Face processing for security: a short review

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Abstract In this paper we give a fast fly over the face image preocessing issue, taking special care to highlight the security related applications. Face detection is the first step for the face recognition systems, posing its own challenges. Face recognition is essentially a classification problem, which can be a large multiclass problem. The emphasis in this paper is the of review the different computational approaches instead of the concrete applications.

1 Introduction

Face recognition is one of the most relevant applications of image analysis. It's a true challenge to build an automated system which equals human ability to recognize faces. There are many different industrial applications interested in it, most of them somehow related to security. Table 1 shows the most salient security applications. Engineering started to show interest in face recognition in the 1960's implementing semi-automatic systems [2, 7, 11, 8, 9, 10]. In the 70's the most salient work was that of Kenade [25]. His face recognition program ran in a special purpose computer system. The algorithm extracted sixteen facial parameters automatically, and he demonstrated that better results were obtained when irrelevant features were not used. In the 1980's and 1990's there were a diversity of approaches, most of them continuing with previous tendencies. Some works tried to improve the methods used measuring subjective features like geometric measurement for eye spacing [34] others introduced novel computational methods, such as artificial neural networks [41]. The work of Turk and Pentland introducing eigenfaces for recognition [44] was a landmark for th development of the area. Their algorithm was able to locate, track and classify a subject's head. Since the 1990's, face recognition area has received a lot of attention, with a noticeable increase in the number of publications.

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The structure of the paper is as follows: section 2 will be devoted to face detection, which is the previous step for robust face recognition that will be reviewed in section 3. For lack of space we will obviate the conclusions section.

Areas	Applications
Information Security	Access security (OS, data bases) Data privacy (e.g. medical records) User authentication (trading, on line banking)
Access management	Secure access authentication (restricted facilities) Permission based systems Access log or audit trails
Biometrics	Person identification (national IDs, Passports, voter registrations, driver licenses) Automated identity verification (border controls)
Law Enforcement	Video surveillance Suspect identification Suspect tracking (investigation) Simulated aging Forensic Reconstruction of faces from remains
Personal security	Home video surveillance systems Expression interpretation (driver monitoring system)

Table 1 Security applications of face recognition.

2 Face detection

Few applications of Face Recognition don't require face detection. Some criminal database images have face images already normalized to a given pose standard. However, the conventional input image of computer vision systems may contain many items and/or faces, either for recognition or tracking. In these cases face detection is mandatory, it is a required preprocessing of the images to determine, first, if there is a face in the image, and second, where it is located.

Knowledge-based face detection methods.

These systems try to capture our knowledge of the structure of faces, and translate it into a set of rules [27]. The big problem encountered by these methods is the difficulty of building the set of rules. It must be complete, consistent, and provide good detection performance. It is quite difficult to introduce noise and uncertainty robustness and to tune the system.

Another critical issue is to find invariant features for face detection like face-like image textures or the color of human skin. Some recent researches use more than one color model. For example, RGB and HSV may be used together successfully

[45]. However, skin color can depend significantly on light conditions. Therefore, other methods, like local symmetry measures or structure and geometry, must be used in conjunction with the color models.

Template matching face detection methods

Template matching methods define a face image as a 3D function that can be compared to a standard template of all the faces [12]. The template can be defined on different features which can be defined independently, like the eyes, face contour, nose and mouth. Also a face model can be built by edges, or a silhouette. But these methods are most effective to find faces that are frontal and unoccluded with little variations in pose, scale and shape. Deformable templates have been proposed to deal with these problems [18].

Appearance-based face detection methods

Appearance-based methods rely on techniques from statistical analysis and machine learning to build the relevant feature extraction processes that will learn from a set of face images. These methods used include Eigenface-based methods [3], Distribution-based algorithms, Neural Networks [37, 39], Decision Trees [22], Support Vector Machines [35], Sparse Network of Winnows, Hidden Markov Models [32], Markov Random Fields or Inductive Learning methods.

Face tracking

Face tracking is essentially a motion estimation problem. Robust tracking have been proposed based on Kalman filters [16]. The state vector of a face includes the center position, size of the rectangle containing the face, the average color of the face area and the first image derivatives. The features are used in order, first a SSD algorithm works on the gray scale image, then the color information is used to confirm the detection. Robust optical-flow based recognition is in [21]

3 Face recogntion

The key face processing is face recognition for most applications [14]. It may consist in the authentication of a user, which a binary decision, or in the identification of a user which is a (large) multiclass problem.

3.1 Template matching face recognition methods

Blanz and Vetter state in [6] that there are different ways of separating shape and orientation of a face in 3D models: To match feature vertexes to image positions and then interpolate deformations of the surface or to use restricted class-specific deformations, defined manually or automatically, from non textured or textured head scans. Separation between texture and illumination is achieved using models of illumination that consider illumination direction and intensity from Lambertian or non-Lambertian reflectance. The database of faces is obtained via 3D scans. The approach requires to manually define some feature points. The recognition process is done by building a 3D model of the subject. Then, this 3D model is compared with the stored patterns using two parameters -shape and texture. They have huge potential towards pose and illumination invariant face recognition. A high-order template based approach is presented in [49]. Incremental templates for video image face recognition are proposed in [17].

3.2 Statistical learning for recognition algorithms

Images of faces, represented as high-dimensional pixel arrays, often belong to a manifold of lower dimension. In statistical learning approaches, each image is viewed as a point (vector) in a d-dimensional space. The dimensionality of these data is too high. Therefore, the goal is to choose and apply the right statistical tool for extraction and analysis of the underlaying manifold. These tools must define the embedded face space in the image space and extract the basis functions from the face space. This would permit patterns belonging to different classes to occupy disjoint and compacted regions in the feature space. Consequently, we would be able to define a line, curve, plane or hyperplane that separates faces belonging to different classes. The classical approach applied Principal Component Analysis (PCA) for feature extraction [44], other approaches use the variations of the Linear Discriminant Analysis (LDA) [30, 53, 52, 29, 36, 47, 38, 13], or the Locality Preserving Projections (LPP) [19]. Other successful statistic tools include Bayesian networks [31], bi-dimensional regression [24], generative models [20], and ensemble-based and other boosting methods [30].

3.3 Neural Network approaches

Artificial Neural Networks (ANN) have succesfull in face recognition. They provide a training algorithm that eases the classifier building task. Some approaches like the Convolutional Neural Networks [28] try that the ANN learns also the feature extraction as well as the classification.

Neural networks with Gabor filters

ANNs combined with Gabor filter [15, 1, 5, 40, 42, 48, 46, 50] assume a feature extraction pre-processing step based on Gabor filters. Every image is normalized in terms of contrast and illumination. Noise is reduce by a “fuzzily skewed” filter. Then, each image is processed through a banck of Gabor filters. For each face image, the outputs are 15 Gabor-images which record the variations measured by the Gabor filters. These images are the input to the ANN, a multilayer perceptron trained with the backprogation algorithm.

Neural networks and Hidden Markov Models

Hidden Markov Models (HMM) are a statistical tool originally developed for voice recognition and audio processing. They have been also used in conjunction with neural networks[4] for face recognition. They propose a pseudo 2D-HMM, defining superstates formed by states. The input of this 2D-HMM process is the output of the artificial neural network (ANN) applied to the input image to perform dimensionality reduction.

3.4 Classifiers for face recognition

Once the features are extracted and selected, the last step is to classify the image. Appearance-based face recognition algorithms use a wide variety of classification methods, and the literature has been very active in this area [51, 26]. An instance of a fuzzy discriminant has been recently proposed [33].

Classifier combination

Sometimes two or more classifiers are combined to achieve better results. The classifier combination problem can be defined as a problem of finding the combination function accepting M-dimensional score vectors from M-classifiers and outputting final classification scores. For lack of space we summarize in table 2 the combination schemes proposed in [43] and [23] that can be tested on face recognition problems.

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Scheme	Architecture	Trainable	Info-level
Voting	Parallel	No	Abstract
Sum, mean, median	Parallel	No	Confidence
Product, min, max	Parallel	No	Confidence
Generalized ensemble	Parallel	Yes	Confidence
Adaptive weighting	Parallel	Yes	Confidence
Stacking	Parallel	Yes	Confidence
Borda count	Parallel	Yes	Rank
Behavior Knowledge Space	Parallel	Yes	Abstract
Logistic regression	Parallel	Yes	Rank
Class set reduction	Parallel/Cascading	Yes	Rank
Dempster-Shafer rules	Parallel	Yes	Rank
Fuzzy integrals	Parallel	Yes	Confidence
Mixture of Local Experts	Parallel	Yes	Confidence
Hierarchical MLE	Hierarchical	Yes	Confidence
Associative switch	Parallel	Yes	Abstract
Random subspace	Parallel	Yes	Confidence
Bagging	Parallel	Yes	Confidence
Boosting	Hierarchical	Yes	Abstract
Neural tree	Hierarchical	Yes	Confidence

Table 2 Classifier combination schemes

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