Expression Invariant Face Recognition using a 3D Morphable Model
Brian Amberg brian.amberg@unibas.ch University of Basel, Switzerland

Contribution
We introduce a method for expression invariant face recognition. A generative 3D Morphable Model (3DMM) is used to separate identity and expression components. The expression removal results in greatly increased recognition performance, even on difficult datasets, without a decrease in performance on expression-less datasets. It is applicable to any kind of input data, and was evaluated here on textureless range scans.

Model
The Model was learnt from 175 subjects. We used one neutral expression scan per identity and 50 expression scans of a subset of the subjects. The identity model is a linear model build from the neutral scans.

\[ f = \mu + M_n \alpha_n \]  

For each of the 50 expression scans, we calculated an expression vector as the difference between the expression scan and the corresponding neutral scan of that subject. This data is already mode-centered, if we regard the neutral expression as the natural mode of expression data. From these offset vectors an additional expression matrix \( M_e \) was calculated, such that the complete linear Model is

\[ f = \mu + M_n \alpha_n + M_e \alpha_e \]  

The assumption here is, that the face and expression space are linearly independent, such that each face is represented by a unique set of coefficients.

Fitting
A Robust Nonrigid ICP method was used to fit the model to the data. Robustness was achieved by iteratively reweighting the correspondences and using hard compatibility test for the closest points. Fitting was initialized by a simple nose detector and proceeded fully automatic.

Expression Neutralization
Expression normalisation for two scans of the same individual. The robust fitting gives a good estimate (b) of the true face surface given the noisy measurement (a). It fills in holes and removes artifacts using prior knowledge from the face model. The pose and expression normalized faces (c) are used for face recognition.

Robustness
The reconstruction (b) is robust against scans (a) with artifacts, noise, and holes.

Distance Measure
The Mahalanobis angle between the identity coefficients \( \alpha_n \) was used for classification.

Results
The method was evaluated on the GavabDB expression dataset which contains 427 Scans, with 3 neutral scans and 4 expression scans per ID. To test the impact of expression invariance on neutral data we used the UND Dataset from the Face Recognition Great Vendor Test, which contains 953 neutral scans with one to eight scans per subject.

Expression neutralization improves results on the expression dataset without decreasing the accuracy on the neutral testset. Plotted is the ratio of correct answers to the number of possible correct answers.

Impostor detection is reliable, as the minimum distance to a match is smaller than the minimum distance to a nonmatch.

Open Questions
While the expression and identity space are linearly independent, there is some expression left in the identity model. This is because a “neutral” face is interpreted differently by the subjects. We investigate the possibility to build an identity/expression separated model without using the data labelling, based on a measure of independence.

References

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