Digital Perception Lab.

Dept. Electrical and Computer Systems Engineering

Monash University

- Research Covers Areas Such as:
  - Computational Mathematics
    - Novel Splines and Fast Approximation of Splines (related to Radial Basis Functions, Support Vector Machines)
    - Finite Element, Wavelets, Multi-pole Methods
  - Image Processing
    - Restoration of Historical Film
    - Biomedical Image Processing
  - Computer Vision/Robotics
    - Optic Flow
    - Motion Segmentation
    - Tracking
    - 3-D structure modelling
- A common thread is: Motion/Displacement Estimation from Images
- Common techniques are robust statistics, model selection, model fitting….

Current (and New) Projects

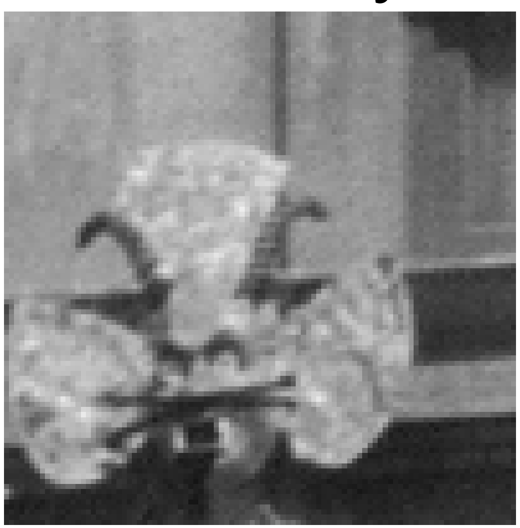
- Robust Model Fitting and Model Selection (with Wang, Bab-Hadiashar, Staudte, Kanatani…..)
- Subspace Methods for SFM and Face recognition (with Chen) (soon to be postdoc with PIMCE)
- Biomedical:Microcalcification in breast X-rays (with Lee, Lithgow), Knee cartilage segmentation (with Cheong and Ciccutini)
- Invariant Matching/Background Modelling (with Gobara)
- Historical Film Restoration and Film Special Effects (with Boukir)
- Wavelet denoising (with Chen)
- (new) Geometric aspects of tracking (ARC 2004-6)
    - Postdoc Wang
- Human motion Modelling and Tracking (with U)
- Visualisation (Monash SMURF vizlab)
- (new) Urban Scanning (Monash NRA – soon to be postdoc Schindler)
- (new) 4-D Recorder Room

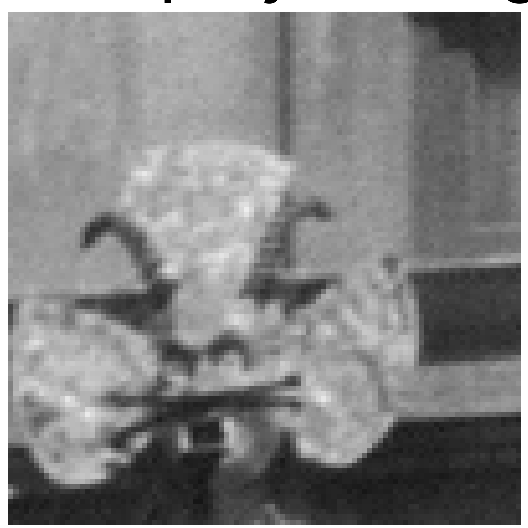
(+Tat-jun Chin + Tk – soon to start phd students)

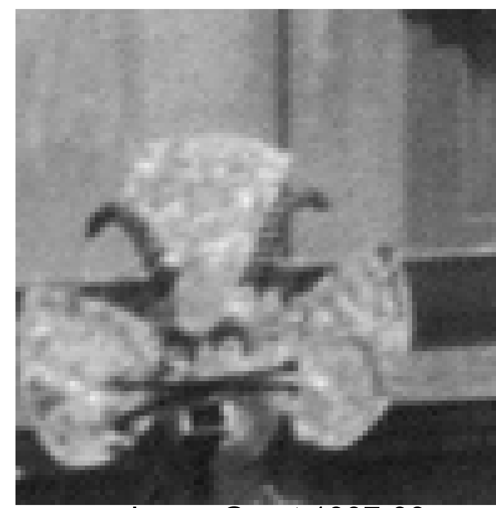
Advance on Previous Restoration Work (with Boukir)

Can't capture distortion – e.g., rotation

Can try to use 3-D projective geom. – below







Large Grant 1997-99

IREX 2001

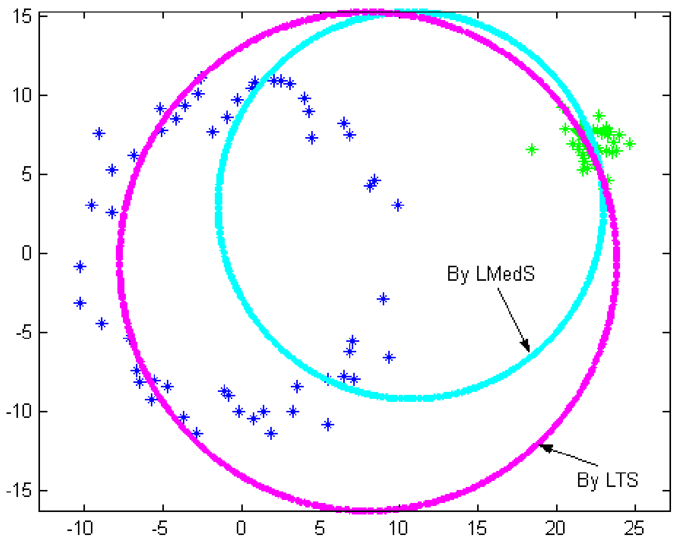
S. Boukir and D. Suter. Application of rigid motion geometry to film restoration.In *Proceedings of ICPR2002*, volume 6, pages 360-364, 2002.

Australian Government
Australian Research Council

Symmetry in (Robust Fitting)

Actually, the assumption that median belongs to "clean" data is false sometimes even when outliers < 50%!

H. Wang and D. Suter.
Using symmetry in robust model fitting.
Pattern Recognition Letters, 24(16):2953-2966, 2003.



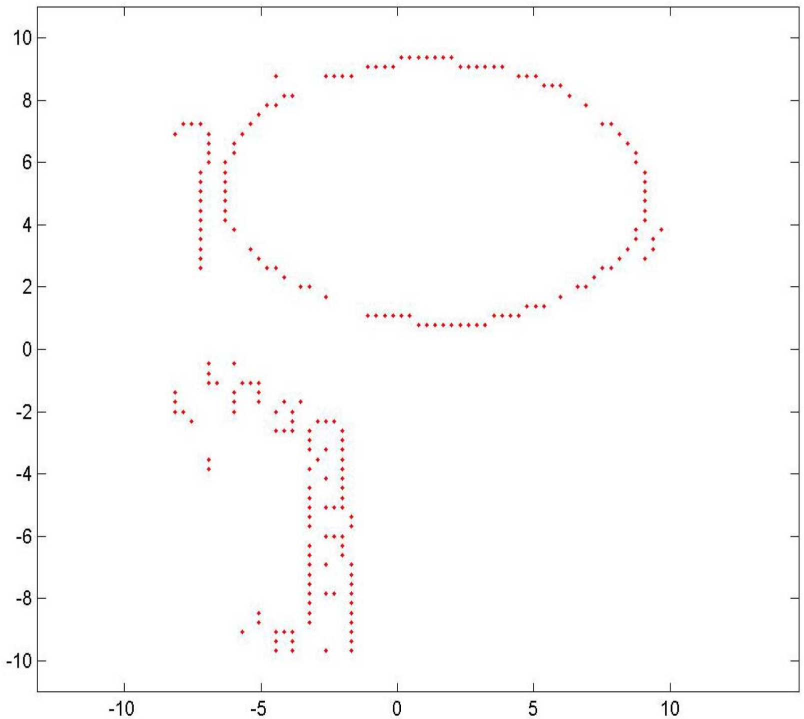
55 inliers – 45 *clustered* outliers

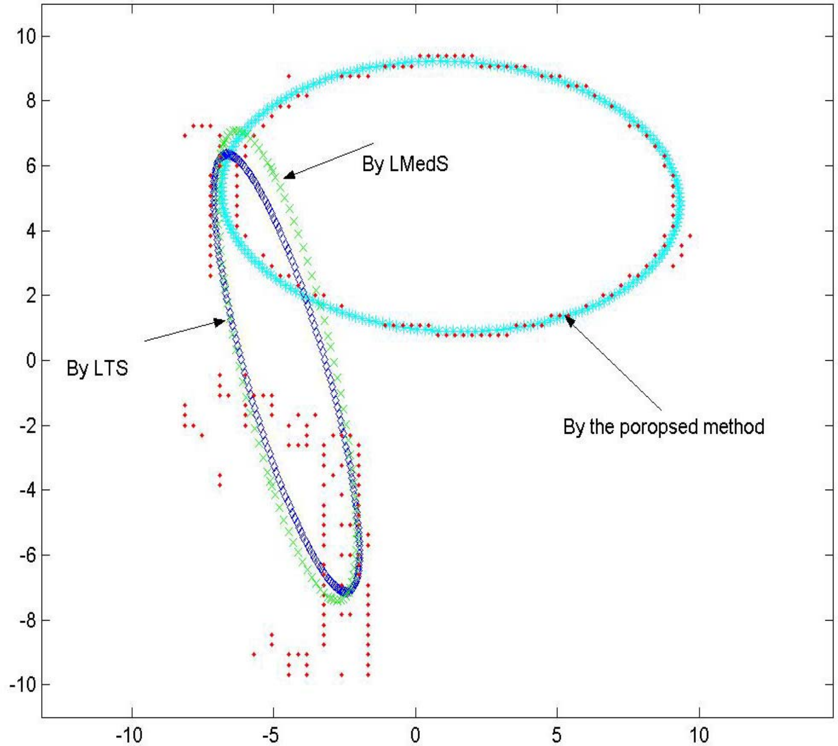
Large Grant 2000-2

Australian Government
Australian Research Council

Symmetry in (Robust Fitting)

about 45% *clustered* outliers





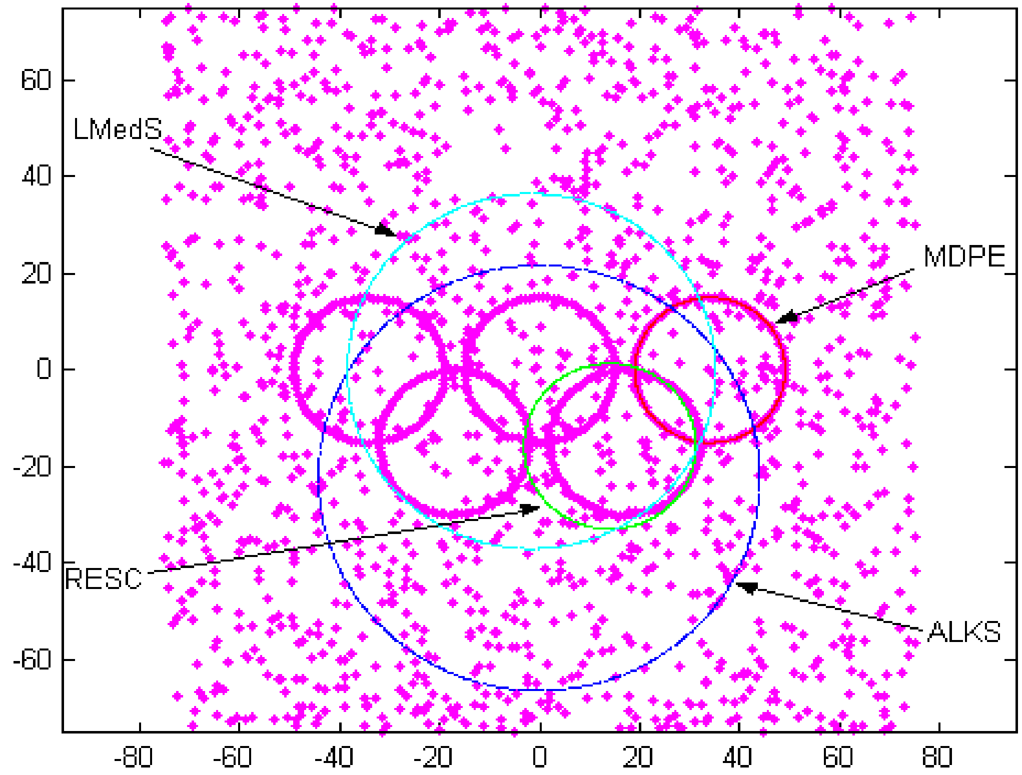
Large Grant 2000-2

Australian Government
Australian Research Council

Very Robust Fitting – Mean-shift

about 95% outliers!

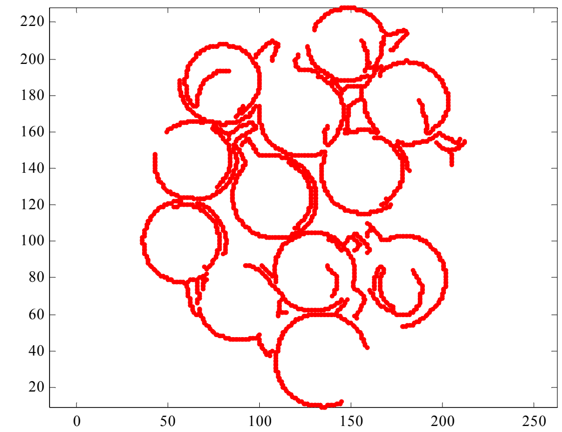
H. Wang and D. Suter.
MDPE: A very robust estimator for model fitting and range image segmentation. *Int. J. of Computer Vision*, to appear, 2004.

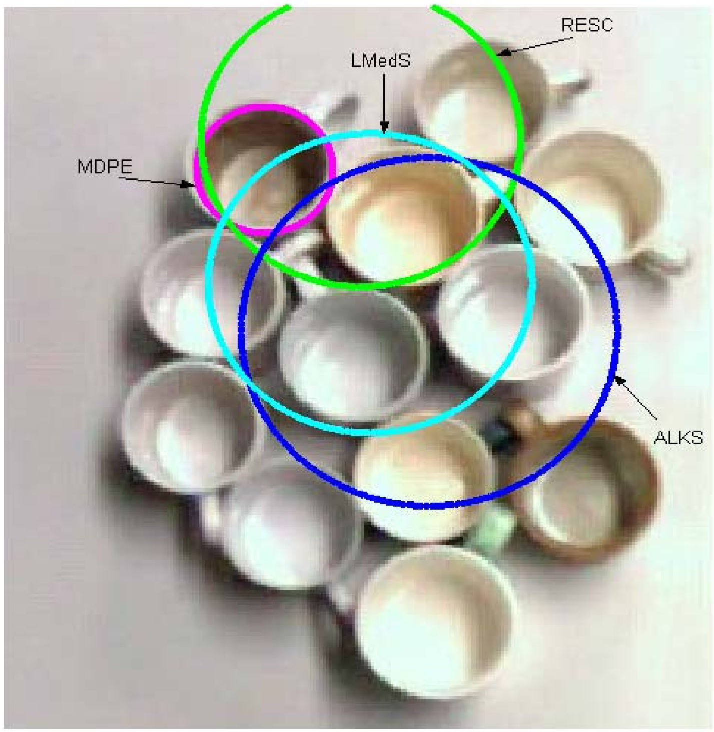


Large Grant 2000-2

Very Robust Fitting

about 95% outliers!





Large Grant 2000-2

Australian Government
Australian Research Council

Very Robust Fitting

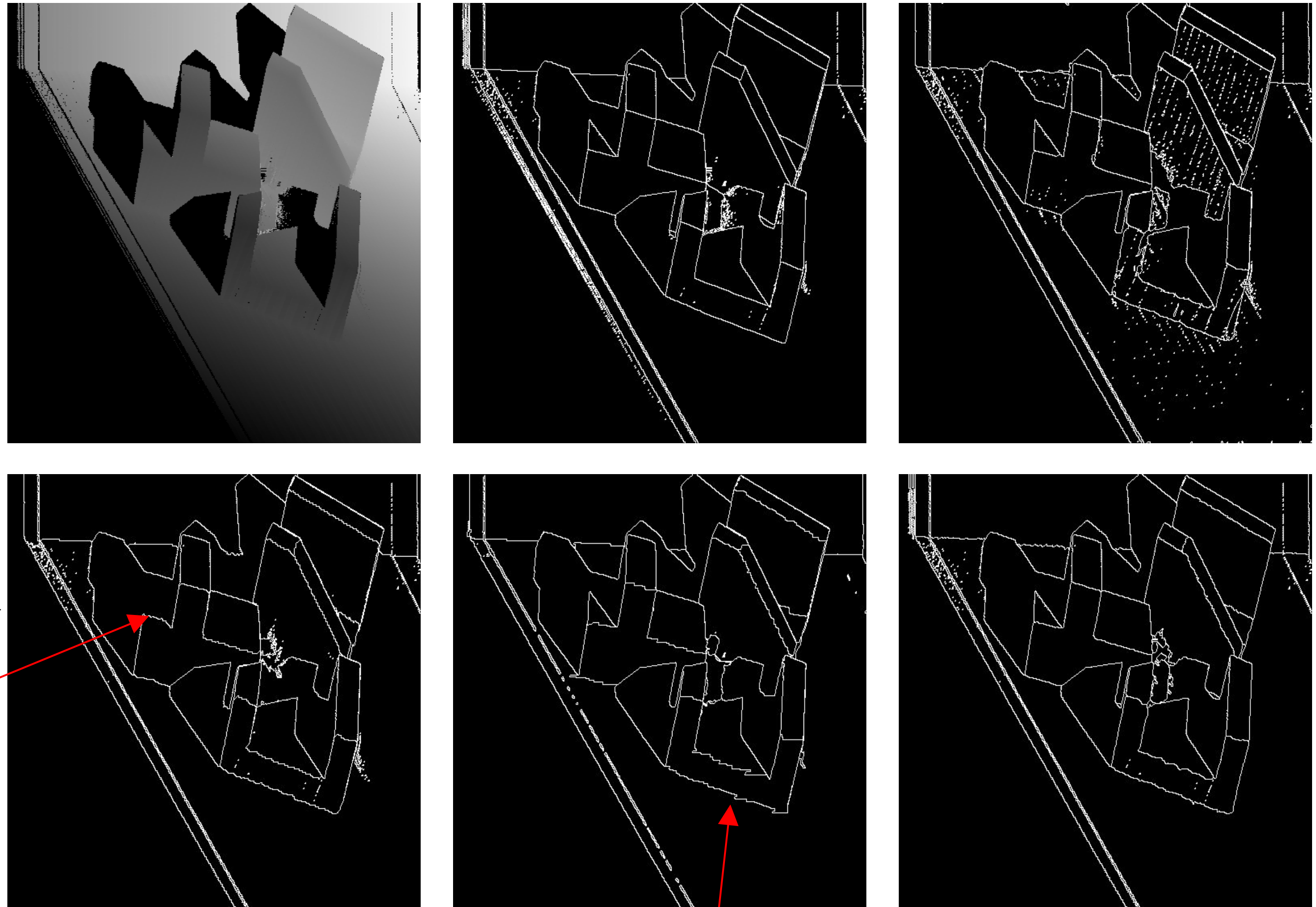
How does it work?

Essentially – not just dependent upon a single stat (the median or the number of inliers) but on the pdf about the chosen estimate.

Uses Mean Shift and maximizes a measure roughly
(sum of inlier pdf – as defined by mean shift window)/(bias – mean residual - centre of mean shift window)

USF
Noisy
Points

WSU
Missed
Surf.



UB – distorted edges

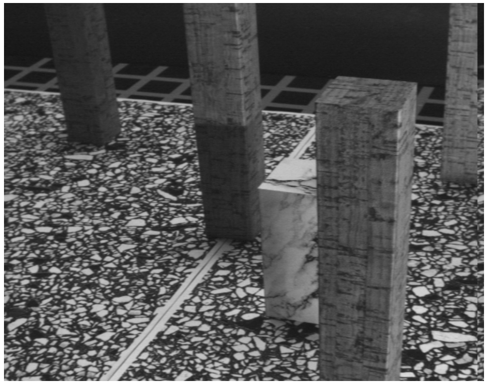
Australian Government
Australian Research Council

Yosemite

Technique	Avg. error (degree)	Std. dev. (degree)	Density (%)
Black (1994)	3.52	3.25	100
Szeliski and Coughlan (1994)	2.45	3.05	100
Black and Anandan (1996)	4.46	4.21	100
Black and Jepson (1996)	2.29	2.25	100
Ju et. al. (1996)	2.16	2.00	100
Memin and Perez (1998)	2.34	1.45	100
Memin and Perez (2002)	1.58	1.21	100
Lai and Vemuri(1998)	1.99	1.41	100
Bab-Hadiashar and Suter (WTLS2, 1998)	2.56	2.34	100
Bab-Hadiashar and Suter (WTLS6, 1998)	1.97	1.96	100
Farneback2 (2000)	1.94	2.31	100
Farneback6 (2000)	1.40	2.57	100
Farneback6 (2001)	1.14	2.14	100
vbQMDPE2 (σ_0=2.0, 17x17, m=30)	2.12	2.08	100
vbQMDPE6 (σ_0=2.0, 17x17, m=30)	1.54	1.99	100
vbQMDPE2 (σ_0=2.0, 25x25, m=30)	2.27	2.07	100
vbQMDPE6 (σ_0=2.0, 25x25, m=30)	1.34	1.69	100

Otte

Technique	Avg. error (degree)	Std. dev. (degree)	Density (%)
Giachetti and Torre (1996)	5.33	-----	100
Bab-Hadiashar and Suter (WLS2, 1998)	3.39	6.55	100
Bab-Hadiashar and Suter (WLS6, 1998)	3.51	6.48	100
Bab-Hadiashar and Suter (WTLS2, 1998)	3.74	8.09	100
Bab-Hadiashar and Suter (WTLS6, 1998)	3.67	7.37	100
Bab-Hadiashar and Suter (WLS2, corrected)	3.02	5.98	100
Bab-Hadiashar and Suter (WLS6, corrected)	3.14	5.84	100
Bab-Hadiashar and Suter (WTLS2, corrected)	3.20	7.02	100
Bab-Hadiashar and Suter (WTLS6, corrected)	3.20	6.59	100
vbQMDPE2 (σ_0=2.0, 17x17, m=30)	2.64	4.98	100
vbQMDPE6 (σ_0=2.0, 17x17, m=30)	2.82	5.03	100
vbQMDPE2 (σ_0=2.0, 25x25, m=30)	2.21	4.16	100
vbQMDPE6 (σ_0=2.0, 25x25, m=30)	2.29	4.06	100



Large Grant 2000-2

Australian Government
Australian Research Council

Imputation\Subspace Learning

(Hallucination if you prefer)

P. Chen and D. Suter.
Recovering the missing components in a large noisy low-rank matrix:
Application to SFM.

IEEE Trans. Pattern Analysis and Machine Inteliigence, page to appear, 2004.

What you start with:

Low rank, large noisy matrix with "holes"

$$\mathbf{M} = \underset{rank\ \ r}{\overset{m \times n}{\begin{pmatrix} \times & \circ & \cdots & \times \\ \times & \times & \cdots & \circ \\ \cdots & \cdots & \cdots & \cdots \\ \times & \times & \cdots & \times \end{pmatrix}}}$$

We want to fill in and de-noise

Why?

- Data Mining – on line recommender systems
- DNA
- Etc……
- Structure From Motion

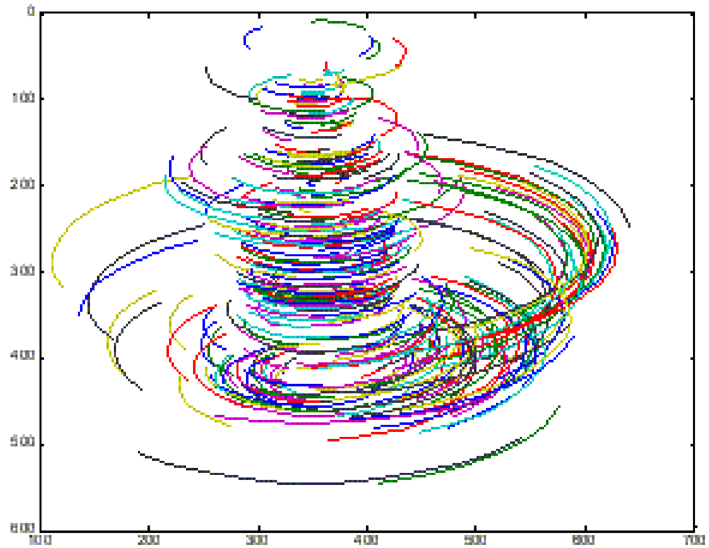
M=RS

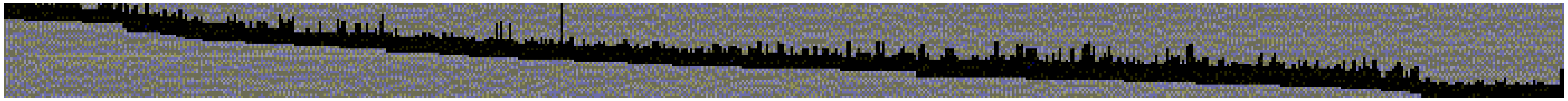
(M- location of features in images

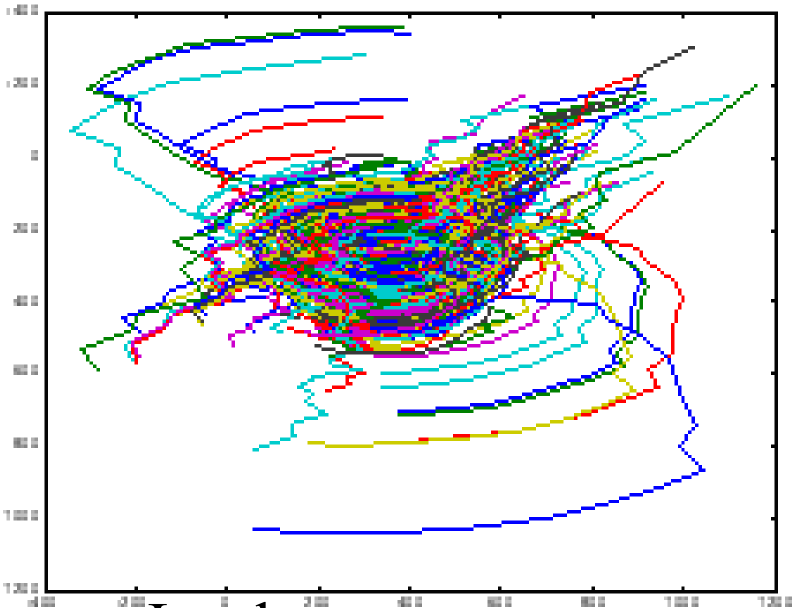
R – camera motion – S – structure)

- Face Recognition – other learning and classification tasks.

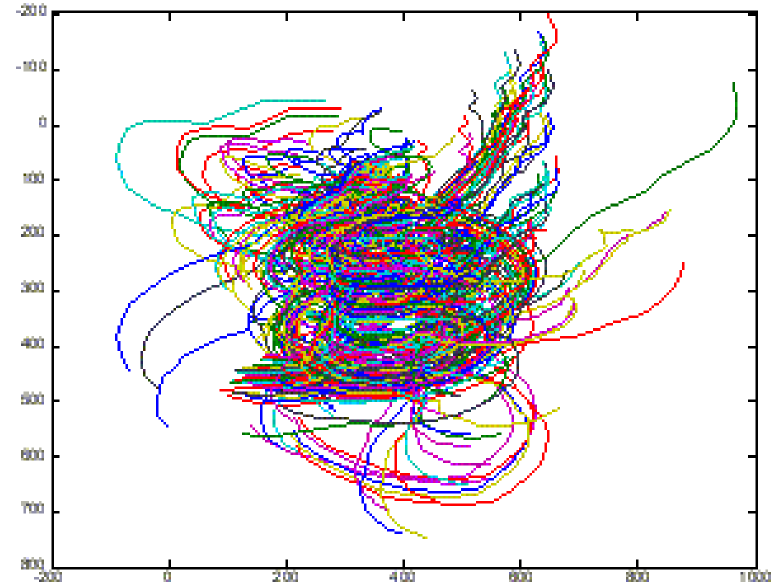
36 frames and 336 feature points – the most reliable by our measure



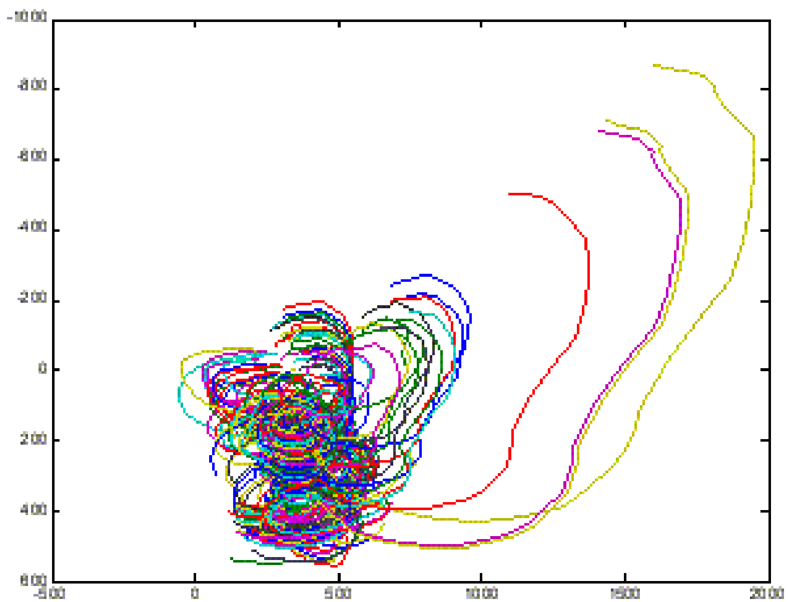




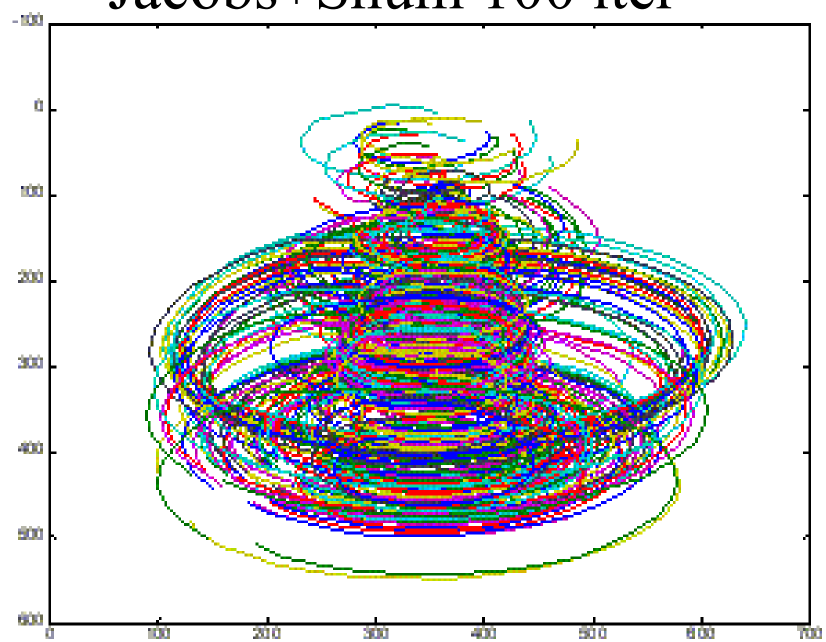
Jacobs



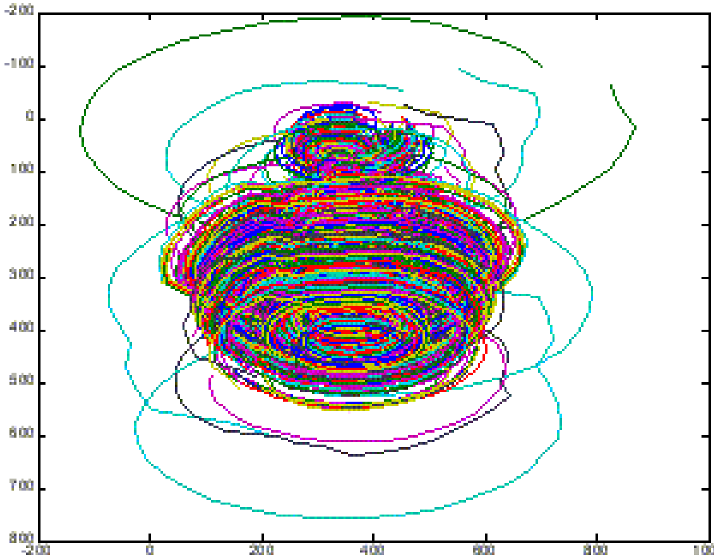
Jacobs+Shum 100 iter



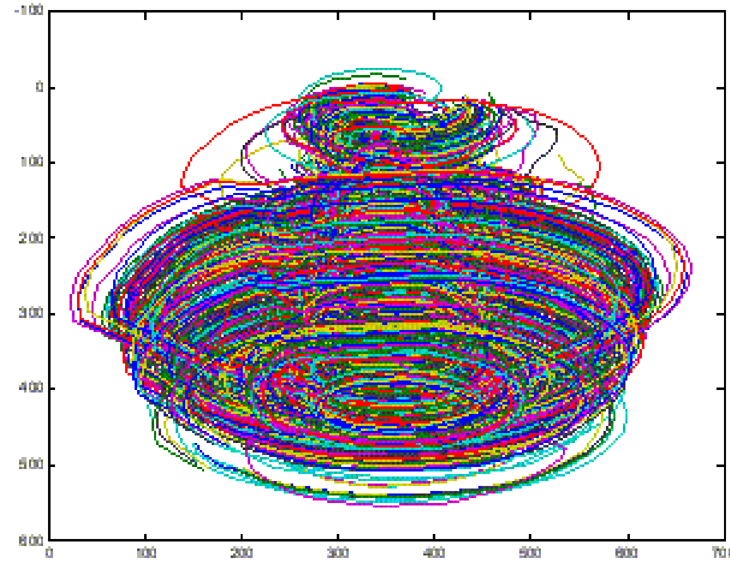
Jacobs+Shum 400 iter



Ours



4983 points over 36 frames



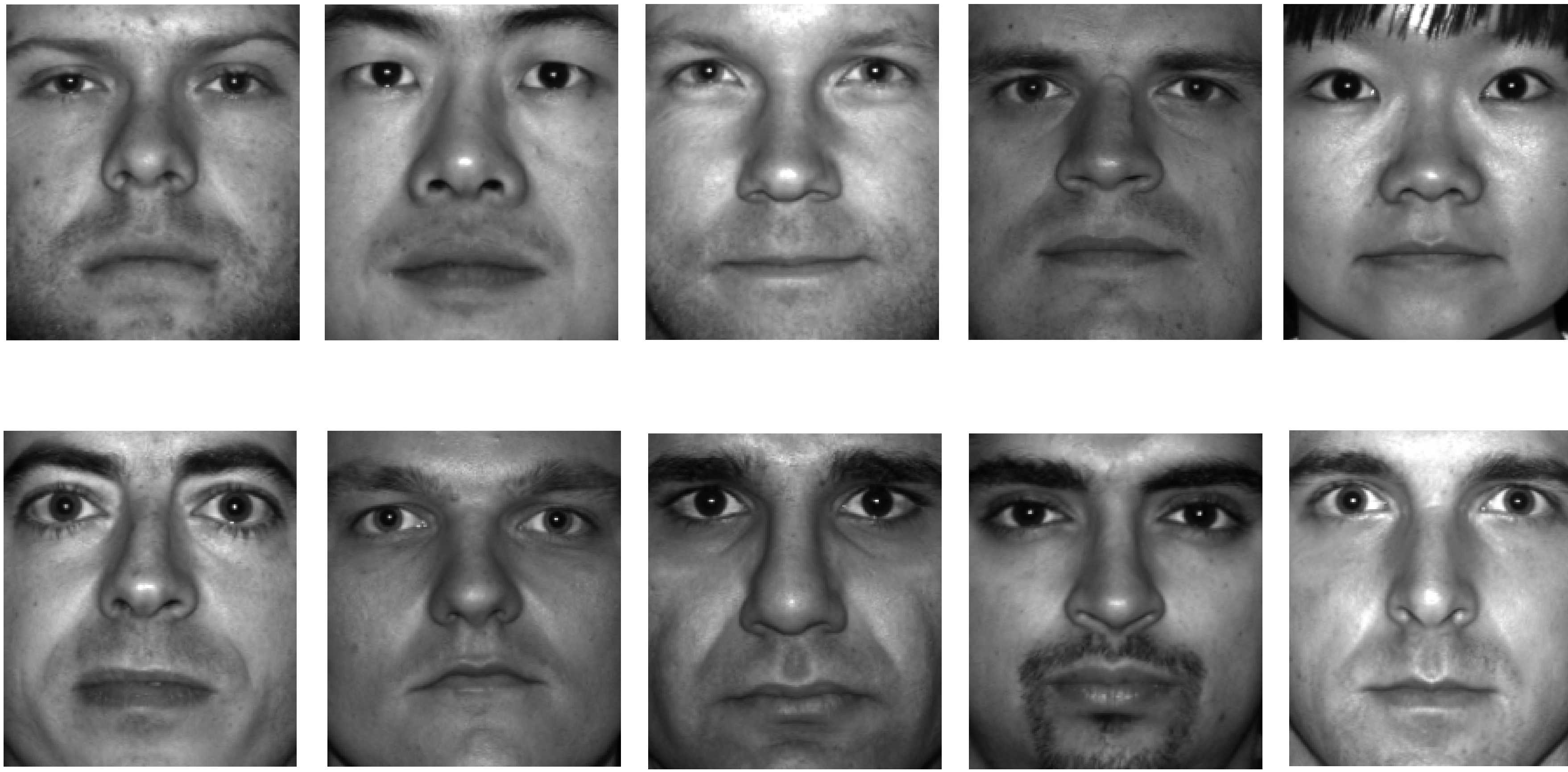
2683 points (those tracked for more than 2 frames)

SUBSPACE-BASED FACE RECOGNITION:
OUTLIER DETECTION
and
A NEW DISTANCE CRITERION FOR MATCHING

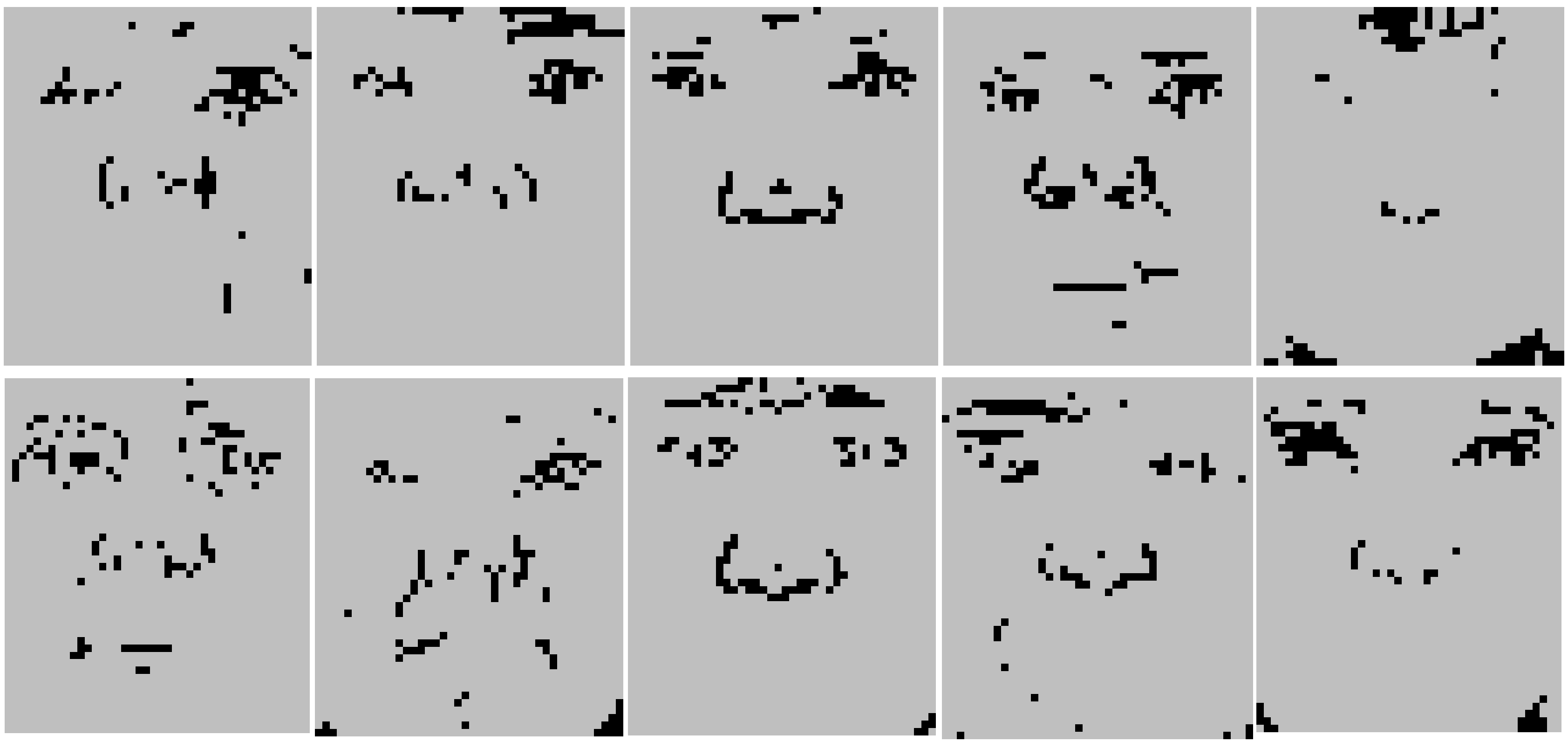
P. Chen and D. Suter.
Subspace-based face recognition: outlier detection and a new distance criterion.

In *Proceedings ACCV2004*, pages 830-835, 2004.

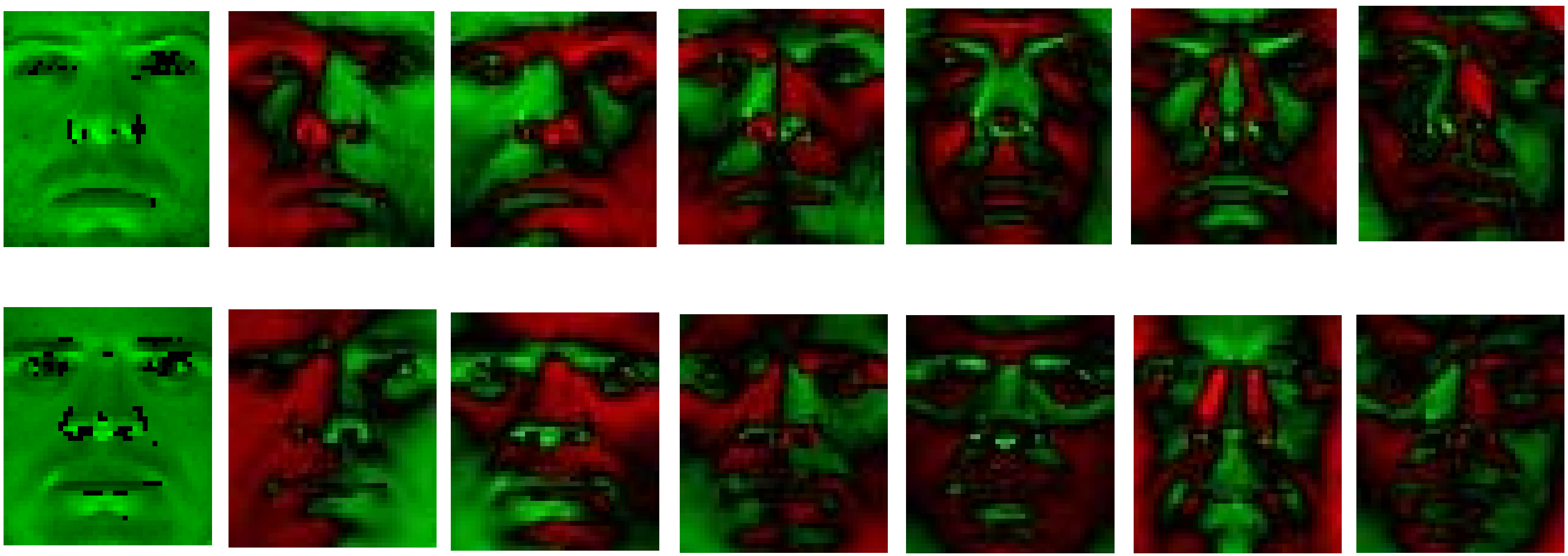
Yale B face database



Outlier detection (Iterative reweighted least square: IRLS)



7D eigenimages



Subsets 1-5

Comparison of the error classification rate (%) on Yale-B face database

Method	Subset 1-3	Subset 4	Subset 5
Linear subspace [9]	0	15	/
Cones-attached [9]	0	8.6	/
Cones-cast [9]	0	0	/
9PL [14]	0	2.8(5.6)	/
Proposed	0	0	7.9