



Robotics: Introduction to perception

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What is image?

- ▶ Camera connected to computer produces images
- ▶ Image is array of numbers¹



167	163	174	168	160	162	159	161	172	162	165	166
165	162	169	74	79	62	39	17	110	239	190	164
180	160	92	14	54	6	10	38	48	190	109	161
206	199	6	124	191	111	130	204	196	19	66	160
194	68	157	251	237	239	239	228	227	87	71	201
172	196	267	239	239	214	220	239	238	94	74	206
188	68	179	209	185	215	211	158	129	75	30	169
168	97	164	84	19	168	134	11	31	62	23	168
199	168	191	163	158	227	178	143	182	194	84	160
205	176	168	262	236	231	149	178	238	49	161	204
190	216	156	149	236	187	65	160	79	36	218	241
190	224	147	146	227	210	127	121	36	161	265	224
196	214	173	66	103	143	96	98	2	109	248	215
187	196	236	76	1	81	47	0	6	217	266	211
183	202	237	145	0	0	12	108	200	188	243	236
196	206	123	267	177	121	120	208	179	19	66	218
167	163	174	168	160	162	159	161	172	162	165	166
165	162	169	74	79	62	39	17	110	239	190	164
180	160	92	14	54	6	10	38	48	190	109	161
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¹Images are from: <https://ai.stanford.edu/~syueung/cvweb/tutorial1.html>

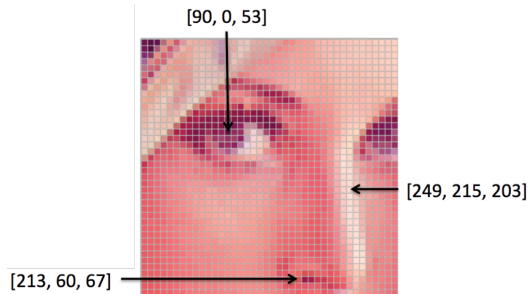
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180	180	82	14	34	6	10	33	40	156	189	181
206	100	6	154	131	111	120	204	146	16	64	180
194	68	137	281	237	239	239	228	227	87	71	201
172	106	207	233	233	214	220	239	238	58	74	206
188	88	178	209	185	216	211	168	189	75	80	188
189	97	188	14	12	188	128	11	21	62	22	148
199	148	191	193	198	227	178	143	182	186	86	190
205	174	191	292	236	231	149	178	238	43	83	204
190	214	116	149	236	187	86	160	79	38	218	241
198	224	147	186	227	210	127	103	36	158	285	224
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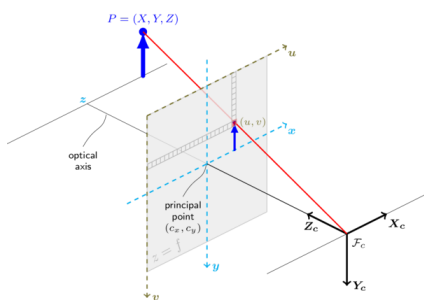


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How is the image formed?

- ▶ Perspective camera
 - ▶ pinhole camera model²
 - ▶ projects spatial point x_c into image point $u = (u \ v)^\top$ by intersecting
 - ▶ image plane and
 - ▶ the line connecting x_c with the projection center
 - ▶ all points on a ray project to the same pixel

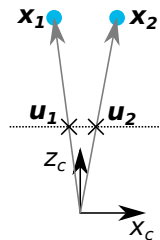
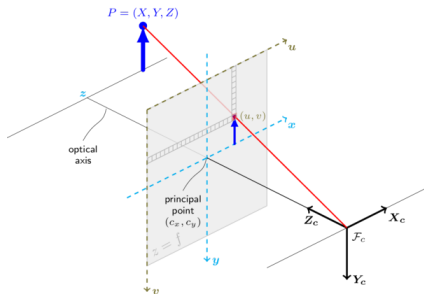


²docs.opencv.org



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Projection of pinhole camera

- ▶ $\mathbf{u}_H = K \mathbf{x}_c$
 - ▶ $\mathbf{u}_H$ is pixel in homogeneous coordinates
 - ▶ if $\mathbf{u}_H = (u_H \quad v_H \quad w_H)^\top$, then pixel coordinates are $(u_H/w_H \quad v_H/w_H)^\top$



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- ▶ K is camera matrix
 - ▶ $K = \begin{pmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{pmatrix}$



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 - ▶ how to find K from points?



What we can study on images?



What we can study on images?

- Segmentation masks (where are the objects of interest)



What we can study on images?

- ▶ Segmentation masks (where are the objects of interest)
- ▶ Objects classification (labeling)



Segmentation masks - color thresholding

- ▶ Thresholding
 - ▶ RGB pixel values for coordinates u : $I_{\text{RGB}}(u)$



Segmentation masks - color thresholding

- ▶ Thresholding

- ▶ RGB pixel values for coordinates $\mathbf{u}$: $I_{\text{RGB}}(\mathbf{u})$
- ▶ $M(\mathbf{u}) = 1$, if $I_{\text{RGB}}(\mathbf{u}) = (0 \ 255 \ 0)^{\top}$?



Segmentation masks - color thresholding

► Thresholding

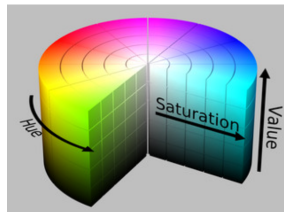
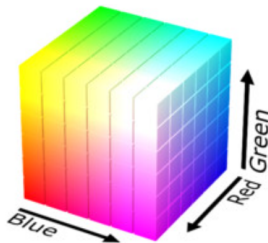
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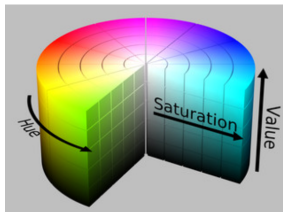
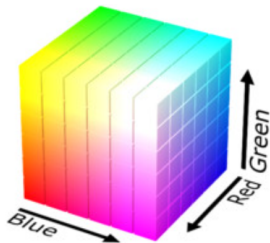
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- ▶ Post-processing
 - ▶ compute connected components
 - ▶ remove small or deformed segments
 - ▶ assign label based on thresholds



Segmentation masks for known 3D objects

- ▶ Neural Network (e.g. Mask R-CNN)



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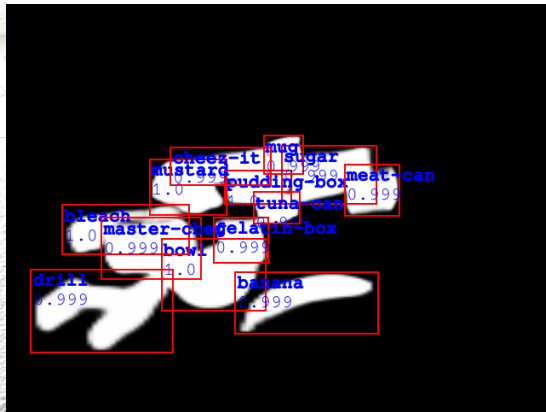


Segmentation masks for known 3D objects

- ▶ Neural Network (e.g. Mask R-CNN)
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- ▶ Inference:
 - ▶ Input: image
 - ▶ Output: segmentation mask, bounding box, label, and confidence



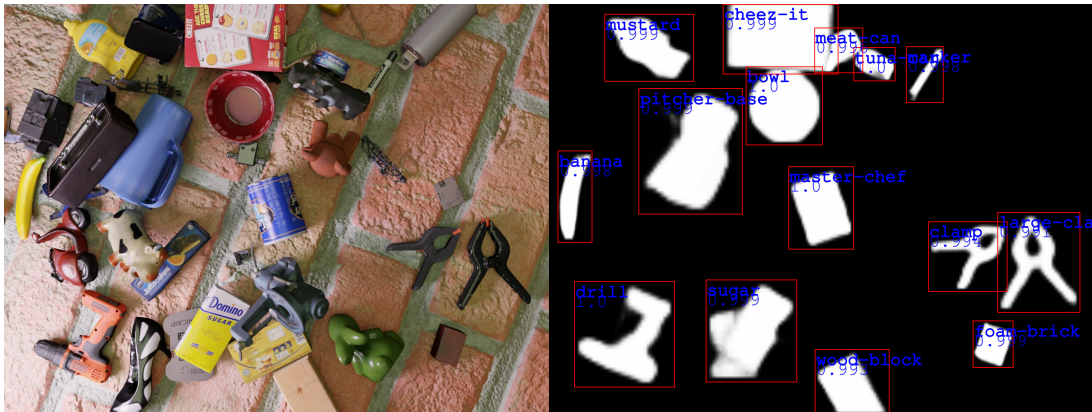
Mask R-CNN results



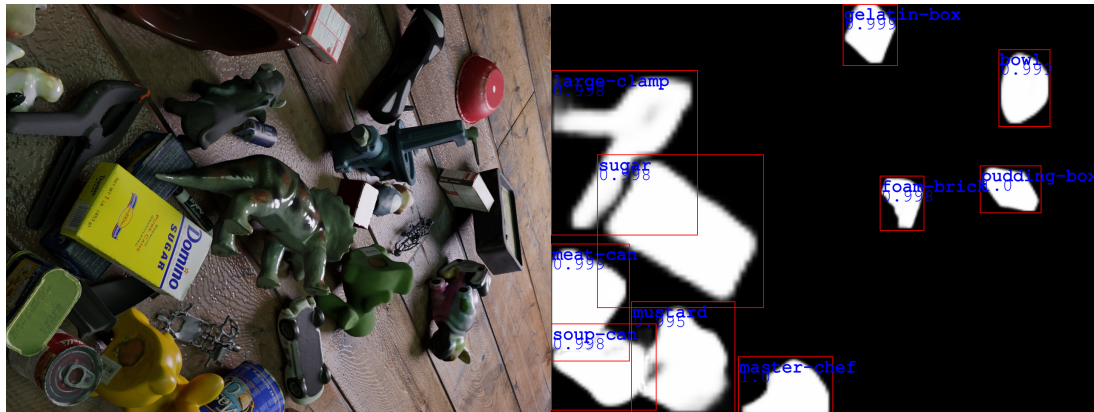
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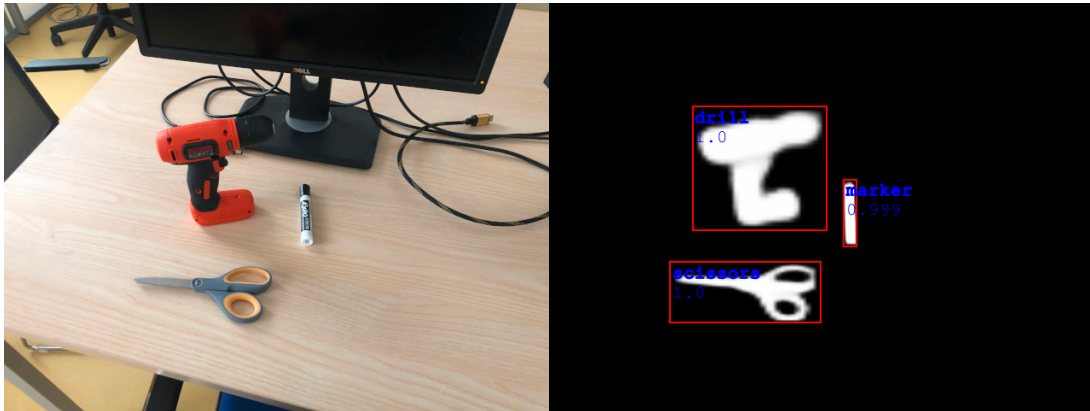
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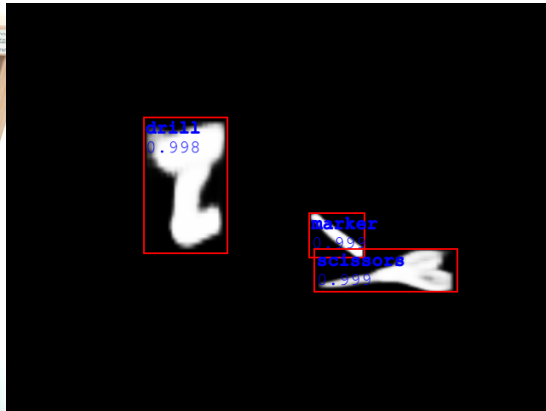
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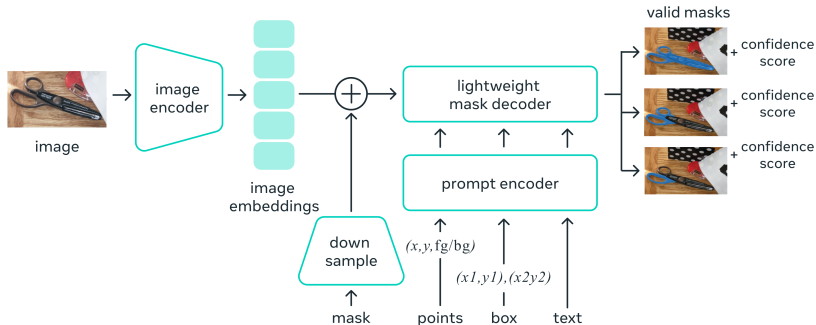
Mask R-CNN results



Segmentation masks without re-training

- ▶ Segment Anything Model (SAM)
 - ▶ segment any object, in any image, with a single click
 - ▶ dataset of 10M images, 1B masks

Universal segmentation model



SAM results



SAM results



SAM results



SAM results





Segmentation

- ▶ Segmentation finds objects in image
 - ▶ segmentation mask
 - ▶ bounding box
 - ▶ label
 - ▶ confidence score



Segmentation

- ▶ Segmentation finds objects in image
 - ▶ segmentation mask
 - ▶ bounding box
 - ▶ label
 - ▶ confidence score
- ▶ Information only in image space
- ▶ How to use it in robot space?



External camera

- ▶ Assume camera mounted rigidly to the reference frame
 - ▶ if we know K and T_{RC} , how to project points x_R to image?



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 - ▶ if we know K and T_{RC} , how to project points x_R to image?
- ▶ Unknown K and T_{RC} and planar problem
 - ▶ e.g. cubes with the same high on table desk
 - ▶ what is the position of cube on 2D table w.r.t. 2D image/pixels coordinates?



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 - ▶ analyzed by **homography**



Homography

- ▶ Homography matrix H is 3×3 matrix that maps points from one plane to another
 - ▶ image plane to table desk
 - ▶ one image plane to another image plane (different view)



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 - ▶ image plane to table desk
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- ▶ $s \begin{pmatrix} x & y & 1 \end{pmatrix}^T = H \begin{pmatrix} u & v & 1 \end{pmatrix}^T$
 - ▶ x, y are coordinates in the first plane
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- ▶ How to find H ?



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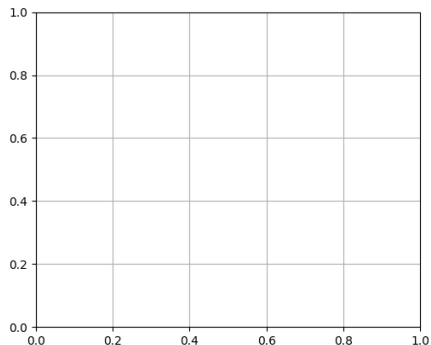
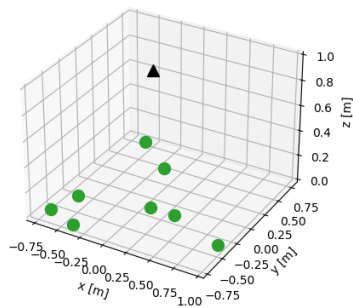


Homography

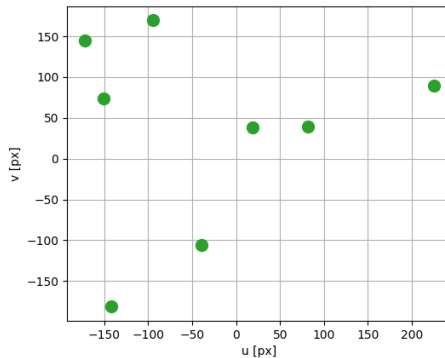
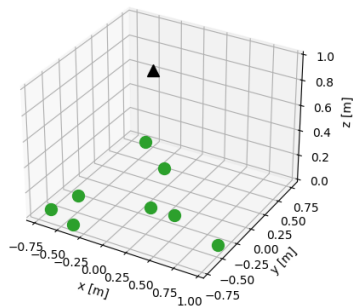
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 - ▶ e.g. measure manually
 - ▶ position of cube center w.r.t. table corner
 - ▶ position of cube center in image



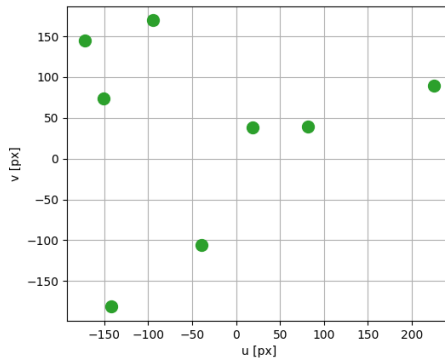
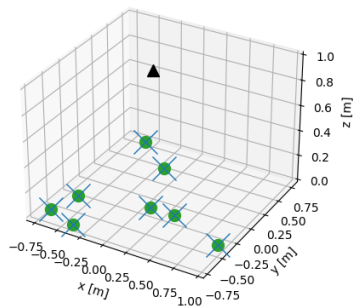
Homography example



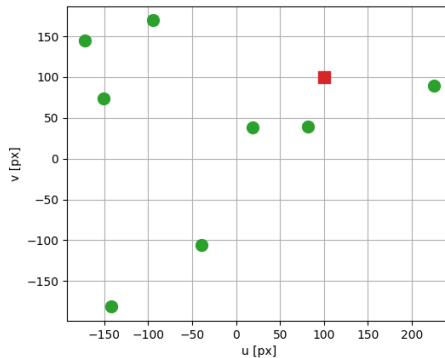
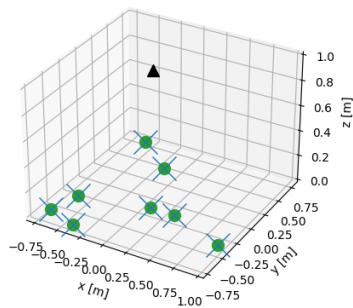
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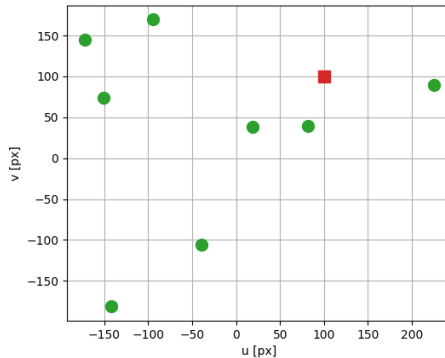
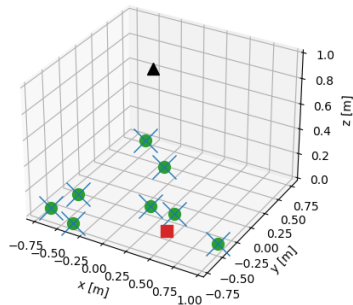
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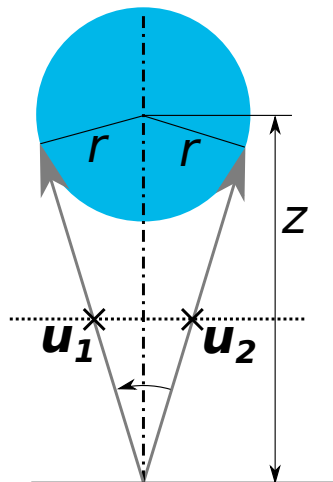
Non-planar pose estimation

- ▶ Homography maps only plane to plane
- ▶ More general object pose estimation in **camera** frame
 - ▶ get depth by mapping from area in pixels to depth for fixed size objects
 - ▶ get depth by additional scene information, e.g. known size/model of the objects
 - ▶ RGBD camera
 - ▶ additional markers



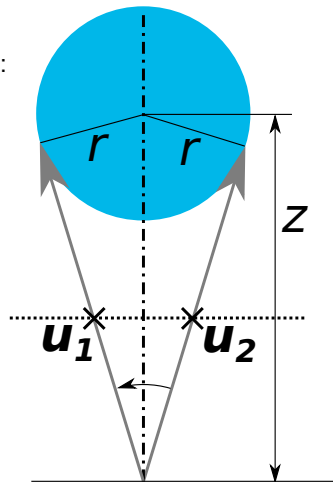
Using prior knowledge about size

- We know radius is fixed



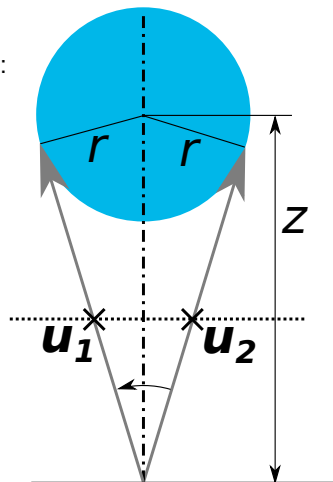
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- ▶ From detected pixels u_1, u_2 , we can compute rays x_1, x_2 :
$$\frac{1}{\lambda_i} x_i = K^{-1} u_i$$



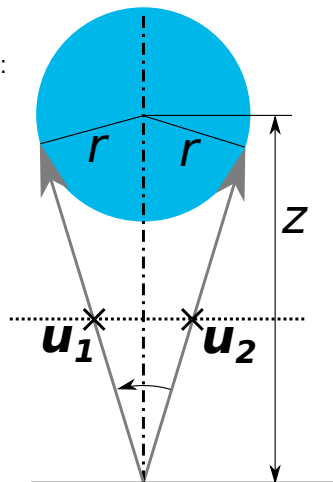
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- ▶ Angle between vectors: $\cos \alpha = \frac{\frac{1}{\lambda_1 \lambda_2} \mathbf{x}_1 \cdot \mathbf{x}_2}{\frac{1}{\lambda_1 \lambda_2} \|\mathbf{x}_1\| \|\mathbf{x}_2\|}$



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- ▶ We know radius is fixed
- ▶ From detected pixels $\mathbf{u}_1, \mathbf{u}_2$, we can compute rays $\mathbf{x}_1, \mathbf{x}_2$:
$$\frac{1}{\lambda_i} \mathbf{x}_i = K^{-1} \mathbf{u}_i$$
- ▶ Angle between vectors: $\cos \alpha = \frac{\frac{1}{\lambda_1 \lambda_2} \mathbf{x}_1 \cdot \mathbf{x}_2}{\frac{1}{\lambda_1 \lambda_2} \|\mathbf{x}_1\| \|\mathbf{x}_2\|}$
- ▶ Depth: $z = \frac{r}{\sin(\alpha/2)}$



Using depth sensor

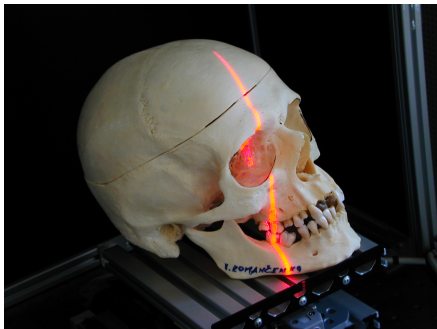
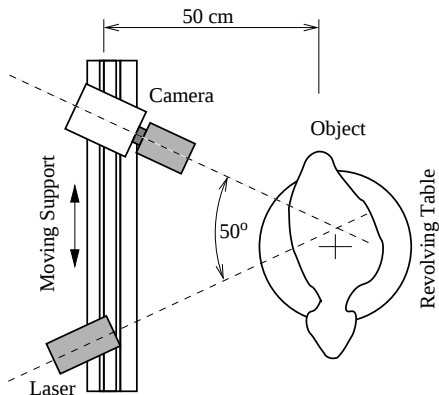
► RGBD sensors

- RGB image ($H \times W \times 3$)
- Depth map ($H \times W \times 1$), distance in meters for each pixel
- Structured point cloud ($H \times W \times 3$), $(x_c \ y_c \ z_c)$ for each pixel



How depth sensor works

- ▶ Laser projects pattern and camera recognizes it
- ▶ Depth information is computed using triangulation



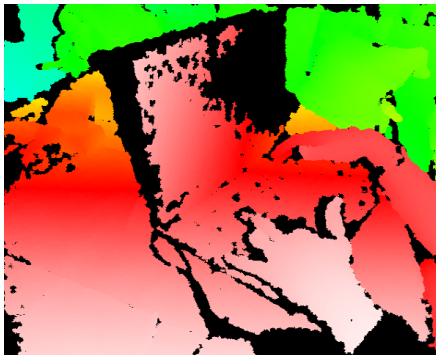
2D depth sensors

- ▶ Based on the structured light
- ▶ Projects 2D infra red patterns
- ▶ One projector and two cameras (RGB + IR)



Issues with depth sensors

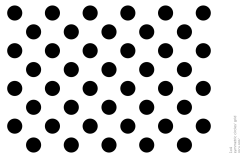
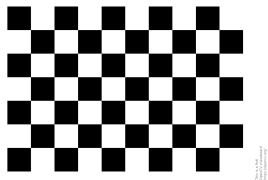
- ▶ Depth reconstruction is not perfect (black areas in the image³)
- ▶ In python represented by NaN
- ▶ Not every pixel in RGB has reconstructed depth value
- ▶ RGB and Depth data are not aligned (you need to calibrate them)



³<https://commons.wikimedia.org>, User:Kolossos

Additional markers

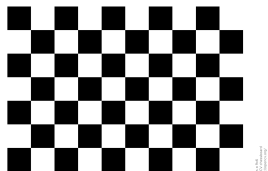
- Can we compute the pose of patterns⁴?



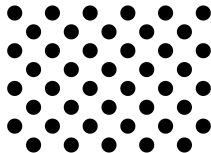
⁴docs.opencv.org

Additional markers

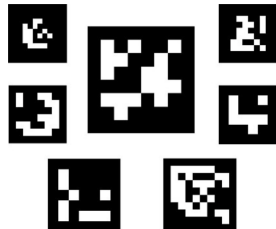
- ▶ Can we compute the pose of patterns⁴?
 - ▶ the size and structure needs to be known
 - ▶ subpixel accuracy
 - ▶ it has to be completely visible
- ▶ Can we compute the pose of ArUco markers?



The OpenCV
Documentation



The OpenCV
Documentation



⁴docs.opencv.org

Additional markers

- ▶ Can we compute the pose of patterns⁴?
 - ▶ the size and structure needs to be known
 - ▶ subpixel accuracy
 - ▶ it has to be completely visible
- ▶ Can we compute the pose of ArUco markers?
 - ▶ less accurate than regular patterns
 - ▶ provides marker id and the pose
 - ▶ it has to be completely visible

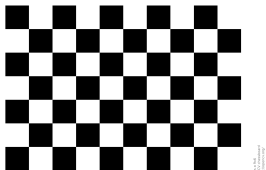


Image courtesy of
OpenCV

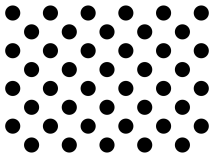
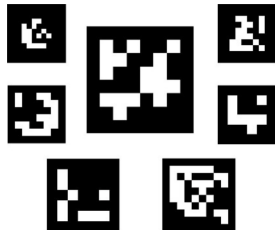
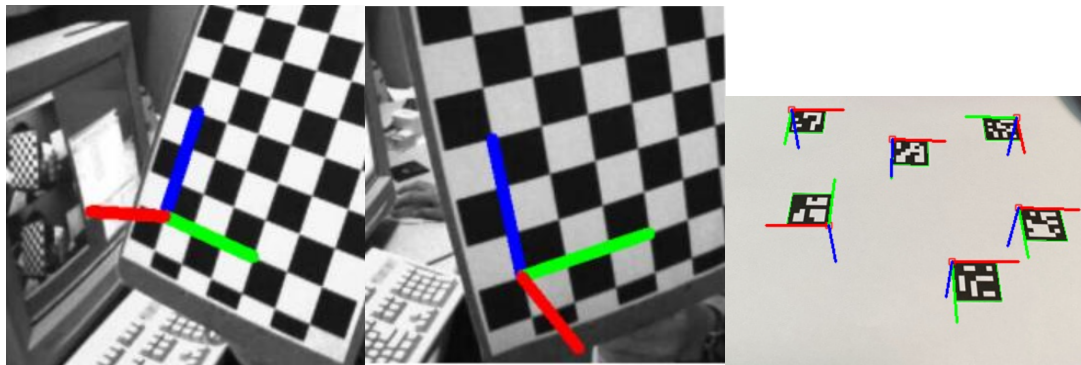


Image courtesy of
OpenCV



⁴docs.opencv.org

Markers pose example

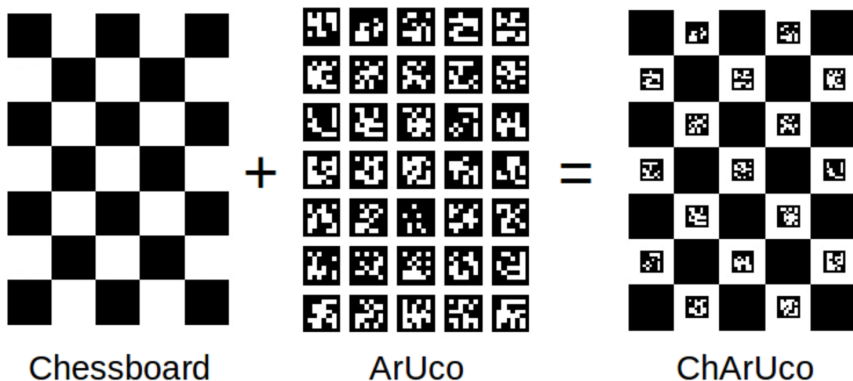


Markers example from real-world



ChArUco board for calibration

- ▶ Combines accuracy of pattern with detections of ArUco
- ▶ Partial visibility detections



Charuco definition



Camera matrix estimation with boards

- ▶ We can estimate camera matrix from correspondences in image space and spatial space
 - ▶ collect images of the board from different views
 - ▶ detect boards
 - ▶ compute correspondences between image points and board frame points
 - ▶ `_, K, dist_coeffs, rvecs, tvecs = cv2.calibrateCamera(obj_points, img_points, img_shape)`
- ▶ In addition we get
 - ▶ distortion coefficients that compensates defects of objective
 - `Knew, roi = cv.getOptimalNewCameraMatrix(K, dist_coeffs, img_shape, 1, img_shape)`
 - `img_undistorted = cv.undistort(img, K, dist_coeffs, None, Knew)`
 - ▶ $SE(3)$ poses of boards in camera frame



Pose estimation from RGB(D)

- ▶ Pose estimation methods
 - ▶ use prior knowledge about the task, e.g. fixed height objects on a plane
 - ▶ use prior knowledge about the objects (size)
 - ▶ use depth sensor
 - ▶ use ArUco markers



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- ▶ Where is robot?



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 - ▶ homography estimates poses of objects w.r.t. plane frame



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 - ▶ other methods estimate poses in camera frame



Pose estimation from RGB(D)

- ▶ Pose estimation methods
 - ▶ use prior knowledge about the task, e.g. fixed height objects on a plane
 - ▶ use prior knowledge about the objects (size)
 - ▶ use depth sensor
 - ▶ use ArUco markers
- ▶ Where is robot?
 - ▶ homography estimates poses of objects w.r.t. plane frame
 - ▶ other methods estimate poses in camera frame
 - ▶ we need to estimate/calibrate T_{RC}



Summary

- ▶ Image representation
- ▶ Projection to/from image
- ▶ Segmentation in image space
- ▶ Homography
- ▶ Pose estimation from image
- ▶ Camera calibration



Laboratory

- ▶ No new homework this week
- ▶ Mandatory exercise - Safety
 - ▶ CIIRC, B670



What is next?

- ▶ Next week, we will start with a test
 - ▶ Questions from the first two lectures
 - ▶ SE2 and SE3 transformations and properties
 - ▶ Forward kinematics a DoF

