Improving the Speed of Convergence of a Maximum–Likelihood Motion Estimation Algorithm of a Human Face

Geovanni Martínez
Image Processing and Computer Vision Research Laboratory (IPCV–LAB)

School of Electrical Engineering
University of Costa Rica

gmartin@pacuare.eie.ucr.ac.cr

http://ipcv–lab.eie.ucr.ac.cr

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Introduction (1)

Challenge

Non–intrusive human face motion estimation from a single video camera.

Applications

Video compression.
Human–machine interfaces.

Approach

The human face motion is estimated by maximizing the conditional probability of the frame to frame intensity differences at observation points.

Introduction (2)

Shape model

The human face shape is described by a rigid 3D mesh of triangles.

Motion model

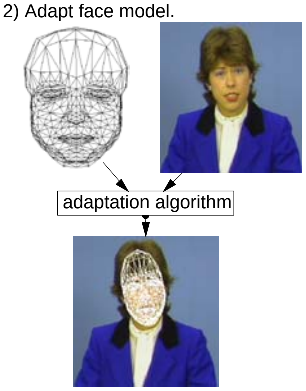
The human face motion is described by 6 parameters ***B***: one 3D translation vector and 3 rotation angles.

Other assumptions

Static camera, perspective projection and diffuse illumination.

Motion estimation algorithm (1)

1) Read first image.
2) Adapt face model.



Motion estimation algorithm (2)

3) Create *J>6* observation points, *j:1..J.*

Each observation point *j* lies on the surface of the mesh and carries the corresponding intensity value at its position.

Only points with high linear intensity gradient are selected as observation points.

Motion estimation algorithm (3)

4) Read next image.

5) Detect outliers in the observation points.

6) Compute the intensity differences ***FD*** between the observation points and the current image. Exclude all detected outliers.

7) Compute the conditional probability *p(**B/FD**)*.

8) Maximize the conditional probability:

$$p(\boldsymbol{FD}/\hat{\boldsymbol{B}}) \geq p(\boldsymbol{FD}/\boldsymbol{B}) \ \forall \ \boldsymbol{B}$$

$\hat{\boldsymbol{B}}$: motion estimates.

NOTE: The algorithm is applied iteratively to improve its accuracy.

Outlier detection algorithm (1)

An outlier is an observation point whose motion can not be described by the assumed human face motion model.

For outlier detection the following algorithm based on Random Sample Consensus (RANSAC) is applied:

1) Select randomly *N<J* observation points.

2) Estimate the human face motion evaluating (without exclusion) each one of the *N* randomly selected observation points. For motion estimation use the previously described algorithm beginning from step 6).

3) Move all *J* observation points with the motion estimates.

Outlier detection algorithm (2)

5) An observation point *j* is detected as outlier if the intensity difference between the observation point and the current image is bigger than 10.

6) Compute the total number of detected outliers *O*.

7) Move back all *J* observation points.

8) If the percentage of detected outliers (100**O/J*) is bigger than 90% goto step 1).

9) End.

NOTE: After 10 iterations the algorithm is considered to be failed and no observation points are detected as outliers.

Results (1)

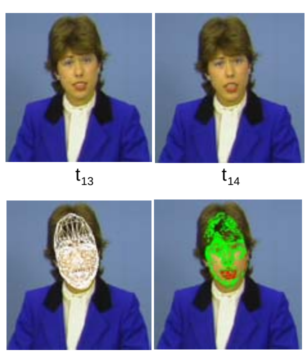
1) The motion estimation algorithm with outlier detection was applied to 150 frames of the test sequence Claire (CIF, 10Hz).

2) The average number of observation points evaluated for motion estimation decreases in 42.05% from 3657.0 to 2119.13 observation points per frame.

3) The average number of iterations for convergence decreases in 45.5% from 32.13 to 17.51 iterations per frame.

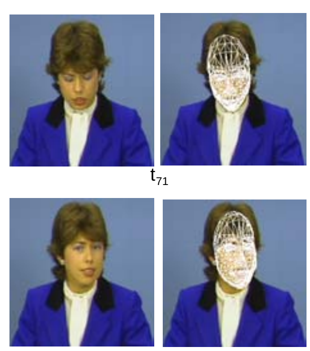
4) The average processing time for motion estimation decreases in 67.49% from 1.0834 to 0.3522 seconds per frame.

Results (2)



t_{13} t_{14}
t_{13} Red: detected outliers
Green: inliers

Results (3)



t_{71}
t_{149}

Conclusions

1) In this paper the speed of convergence of a Maximum–Likelihood motion estimation algorithm is improved by detecting outliers in the observation points and excluding them from motion estimation.

2) For outlier detection an algorithm based on RANSAC is used.

3) The average number of iterations per frame for motion estimation is reduced in 45.50%.

4) The average processing time per frame for motion estimation is reduced in 67.49%.