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Inertial measurement unit-camera calibration based on incomplete inertial sensor information

Key words: Calibration, Computer vision, Inertial sensor, Smart phone, Incomplete information

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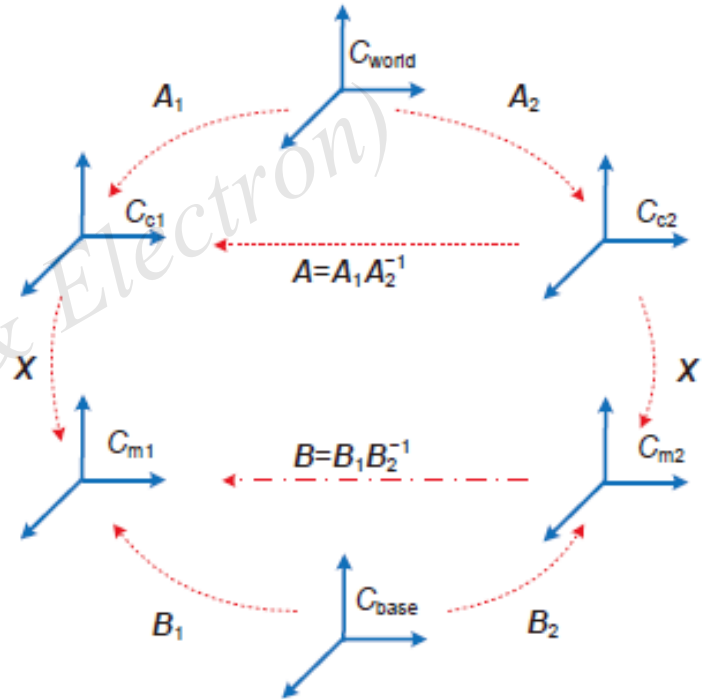
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Motivation

- This paper addresses the incomplete information based IMU camera calibration problem by exploiting the intrinsic restrictions among the coordinate transformations
- Disadvantages of existing methods:
 - Cannot deal with calibration with incomplete IMU information such as just Roll and Pitch
 - Analytical solutions are not given

Features of our method

- Use only roll and pitch of the IMU output
- Recover IMU Rotation R_B from property of similar matrices
- Using LM optimization to refine final result



$$R_A R = R R_B,$$

$$\text{tr}(R_A) = \text{tr}(\widetilde{R_B})$$

Framework of our method (I)

The algorithms of camera-IMU calibration can be divided into two parts:

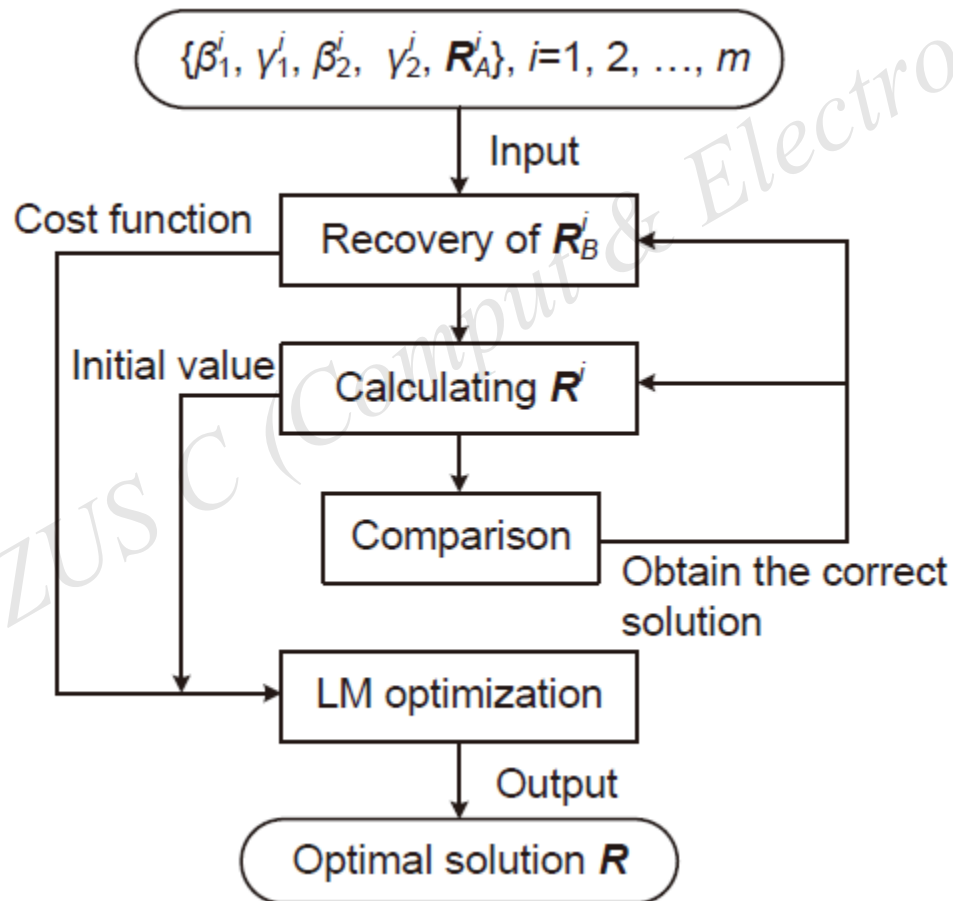
1. Recovery of R_B

Algorithm 1 Recovery of R_B

- 1: **Input:** R_A and four Euler angles $\beta_1, \beta_2, \gamma_1, \gamma_2$
 - 2: **Output:** R_B
 - 3: **Begin**
 - 4: Calculate O_i and $P_i, i=1, 2$
 - 5: Calculate T
 - 6: Formulate $\widetilde{R}_B = \text{yaw}(\alpha)T$
 - 7: Compute $\text{tr}(R_A)$ and $\text{tr}(\widetilde{R}_B)$
 - 8: Solve α from Eq. (17)
 - 9: Recover $R_B = O_1 P_1 \text{yaw}(\alpha) P_2^T O_2^T$
 - 10: **End**
-

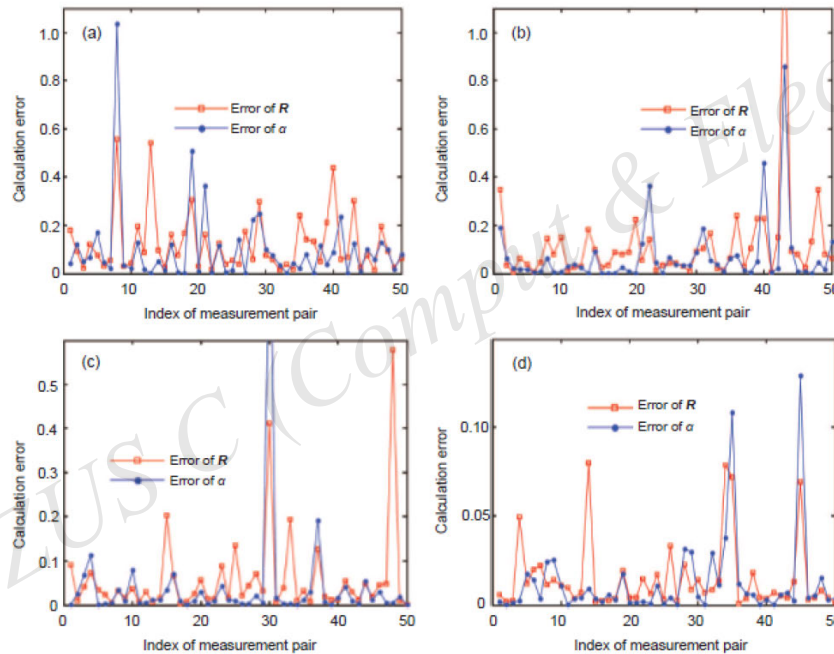
Framework of our method (II)

2. Calculating R and LM optimization



Simulation & results

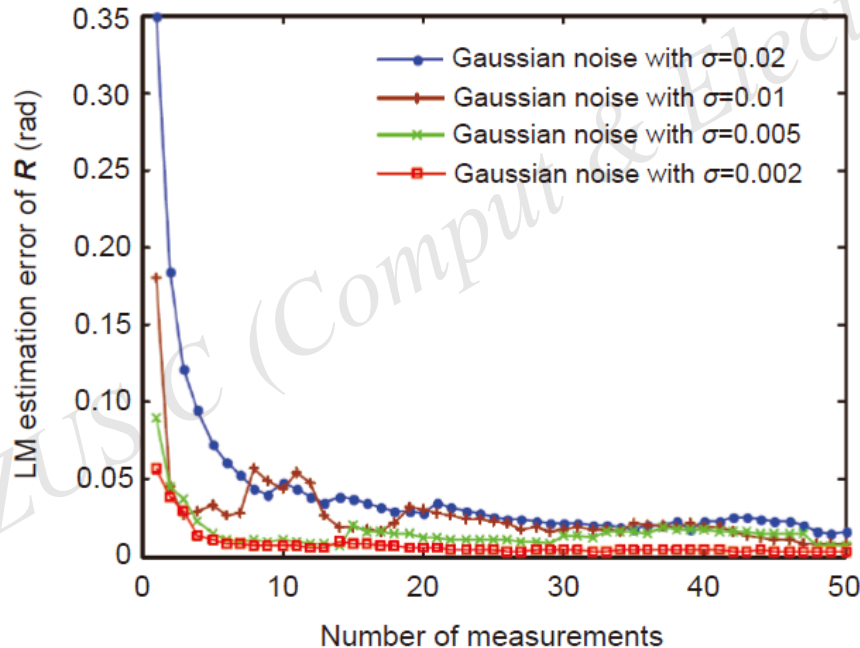
For comparison, the mean of the two e is regarded as the error of R for each pair since there are two measurements in each pair. The experimental results are:



Most errors of R are within the limits of 20σ whereas a few errors are relatively large which is not surprising due to the strong noise there. The two curves generally followed the same trends. Inconsistencies of the two curves may result from the error of R_A or other computational errors

Simulation & results

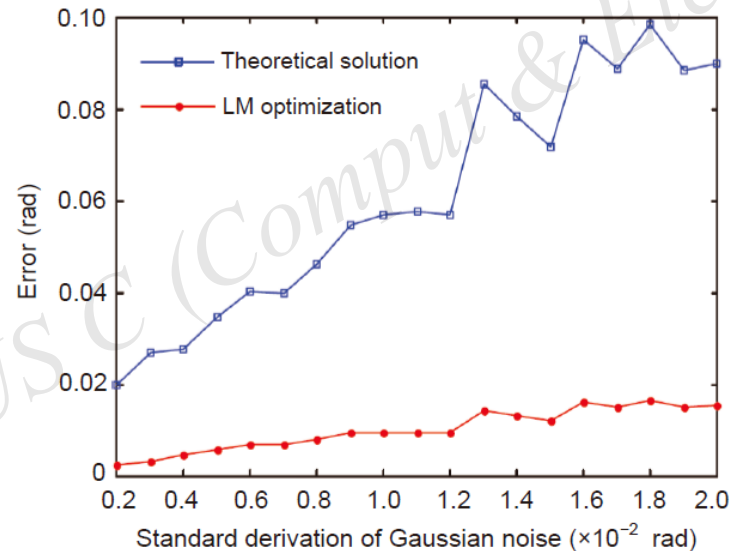
The number of the measurements m is assigned from 1 to 50 in the cost function. As a consequence, the LM algorithm is called 200 times in four Gaussian noise environments. The experimental results are:



It is seen that the error curves converge as m increases and the converged error value is about the same as σ

Simulation & results

To better tell how the errors of the estimates grow with the Gaussian noise, we carried out experiments in 19 Gaussian noise environments with standard derivations ranging from 0.002 to 0.02 using both the theoretical method and LM optimization



The average error of the theoretical method is about 5σ – 10σ and the error of LM optimization is about σ

Real experiments & results

Result:

$$\hat{\mathbf{R}} = \begin{bmatrix} -0.1478 & 0.9836 & -0.1029 \\ -0.9890 & -0.1464 & 0.0205 \\ 0.0051 & 0.1048 & 0.9945 \end{bmatrix} \approx \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$