Deep learning-based covariance estimation for relative pose measurements

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EVENTS Summary

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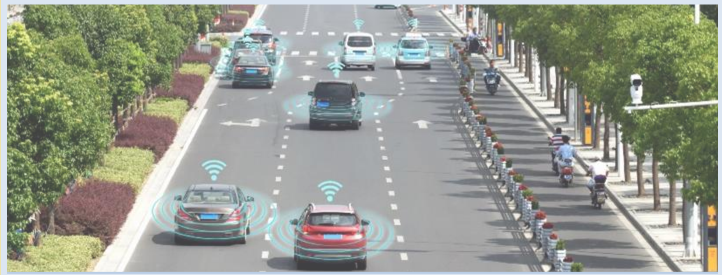

Funded by the European Union

European Research Council

Objectives

- Development of robust and reliable perception of objects, and especially VRUs, under complex urban traffic and bad weather or low visibility conditions
- Improved perception performance while using cost-efficient sensor suites

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Introduction

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- Relative pose measurements obtained/derived from onboard vehicle sensors are often quite important for localisation and mapping tasks.

- The integration/fusion of such measurements can be used to obtained a vehicles pose in some “odometry” coordinate frame.

- Covariance estimates/measurements can be used to help improve accuracy via measurement weighting during estimation/optimisation.

- Relative pose measurement errors can vary dramatically depending on scene/time (variation that is not Gaussian like).

- To this end, estimating covariance of relative pose measurements (with heteroscedastic errors) can potentially help improve accuracy of estimated vehicle pose.

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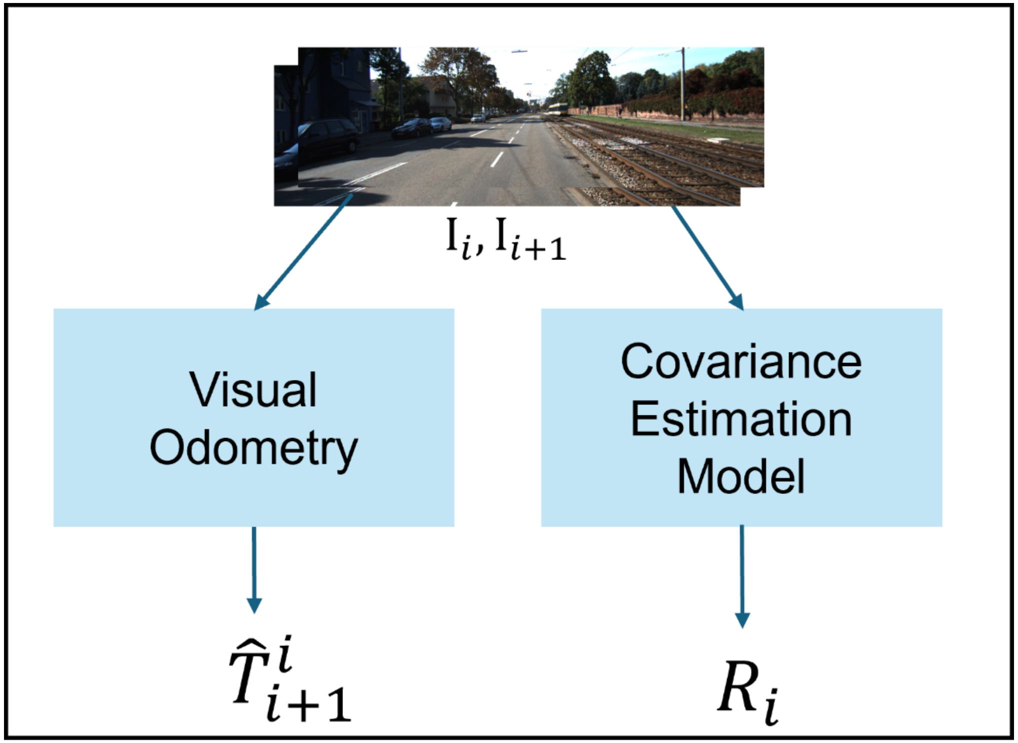
Background – Existing Approaches

- In this work we build upon the methods proposed in the following:
  - K. Lui et al, “Deep Inference for Covariance Estimation: Learning Gaussian Noise Models for State Estimation”, 2018
  - A.D. Maio et al, “Simultaneously Learning Corrections and Error Models for Geometry-based Visual Odometry methods”, 2020.



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Background – Covariance Estimation (Localisation)

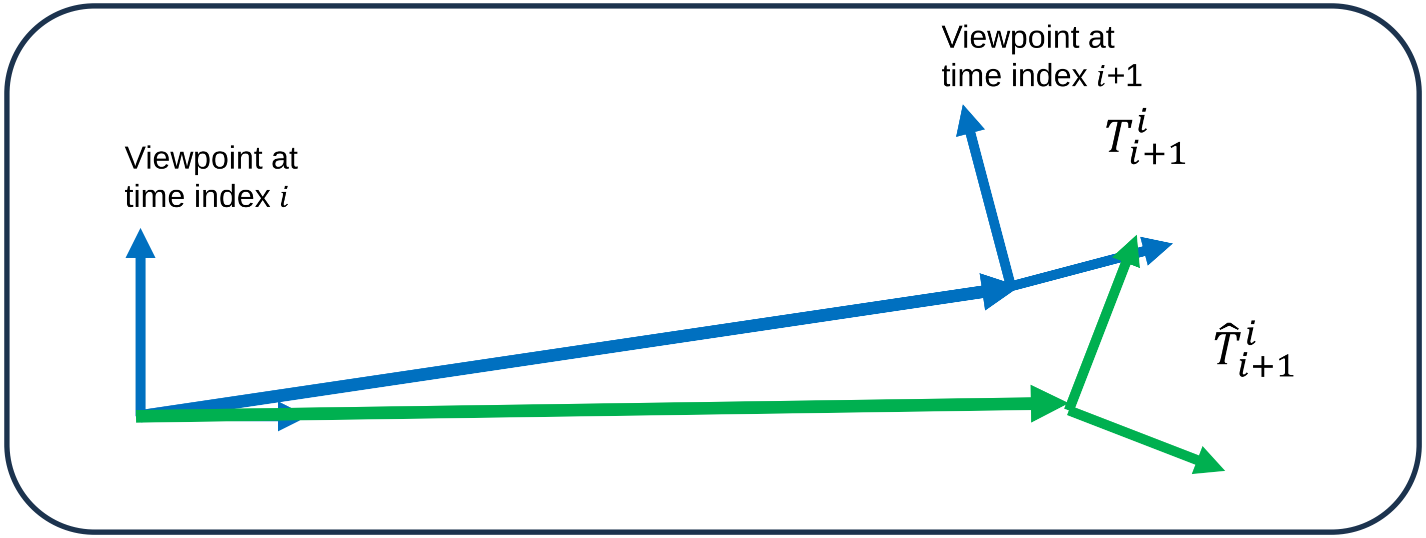
- The relative pose measurements ($\hat{T}_{i+1}^{i} \in R^{4\times4}$) are obtained from a visual odometry algorithm

- The error between ground truth relative pose (T_{i+1}^{i}) and estimated relative pose is given by:

$$\mathrm{e_i} = \log(\hat{T}_{i+1}^{i} T_{i}^{i+1})$$

- To this end, the covariance estimation models seek to determine the covariance R_i of the following error distribution:

$$\mathrm{e_i} \sim \mathcal{N}(0, R_i)$$



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Limitations and Proposed Approach

- Our rational is that a diagonal estimation of covariance reflects the available information, and furthermore, and ultimately the diagonal covariance for a single measurement is the square of the error.

- To this end, our objective is to measure the squared error of the estimated relative pose and ground truth relative pose (error specified in previous slide).

- Prior work estimate covariance using a pair of mono or stereo images obtained from two different viewpoints.

- Prior approaches consume as input images obtained from two different viewpoints, therefore they are not able to estimate squared error for an arbitrary relative pose measurement.

- Our proposed approach seeks to include the relative pose measurement as an additional input in order to capture error variation for a **general** relative pose measurement.

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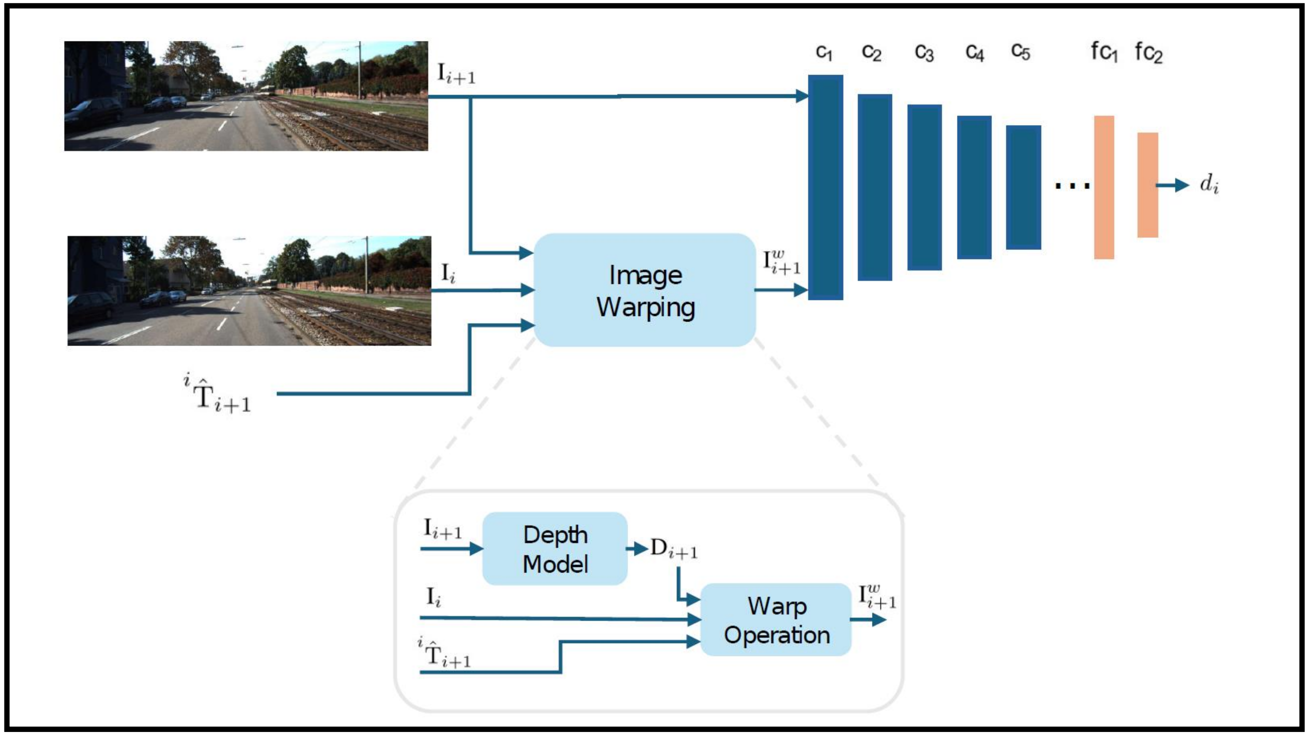
Proposed Approach

- The input consists of images acquired from two different viewpoints along with the measured relative pose, while the output is the estimated covariance.

- The model utilises the measured relative pose via an image warping operation, thereby enabling the covariance estimate to vary according to measured relative pose.



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Training Details

- For the ***depth estimation network,*** we propose to utilise the pre-trained monocular depth network (monodepth2) and more specifically the 1024x320 version.

- As this is unscaled depth we use LiDAR measurements to compute a scale factor. Specifically using the ratio mean radial distance derived from LiDAR measurements and mean depth of unscaled depth estimates.

- The hyperparameters for covariance estimation network training were set as follows: batch size: 84, optimiser: Adam, and learning rate: 1e-04.

- Stoppage criterion: We stopped training according to that is, once we observed diverging train and evaluation losses.

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Experimental Description

- We train and evaluate on the KITTI dataset. More specifically we use sequences 04-09 for training and sequence 10 for evaluation.

- Ground truth measurements were assumed to be the RTK-GPS measurement,

- In our work we considered relative pose measurements from the following “system”:
  - System 1: Sparse visual odometry
  - System 2: RTK-GPS

- Prior approaches would not be able to compute a covariance that considered the measured relative pose.

- We compute a variation of median absolute error between the ground truth squared error against the estimated squared error.

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Results – Inference Examples

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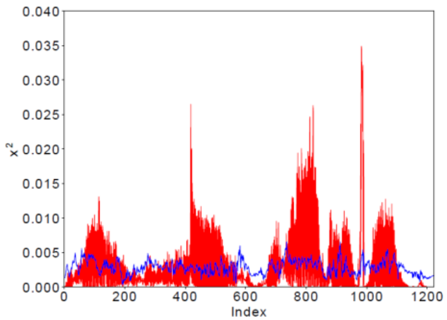
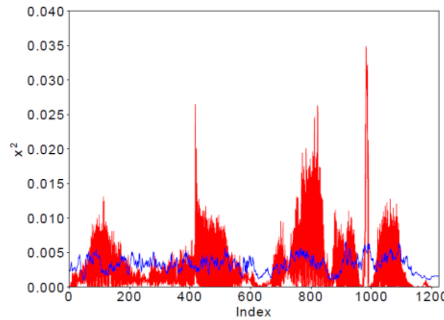
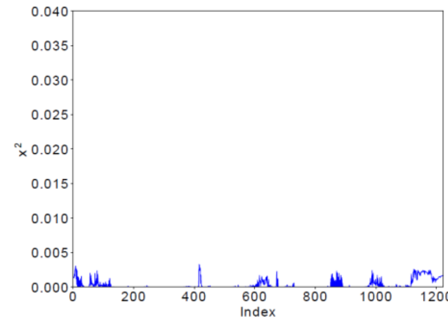
Translation - x



(a) Proposed method - System 1

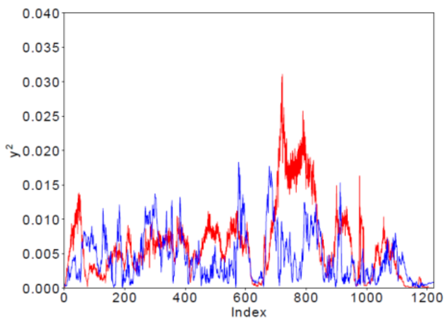


(b) [7] - System 1

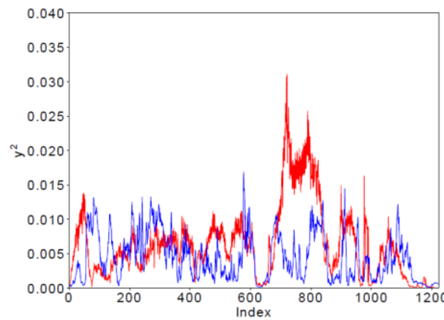


(c) Proposed method - System 2

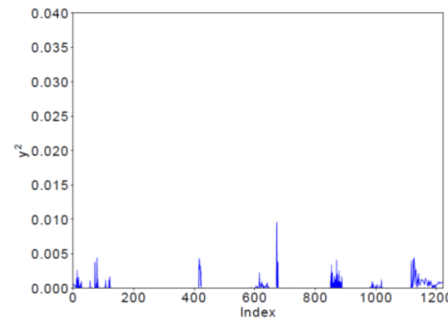
Translation - y



(d) Proposed method - System 1

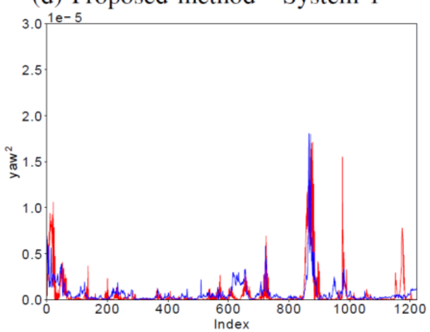


(e) [7] - System 1

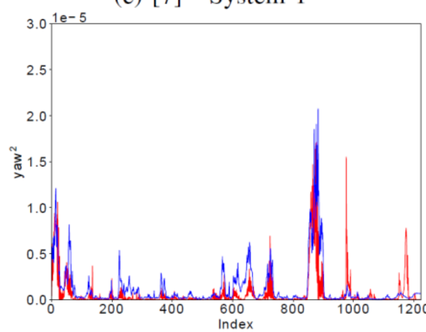


(f) Proposed method - System 2

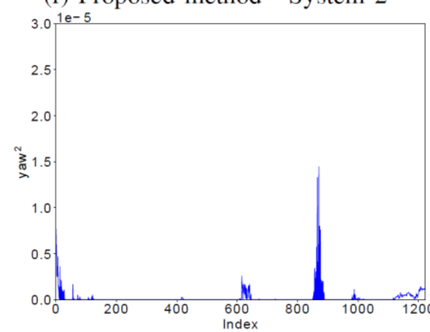
Rotation - yaw



(g) Proposed method - System 1



(h) [7] - System 1



(i) Proposed method - System 2

Ground Truth – Red line
Inference – Blue Line

[7] A.D. Maio et al, “Simultaneously Learning Corrections and Error Models for Geometry-based Visual Odometry methods”, 2020.

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Results

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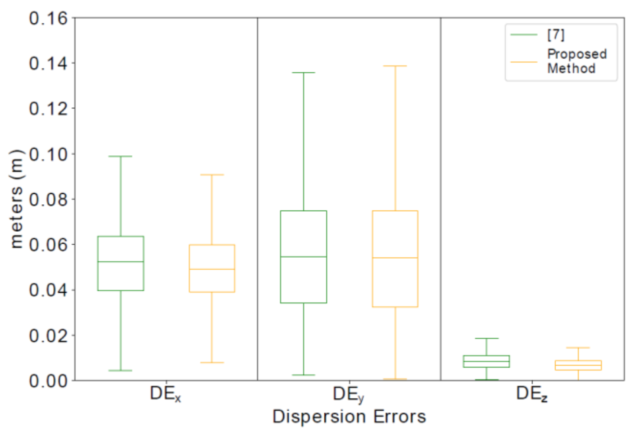
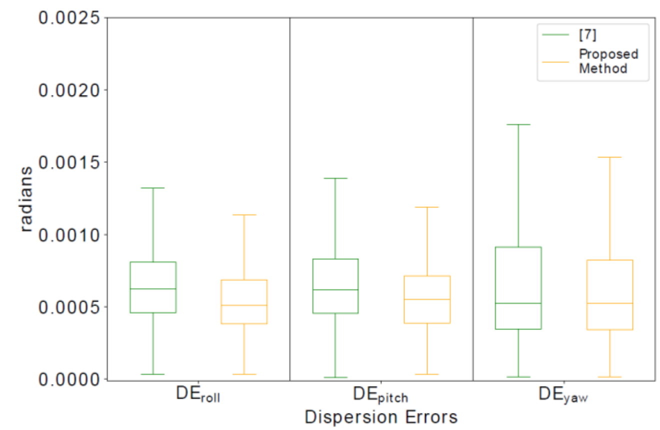
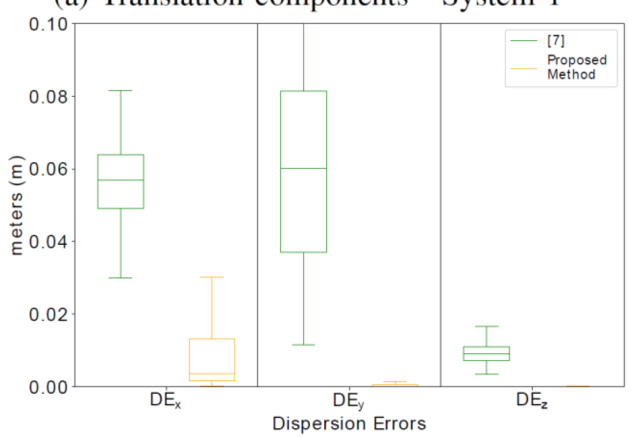


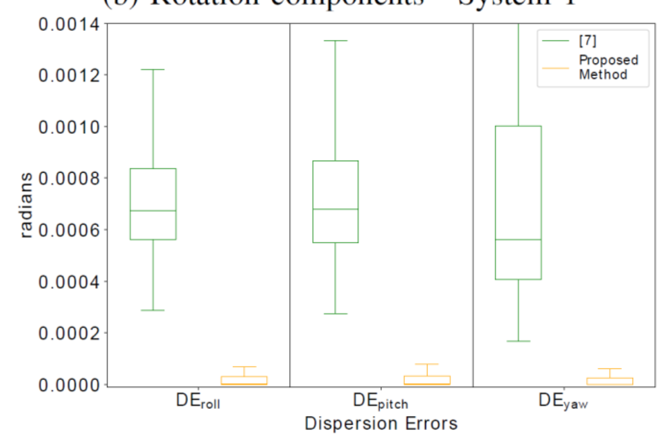
(a) Translation components - System 1



(b) Rotation components - System 1



(c) Translation components - System 2



(d) Rotation components - System 2

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Conclusion

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- In this work we have proposed a covariance estimation method for relative pose measurements obtained from an arbitrary system

- We achieve this by utilising the measured relative pose along with the images acquired between the two viewpoints to compute a covariance

- We demonstrate the ability of our model to estimate covariance for relative pose measurements obtained from two different systems

- Finally, in future work, we aim to investigate viewpoint synthesis via NeRFs as replacement to image warping, along with relative pose measurement generation to augment existing real-world datasets

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END

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