

Expression Transfer with Multilinear AAM's

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Summary

- **Introduction**
- **Active Appearance Models**
- **Multilinear Analysis**
- **Expression Transfer**
- **Results and Discussions**
- **Conclusions**
- **Future Work**

Introduction

- *Expression transfer definition*
 - *“Given two images from different subjects map the expression performed by the source subject onto the target subject’s face”*
- *Subproblems*
 - *Face image capture and representation*
 - *Face region localization*
 - *Identity and expression modeling and recognition*
 - *Photo-realistic resynthesis*

Introduction

- **As many subproblems relates to known problems approached by the *computer vision* community, it is natural to search methods in this literature**
- **We build on the (computer vision) work of *Wang and Ahuja* about facial expression decomposition, who based their work on results of:**
 - *Cootes, Edwards and Taylor* (AAM's)
 - *Vasilescu and Terzopoulos* (Multilinear Analysis)

Active Appearance Models

- *Cootes, Edwards and Taylor (ECCV 1998)*
- **Generative model-based representation and interpretation of images (*shape and texture*)**
- **Closely related to other models for computer vision (*e.g. morphable models and active blobs*)**
- **Linear in both features (PCA-based)**
- **Sort of “shape enhanced” *Eigenfaces* (*Turk and Pentland, JCN 1991*)**

Multilinear Analysis

- Introduced to the computer vision and graphics communities by *Vasilescu* and *Terzopoulos*
- Based on *multilinear algebra* (the algebra of higher-order tensors), a generalization of *linear algebra*
- Designed as a mathematical framework for *analysis* and *representation* of image ensembles
- Has as basic object a generalization of vectors and matrices, the *tensor*

Multilinear Analysis

- ***Tensor***: a natural generalization of vectors (1^{st} -order tensors) and matrices (2^{nd} -order tensors) to multiple indices
- an N^{th} -order tensor can be thought of as a block of data indexed by N indices, $\mathcal{T} = (t_{i_1 i_2 \dots i_N})$

vector
(1^{st} -order tensor)



matrix
(2^{nd} -order tensor)

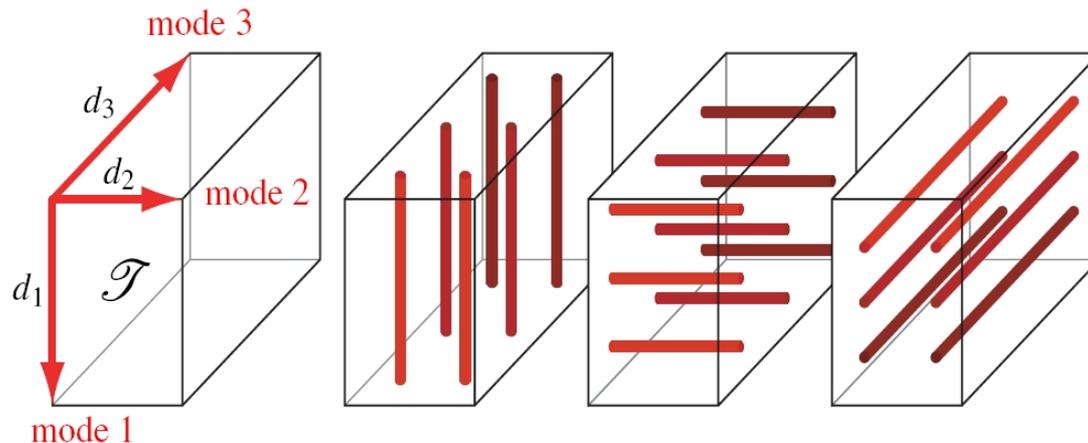


3^{rd} -order tensor



Multilinear Analysis

- ***Mode spaces***: a matrix has two characteristic spaces, row and column space; a tensor has one for each mode, hence we call them *mode spaces*
 - below, is depicted a 3rd-order (or 3-mode) tensor of dimensions $d_1 \times d_2 \times d_3$



Multilinear Analysis

- ***Mode-n flattening***: the “stacking” of mode-n vectors of a tensor as columns in a matrix, denoted as a subscript (n) after the tensor name: $\mathcal{T}_{(n)}$ or $\mathbf{T}_{(n)}$
- ***Mode-n product***: a linear transformation on all mode-n vectors of a tensor. It is defined between a tensor \mathcal{T} and a matrix \mathbf{M} and is denoted by $\mathcal{T} \times_n \mathbf{M}$
- ***Rank-1 tensor***: is defined by vectors $\mathbf{u}_1 \in \mathbb{R}^{d_1}, \dots, \mathbf{u}_N \in \mathbb{R}^{d_N}$ as $\mathcal{T} = \mathbf{u}_1 \otimes \dots \otimes \mathbf{u}_N$, where \otimes denotes the tensor product (note that \mathcal{T} has dimensions $d_1 \times \dots \times d_N$)

Multilinear Analysis

- ***Singular Value Decomposition (SVD)***: states that any matrix \mathbf{M} can be decomposed as: $\mathbf{M} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T$, in tensor notation it is written as $\mathbf{M} = \mathbf{\Sigma} \times_1 \mathbf{U} \times_2 \mathbf{V}$
- ***N-mode SVD (HOSVD – Higher Order SVD)***: is one (of many possibles) “generalization” of the SVD, denoted as $\mathcal{F} = \mathcal{L} \times_1 \mathbf{U}_1 \times_2 \dots \times_N \mathbf{U}_N$

Obs.: unlike in the SVD, the tensor \mathcal{L} (core tensor) isn't a diagonal tensor (this is an example of some properties which don't generalize well to tensors)

Multilinear Analysis

- *N-mode SVD Algorithm:*

(1) For $n = 1, \dots, N$, compute matrix \mathbf{U}_n by computing the SVD of the flattened matrix $\mathcal{F}_{(n)}$ and setting \mathbf{U}_n to be the left matrix of the SVD

(2) Solve for the core tensor (\mathcal{L}) as follows

$$\begin{aligned}\mathcal{L} &= \mathcal{F} \times_1 \mathbf{U}_1^{-1} \times_2 \dots \times_n \mathbf{U}_n^{-1} \times_{n+1} \dots \times_N \mathbf{U}_N^{-1} \\ &= \mathcal{F} \times_1 \mathbf{U}_1^T \times_2 \dots \times_n \mathbf{U}_n^T \times_{n+1} \dots \times_N \mathbf{U}_N^T\end{aligned}$$

Multilinear Analysis

- ***TensorFaces and Multilinear PCA:***
 - **In a similar spirit as PCA is based on the SVD, *Vasilescu* and *Terzopoulos* generalized the method and developed a *Multilinear PCA***
 - **With this method in hand, they developed the *TensorFaces* representation of image ensembles in a manner analog to the *Eigenfaces* approach (which is based on the linear PCA), allowing for a better control of the multiple varying factors in images**

Expression Transfer

- Inspired by the *expression transfer* work of *Vlasic, Brand, Pfister and Popovic* (SIGGRAPH 05)
- Influenced by the *Identity × Expression recognition* method of *Wang and Ahuja* (ICCV 03)
- Based on the assumption:
“*good analysis is the first step to good (re)synthesis*”
Unknown 😊

Expression Transfer

- **Method Overview**
 - *Data acquisition*
 - *Training (Linear AAM + Multilinear Analysis)*
 - *Expression Transfer*

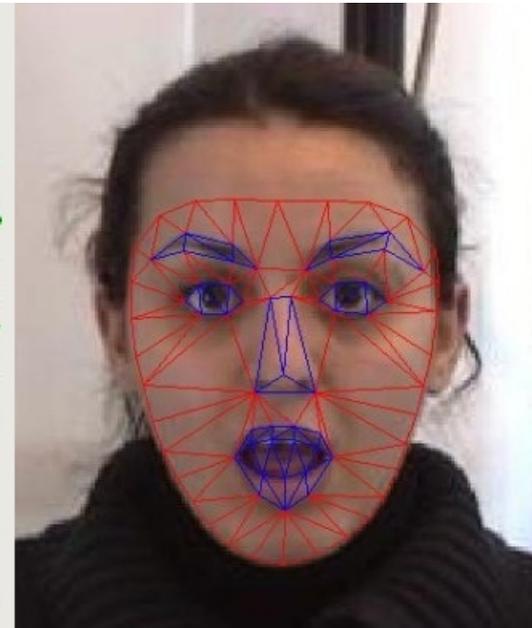
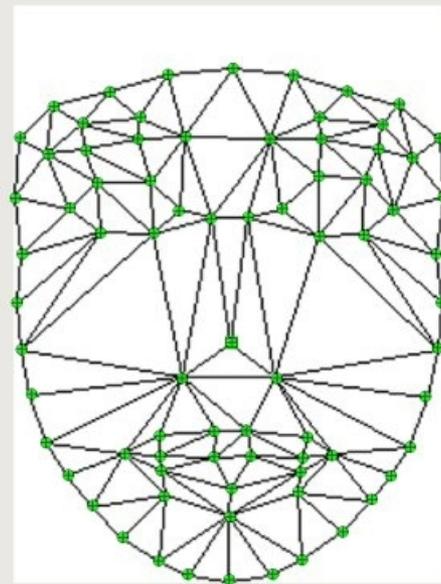
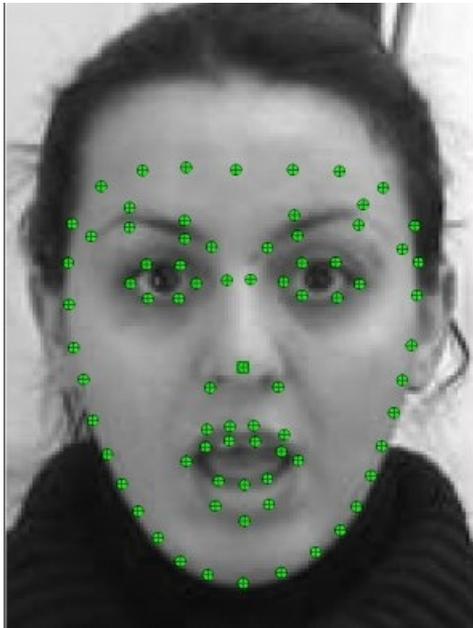
Expression Transfer

- *Data acquisition – Image capture*
 - The image data used is from “*The FGnet – Facial Emotion and Expression Database*”, kindly provided by *Prof. Frank Wallhof* from *Technische Universität München*
 - It features *19 subjects* performing the *6 basic expressions* under the same illumination conditions



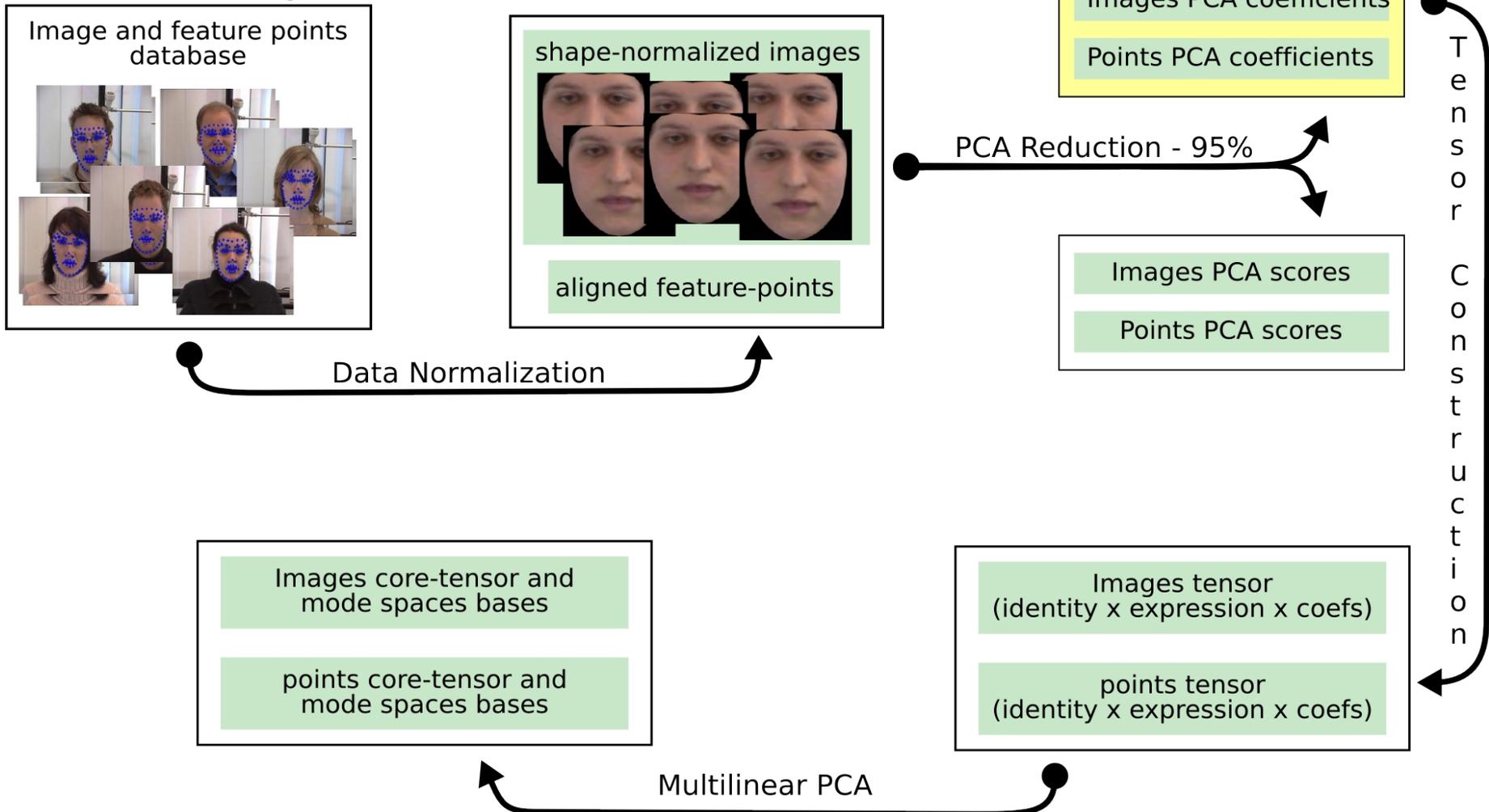
Expression Transfer

- *Data acquisition – Feature-Point Marking*
 - **77** feature-points were *hand-marked* in each of the **133** images according to a template triangulation of a face (research assistants are welcome !!! 😊)



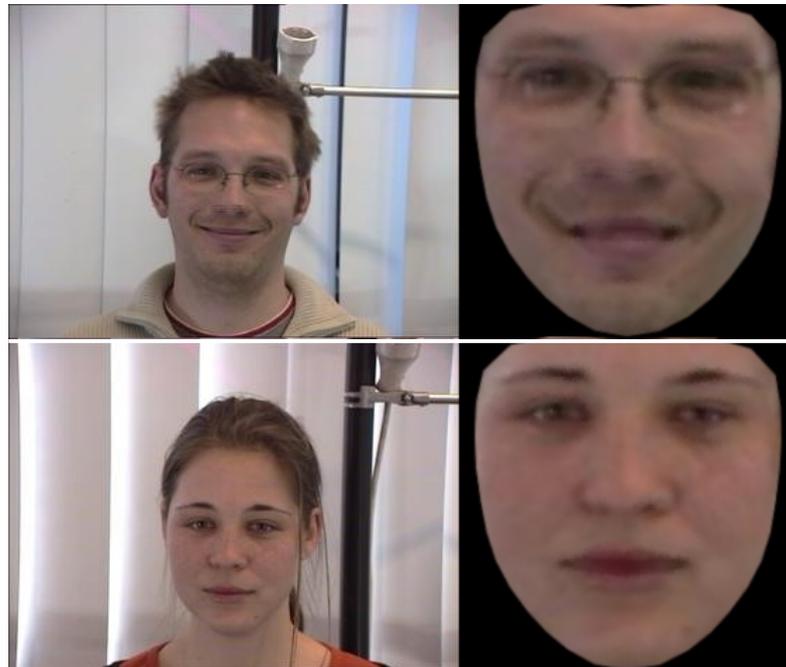
Expression Transfer

• Training



Expression Transfer

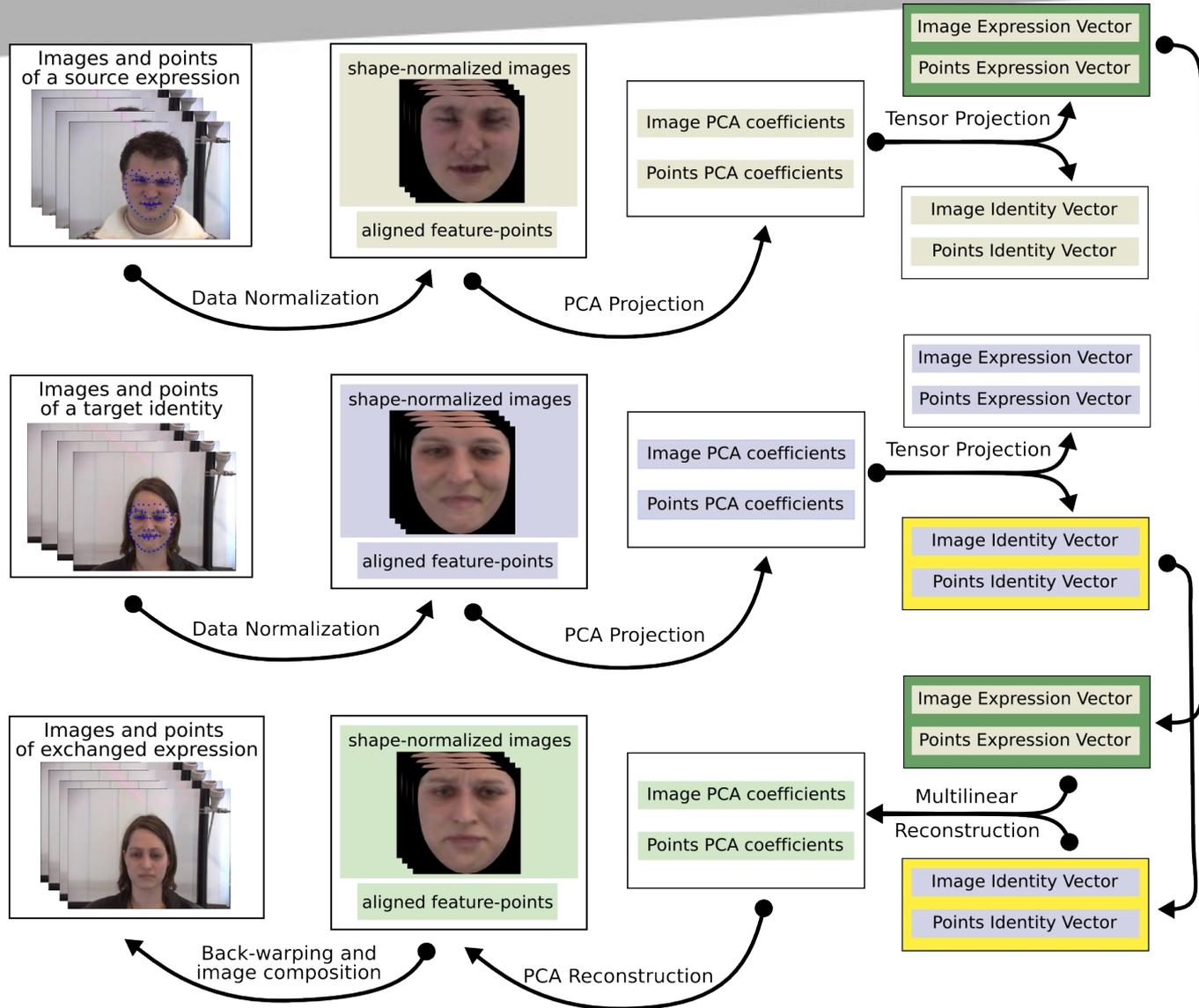
- *Training – Data Normalization*
 - Procrustes' alignment of feature-points
 - Face extraction and shape-normalization of image (warping)



Expression Transfer

- *Training – PCA-based dimensionality reduction*
 - Separately, we apply a *PCA reduction* (keeping 95% of variance) on the *aligned feature-points* and the *shape-normalized images*
- *Training – Multilinear PCA (Identity × Expression × Coefs.)*
 - With the coefficients of our database after PCA reduction, we build two *3rd-order tensors* in which each mode represents *identity, expression* and *coefficients variations*
 - After that, a *Multilinear PCA* is applied to separate the influence along each factor (*identity and expression*)

Expression Transfer



Expression Transfer

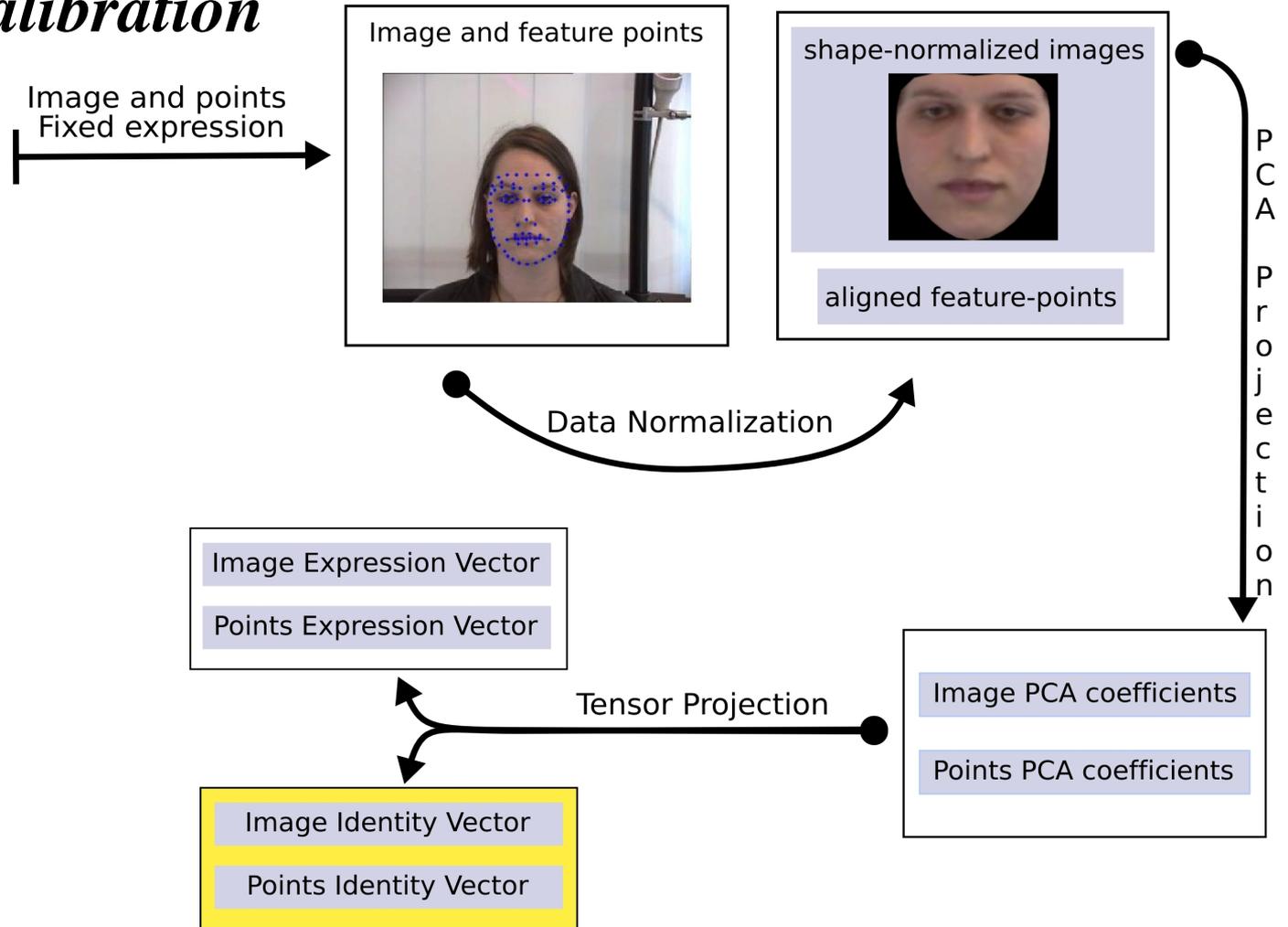
- *Expression transfer – Image Normalization*
 - Feature-points linear conformal alignment
 - Shape-normalization of facial image
- *Expression transfer – Projection onto PCA basis*
 - With the aligned feature-points and the shape-normalized texture, the mean is subtracted from each and the result is projected onto the space spanned by the basis acquired after the linear PCA reduction

Expression Transfer

- *Expression transfer – Identity calibration*
 - Fixating an expression, it's possible to estimate the identity characteristic vector in a given pose via *linear LSQ*
(as the bilinear tensor becomes a linear operator)
- *Expression transfer – Expression estimation*
 - As in the previous, having the identity vector, a new image has the expression vector estimated via *linear LSQ*

Expression Transfer

- Identity calibration**



Expression Transfer

- *Expression transfer – Multilinear reconstruction*
 - Exchanging the estimated expression vectors, it's possible to reconstruct the new PCA coefficients just applying the tensor on the desired combination of identity and expression vectors
- *Expression transfer – PCA reconstruction*
 - With the new PCA coefficients at hand, a matrix-vector multiplication is sufficient to reconstruct the aligned feature-points and shape-normalized image of the exchanged expression mapped onto the target subject

Expression Transfer

- *Expression transfer – Normalized image (back-)warping*
 - Applying the inverse alignment transform onto the reconstructed feature-points and mapping the shape-normalized face on their triangulation is possible to warp back the new image



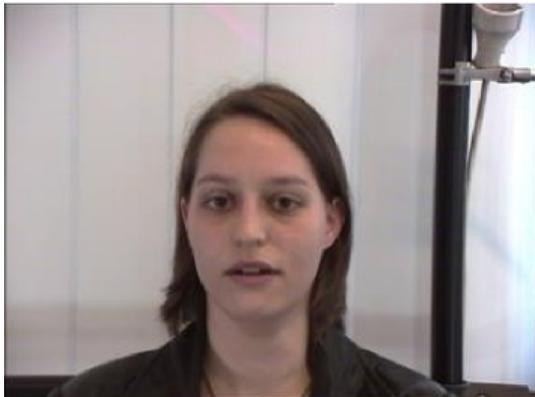
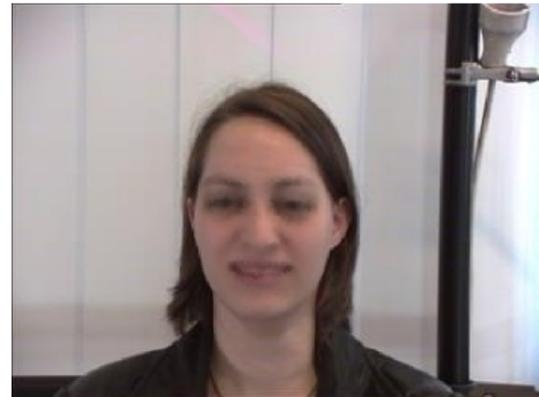
Expression Transfer

- *Expression transfer – Face image compositing*
 - Having the transferred expression mapped onto the target face, an image composition operation is applied and a rewrite of the original image is generated



Expression Transfer

- *Expression transfer – The transfer is completed !!!*



Results and Discussions

- **From the original database, 17 (out of 19) subjects where used to train our algorithm and 2 to test it**



Results and Discussions

- We have tried a number of different approaches and chosen *two* of them as the best with respect to the *trade-off quality/storage*
(as their computational cost is similar ...)
 - *{Luminance (from LAB image) / RGB}-based AAM*
 - *Keeping the variance of the PCA dimensionality reduction on 95%, 98% and 100%*
 - *Without applying the PCA step and build the tensor directly with aligned feature-points and shape-normalized images*

Results and Discussions

- We have made *three* different experiments to evaluate the performance (quality) of our approach
 - *Projection tests*: where we evaluate how well the original image is represented by our bilinear model
 - *Basic expression assignment tests*: where, given an image of a neutral face, we transfer the other 6 basic expressions to it
 - *Expression transfer tests*: in which we test the recognition and transfer of basic expression between two different subjects that aren't in the training base

Results and Discussions

- *Projection tests (Subject 1 / Luminance)*



Results and Discussions

- *Projection tests (Subject 1 / RGB)*



Results and Discussions

- *Projection tests (Subject 2 / Luminance)*



Results and Discussions

- *Projection tests (Subject 2 / RGB)*



Results and Discussions

- *Basic expression assignment tests (Subject 1 / Luminance)*



Results and Discussions

- *Basic expression assignment tests (Subject 1 / RGB)*



Results and Discussions

- *Basic expression assignment tests (Subject 2 / Luminance)*



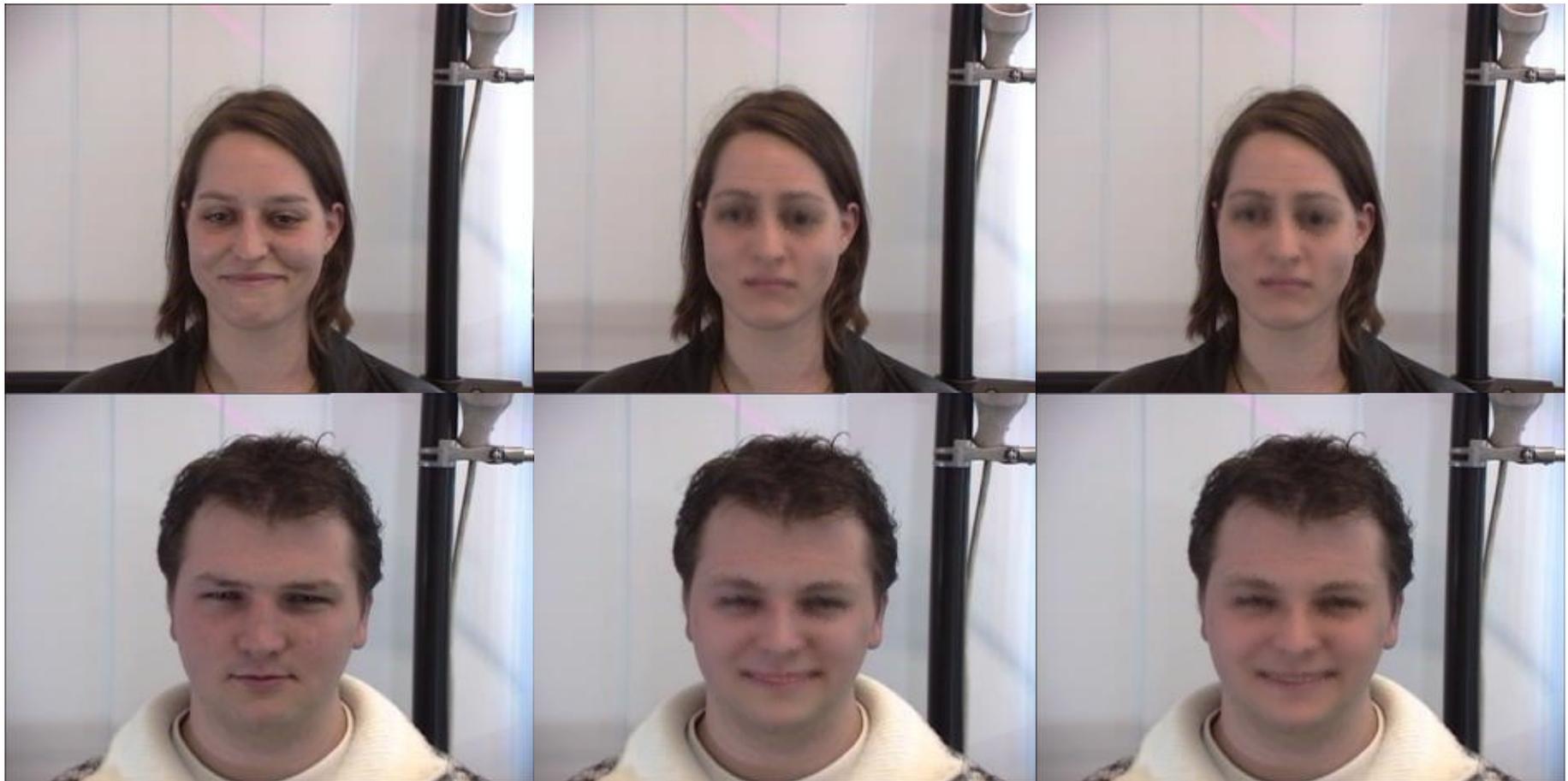
Results and Discussions

- *Basic expression assignment tests (Subject 2 / RGB)*



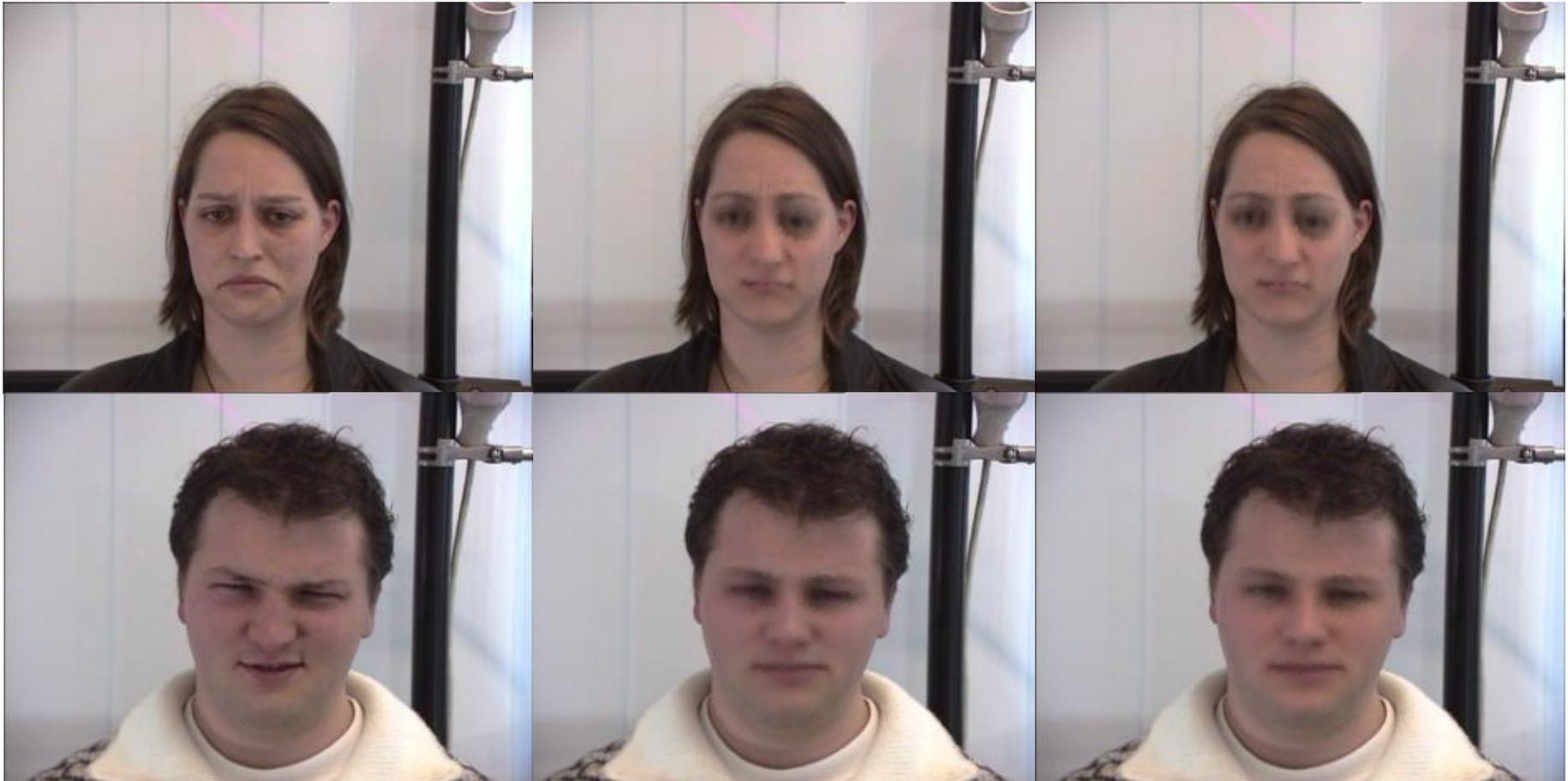
Results and Discussions

- *Expression transfer tests*



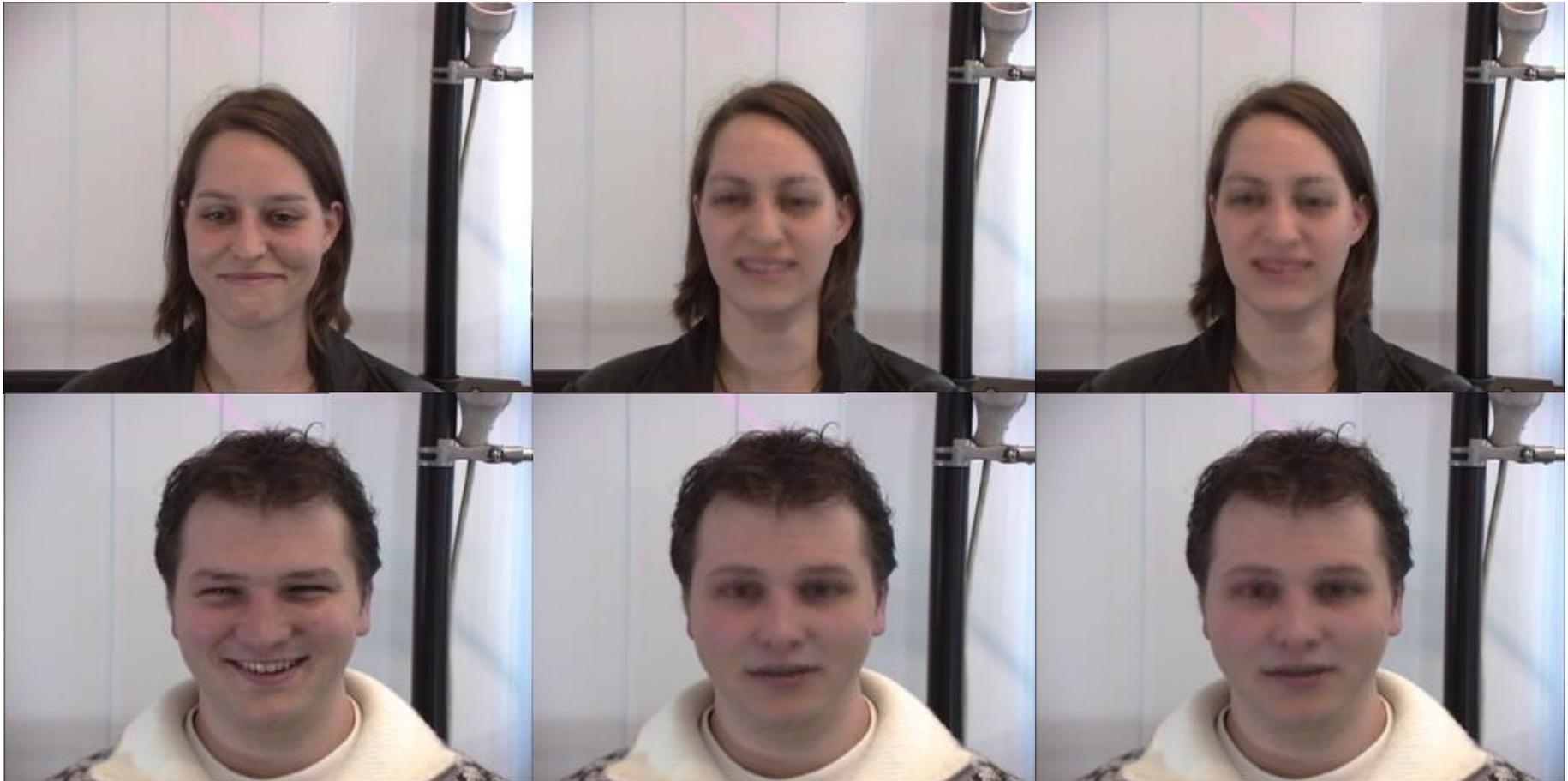
Results and Discussions

- *Expression transfer tests*



Results and Discussions

- *Expression transfer tests*



Results and Discussions

- *Expression transfer tests*



Conclusions

- A *luminance* based approach captures rather well photometric details in facial expressions and frees *at least 2/3* of the total memory requirements !!!
- Keeping **95%** of the variance, in the PCA reduction, resulted in a good generalization to the modeling of unknown subjects and yielded a good reduction in the total number of PCA coefficients

Feature-points: 28 (95%), 46 (98%) and 118 (100%)

Normalized images (LAB): 33 (95%), 61 (98%) and 118 (100%)

Normalized images (RGB): 35 (95%), 65 (98%) and 118 (100%)

Conclusions

- *Facial expression modeling is a hard problem !!!*
- **The use of methods designed primarily for *analysis* is a good starting point for *example-based (re)synthesis***
- **Multilinear analysis is a very good approach to model problems involving multiple factors, but ...**
 - **a great amount of data is needed to complete a full tensor, leading to problems in data *acquisition, storage and management***

Future Work

- Implement a *model fitting* algorithm to automate the feature-point placement in images (**uff !!!**)
- Experiment with *video rewrite* and *puppetry* (and problems related to the modeling of the complex dynamics of facial expressions)
- Evaluate a *rigid-motion invariant representation* for feature-points (eliminate spurious variations from the alignment transformations)

Future Work

- **Develop a method to allow *incomplete entries* in the tensor *HOSVD* (to deal with acquisition problems and occlusion of some feature-points)**
- **Work on the problem of *illumination inconsistencies* among captured images (a great source of errors)**
- **Experiment with *different architectures* of multilinear separation methods (e.g. a waterfall architecture, where each step solves for a subproblem)**

Future Work

- **Incorporate a new *viseme mode* to our model (comprising a 4th-order tensor) in a manner similar to that proposed by *Vlasic et al.***
- **Evaluate the quality of *other dimensionality reduction methods* (e.g. *ICA, MDS, Isomap, LLE, Laplacian eigenmaps, Hessian eigenmaps, Principal manifolds, Lipschitz embedding, etc.*)**
- **And, at last but not least, generalize these approaches to model and animate *3D puppets* from monocular video streams**

References

- **T.F. Cootes, G. J. Edwards, and C. J. Taylor.** *Active Appearance Models.* ECCV'98.
- **M. Turk, and A. Pentland.** *Eigenfaces for Recognition.* Journal of Cognitive Neuroscience 1991.
- **M. A. O. Vasilescu, and D. Terzopoulos.** *Multilinear Analysis of Image Ensembles: TensorFaces.* ECCV'02.

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- **D. Vlastic, M. Brand, H. Pfister, and J. Popovic.** *Face Transfer with Multilinear Models.* SIGGRAPH'05.
- **H. Wang, and N. Ahuja.** *Facial Expression Decomposition.* ICCV'03.

Thank you !!!

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