

Unconstrained Periocular Face Recognition: From Reconstructive Dictionary Learning to Generative Deep Learning and Beyond

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To Jaclyn Jieqing Ding
My friend, my love, and my star.

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You raise me up so I can stand on mountains

You raise me up to walk on stormy seas

You raise me up to more than I can be

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Abstract

Many real-world face recognition tasks are under unconstrained conditions such as off-angle pose variations, illumination variations, facial occlusion, facial expression, *etc.* In this work, we are focusing on the real-world scenarios where only the periocular region of a face is visible such as in the ISIS case.

In Part I of the dissertation, we will showcase the face recognition capability based on the periocular region, which we call the periocular face recognition. We will demonstrate that face matching using the periocular region directly is more robust than the full face in terms of age-tolerant face recognition, expression-tolerant face recognition, pose-tolerant face recognition, as well as contains more cues for determining the gender information of a subject. In this dissertation, we will study direct periocular matching more comprehensively and systematically using both shallow and deep learning methods.

Based on this, in Part II and Part III of the dissertation, we will continue to explore an indirect way of carrying out the periocular face recognition: periocular-based full face hallucination, because we want to capitalize on the powerful commercial face matchers and deep learning-based face recognition engines which are all trained on large-scale full face images. The reproducibility and feasibility of re-training for a proprietary facial region, such as the periocular region, is relatively low, due to the non-open source nature of commercial face matchers as well as the amount of training data and computation power required by the deep learning based models. We will carry out the periocular-based full face hallucination based on two proposed reconstructive dictionary learning methods, including the

dimensionally weighted K-SVD (DW-KSVD) dictionary learning approach and its kernel feature space counterpart using Fastfood kernel expansion approximation to reconstruct high-fidelity full face images from the periocular region, as well as two proposed generative deep learning approaches that build upon deep convolutional generative adversarial networks (DCGAN) to generate the full face from the periocular region observations, including the Gang of GANs (GoGAN) method and the discriminant nonlinear many-to-one generative adversarial networks (DNMM-GAN) for applications such as the generative open-set landmark-free frontalization (Golf) for faces and universal face optimization (UFO), which tackles an even broader set of problems than periocular based full face hallucination.

Throughout Parts I-III, we will study how to handle challenging real-world scenarios such as unconstrained pose variations, unconstrained illumination conditions, and unconstrained low resolution of the periocular and facial images. Together, we aim to achieve unconstrained periocular face recognition through both direct periocular face matching and indirect periocular-based full face hallucination.

In the final Part IV of the dissertation, we will go beyond and explore several new methods in deep learning that are statistically efficient for general-purpose image recognition. Methods include the local binary convolutional neural networks (LBCNN), the perturbative neural networks (PNN), and the polynomial convolutional neural networks (PolyCNN).

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Part I

Unconstrained Periocular Face Recognition

Part II

Periocular-Based Full Face Hallucination via Reconstructive Dictionary Learning

Part III

Periocular-Based Full Face Hallucination via Generative Deep Learning

Part IV

New Methods in Deep Learning

Part V

Appendix

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