4th Stochastic geometry days, August 2015



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Summary

- Introduction
- Early works
- A deformable face model
- Model fitting and data representation
- Conclusion

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#### Why face analysis?



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- Identity recognition
- Morphing/VFX
- Aging simulation
- Fatigue monitoring (road safety)
- Behavior analysis (reactions, emotions...)
- Virtual mirror (online shopping: makeup, glasses...)
- Visio-conference, videos games...

A challenging task...

Pose



### Expression



#### Illumination



Resolution



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#### Matching a reference image (template)



**Object tracking** associates image objects in consecutive video frames

$$I(x', y', t + \partial t) = I(x, y, t) \quad (x, y) \in \Omega$$

#### Matching a reference image (template)



Image alignment associates target objects from a reference

$$I(x', y') = T(x, y) \quad (x, y) \in \Omega$$

Both problems are traditionally solved using optical flow estimation

• <u>Common assumption</u>: flow is constant within the image object *I*(*x*,*y*)

$$I(x, y, t) = I(x + Vx, y + Vy, t + \partial t) \quad \mathbf{v} = \begin{bmatrix} Vx \\ Vy \end{bmatrix}$$
$$\Rightarrow -I_t(x, y, t) \approx \nabla I^T(x, y, t) \mathbf{v}$$

• Example: least mean squares method (Lucas-Kanade)

$$\xi(\mathbf{v}) = \sum_{(x,y)\in\Omega} \left( -I_t(x,y,t) - \nabla I^T(x,y,t)\mathbf{v} \right)^2 \qquad \frac{\partial \xi(\hat{\mathbf{v}})}{\partial \mathbf{v}} = 0$$

#### Lucas-Kanade tracker



A constant flow within the image object?



#### A constant flow within the image object?



$$\xi(\mathbf{W}) = \sum_{(x,y)\in\Omega} \left( \underbrace{T(x,y)}_{template} - I\left(\underbrace{\mathbf{W}(x,y)}_{warp}\right) \right)^2 \qquad \mathbf{W}(x,y) = \begin{bmatrix} s_x x + w_z y + t_x \\ -w_z x + s_y y + t_y \end{bmatrix}$$

#### Matthews-Baker ICIA tracker



#### A constant flow within the image object?



**Rigid** objects : 3D-to-2D projections **Non-rigid** objects : a deformable model is needed!

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#### From rigid to deformable models

We want to enhance a previously static alignment model (i.e. template image) to take into account changes of identity, expression or luminosity. In computer vision, these changes are seen as local variations of shape and/or texture



#### Active Appearance Models (Cootes et al.)

are able to jointly synthesize an image (texture) and the shape it relates to. An AAM model is built through principal component analysis (PCA) of aligned texture and shape data from a (manually annotated) image database

















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Face synthesis from an AAM model



Shape model: 
$$\mathbf{s} = \mathbf{s}_0 + \sum_{p=1}^{P_s} \Phi_p \mathbf{s}_p$$

Texture model: 
$$\mathbf{A} = \mathbf{A}_0 + \sum_{p=1}^{P_g} \Psi_p \mathbf{A}_p$$

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Fitting a model to new data

- Original AAM (Cootes) : generating shape samples from the database with random noise and learning a regression model which minimizes the error between observed and synthesized textures
- Gradient-descent method (Matthews-Baker) : a least mean squaresbased approach inspired by Lucas-Kanade, where AAM parameters are estimated together with global transform parameters

$$\xi(\Psi, \mathbf{p}, \Phi) = \sum_{(x, y) \in \Omega} \left( \underbrace{A(x, y; \Psi)}_{template} - I\left(\underbrace{W(x, y; \mathbf{p}, \Phi)}_{warp}\right) \right)^2$$

 $(\Psi, \Phi)$ : AAM parameters **p**: global (e.g. affine) transform parameters **W**: image warping function, computed from all geometry-related parameters

#### Fitting a model to new data



# Further data analysis from estimated AAM parameters *Motion capture and animation*



### Further data analysis from estimated AAM parameters

Emotion analysis (e.g. online learning)



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### Conclusion

- A statistical face model learned from observed data
- Compacts relevant information into just a few parameters
- Applications in the field of information retrieval
- Current work : polynomial representation of texture model and applications in animation and e-learning
- Next : force semantic information into PCA analysis i.e. individual muscle activity parameters (local constraints)

### Applications in alignment, tracking and landmarking

## Thank you ! 🙂