CSE 252B: Computer Vision II, Winter 2014 – Assignment 1

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Due date: Tuesday, January 28, 2014

1. The line in 3D defined by the join of the points $\mathbf{X}_1$ and $\mathbf{X}_2$ can be represented as a Plücker matrix $\mathtt{L} = \mathbf{X}_1\mathbf{X}_2^\top - \mathbf{X}_2\mathbf{X}_1^\top$ or pencil of lines $\mathbf{X}(\lambda) = \lambda\mathbf{X}_1 + (1-\lambda)\mathbf{X}_2$. The line intersects the plane $\boldsymbol{\pi}$ at the point $\mathbf{X}_{\mathtt{L}} = \mathtt{L}\boldsymbol{\pi}$ or $\mathbf{X}_{\mathbf{X}(\lambda)}$, where $\mathbf{X}_{\mathbf{X}(\lambda)}^\top\boldsymbol{\pi} = 0$. Show that $\mathbf{X}_{\mathtt{L}}$ is equal to $\mathbf{X}_{\mathbf{X}(\lambda)}$ up to scale.

2. Automatic estimation of the planar projective transformation $\mathtt{H}$

   (a) Download input images
   `http://vision.ucsd.edu/~bochoa/cse252b-wi14/price_center20.JPG`
   and
   `http://vision.ucsd.edu/~bochoa/cse252b-wi14/price_center21.JPG`

   (b) Feature detection. For each input image, calculate an image where each pixel value is the minor eigenvalue of the gradient matrix

   $$\mathtt{N} = \begin{bmatrix} \sum_w I_x^2 & \sum_w I_x I_y \\ \sum_w I_x I_y & \sum_w I_y^2 \end{bmatrix}$$

   where w is the window about the pixel, and I_x and I_y are the gradient images in the x and y direction, respectively. Set resulting values that are below a specified threshold value to zero (hint: calculating the mean instead of the sum in $\mathtt{N}$ allows for adjusting the size of the window without changing the threshold value). Apply an operation that suppresses (sets to 0) local nonmaximum pixel values in the minor eigenvalue image. For resulting nonzero pixel values, determine the subpixel feature coordinate using the Förstner corner point operator.

   (c) Feature matching. Determine the set of putative feature correspondences by performing a brute-force search for the greatest normalized cross correlation value between features in each of the images. Only allow matches that are above a specified threshold value (hint: calculating the correlation coefficient (in the range [-1, 1]) allows for adjusting the size of the matching window without changing the threshold value). Consider constraining the search to coordinates within a proximity of the feature coordinates.

   (d) Outlier rejection. Determine the set of inlier point correspondences using the M-estimator Sample Consensus (MSAC) algorithm. Use the Sampson error as a first order approximation to the geometric error.

   (e) Linear estimation. For the set of inlier correspondences, estimate the projective transformation $\mathtt{H}_{\mathrm{DLT}}$ using the direct linear transformation (DLT) algorithm (with data normalization).

   (f) Nonlinear estimation. Use $\mathtt{H}_{\mathrm{DLT}}$ as an initial estimate to an iterative estimation method, specifically the Levenberg-Marquardt algorithm, to determine the

Maximum Likelihood estimate of the projective transformation H that minimizes reprojection error in both images. List the initial cost (i.e., the (weighted) reprojection error) and the cost at the end of each iteration.

(g) Figures. Produce a pair of figures for each of the above steps. For feature detection, draw a square about the detected feature where the size of the square is the size of the window in the gradient matrix N. For feature correspondences, draw a square that is the size of the matching window and a line segment from the feature to the coordinates of the corresponding feature in the other image (see Fig. 4.9 in the Hartley & Zisserman book as an example).