

Main.py

Notations:

- Ms_t : Many Matrices transposed
- Prefix specify input or estimate variable, eg $inputCs, estCs$.
- C : ellipse in dual form, 3×3
- Q : Quadric/ellipsoid in dual form 4×4 , in the world frame.
- K : camera intrinsics 3×3
- M : pose matrix, 3×4 , transforms points from world frame to camera frame.
- P : projection matrix: $P = KM \in \mathbb{R}^{3 \times 4}$.
- visibility:
 - false: object not in image, or detector fails.
 - object not detected in at least 3 frames is ignored.

Set the parameters for the algorithm and load the input data.

- Data allocation is implicitly defined in the data structures, each column of visibility corresponds to one object.
- In bbs, each object has four columns,
 - bounding boxes $[x_0, y_0, x_1, y_1]$
 - $[x_0, y_0]$ = top-left corner
 - $[x_1, y_1]$ = bottom-right corner
 - $[n_frames \times n_objects \times 4]$ size
- Ms_t is camera pose matrices, transposed and stacked.
 - $[n_frames \times 4 \times 3]$
 - Each 3×4 matrix transforms points from world frame to camera frame.
- visibility:
 - indicate whether a detection is available for a given object, on a frame.
 - $[n_frames \times n_objects]$.
 - $n_frames = visibility.shape[0]$
 - $n_objects = visibility.shape[1]$.

run the algorithm, estimate the ellipsoids.

$[inputCs, estCs, estQs] = compute_estimates(bbs, K, Ms_t, visibility)$

- estimate one ellipsoid per object, given detection bounding boxes and camera parameters.
- returns
 - input Cs : ellipses fitted to the input bounding boxes, for each image and each object, in dual form, size: $n_frames \times 3 \times n_objects \times 3$, each ellipse is described by a 3×3 matrix.
 - $estCs$: ellipses resulting from the projection of the estimated ellipsoids, in dual form, size: $n_frames \times 3 \times n_objects \times 3$, each ellipse is 3×3 .
 - $estQs_second_step$: estimated ellipsoids, one per detected object, in dual form, size: $n_objects \times 4 \times 4$.
- Compute the stacked and transposed projection matrices.
 - $Ps_t = (K Ms_t^T)^T$, size: $n_frames \times 4 \times 3$.

- Compute ellipses inscribed in the detection bounding boxes.

- input $Cs = fit_ellipses_in_bbs(bbs, visibility)$

- it calls $fit_one_ellipse_in_bb(bb)$.

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# Encode the ellipse size (axes)
width = abs(bb[2]-bb[0])/2
height = abs(bb[3]-bb[1])/2 } bounding box size
Ccn = np.vstack([(np.hstack([np.diag([1/width**2, 1/height**2]), np.zeros((2,1)]), np.array([0,0,-1]))]
```

$C_{cn} = \begin{bmatrix} \frac{1}{a^2} & 0 & 0 \\ 0 & \frac{1}{b^2} & 0 \\ 0 & 0 & -1 \end{bmatrix}$

Bounding box to ellipse:

- bounding box is $p = [x_{min}, y_{min}, x_{max}, y_{max}]$

- $a = \left| \frac{x_{max} - x_{min}}{2} \right|$, $b = \left| \frac{y_{max} - y_{min}}{2} \right|$

- $X_c = \begin{bmatrix} \frac{x_{min} + x_{max}}{2} \\ \frac{y_{min} + y_{max}}{2} \end{bmatrix}$

- $C_c = \begin{bmatrix} \frac{1}{a^2} & 0 & 0 \\ 0 & \frac{1}{b^2} & 0 \\ 0 & 0 & -1 \end{bmatrix}$

Encode ellipse location

$center = np.array([(bb[0]+bb[2])/2, (bb[1]+bb[3])/2])$

$P = np.vstack([np.hstack([np.eye(2,2), center.reshape(2,1)]), np.array([0,0,1])])$

$Cinv = P.dot(np.linalg.inv(Ccn)).dot(P.transpose())$

- $P = \begin{bmatrix} 1 & 0 & x_c(1) \\ 0 & 1 & x_c(2) \\ 0 & 0 & 1 \end{bmatrix}$

- $Cinv = PC_c^{-1}P^T$

Force matrix to be symmetric:

$Cinv = 0.5 * (Cinv + Cinv.transpose())$

$C_i = \frac{Cinv + Cinv^T}{2}$

Scale ellipse so that element $C_{2,2} = 1$.

$C = Cinv / Cinv[2,2]$

- $C_i = \frac{C_i}{C_i(3,3)}$

$C = C + np.sign([C[0,0] + C[1,1]])$

- $C = (C + np.sign([C(1,1) + C(2,2)]))$

sign is signum function.

return C.

- Set the initial ellipsoids centers to the origin.

$input_ellipsoids_centers = np.dot(np.array([[0,0], [0,0], [0,0]]), (np.ones((1, n_objects))))$

perform the first round of estimation

- $estQs_first_step = estimate_ellipsoids(Ps_t, input_ellipsoids_centers, inputCs, visibility)$
- Ps_t : stacked transposed projection matrix, $n_frames \times 4 \times 3$.
- $input_ellipsoids_centers$: represented in homogeneous coordinates, $4 \times n_objects$.
- $inputCs$: ellipses fitted to the bounding box in dual form, $n_frames \times 3 \times n_objects \times 3$.
- visibility: object visibility, $n_frames \times n_objects$.
- returns: estimated ellipsoids in dual form, $n_objects \times 4 \times 4$.

Initialize output structure

$estQs = np.zeros((n_objects, 4, 4))$

for obj in range(n_objects):

if there are at least 3 detections

if sum(visibility[:, obj]) >= 3:

select only the Cs $[3 \times 3]$ for the current object, for the frames in which

it was detected

Create a mask with true in the desired location.

$row_selector = np.kron(visibility[:, obj], np.ones(3), reshape(1, 3))$

$row_selector = np.array(row_selector, dtype=bool)[0]$

Apply the mask

$selectedCs = inputCs[row_selector, obj] \times 3: obj \times 3 + 3]$

select the corresponding projection matrices.

Create the mask

$row_selector = np.kron(visibility[:, obj], np.ones(4), reshape(1, 4))$

$row_selector = np.array(row_selector, dtype=bool)[0]$

Apply the mask.

$selectedPs_t = Ps_t[row_selector, :]$

Compute the translation matrix due to the center of the current ellipsoid.

$translM = np.eye(4)$

$translM[0:3, 3] = input_ellipsoids_centers[0:3, obj]$

loop over the frames in which the current object is present

apply the translation matrix to each projection matrix, to apply the initial estimate.

for instance_id in range(math.floor(selectedPs_t.shape[0]/4)):

first = np.hstack([np.eye(3), np.zeros((3,1))])

second = np.vstack([selectedPs_t[instance_id*4: instance_id*4+4, :].transpose(1), np.array([0,0,0,1])])

selectedPs_t[instance_id*4: instance_id*4+4, :] = np.dot(np.dot(first, second), translM).transpose()

Estimate the parameters of the current ellipsoid.

$estQ = estimate_one_ellipsoid(selectedPs_t, selectedCs)$

num of frames the object is detected.

$n_views = math.floor(Cs.shape[0]/3)$

matrix of the linear system

$M = np.zeros((b*n_views, 10+n_views))$

compute B matrix and stack them into M.

for idx in range(n_views):

get center and axes of current ellipse.

$[center, axes, _] = dual_ellipse_to_parameters(Cs[3*idx: 3*idx+3, :])$

if $[2,2] > 0$:

$C = C / -C[2,2]$

$center = (-C[0:2, 2]).reshape(2,1)$

$T = np.vstack([np.hstack([np.eye(3), -center]), np.array([0,0,0,1])])$

$C_center = T.dot(C).dot(T.transpose())$

$C_center = 0.5 * (C_center + C_center.transpose())$

$D, V = np.linalg.eig(C_center[0:2, 0:2])$

$axes = np.sqrt(abs(D))$

$R = V$

return center, axes, R.

This corresponds to $C_{if}^* = H_{if}^T C_{if}^* H_{if}^T$

Compute T, a transformation used to precondition the ellipse.

T centers the ellipse and scales the axes.

$div_t = np.linalg.norm(axes)$

$T = np.linalg.inv(np.vstack([np.hstack([np.eye(2) * div_t, center]), np.array([0,0,0,1])])$

$T_t = T.transpose()$

compute P.fr, applying T to the projection matrix.

$P_fr = np.dot(Ps_t[4*idx: 4*idx+4, :], T_t)$

Code block above corresponds to

$P_{fr} C_{if}^* = H_{if}^T P_{fr} Q_{fr}^* P_{fr}^T H_{if}^T$ (15)

$P_{fr} C_{if}^* = H_{if}^T P_{fr} T_i^{-T} Q_{fr}^* T_i^{-1} T_i^T P_{fr}^T H_{if}^T$ (16)

- T_i is the translation matrix whose last column contains the

translation parameters of Q_{fr}^* .

- $H_{if}^T P_{fr} T_i$ is the new projection matrix.

compute the coefficients for the linear system

$B = compute_B(P_fr)$

$B = np.zeros((b, 10))$

vectorize P, one row after the other

$C_order = row_major$

$vec_p = np.reshape(P_fr, (b, 11), order='C')$

$r = vec_p[0:9]$

$t = vec_p[9:10]$

Fill B

$B[0,:] = (r[0]) \times 2$

...

return B

The B matrix is G in (4) in paper

$G_{fr} = D(P \otimes P) \in$

The $B[9, :] = \dots$ terms come from (5) in paper.

$P_{fr} C_{if}^* = H_{if}^T P_{fr} Q_{fr}^* P_{fr}^T H_{if}^T$ in (15)

apply T to the ellipse $\rightarrow$ convert C_{if}^* to $\check{C}_{if}^*$ as in (12)

$C_t = np.dot(np.dot(T, Cs[3*idx: 3*idx+3, :]), T_t)$

transform the ellipse to vector form.

$C_tv = symmetric_mat_2_to_vector(C_t)$

Realizes a symmetric 3×3 matrix

$C_tv /= -C_tv[6]$

- C_tv is the C_{if}^* in (6), $C_{if}^* = vec(C_{if}^*)$.

- C_t is C_{if}^* in (3).

write the obtained coefficients to the correct size of M.

$M[b*idx: b*idx+b, 0:10] = B$

$M[b*idx: b*idx+b, 10+idx] = -C_tv$.

~, ~, $V = np.linalg.svd(M)$

$W = V[-1, :]$

Above code block is from (9)

$\hat{w}_i = \argmin \| \hat{A}_i^T w_i \|$ s.t. $\| w_i \|_2 = 1$

(9) is solved by applying SVD to $\hat{A}_i^T$, taking the right singular vector

associated to the minimum singular value.

$adjQ = w[0:w]$

$adjQ = vector_to_symmetric_mat_4(adjQ)$

return adjQ.

The code block above: after (9) in paper

The first 10 entries of $\hat{w}_i$ are the vectorized elements of the estimated

dual quadric, denoted by $\check{V}_i^*$.

To get back the estimated matrix of the quadric in the primal space,

we obtain first the dual estimated quadric by:

$\check{Q}_i^* = vec^{-1}(\check{V}_i^*)$ (10)

reapply the translation which had been removed.

$estQ = np.dot(translM, np.dot(estQ, translM.transpose()))$.

force the $estQ$ matrix to be symmetric

$estQ = (estQ + estQ^T)/2$

$estQ = 0.5 * (estQ + estQ.transpose())$

scale the ellipsoid to put it in standard form

element $C[3,3]$ set to -1

$estQ /= -estQ[3,3]$

Store the results for the current ellipsoid into the output data structure.

$estQs[obj, :, :] = estQ$

else:

In case there are fewer than 3 detections

$estQs[obj, :, :] = np.nan$

return estQs.

first round of estimation

Note that the code only performs the linear optimization, and does not

do the non-linear refinement.

- extract the centers of the current estimate for the ellipsoids

$first_step_ellipsoids_centers = input_ellipsoids_centers$

for object_id in range(n_objects):

$first_step_ellipsoids_centers[0:3, object_id] = estQs_first_step[object_id, 0:3, 3]$

- perform the second round of estimation, exploiting the centers estimated at the

previous step

$estQs_second_step = estimate_ellipsoids(Ps_t, first_step_ellipsoids_centers, inputCs, visibility)$

- Project the estimated ellipsoids onto the images

$estCs = project_ellipsoids(Ps_t, estQs_second_step, visibility)$.