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Low rank driven robust facial landmark regression

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ABSTRACT

Localizing facial landmarks is an essential prerequisite to facial image analysis. However, due to the large variability in expression, illumination, pose and the existence of occlusions in the real-world face images, how to localize facial landmarks more efficiently is still a challenging problem. In this paper, we present a low-rank driven regression model for robust facial landmark localization. Our approach consists of low-rank face frontalization and sparse shape constrained cascade regression steps, which lies on, (1) in terms of the low rank prior of face image, we recover such a low-rank face from its deformed image and the associated deformation despite significant distortion and corruption. Alignment of the recovered frontal face image is more simple and effective. And (2) in terms of the sparse coding of face shape on the shape dictionary learnt from training data, sparse shape constrained cascade regression model is proposed to simultaneously suppress the ambiguity in local features and outlier caused by occlusion, and sparse residual error deviated from low-rank face texture is also utilized to predict the occlusion area. Extensive results on several wild benchmarks such as COFW, LFPW and Helen demonstrate that the proposed method is robust to facial occlusions, pose variations and exaggerated facial expressions.

1. Introduction

Face alignment intends to locate semantic facial landmarks on face components such as eye brows, eyes, nose, mouth and face contour, which is an essential prerequisite to face based applications [1], such as face recognition, face tracking, face animation and expression analysis. A great deal of works were proposed to advance face alignment, and notable achievement has been achieved on the wild benchmark datasets, such as HELEN [2], LFPW [3] and AFLW [4]. However, accurate facial landmark localization in the wild is still a challenging problem due to complex pose variations, expressions and occlusions.

Active shape model (ASM) [5] and active appearance model (AAM) [6,7] are two pioneering works for face alignment. They use Principle component Analysis (PCA) bases to model face shape and appearance, but PCA model is too simple to efficiently capture complex face shape variations. To represent face shape variations well, some works use Markov Random Fields (MRF) [8–10] or Graph [11,12] to model global face deformation. Exemplars based model is another representation way, and it uses a set of similar face exemplars as the model, which are generated from training data set by RANdom SAmple Consensus (RANSAC) [3,12].

Different from the above model based methods, regression based approaches treat the face alignment as a regression problem without explicit face shape model. Sun [13] and Zhou [14] proposed a convolutional network cascade to tackle face alignment. Cao [15], Xiong [16] and Yan [17] followed cascade regression framework [18] to localize facical landmarks. Ren et al. [19] utilized local binary features to accelerate the alignment. Robust Cascade Pose Regression (RCPR) [20] reduced exposure to outliers by detecting occlusions explicitly and using robust shape-indexed features. The advantages of cascade regression based approaches are two folders. They not only benefit from robust local descriptors and regressors, but also they are more efficient without iterative fitting steps or sliding window search steps. However, the above methods may still fail in the cases of partial occlusions and serious pose variations. Although RCPR [20] can handle facial images with partial occlusions, the prior of occlusion labels is needed for training.

In this paper, we present a new method for robust face alignment jointly utilizing the low rank prior of human face and sparse shape constraint to effectively deal with serious pose variations and partial occlusions in the faces. Face images are near-regular structures and symmetric patterns that are approximately low-rank [21]. We recover frontal face from its deformed image and the precise domain transformation despite significant distortion and corruption in terms of the low rank prior of face image. Alignment of the recovered frontal face is more simple and effective. Thus, the obstacles of pose variations and occlusions can be somewhat simplified. The residual error from low-rank texture is also utilized to predict occlusion area.

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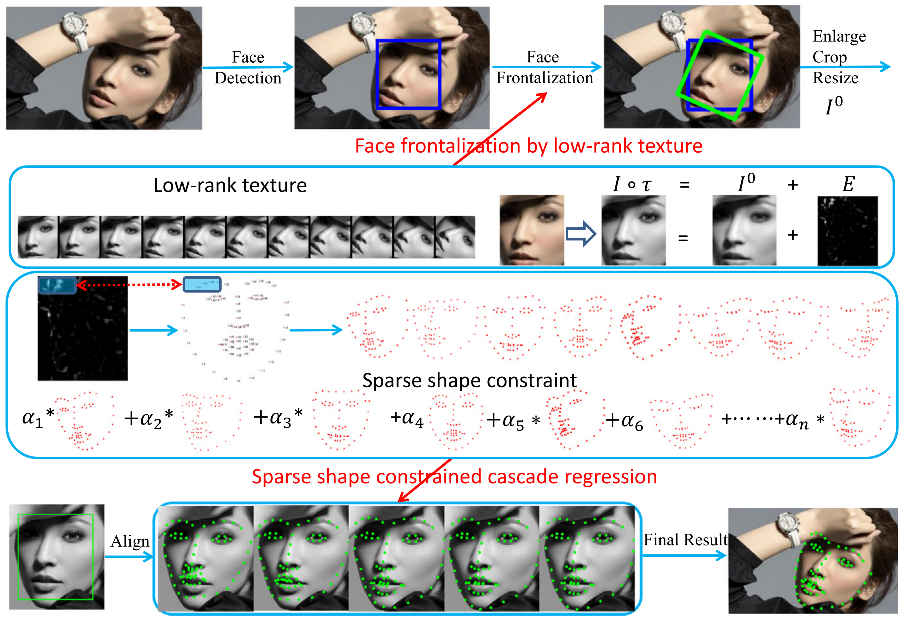

Fig. 1. Low rank driven robust facial landmark regression.

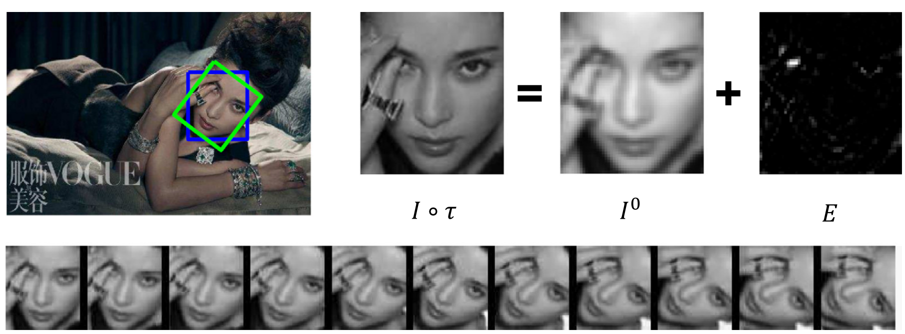

Fig. 2. The face frontalization by recover the low rank face texture.

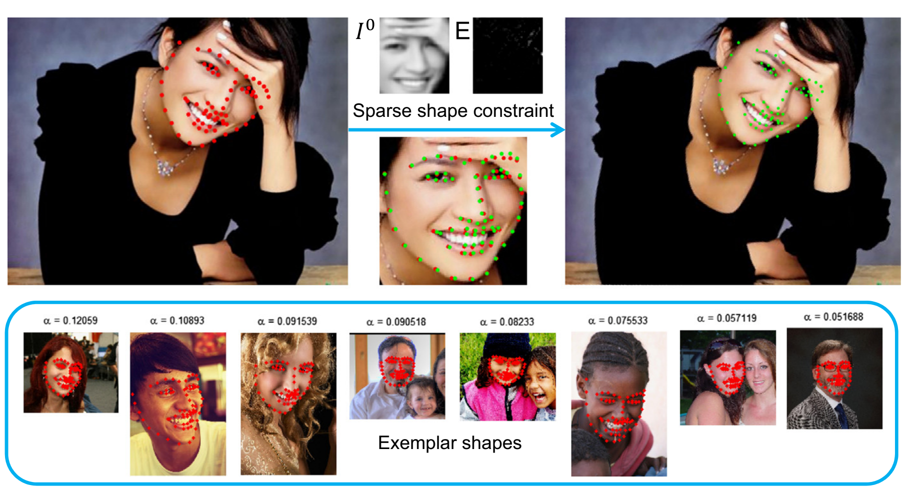

Fig. 3. Sparse shape constraint from the exemplar shape dictionary (sparse low-rank texture error is utilized to estimate the transformation parameter β).

After face frontalization, sparse shape constrained cascade regression model is proposed to robustly localize the facial landmarks with cascade regression and sparse shape constraint alternately used in the alignment process. The explicit shape constraint is able to suppress the ambiguity in local features. Through face frontalization by low-rank texture and sparse shape constraint, our method is more robust under occlusion and outperforms the traditional cascade regression models. Extensive experiments on several challenging wild data sets demonstrate the advantages of our method over the state-of-the-art methods.

2. Overview

The flowchart of our method is shown in Fig. 1. Our approach mainly consists of two steps. The first step is to use low rank prior