Robust Visual Motion Analysis:
Piecewise-Smooth Optical Flow and Motion-Based Detection and Tracking

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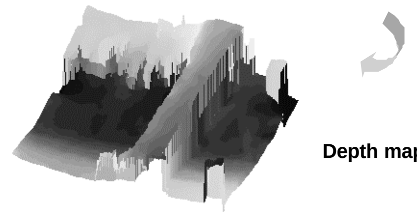
Structure From Motion

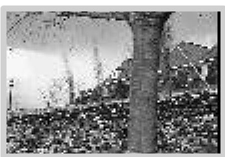
Rigid scene + camera translation

Estimated horizontal motion

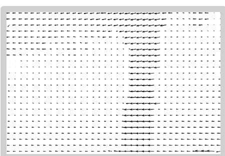


Depth map

What Is Visual Motion



- **2D image velocity**
  - 3D motion projection
  - Temporal correspondence
  - Image deformation

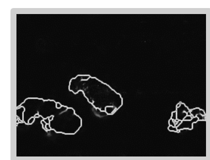


- **Optical flow**
  - An image of 2D velocity
  - Each pixel $V_{s=(x,y)} = (u_s, v_s)$
  - $(x,y,t) \Leftrightarrow (x+u,y+v,t+1)$

Scene Dynamics Understanding

Estimated horizontal motion

- **What're moving? How?**
  - Surveillance
  - Event analysis
  - Video compression



Motion smoothness

Target Detection and Tracking

A tiny airplane --- only observable by its distinct motion

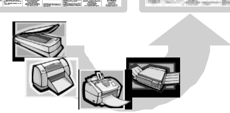
Tracking results

Research Areas

- **Structure from motion**
- **Scene dynamics analysis**
- **Object detection and tracking**
- **Video compression**
- **Image/video enhancement**
- **Image-based rendering**

- **Visual motion estimation**

Image Distortion Measurement



- **Image deformation**
  - Measure it. Remove it.
  - Image-based rendering

Outline

- **Optical flow estimation**
  - Background
  - A local method with error analysis
  - A Bayesian approach with global optimization
- **Motion-based detection and tracking**

Optical Flow Estimation

Basics

- **Template matching**

- **Assumptions:**
  - Brightness conservation
  - Flow smoothness
- **Difficulties:**
  - Aperture problem (local information insufficient)
  - Outliers (motion boundaries, abrupt image noise)

Previous Work (1/2)

- **Brightness conservation**
  - Matching-based $I(x,y,t) = I(x+u, y+v, t+1)$
  - Gradient-based $I_x u + I_y v + I_t = 0$ (OFC)
- **Flow smoothness**
  - Local parametric $AV = b:$ $\begin{pmatrix} I_{x_1} & I_{y_1} \\ \vdots & \vdots \\ I_{x_N} & I_{y_N} \end{pmatrix} \begin{pmatrix} u \\ v \end{pmatrix} = - \begin{pmatrix} I_{t_1} \\ \vdots \\ I_{t_N} \end{pmatrix}$ [Lucas-Kanade 81] [Haralick-Lee 83]
  - Global optimization $\operatorname{argmin} \sum_{\text{all sites } s} \{(I_{x_s} u_s + I_{y_s} v_s + I_{t_s})^2 + l \sum_{n \in N_s^4} [(u_s - u_n)^2 + (v_s - v_n)^2]\}$ [Horn-Schunck 81]

Previous Work (2/2)

- **Handle motion discontinuities & Outliers**
  - Robust statistics **[Black–Anandan 96]**

$$\arg\min \sum_{\text{all sites } s} \{r(I_{x_s} u_s + I_{y_s} v_s + I_{t_s}, s_B) + l \sum_{n \in N_s^4} [r(u_s - u_n, s_S) + r(v_s - v_{n_j}, s_S)]\}$$

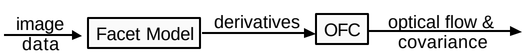
  - Many others
- **Higher-level methods**
- **Problems:**
  - Gradient calculation
  - Global formulation: s_B, s_S, l values?
  - Computational complexity

Two-Stage Robust Optical Flow Estimation with Error Propagation

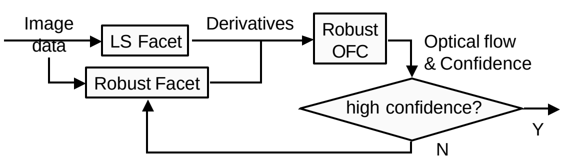
A Local Approach

Method

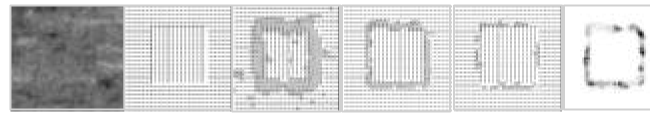
- **2-stage regression (LS)** [Haralick-Lee 83, Ye-Haralick 98]



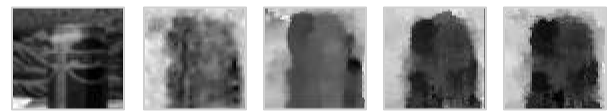
- **Previous: robust OFC only**
- **2-stage-robust adaptive scheme** [Ye-Haralick 00]



Results



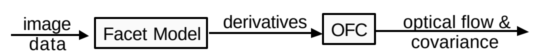
Sampled by2: True LS-LS LS-R R-R Confidence



Horizontal flow: M-OFC LS-LMedS LS-R R-R

Error Analysis

- **Covariance propagation** [Haralick 96]
  - (Approx.) linear system + small errors



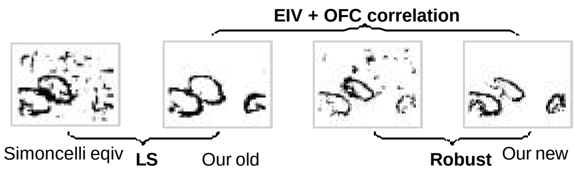
- **Previous work**

	Image noise var.	EIV	OFC corr.
Simoncelli 91	No	No	No
Szeliski 89	Yes	No	No
Nagel 94	No	Yes	Yes
Ye-Haralick 98	Yes	Yes	Yes

- **New: reject outliers first**

Results

- **A simple motion boundary detector**



- **Error analysis: why bother**
  - Accurate uncertainty is just as important
  - Uncertainty is anisotropic, varies from site to site

Problem Statement

Assuming only brightness conservation and piecewise-smooth motion, find the optical flow to best describe the intensity change in three frames.

Estimating Piecewise-Smooth Optical Flow with Global Matching and Graduated Optimization

A Bayesian Approach

MAP/MRF Formulation

- **Maximum A Posterior Criterion:**

$$\tilde{V} = \text{argmax}_V\, P(V/D) = \text{argmax}_V\, \underbrace{P(D\,|\,V)}_{\textbf{Likelihood}}\underbrace{P(V)}_{\textbf{Prior}}$$

- **Prior: Markov Random Fields**
  - Neighborhood system: 8-connected N_s^8 , pairwise
  - Gibbs distribution equivalent ⇒

$$P(V) = \exp(-E_s(V))/Z, \quad E_s(V) = \sum_{n\in N_s^8} r(|V_s - V_n|, s_{S_s})$$

- **Likelihood: exponential**
- **Global optimization problem**

Global Energy Design

- **Global energy** $E = \sum_{\text{allsitess}} E_B(V_s) + E_S(V_s)$
- **Matching error** $E_B(V_s) = r(e_W(V_s), s_{B_s})$
  - Warping error $e_W(V_s) = \min(|I^-(V_s) - I_s|, |I^+(V_s) - I_s|)$
  - 3-Frame Matching Without aliasing, all pixels in a frame are visible in the previous or the next frame.
- **Smoothness error** $E_S(V_i) = \frac{1}{8} \sum_{n \in N_s^8} r(|V_s - V_n|, s_{S_s})$

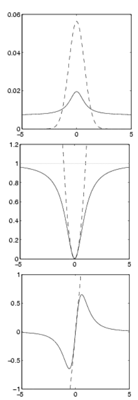
Advantages

- **Compare with [Black-Anandan 96]**

$$\arg\min \sum_{\text{allsites}} \{ r(I_{x_s} u_s + I_{y_s} v_s + I_{t_s}, s_B) + l \sum_{n \in N_s^4} [r(u_s - u_n, s_S) + r(v_s - v_{n_j}, s_S)] \}$$

	Proposed	Black-Anandan 96
Brightness constr	Matching-based	Gradient-based
Scales s_B, s_S l	Local adaptive	Rigid+tuning
Contral para	Constant	Tuning

Error Function $r(x, s)$:



- **A distribution with fatter tails**
- **An error norm less drastic than L2**
  - Robust against outliers
  - Simultaneous segmentation
    - Smoothness outliers = motion discontinuities
- **Use Geman-McClure for redescending & normalization**

$$r(x, s) = \frac{x^2}{s^2 + x^2} \qquad y(x, s) = r'(x, s) = \frac{2xs}{(s^2 + x^2)^2}$$

Solution Technique

- **Largescale nonconvex problem**
  - Statistical relaxation: slow
  - Graduated NonConvexity: LS initialization, scales control annealing
- **Our strategy**
  - Fastest descent
  - 3-step graduated optimization
  - Two sub-optimal formulations
    - Provide robust initial estimates
    - Gradually learn the local parameters

I: OFC-Based Local Regression

- **Lucas-Kanade constraint:** $AV = b$
- **High-breakdown criterion (LMS/LTS)**
- **Fast deterministic algorithm**
  - Least-squares (LS) initial estimate
  - Propagate using an LMS-LS procedure
  - Adaptive outlier resistance
  - Faster, more stable accuracy
- **Estimate scales** s_{B_s}, s_{S_s} **from inliers**

II: OFC-Based Global Optimization

- **Given** V, s_{B_s}, s_{S_s}**, find** ΔV **to minimize**

$$E(\Delta V) = \sum_{\text{all sites } s} \{ r(e_B(\Delta V_s), s_{B_s}) + \frac{1}{8} \sum_{n \in N_s^8} r(|V_s + \Delta V_s - V_n - \Delta V_n|, s_{S_s}) \}$$

- **Solution: Successive Over Relaxation**

$$u_{\text{new}} = u_{\text{old}} - w \frac{1}{T(u_{\text{old}})} \frac{\partial E}{\partial u_{\text{old}}}, \ T(u) = \frac{I_x^2}{s_B^2} + \frac{8}{s_S^2}$$

  - Adaptive step size
  - Initial has dominantly high-freq errors
  - Fast convergence

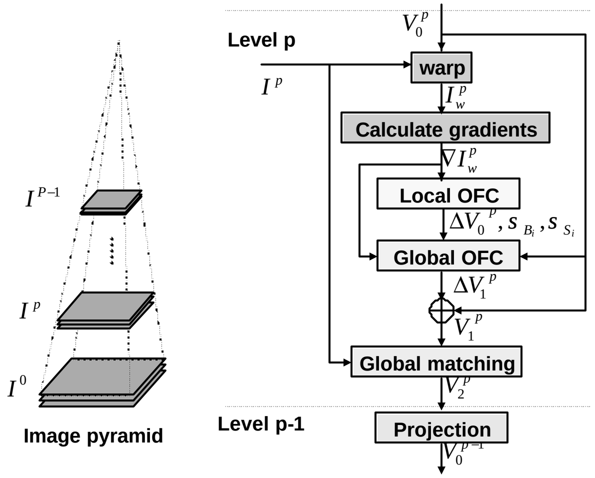
III: Minimizing the Global Energy

- **Given** V_{initial}
- **Calculate** s_{B_s}, s_{S_s}
- **Fastest descent by propagation**
  - Generate candidates: $V_c \in \{V_i, i \in N_s^8; \overline{V_i}\}$
  - Replace V_s by V_c if global energy E drops

Hierarchical Process

- **Handle large motions (>2 pixels/frame)**
- **Limitations:**
  - Sub-sampling, warping and projection errors
  - May become the accuracy bottleneck
- **Step III directly works on the image data and is less sensitive to such errors**

Overall Algorithm



Experiments

Advantages

- **Best of Everything**
  - Local OFC
    - High-quality initial flow estimates
    - Robust local scale estimates
  - Global OFC
    - Improve flow smoothness
  - Global Matching
    - The optimal formulation
    - Correct errors caused by poor gradient quality and hierarchical process
- **Results: fast convergence, high accuracy, simultaneous motion boundary detection**

Quantitative Measures

- **True:** $V_0 = (u_0, v_0)'$ **, estimate:** $V = (u, v)'$
- **Our error measure**

$$e = (|u - u_0|, |v - v_0|)\Big|_{\text{all sites}}$$

  - Cdf curve of e, Average: $\bar{e}$
- **Barron's angular error** [Barron 94]

$$e_{\angle} = \overline{\Delta q}\,(^\circ),\ \Delta q = \arccos\frac{(V_0',1)\cdot(V',1)'}{|(V_0',1)|\cdot|(V',1)|}$$

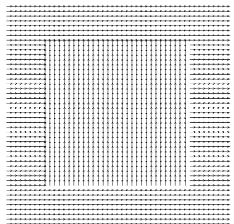
- **Error magnitude:**

$$e_{|\,|} = \overline{|\Delta V|}(\text{pixels}),\ |\Delta V| = |V - V_0|$$

TS: Translating Squares

- **Homebrew, ideal setting, test performance upper bound**

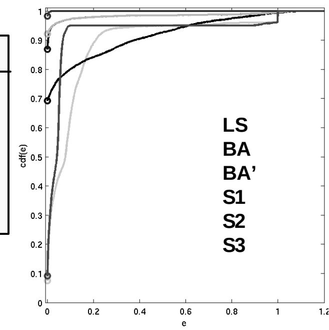
64x64, 1pixel/frame



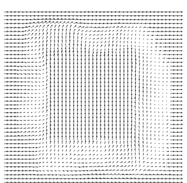
Groundtruth (cropped),
Our estimate looks the same

TS: Quantitative Comparison

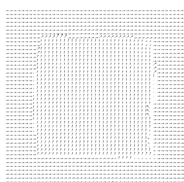
	$e_\angle(^\circ)$	$e_{\lvert\cdot\rvert}(\text{pix})$	$\bar{e}(\text{pix})$
LS	**6.14**	**0.151**	**0.0925**
BA	**8.04**	**0.209**	**0.120**
BA'	**5.88**	**0.149**	**0.0815**
S1	**1.09**	**0.0266**	**0.0180**
S2	**1.09**	**0.0264**	**0.0179**
S3	**1.15e-2**	**3.50e-4**	**2.23e-4**



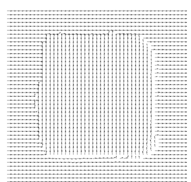
TS: Flow Estimate Plots



LS



BA



S1 (S2 is close)

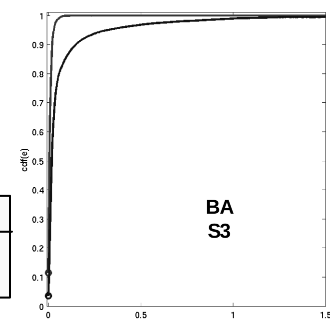
S3 looks the same as the groundtruth.

- S1, S2, S3: results from our Step I, II, III (final)

TT: Translating Tree

150x150 (Barron 94)

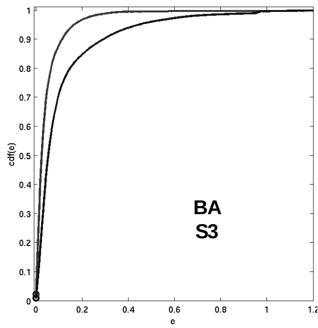
	$e_\angle(^\circ)$	$e_{\lvert\cdot\rvert}(\text{pix})$	$e(\text{pix})$
BA	**2.60**	**0.128**	**0.0724**
S3	**0.248**	**0.0167**	**0.00984**



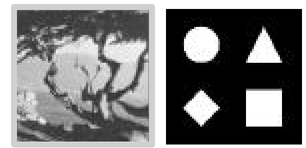
DT: Diverging Tree

150x150 (Barron 94)

	$e_\angle(^\circ)$	$e_{\lvert\bullet\rvert}(\text{pix})$	$e(\text{pix})$
BA	6.36	0.182	0.114
S3	2.60	0.0813	0.0507

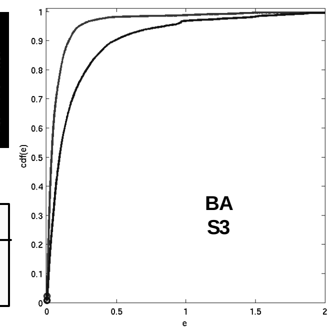


DTTT: Motion Discontinuities



TT + DT + cookie-cutters

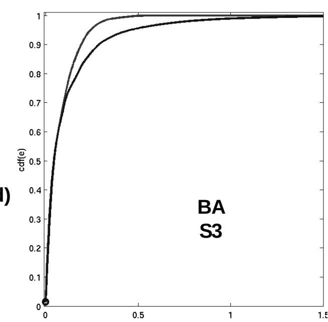
	$e_\angle(^\circ)$	$e_{\lvert\bullet\rvert}(\text{pix})$	$e(\text{pix})$
BA	10.9	0.331	0.204
S3	4.03	0.132	0.0807



YOS: Yosemite Fly-Through

316x252 (Barron, cloud excluded)

	$e_\angle(^\circ)$	$e_{\lvert\bullet\rvert}(\text{pix})$	$\bar{e}(\text{pix})$
BA	2.71	0.185	0.118
S3	1.92	0.120	0.0776

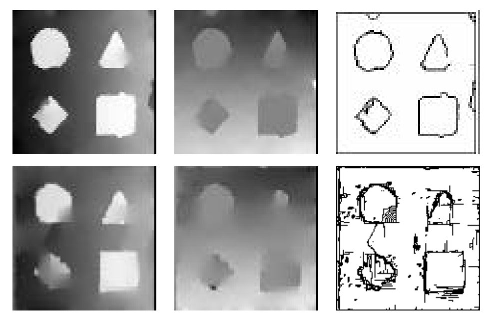


DTTT

- u-, v-components as intensity images

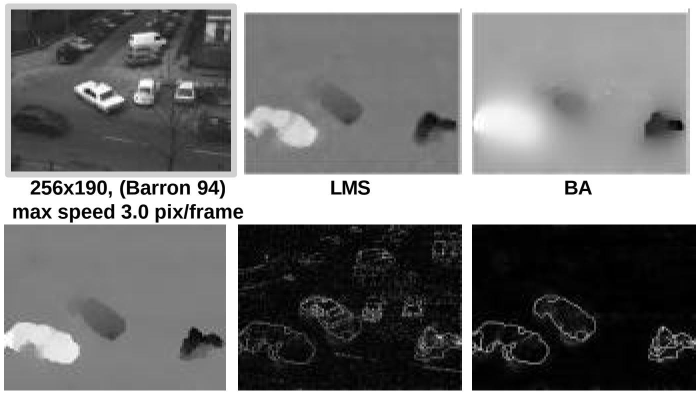
Ours:

BA:

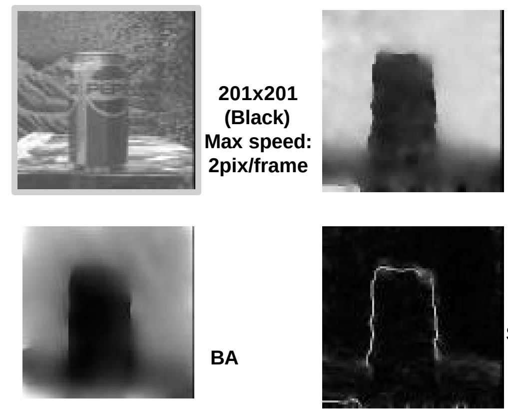


u v Boundary

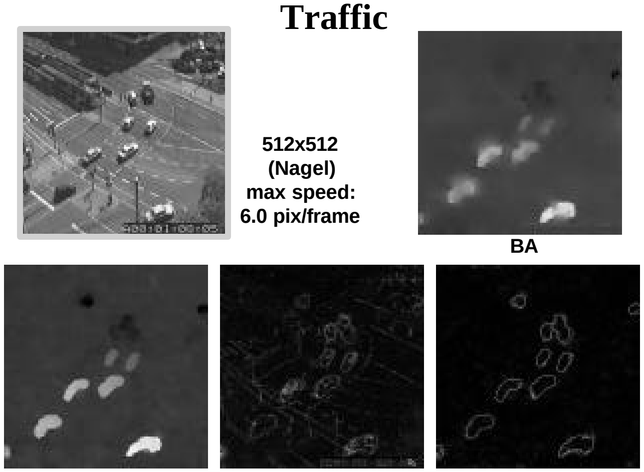
TAXI: Hamburg Taxi



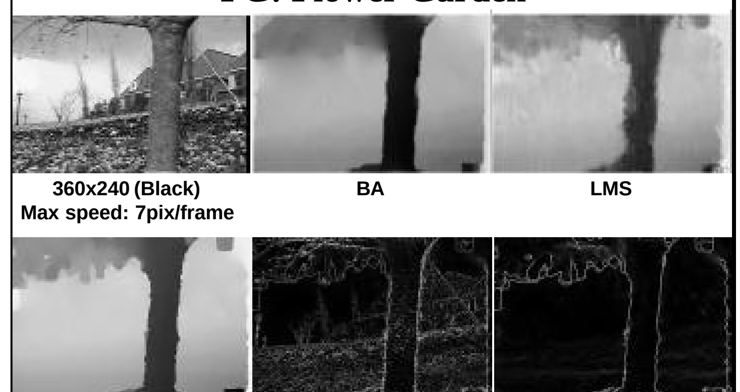
Pepsi Can



Traffic



FG: Flower Garden



Conclusion and Discussion

Contributions (1/2)

- **Formulation**
  - More complete design, minimal parameter tuning
    - Adaptive local scales
    - Strength of two error terms automatically balanced
  - 3-frame matching to avoid visibility problems
- **Solution: 3-step optimization**
  - Robust initial estimates and scales
  - Model parameter self-learning
  - Inherit merits of 3 methods and overcome shortcomings

Contributions (2/2)

- **Results**
  - High accuracy
  - Fast convergence
  - By product: motion boundaries
- **Significance**
  - Foundation for higher-level (model-based) visual motion analysis
  - Methodology applicable to other low-level vision problems

Future Work

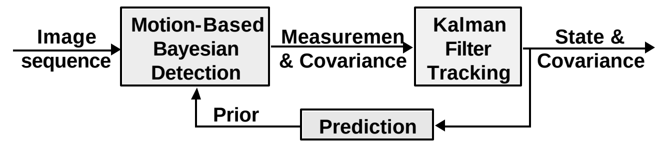
- **Applications**
  - Non-rigid motion estimation (medical, human)
  - Higher-level visual motion analysis
    - Motion segmentation, model selection
    - Occlusion reasoning
    - Layered / contour-based representation
  - Warping w/ discontinuities
- **Refinement**
  - Bayesian belief propagation (BBP)
  - Better global optimization (BBP, Graph cuts etc)

A Motion-Based Bayesian Approach to Aerial Point-Target Detection and Tracking

The Problem

- **UAV See And Avoid System**
- **Point target detection and tracking**

The Algorithm

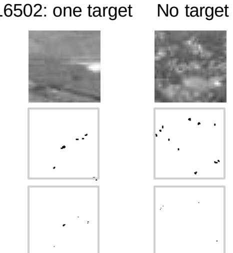


- **State variable: 2D position and velocity**
- **Track initialization, termination and maintenance**

Motion-Based Bayesian Detection

- **Background motion:**
  - Parametric optical flow
- **Object candidates:**
  - Fitting outliers
  - Motion: 3x3 SSD + fitting
- **Independent motion**
  - χ^2 test
- **Bayesian mode**
  - Augment candidate set
  - Validate/update motion

F16502: one target   No target



F16503

Experiments

- **1800-frame data:**
  - One target 1x2-3x3
  - Clutter (ground objects)
  - Camera wobbling
  - Low image quality
- **Results**
  - Target in track since 2nd frame
  - No false detection
  - Error: mean=0.88, sd=0.44 pixels
- **Show demo**

Publications

Patent Pending

- "Document Image Matching and Annotation Lifting", with Marshall Bern and David Goldberg, *US Patent Application* (filed by Xerox Corp.), September 2001.

Book Chapter

- 1. Ming Ye and Robert M. Haralick, "Image Flow Estimation Using Facet Model and Covariance Propagation", *Vision Interface : Real World Applications of Computer Vision (Machine Perception and Artificial Intelligence Book Series Vol. 35)*, (Ed.) M. Cherietand Y. H. Yang, World Scientific Pub Co., pp. 209-241, Jan. 2000.

Submission/Preparation

- 2. Ming Ye, Robert M. Haralick and Linda G. Shapiro, "Estimating Piecewise-Smooth Optical Flow with Global Matching and Graduated Optimization", (submitted to) *IEEE Trans. on Pattern Analysis and Machine Intelligence*, Feb. 2002.
- 3. "A motion-based Bayesian approach to aerial point target detection and tracking" (in preparation).

Conference Papers

- 4. Ming Ye, Robert M. Haralick and Linda G. Shapiro, " Estimating Optical flow Using a Global Matching Formulation and Graduated Optimization ", (accepted to) *I6th International Conference on Image Processing*, 2002.
- 5. Ming Ye and Robert M. Haralick, "Local Gradient Global Matching Piecewise-Smooth Optical Flow", *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, Vol. 2, pp. 712-717, 2001.
- 6. Ming Ye, Marshall Bern and David Goldberg, " Document Image Matching and Annotation Lifting", *Proc. International Conference on Document Analysis and Recognition*, pp. 753-760, 2001.
- 7. Ming Ye and Robert M. Haralick, "Two-Stage Robust Optical Flow Estimation", *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, Vol. 2, pp. 623-8, 2000.
- 8. Ming Ye and Robert M. Haralick, "Optical Flow From A Least-Trimmed Squares Based Adaptive Approach", *Proc. 15th International Conference on Pattern Recognition*, Vol. 3, pp. 1052-1055, 2000.
- 9. S. Aksoy, M. Ye, M. Schauf, M. Song, Y. Wang, R. M. Haralick, J. R. Parker, J. Pivovarov, D. Royko, S. Sun and S. Farneback, "Algorithm Performance Contest", *Proc. 15th International Conference on Pattern Recognition*, Vol. 4, pp. 870-876, 2000. ICPR'00
- 10. Ming Ye and Robert M. Haralick, "Image Flow Estimation Using Facet Model and Covariance Propagation", *Proc. Vision Interface'98*, pp. 51-58, 1998.