighted Fisherfaces (NW-Fisherfaces) extraction technique to extract the features of a hyperspectral image and also increase the separability for different person faces. The NW-Fisherfaces was compared with Orthogonal Laplacian faces, Eigenfaces, Fisherfaces, direct linear discriminants analysis, and null space linear discriminants analysis methods [25].

In 2010, a hyperspectral face recognition system was developed by Wei Di and Lei Zhang, in which three classes of methods, namely: WB (Whole Band) PCA, SBD (Single Band) PCA and BS-xFD (Band Subset Fusion Based) PCA are proposed for face recognition. The spectral measurements were limited over the hyperspectral frontal imagery database of 25 individuals with 33 spectral bands in visible range (0.4–0.72 μm) [26].

To overcome the orientation problem in 2D face recognition system, a Hyperspectral Face Recognition System (HFRS) was developed in 2010 by Andrew Wimberlya, in which an efficient method for face recognition was developed using hyperspectral imaging and orthogonal subspaces (compactness and reduction of redundancies). The author mainly focused on two approaches: Principal Component Analysis and Orthogonal Subspace Projection and categorized the research work in three stages. First, the author created a hyperspectral image database (HYPDB 3.0) of 17 subjects each with five different facial expressions and viewing angles, secondly, development of fused gray scale imagery data. Third, the PCA and OSP based methods were designed and tested a HFRS. The experimental results show that spectral fusion of visible and infrared images leads to improvement in recognition accuracy when compared to regular imaging [27].

To efficiently estimate the age of an individual based on his/her facial characteristic is important part of an effective HFRS. In a research work in 2011 by Petra Koruga,, the face recognition algorithms: Principal Component Analysis (PCA), Independent Component Analysis (ICA), Linear Discriminants Analysis (LDA) and Elastic Bunch Graph Matching (EBGM) were implemented and compared to estimate the age of a human face . The experiments proved that the EBGM algorithm has the great significance than other face recognition algorithms [28].

Interest points of a human face are widely used as point-features in Face Recognition. In a study conducted by Amit Mukherjee in the year of 2009, face recognition method based on interest points was proposed using hyperspectral images. The formulation of the hyperspectral data cube is based on a Gaussian scale-space representation, and principal components decomposition is used to combine information efficiently across different spectral bands [29].

In a study conducted by Zhihong Pan in 2003, a Hyperspectral Face Recognition algorithm was developed that exploits spectral measurements for the multiple facial tissue types in NIR range (700nm-1400nm). A hyperspectral images database of 200 subjects was developed using CCD (Charge Coupled Devices) camera equipped with a liquid crystal tunable filter to provide 31 bands. Spectral measurements allow the sensing of subsurface tissue structure which is significantly different from person to person, but relatively stable over time. The local spectral properties of human tissue are nearly invariant to face orientation and expression which allows hyperspectral discriminants to be used for recognition over a large range of poses and expressions [30].

4. CONCLUSION

Face recognition has become a technology in the field of pattern recognition and earned a great significance in the area of research as well as in the real-world practical applications. This paper provides a classified and detailed knowledge about the traditional imaging systems based on single image, videos and 3-D images, also proven by different face recognition methods such as kernel learning, manifold learning etc. In this research paper, we tried to enlighten few researches based on multidimensional (multispectral/hyperspectral) imagery data sets; known as Multidimensional Face Recognition System (MFRS). This new imaging system is trying to prove its rigidness in the area of face recognition, dermatology, biological analysis etc., however some gaps like improper functioning of traditional methods against these multidimensional images, lack of information in Visual, NIR, VNIR, SWIR and TIR spectral ranges and so on. So these gaps can be filled by the researchers to design better methods and models using high resolution and improved multidimensional images focusing on the more difficult test.

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