16:332:570 ROBUST COMPUTER VISION

Spring 2013

Description. The goal of this course is to provide a set of versatile tools for solving general computer vision problems. We will focus on the mathematical/statistical foundations and not on some particular application. Robust estimators, which can reliably recover models under corruption from outliers, will be also discussed. The students should be familiar with the basic concepts of linear algebra, random processes and should have already taken an introductory course in computer vision. Knowledge of MATLAB is required for the assignments and projects.

Webpage. `http://cronos.rutgers.edu/~meer/TEACH/570.html`

Schedule. Tuesday 3:20–6:20 pm, CoRE 538.

Instructor. Peter Meer
CoRE 519. Ph: (848) 445-5243. E-mail: meer@cronos.rutgers.edu
Office hours: During the day of the lecture, or by appointment.

Textbook. There is no textbook. The paper *Robust techniques for computer vision* (RTCVSecx.x), will be used in a few lectures. Second part of this paper is already old and newer routines, which we will study, replaced what was written in 2003. Other papers and dedicated webpages are at the specific lecture.

Lectures

Lecture 1. *Human vs. computer vision.*
The human visual system functions in a completely different way then computer vision algorithm try to do. For example, the world of optical illusions are probably not mistakes of the visual system, as we will show. Computer vision often works with the 2D projections of the 3D world through a noneuclidean projections. How this transformation was learned around 1400 by the artists. Video: "*Masters of Illusion*." This course will be (mostly) about state-of-the-art routines which solves either nonrobustly or robustly different aspects of the 2D images.

Lecture 2. *Review of some linear algebra we will need.*
Vector calculus. Jacobian and Hessian matrix. Matrix calculus. Block matrix multiplication. Eigenvalues and eigenvectors. Normal matrices. Quadratic forms. Antisymmetric matrices in R^3. 3D rotation matrices. Singular value decomposition (SVD). Linear mapping. Pseudoinverse. Orthogonal projections of matrices. Approximation theorem. Effective rank. ****Assignment No.1.*

Lecture 3. *Quiz No.1. What simple bottom-up operations can achieve.*
Color vision in the human visual system. Smoothed differentiation filters. The confidence in the presence of an edge, but not its magnitude, is an independent measure. The two measures together give a more precise edge detection. What can be achieved in a segmentation with solely bottom-up approach? We add together the gradient and confidence images without thresholds or weights and built the segmented regions. ****Assignment No.2.*

References. *Edge detection with embedded confidence.* Edge detection as a 2D problem. A short introduction to bottom-up segmentation. The EDISON code.

Lecture 4. *Homoscedastic and heteroscedastic models in computer vision.*
Elements of a models are in general heteroscedastic. Epipolar relation. Nonrobust and robust objective functions: TLS, LAD, LMedS, GPbM, M-estimator, RANSAC. ****Assignment No.3.*
References. RTCVSec.4.2.1 and 4.2.2.

Lecture 5. *Quiz No.2. Taxonomy of estimation. Linear errors-in-variables (EIV) regression.*
Errors-in-variables vs. traditional regression. Location estimation. What is the algebraic distance and the difference between algebraic and geometric distances. Three different ways how to do the EIV regression and the solution with SVD. Total least squares (TLS) estimator and ordinary least squares. ****Assignment No.4.*
References. RTCVSec.4.2.5, 4.2.6 and 4.4.1.

Lecture 6. *Generalized total least squares. Example: 3D similarity estimation.*
The generalized total least squares. Solving generalized symmetric eigenproblems with GSVD. Change of rotation in Euclidean bases. An example of TLS: 3D similarity transformation between two matched 3D point patterns. ****Assignment No.5.*
References. Generalized total least squares. *Least-squares estimation of transformation parameters between two point patterns.* It is more complicated than it appears.

Lecture 7. *Quiz No.3. M-estimator. Simplex direct search. RANSAC.*
The redescending M-estimator is a total least squares estimate done iteratively with weights. Structured outliers fail for larger sigmas. Theory of simplex which is not the simplex algorithm of linear optimization. RANSAC for regression. ****Assignment No.6.*
References. RTCVSec4.2.7, 4.4.2 and 4.4.7.

Lecture 8. *Mean shift for segmentation.*
A global parameter can be recovered by simple mode detection. Kernel density estimation with squared Mahalanobis distances. Adaptive mean shift. Synergetic image segmentation. The EDISON segmentation window. Introduction to nonlinear mean shift for different groups from the Riemannian manifold. ****Midterm project.*
References. RTCVSec4.3.1-4.3.3. *Mean shift: A robust approach toward feature space analysis.* Segments into piecewise (quasi)-constant planes. *Synergism in low level vision.* What happens is you fuse mean shift and edge detection.
Supplementary Reference. *Nonlinear mean shift over Riemannian manifolds.* More complex mean shift on groups.

Lecture 9. *Quiz No.4. Generalized Projection-Based M-Estimator (GPbM).*
The algorithm has three distinct stages: scale estimation, robust model estimation, and inlier/outlier dichotomy. The estimator iteratively determines one structure after the other. ****Assignment No.7.*
References. *Generalized Projection-Based M-Estimator.* A robust estimator without any user supplied parameters. The gpbM code.
Supplementary Reference. *Conjugate gradient on Grassmann manifolds for robust subspace estimation.* Local optimization further improves the score.

Lecture 10. *Mean shift for tracking.*
The Bhattacharyya coefficient. A few simple extensions of tracking. An introduction into Kalman filtering and a simple example used in tracking. Videos of mean shift tracking. ****Assignment No.8.*
References. RTCVSec4.3.4. *Kernel-based object tracking.* Currently one of the best algorithms for tracking. A MATLAB version of the tracking program.

Lecture 11. *Quiz No.5. What can be done with some of the learned algorithms.*
Harris corner detector can be used in projective matching with large image deformations. Planar homography between two planes and its block inverse transform. Optical flow-based registration and matching color distributions. The joint estimation exceeds both individual methods. ****Assignment No.9.*
References. *Point matching under large image deformations and illumination changes.* A nonrobust projective point matcher different from the affine matcher. The matching code.

Lecture 12. *Mean shift clustering in kernel space.*
The advantages of clustering in the kernel space with similarity and dissimilarity point pairs. Learning using linear projections and by logarithm-determinant Bregman divergence. Clustering algorithm with only a few supervised pairs. ****Assignment No.10.*
Reference. *Semi-supervised kernel mean shift clustering.* A novel semi-supervised clustering procedures.

Lecture 13. *Quiz No.6. Nonlinear least squares estimation.*
First-order nonlinear LS estimation. Estimators: gradient descent, Newton's method, Gauss-Newton's method, Levenberg-Marquardt method. The sparse Levenberg-Marquardt algorithm in computer vision. Example for homography. ****Final project.*
Reference. The Levenberg-Marquardt algorithm.
Supplementary Reference. *Estimation of nonlinear errors-in-variables models for computer vision applications.* An other nonrobust method which works well in a lot of conditions.

Lecture 14. *Bootstrap. What can and what cannot be achieved today in computer vision.*
A short introduction to bootstrap which is a powerful tool. How to apply to heteroscedastic regression. Example: direct camera calibration.
References. *Input guided performance evaluation.* Examples of bootstrap in computer vision. *Are we making real progress in computer vision today?* What do you think?

Grading. Homeworks (35%). Quizzes (15%). Midterm project (25%). Final project (25%).