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Face Image Retrieval in Image Processing – A Survey

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Abstract - The task of face recognition has been actively researched in recent years. Face recognition has been a challenging and interesting area in real time applications. With the exponentially growing images, large-scale content-based face image retrieval is an enabling technology for many emerging applications. A large number of face recognition algorithms have been developed in last decades. In this paper an attempt is made to review a wide range of methods used for face recognition comprehensively. Here first we present an overview of face recognition and discuss the methodology and its functioning. Thereafter we represent the most recent face recognition techniques listing their advantages and disadvantages. Some techniques specified here also improve the efficiency of face recognition under various illumination and expression condition of face images This include PCA, LDA, SVM, Gabor wavelet soft computing tool like ANN for recognition and various hybrid combination of these techniques. This review investigates all these methods with parameters that challenges face recognition like illumination, pose variation, facial expressions. This paper also focuses on related work done in the area of face image retrieval.

Keywords-*Content-based image retrieval,PCA,LDA,SVM and ANN.*

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I. INTRODUCTION

Face recognition is an important research problem spanning numerous fields and disciplines, because face recognition is a fundamental human behavior that is essential for effective communications and interactions among people. In addition, it is having numerous practical applications such as Military, Intelligence, Homeland Security, Law Enforcement, Private Security, Criminal Investigations, bio-metrics, bankcard identification, security monitoring, and surveillance system etc.

Many commercial systems are available for face detection. Recently, significant research efforts have been focused on video-based face modeling or tracking, recognition and system integration. One notable aspect of face recognition is its inter disciplinary nature of the interest within computer recognition and pattern recognition; bio metrics and security; multimedia processing; psychology and neuro science.

A general statement for the problem of machine recognition of faces can be formulated as follows: given still or video images of a scene, identify or verify one or more persons in the scene using a stored database of faces. Available collateral information such as race, age, gender, facial expression, or speech may be used in narrowing the search (enhancing recognition).

The solution to the problem involves segmentation of faces (face detection) from litter scenes, feature extraction and recognition from the face regions, or verification (Figure 1). In identification problems, the input to the system is an unknown face, and the system outputs the determined identity from a database of known faces, whereas in verification, the system needs to verify one or more individuals in the scene using stored database of known images. Generally, Face perception refers to understanding and interpretation of the individual's face, particularly the human face, while building a similar computer system is still an on-going research area.

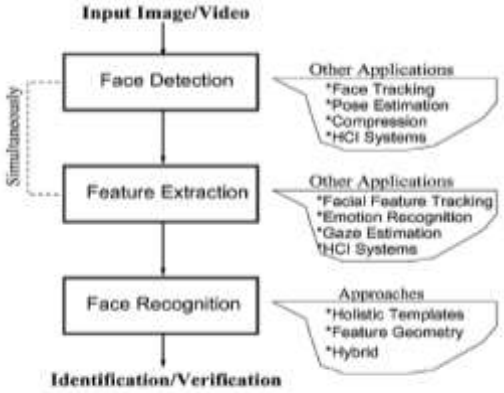

Fig. 1. Configuration of a generic face recognition system.

II. FACE RECOGNITION ALGORITHMS

A. Principal Component Analysis (PCA)

PCA also known as Karhunen-Loeve method is one of the popular methods for feature selection and dimension reduction. Recognition of human faces using PCA was first done by Turk and Pentland [1] and reconstruction of human faces was done by Kirby and Sirovich [2]. The recognition method, known as eigenface method defines a feature space which reduces the dimensionality of the original data space. This reduced data space is used for recognition. But the well known common problems in PCA method are its poor discriminating power within the class and large computation. Linear Discriminant Analysis (LDA) is used to overcome these limitations. LDA is the most dominant algorithms for feature selection in appearance based methods [2].

But many LDA based face recognition system first used PCA to reduce dimensions and then LDA is used to maximize the discriminating power of feature selection. The reason is that LDA has the small sample size problem in which dataset selected should have larger samples per class for good

discriminating features extraction. Thus implementing LDA directly resulted in poor extraction of discriminating features. In the proposed method [3] Gabor filter is used to filter frontal face images and PCA is used to reduce the dimension of filtered feature vectors and LDA is used for feature extraction. When the performances of PCA, LDA and ICA are tested and compared for the face recognition in colored images in [4], it is noticed that PCA is better than LDA and ICA under different illumination variations but LDA is better than ICA.

LDA is more sensitive than PCA and ICA on partial occlusions, but PCA is less sensitive to partial occlusions compared to LDA and ICA. PCA is used as a dimension reduction technique in [5] and for modeling expression deformations in [6]. PCA can outperform over many other techniques when the size of LDA is more sensitive than PCA and ICA on partial hidden objects, but PCA is less sensitive compared to LDA and ICA. PCA is used as a dimension reduction technique in [5] and for modeling expression deformations in [6]. PCA can outperform over many other techniques when the size of database is small. In proposed algorithm [7] the database was subgrouped using some features of interest in faces. Only one of the obtained subgroups was provided by PCA for recognition. Despite the good results of PCA, this technique has the disadvantage of being computationally expensive and complex with the increase in database size, since all the pixels in the image are necessary to obtain the representation used to match the input image with all others in the database.

Modified PCA algorithm for face recognition were proposed in [8], this method was based on the idea of reducing the influence of eigenvectors associated with the large eigen values by normalizing the feature vector element by its corresponding standard deviation. The simulation results showed that the proposed method results in a better performance than conventional PCA and LDA approaches and the computational cost remains the same as that of PCA and much less than that of LDA.

A new face recognition method based on PCA, LDA and neural network were proposed in [9]. This method consists of four steps: i) Preprocessing ii) Dimension reduction using PCA iii) feature extraction using LDA and iv) classification using neural network. Combination of PCA and LDA were used for improving the capability of LDA when a few samples of images were available and neural classifier was used to reduce number misclassification caused by not-linearly separable classes. Experimental results on Yale database demonstrated the effectiveness of the proposed method for face recognition with less misclassification in comparison with previous methods.

A different approach for face detection (GRNN) was proposed in [10], which minimizes computation time while achieving higher detection accuracy. PCA was used to reduce the dimension by feature extraction. GRNN used as a function approximation network to detect whether the input image contains a face or not and if existed it reports about its orientation. The proposed system had shown that GRNN can perform better than back propagation algorithm and give some solution for better regularization.

B. Support Vector Machine (SVM)

Support Vector Machine (SVM) is one of the most useful techniques in classification problems. One clear example is face recognition. However, SVM cannot be applied when the feature vectors defining samples have missing entries. A classification algorithm that has successfully been used in this framework is the all-known Support Vector Machines (SVM) [11], which can be applied to the original appearance space or a subspace of it obtained after applying a feature extraction method [12] [13] [14]. The advantage of SVM classifier over traditional neural network is that SVMs can achieve better generalization performance.

C. Linear Discriminant Analysis (LDA)

The Linear Discriminant Analysis (LDA) is a powerful method for face recognition. It yields an effective representation that linearly transforms the original data space into a low-dimensional feature space where the data is well separated. However, the within-class scatter matrix (SW) becomes singular in face recognition and the classical LDA cannot be solved which is the undersampled problem of LDA (also known as small sample size problem). Kernel discriminant locality preserving projections (MMDLPP) is a method for face recognition for subspace analysis was proposed in [15] based on the analysis of LDA, LPP and kernel function. A non linear subspace which can not only preserves the local facial manifold structure but also emphasizes discriminant information. Combined with Maximum Margin Criterion (MMC) a new method called Maximizing Margin and Discriminant Locality Preserving Projections (MMDLPP) was proposed in [16] to find the subspace that best discriminates different face change and preserving the intrinsic relations of the local neighborhood in the same face class according to prior class label information. The proposed method was compared with PCA as well as other methods like Locality Preserving Projections (LPP), ORL, YALE, YALEB face database and results had shown that it provides a better representation of class information and achieved better recognition accuracy. To solve illumination variation problems in face recognition a method called Illumination Adaptive Linear Discriminant Analysis (IALDA) was proposed in [17].

The recognition accuracy of the suggested method (IALDA) was far higher than that of PCA method and LDA method and was lower than that the Logarithmic Total Variation (LTV) algorithm [18]. However, The LTV algorithm has high time complexity. Therefore, the LTV method is not practically applicable. At the same time, this also indicates that the proposed IALDA method is robust for illumination variations. David Monzoet.al. [19] compared several approaches to extract facial landmarks and studied their influence on face recognition problems. In order to obtain fair comparisons, they used the same number of facial landmarks and the same type of descriptors (HOG descriptors) for each approach. The comparative results were obtained using FERET and FRGC [20] datasets and shown that better recognition rates were obtained when landmarks are located at real facial fiducial points. In this work, comparison was done using Principal Component Analysis (PCA)[21], Linear

Discriminant Analysis (LDA) [22] and Orthogonal Linear Discriminant Analysis (OLDA)[23]. OLDA is one of the many variations of LDA which aims to tackle the problem of undersampling. The key idea of OLDA, the discriminant vectors are orthogonal to each other. In [23] Ye proposed an efficient way for computing OLDA.

D. Artificial Neural Network (ANN)

Multi-Layer Perceptron (MLP) with a feed forward learning algorithms was chosen for face recognition problems because of its simplicity and its capability in supervised pattern matching.[24]. A new approach to face detection was presented with Gabor wavelets and Feed Forward Neural Network [25]. The proposed method used Gabor wavelet transform and FFNN for feature extraction and classification of facial image. The experimental results shown that the proposed method achieves better results compared to the well known algorithms like graph matching and eigenfaces methods.

A new class of convolutional neural network was proposed in [26] where the processing cells are divisive inhibitory neurons. Previously divisive inhibitory neurons have been used in conventional feedforward architecture for classification and non-linear regression and were shown to be more powerful than MLPs [27] [28] i.e. they can approximate complex decision surfaces much more readily than MLPs. A hybrid neural network solution was presented in [29] which combines local image sampling,Sself-Organizing Feature Map (SOFM) neural network, and a Convolutional Neural Network (CNN). The self organizing map provides a quantization of the image samples into a topological space where inputs that are nearby in the original space are also nearby in the output space, hence provides dimensionality reduction and invariance to minor changes in the image sample, and the convolutional neural network (CNN) provides for partial invariance to translation, rotation, scale, and deformation. PCA+CNN & SOM+CNN methods are both superior to eigenfaces technique even when there is only one training image per person.SOM +CNN method consistently performs better than the PCA+CNN method.

A new face detection method is proposed in [30] using Polynomial Neural Network (PNN) [31] [32]. The PNN functions as a classifier to evaluate the face likelihood of the image patterns of the multiscale shifted local regions. The PCA technique used to reduce the dimensionality of image patterns and extract features for the PNN. Using a single network the author had achieved fairly high detection rate and low false positive rate on images with complex backgrounds. The performance of PNN is superior to a multilayer perceptron.

To improve face recognition, Spectral Regression Kernel Discriminate Analysis (SRKDA) [33] based on regression and spectral graph analysis was introduced in proposed [34] method. When the sample vectors are linearly independent, which is usually the case for small sample size problems; SRKDA can efficiently give more exact solutions than ordinary subspace learning approaches. It not only solves high dimensional and small sample size problems, but also enhances feature extraction from a face local non-linear structure. Detailed comparisons between SRKDA [33], PCA [8], LPP[35], OLPP [36], SR [33], and KDA [33] to show the efficiency of proposed method for 3D face recognition, especially with respect to expression variations. SRKDA only needs to solve a set of regularized regression problems and no eigenvector computation involved, which is a huge saving in computational cost.

III. RELATED WORK ON FACE DETECTION

Ya ng, and David Z hang, proposed new scheme, namely the robust sparse coding (RSC), by modelling the sparse coding as a sparsity constrained robust regression problem. Many researches has been done on face recognition and detection from large bases including content-based image retrieval (CBIR), human attribute detection, and content-based face image retrieval. This section gives the details of the previous work carried out in the direction of face image retrieval and the scope of sparse coding method in face recognition.

[34] Meng Ya ng Lei Z hang, Jian iteratively reweighted sparse coding algorithm was proposed to solve the RSC model using Robust Sparse Coding algorithm. PCA (i.e., Eigenfaces) was used to reduce the dimensionality of original face features, and the eigenface features were used for all the competing methods. The RSC seeks for the MLE (Maximum Likelihood Estimation) solution of the sparse coding problem, and it is much more robust to outliers (e.g., occlusions, corruptions, etc.) than SRC. RSC gives 94.7% accuracy compared to other algorithms like SRC, GSRC etc. But the performance degrades on multiple features, and had high computational complexity. To address this issue, sparse coding was introduced, which can improve the performance on multiple features.

[35] T. Ahonen, A. Hadid, and M. Pietikainen proposed a novel method for face recognition with local binary patterns which considers both shape and texture information to represent facial images. The methods used were Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) and Elastic Bunch Graph Matching (EBGM) algorithm. The proposed method tests the robustness of the method against different facial expressions, lighting and aging of the subjects. The efficiency and simplicity of the proposed method allows for very fast feature extraction.

The proposed method achieved a recognition rate of 97% in the case of recognizing faces under different facial expressions while the best performance among the tested methods did not exceed 90%. Under different lighting conditions the LBP-based approach has also achieved the best performance with a recognition rate of 79% against 65%, 37% and 42% for PCA, BIC and EBGM, respectively. But the face representation extraction and its robustness with respect to facial expression, aging, illumination and alignment, some improvements are still possible.

One drawback of this approach lies in the length of the feature vector which is used for face representation. Recognizing duplicate faces (when the photos are taken later in time) was another challenge.

[36] B. Siddiquie, R. S. Feris, and L. S. Davis, proposed propose a novel approach for ranking and retrieval of images based on multi attribute queries. The aim was to propose a principled approach for multi-attribute image retrieval and ranking, which explicitly models the correlations that are

present between the attributes, which retrieves images based not only on the words that are part of the query, but the remaining attributes are also considered within the vocabulary that could potentially provide information about the query.

A new approach called Multi-Attribute Retrieval and Ranking (MARR) was introduced where, the image retrieval method was based on the concept of reverse learning. First, a single framework for both retrieval and ranking was given. Secondly, it facilitates training, retrieval and ranking, based on queries consisting of multiple-labels. Finally, modeling and learning the pairwise correlations between different labels (attributes) and exploit them for retrieval and ranking.

The main advantage of reverse learning is that it allows for learning based on the minimization of loss functions corresponding to a wide variety of performance measures such as hamming loss, precision and recall. MARR (proposed method) was significantly better for single attribute queries 7.4% improvement) and marginally better for double attribute queries (2.4% improvement), The retrieval results MARR outperforms by about 5% and Reverse Multi-Label Learning (RMLL) by about 2%.The image retrieval and ranking can be explored based on more complex queries such as scene descriptions, where a scene is described in terms of the objects present, along with their attributes and the relationships among them. The performance of the proposed method was not good for triple attribute queries, which can be improved further.

[37] N. Kumar, A. C. Berg, P. N. Belhumeur, and S. K. Nayar, proposed an approach to the unconstrained face verification problem (with non-cooperative subjects) by comparing faces using the attribute and similar classifier outputs, instead of low-level features directly. The aim was to focus on images of faces and the attributes used to describe them, using describable visual attribute, i.e labels that can be given to an image to describe its appearance which are used for face verification and image search.

The advantages of attribute-based representation are,1) They can be composed to create descriptions at various levels of specificity.2) They are generalizable, as they can be learned once and then applied to recognize new objects or categories without any further training.3) They are efficient, possibly requiring exponentially fewer attributes (and training data) than explicitly naming each category. The experimental results showed that, the face verification performance on LFW with highest accuracy was 85.54%, which is comparable to the current state-of-the-art accuracy of 86.83% and the face verification performance on LFW with 18 attributes, human attribute labels reach 91.86% accuracy, compared to only 81.57% using classifier outputs.

Here, adding more attributes and improving the attribute training process could yield great benefits for face verification. Another direction to explore is how best to combine attribute and simile classifiers with low-level image cues. Finally, how attributes can be applied to domains other than faces? is a challenging work.

[38] Mr.Arulmurugan.R, Laxmi Priya M R, proposed a novel framework for face recognition using ASM and sparse coding. The aim was to provide the better recognition performance when compare to the existing methods by detecting the face by the Active Shape Model algorithm which is reliable to uncontrolled pose images. The Extended Active Shape Model was used to segment the face. Based on how pose changes, the features can be extracted, extracted values then matches with the database and identify the original central image of a particular person.

The Extended Active shape model Algorithm is advantageous because it is reliable to uncontrolled pose images. The proposed method has given 79% accuracy for FERET, and 83% accuracy for ORL. The proposed system displays the central image of a particular person but there is some misclassification while identifying the face. This problem can be addressed by using sparse coding which can be used to extract the important feature points of the face images.

[39] Dayong Wang, Steven C.H. Hoi, Ying He, Jianke Zhu, proposed a novel WLRLCC algorithm for the retrieval-based face annotation paradigm for automated face annotation on two large-scale web facial image databases. The aim was to address the problem of face annotation by investigating a retrieval-based annotation scheme of mining massive web facial images that are freely available over the internet.

The proposed method has, 1) Adopted the LCC algorithm for the coding step of Weak Label Regularized Local Coordinate Coding (WLRLCC). 2) Adopted the Fast Iterative Shrinkage and Thresholding Algorithm (FISTA), a popular and efficient algorithm for the linear inverse problem that has been already implemented for sparse learning. 3) Used PCA dimension reduction techniques to reduce the computational cost time. The WLRLCC algorithm consistently obtains the best annotation performance among all the compared algorithms under different database sizes. The performance of WLRLCC algorithm was 76.5% and the hit rate performances of WLRLCC and SMW were 85.1 and 80.1 percent, respectively.

The limitations were,1) When extra noise labels are added into the retrieval database, the task becomes more difficult, and thus the annotation performance decreases, which can be handled in future work. 2) Can further improve the efficiency and scalability, saving a significant amount of computational time while maintaining comparable performance.

[40] Bor-Chun Chen, Yan-Ying Chen, Yin-Hsi Kuo, and Winston H. Hsu, proposed an approach to provide a new perspective on content-based face image retrieval by incorporating high-level human attributes into face image representation and index structure. The aim was to address one of the important and challenging problems like large-scale content-based face image retrieval. The authors proposed two techniques,

- *Attribute-enhanced sparse coding* – It exploits the global structure of feature space and uses several important human attributes combined with low-level features to construct semantic codewords.
- *Attribute-embedded inverted indexing* – It locally considers human attributes of the designated query image in a binary signature and provides efficient retrieval in the online stage.

By incorporating these two methods, a large-scale content-based face image retrieval system is build by taking advantages of both low-level (appearance) features and high-level (facial) semantics. And also it can improve the content based image retrieval, in large scale dataset. By utilizing

automatically detected human attributes, Content-based face image retrieval has improved up to 43% relatively in MAP.

For future work, 1) The quantization error can be reduced and can achieve salient gains in face retrieval on public datasets; the proposed indexing scheme can be easily integrated into inverted index, thus maintaining a scalable framework. 2) To investigate methods to dynamically decide the importance of the attributes and further exploit the contextual relationships between them. 3) To discover certain informative attributes for face retrieval across different datasets and these attributes are also promising for other applications (e.g., face verification).

IV. CONCLUSION

This paper has attempted to review a significant number of papers to cover the recent development in the field of face recognition. This research analyzed the strengths and weaknesses of various face recognition methods proposed. However, the results presented in the paper shows that the sparse coding is a promising method which is used in the field of face image retrieval from large scale image databases. In the existing systems, only the low level features are used on the human images, whose performance was comparatively less. In future, the high level attributes can be used for face detection which can increase the effectiveness of the image. Attribute enhanced sparse codewords retrieve less number of images due to that we can get only the related images. From that we can obtain the main image from the large image database.

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