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AUTOMATIC FACE RECOGNITION APPROACHES

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ABSTRACT

This paper deals with automatic face recognition, which means to use a computer for automatic identification of a person from a digital image or from a video frame. This field became intensively studied in the last two decades. Concerning other biometrics methods, automatic face recognition seems to be one of the most important ones. Therefore, automatic face recognition is used in many applications as for example access control to restricted areas, surveillance of persons, various programs for sharing and labelling of photographs, social networks and many others. The main goal of this paper is to review most important face recognition approaches with their theoretical and practical advantages and drawbacks. We further evaluate and compare these approaches with each other. We conclude that it is generally not possible to identify a best performing face recognition approach and that the choice of the optimal method is strictly related to the target application. We assume that the future research directions will address the main issue of the current approaches, insufficient recognition accuracy in the totally uncontrolled environment.

Keywords: *Approaches Comparison, Face Database, Face Recognition, Personal Identification, Review*

1. INTRODUCTION

Automatic Face Recognition (AFR) consists in identification of a person from an image or from a video frame by a computer. This field has been intensively studied by many researchers during the past few decades and nowadays, it can be seen as one of the most progressive biometric authentication methods.

Numerous AFR methods have been proposed and the face recognition has become the key task in several applications as for instance surveillance of wanted persons, access control to restricted areas, automatic annotation of the photos used in the recently very popular photo sharing applications or in the social networks, and so on.

The main goal of this paper is to review most important face recognition approaches with their theoretical and practical advantages and drawbacks. We further evaluate and compare these approaches with each other. Unfortunately, these approaches are usually evaluated on the different face datasets. Moreover, the experimental set-up usually differs also in cases when using the same databases. Therefore this task is very challenging, because a straightforward comparison is not possible.

The paper structure is as follows. The following section summarizes most important face recognition approaches. Section 3 compares and evaluates the methods described previously. The last section concludes the paper and proposes some future research directions.

2. FACE RECOGNITION

2.1 Early Face Recognition Methods

The first attempts to recognize faces automatically were made in the 1960s. The initial methods were semi-automatic. A set of facial landmarks was manually determined and normalized measures between these landmarks were used to create the face model.

In 1966, one of the first methods was proposed by Woody Bledsoe [1]. The goal of the application was selecting a small subset of faces from the database which contains the wanted face. The system was not fully automated. Coordinates of important facial features were manually labelled by the operator. Examples of features are centres of pupils, eye corners, nose tip etc. From the features coordinates, 20 distances were computed. These distances were normalized, so that they correspond to the frontal face (elimination of pose, tilt and lean variations). A vector composed of such normalized distances was used in the matching procedure. The nearest neighbour classifier was employed. This system was highly successful and could even outperform humans in some recognition tasks.

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Bledsoe also stated the main problem in face recognition: The recognition is made difficult by great variability in head rotation and tilt, lighting intensity and angle, facial expression, ageing, etc. A similar method was designed in the 1970s by Goldstein et al. [2]. In that case, 22 features were used to describe a face.

In 1977, Takeo Kanade [3] developed an approach based on similar measurements. This method determines the feature points positions automatically. The positions are detected using edge maps, signatures and other image processing techniques.

2.2 Correlation Method

The simplest and most straightforward method how to compare two images is to directly compute the correlation between them. The images are handled as one dimensional vectors of intensity values. The nearest neighbour classifier is used directly in the image space. The images must be normalized to have a zero mean and unit variance. Under these conditions, the influence of light source intensity and camera characteristics is suppressed. Such method has some substantial weaknesses:

- If the images are taken under varying lighting conditions, the corresponding points in the image space may not be tightly clustered.
- It is computationally expensive.
- Huge amount of memory storage is needed

Therefore, a practical use of this method is very problematic.

2.3 Eigenfaces

One of the first successful approaches to face recognition uses Principal Component Analysis (PCA). The name Eigenfaces is derived from Eigenvalues. This method was first used by Sirovich and Kirby [4] in 1987 and then in 1991 by Turk and Pentland [5]. Eigenfaces are a statistical method that takes into account the whole image as a vector. The performance of Eigenfaces is very good when images are well aligned and have approximately the same pose. Changing lighting conditions, pose variations, scale variations and other dissimilarities between images decrease the recognition rate rapidly.

The first step of this algorithm is creating a data matrix. The facial images are handled as one dimensional vectors. These vectors are created by concatenating the rows (or columns) of the image matrix. An average vector is computed from all image vectors. One row of the data matrix is then created as a difference between the face vector and the average vector. The covariance matrix is computed by multiplying the data matrix with its transposition. Subsequently, the eigen decomposition of the matrix is realized. Only certain number of eigenvectors which correspond to the largest eigenvalues is used for the face representation. Around 50 Eigenface values are sufficient. The appropriate number depends on the size of the face database. Particular eigenvectors can be seen as face components from which the face is composed. The vector defining the linear combination of eigenvectors is used as a representation of the face. Usually the nearest neighbour rule is employed for feature vectors comparison.

As mentioned above, the dissimilarities in the facial images influence the recognition rate dramatically. In order to overcome this drawback, an extensive pre-processing of input images should be realized. An essential step is to perform the histogram equalization. Then, some transformations for unifying lightning conditions should be made. Even more important is transforming the images so that they were well aligned. The face must be placed at the same position and its proportion must be unified. Also the lean of the face have to be justified so that the eyes are on the horizontal line. Transforming the face pose is also possible but is usually not performed. Fulfilling these conditions makes the algorithm highly accurate and useful. Some of the best performing commercial systems for face recognition are based on this approach.

2.3.1 View based Eigenfaces

Pentland et al. [6] presented an approach based on the original Eigenfaces. This method is very interesting in two basic ideas:

- Evaluating the method on a large database;
- Addressing the problem of different viewing orientation.

Contrary to the previously developed methods, this one was tested with a dataset containing several thousands of individuals. Two general methods how to extend the classic Eigenfaces in order to handle different face orientations are proposed. The first one is to use several face images of one individual, each of them having different orientation. Such extended eigenspace is able to encode both identity and viewing orientation. The second one is to create several eigenspaces, each of them representing one face orientation. In this case, the first step while

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identifying a new face is to determine its orientation. This is done by calculating the residual description error (measuring the distance from the particular eigenspace). Then, this eigenspace is used to identify the person.

2.4. Independent Component Analysis

Independent component analysis (ICA) is used for separating a signal into sub-components. The main goal is to find a linear combination of non-Gaussian data signals that reconstructs the original signal [7]. It is assumed that these components are statistically independent.

The ICA algorithm is usually used in signal processing for signal separation. Another application of the ICA is the feature extraction. There are two different scenarios of using independent component analysis for the face recognition [8]:

- Images are treated as random variables and pixels as observations;
- Pixels are treated as random variables whereas images as observations.

Contrary to PCA, ICA uses higher order statistics (two orders in case of PCA). ICA thus provides more powerful data representation. Authors show in [9] that ICA performs slightly better than PCA approach. The comparison is carried out on the FERET [10] dataset.

2.5. Fisherfaces

The Fisherfaces [11] are derived from Fisher's Linear Discriminant (FLD). Similarly to the Eigenfaces approach, the Fisherfaces project an image into another, less dimensional, space. The original dimensionality, which is given by the resolution of the images, is reduced to the number of images (number of distinct classes). The projections of facial images are then compared using some suitable similarity measure. The key point is maximization of the ratio of between-class scatter and within-class scatter. Conversely, the Eigenfaces maximize the total scatter across all images. PCA is thus significantly influenced by the variations in lighting conditions and facial expression, while this drawback is substantially reduced by the Fisherfaces approach, which should be insensitive to changing lighting conditions.

2.6. Kernel Methods

For both PCA and FLD based methods (Eigenfaces and Fisherfaces) also kernel versions (KPCA and KFLD) were proposed [12]. The kernel versions address the issue that original methods are based on second order statistics.

The methods take into account dependencies among multiple pixels. It allows to capture more information important for the face representation. Both methods are tested on the ORL [13] and Yale [14] databases. The kernel methods reach higher recognition rates than the original ones.

Another interesting method based on the kernel LDA was proposed in [15]. The authors present a rotation and illumination invariant polynomial kernel Fisher discriminant analysis. This method combines features extracted by the Discrete Cosine Transform (DCT) and Radon Transform [16]. The significant coefficients of the DCT are used as a feature vector. Further, the kernel Fisher linear discriminant is applied to the vectors to increase the discrimination abilities.

This approach was tested on FERET, Yale and ORL databases. It outperforms other methods such as PCA, KPCA and KFLD.

2.7. Adaptive Local Hyperplane

A novel Adaptive Local Hyperplane (ALH) classifier is proposed for the face recognition in [17]. It is an extension of the K-local Hyperplane distance Nearest Neighbour (HKNN) [18]. ALH approximates the possibly missing instances in manifolds of particular classes by a local hyperplane. When classifying unknown vector first the K nearest neighbours are identified. Based on these K nearest neighbours the local hyperplane is constructed. The class label is assigned to the vector according to the distances between the vector and hyperplanes of each class.

The classifier is tested together with several feature extraction methods. Namely 2DPCA, $(2D)^2$2PCA, 2DLDA and $(2D)^2$2LDA. The tests were performed on the ORL and Yale datasets. It is stated there that the ALH classifier outperforms all traditionally used classifiers (Nearest Neighbours, Support Vector Machines, etc.) for this testing set-up. The best recognition results are obtained when Linear Discriminant Analysis (LDA) [19] was used for feature creation.

2.8. Genetic Algorithms

Genetic Algorithms (GAs) were also tried for the face recognition task. One example is a work proposed by Liu in [20]. Author proposes an approach called Evolutionary Pursuit (EP). It is an adaptive dictionary method. The author states that using genetic algorithms, it determines optimal basis of human faces encoding.

In this approach, the facial image is processed in lower dimensional PCA sub-space. The genetic algorithm searches for optimal rotation of a basis vector. The rotations are random and the search of the optimal one is done based on a fitness function. It is reported by the authors that this method outperforms both Eigenfaces and Fisherfaces methods.

2.9. Trace Transform

In [21], a face recognition approach based on the Trace Transform (TT) is proposed. The Trace transform is a generalization of Radon transform. It is invariant to image transformations (rotation, scaling and translation).

The image is first transformed into the trace transform space. Thus, the face representation is created. Further, a novel similarity measure is proposed for matching of face representations. The algorithm was tested on the AR [22] face database. This method outperforms the Eigenfaces approach on this dataset.

2.10. Linear Regression

An interesting approach using linear regression for the face recognition is proposed in [23]. This approach is based on the assumption that the faces from one class (one individual) are placed in one linear subspace. It assumes multiple training images for each person. Each training image is down-sampled and representing vector is created. The vectors belonging to one individual are put together to create the face model. In the classification step, the image must be also down-sampled and transformed to a vector. The recognized face should be expressed as a linear combination of model vectors of a relevant class. The estimate is based on the least-square [24] estimation method.

The method was evaluated on the FERET, ORL and Yale datasets. It reaches interesting results on lower quality images (different facial expressions, partial occlusions, etc.).

2.11. Active Appearance Models

The Active Appearance Models (AAM) was proposed for the face analysis in [25]. This approach uses a statistical model of object shape and grey level appearance. A set of training examples is used to learn the valid shapes. The examples must be labelled. It means the facial landmarks are manually marked. Then, the algorithm tries to match the model to an image. It is done by minimizing the distance between the synthesized model and the image. The minimization is performed iteratively.

View based variation of this method was proposed in [26]. Five different models are constructed for different poses (from left profile to right profile). These models are sufficient to cover most variations in the face pose.

2.12. Neural Networks

Another group of approaches use Neural Networks (NNs). Several NNs topologies were proposed. One of the best performing methods based on neural networks is presented in [27]. The image is first sampled into a set of vectors. Vectors created from all labelled images are used as a training set for a Self Organizing Map (SOM). Image vectors of the recognized face are used as an input of the trained SOM. The output of the SOM is then used as an input of the classification step, which is a convolutional network. This network has a few layers and ensures some amount of invariance to the face pose and scale.

Another approach [28] uses the PCA algorithm for the face representation. Then, an auto-associative neural network is used in order to reduce the features size to five dimensions. The face recognition is realized, as in the previous case, by a convolutional Multi-layer Perceptron (MLP). This approach achieves good results on a quite simple dataset with manually aligned images of 20 people with no lighting variation, rotation and tilting.

Authors use in [29] also the PCA algorithm and neural networks for the face recognition. The Fisher's linear discriminant technique is used for dimensionality reduction instead of the auto-associative neural network in the previous case. The Radial Basis Function (RBF) neural network is used as a classifier. Experimental results show that this approach achieves very good recognition accuracy and outperforms the majority of the other evaluated methods on the ORL corpus.

However, it is possible to use a network of the type MLP directly with the face images [30]. The intensity values of the pixels are used as the input of the MLP. The main drawback of this approach is the complexity of the network and usually the amount of the training data for a correct estimation of the face models is often not sufficient. Therefore, this approach usually does not achieve interesting results.

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2.13. Hidden Markov Models

The first method using Hidden Markov Models (HMMs) for the face recognition was proposed in [31]. The face is divided into regions (mouth, nose, eyes, etc.). These regions are then associated with the states of a HMM. The boundaries between regions are represented by probabilistic transitions between the states. The first step of the algorithm is image sampling. The image is thereby converted to a 1D sequence of the observations. Usually a left-right and top-bottom sampling direction is used. A square sliding window is employed. First, the image is traversed from the left to the right with the specified step. When the right border is reached, the window is shifted downwards with the same step and traverses back to the left side. This process is repeated till the bottom-right corner is reached. An alternative technique samples the image with a rectangular window, which has the same width as the image. It is shifted downwards with a specified overlap. The HMM has 8 or 5 states respectively. The algorithm was tested on a dataset containing 5 images of each of the 24 individuals. Indicated recognition rate of this approach is 84%. For comparison, the Eigenfaces were tested using the same dataset and the recognition rate of 74% is reported.

Another HMM-based approach is described in [32]. It is stated there, that the method significantly reduces the computational complexity in comparison with the older methods while the recognition rate remains the same. The image sampling is performed in the same manner as in the above mentioned method. Instead of using pixel intensity values directly, a 2D-Discrete Cosine Transform (2D-DCT) is performed. Then, the resulting coefficients are used.

Another more recent use of the HMM for face recognition is presented in [33].

2.14. Support Vector Machine

In [34] an algorithm using Support vector machine (SVM) for classification is described. Authors propose one component based and two global methods for creation of vectors representing the face. The SVM is then used for classification.

The first global approach takes into account all pixel values as the input vector for a SVM classifier. The second one uses several view-point specific classifiers. The component based method uses separate representations of important parts of the face and classifies them individually. It is proved that the component based approach is less sensitive to image variations.

Another method proposed in [35] uses SVM for the feature extraction. The method is derived from the linear discriminant analysis. It is called SVM-based Discriminant Analysis (SVM-DA). Employing the SVM for feature extraction should enhance the abilities of the method in case of recognition under uncontrolled conditions. The results on the FERET, AR and CMU-PIE [36] datasets are reported. This approach outperforms several other LDA-based methods.

2.15. Cost-Sensitive Face Recognition

Zhang et al. propose in [37] an interesting concept of classification of recognition errors according to their cost. Usually when evaluating the face recognition methods, only the recognition error rate is considered. But in some applications, different types of misclassification may have different impact on the whole application performance. The term “loss of the misclassification” is defined and each type of classification error may have different loss value.

Two methods for cost-sensitive classification are proposed: mckNN and mcKLR. Authors state that the proposed methods achieve better performance than other cost-based methods.

2.16. Elastic Bunch Graph Matching and Related Approaches

Another efficient AFR approach is the Elastic Bunch Graph Matching (EBGM) [38]. This approach uses features constructed by the Gabor wavelet transform. Initially, a set of manually labelled landmarks is presented to the algorithm. These landmarks are used as examples to determine the landmark positions in novel images. The Gabor wavelet convolutions (so called Jets) are computed in the landmark positions and are used for face representation. A “bunch graph” is created from these examples. Each node in the graph contains a set of Jets for one landmark across all of the images. The similarity of faces is determined from the landmark positions and jet values.

In the last couple of years, several other successful approaches based on Gabor wavelets have been introduced [39]. Some approaches [40] combine the pre-processing with Gabor wavelets with well-established methods such as Eigenfaces, Fisherfaces, etc. These groups of approaches are very efficient and can handle real images because the locally created wavelet features are robust to

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differences in illumination, distortion, rotation and scaling in the images.

2.17. Kepenekci Method

Kepenekci proposes in [41] an algorithm that outperforms the EBGM approach. Moreover, he addresses the main issue of elastic bunch graph matching, manual labelling of the landmarks. In this algorithm, landmark positions are not labelled manually, while obtained dynamically by Gabor filter responses as follows: the image is scanned using a sliding window and the maxima of Gabor filter responses within a window are identified as fiducial points. The number of fiducial points is thus not constant. The feature vectors are calculated in these points (similar as in EBGM). The similarity of two vectors is computed using the cosine similarity.

The size of the sliding window is very important for the performance of this method. It determines the number of detected fiducial points and influences its accuracy. The higher the window size is the less fiducial points are detected. On the other hand, searching larger window needs more computation time. In the comparison stage, the number of fiducial points determines the time needed.

Author states that his method outperforms significantly the Eigenfaces method on the Purdue [42] face dataset. He further shows that recognition accuracy of the proposed method on the ORL corpus is about 95% and significantly higher than the results of the Eigenfaces, elastic bunch graph matching and neural networks.

2.18. Local Binary Patterns

Other successful approaches [43, 44] use the so called, Local Binary Patterns (LBP) for facial features extraction. The LBP operator [45] was first used as a texture descriptor. This operator thresholds a local image region by the value of the central pixel. It labels the pixels either 0 or 1 if the value is lower or higher than the threshold. Then, a histogram of the labels is computed and used as a descriptor. The original method used a 3x3 neighbourhood which was later extended to use neighbourhoods of various sizes.

In the face recognition applications, an image is first divided into rectangular regions, the LBP descriptor is constructed in each region and the results are put together to create one vector representing the face. The face representations are compared using the nearest neighbour rule.

Lei et al. [46] propose another method using LBP. In this approach, the Gabor wavelets are combined with the LBP operator. First, a set of Gabor filters with different scales and orientations is applied to the input image. Then local binary operators are applied.

2.19. Local Derivative Patterns

A novel pattern descriptor called Local Derivative Pattern (LDP) is proposed in [47]. The method constructs pattern features from local derivative variations. The advantage over the previously described LBP is its higher order. It thus can represent more information than the LBP. The LDP can be applied both on original grey level images and images processed by Gabor filter. Using the LDP on Gabor filtered images should improve the recognition results. Results on several standard dataset such as FERET, CMU-PIE and Yale are reported.

2.20. Scale Invariant Feature Transform

The Scale Invariant Feature Transform (SIFT) [48] proposed by David Lowe has been also used to create the facial features leading to high recognition accuracy. It has the ability to detect and describe local features in images. The features are invariant to image scaling, translation and rotation. The algorithm is also partly invariant to changes in illumination. The SIFT algorithm was originally developed for object recognition. The features of the reference and test images are usually compared using the Euclidean distance of their feature vectors. This algorithm is very efficient and it belongs, in our opinion, to one of the best performing face recognition methods. Therefore, it will be detailed next.

The algorithm has basically four steps: extrema detection, removal of key-points with low contrast, orientation assignment and descriptor calculation [49]. The first step is the determination of extrema in the image filtered by the Difference of Gaussian (DoG) filter. The input image is gradually down-sampled and the filtering is performed in several scales. It ensures the scale invariance. Each pixel is compared with its neighbours. Neighbours in its level as well as in the two neighbouring (lower and higher) levels are examined. If the pixel is maximum or minimum of all the neighbouring pixels, it is considered to be a potential key-point. For the resulting set of key-points their stability is determined. Locations with low contrast and unstable locations along edges are discarded. Further, the orientation of each key-point is computed. The computation is based upon gradient

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orientations in the neighbourhood of the pixel. The values are weighted by the magnitudes of the gradient. The final step is the creation of the descriptors. The computation involves the 16 × 16 neighbourhood of the pixel. Gradient magnitudes and orientations are computed in each point of the neighbourhood. Their values are weighted by a Gaussian. For each sub-region of size 4 × 4 (16 regions), the orientation histograms are created. Finally, a vector containing 128 (16 × 8) values is created.

One of the first applications of this algorithm for the face recognition is proposed in [50]. The author takes the original SIFT algorithm and creates for every image a set of the descriptors (face features). The recognized face image is matched against the faces stored in the gallery. The face that has the largest number of matching features is identified as the closest one. The feature is considered to be matched if the difference between similarities of two most similar gallery features is higher than a specified threshold. Author shows that his approach significantly outperforms both the Eigenfaces and Fisherfaces methods on the ORL and Yale databases. The reported recognition rates are 96.3% and 91.7% respectively.

Another interesting approach using the SIFT features in the AFR field is presented in [49]. This method is called Fixed-key-point-SIFT (FSIFT). Contrary to the previous method, the SIFT keys are fixed in predefined locations determined in the training step as follows. The key-point candidates are localized in the same manner as in the original SIFT. A clustering algorithm is then applied to this key-point candidate set. The number of clusters is set to 100. The centroids of the clusters are used as the fixed key-point locations. The number of the features thus remains constant. The distance between faces can be computed as a sum of the Euclidean distances between the corresponding features. The reported recognition rate for the Extended Yale database [14] is comparable to the previously described approaches.

2.21. Speeded-Up Robust Features

Speeded-Up Robust Features (SURF) [51] is another useful method for key-point detection and descriptor creation. An integral image [52] is utilized to speed-up the key-point detection process. The detector is based on the Hessian matrix[1]. Therefore, it is called the "Fast-Hessian" detector. Box filters are used as an approximation of the second order Gaussian derivatives. The box filters are then up-scaled and applied to the original image. This method is invariant to the face rotation. To ensure the rotation invariance, one orientation is assigned to the each key-point. The computation is based on the circular neighbourhood of the key-points.

An upright version of the SURF (U-SURF) was further proposed by the authors of the original SURF approach. It doesn't compute the orientation of the key-points (is not orientation invariant) which simplifies and accelerates the computation process. The authors show in [53] that SURF performs comparably to the SIFT based face recognition algorithms.

2.22. 3D Face Recognition Methods

The aim of the 3D methods is to perform the recognition of faces with any pose. One of such methods is presented in [54]. The algorithm uses linear equations to make out the face description. It should work independently on the facial pose and lighting conditions. The main drawback of this method is the computational complexity of the face fitting process.

A 3D model is used to create images of different pose and illumination from a frontal face image in [55]. Consequently the 2D recognition methods are used for recognition. The 3D methods have a great potential to outperform existing 2D methods. However, the successful implementation of the methods is still problematic. A challenging schema is to combine the 3D and 2D approaches.

3. DISCUSSION

As already stated, the above described methods are usually evaluated on the different face datasets. Moreover, the experimental set-up usually differs even when using the same data. Therefore, a straightforward comparison and evaluation of the methods with identification of a generally best/worst performing approach is not possible. However, the performance of these methods depends on their characteristics which will be used next for method classification.

A usual categorization is into three groups: holistic, feature based and hybrid methods. Holistic methods are considered the methods which use a whole face image as an input. The typical representatives belonging into this group are popular Eigenfaces or Fisherfaces. In contrast, the feature bases approaches use local features for

[1] Hessian matrix is a square matrix of the second order partial derivatives of a given function.

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recognition. These features correspond to the important face characteristics such as the eyes, nose, etc. For example Elastic bunch graph matching or the popular SIFT approach belong to this group. Hybrid methods combine both these types.

Another classification criterion could be the number of different steps in the face recognition. The simplest "one step" methods use for classification directly the raw intensity values of the image pixels. The most of the proposed approaches are "two step" methods. These approaches realise the dimensionality reduction in the first step. The feature vector is created in this step. The classification itself is done in the second step. The remaining methods belong to the "more step" approaches. These approaches use two or more steps for dimensionality reduction when a feature vector is created.

Recognition accuracy of the presented methods differs significantly according to their complexity. Holistic methods use usually sophisticated parameterizations (PCA, LDA, FLD, etc.) and a simple classifier based often only on the distance measurement. Therefore, these methods are very fast and perform well on the corpora with few face variation. The small number (often only one example) of the data for training does not influence the recognition accuracy. Conversely, more training data can decrease the recognition accuracy when the training images differ. However, the number of the recognized people does not play an important role when the data dissimilarity is small. For example recognition rates of the Eigenfaces method on monotone images are very good, while the differences in the lighting conditions influence significantly the accuracy when only one training example used.

The feature based methods use mostly a complex classifier, e.g. neural networks, support vector machines, etc. Therefore, the time and computational complexity is usually higher than the holistic methods. Conversely, these methods are able to handle more differences in the facial data when enough training data available.

The above mentioned conclusions support the fact that it is not possible to identify a general best performing AFR method and that the choice of an optimal method is strictly related to the target application.

Most of the previously described methods perform well under certain "good" conditions (face images are well aligned, the same face pose and lighting conditions, etc.). However, their performance is significantly degraded when these conditions are not accomplished. Several methods try handling more or less these limitations, but only few of them perform sufficiently in a fully uncontrolled environment. However, the importance of such application is growing. Therefore, we assume that the main future direction will try to solve this issue which is particularly challenging.

Although the most important face recognition approaches were described in this paper, it was not possible to provide all available information. For further information in this field, you can refer to the surveys [56, 57]. Note that the authors of these reviews mention also some commercial face recognition systems. Unfortunately, neither the system architecture nor the approaches used are usually reported. Moreover, these systems are not evaluated on the standard face datasets and it is thus impossible to compare them with the other systems.

4. CONCLUSIONS

This paper summarized the most important approaches in the face recognition field. These approaches were described with their theoretical and practical advantages and disadvantages. We concluded that it is not possible to identify a general best performing face recognition method and that the choice of an optimal method is strictly related to the target application.

We identified the main issue of the current approaches, insufficient recognition accuracy in the totally uncontrolled environment. We suppose that the most of the future approaches will address this research challenge. Two alternative ways will be explored. The first one consists in proposing more suitable face pre-processing. The recognition method itself should remain without modification. Conversely, the second way will be focussed on proposing better face representation techniques which will process sufficiently the faces with significant singularities.

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