

# Pose Estimation Algorithms

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## Overview of Pose Estimation

- Problem statement:
  - Given: 3D coordinate vectors  $p_1 \dots p_n$  and corresponding projections  $q_1 \dots q_n$
  - Compute:  $R \in \text{SO}(3)$  and  $T \in \mathbb{R}(3)$  so that  $q_i$  is the projection of  $p_i$
- Iterative Approaches
  - photogrammetry style equations and gradient descent (Lowe, Haralick, ...)
  - Lu Hager Mjolsness: iteration on  $\text{SO}(3)$
- Direct Approaches
  - known algebraic solutions for 3 and 4 pts (Fischler, Horaud ...)
  - no known solutions for lines?
  - Embed nonlinear problem in a higher-dimensional linear space
    - usually release the constraints on rotations and fix it up later
    - Ansar and Daniilidis: algebraic varieties gives correct nonlinear solution within linear framework

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## Computing Pose

- Problem:
  - given points  $p_1 \dots p_n$  and corresponding points  $q_1 \dots q_n$  s.t.  $q_i = R p_i + T$
  - compute  $R \in SO(3)$  and  $T \in R(3)$
- Solution:
  - define
    - $p'_i = p_i - \text{mean}(p_1 \dots p_n)$
    - $q'_i = q_i - \text{mean}(q_1 \dots q_n)$
    - $M = \sum q'_i p'^t_i$
  - compute
    - $M = U D V^t$
    - $R = V U^t$

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## An Observation on Errors

- Consider  $v_i = (R p_i + t) / (r_3 p_i + t_z)$
- Define  $V = v_i v_i^t / (v_i^t v_i)$ 
  - note that  $V$  is a projection operator (symmetric, idempotent) and
    - $\|x\| \geq \|V x\|$
  - as such, it projects any point to the line of sight  $v_i$
  - in particular, note  $R p_i + t = V_i (R p_i + t)$  since  $p_i = k v_i$  for some  $k$
- Consider now define error as
  - $e_i = (I - V_i) R p_i + t$
  - $E(R, t) = \sum \| (I - V_i)(R p_i + t) \|^2$
- Observe that  $t(R)$  can be easily computed in closed form

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## Solving for Rotation

- Define
  - $q_i(R) = V_i(Rp_i + t(R))$
  - $q'_i(R) = q_i(R) - \text{mean}(q_1(R) \dots q_n(R))$
  - $M(R) = \sum q'_i(R) p_i^t$
- Observe that given an  $R$ , we can compute a new value of  $R$  using SVD as before.
- Algorithm:
  - Pick a starting  $R_0$
  - Repeat
    - compute  $t(R_k)$
    - compute  $q'_i(R_k)$
    - compute  $M(R_k)$
    - compute  $M(R_k) = U D V^t$
    - set  $R_{k+1} = V U^t$
  - Until convergence

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## Algorithm Convergence

- In order to show convergence, necessary to show that the mapping defined by this algorithm is
  - A closed mapping
    - this follows from closedness of SVD plus continuity of underlying calculations
  - All of the intermediate results come from a compact set
    - $SO(3)$  is closed and bounded; therefore it is compact.
  - Strictly decreasing
    - This follows from the basic geometry of the situation together with properties of projection operators.
- Note this is global convergence (previously all algorithms were local)
  - Note this \*does not\* imply that we are guaranteed to find the right solution
  - In fact, if we choose an initial guess that puts the points behind the camera, we are almost guaranteed to find the wrong solution!

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## Initialization

- Initialized using weak perspective model
  - $E(R, t, s) = \sum \| R p_i + t - s v_i \|^2$
  - Note that we can still solve the analogous absolute orientation problem
    - $s = (\sum \|p'_i\|^2 / \sum \|v'_i\|^2)^{1/2}$  where  $v'_i = v_i - \text{mean}(v_1 \dots v_n)$
    - $R$  as before
    - $t = s \text{ mean}(v_1 \dots v_n) - R \text{ mean}(p_1 \dots p_n)$
  - Not unexpectedly, it is not hard to show this is a good approximation when the image of the object is small in the image and near the optical center.

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## Evaluation

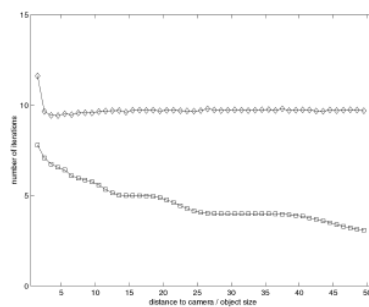


Fig. 3. Number of iterations as a function of distance to camera. The results for OI initialized with weak-perspective pose are plotted as squares (□) and the results for OI randomly initialized are plotted as diamonds (◊). Each point represents results averaged over 1,000 uniformly distributed rotations.

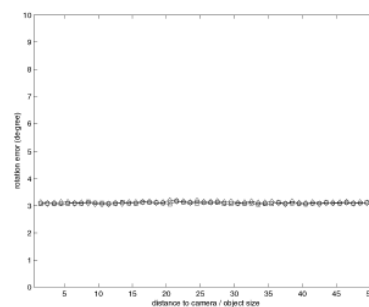


Fig. 4. Rotation error as a function of distance to camera. The results for OI initialized with weak-perspective pose are plotted as squares (□) and the results for OI randomly initialized are plotted as diamonds (◊). Each point represents results averaged over 1,000 uniformly distributed rotations.

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## Evaluation

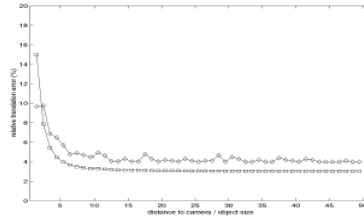


Fig. 5. Translation error as a function of distance to camera. The results for OI initialized with weak-perspective pose are plotted as squares ( $\square$ ), and the results for OI randomly initialized are plotted as diamonds ( $\diamond$ ). Each point represents result averaged over 1,000 uniformly distributed rotations.

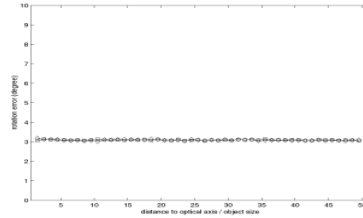


Fig. 7. Rotation error as a function of distance to optical axis. The results for OI initialized with weak-perspective pose are plotted as squares ( $\square$ ) and the results for OI randomly initialized are plotted as diamonds ( $\diamond$ ). Each point represents results averaged over 1,000 uniformly distributed rotations.

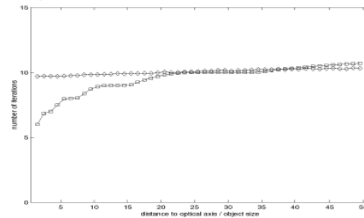


Fig. 6. Number of iterations as a function of distance to optical axis. The results for OI initialized with weak-perspective pose are plotted as squares ( $\square$ ) and the results for OI randomly initialized are plotted as diamonds ( $\diamond$ ). Each point represents results averaged over 1,000 uniformly distributed rotations.

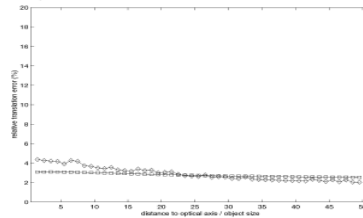


Fig. 8. Translation error as a function of distance to optical axis. The results for OI initialized with weak-perspective pose are plotted as squares ( $\square$ ) and the results for OI randomly initialized are plotted as diamonds ( $\diamond$ ). Each point represents results averaged over 1,000 uniformly distributed rotations.

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## Evaluation

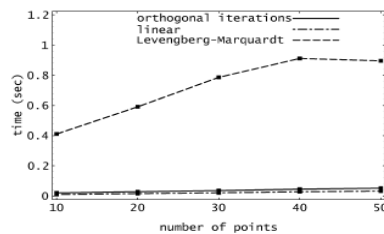


Fig. 9. Average running times used by the tested methods. Each point in the plot represents 1,000 trials.

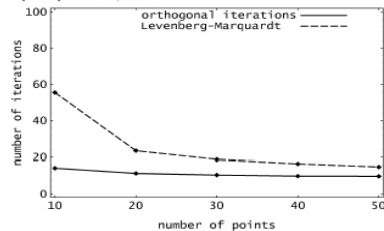


Fig. 10. Average numbers of iterations used by the tested methods. Each point in the plot represents 1,000 trials.

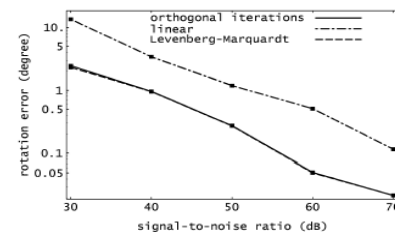


Fig. 11. Result (average rotation errors) of Experiment C1 for comparing with the Levenberg-Marquardt method. Error is in log scale. Each point in the plot represents 1,000 trials.

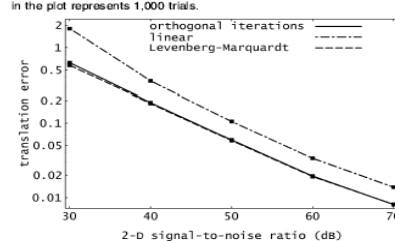


Fig. 12. Result (average translation error) of Experiment C1 for comparing with the Levenberg-Marquardt method. Error is in log scale. Each point in the plot represents 1,000 trials.

place the object behind the camera. OI seems to be able to

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## Evaluation

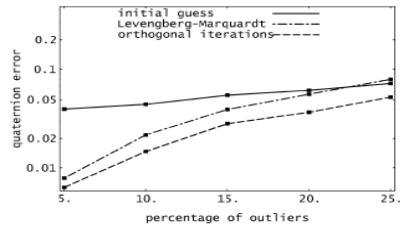


Fig. 13. Result (average rotation errors) of Experiment C2 for comparing with the Levenberg-Marquardt method. Error is in log scale. Each point in the plot represents 1,000 trials.

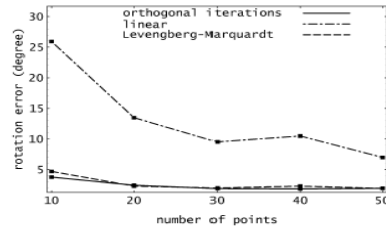


Fig. 15. Result (average rotation errors) of Experiment C3 for comparing with the Levenberg-Marquardt method. Error is in log scale. Each point in the plot represents 1,000 trials.

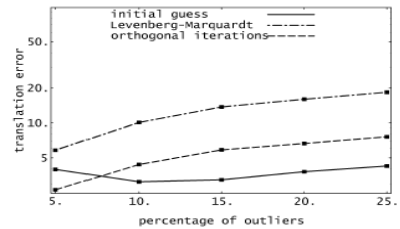


Fig. 14. Result (average translation errors) of Experiment C2 for comparing with the Levenberg-Marquardt method. Error is in log scale. Each point in the plot represents 1,000 trials.

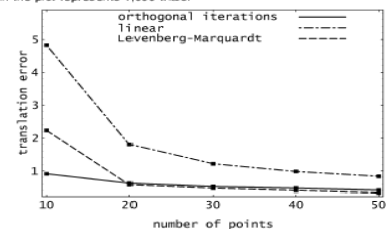


Fig. 16. Result (average translation errors) of Experiment C3 for comparing with the Levenberg-Marquardt method. Error is in log scale. Each point in the plot represents 1,000 trials.

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