Chapter 34 Invariant Model Combining Geometry and Appearance for Facial Detection and Gender Classification From Arbitrary Viewpoints

Mokhtar Taffar University of Jijel, Algeria

Serge Miguet LIRIS, Université de Lyon 2, UMR CNRS 5205, France

ABSTRACT

In this chapter, we tackle in the same process the problems of face detection and gender classification, where the faces present a wide range of the intra-class appearance are taken from arbitrary viewpoints. We try to develop complete probabilistic model to represent and learn appearance of facial objects in both shape and geometry with respect to a landmark in the image, and then to be able to predict presence and position of the appearance of the studied object class in new scene. After have predicted the facial appearance and the geometry of invariants, geometric hierarchical clustering combines different prediction of positions of face invariant. Then, the algorithm of cluster selection with a best appearance localizes faces in the image. Using a probabilistic classification, each facial feature retained in the detection step will be weighted by a probability to be male or female. This set of features contributes to determine the gender associated to a detected face. This model has a good performance in presence of viewpoint changes and a large appearance variability of faces.

DOI: 10.4018/978-1-5225-6912-1.ch034

INTRODUCTION

The face image analysis has become a field of study in the world. One of the most common visual trait classification task is to determine the gender from images of face. We try to treat the face detection and gender classification simultaneously. Several models exist which perform detection with high accuracy, but not across all views of face.

Local Haar wavelets can be computed very efficiently and is proved useful for frontal face detection using boosted classifiers (Viola & Jones, 2001). The integral image approach is less effective in coping with arbitrary viewpoints. It needs a series of classifiers or a set of detectors to model the in-plane deformation parameters such as the image scale and orientation and the out-of-plane viewpoint changes (Toews & Arbel, 2006).

Contrary to global features, the local feature approaches give robust invariance to illumination, viewpoint and orientation changes. Thus, they offer opportunity for further performances to detect faces and to classify their gender.

Local invariant features (Lowe, 2004; Kadir & Brady, 2001; Mikolajczyk & Schmid, 2004; Yu & Morel, 2009; Herbert, Tinnr, & Gool, 2006) are widely used in object recognition, stitching images in panorama and scene reconstruction, etc. (Hartley & Zisserman, 2000; Lowe, 1999; Schmid & Mohr, 1997; Mikolajczyk & Schmid, 2002; Tuytelaars & Van Gool, 2000; Fergus, Perona, & Zisserman, 2003). They have a high capability to capture appearance information. They allow to select the sparse appearance patches of objects, as faces. Thus, it becomes possible to model the faces and to learn their appearance variability through a model that embeds features and that presents invariant properties.

Using the co-occurrence statistics of features with interest trait, we train a classifier to recognize the gender of faces in terms of visual traits. The gender of a face can be inferred from a collection of image features which define the traits of gender.

The human vision uses a wide range of visual traits to describe objects in images. In general, databases used for learning of the appearance of an object class with low supervision contain many images but small numbers of instances of a single object of class (Toews & Arbel, 2009). These databases focus on labeling the object identity and its location but provide little information regarding further traits, and also the number of images may be insufficient for learning traits. In the case of the face class, it is a limit to use these databases for learning and classifying traits through many different instances of face class. In the interest of comparison, most approaches train and test on the FERET database (Color FERET Face Database, 2009), which contains detailed labels for visual traits such as sex and age.

The model of face class appearance is based on learning of the relationship between the appearance of facial patches and the geometry of face invariant, denoted FI. The visual facial features that have contributed to infer face are then used to recognize its gender. The FI is a common geometric landmark to all face features; it connects them across all different viewpoints. The extraction of such invariants directly from an image is complex (Burns, Weiss, & Riseman, 1993). We have boosted this geometric structure by a probabilistic model in order to capture the multimodal nature of face and to learn the geometric transformations that link facial appearance to instances of FI through images.

The face detection process uses a probabilistic model and the geometric transformations to infer a face instance in the form of a FI in a new image even in the presence of changes in illumination and head pose, see Figure 1. A clustering of invariants is performed to correct the geometric error and efficiently locate the face appearance. The proposed clustering algorithm, based on the features appearance and using the Ward criterion, presents simplicity, a low cost, and an accurate localization. Then, a cluster is selected

35 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage: <u>www.igi-global.com/chapter/invariant-model-combining-geometry-and-</u> <u>appearance-for-facial-detection-and-gender-classification-from-arbitrary-</u> <u>viewpoints/209002</u>

Related Content

Beyond Incarcerated Identities: Identity, Bias and Barriers to Higher Education in Australian Prisons

Marcus K. Harmes, Susan Hopkinsand Helen Farley (2019). International Journal of Bias, Identity and Diversities in Education (pp. 1-16).

www.irma-international.org/article/beyond-incarcerated-identities/216370

Community of Inquiry: Research-Based Learning for Inclusive Practice

Benjamin Brassand Heike de Boer (2018). International Journal of Bias, Identity and Diversities in Education (pp. 45-59).

www.irma-international.org/article/community-of-inquiry/204614

Job Insecurity and Performance: Contributions for an Integrative Theoretical Framework

Ligia Portovedo, Ana Velosoand Miguel Portela (2023). *Developing Diversity, Equity, and Inclusion Policies* for Promoting Employee Sustainability and Well-Being (pp. 61-98). www.irma-international.org/chapter/job-insecurity-and-performance/321294

Using Digital Storytelling to Inform Students About Bullying: Results of a Pilot Program

Emmanuel Fokides (2017). International Journal of Bias, Identity and Diversities in Education (pp. 27-39). www.irma-international.org/article/using-digital-storytelling-to-inform-students-about-bullying-results-of-a-pilotprogram/169967

How Does Empowering Leadership Contribute to Organizational Commitment of Millennials?: An Indian Perspective

Mohammad Faraz Naim (2022). Research Anthology on Changing Dynamics of Diversity and Safety in the Workforce (pp. 150-163).

www.irma-international.org/chapter/how-does-empowering-leadership-contribute-to-organizational-commitment-ofmillennials/287928