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Face Recognition with Different Approaches: A Survey

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Abstract: *Face recognition, which presents a challenging problem in the field of computer vision and image analysis, and as such it has received a great deal of attention over the last few years because of its many applications in a assortment of domains. Face recognition techniques can be mostly divided into three categories based on the face data acquisition methodology: methods that operate on intensity images; those that deal with video sequences; and those that require other sensory data such as 3D information or infra-red metaphors. In this paper, an outline of some of the well-known approaches for face recognition in each of these categories is provided and some of the benefits and drawbacks of the schemes mentioned therein are examined. This paper also mentions some of the most recent approaches developed for this purpose and attempts to give an idea of the state of the art of face recognition technology.*

Keywords: *Face Recognition, Data Acquisition, intensity, infra-red metaphors, computer vision.*

1. Introduction

Biometric systems recognize users based on their physiological and behavioral features[1]. Unimodal biometric systems make use of a single biometric trait for user recognition. It is convoluted to accomplish very high recognition rates using unimodal systems due to problems like noisy sensor data and non-universality and/or lack of distinctiveness of the chosen biometric characteristic. Multimodal biometric systems report some of these problems by combining evidence obtained from multiple sources [2].A wide assortment of biometric systems have been developed for automatic recognition of individuals based on their anatomical (e.g., fingerprint, face, and iris) and behavioral(e.g., signature and gait) characteristics [3]. Soft biometric traits are defined as characteristics that provide some information about the individual, but lack the uniqueness and immovability to sufficiently differentiate any two individuals [4]. The use of soft biometric traits is expected to improve the face-recognition performance when appropriately combined with a face matcher.

2. Face Recognition: Different Approaches

There are several different approaches available for identifying a person. Here, we discuss about some approaches for face recognition such as Geometric/ Template Based approaches, Piecemeal/ Wholistic approaches, Appearance-based/ Model-based approaches, Template/ statistical/ neural network approaches.

2.1. Geometric/ Template Based Approaches

Face recognition algorithms can be classified as either geometry based or template based algorithms [5, 6]. The template based methodology contrast the input image with a set of templates. The set of templates can be created using statistical tools like Support Vendor Machines (SVM) [7, 8, 9], Principal Component Analysis (PCA) [10,11,12], Linear Discriminant Analysis (LDA) [13], Independent Component Analysis (ICA) [14, 15,16], Kernel approach [17, 18, 19, 20], or Trace Transforms [21, 22, 23]. The geometry feature-based methods analyze local facial features and their geometric association. This methodology is sometimes called feature based approach [24]. Some Elastic Bunch Graph Matching algorithms [25, 26] are used as examples for feature based approach. This approach is less used at the moment [27]. There are algorithms established using both approaches. For instance, a 3D morphable model style can use feature points or texture as well as PCA to build a recognition system [28].

2.2. Piecemeal/Holistic Approaches

Faces can often be identified from little information. Some algorithms follow this idea, processing facial features autonomously. In other words, the relation between the features or the relation of a feature with the whole face is not taken into account. Many early researchers followed this approach, trying to presume the most relevant characteristics. Some approaches credible to use the eyes [29], a combination of features [24], and so on. Some Hidden Markov Model (HMM) methods also fall in this category [30]. Although characteristic processing is very important in face recognition, relation between features (configural processing) is also important. In fact, facial features are processed holistically [31]. That's why nowadays most algorithms follow a holistic approach.

2.3. Appearance-Based/Model-Based Approaches

Facial recognition methods can be divided into appearance-based or model based algorithms. The differential element of these methods is the representation of the face. Appearance-based methods represent a face in terms of several raw intensity images. An image is considered as a high-dimensional vector. Then statistical techniques are usually used to derive a feature space from the image distribution. The sample image is compared to the training set. On the other hand, the model-based approach tries to model a human face. The new sample is fitted to the model, and the parameters of the fitten model used to identify the image. Appearance methods can be confidential as linear or non-linear, although model-based methods can be 2D or 3D [32]. Linear appearance-based methods accomplish a linear dimension reduction. The face vectors are projected to the foundation vectors, the projection quantity are used as the feature representation of every face image. Examples of this approach are PCA, LDA or ICA. Non-linear appearance methods are more complicate. In fact, linear subspace analysis is an approximation of a nonlinear manifold. Kernel PCA (KPCA) is a method widely used [33]. Model-based approaches can be 2-Dimensional or 3-Dimensional. These algorithms try to build a model of a human face. These models are often morphable. A morphable model allows classifying faces even when pose changes are present. 3D models are more complicate, as they try to capture the three dimensional nature of human faces. Examples of this approach are Elastic Bunch Graph Matching [25] or 3D Morphable Models [36, 37, 38, 39, 40].

2.4. Template/ Statistical/ Neural Network Approaches

A similar separation of pattern recognition algorithms into four groups is proposed by Jain and colleges in [41]. We can group face recognition methods into three main groups. The following approaches are proposed:

Template Matching: Patterns are represented by samples, models, pixels, curves, textures. The recognition function is usually a correlation or distance measure.

Statistical Approach: Patterns are represented as features. The recognition function is a discriminant function.

Neural Networks: The representation may vary. There is a network function in some point.

3. ADVANTAGE OF FACE RECOGNITION

- Photos of faces are widely used in passports and driver's licenses where the possession authentication protocol is augmented with a photo for manual inspection purposes; there is wide public acceptance for this biometric identifier
- Face recognition systems are the least intrusive from a biometric sampling point of view, requiring no contact, nor even the awareness of the subject
- The biometric works, or at least works in theory, with legacy photograph data-bases, videotape, or other image sources
- Face recognition can, at least in theory, be used for screening of unwanted individuals in a crowd, in real time.
- It is a fairly good biometric identifier for small-scale verification applications.

4. DISADVANTAGE OF FACE RECOGNITION

- A face needs to be well lighted by controlled light sources in automated face authentication systems. This is only a first challenge in a long list of technical challenges that are associated with robust face authentication
- Face currently is a poor biometric for use in a pure identification protocol

- An obvious circumvention method is disguise
- There is some criminal association with face identifiers since this biometric has long been used by law enforcement agencies ('mugshots').

5. CONCLUSION

This work has presented a survey about face recognition. It isn't a trivial task, and today remains unresolved. These are the current lines of research:

New or Extended Feature Extraction Methods: There is much literature about extending or improving well known algorithms. For example, including weighting procedures to PCA [42], developing new kernel based methods [43] or turning methods like LDA into semi-supervised algorithms [44].

Feature Extraction Method Combination: Many algorithms are being built around this idea. As many strong feature extraction techniques have been developed, the challenge is to combine them. For example, LDA can be combined with SVD to overcome problems derived from small sample sizes [45].

Classifier and Feature Extraction Method Combinations: It's a common approach to face recognition. For instance, there are recent works that combine different extraction methods with adaptive local hyperplane (ALH) classification methods [46].

Classifier Combination: There are strong classifiers that have achieved good performance in face recognition problems. Nowadays, there is a trend to combine different classifiers in order to get the best performance [47]. .Data gathering techniques: There are some novel methods to gather visual information. The idea is to obtain more information that provided by simple images. Examples of this approach include 3D scans [48] and continuous spectral images [49].

Works on Biologically Inspired Techniques: The most common techniques that fall into this category are genetic algorithms [50] and, above all, artificial neural networks [51, 52].

Boosting Techniques: Diverse boosting techniques are being used and successfully applied to face recognition. One example is Ada Boost in the well known detection method developed by Viola and Jones [53]. Face recognition is also resulting in other dares, like expression recognition or body motion recognition. Overall, face recognition techniques and the emerging methods can see use in other areas. Therefore, it isn't just a unresolved problem but also the source of new applications and challenges.

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