Direct 3D Pose Estimation of a Planar Target

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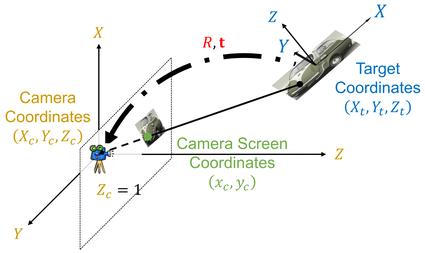
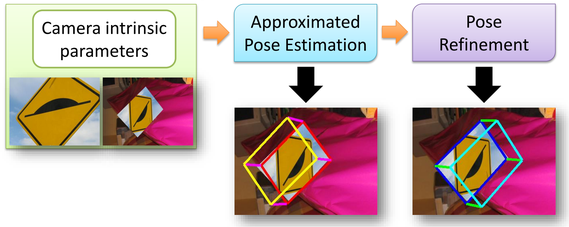
Introduction

- Robust 3D pose estimation on both texture and textureless planar target.



Estimate **R** and **t**, which is six degree of freedom.

- Two-step algorithm. Estimate the pose in the first stage, refine and disambiguate the pose in refinement stage.



Experiment I

- Compared algorithms

SIFT / ASIFT → RANSAC → OPnP

- Evaluation
  - Rotation error (degree) : $E_{\mathbf{R}} = acosd((Tr(\mathbf{R}^{\mathrm{T}} \cdot \hat{\mathbf{R}}) - 1)/2)$
  - Translation error (%) : $E_{\mathbf{t}} = \|\hat{\mathbf{t}} - \mathbf{t}\| / \|\hat{\mathbf{t}}\| \times 100$
  - Success rate (%) : SR indicates the percentage of poses that $E_{\mathbf{R}} < 20^{\circ}$ and $E_{\mathbf{t}} < 10\%$
- Real dataset from [5]
  - Compute all candidate poses with 4 corners using OPnP.
  - Select the correct pose from all candidates.

Proposed Algorithm

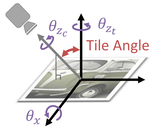
Approximated Pose Estimation

- Find the pose with minimum appearance distance.

$$E_a(\mathbf{p}) = \frac{1}{n_t}\sum_{i=1}^{n_t} |I_c(\mathbf{u}_i) - I_t(\mathbf{x}_i)| \quad (1) \qquad \mathbf{x} = (X_t, Y_t),\ \mathbf{u} = (x_c, y_c)$$

I_c: Camera image, I_t: Target image, n_t: Number of sample points

- Theorem
  - It is shown in [1] that (Mean variation of I_t)
    $|E_a(\mathbf{p}_1) - E_a(\mathbf{p}_2)| = O(\varepsilon \bar{V})$, if (2)
    $\forall \mathbf{x}_i \in I_t : d\left(T_{\mathbf{p}_1}(\mathbf{x}_i) - T_{\mathbf{p}_2}(\mathbf{x}_i)\right) = O(\varepsilon)$. (3)



- ε-Covering Set Construction
  - Factorize the rotation matrix $\mathbf{R}$ as $\mathbf{R}_{\mathbf{z}}(\theta_{z_c})\mathbf{R}_{\mathbf{x}}(\theta_x)\mathbf{R}_{\mathbf{z}}(\theta_{z_t})$.
  - Any two consecutive poses $\mathbf{p}_k$ and $\mathbf{p}_k + \Delta\mathbf{p}_k$ on each dimension in the set must satisfy (3).
  - Minimum appearance distance $E_a(\mathbf{p}_b) = O(\varepsilon)$.
- Coase-to-fine search Estimation
  1. Construct pose set S with coarser ε.
  2. Evaluating E_a of each pose and obtain best pose $\mathbf{p}_b$ associated with $E_a(\mathbf{p}_b)$.
  3. Select the poses within a threshold.

     $S_L = \{\mathbf{p}_L \mid E_a(\mathbf{p}_L) < E_a(\mathbf{p}_b) + L\}$ (4)
  4. Expand S_L with finer ε'.

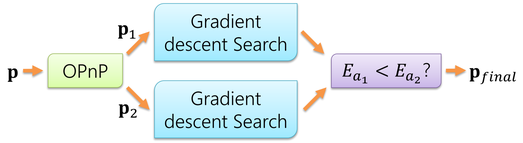
     $S' = \{\mathbf{p}' \mid \exists \mathbf{p}_L \in S_L : (3) \text{ holds for } \mathbf{p}', \mathbf{p}_L, \varepsilon'\}$ (5)
  5. Repeat 2, 3 and 4 until reaching wanted ε^*.

Pose Refinement

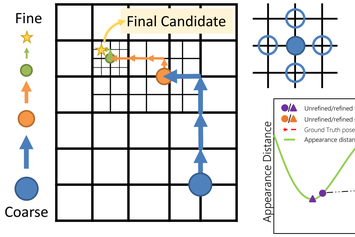
- Solve pose ambiguity problem and further refine the estimated pose.

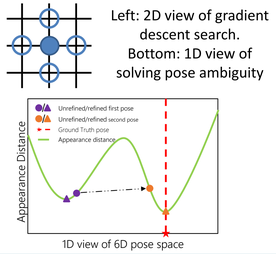
Pose Ambiguity : Different poses with similar appearance

- Refinement with two candidate poses.



1. Apply OPnP[2] to compute all stationary points, select two points with smallest error as the candidate poses.
2. Use gradient descent search to further refine each poses.
3. Choose the one with smaller E_a to be the final pose.



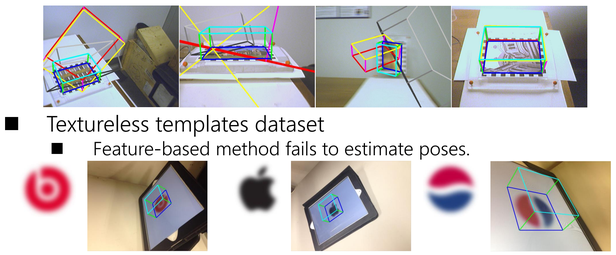


Left: 2D view of gradient descent search.
Bottom: 1D view of solving pose ambiguity

- Real dataset from [3]
  - 6 templates, each contains 16 video sequences.

video	Unconstraint			Perspective Distortion			Motion 9			Dynamic Lighting		
	$E_{\mathbf{R}}(^{\circ})$	$E_{\mathbf{t}}(\%)$	SR(%)	$E_{\mathbf{R}}(^{\circ})$	$E_{\mathbf{t}}(\%)$	SR(%)	$E_{\mathbf{R}}(^{\circ})$	$E_{\mathbf{t}}(\%)$	SR(%)	$E_{\mathbf{R}}(^{\circ})$	$E_{\mathbf{t}}(\%)$	SR(%)
SIFT	89.4	167	26.6	69.0	134	41	115	107	7.33	105	136	16.3
ASIFT	60.2	**17.9**	46.9	39.3	**12.1**	70.7	95.7	41.6	6.14	38.5	**13.1**	63.8
Direct	**29.1**	18.7	**65.7**	**27.7**	23.3	**77**	**50.4**	**6.58**	**26.7**	**27.5**	22.7	**71.7**

- Textureless templates dataset
  - Feature-based method fails to estimate poses.

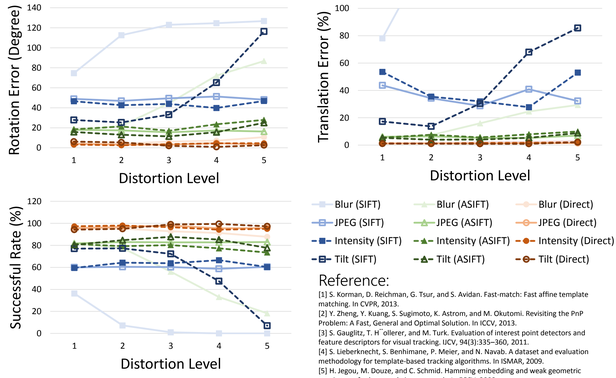


Experiment II

- Synthetic dataset
  - 8 template images from [4], 100 background images from [5].
  - Totally 8400 test images, each image is generated according to the random generated pose.
  - 4 varying conditions : blur, JPEG, intensity, tilt angle.

	Bump Sign			Stop Sign			Lucent			MacMini Board		
	$E_{\mathbf{R}}(^{\circ})$	$E_{\mathbf{t}}(\%)$	SR(%)	$E_{\mathbf{R}}(^{\circ})$	$E_{\mathbf{t}}(\%)$	SR(%)	$E_{\mathbf{R}}(^{\circ})$	$E_{\mathbf{t}}(\%)$	SR(%)	$E_{\mathbf{R}}(^{\circ})$	$E_{\mathbf{t}}(\%)$	SR(%)
SIFT	100	54.8	10	69.2	35.3	38	30.1	16.5	72	28.0	13.4	78
ASIFT	72.1	24.3	22	5.07	**0.74**	96	**1.90**	**0.38**	**100**	6.37	2.59	**96**
Direct	**3.84**	**0.80**	**96**	**2.81**	0.91	**98**	2.62	1.06	98	**5.37**	**2.56**	**96**

	Isetta			Philadelphia			Grass			Wall		
	$E_{\mathbf{R}}(^{\circ})$	$E_{\mathbf{t}}(\%)$	SR(%)	$E_{\mathbf{R}}(^{\circ})$	$E_{\mathbf{t}}(\%)$	SR(%)	$E_{\mathbf{R}}(^{\circ})$	$E_{\mathbf{t}}(\%)$	SR(%)	$E_{\mathbf{R}}(^{\circ})$	$E_{\mathbf{t}}(\%)$	SR(%)
SIFT	20.6	16.2	82	13.5	4.57	90	97.3	212	24	17.1	27.3	86
ASIFT	2.08	**0.49**	98	**1.16**	**0.35**	**100**	51.2	16.7	52	**2.76**	**0.36**	**96**
Direct	**1.49**	0.87	**100**	1.95	0.87	**100**	**2.87**	**1.06**	**96**	6.68	1.64	94



Reference:
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Conclusion

The proposed direct pose estimation performs favorably in terms of accuracy and robustness against state-of-the-art feature-based approaches on both synthetic and real dataset.