UNSUPERVISED CLASSIFICATION OF EXTREME FACIAL EVENTS USING ACTIVE APPEARANCE MODELS TRACKING FOR SIGN LANGUAGE VIDEOS

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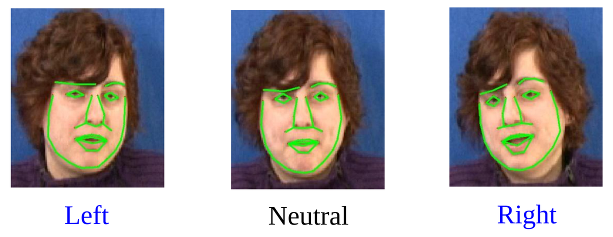
1. Outline - Contributions

- Unsupervised detection of facial events:
  - Head pose, local actions of eyes, mouth, eyebrows etc.
  - Classification of the extreme states; not precise calculation
  - Important in Sign Language comprehension and recognition
  - Lack of annotations; Manual Annotations are expensive
- Face tracking framework using Active Appearance Model
  - Initialization of AAM similarity transform parameters
  - Face detection, skin detection, morphological operators
- Unsupervised method for Extreme States Classification (UnESC)

Figure 1. Example of pose over the yaw angle extreme states classification.



2. AAM fitting initialization

- *AAM fitting* estimates the shape and texture parameters vector **q** that minimizes the error between the reconstructed texture and the image texture.

$$\mathbf{q} = \begin{bmatrix}\tilde{\mathbf{p}}\\ \tilde{\boldsymbol{\lambda}}\end{bmatrix} = \begin{bmatrix}\mathbf{t}_{4\times1}\\ \mathbf{p}_{n\times1}\\ \mathbf{u}_{2\times1}\\ \boldsymbol{\lambda}_{m\times1}\end{bmatrix}$$

$\mathbf{t}_{4\times1}$ → Similarity transform parameters
$\mathbf{p}_{n\times1}$ → Shape parameters
$\mathbf{u}_{2\times1}$, $\boldsymbol{\lambda}_{m\times1}$ → Texture parameters

- *AAM fitting initialization framework*:
  - high pose variation in Sign Language videos
  - need for robust and accurate AAM fitting
  - Initialization on each new video frame; no dynamics
  - *Non-occlusion frames*; detection from number of skin regions

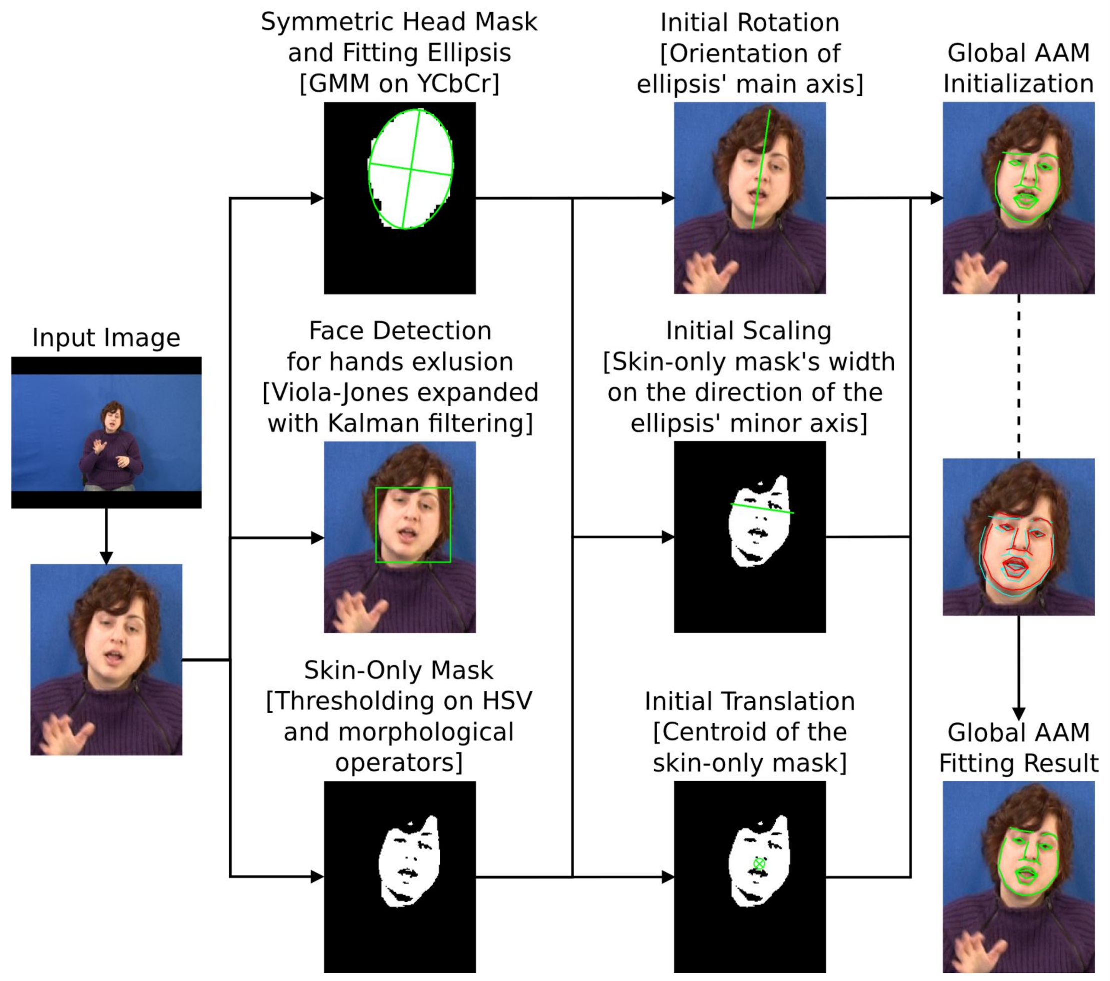


Figure 2. AAM initialization framework for similarity transform parameters.

3. Fitting and tracking results

- Comparison between proposed initialization and Viola-Jones face detection initialization framework
  - 76.7% MSE decrease

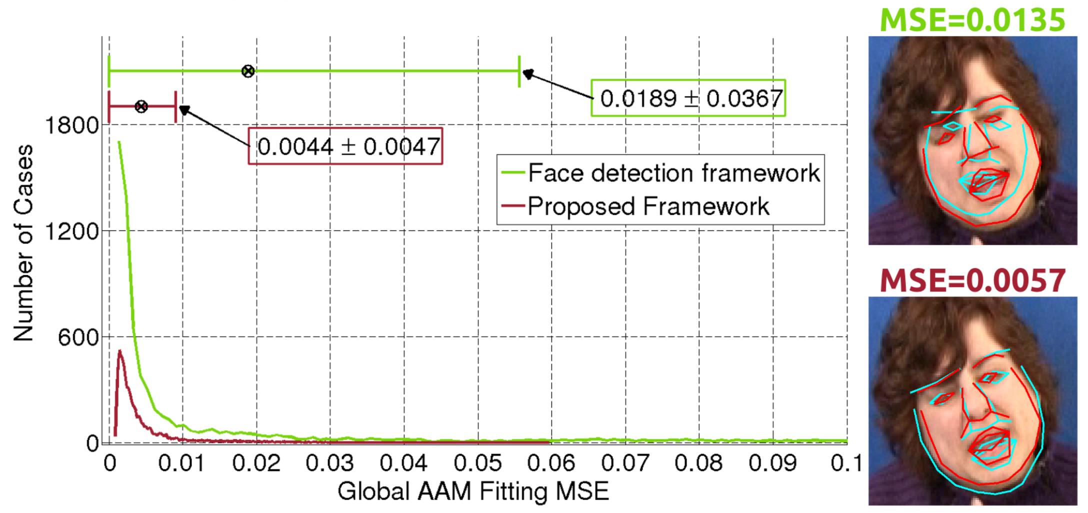
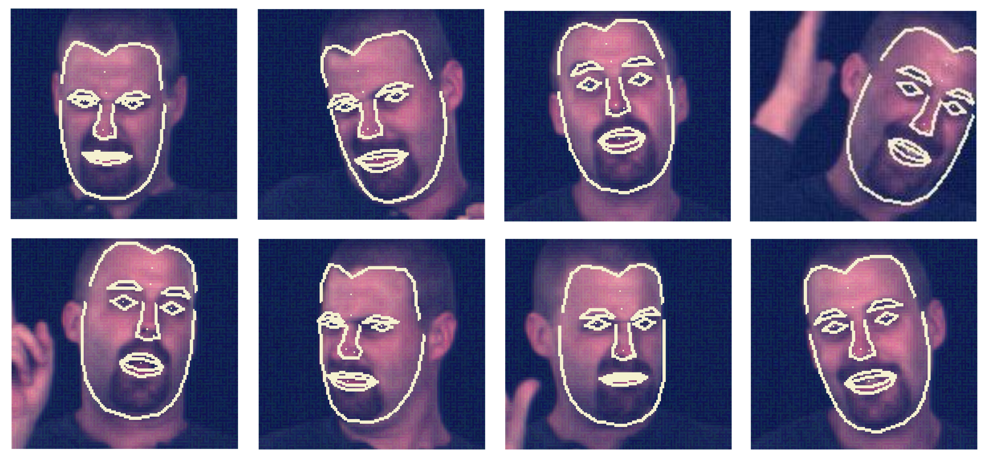


Figure 3. MSE error histogram for comparison between proposed initialization and Viola-Jones face detection initialization.

- Greek Sign Language (GSL)
  - Subject 012B, Task 4; 720x576; 8082 frames
  - Face resolution: ~2400 pixels; 49x49; 0.6%

- American Sign Language, Univ. of Boston (BU)
  - "Accident" task; 640x480; 16845 frames
  - Face resolution: ~5600 pixels; 75x75; 1.8%



4. Local AAMs

- Model a specific facial area (mouth, eyes, brows etc.)
- Decompose the area's variance from the rest of the face
- Projection of Global AAM's fitting parameters to the eigenvectors of the Local AAM

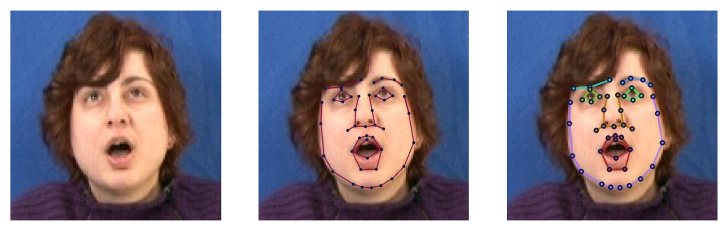
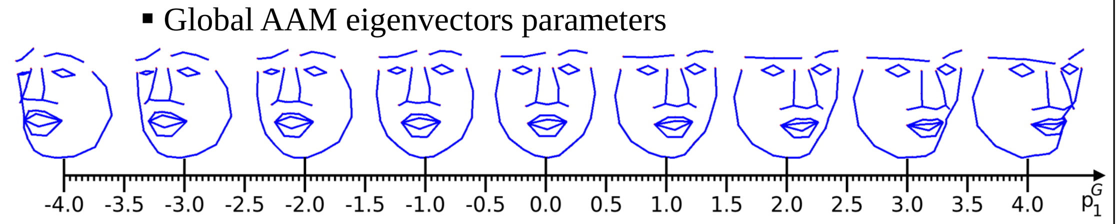


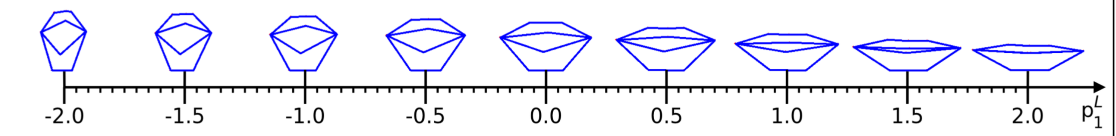
Figure 4. Example of Global AAM projection to various Local AAMs. *Left:* Original image. *Central:* Global AAM fitting. *Right:* Local AAMs projection.

5. UnESC feature selection

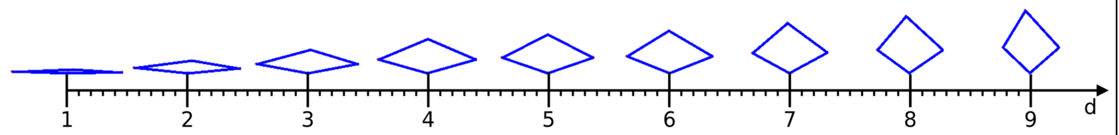
- Possible features:
  - Global AAM eigenvectors parameters



  - Local AAMs eigenvectors parameters



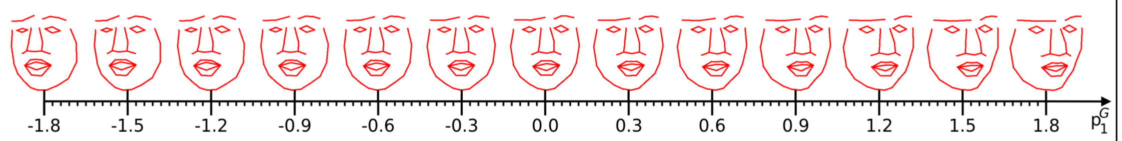
  - Geometrical measures on the mask's landmark points



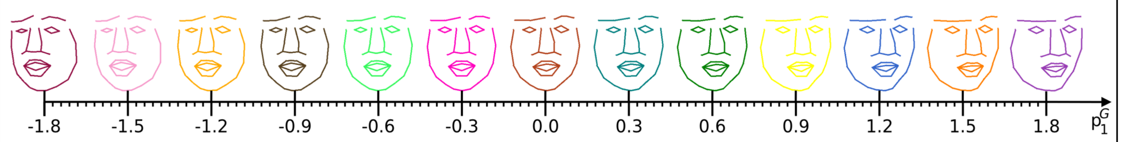
- Single-dimensional (1D) feature space
- $\mathbf{s_p} = \mathbf{s}_0 + \sum_{i=1}^{n} p_i \mathbf{s}_i$ ⇨ Facial event variation continuity wrt. feature value change.

5. UnESC training

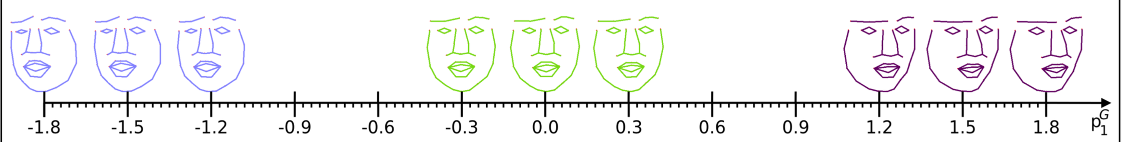
- *Main idea*: Partition 1D feature space in 3 representative clusters:
  - Two on the edges corresponding to the extreme states
  - One on the center corresponding to the neutral state
- *Step 1*: Selection of 1D feature that best describes the facial event.



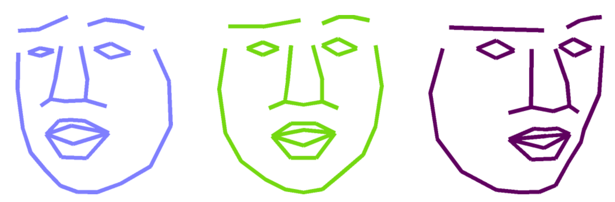
- *Step 2*: Hierarchical Breakdown for density equalization
  - Agglomerative Hierarchical Clustering



- *Step 3*: Maximum-Distance Cluster Selection with Subjective Perceived Threshold (SPThres) parameter
  - Some training data points are not classified in any cluster!
  - SPThres controls the edge clusters' spread towards the central



- *Step 4*: Training of three 1D Gaussians, one per cluster



6. Experimental results

I) Qualitative results (GSL)

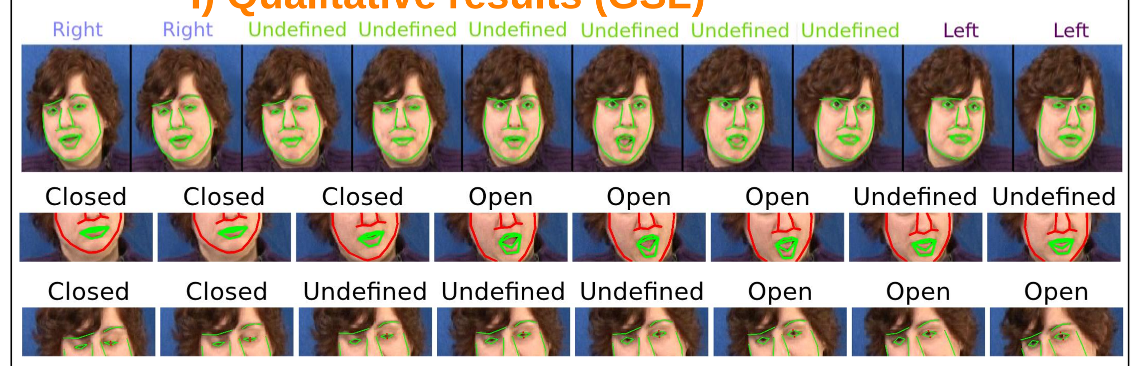
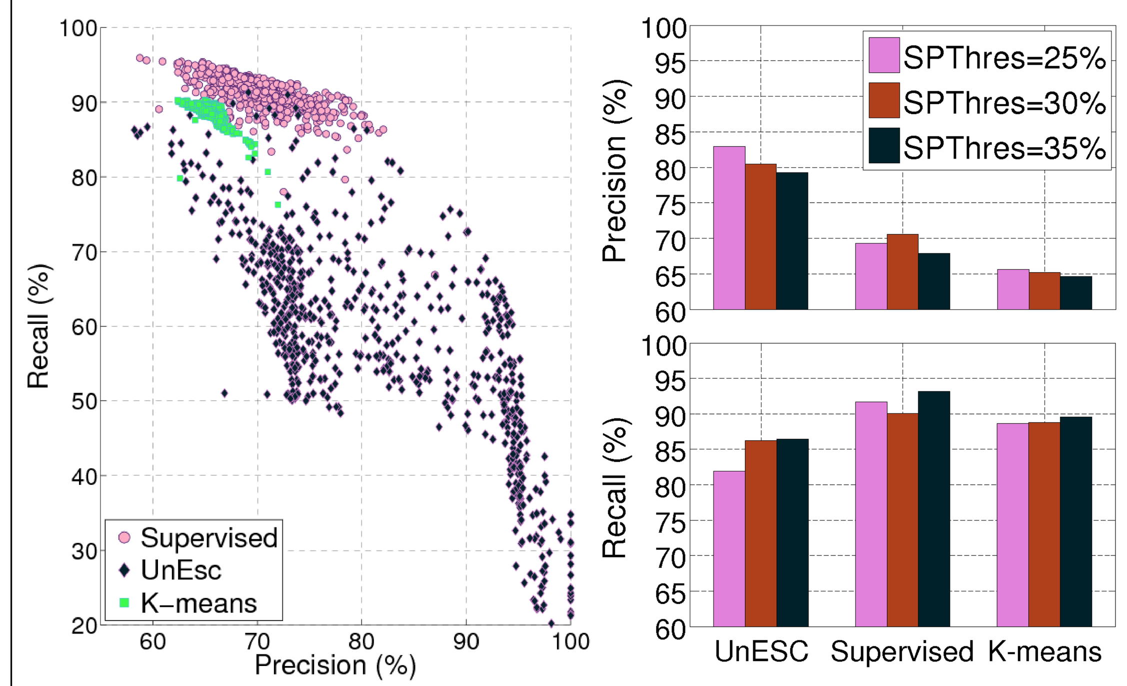


Figure 5. Qualitative results on GSL database. *First:* Pose over the yaw angle using Global AAM's 1st shape parameter. *Second:* Mouth open/close using Local AAM's 1st shape parameter. *Third:* Left eye open/close using distance between eyelids.

II) Quantitative results (BU)

- UnESC vs. Supervised Classification vs. Kmeans for pose yaw
- 729 experiments for various values of SPThres
- Supervised & Kmeans trainig set size =UnESC clusters' size



- High precision
- User can achieve high precision or recall through SPThres.

Relevant work

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