

DOCTORAL THESIS

Single sample face recognition under complex environment

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Abstract

Single sample per person face recognition (SSPP FR), i.e., recognizing a person with a single face image in the biometric enrolment database only for training, has lots of attractive real-world applications such as criminal identification, law enforcement, access control, video surveillance, just to name a few.

This thesis studies two important problems in SSPP FR, i.e., 1) SSPP FR with a standard biometric enrolment database (SSPP-se FR), and 2) SSPP FR with a contaminated biometric enrolment database (SSPP-ce FR). The SSPP-ce FR is more challenging than SSPP-se FR since the enrolment samples are collected under more complex environments and can be contaminated by nuisance variations. In this thesis, we propose one patch-based method called robust heterogeneous discriminative analysis (RHDA) to tackle SSPP-se FR, and propose two generic learning methods called synergistic generic learning (SGL) and iterative dynamic generic learning (IDGL), respectively, to tackle SSPP-ce FR.

RHDA is proposed to address the limitations in the existing patch-based methods, and to enhance the robustness against complex facial variations for SSPP-se FR from two aspects. First, for feature extraction, a new graph-based Fisher-like criterion is presented to extract the hidden discriminant information across two heterogeneous adjacency graphs, and meanwhile improve the discriminative ability of patch distribution in underlying subspaces. Second, a joint majority voting strategy is developed by considering both the patch-to-patch and patch-to-manifold distances, which can generate complementary information as well as increase error tolerance for identification.

SGL is proposed to address the SSPP-ce FR problem. Different from the existing generic learning methods simply based on prototype plus variation (P+V) model, SGL presents a new “learned P + learned V” framework that enables the prototype learning and variation dictionary learning to work collaboratively to identify new probe samples. Specifically, SGL learns prototypes for contaminated enrolment samples by preserving the more discriminative parts while learns variation dictionary by extracting the less discriminative intra-personal variants from an auxiliary generic set, on account of a linear Fisher information-based feature regrouping (FIFR).

IDGL is proposed to address the limitations in SGL and thus better handling the SSPP-ce FR problem. IDGL is also based on the “learned P + learned V” framework. However, rather than using the linear FIFR to recover prototypes for contaminated enrolment samples, IDGL constructs a dynamic label-feedback network to update prototypes iteratively, where both linear and non-linear variations can be well removed. Besides, the supplementary information in probe set is effectively employed to enhance the correctness of the prototypes to represent the enrolment persons. Furthermore, IDGL proposes a new “sample-specific” corruption strategy to learn a representative variation dictionary.

Comprehensive validations and evaluations are conducted on various benchmark face datasets. The computational complexities of the proposed methods are analyzed and empirical studies on parameter sensitivities are provided. Experimental results demonstrate the superior performance of the proposed methods for both SSPP-se FR and SSPP-ce FR.

Keywords: Face recognition, single sample per person, Fisher-like criterion, contaminated enrolment database, prototype plus variation model.

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