

## VAN – Homework #2

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### Basic probability and Bayesian Inference

1)

$$x \sim N(\mu, \Sigma)$$

$$\Lambda = \Sigma^{-1}; \quad \eta = \Lambda\mu$$

$$\begin{aligned} p(x) &= \frac{1}{\sqrt{|2\pi\Sigma|}} \exp\left(-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu)\right) \\ &= \frac{1}{\sqrt{|2\pi\Lambda^{-1}|}} \exp\left(-\frac{1}{2}(x-\Lambda^{-1}\eta)^T \Lambda(x-\Lambda^{-1}\eta)\right) \\ &= \frac{1}{\sqrt{|2\pi\Lambda^{-1}|}} \exp\left(-\frac{1}{2}(x-\Lambda^{-1}\eta)^T (\Lambda x - \eta)\right) \\ &= \frac{1}{\sqrt{|2\pi\Lambda^{-1}|}} \exp\left(-\frac{1}{2}(x^T \Lambda x - x^T \eta - \eta^T x + \eta^T \Lambda^{-1} \eta)\right) \\ &= \frac{1}{\sqrt{|2\pi\Lambda^{-1}|}} \exp\left(-\frac{1}{2}(\eta^T \Lambda^{-1} \eta)\right) \exp\left(-\frac{1}{2}x^T \Lambda x + \eta^T x\right) = N^{-1}(\eta, \Lambda) \end{aligned}$$

2)

$$z = h(x) + v, \quad v \sim N(0, \Sigma_v)$$

$$x \sim N(\hat{x}_0, \Sigma_0)$$

a.

$$\begin{aligned} p(x) &= \frac{1}{\sqrt{|2\pi\Sigma_0|}} \exp\left(-\frac{1}{2}\|x - \hat{x}_0\|_{\Sigma_0}^2\right) \\ p(z|x) &= \frac{1}{\sqrt{|2\pi\Sigma_v|}} \exp\left(-\frac{1}{2}\|z - h(x)\|_{\Sigma_v}^2\right) \end{aligned}$$

b.

you were asked to express the pdf  
in terms of prior & observation models.....  
[-1]

$$\begin{aligned} p(x|z_1) &= \frac{p(z_1|x)p(x)}{p(z_1)} = \eta p(z_1|x)p(x) \\ &= \eta \frac{1}{\sqrt{|2\pi\Sigma_v|}\sqrt{|2\pi\Sigma_0|}} \exp\left(-\frac{1}{2}(\|z_1 - h(x)\|_{\Sigma_v}^2 + \|x - \hat{x}_0\|_{\Sigma_0}^2)\right) \end{aligned}$$

c.

$$\begin{aligned} x^* &= \arg \max_x p(x|z_1) = \arg \min_x [-\log p(x|z_1)] \\ &= \arg \min_x [-\log p(z_1|x) - \log p(x)] = \arg \min_x J(x) \end{aligned}$$

$$x = \tilde{x} + \Delta x$$

First iteration we choose:

$$\tilde{x} = \hat{x}_0$$

$$z - h(\tilde{x} + \Delta x) = z - h(\tilde{x}) + H\Delta x, \quad H = \left[ \frac{dh}{dx} h \right]_{\tilde{x}}$$

$$\Delta x^* = \arg \min_{\Delta x} J(\tilde{x} + \Delta x)$$

Where:

$$\begin{aligned} J(\tilde{x} + \Delta x) &= \left\| \Sigma_0^{-\frac{1}{2}} (\Delta x + \tilde{x} - \hat{x}_0) \right\|^2 + \left\| \Sigma_v^{-\frac{1}{2}} (H\Delta x + h(\tilde{x}) - z_1) \right\|^2 \\ &= \left\| \begin{pmatrix} \overbrace{\Sigma_0^{-\frac{1}{2}}}^A \\ \underbrace{\Sigma_v^{-\frac{1}{2}} H}_b \end{pmatrix} x - \begin{pmatrix} \overbrace{\Sigma_0^{-\frac{1}{2}} (\hat{x}_0 - \tilde{x})}^b \\ \underbrace{\Sigma_0^{-\frac{1}{2}} (z_1 - h(\tilde{x}))}_b \end{pmatrix} \right\|^2 = \|Ax - b\|^2 \\ &= \left\| (A^T A)^{\frac{1}{2}} \left( x - (A^T A)^{-\frac{1}{2}} b \right) \right\|^2 = \left\| \left( x - (A^T A)^{-\frac{1}{2}} b \right) \right\|_{(A^T A)^{-1}}^2 \end{aligned}$$

$$\Delta x^* = \arg \min_{\Delta x} J(\tilde{x} + \Delta x) = \arg \min_{\Delta x} \|Ax - b\|^2$$

$$\Sigma_1 = (A^T A)^{-1}$$

$$A\Delta x^* - b = 0$$

$$\Delta x^* = (A^T A)^{-1} A^T b$$

until convergence

$$\tilde{x} + \Delta x^* \rightarrow \tilde{x}$$

After convergence

$$p(x|z_1) = N(\tilde{x}, (A^T A)^{-1})$$

d.

$$p(x|z_1, z_2) = \frac{p(z_2|x, z_1)p(x|z_1)}{p(z_2|z_1)} = \frac{p(z_2|x)p(x|z_1)}{p(z_2|z_1)} = \eta p(z_2|x)p(x|z_1)$$

$$\begin{aligned} J(\tilde{x} + \Delta x) &= \left\| \Sigma_1^{-\frac{1}{2}} (\Delta x + \tilde{x} - \hat{x}_1) \right\|^2 + \left\| \Sigma_v^{-\frac{1}{2}} (H\Delta x + h(\tilde{x}) - z_2) \right\|^2 \\ &= \left\| \begin{pmatrix} \overbrace{\Sigma_1^{-\frac{1}{2}}}^A \\ \underbrace{\Sigma_v^{-\frac{1}{2}} H}_b \end{pmatrix} x - \begin{pmatrix} \overbrace{\Sigma_0^{-\frac{1}{2}} (\hat{x}_1 - \tilde{x})}^b \\ \underbrace{\Sigma_0^{-\frac{1}{2}} (z_2 - h(\tilde{x}))}_b \end{pmatrix} \right\|^2 \end{aligned}$$

$$\Delta x^* = \arg \min_{\Delta x} J(\tilde{x} + \Delta x) = \arg \min_{\Delta x} \|Ax - b\|^2$$

$$\Sigma_1 = (A^T A)^{-1}$$

$$A\Delta x^* - b = 0$$

$$\Delta x^* = (A^T A)^{-1} A^T b$$

until convergence

$$\tilde{x} + \Delta x \rightarrow \tilde{x}$$

After convergence

$$p(x|z_1, z_2) = N(\tilde{x}, (A^T A)^{-1})$$

3)

$$x_{k+1} = f(x_k, u_k) + w_k, \quad w_k \sim N(0, \Sigma_w)$$

$$z = h(x_k) + v, \quad v \sim N(0, \Sigma_v)$$

a.

$$p(x_k | x_{k-1}, u_{k-1}) = \frac{1}{\sqrt{|2\pi\Sigma_w|}} \exp\left(-\frac{1}{2}\|x_k - f(x_{k-1}, u_{k-1})\|_{\Sigma_w}^2\right)$$

b.

$$\begin{aligned} p(x_1 | z_1, u_0) &= \frac{p(z_1 | x_1, u_0) p(x_1 | u_0)}{p(z_1 | u_0)} \\ &= \frac{p(z_1 | x_1) p(x_1 | x_0, u_0) p(x_0)}{p(z_1 | u_0)} \sim p(z_1 | x_1) p(x_1 | x_0, u_0) p(x_0) \end{aligned}$$

incorrect & incomplete [-2]  
incorrect since you are missing an integral over  $x_0$   
since you added it to the expression  
incomplete since you were asked to express the pdf  
in terms of prior motion & observation models.....

c.

$$\begin{aligned} p(x_k | u_{0:k-1}, z_{1:k}) &\stackrel{\text{bayes rule}}{=} \frac{p(z_k | x_k, u_{0:k-1}, z_{1:k-1}) p(x_k | u_{0:k-1}, z_{1:k-1})}{p(z_k | u_{0:k-1}, z_{1:k-1})} \\ &\stackrel{\text{Makrov assumption}}{=} \eta \frac{\overbrace{p(z_k | x_k)}^{\text{Marginalization}} p(x_k | u_{0:k-1}, z_{1:k-1})}{\text{Marginalization}} \\ &= \eta p(z_k | x_k) \int p(x_k, x_{k-1} | u_{0:k-1}, z_{1:k-1}) \end{aligned}$$

$$\begin{aligned} &\stackrel{\text{chain rule}}{=} \eta p(z_k | x_k) \int p(x_k | x_{k-1}, u_{0:k-1}, z_{1:k-1}) p(x_{k-1} | u_{0:k-1}, z_{1:k-1}) \\ &= \eta p(z_k | x_k) \int \overbrace{p(x_k | u_{0:k-1}, z_{1:k-1})}^{\text{Makrov assumption}} p(x_{k-1} | u_{0:k-1}, z_{1:k-1}) \end{aligned}$$

$$p(x_k | u_{0:k-1}, z_{1:k}) \sim \overbrace{p(x_{k-1} | u_{0:n-2}, z_{1:k-1})}^{\text{posteriori previous}} \overbrace{p(z_k | x_k)}^{\text{observation}} \overbrace{p(x_k | x_{k-1}, u_{k-1})}^{\text{motion}}$$

$$J(x) = \left\| \Sigma_{prv}^{-\frac{1}{2}} (x_k - \hat{x}_{prv}) \right\|^2 + \left\| \Sigma_v^{-\frac{1}{2}} (h(x_k) - z_k) \right\|^2 + \left\| \Sigma_w^{-\frac{1}{2}} (x_k - f(x_{k-1}, u_{k-1})) \right\|^2$$

$$x_k = \tilde{x} + \Delta x$$

$$\begin{aligned} J(\bar{x} + \Delta x) &= \left\| \Sigma_{prv}^{-\frac{1}{2}} (\Delta x + \tilde{x} - \hat{x}_{prv}) \right\|^2 + \left\| \Sigma_v^{-\frac{1}{2}} (H \Delta x + h(\tilde{x}) - z_k) \right\|^2 \\ &\quad + \left\| \Sigma_w^{-\frac{1}{2}} (\Delta x + \tilde{x} - f(x_{k-1}, u_{k-1})) \right\|^2 \\ &= \left\| \overbrace{\begin{pmatrix} \Sigma_{prv}^{-\frac{1}{2}} \\ \Sigma_v^{-\frac{1}{2}} H \\ \Sigma_w^{-\frac{1}{2}} \end{pmatrix}}^A x - \overbrace{\begin{pmatrix} \Sigma_{prv}^{-\frac{1}{2}} (\tilde{x} - \hat{x}_{prv}) \\ \Sigma_v^{-\frac{1}{2}} (h(\tilde{x}) - z_k) \\ \Sigma_w^{-\frac{1}{2}} (\tilde{x} - f(x_{k-1}, u_{k-1})) \end{pmatrix}}^b \right\|^2 \end{aligned}$$

$$\Delta x^* = \arg \max_{\Delta x} p(x_k | u_{0:k-1}, z_{1:k}) = \arg \min_{\Delta x} J(\bar{x} + \Delta x) = \arg \min_{\Delta x} \|Ax - b\|^2$$

$$\Delta x^* = (A^T A)^{-1} A^T b$$

until convergence

$$\tilde{x} + \Delta x^* \rightarrow \tilde{x}$$

After convergence

$$p(x_k | u_{0:k-1}, z_{1:k}) = N(\tilde{x}, (A^T A)^{-1})$$

d.

$$p(x_{0:1} | u_0, z_1) = N(\hat{x}_{0:1}, \Sigma_{0:1}) = N^{-1}(\hat{\eta}_{0:1}, I_{0:1})$$

$$\Sigma_{0:1} = \begin{bmatrix} \Sigma_{00} & \Sigma_{01} \\ \Sigma_{01}^T & \Sigma_{11} \end{bmatrix}$$

what about dimensions?  
[-1]

$$I_{0:1} = \begin{bmatrix} I_{00} & I_{01} \\ I_{01}^T & I_{11} \end{bmatrix}$$

covariance and information from Marginalization:

$$p(x_1 | u_0, z_1) = N(\hat{x}_1, \Sigma_{11}) = N^{-1}(\eta_1 - I_{01}^T I_{00}^{-1} \eta_0, I_{11} - I_{01}^T I_{00}^{-1} I_{01})$$

## Hands-on Exercises

1.

(a)

$$P = K [ R \ t ] =$$

$$\begin{pmatrix} ax & 0 & 0 & u0 \\ 0 & ay & 0 & v0 \\ 0 & 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} R1 & R2 & R3 & t1 \\ R4 & R5 & R6 & t2 \\ R7 & R8 & R9 & t3 \\ 0 & 0 & 0 & 1 \end{pmatrix} =$$

$$\begin{pmatrix} 480 & 0 & 0 & 320 \\ 0 & 480 & 0 & 270 \\ 0 & 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} 0.5363 & -0.8440 & 0 & -451.2459 \\ 0.8440 & 0.5363 & 0 & 257.0322 \\ 0 & 0 & 1 & 400 \\ 0 & 0 & 0 & 1 \end{pmatrix} =$$

$$1.0e+05 \begin{pmatrix} 0.0026 & -0.0041 & 0 & -2.1628 \\ 0.0041 & 0.0026 & 0 & 1.2365 \\ 0 & 0 & 0 & 0.0040 \end{pmatrix}$$

(b)

$$(x, y, z)^T = P X G = K [ R \ t ] X G \rightarrow (u, v)^T = (x_z, y_z)^T$$

function [u v] = project3DPointToPixels(K, R, t, X)

Rt = [R(1,1) R(1,2) R(1,3) t(1); R(2,1) R(2,2) R(2,3) t(2); R(3,1) R(3,2) R(3,3) t(3)];

P = (K \* Rt);

projected = P \* X;

u = (projected(1) / projected(3));

v = (projected(2) / projected(3));

end

K = [480 0 320; 0 480 270; 0 0 1];

R = [0.5363 -0.8440 0; 0.8440 0.5363 0; 0 0 1];

t = [-451.2459 257.0322 400];

X = [350; -250; -35; 1];

[u v] = project3DPointToPixels(K, R, t, X)

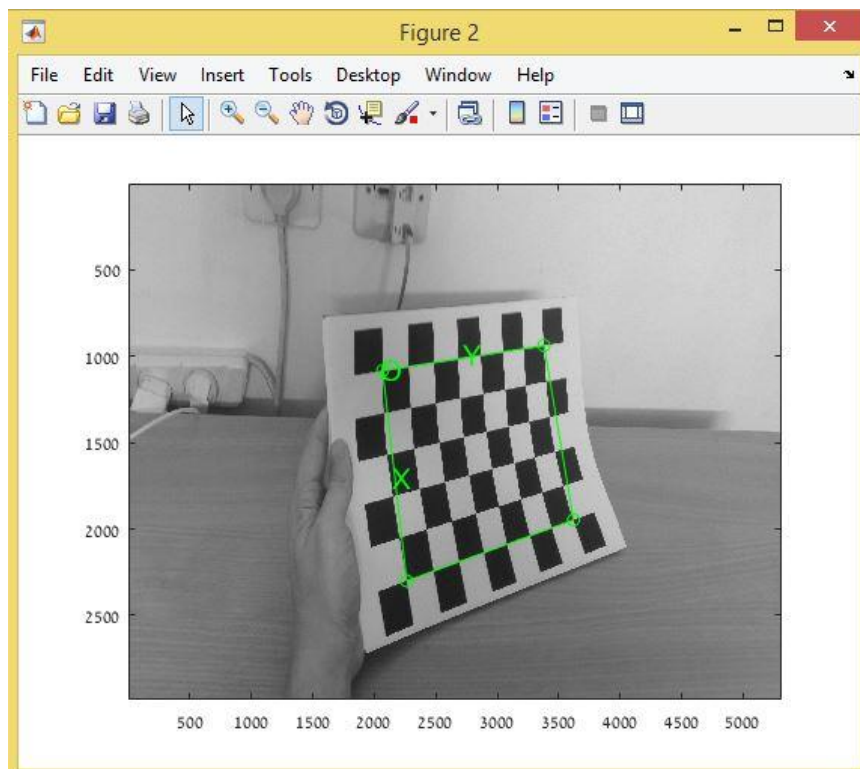
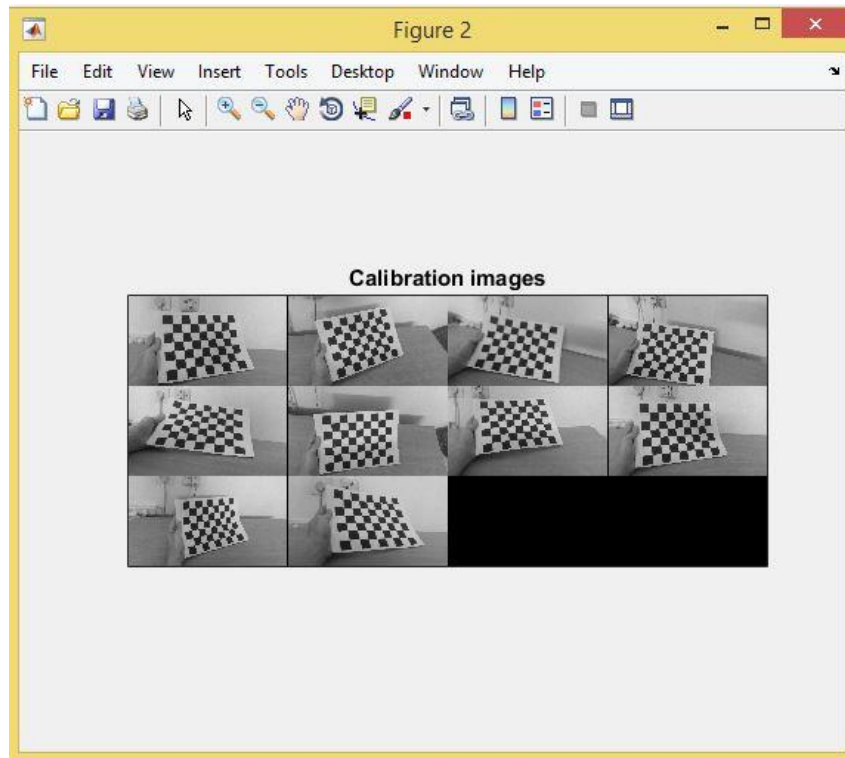
(c)

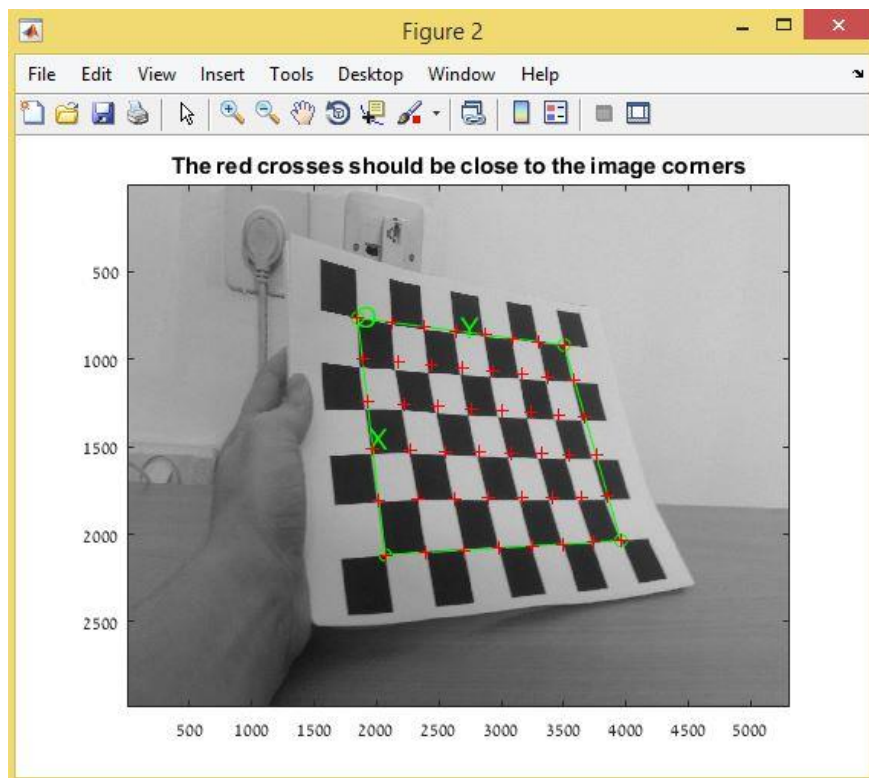
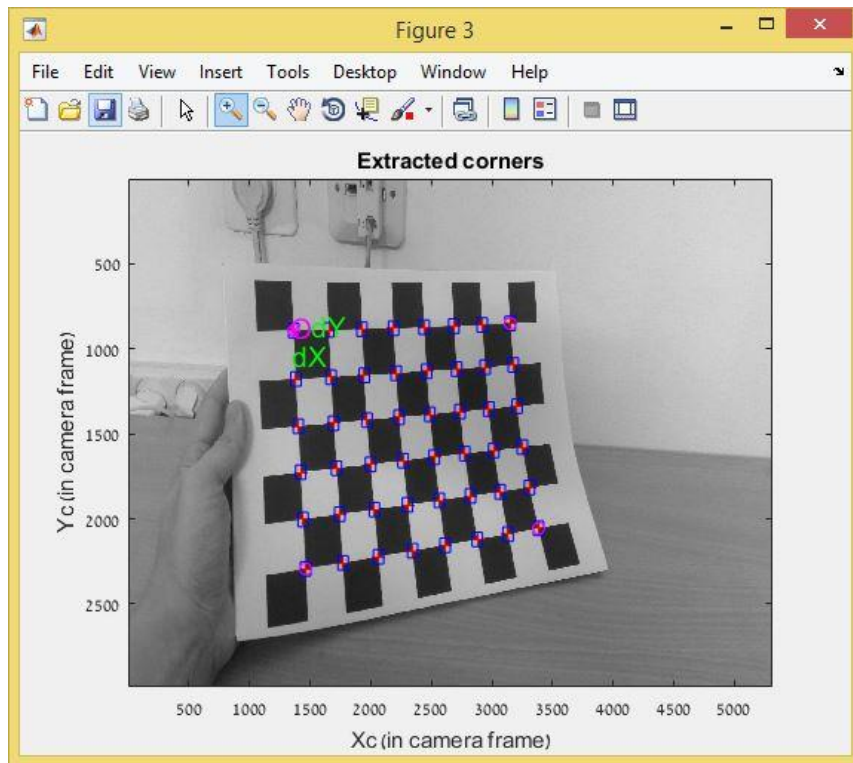
and what about writing your results?

[-5]

$\text{norm}([u \ v] - [241.5 \ 169]) = 651.2363$   
incorrect  
[-3]

2)





```
Command Window

Aspect ratio optimized (est_aspect_ratio = 1) -> Both components of fo are estimated (DEFAULT).
Principal point optimized (center_optim=1) - (DEFAULT). To reject principal point, set center_optim=0
Skew not optimized (est_alpha=0) - (DEFAULT)
Distortion not fully estimated (defined by the variable est_dist):
Sixth order distortion not estimated (est_dist(5)=0) - (DEFAULT) .
Initialization of the principal point at the center of the image.
Initialization of the intrinsic parameters using the vanishing points of planar patterns.
Initialization of the intrinsic parameters - Number of images: 10

Calibration parameters after initialization:

Focal length:      fu = [ 4999.58946  4999.58946 ]
Principal point:   cu = [ 2455.50000  1499.50000 ]
Skew:              alpha_u = [ 0.00000 ] -> angle of pixel = 90.00000 degrees
Distortion:        kd = [ 0.00000  0.00000  0.00000  0.00000  0.00000 ]

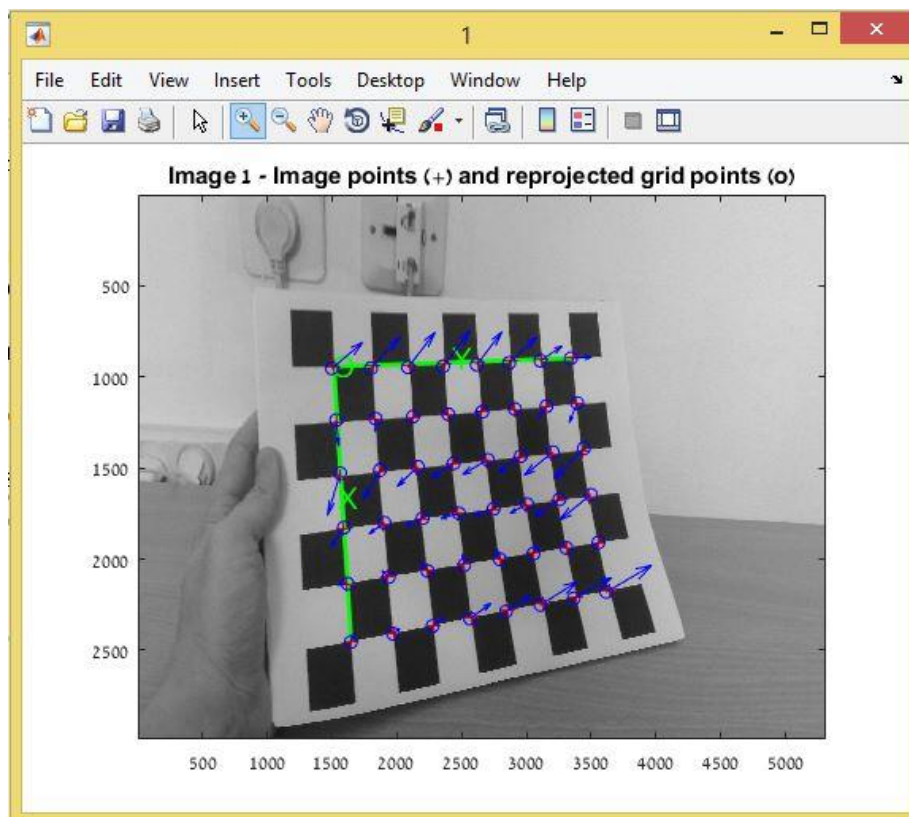
Main calibration optimization procedure - Number of images: 10
Gradient descent iterations: 1...2...3...4...5...6...7...8...9...10...11...12...13...14...15...16...17...18...19...20...21...22...23...24...25...26...27...28...29...30...done
Estimation of uncertainties...done

Calibration results after optimization (with uncertainties):

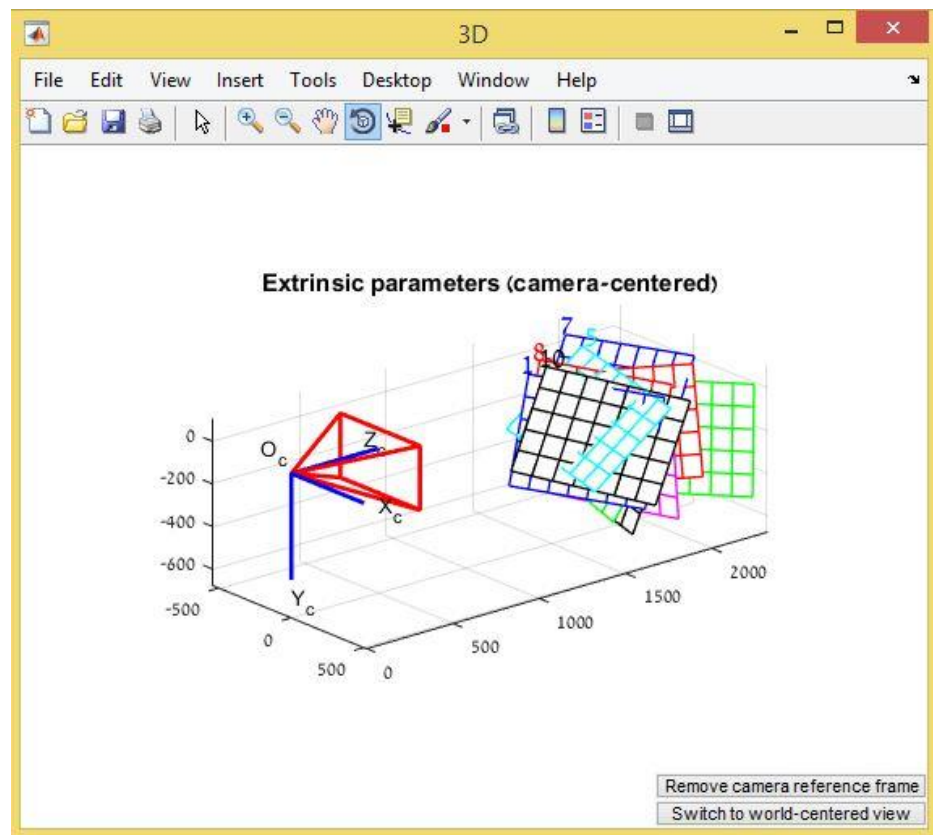
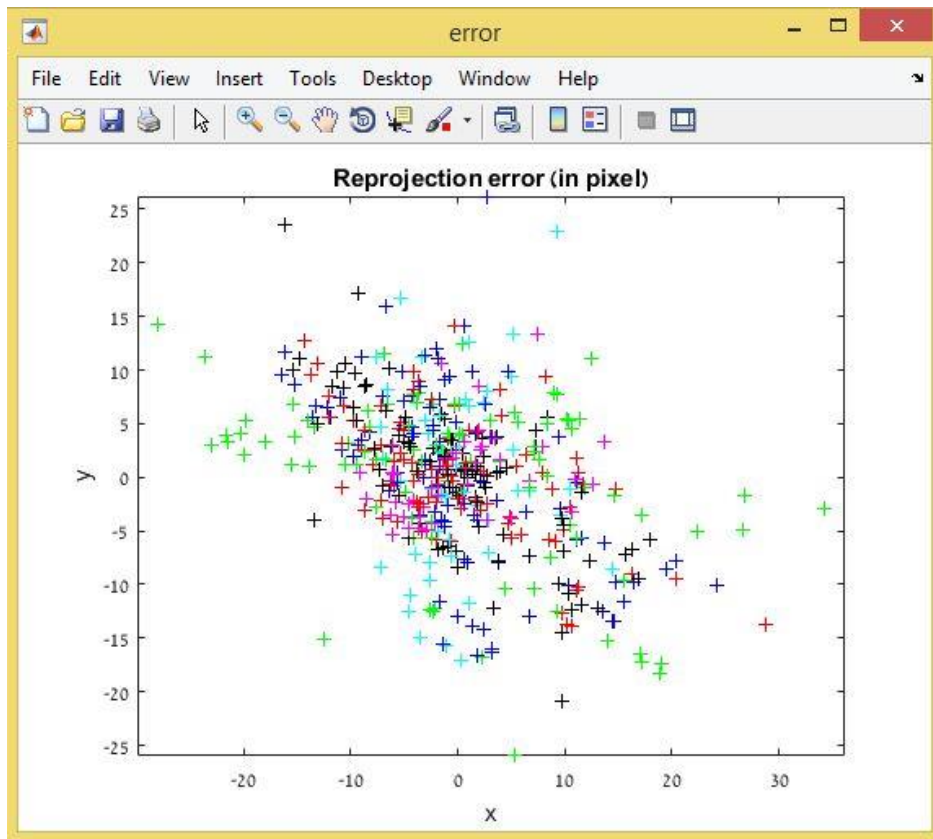
Focal length:      fu = [ 4851.53764  4956.86251 ] +/- [ 326.43008  392.43450 ]
Principal point:   cu = [ 2512.87444  922.34861 ] +/- [ 191.14057  294.40907 ]
Skew:              alpha_u = [ 0.00000 ] +/- [ 0.00000 ] -> angle of pixel skew = 90.00000 +/- 0.00000 degrees
Distortion:        kd = [ 0.28791  0.05202  -0.08281  -0.01321  0.00000 ] +/- [ 0.17487  0.79740  0.03016  0.01769  0.00000 ]
Pixel error:       mrr = [ 8.45466  7.17735 ]

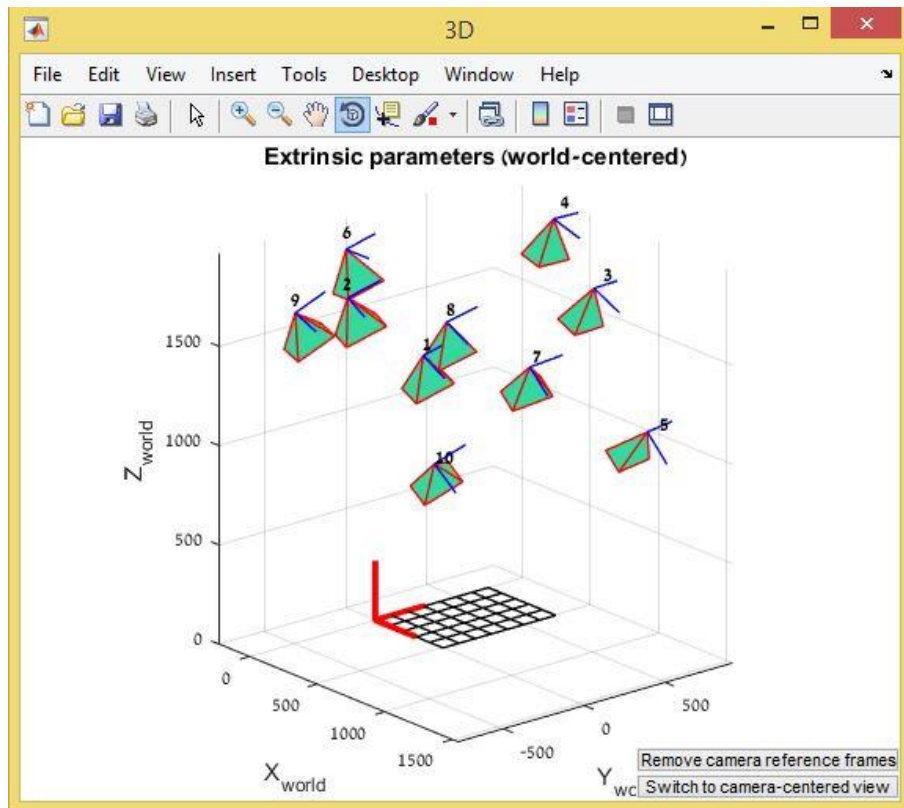
Note: The numerical errors are approximately three times the standard deviations (for reference).

Recommendation: Some distortion coefficients are found equal to zero (within their uncertainties).
To reject them from the optimization set est_dist=[1;0;1;1;0] and run Calibration
```









Calibration results (with uncertainties):

Focal Length:  $f_c = [ 4851.53764 \quad 4956.86251 ] \pm [ 326.43008 \quad 392.43450 ]$   
Principal point:  $cc = [ 2512.87444 \quad 922.34861 ] \pm [ 191.16057 \quad 294.40907 ]$   
Skew:  $\alpha_c = [ 0.00000 ] \pm [ 0.00000 ] \Rightarrow \text{angle of pixel axes} = 90.00000 \pm 0.00000 \text{ degrees}$   
Distortion:  $k_c = [ 0.28781 \quad 0.05202 \quad -0.08281 \quad -0.01321 \quad 0.00000 ] \pm [ 0.17487 \quad 0.79740 \quad 0.03016 \quad 0.01769 \quad 0.00000 ]$   
Pixel error:  $err = [ 8.45466 \quad 7.17735 ]$

Calibration Matrix:

$$\begin{pmatrix} 4851.53 & 0 & 2512.87 \\ 0 & 4956.86 & 922.34 \\ 0 & 0 & 1 \end{pmatrix}$$

Principal point: (2512.87, 922.34)

Focal length: (x: 4851.53, y: 4956.86)

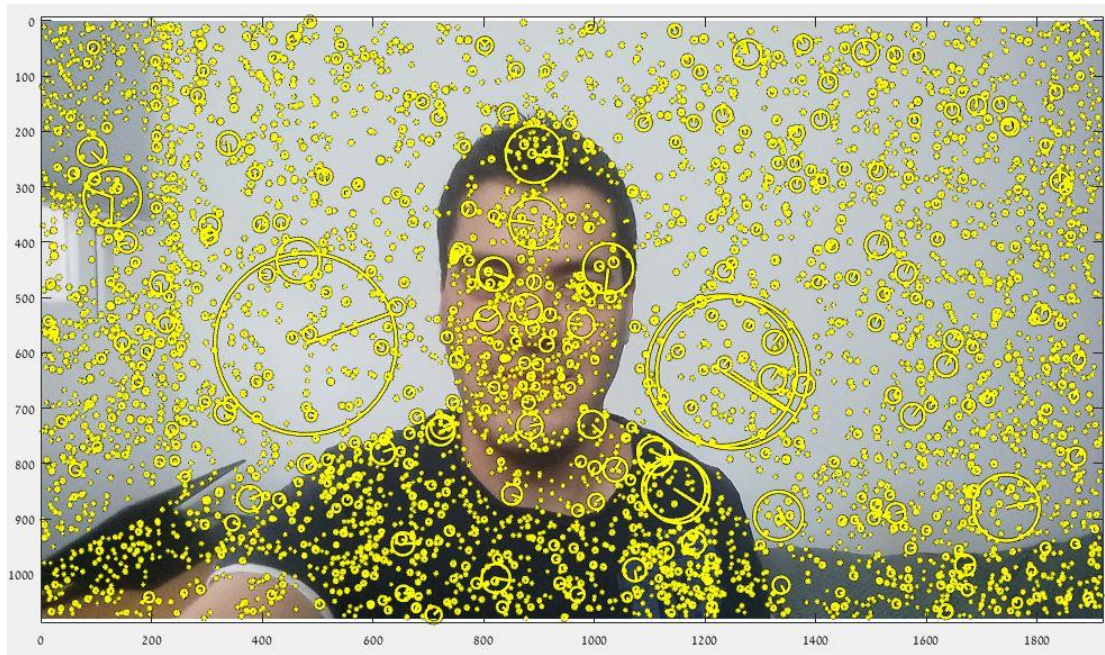
3)

(a)

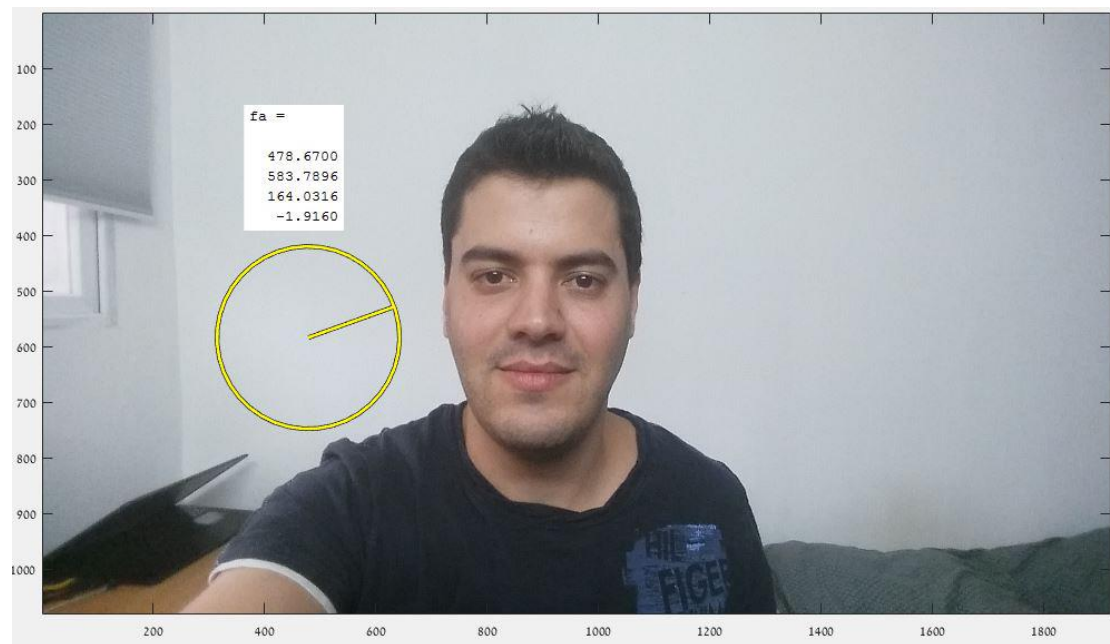


(b)

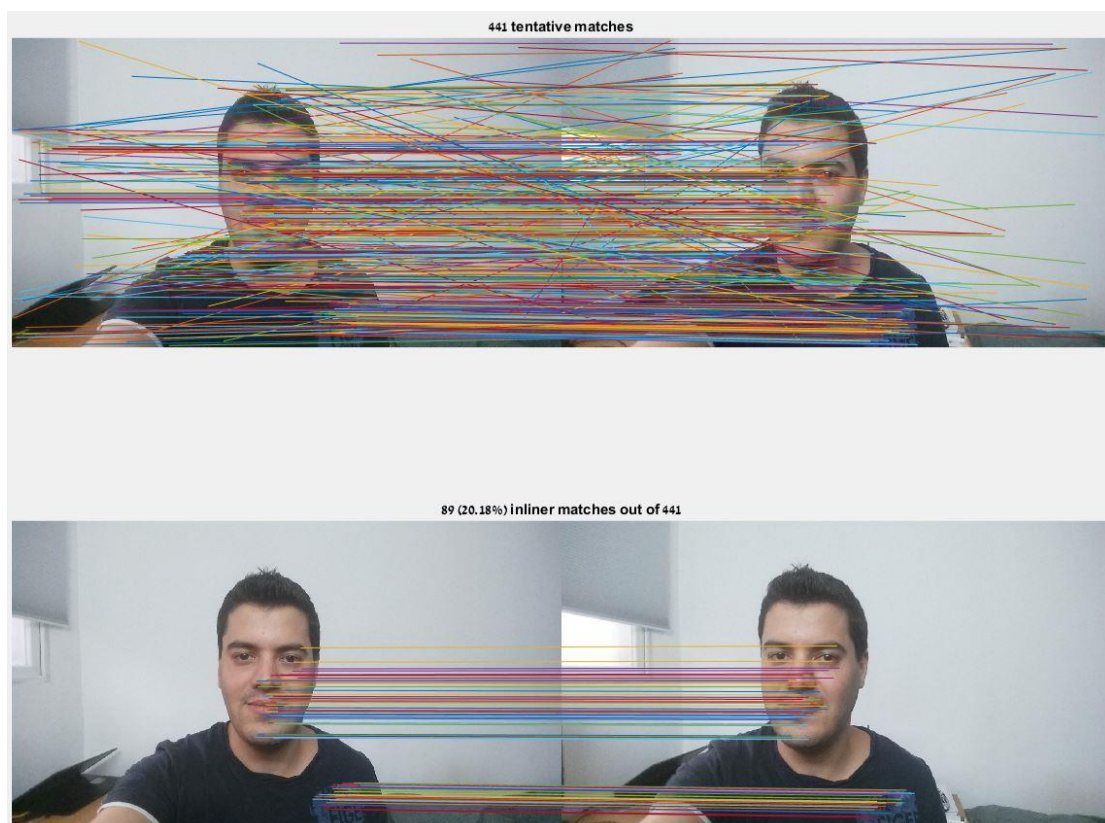








(c)



Outliner:

5255:  $1.0e+03 * (1.3778, 0.6584, 0.0192, -0.0023)$  –

5260:  $1.0e+03 * (1.5481, 0.6929, 0.0198, -0.0023)$

Inliner:

5252:  $1.0e+03 * (1.1800, 0.9437, 0.0211, 0.0012)$  –

5268: 1.0e+03 \* (1.1887, 0.9723, 0.0241, 0.0010)

## Code:

```
function [matches, scores] = sift()
clc;
Ia = imread('1.jpg') ;
Ib = imread('2.jpg') ;

[fa,da] = vl_sift(im2single(rgb2gray(Ia))) ;
[fb,db] = vl_sift(im2single(rgb2gray(Ib))) ;

% image(Ia);
% axis image
% perm = randperm(size(fa,2)) ;
% sel = perm(1:50) ;
% h1 = vl_plotframe(fa(:,:)) ;
% h2 = vl_plotframe(fa(:,:)) ;
% set(h1,'color','k','linewidth',3) ;
% set(h2,'color','y','linewidth',2) ;

% image(Ib);
% axis image
% perm = randperm(size(fb,2)) ;
% sel = perm(1:50) ;
% h1 = vl_plotframe(fb(:,:)) ;
% h2 = vl_plotframe(fb(:,:)) ;
% set(h1,'color','k','linewidth',3) ;
% set(h2,'color','y','linewidth',2) ;

[matches, scores] = vl_ubcmatch(da,db) ;

% -----

numMatches = size(matches,2) ;

X1 = fa(1:2,matches(1,:)) ; X1(3,:) = 1 ;
X2 = fb(1:2,matches(2,:)) ; X2(3,:) = 1 ;
clear H score ok ;
for t = 1:100
    % estimate homography
    subset = vl_colsubset(1:numMatches, 4) ;
    A = [] ;
    for i = subset
        A = cat(1, A, kron(X1(:,i)', vl_hat(X2(:,i)))) ;
    end
    [U,S,V] = svd(A) ;
    H{t} = reshape(V(:,9),3,3) ;

    % score homography
    X2_ = H{t} * X1 ;
    du = X2_(1,:)./X2_(3,:) - X2(1,:)./X2(3,:) ;
    dv = X2_(2,:)./X2_(3,:) - X2(2,:)./X2(3,:) ;
    ok{t} = (du.*du + dv.*dv) < 6*6 ;
    score(t) = sum(ok{t}) ;
end
```

```

[score, best] = max(score) ;
H = H{best} ;
ok = ok{best} ;

function err = residual(H)
    u = H(1) * X1(1,ok) + H(4) * X1(2,ok) + H(7) ;
    v = H(2) * X1(1,ok) + H(5) * X1(2,ok) + H(8) ;
    d = H(3) * X1(1,ok) + H(6) * X1(2,ok) + 1 ;
    du = X2(1,ok) - u ./ d ;
    dv = X2(2,ok) - v ./ d ;
    err = sum(du.*du + dv.*dv) ;
end

if exist('fminsearch') == 2
    H = H / H(3,3) ;
    opts = optimset('Display', 'none', 'TolFun', 1e-8, 'TolX', 1e-8) ;
    H(1:8) = fminsearch(@residual, H(1:8)', opts) ;
else
    warning('Refinement disabled as fminsearch was not found.') ;
end

dh1 = max(size(Ib,1)-size(Ia,1),0) ;
dh2 = max(size(Ia,1)-size(Ib,1),0) ;

figure(1) ; clf ;
subplot(2,1,1) ;
imagesc([padarray(Ia,dh1,'post') padarray(Ib,dh2,'post')]) ;
o = size(Ia,2) ;
line([fa(1,matches(1,:));fb(1,matches(2,:))+o], ...
     [fa(2,matches(1,:));fb(2,matches(2,:))]) ;
title(sprintf('%d tentative matches', numMatches)) ;
axis image off ;

subplot(2,1,2) ;
imagesc([padarray(Ia,dh1,'post') padarray(Ib,dh2,'post')]) ;
o = size(Ia,2) ;
line([fa(1,matches(1,ok));fb(1,matches(2,ok))+o], ...
     [fa(2,matches(1,ok));fb(2,matches(2,ok))]) ;
title(sprintf('%d (%.2f%%) inliner matches out of %d', ...
              sum(ok), ...
              100*sum(ok)/numMatches, ...
              numMatches)) ;
axis image off ;

drawnow ;
end

```