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A Study on Gender and Age Classification as the Two Most Vital Tools in the Identification and Verification System

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Abstract: Gender identification and age classification is one of the challenging aspect in biometric authentication and verification system which capture walk from far distance and study physical information of the subject such as gender, race and emotional state of the subject. It was established that most of the gender identification methods have focused only with frontal pose of diverse human subject, image size and type of database used in the procedure. Different feature extraction process such as, Principal Component Analysis (PCA) and Local Directional Pattern (LDP) that are used to extract the authentication features of a person will also be classified in this study. The aims of this paper, is to analyze the different gender classification methods and age estimation framework in computer vision that help in evaluating strength and weakness of existing gender identification algorithm. Hence, a new gender classification algorithm will be develop with less computational cost and accuracy. An overview as well as classification of various gender identification methods will be presented first and then compared with other existing human identification system by means of their performance.

Keywords: Aging pattern, Feature selection, Feature extraction, Human identification system, Gender classification methods

Introduction

There are many applications such as monitoring, surveillance, commercial profiling and human computer interaction which benefits from reliable approaches for gathering age and gender of users. Such applications exist through a wide array of fields, from personalized advertising to law enforcement to reputation management. With the development of the recent technology, every individual requires security, accuracy and privacy in all aspects of his daily activities, where accuracy of any identification and verification system of human is one of the basic requirements for any biometric authentication system. Some of the wide range of application in which gender identification and classification techniques are very much essential includes; surveillance and security system, real time electronic marketing, biometric authentication, demographic information collection, marketing research, criminology, and augmented reality in social network. An effective gender identification algorithm can boot the overall performance of entire system, which involves feature detection and gender identification of individual subject parameter. Human face can be one of the subject parameter which provides most important visual information that can reveal a wide variety of information, whether identity, age, gender, race etc. These basic attributes like age and gender play fundamental roles in our day to day lives. Facial information differs from person to person, still human can determine the gender and age of the person just by a simple inspection of their face, and on the other hand to accomplish the same task computationally by analysis of human facial image is a challenging one for computer system. As it requires extraction of distinct features and attributes from the persons face image to classify them as ‘male’ or ‘female’ of age group as ‘child’, ‘teenage’, ‘mid-age’ or ‘senior-citizen’. Thus, enabling a computer system to discriminate the face images on the basis of gender and age of the person is yet to be a challenging task. The two most common feature extraction processes used to extract functional parameters in gender identification methods are; principal Component Analysis (PCA) and Linear Discriminate Analysis (LDA). LDA is used to obtain discriminate features of a subject, which maximize the difference between classes of information. In addition, LDA feature extraction process is built on the variance rather than resemblances of information and the total number of discriminate feature. In PCA, to capture the direction of maximum variance that helps in reducing the amount of noise in gender identification method a set of mutually orthogonal basis function is used. The extracted features for gender identification, are given to classifier algorithm such as Adaboost, multilayer Neural Network (NN), Radial Basis Function (RBF) and Support Vector Machine (SVM) [1]. A research of comparison was carried out by Makinen and Raisamo [2] on the performance of several classifier algorithms in gender identification process and it was found that SVM classifier has achieved the better performance.

The performance of gender classification techniques also depend on the type of database and quality of the image. Some of the common database used for gender identification/classification process are FERET, FRGCv2, LFW, IRIP, CASIA dataset B. It is evident from the literature that, regular frontal image of a person used in gender classification process has reach maximum efficiency and accuracy.

An image fusion process was proposed by selecting different spatial scale features with mutual information Juna and Claudio [3]. The image fusion has used the histogram of LBP, intensity and shape in gender identification process. The proposed technique is analyzed using FERET database with 1009 images of size (64 x 72) and UND database with 487 frontal images of size (20 x 20, 36 x 36, 128 x 128). Another technique of gender identification algorithm with mixture of experts to classification of gender, ethnic origin and pose of a human faces was proposed Srinivas Gutta et al. [4].

Table 2 characterizes different database available for gender identification and the total number of images in each database. A complete overview of different gender classification methods will be the aim of this study with emphasis on advantages and disadvantages and the comparative study of various gender classification methods that helps in identifying good classification process. The analysis will also highlights some of the factors such as, feature extraction method used in each process with restricted database and parameters taken into account for gender identifying process. The above analysis helps in inspiring us to develop a system with maximum accuracy and efficiency.

Literature Review

This section describes an extensive review of the research undertaken in the domain related to different existing gender classification methods along with feature selection and extraction process in different database. A new age estimation approach considering the intrinsic factors of human ages has been proposed by Wei-Lun, JunZua and Jian-Jiun [5]. They presented an age-oriented local regression algorithm called KNN-SVR to capture the complicated facial aging process over the most widely used FG-NET aging database. The proposed approach achieves the lowest mean absolute error (MAE) against the state-of-art algorithms under several experimental settings. A gender classification by fusing different spatial scale features obtained from mutual information, intensity and shape has been proposed by Juan et al. [2]. Intensity feature was extracted from each pixel in the gray image and shape feature is also extracted by edge histogram of horizontal and vertical edge map. Additionally, texture features was extracted by mutual information obtained from different measurement such as mRMR, NMIFS, CMIFS and CMIM. The investigation results ensure that FERET are found to be better than other two databases (UND and LFW) and it also depends on face image quality. A gender classification via lips: static and dynamic features was proposed before [6]. The authors compares the performance of the mouth, chin, nose, eyes, full-face and inner/outer faces of still images obtained from the FERET and XM2VTS database to design an automatic speech recognition system of unknown individuals. Lip modeling framework based on GMM and DCT gave more information about appearance and dynamics features of male and female image. The experimental result of the above process has attained 100% accuracy. The major constraint such as conditional pose and change in speaker pose is also demonstrated. An algorithm based on human gait skeleton gender classification was proposed by using class B of Chinese Academy of Science dataset (CASIC B) [7]. The technique use 2D human gait skeleton walking model and it also calculated joint angle values at major points of human parts, i.e. difference between left and right legs and obtained 85.33% classification accuracy. This was found to be good in analyzing five different features of human gait. In previous literature, a multi-scale Independent Component Analysis (ICA) texture pattern for automatic gender recognition system was presented [8]. In this process, each individual face image will be analyze and it is encoded by sorting the responses obtained from ICA filter. However, the non-overlapping sub-regions histogram of the encoded image is fused into single histogram to enhance feature extraction process. This experiment has created better results with Sparse Classification (SC). A geometric based 3D gender classification technique was proposed by earlier researchers [9, 10]. The facial image obtained by laser scanning is subjected to radial and iso-level curves are used to study face image shape. The radial curve is used to locate upper part of the face and iso- level curve is used to cover the central strip of the face which is used to compute similarities between male and female template. After finding the similarity, the method used a machine learning algorithm, which includes adaboost, neural network and SVM to attain maximum accuracy and efficiency. The process used FRGCv2 dataset of different subject and produced 84.98% classification accuracy. But, it fails to explain about ethnicity and facial expression. A gender recognition using 3D human body shape was developed [11]. The method have used different machine learning algorithm to analyze breast regions of human body that helps in identifying male or female subject. On the other hand, SVM is used for gender classification and to produced maximum accuracy in geometric 3D gender classification. Maodi Hu.et al. [12] have presented a gait-based gender classification with Mixed Conditional Random Field (MCRF). The method explains about shape, appearance and temporal dynamics of both genders are given to a sequential model to extract major feature of the subject. In temporal part, neighborhood preserving embedding scheme is clustered to allocate the stance indexed over gait cycle and in shape descriptor part, ellipse fit parameters are used. Further, by fusing temporal and shape descriptor part the process has attained better classification mechanism. Srinivas Gutta et al. [13] have proposed a mixture of experts to classify gender, ethnic origin, and pose of human faces. RBF/DT architecture is used to identify the gender, ethnic origin and pose of a human faces, further it is analyzed by using SVM classifier. The feasibility of this approach is demonstrated using FERET database and attained 96% accuracy. FERET is known as the most widely used dataset for evaluating gender recognition methods, and for age estimation FG-NET and MORPH [14] has been widely used. Hence, to reduce computation time a separate process for extraction and identification is required. Moreover, the performance of age estimation system in different situation separated into three different cases, which is usually measured by the Mean Absolute Error (MAE) [15], defined as the average of the absolute errors between ages and the ground truth ages.

A very simple process with low computational time was proposed by Juan bekios et al. [16]. The proposed process was a reassessment of linear discriminant technique for gender recognition. In selecting linear set of features to achieved maximum accuracy on a single database experiment we employs the use of linear classification technique and boosting algorithm. Tan levels and races [17], implemented a method called adaptive skin classification method to discriminate skin and non-skin pixels and to have great variability in terms of lighting conditions.

Human versus Machine performance has been proposed by Hu Han, Charles Otto, and Anil K. Jain [18][19]. They proposed a hierarchical approach for automatic age, gender and race estimation and provided an analysis for how long aging influence, individual facial components. Juan Bekios-Calfa, Jose m. Buenaposada and Luis Baumela [20], studied the problem of gender recognition from a multi attribute perspective. Gender recognition under constrained conditions (e.g. the color FERET database) is a well-known problem for which statement of the art algorithms provide performances well above 90%. However, when these algorithms are tested under real life conditions, significant drop in performance can be seen. The existence of conditional dependencies among various attributes like; gender, age and pose facial attributes, proves improvements in the performance of gender classifier by exploiting these relations. They achieved an 80.53 % success rate for the real setting in GROUPS database using an appearance based multi attribute linear classifier.

The multiple regression normalization strategy of gender identification process is a result oriented approach to study subject age, gender and it is used to identify differences in special temporal gait features [21]. The different gender classification methods, databases, testing methods, parameters and demerits in each gender identification process are analyzed to develop a novel gender identification technique with more accuracy and efficiency [1].

Table 1. Review of Some Feature Extraction Methods [15]

Feature Extraction method	**Summary**
Principal Component Analysis	PCA is mathematically defined as an orthogonal linear transformation that transforms the data to a new coordinate system such that the greatest variance by some projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on. For example, consider a data matrix, **X**, with column-wise zero empirical mean (the sample mean of each column has been shifted to zero), where each of the *n* rows represents a different repetition of the experiment, and each of the *p* columns gives a particular kind of feature (say, the results from a particular sensor).

Multi-Manifold Discriminant Analysis	In MMDA, the within-class graph and between-class graph are designed, respectively to characterize the within-class compactness and the between- class separability, and define the criterion function to calculate projection matrix, seeking for the discriminant matrix to simultaneously maximize the between-class scatter and minimize the within-class scatter. Thus, the within-class graph can represent the sub-manifold information, while between class graph can represent the multi manifold information
Local Binary Patterns	In LBP, LBP feature vector is created in its simplest form by using following steps: ▪ Examine window id divided into cells (e.g. 20X20 pixels for each cell.) ▪ Comparison for each pixel in a cell to each its 8 neighbors (i.e. on its right top, left-top, right-bottom, left-middle and etc.), along a circle in clockwise or counter clockwise direction. ▪ A 8-digit binary number is generated (which is usually converted into decimal for convenience) by putting “0” where the center pixels value is greater than the neighbors value else put “1”. ▪ Now, histogram is computed over the cell, of the frequency of each number occurring. This histogram can be seen as a 256-dimensional feature vector. ▪ Normalization of the histogram, which is the optional step. ▪ Concatenation of histograms (normalized) of all cell, gives a feature vector for the entire window. ▪ The feature vector can now be processed using any classifier.
Gabor	In the fields of computer vision, pattern recognition and image processing, gabor filter has large number of applications [22]. 2D Gabor filter is a selective filter in terms of frequency and orientation. Gabor filter response hasn’t been disturbed by noise and distortion exists at different locations due to accuracy in time-frequency localization.Hence, performance of gabor filter is upto mark for noisy images [23]. As modulated by Gaussian envelop [57], for particular frequency and orientation, gabor filter is being considered as a sinusoidal plane. $h\ x, y = s(x, y) \times g(x, y)$ Where, $s(x, y)$ is a sinusoidal plane of particular frequency and orientation; and $g(x, y)$ is a 2D Gaussian function known as envelop.
Discrete Cosine Transform	A DCT expresses a finite sequence of data points in terms of a cosine functions oscillating at different frequencies, while small high-frequency components can be discarded. The DCT is a Linear invertible function or equivalently an invertible N X N square matrix. There are several variants of the DCT with slightly modified definitions. The N real numbers $x_0, ..., x_{N-1}$ are transformed into the N real numbers $X_0, ..., X_{N-1}$.
Scale invariant feature transform	SIFT extracts feature descriptors from various key points in an image. The key points are detected from the scale-space extrema, which typically correspond to edges, corners and other informative structural changes in the image. The descriptors are formed by the orientation histograms of gradient directions over local regions around the key point. SIFT features are invariant to image scaling and rotation, and partially invariant to illumination changes and affine distortions. Using these descriptors, objects can be reliably recognized even from different views or

Age Estimation Outline

There were several age estimation algorithms published in the last decade, these algorithms can be separated into two categories [24]: First is to estimate the actual age (for e.g. 20- year old); and the second is to classify a person image into an age range, like a baby, teenage, middle-age or a senior person. An age estimation system can be simply divided into three steps: image input, feature extraction and age estimation or age determination. The typical age estimation system diagram is shown in figure 3.

For facial feature related to human ages or facial appearance, change are extracted from human faces for compact representation; subsequently an age estimation function can be built to estimate the age based on the extracted features.

If considered an age estimation as a conventional classification problem [27], then the simplest way is to model face images at each age. Researchers found out that; 'Age' is a comparative concept specified to each person; every person age is different in a different ways [25] [26] [27]. A face at particular age is more related to the same persons face at different age rather than to other persons face at different age. Therefore, they prepared an aging pattern, the concept of aging pattern can be described as an aging pattern is a sequence of personal face images sorted in time order. Figure 4 shows some typical examples of the "full-filled" aging patterns when AGES (Aging pattern Subspace, an algorithm for automatic age estimation) [28] is applied over FG-NET Aging database.

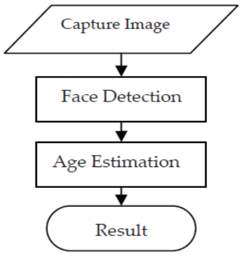

Figure 3. Age estimation system

Table 2. Different database available for gender classification with various poses, feature and total number of images in each database [1]

Database	**Expansion**	**Total no of images in the database**	**Type of images**
FERET	Face recognition technology	2413	Facial
IRIP	The laboratory of intelligent recognition and image processing	1089	Facial, Gait
LFW	Labeled faces in the wild	13,000	Facial
CASIA (dataset B)	Chinese academy of sciences	19,139	Gait
FRGC	Face recognition grand challenge	33,287	Facial
JAFFE	Japanese female facial expression	213	7 different emotional facial expressions
IMM	Informatics and mathematical modeling	240	Facial (still)
Purdue U	Purdue U database	3203	Facial
UND Biometrics	UND	33,287	Facial

Comparative Analysis of Different Gender Classification Methods

In Figure 1 below, different types of gender classification techniques have been described. Database available for human identification system and the methods used to extract features are shown for clear understanding.

According to the review of the previous investigation on the aforementioned gender classification methods, each has distinct advantages and disadvantages depending upon the requirements of the application. The review lists some of the major gender classification algorithms, database, methods used for feature extraction and classification. Some of the most commonly used parameters that help in gender identification process are, shape, texture, gender, ethnic origin, pose, gait shape, etc. Few gender classification methods were mentioned in Table 2,-together with their merits and demerits in each process. Moreover, the correct recognition result of five different gender classification methods with frontal face and gait from different database are examined and it is shown in Fig. 2. It is obvious that FERET database (frontal face) with mutual information has attained maximum accuracy of 99% accuracy. Next, the static and dynamic lip movement using DCT feature extraction process have attained 100 percentage accuracy. Finally, other feature extraction process with different parameters (frontal face and gait) has produce 96% of accuracy.

Analysis of five different gender identification methods with frontal face feature was done using different parameters such as, static dynamic lip movement, gender, ethnic, origin, pose, intensity, shape and various pose angle of human parts and it is shown in Fig. 2. Moreover, the database and accuracy of each classification process helps in understanding more about each gender identification algorithms. The advantages and disadvantages of different human identification process inspire us to develop a novel gender classification method with minimum computation time and maximum accuracy.

Discoveries from the Different Classification Methods for Gender Identifications

Several challenges have been faced by the existing classification methods in both the areas of application of 2D and 3D gender classification environment. For clear understanding of this process, result from the various gender classification methods for gender identification process are itemized. Resizing of image before and after feature extraction, computational time, pose variation, size, the classification using single database system, ethnicity, age and shape contribute to the most common parameters that are required to be analyzed for a good gender identification technique. High level of confidentiality on the datasets available for gender identification process to several hundreds of thousands of face images. Moreover, for different vector size feature selection process using mRMR, NMIFS, CMIFS and CMIM has minimum computation time. Though, research has shown that most common face identification system requires frontal pose of a subject.

From the literature, it was established that the proposed gender identification system fails for a person with different image positioning. Therefore, it is important to differentiate likely pose and to estimate original pose of an individual by using different process such as, normalization and detection of correct positioning. Getting a clear image quality when capturing frontal face of an individual, either the subject matter or the system must interact with each other. Then, there is also need for an unaligned facial image to be tested with several noises attacks in order to reduce the computational time in a large database and also to get maximum accuracy. Frontal face image normally requires specific region of interest to examine feature extraction process. The gender classification method with specific region of operation has produced poor results. Therefore, it is important to propose a gender classification method in a real time environment with less computation cost and to produce maximum accuracy for a system with autonomous size of the input images.

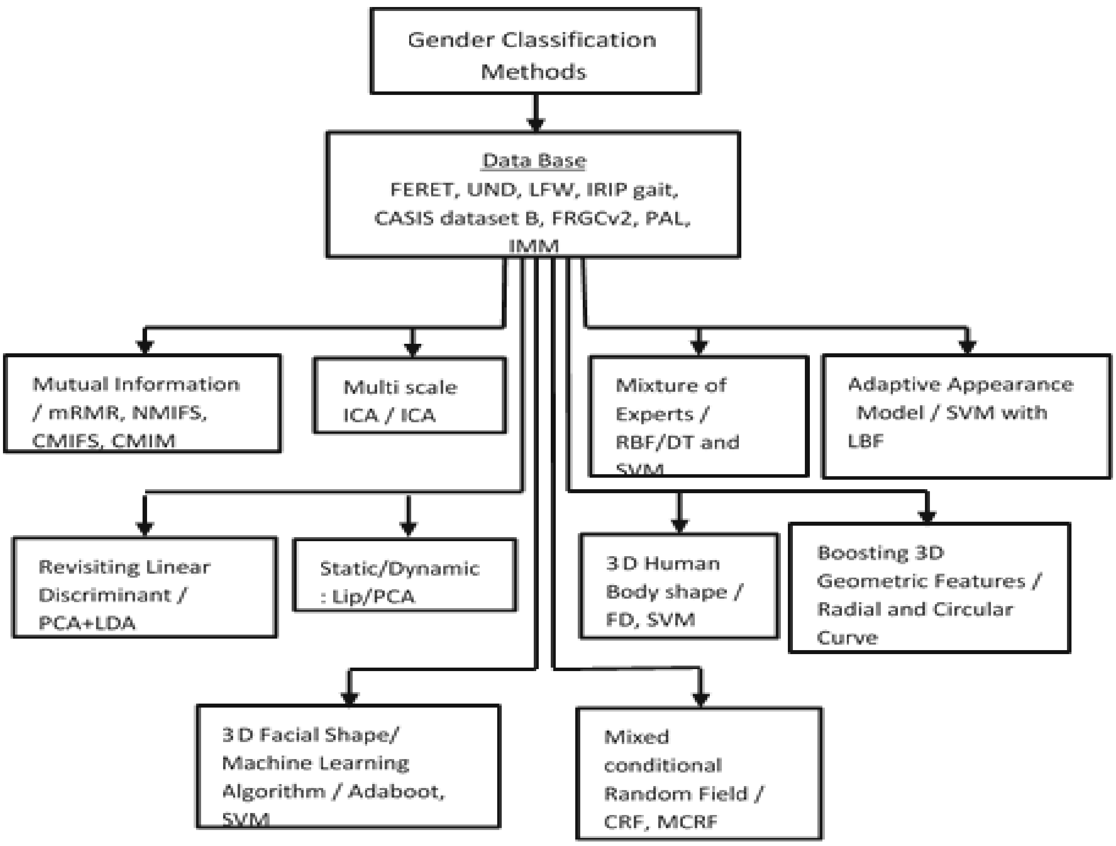

Figure 1. Various gender classification methods [1]. sourcet: https://www.researchgate.net/publication/321637452

<u>Database</u>

1. FERET- Face Recognition Technology.
2. PAL- Programmatic Agreements Library.
3. LFW - Labeled Faces in the Wild
4. CASIA (dataset B) - Chinese Academy of Sciences
5. FRGC - Face Recognition Grand challenge.
6. IMM - Informatics and Mathematical Modeling.
7. IRIP - The laboratory of intelligent recognition and image processing

<u>Techniques</u>

1. SVM- Support Vector Machine.
2. MCRF- Mixed conditional Random Field
3. PCA - Principal Component Analysis
4. LDA- Linear Discriminate analysis
5. ICA- Independent Component Analysis.
6. RBF/DT- Radial Basis Function / Decision Tree.
7. FD – Fourier Descriptor.
8. mRMR – minimum Redundancy and Maximal Relevance.
9. NMIFS – Normalized Mutual Information Feature Selection.
10. CMIFS- Conditional Mutual Information Feature Selection.
11. CMIM - Conditional Mutual Information Maximization.

Table 2. Shortcomings in different gender classification methods

Techniques	**Database**	**Method**	**Testing Result**	**Parameters**	**Demerits**
Mixture of experts	FERET	RBF/DT, SVM	100%	Gender, Ethnic origin and pose	Single data base analysis and require more training for improved results Frontal face image
Mutual information	FERET,UND, LFW	mRMR, NMIFS, CMIFS, CMIM	90%	Intensity, shape and texture	Restricted database and size
Mixed Conditional random field	CASIS dataset B	CRF, MCRF	-	Gait shape	Appearance based feature extraction and computation cost
Multi scale ICA	PAL	ICA	-	Size and coefficient of mask	Computation cost, restricted database and Size
Static/dynamic: lip	FERET and FRGCv2	PCA	100%	Lip Movement	Condition and change in speaker pose
Revisiting linear Discriminant	FERET and UCN	PCA + LDA	80%	Linear feature selection (pixel within the sample)	Limited data and computation resources

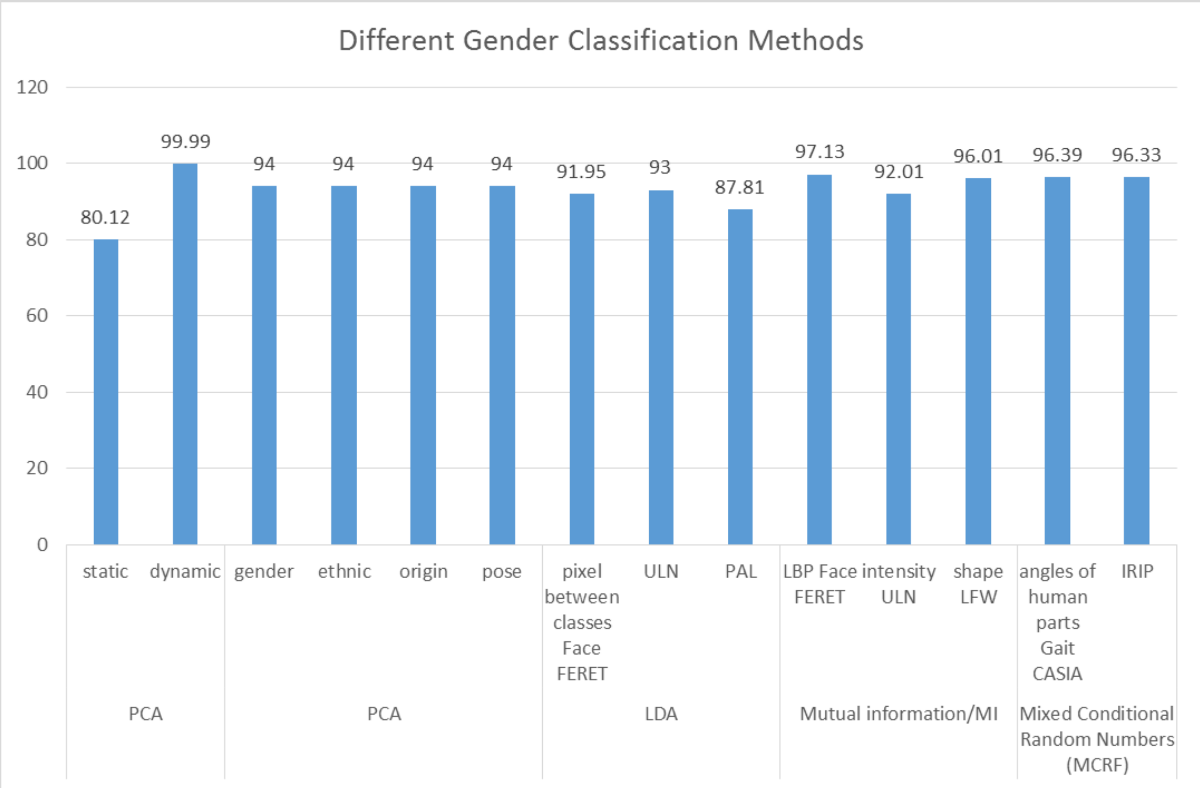

Figure 2. Accuracy of different gender classification methods
Source: https://www.researchgate.net/publication/321637452

<u>Database</u>
1. FERET- Face recognition technology.
2. PAL- Programmatic agreements library.
3. LFW - Labeled faces in the wild.
4. CASIA (dataset B) - Chinese academy of sciences
5. FRGC - Face recognition grand challenge
6. IRIP- The laboratory of intelligent recognition and image processing.

<u>Technique</u>
1. MCRF- Mixed conditional random field.
2. LDA- Linear discriminate analysis
3. RBF/DT- Radial basis function / decision tree

Conclusion

In this paper different gender classification algorithms and the various parameters used for gender identification methods were study. These parameters used to identify the Gender of a person are; Gender, pose, ethnic origin, shape, intensity, face, fingerprint, texture, gait shape, iris, lip movement and 3D face from laser scanning. Analysis on the experimental results of the existing processes was done to improve the performance of gender classification/identification methods. From the study, it was concluded that the applicability of a particular gender classification technique depends on the environmental requirements. Thus a single approach cannot satisfy all the gender classification requirements in various conditions, and each gender classification approach is suitable in a particular field according to the characteristic of performance. The Mutual information (MI) obtained using histogram of LBF, intensity and shape has produced 90% accuracy, which is found to be an improved result than the other existing algorithm. Subsequently, the computation time of gender classification method is reduced in advantage of gait and Mixed Conditional Random Field (MCRF), and it has attained 100% accuracy. An improved result was also achieved by the geometric based 3D gender classification method in terms of accuracy. Previous researchers have usually attempted to select only the features they require, rather than using all the features by exchanging efficiency for accuracy of classification. Therefore, data reduction methods are more convenient for selecting the target features. It is concluded that the gender classification accuracy changes with biometric authentication environment with different face orientation. The current gender identification methods have not focus more on different face orientation, which is very much essential for a gender classification technique to meet high amount of accuracy and efficiency in different environment. Additionally, a new multi feature SVM using face pyramid has achieved good results in gender recognition, age identification and name identification of an individual. The multiple regression normalization is considered to be more suitable for identifying spatial temporal gait features. Thus, the study reveals that the existing approaches also have some limitations such as low accuracy, low efficiency, and restricted application domain in various gender identification algorithms that helps in developing a new gender identification method with high accuracy, low computational cost and high efficiency in future.

Recommendations

Future research effortd should focus on the enhancement of the accuracy and realiability of the new system that will improve the performance of gender and age classification system.

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