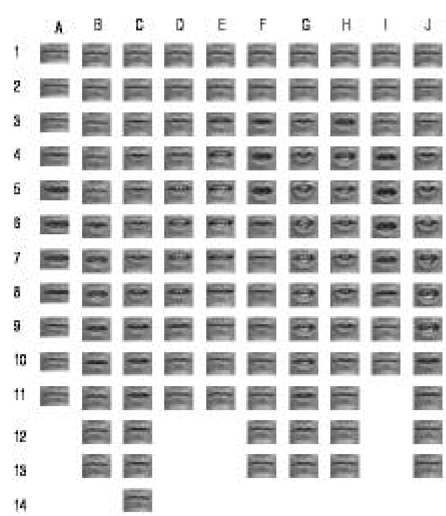
Visual Lipreading

Image Sequences of “A” to “J”



Particulars

- Problem: Pattern differ spatially
- Solution: Spatial registration using SSD
- Problem : Articulations vary in length, and thus, in number of frames.
- Solution: Dynamic programming for temporal warping of sequences.
- Problem: Features should have compact representation.
- Solution: Principle Component Analysis.

Feature Subspace Generation

- Generate a lower dimension subspace onto which image sequences are projected to produce a vector of coefficients.
- Components
  - Sample Matrix
  - Most Expressive Features

Generating the Sample Matrix

- Consider e letters, each of which has a training set of K sequences. Each sequence is compose of images:

$$I_1, I_2, \dots, I_P$$

- Collect all gray-level pixels from all images in a sequence into a vector:

$$u = (I_1(1,1), \dots, I_1(M,N), I_2(1,1), \dots, I_2(M,N), \dots I_P(1,1), \dots, I_P(M,N))$$

. Generating the Sample Matrix

- For letter w , collect vectors into matrix T

$$T_w = \left[u^1, u^2, \dots u^K\right]$$

- Create sample matrix A:

$$A = \left[T_1, T_2, \dots T_e\right]$$

- The eigenvectors of a matrix $L = AA^T$ are defined as:

$$Lf_i = l_i f_i$$

The Most Expressive Features

- f is an orthonormal basis of the sample matrix.

•Any image sequence, u, can be represented as:

$$u = \sum_{n=1}^{Q} a_{n f_n} = fa$$

- Use Q most significant eigenvectors.
  - The linear coefficients can be computed as:

$$a_n = u^T f_n$$

Training Process

- Model Generation
  - Warp all the training sequences to a fixed length.
  - Perform spatial registration (SSD).
  - Perform PCA.
  - Select Q most significant eigensequences, and compute coefficient vectors “a”.
  - Compute mean coefficient vector for each letter.

Recognition

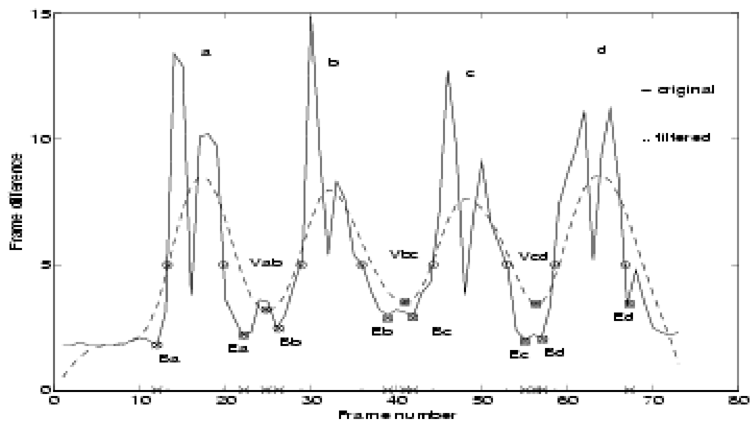
- Warp the unknown sequence.
- Perform spatial registration.
- Compute: $$a_i^x = u_x^T . \boldsymbol{f}_i$$ $$d^w = \| a^w - a^x \|$$
- Determine best match by $\min_w (d^w)$

Extracting letters from Connected Sequences

- Average absolute intensity difference function

$$f(n) = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} \| I_n(x,y) - I_{n-1}(x,y) \|$$

- f is smoothed to obtain g.
- Articulation intervals correspond to peaks and non-articulation intervals correspond to valleys in "g".



Extracting letters from Connected Sequences

- Detect valleys in g.

- From valley locations in g, find locations where f crosses high threshold.

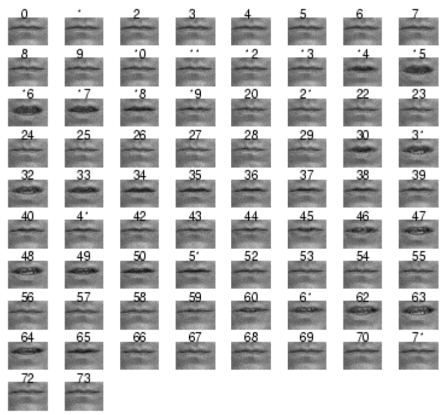
- Locate beginning and ending frames.

A 12-22

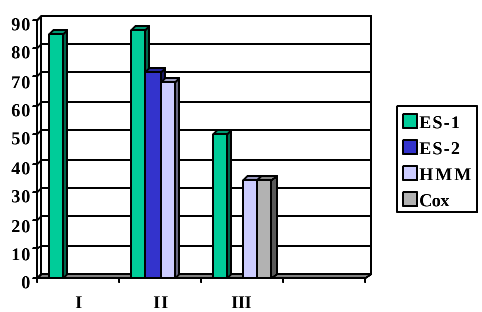
B 26-39

C 42-55

D 57-67

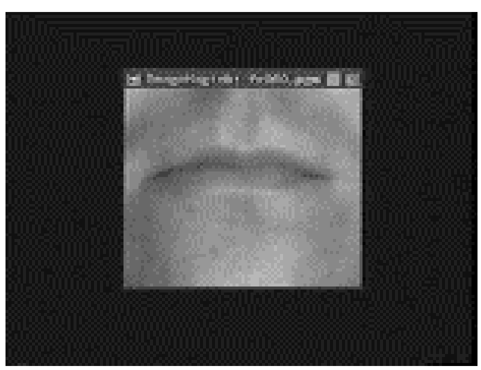


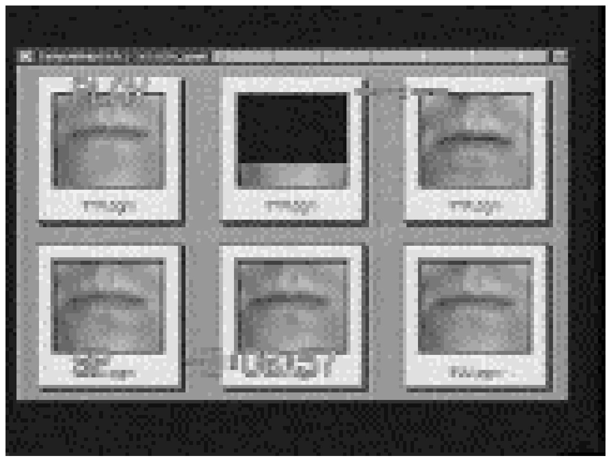
Results

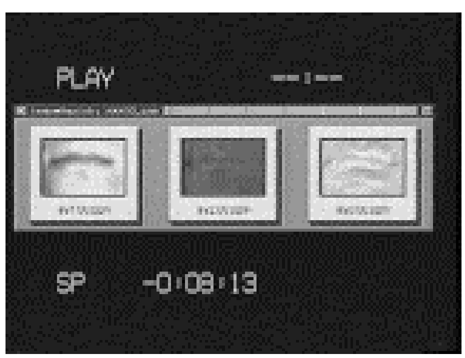


I: “A” to “J” one speaker, 10 training seqs
II. “A” to “M”, one speaker, 10 training seqs
III. “A” to “Z”, ten speakers, two training seqs/letter/person

Show Video Clip






PLAY
SP -0:08:13

Making Faces

Guenter et al

SIGGARPH'98

Making Faces

- System for capturing 3D geometry and color and shading (texture map).
- Six cameras capture 182 color dots (six colors) on a face.
- 3D coordinates for each color dot are computed using pairs of images.
- Cyberware scanner is used to get dense wire frame model.

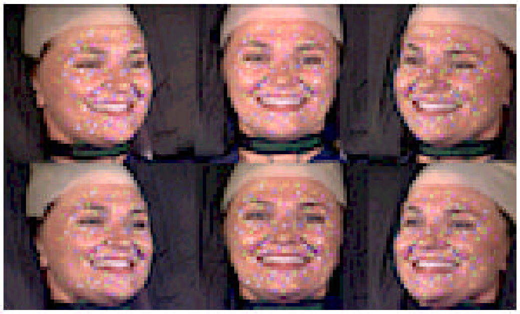
Making Faces

- Two models (cyberware and frame data) are related by a rigid transformation.
- Movement of each node in successive frames is computed by determining correspondence of nodes.

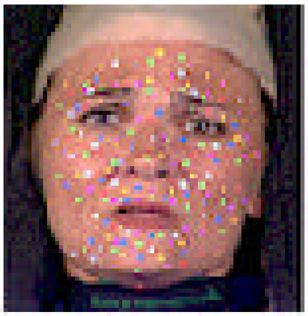
Applications

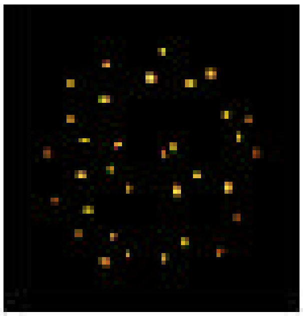
  - Facial expressions can be captured in a studio,
  - delivered via CDROM or internet to a user
  - reconstructed in real time on a user's computer in a virtual 3D environment
- User can select
  - any arbitrary position for the face,
  - any virtual camera view point,
  - any size

Six Views

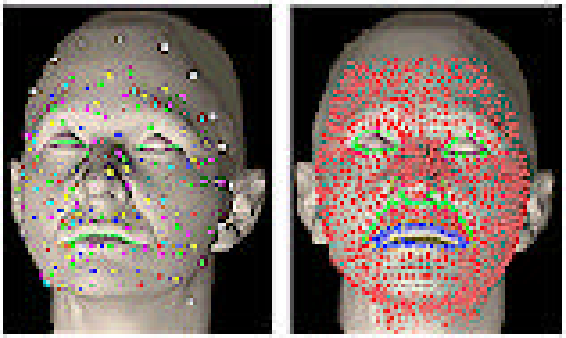


Color Dots



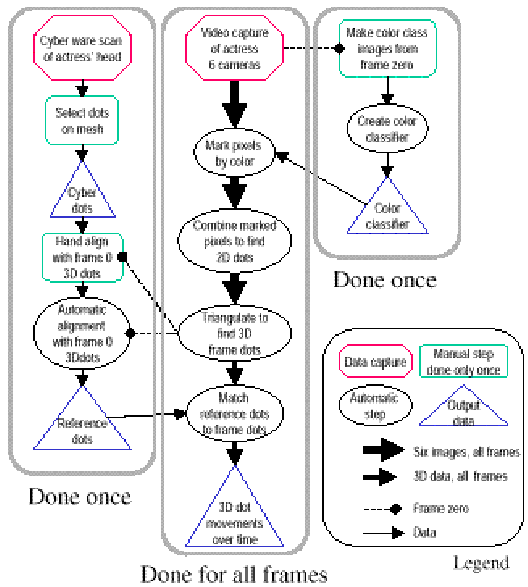


Wireframe Model

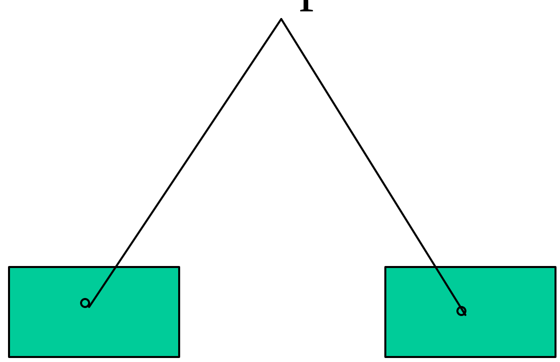


Main Steps

- 3-D reconstruction from 2-D dots
- Correspondence of Cyberware dots (reference) with 3-D frame dots
- Frame to frame dot correspondences
- Constructing The Mesh
- Compression of Geometric Data



Intersection of two rays is 3-D point



3-D reconstruction from 2-D dots

- Generate all potential 2-D point correspondences for k cameras with n points in each camera: $\binom{k}{2} n^2$
- Each point correspondence gives rise to a 3-D candidate point defined as intersection of two rays cast from 2-D points.
- Project 3-D candidate point to each of two camera views, if the projection is not within some bound from the centroid of either 2-D point then discard it as a potential 3-D candidate point.

3-D reconstruction from 2-D dots

- Each of the points in 3-D list is projected into a reference view, which is the camera with the best view of all points on the face.
  - If the projected point is not within a threshold distance from the centroid of 2-D dot it is deleted from the list
  - The remaining points constitute 3-D match list for that point
- For each 2-D point $\binom{m}{3}$ possible combinations of three points in the 3-D list are computed, and the combination with the smallest variance is chosen.
  - The average of three points in the best combination is the true 3-D position corresponding to a 2-D dot.

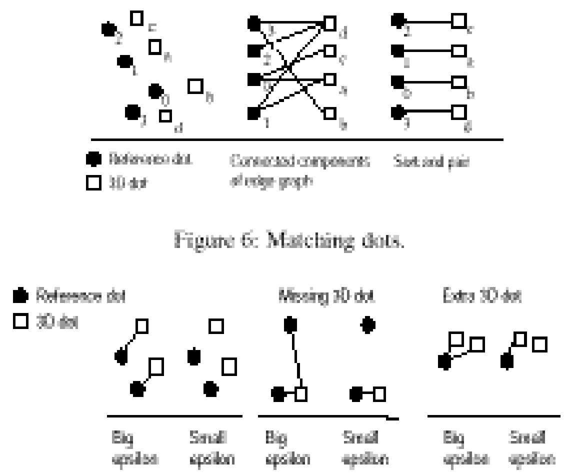
Correspondence of Cyberware dots (reference) with 3-D frame dots

- Obtain Cyberware scan of a face.
- Place reference dots on the Cyberware model by manually clicking on the dots.
- Align reference dots in Cyberware scan with the video frame dots.
  - Manually align frame dots in frame zero with the reference dots

Correspondence of Cyberware dots (reference) with 3-D frame dots

- Automatically align reference dots with frame dots in other frames by solving correspondence using graph matching
  - For each reference dot add an edge for every frame dot of the same color that is within a distance *e*.
  - Search for connected components of graph which has equal number of reference and frame dots (most connected components will have two dots, one for reference and other from frame dots).

Correspondence of Cyberware dots (reference) with 3-D frame dots



Frame to frame dot correspondences

- Assume Cyberware scan as a reference nodes
- Solve correspondence between reference dots and frame dots for frame 0.
- For each frame *i>0* move the reference dots to the location in previous frame, then find the best match between the reference dot and neighboring frame dots.
- Move each reference dot to the location of its corresponding 3D location.

$$d_j^i = d_j + \vec{v}_j^i$$

Constructing The Mesh

- Move vertices by a linear combination of the offsets of the nearest matching dots.

$$p_j^i = p_j + \sum_k a_k^j \parallel d_k^i - d_k \parallel$$

Compression of Geometric Data

- 182 3-D dots in each frame
- Use eigen vector approach to reduce dimensionality to only 45 principal components
- Need to transmit the coefficients and eigen vectors
- They reduced geometric data using this approach to 26kbps for coefficients, and 13kbps for eigen vectors

Compression

Figure 14: Left to Right: Mesh with uncompressed textures, compressed to 400 kbits/sec, and compressed to 200 kbits/sec

Original 400 kbps 200 kbps

Rendered Images

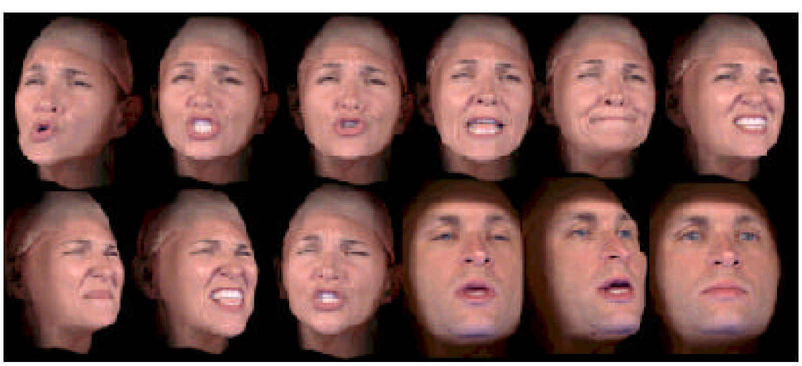


Figure 16: Sequence of rendered images of textured mesh.