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Face Recognition through Different Facial Expressions for Women Security: A Survey

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***Abstract*— Face is an essential part of our daily life. It is a complex multidimensional structure and needs a good computing technique for recognition. Face recognition has been a fast growing, challenging and interesting area in real time 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. While using automatic system for face recognition, computers are easily confused by changes in illumination, variation in poses and change in angles of faces. A numerous techniques are being used for security and authentication purposes which includes areas in detective agencies and military purpose. These surveys give the existing methods in automatic face recognition and formulate the way to still increase the performance.**

***Keywords*— Face Recognition, Illumination, Authentication, Security**

I. INTRODUCTION

Face recognition is an important part of the capability of human perception system and is a routine task for humans, while building a similar computational model of face recognition. The computational model not only contribute to theoretical insights but also to many practical applications like automated crowd surveillance, access control, design of human computer interface (HCI), content based image database management, criminal identification and so on.

Developed in the 1960s, the first semi-automated system for face recognition required the administrator to locate features (such as eyes, ears, nose, and mouth) on the photographs before it calculated distances and ratios to a common reference point, which were then compared to reference data. In the 1970s, Goldstein, Armon, and Lesk used 21 specific subjective markers such as hair color and lip thickness to automate the recognition. The problem with both of these early solutions was that the measurements and locations were manually computed. The face recognition problem can be divided into two main stages: face verification (or authentication), and face identification (or recognition).The detection stage is the first stage; it includes identifying and locating a face in an image. The recognition stage is the second stage; it includes feature extraction, where important information for the discrimination is saved and the matching where the recognition result is given aid of a face database.

II. LITERATURE SURVEY

A .Local approach

The local approach was the foremost strategy used by early face recognition systems. The hypothesis behind this approach is that face recognition system is completely damaged when facial features are edited or spatially reorganized [8]. In fact, before performing face recognition, the local features such as eyes, nose and mouth are detected. Then, facial features positions and local geometric and/or appearance statistics are supplied for a structural classifier [23]. Methods within this approach may be classified into mainly classes: Geometric methods ,and Template based methods Correlation based methods, Model based methods.

Geometric Feature Based Methods*:*

The geometric feature based approaches are the earliest approaches to face recognition and detection. In these systems, the significant facial features are detected and the distances among them as well as other geometric characteristic are combined in a feature vector that is used to represent the face. To recognize a face, first the feature vector of the test image and of the image in the database is obtained. Second, a similarity measure between these vectors, most often a minimum distance criterion, is used to determine the identity of the face. In the geometric methods, some heuristic rules that involve angles, distances and areas are used to define the distribution of the facial features. It computes the distance and angles between eye corners, the width of the head, the distance between the eyes and from eyes to the mouth, etc. [26]. In [7], the authors defined facial features as points in one form for which objectively meaningful and reproducible biological counterparts exist in all the other forms of a data set.The most used facial features are on the nose tip, eye and mouth corners, centre of the iris, tip of the chin, the nostrils, and the eyebrows.

Indeed, ***Scale Invariant Feature Transform (SIFT)*** technique [16] was used in to detect facial feature points on eight different Perceived Facial Images. An important aspect of this approach is that it generates large numbers of features that densely cover the image over the full range of scales and locations. A typical image of size 500x500 pixels will give rise to about 2000 stable features (although this number depends on both image content and choices for various parameters). The quantity of features is particularly important for object recognition, where the ability to detect small objects in cluttered backgrounds requires that at least 3 features be correctly matched from each object for reliable identification. For image matching and recognition, SIFT features are first extracted from a set of reference images and stored in a database. A new image is matched by individually comparing each feature from the new image to this previous database and finding candidate matching features based on Euclidean distance of their feature.

Later a ***Speeded-Up Robust Features (SURF)*** was introduced for face recognition [11]. Instead, in SURF the scale space is rather analyzed by up-scaling the integral image based filter sizes in combination with a fast Hessian matrix based approach. As the processing time of the filters used in SURF is size invariant, it allows for simultaneous processing and negates the need to subsample the image hence providing performance increase.In [15], the authors used Gabor wavelets for key-point detection. Then, these points are clustered by the k-means algorithm. The face comparison was performed using the Chi square statistic.

Template Based Methods

The template based approaches represent the most popular technique used to recognize and detect faces [5]. Unlike the geometric feature based approaches, the template based approaches use a feature vector that represent the entire face template rather than the most significant facial features.

Correlation Based Methods

Correlation based methods for face detection are based on the computation of the normalized cross correlation coefficient Cn [12, 13]. The first step in these methods is to determine the location of the significant facial features such as eyes, nose or mouth. The importance of robust facial feature detection for both detection and recognition has resulted in the development of a variety of different facial feature detection algorithms. The facial feature detection method proposed by Brunelli and Poggio uses a set of templates to detect the position of the eyes in an image, by looking for the maximum absolute values of the normalized correlation coefficient of these templates at each point in test image [3, 21]. To cope with scale variations, a set of templates at different scales was used.

The problems associated with the scale variations can be significantly reduced by using hierarchical correlation. For face recognition, the templates corresponding to the significant facial feature of the test images are compared in turn with the corresponding templates of all of the images in the database, returning a vector of matching scores computed through normalized cross correlation. The similarity scores of different features are integrated to obtain a global score that is used for recognition. Other similar method that use correlation or higher order statistics revealed the accuracy of these methods but also their complexity.

Beymer extended the correlation based on the approach to a view based approach for recognizing faces under varying orientation, including rotations with respect to the axis perpendicular to the image plane(rotations in image depth) [18]. To handle rotations out of the image plane, templates from different views were used. After the pose is determined ,the task of recognition is reduced to the classical correlation method in which the facial feature templates are matched to the corresponding templates of the appropriate view based models using the cross correlation coefficient. However this approach is highly computational expensive, and it is sensitive to lighting conditions.

Model based method

Indeed, the **MM-AAM technique** was first proposed in [9] to generate face models both in terms of shape and texture. The MM-AAM is an extension of Active Appearance Model (AAM) algorithm [10]. The MM-AAM was recently applied in the context of face recognition [14] to deal with significant variation in face illumination, pose and expression. To detect the features more reliably, recent approaches have used structural matching methods, for example, the Active Shape Model [Cootes et al. 1995]. Compared to earlier methods, these recent statistical methods are much more robust in terms of handling variations in image intensity and feature shape.

An even more challenging situation for feature extraction is feature “restoration”, which tries to recover features that are invisible due to large variations in head pose. The best solution here might be to hallucinate the missing features either by using the bilateral symmetry of the face or using learned information. For example, a view-based statistical method claims to be able to handle even profile views in which many local features are invisible [Cootes et al. 2000].The manually designed, the *statistical* shape model (Active Shape Model, ASM) proposed in [Cootes et al. 1995] offers more flexibility and robustness. The advantages of using the so-called analysis through synthesis approach come from the fact that the solution is *constrained* by a *flexible* statistical model. To account for texture variation, the ASM model has been expanded to statistical appearance models including a Flexible Appearance Model (FAM) [Lanitis et al. 1995] and an Active Appearance Model (AAM) [Cootes et al.

2001]. In [Cootes et al. 2001], the proposed AAM combined a model of shape variation (i.e., ASM) with a model of the appearance variation of shape-normalized(shape-free) textures.

B.**Global Approach**

This approach represents faces as arrays of pixel intensities or wavelet outputs that are similar to the response patterns of photoreceptors on the retina. It uses the whole face image as a raw input of a recognition system and requires to provide meaningful data to present efficiently the face.

Karhunen- Loeve Expansion Based Methods

Eigen Face Approach

In this approach, face recognition problem is treated as an intrinsically two dimensional recognition problem [17]. The system works by projecting face images which represents the significant variations among known faces. This significant feature is characterized as the Eigen faces. They are actually the eigenvectors. Their goal is to develop a computational model of face recognition that is fact, reasonably simple and accurate in constrained environment. Eigen face approach is motivated by the information theory.

Recognition Using Eigen Features

While the classical eigenface method uses the KLT (Karhunen- Loeve Transform) coefficients of the template corresponding to the whole face image, the author Pentland et.al. introduce a face detection and recognition system that uses the KLT coefficients of the templates corresponding to the significant facial features like eyes, nose and mouth [19] . For each of the facial features, a feature space is built by selecting the most significant "eigenfeatures", which are the eigenvectors corresponding to the largest eigen values of the features correlation matrix. The significant facial features were detected using the distance from the feature space and selecting the closest match. The scores of similarity between the templates of the test image and the templates of the images in the training set were integrated in a cumulative score that measures the distance between the test image and the training images [19,6]. The method was extended to the detection of features under different viewing geometries by using either a view-based Eigen space or a parametric eigenspace.

Subspace Recognition Approaches

Principal Component Analysis, LDA[6], and Bayesian analysis are the three most representative subspace face recognition approaches . In this paper, we show that they can be unified under the same framework. In this approach the author first model face difference with three components: intrinsic difference, transformation difference, and noise. A unified framework is then constructed by using this face difference model and a detailed subspace analysis on the three components. Then they explain the inherent relationship among different subspace methods and their unique contributions to the extraction of discriminating information from the face difference. Based on the framework, a unified subspace analysis method is developed using PCA, Bayes, and LDA [6]as three steps. A 3D parameter space is constructed using the three

Linear Discriminant Based Method

The Fisher face method uses the class membership information and develops a set of feature vectors in which variations of different faces are emphasized while different instances of faces due to illumination conditions, facial expressions and orientations are de-emphasized . While the Karhunen-Loeve Transform performs a rotation on a set of axes along which the projection of sample vectors differ most in the autocorrelation sense, the LDT(Linear Discriminant transform) performs a rotation on a set of axes along which the projection of sample vectors differ most in the autocorrelation sense, the LDT performs a rotation on a set of axes along which the projection of sample vectors show maximum discrimination. Each test image is projected onto the optimal LDT space and the resulting set of coefficients is used to compute the Euclidean distance from the images in the training set. Another method of face description for facial image retrieval is from a large data base and for MPEG-7 (Moving Picture Experts Group) standardization . The novel descriptor is obtained by decomposing a face image into several components and then combining the component features [9]. The decomposition combined with LDA (Linear Discriminant Analysis) provides discriminative facial descriptions that are less sensitive to light and pose changes. Each facial component is represented in its Fisher space and another LDA is then applied to compactly combine the features of the components. To enhance retrieval accuracy further, a simple pose classification and transformation technique is performed, followed by recursive matching. Their algorithm has been developed to deal with the problem of face image retrieval from huge databases such as those found in Internet environments. Such retrieval requires a compact face representation which has robust recognition performance under lighting and pose variations. The partitioning of a face image into components offers a number of benefits that facilitate the development of an efficient and robust face retrieval algorithm. Variation in image statistics due to pose and/or illumination changes within each component region can be simplified and more easily captured by a linear encoding than that of the whole image. So an LDA encoding at the component level facilitates better classification. Furthermore, a facial component can be weighted according to its importance. The component with a large variation is weighted less in the matching stage to yield a more reliable decision.

Class Specific Linear Projection Approach

A face recognition algorithm which is insensitive to lighting direction and facial expression is developed. They adopt the pattern recognition approach for faces in lambertian surface [2]. The method for projection is based on the Fisher's Linear Discriminant and eigen face technique along with correlation and linear subspace. By this they concluded that fisher face method is best at extrapolating and interpolating over variation in lighting.

Active Pixels Based Approach
With the recent advances in smart phones and their ease of availability to common man, researchers are exploring efficient algorithms for face recognition on mobile devices for entertainment applications. The limited memory and processing power on mobile devices pose significant challenge to the satisfactory of popular face recognition algorithms like LBP (Local Binary Patterns), Independent Component Analysis, PCA, Neural Networks etc. In this method, the author proposed a novel and efficient algorithm is proposed using Active Pixels which capture the essential local information of the facial image. The brody transform makes the approach more robust to rotational, translational invariance's. The experiments were conducted on standard face recognition databases like FGNET age dataset and color FERET dataset, Texas 3D Face Recognition Database (Texas 3DFRD). The results demonstrated that our approach reduced memory requirement by 80% and the computational time by 70% in comparison with LBP approach.

The "Parametric" Approach Verses The "View-Based Approach
In parametric model methods [4], parameters are estimated from the image data itself. Then, every image set is represented using some parametric distribution with the already estimated parameters. In this way a single "parametric" describes the object identity as well as the viewing or illumination conditions. The eigenface decomposition of this space was used for feature extraction and classification. However, in order to ensure discrimination between different objects, the number of eigenvectors used in this method was increased compared to the classical eigenface method. Nonetheless, the parameter estimation need that gallery and the probe sets have strong statistical correlations, which may not always be true [26]. To avoid the inconvenience of parametric methods, nonparametric model methods were introduced to represent an image set as a linear/affine subspace [9] or non-linear manifolds [24]**. The "view based" approach** for human face recognition under general viewing condition. The "view based" approach is essentially an extension of the eigenface technique to multiple sets of eigenvectors, one for each face orientation. First, the orientation of the test face is determined by calculating the residual description error (distance from feature space) for each view space, and selecting the sparse for which the distance is minimized. Once the proper view is determined, the face image is classified using the eigenface method in the corresponding space. As expected, the view based representation has better recognition results than the parametric approach, at a cost of a higher computational complexity.

Artificial Intelligence Method
Concerning the artificial intelligence methods, they use a training phase in which different artificial techniques such as Neural Network [22], Support Vector Machine or Multiwavenet classifer may be applied. These methods perceive the face as one block whose features are learned. Some prior knowledge about pixel information and face structure data is encoded as a features vector.

Support Vector Machine Approach

Face recognition is a K class problem, where K is the number of known individuals; and support vector machines (SVMs) are a binary classification method . By reformulating the face recognition problem and reinterpreting the output of the SVM classifier, they developed a SVM-based face recognition algorithm. The face recognition problem is formulated as a problem in difference space, which models dissimilarities between two facial images. In difference space we formulate face recognition as a two class problem. The classes are: dissimilarities between faces of the same person, and dissimilarities between faces of different people. By modifying the interpretation of the decision surface generated by SVM, we generated a similarity metric between faces that are learned from examples of differences between faces. In fact, the Support Vector Machine builds a plane using the criterion of the large margin between two classes of examples. When the face database is large, both of the training and testing steps are time expensive. Adaboost algorithm was another alternativeof large margin classifiers proposed to deal with machine learning problems. Introduced by Freund and Schapire [1], the Adaboost algorithm is applied to select the most discriminating LBP descriptors and provide a similitude function as a linear combination of the weak classifiers based on the LBP descriptors.

Although these methods are simple and yield important recognition rates, they have difficulties to deal with variation in illumination, facial expression and pose, which aspects the face appearance. Compared to the global approach, the local approach is less sensitive to illumination and pose variations. However, it depends on the face image resolution which makes it tricky to detect accurately some facial features. Moreover, it is more sensitive to occlusion than the global approach which extracts data from the whole face. Furthermore, the difficulty of developing robust methods for automatic facial features detection under challenging constraints has limited the success of local approach. In fact, the best performance was achieved when the facial features are detected manually[25] .

Being aware of the advantages and disadvantages of each approach, our choice depends mostly on the context of application. For instance, the local approach cannot be performed on poor resolution face images since facial features points are not clear enough to be extracted. Indeed, in the global approach, the choice of the dimension reduction technique depends on the size of the training set. In fact, if the number of training samples per class is large, LDA is better than PCA.

III. CONCLUSION

This paper discusses the different approaches which have been employed in automatic face recognition such as Global and Local approach.. In the geometrical based methods, the geometrical features are selected and the significant facial features are detected. The correlation based approach needs face template rather than the significant facial features. Singular value vectors and the properties of the SV vector provide the theoretical basis for using singular values as image features. The Karhunen-Loeve expansion works by projecting the face images which represents the significant variations among the known faces. Eigen values and Eigen vectors are involved in extracting the features in KLT. Neural network based approaches are more efficient when it contains no more than a few hundred weights. Hence this will give some idea about the existing methods for automatic face recognition. .

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REFERENCES

[1] Ahonen, T. and H.A.P.M. (2004). "Face recognition with local binary patterns", the European Conference on Computer Vision.

[2] A.J Goldstein L.Harmon And A.Lesk,. " Identification Of Human Faces',Proceedings Of The IEEE,,Vol59,issue 5,pp. 748 -760,1971.

[3]. Anastasios N. Venetsanopoulos " Face Recognition Using Kernel Direct Discriminant Analysis Algorithms";IEEE Transactions On Neural Networks, Vol. 14, No. 1, pp.117-126,2003.

[4] Arandjelovic, O., and S.G.F.J.C.R.D.T. (2005). "Face recognition with image sets using manifold density divergence",In: CVPR.

[5] Ara V.Nefian, And Monsoon H.Hayes, " Hidden Markov Models For Face Detection And Recognition",IEEE Transcations On Pattern Analysis And Machine Intelligence,Vol.1,pp.141-145,1999.

[6] Belhumeur P.N., and H.J.K.D. (1997). "Eigenfaces vs. _sherfaces, Recognition using class specific linear projection", J. IEEE Trans (PAMI),vol.19,no. 7,July 1997.

[7] Bookstein, F. (1989). "Principal warps: Thin-plate splines and the decomposition of deformations",IEEE Transaction Pattern' Analog Machine Intelligence,vol. 11,no. 6,1989.

[8] Bruce, V., and Y.A. (1998). "In the eye of the beholder: The science of face perception",In: Oxford University Press.

[9] Cevikalp, H. , and T.B. (2010). "Face recognition based on image sets"., In: CVPR.

[10] Cootes, T., and E.G.T.C. "Active appearance models", In: Computer Visio Dreuw, P.,and S.P.H.H.N.H.A.G. (2009),vol. 2 ,p.p 484-498.

[11] Dreuw, P., and S.P.H.H.N.H.A.G. (2009). Surf-face: "Face recognition under viewpoint consistency constraints".In: BMVC.

[12] Dr. H.B.Kekre, Sudeep D. Thepade , Akshay Maloo , MPSTME(2011); "Face Recognition Using Texture Feartures Extracted Form Walshlet Pyramid",Int. J. on Recent Trends in Engineering & Technology, Vol. 05, No. 0,pp.186,2011.

[13] Dr.H.B.Kekre, Dr.Sudeep, D.Thepade, Sanchit Khandelwal, "Face Recognition Using Multilevel Block Truncation Coding";International Journal of Computer Applications () Volume 36– No.11,pp.0975 – 8887,2011.

[14] Khan, M.A., and X.C.A.H. (2013). "Multi-model aam framework for face image model-ing",In: International Conference on Digital Signal Processing .

[15] Lenc, L., and K. P. (2014). "Automatically detected feature positions for lbp based face recognition",In: AIAI.

[16] Lowe, D. (2004). "Distinctive image features from scale-invariant keypoints", Internatio[22]Rubiolo, M., and S. G. M. D. (2013). "Compressing arrays of classi_ers using volterra-neural network: application to face recognition",Neural Computing and Applications.

[17] M. Daesik Jang; "User Oriented Language Model for Face Detection"; IEEE workshop on person oriented vision,pp.21-26,2011.

[18] M.LADES, J. Buhman ,J.Lange,C.Malsburg And R.Wurtz, " Distortion Invariant Object Recognition In The Dynamic Link Architecture,"; IEEE Transactions On Computers, Vol. 42,No.3,pp .300-311,1993

[19] Mathew Turk And Alex Pentland, " Eigen Faces For Recognition"; Journal Of Cognitive Neuroscience Vol.3,No.1,pp.71-86,1991.

[20] Philips, "Matching Pursuit Filters Design",Proceedings of the 12th International Conference On Pattern Recognition,Vol.3,Pp 57-61,1994.

[21] R.Chellappa.C. Wilson and S.Sirohey; "Human and Machine recognition of face", Proceedings of IEEE, vol 83,pp.705-741,1995.

[22] Rubiolo, M., and S. G. M. D. (2013). "Compressing arrays of classi_ers using volterra-neural network: application to face recognition",Neural Computing and Applications.

[23] Sadr, J., and J. I. S. P. (2003). "The role of eyebrows in face recognition"., Perception.

[24] Wang, R., and S. S. C. X. G.W. (2008)." Manifold-manifold distance with application to face recogniton based on image set", In: CVPR.nal Journal of Computer Vision.

[25] Zhang, X., and G. Y. L. M. (2008)."Recognizing rotated faces from frontal and side views: an approach towards e_ective use of mugshot databases",IEEE Trans. Inf. Forensic Secur.7.

[26] Zobel, M., and G. A. P. D. D. J. N. H. (2000). "Robust facial feature localization by coupled features", In 4th IEEE International Conference on Automatic Face and Gesture Recognition.