A Novel Illumination-Invariant Loss for Monocular 3D Pose Estimation

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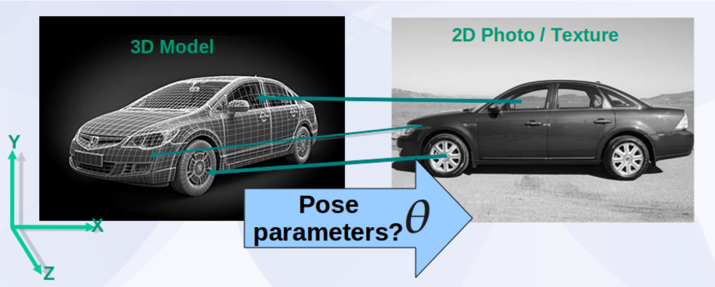
DICTA 2011

The problem



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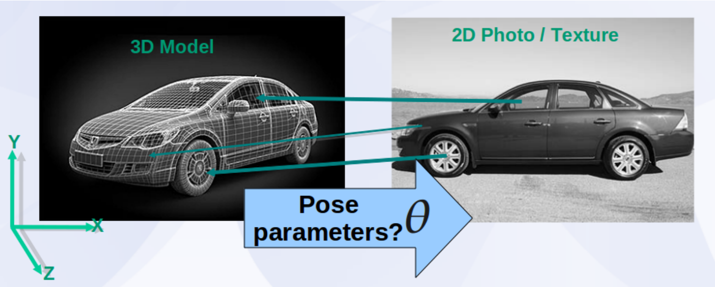

- Input: Photo of a known object and 3D CAD Model

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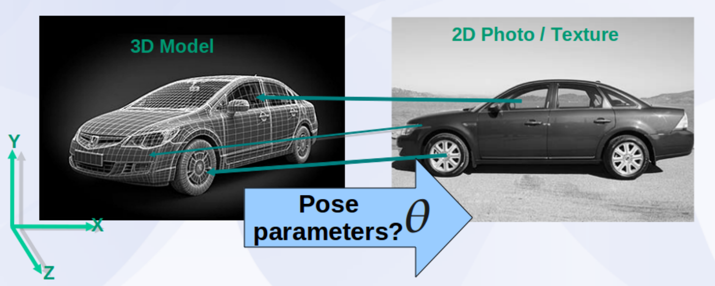

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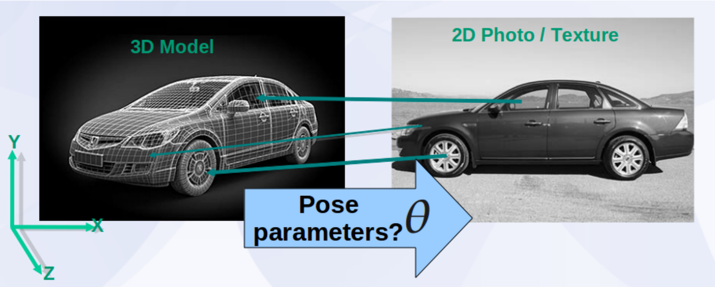

- Input: Photo of a known object and 3D CAD Model
- Output: Pose parameters $\boldsymbol{\theta}$ that register the model on the photos
- Pose - Position/orientation of 3D object w.r.t. camera

Applications

- Use as a ground truth for detailed image analysis

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- Augmented reality applications

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- Process control work

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- CV applications needing a non-articulated full monocular 3D pose

Features of our pose estimation method

- Use only a single, static image limited to a single view

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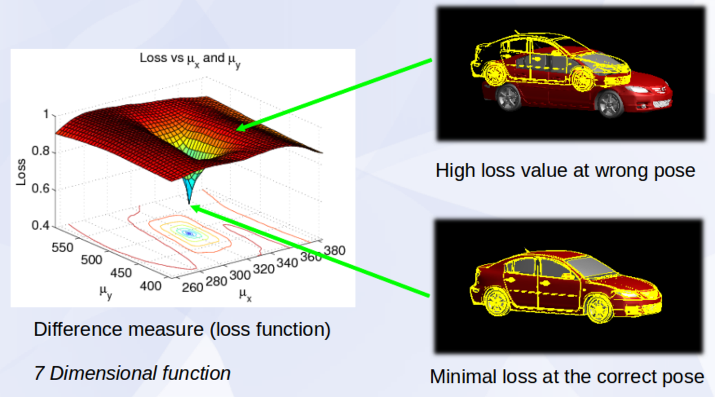
- Works in an uncontrolled environment
- Work under varying and unknown lighting conditions
- Avoid user interaction
- Avoid training/learning [Arie-Nachimson and Basri, 2009, ICCV]
- Estimate the full 3D pose of the object (Not a set of finite Poses [Ozuysal et al., 2009, CVPR] or XY position and angle on ground plane [Sun et al., 2011, 3DIMPVT])

Approach - Minimise a loss function



μ_x and μ_y are 2 of the 7 pose parameters estimated (explained later)

Phong reflection model

Based on the Phong reflection model [Foley, 1996]

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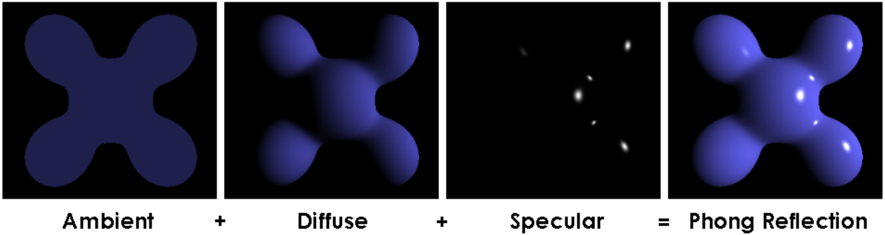

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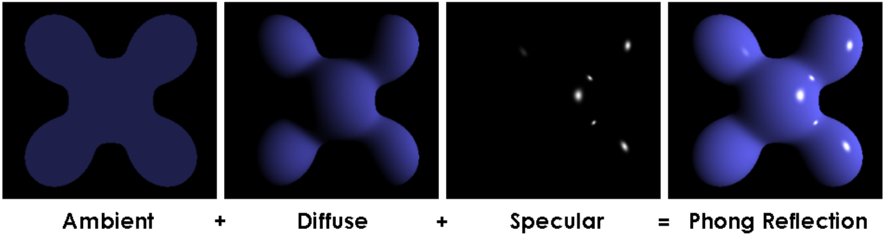
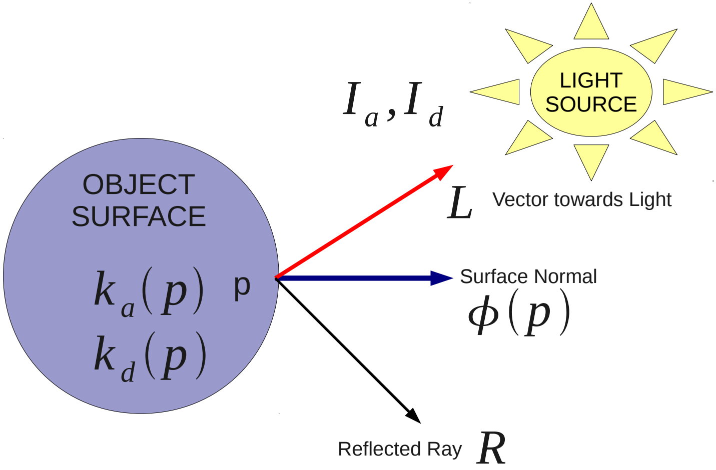


Approximation: Consider only (Ambient) + (Diffuse) terms

Phong reflection model - linear relation



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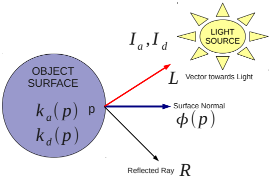

Intensity at pixel location p (neglecting specular terms)

$$I(p) \equiv \underbrace{\begin{bmatrix} I_a & I_d \mathbf{L} \end{bmatrix}}_{\mathbf{A}} \cdot \underbrace{\begin{bmatrix} I_a \\ I_d \phi(\mathbf{p}) \end{bmatrix}}_{\mathbf{M}_\theta(p)} + b$$

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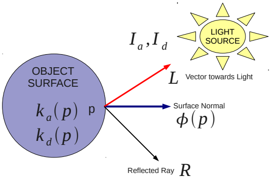

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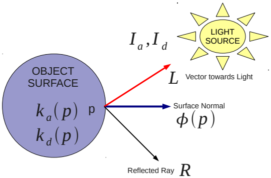

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Not realistic but sufficient for matching purposes.

Loss function

Loss at pose θ

$$L(\theta) := \mathbf{E}[||I(p) - F(p)||^2]$$

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At correct illumination,

$$\text{Loss}(\theta) \;:=\; \min_{A \in \boldsymbol{R}^{m \times n}} \min_{b \in \boldsymbol{R}^m} \mathbf{E}[||A \cdot M_\theta + b - F||^2] \qquad (3)$$

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Details of the derivation are in the paper!

Loss Function - Illumination Invariance

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- Invariant under regular (non-singular) linear transformation of M_θ and F

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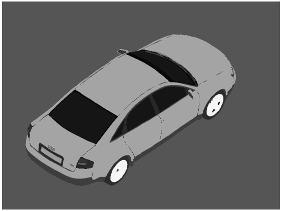
- Simillarly for linear transformations of F
- Independent of lighting A

Loss Function - Illumination Invariance



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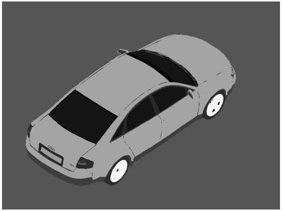

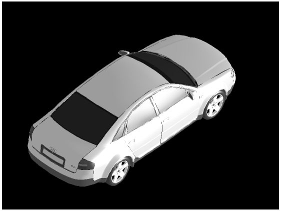

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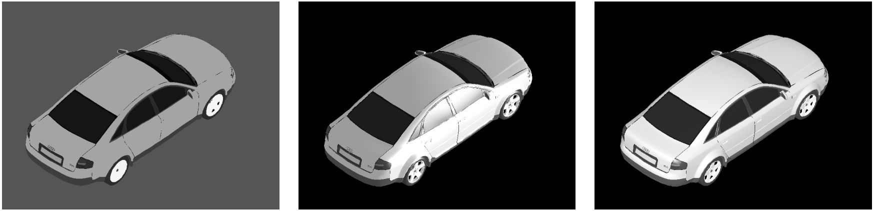

Pose representation

Orthographic projection (6 d.f)

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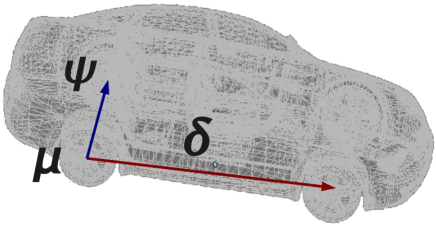

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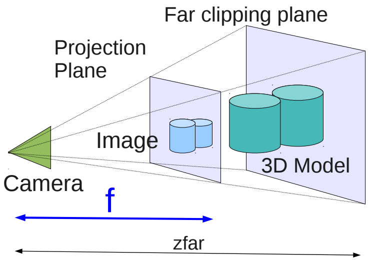
Perspective projection (7 d.f)



(a) Large f

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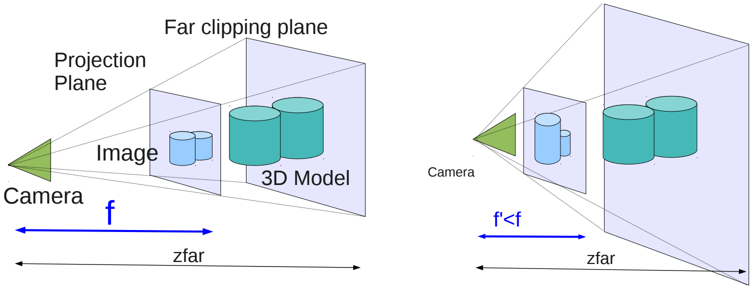
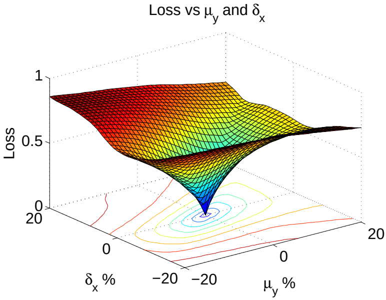


(a) Large f (b) Small f

Loss landscapes



(a) Synthetic photo

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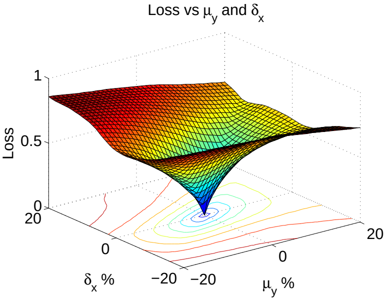

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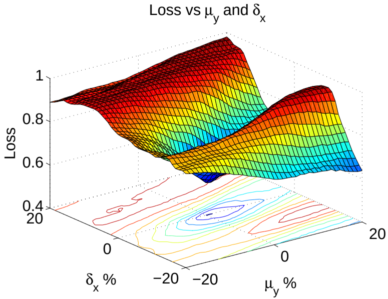

(b) Real photo

Initial rough pose to initialise the optimiser

- Several ways to obtain an initial (rough) pose: [Arie-Nachimson and Basri, 2009, ICCV] [Ozuysal et al., 2009, CVPR] [Sun et al., 2011, 3DIMPVT]

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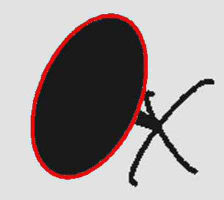

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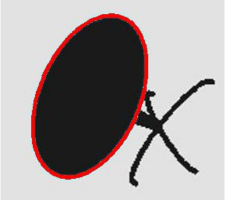

(a) (b) (c) (d) (e) (f) (g)

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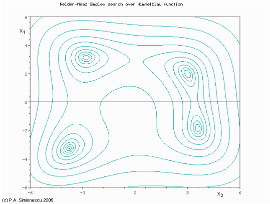
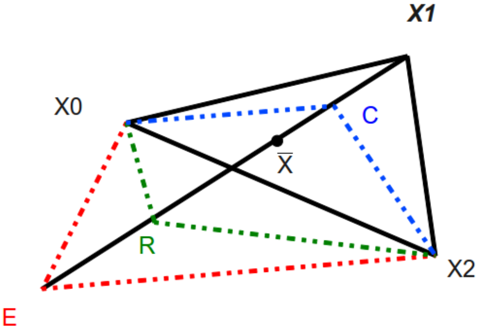
A 2D example:



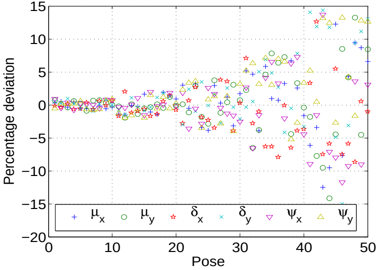
(a) Rosenbrock (2D)



(b) The simplex (3 points)

Reliability tests on loss based pose estimation

Reliability tests of pose estimation (initial rough pose with increasing deviations)



(a) Initial rough pose deviations

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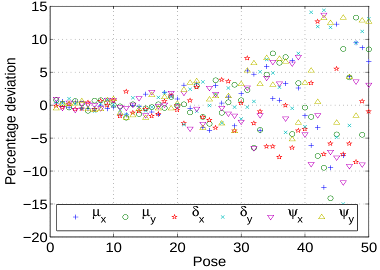

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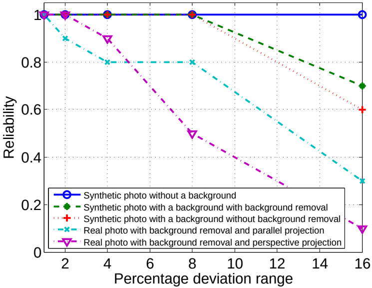
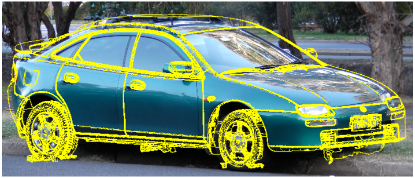


(b) Reliability $= \frac{NoCorrectCases}{TotalTestsPerDevnRange}$

Background removal using GrabCut [Rother et al., 2004, ACM]

Results - Scanned 3D CAD (Mazda Astina)



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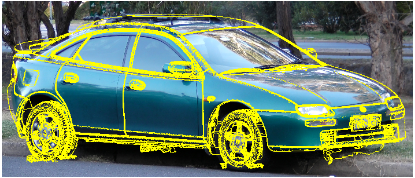

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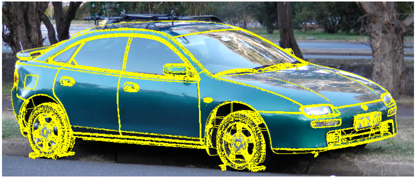
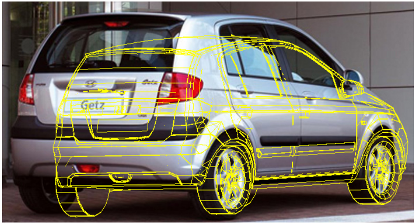


(b) Final pose

Results - Internet 3D CAD models



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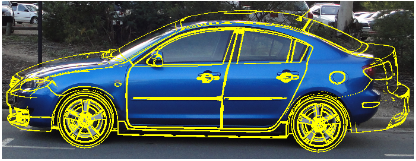

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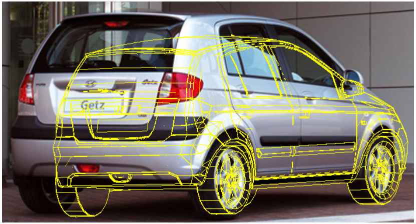

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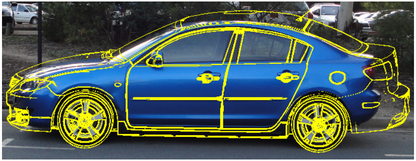
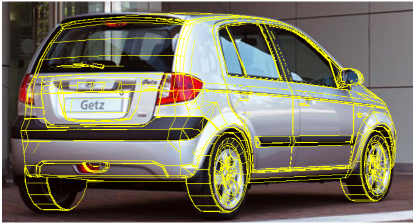
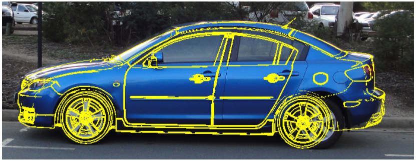


(b) Initial



(c) Final



(d) Final

Results - Internet 3D CAD models

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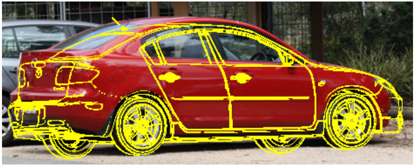

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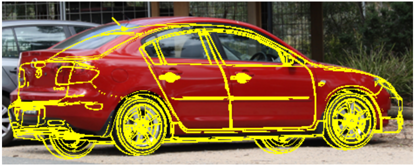

(b) Initial

(c) Final

(d) Final

Computation times

Table: Rendering and loss calculation times.

Approach	**Loss calc.**	**Render**
MATLAB	0.16 s	2.28 s
C/OpenGL	0.04 s	0.17 s

Approx 2 minutes to optimise 800x600 image

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Thank you!

References I

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