Chapter 68
Unconstrained Face Recognition

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ABSTRACT

The human face is the most well-researched object in computer vision, mainly because (1) it is a highly deformable object whose appearance changes dramatically under different poses, expressions, and illuminations, etc., (2) the applications of face recognition are numerous and span several fields, (3) it is widely known that humans possess the ability to perform, extremely efficiently and accurately, facial analysis, especially identity recognition. Although a lot of research has been conducted in the past years, the problem of face recognition using images captured in uncontrolled environments including several illumination and/or pose variations still remains open. This is also attributed to the existence of outliers (such as partial occlusion, cosmetics, eyeglasses, etc.) or changes due to age. In this chapter, the authors provide an overview of the existing fully automatic face recognition technologies for uncontrolled scenarios. They present the existing databases and summarize the challenges that arise in such scenarios and conclude by presenting the opportunities that exist in the field.

INTRODUCTION

Unveiling the way humans perceive identities has been of great interest to psychologists for at least five decades (Bruner & Tagiuri, 1954). It nowadays constitutes one of the most popular research areas in experimental psychology (Bruce & Young, 1986; Sinha, Balas, Ostrovsky, & Russell, 2006). The interested reader can find a nice summary of research findings regarding human perception of identities in (Sinha, Balas, Ostrovsky, & Russell, 2006).

Automatic face recognition was first attempted in the 1960s (Bledsoe, 1964) and 1970s (Kelly, 1970). A pioneer in the field was Takeo Kanade (1973), who first attempted facial features localization in order

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to match them for face recognition. Since then, face recognition became one of the mainstream applications of image analysis and computer vision, creating a wealth of scientific research (the interested reader may refer to Chellappa, Charles, and Saad (1995) and Zhao, Chellappa, Phillips, and Rosenfeld (2003) to see the progress of face recognition during the past 30 years and until 2003).

The collection of face databases, among the first large object databases that were created, made face recognition the main application for certain domains of statistical machine learning and pattern recognition and particular for the domain of component analysis (CA). CA includes methods such as Principal Component Analysis (Turk & Pentland, 1991; Kirby & Sirovich, 1990), Linear Discriminant Analysis (Belhumeur, Hespanha, & Kriegman, 1997), Independent Component Analysis (Bartlett, Movellan, & Sejnowski, 2002) and Nonnegative Matrix Factorization (Zafeiriou, Tefas, Buciu, & Pitas, 2006).

Face recognition can be further distinguished into a set of sub-problems, each of which dealing with the different challenges met by using different problem formulations according to the machine learning and matching algorithms it employs:

1. Closed-set Face Identification (CFI) (Chellappa, Charles, & Saad, 1995; Zhao, Chellappa, Phillips, & Rosenfeld, 2003). In CFI all testing identities are known at training. That is, the system always assigns an identity to the testing images and the identity will be of a subject from the training set. CFI falls under the general category of multiclass classification problems and can be easily formulated within the current statistical machine learning frameworks. The measure that is usually used in CFI is the classification accuracy (i.e., number of correctly classified samples over the number of total samples in the dataset).

2. Open-set Face Identification (OFI), also known as Watch List (Li & Wechsler, 2005; Scheirer, Boult, de Rezende Rocha, & Sapkota, 2013). In OFI incomplete knowledge of the world is given by the training data and images of unknown persons can be submitted to the system during testing. The system should be able to not only assign one of the identities in the Watch List but also to assign the identity “Other” if the submitted face does not belong to one of the subjects in the list (Scheirer, Boult, de Rezende Rocha, & Sapkota, 2013). It is obvious that OFI can be applied to considerably more problems than CFI. However using a huge class “Other” introduces considerable challenges in formulating proper statistical machine learning frameworks.

3. Face Identity Verification (Zafeiriou, Tefas, & Pitas, 2007) (also referred to as Face Authentication (Duc, Fischer, & Bigun, 1999; Kotropoulos, Tefas, & Pitas, 2000)). A FIV system should be able to automatically decide, given a test facial template and a reference one, whether they correspond to the same subject. FIV has numerous applications including identity control in airports, identity verification in biometric systems etc. Usually, FIV is formulated as a two class problem, i.e client (or genuine) faces vs impostor faces. That way, given enough samples per person, powerful person-specific models can be built (Zafeiriou, Tefas, & Pitas, 2007). The performance of face verification systems is measured in terms of the False Rejection Rate (FRR) achieved at a fixed False Acceptance Rate (FAR). There is a trade off between FAR and FRR. That is, it is possible to reduce either of them with the risk of increasing the other one. This trade off between the FAR and FRR can create a curve, where FRR is plotted as a function of FAR. This curve is called Receiver Operating Characteristic (ROC) curve. The performance of a verification system is often quoted by a particular operating point of the ROC curve where FAR=FRR. This operating point is called Equal Error Rate (EER).