Robotized metrology: Wait, it's all calibration ?

Caroline PASCAL

U2IS & UME – ENSTA Paris

April 4, 2024

Bring in **automation** and **versatility** to metrology processes through the use of **robotic arms**.

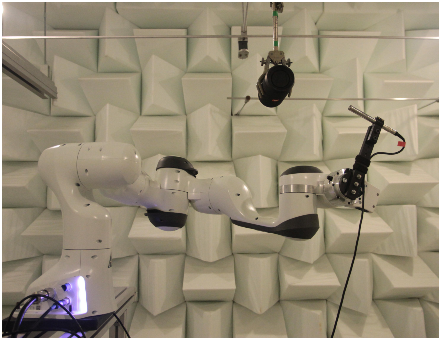


Figure 1: Acoustic measurements for Sound Field Estimation (SFE) [1]

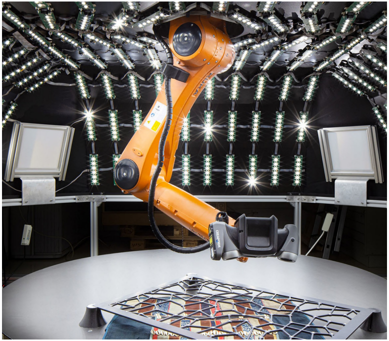


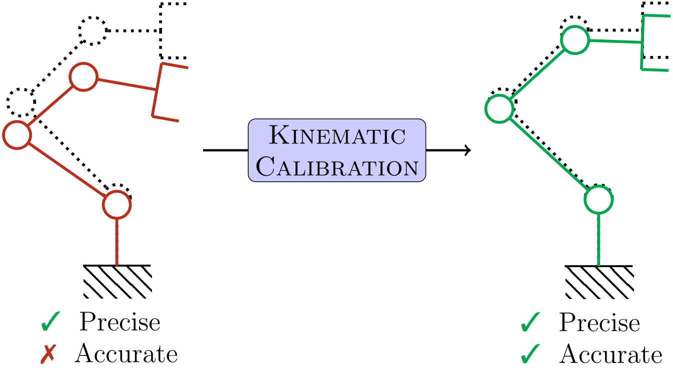
Figure 2: Opto-numeric measurements for cultural heritage digitization [2]

Why is calibration essential ?

Accurate Metrology

⇔ **Knowledge** of all elements in the acquisition chain

⇔ **Calibration** of both sensors *and* actuators !



Objective: one calibration procedure to rule them all

→ Sensor calibration

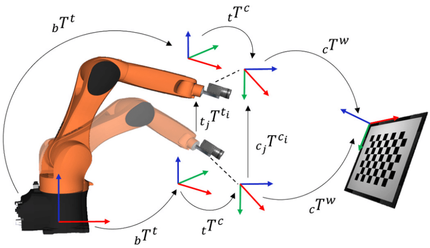


Figure 3: Hand-Eye-World camera calibration [3]

→ Robot calibration

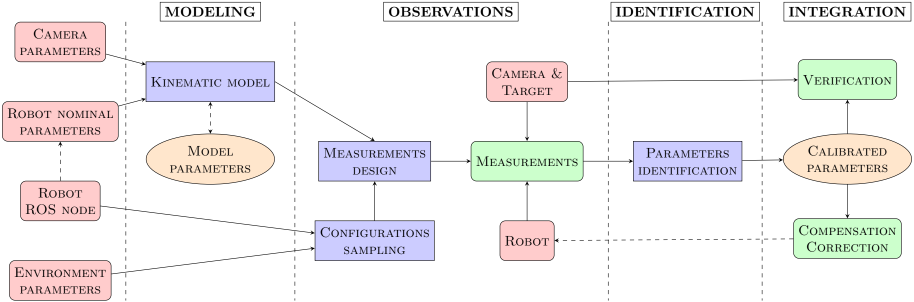
Figure 4: Position-based robot calibration [4]

Merge both procedures into a single **robot-camera calibration** procedure.

Table of Contents

Table of Contents

Robot & Camera calibration in 4 steps



→ *Remark:* The camera intrinsic parameters are calibrated separately, upstream to this study.

Step 1 : Modeling

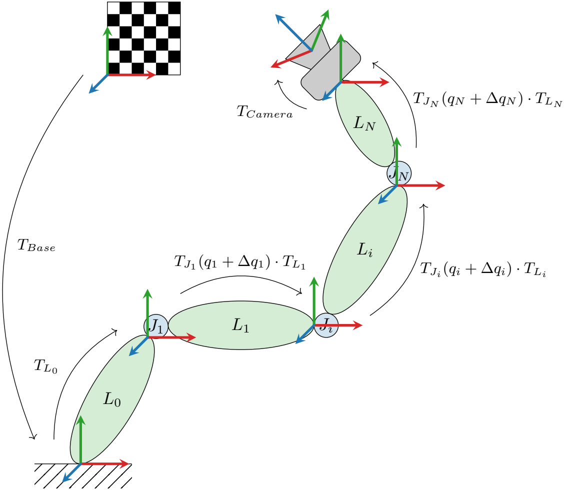


Figure 5: Combined model : robot & camera transformations.
→ *Faithfull, complete, not-redundant and differentiable.*

Step 1 : Modeling

Full-pose geometric modeling

$$
\begin{aligned}
T_T^C(q,\pi) = &T_{Base}(\pi_{Base}) \cdot T_{Link_0}(\pi_{L_0}) \\
&\cdot [T_{Joint_1}(q_1 + \Delta q_1, \pi_{J_1}) \cdot T_{Link_1}(\pi_{L_1})] \dots \\
&\cdot [T_{Joint_N}(q_N + \Delta q_N, \pi_{q_N}) \cdot T_{Link_N}(\pi_{L_N})] \cdot T_{Camera}(\pi_{Camera}), \\
= &\begin{pmatrix} R(q,\pi) & P(q,\pi) \\ 0_3 & 1 \end{pmatrix},
\end{aligned}
$$

Where $\pi = (\pi_{Base}, \pi_{J_i}, \pi_{L_i}, \pi_{Camera})$ are the *model parameters*, and π_0 holds their nominal values.

Step 2 : Observations

→ **Loop-closure**: computation of $\tilde{T}_T^C$ using a ChAruco board.

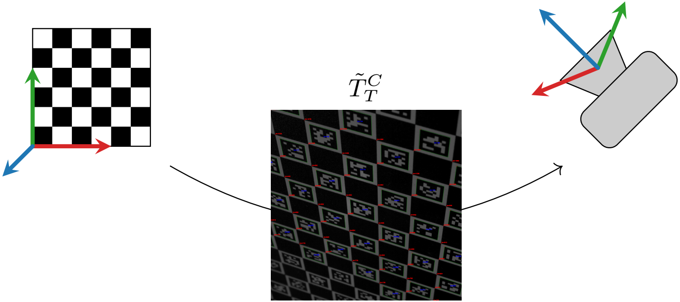


Figure 6: Camera pose measurement.
The camera model is used to solve the PnP problem.

– Randomly aimed position on the board at fixed distance ($0.2\ m$);

– Selection of non-overlapping and obstuction-less camera angles;

Step 3 : Identification

Identification delta and jacobian

$$\Delta(q,\pi) = \big(\underbrace{P(q,\pi) - \tilde{P}_q}_{\text{Cartesian coordinates (3)}},\quad L \times \underbrace{\tilde{R}_q{}^T.R(q,\pi)}_{\text{Modified Rodrigues parameters (3)}}\big),$$

$$J_\pi(q,\pi)_{i,j} = \left(\frac{\partial \Delta(q,\pi)_i}{\partial \pi_j}\right)_{i,j}.$$

Identification problem

$$\min_\pi \underbrace{\sum_{i=1}^{M_{\text{measured}}} \Delta(q_i,\pi)^T \Delta(q_i,\pi)}_{\text{Identification fitness}}.$$

→ **Well-conditionned** problem, solved using the **Gauss-Newton algorithm**.

Step 4 : Verification & Integration

Experimental setup

- **30 parameters**: 6 (Base) + 6 (Camera) + 18 (6-axis KUKA Robot);
- **20 shots**: 15 (Identification), 5 (Verification);
  $\rightarrow$ **90 equations**;
- **Initial Hand-Eye-World calibration** performed with all measurements using Shah's method [5].

	H-E-W calibration	**Combined calibration**
Fitness score ($\times 10^{-6}$)	14	**7.8**
Average position error (µm)	3.8	**1.3**
Average rotation error ($\times 10^{-6}$ **rad**)	**16**	21
Reprojection error (pixels)	51	**20**

Table of Contents

What about error preconditionning ?

Improve calibration results using a **modified formulation of the identification delta** - *Weighting, change of basis, etc*.

→ Improve the problem conditionning;

→ Take the sensor physics into account;

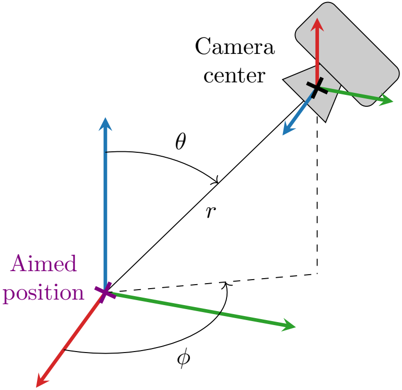
→ Find a more relevant basis for the weightings.

preconditionning integration

$$\begin{aligned} \hat{\Delta}(q,\pi) &= f(\Delta(q,\pi)) && (\textit{Identification delta}), \\ \hat{J}_\pi(q,\pi) &= J_f(\Delta(q,\pi)).J_\pi(q,\pi) && (\textit{Identification jacobian}). \end{aligned}$$

→ *Remark:* The preconditionning function must not degrade the model properties - *differentiability, completeness, non-redundancy*.

Robot & Camera : a spherical approach ?



Spherical preconditionning

$$\Delta_S(q,\pi) = (\ \underbrace{r(q,\pi) - \tilde{r}_q,\ \theta(q,\pi) - \tilde{\theta}_q,\ \Phi(q,\pi) - \tilde{\Phi}_q}_{\text{Spherical coordinates (3)}},\ L \times \underbrace{\tilde{R}_q{}^T . R(q,\pi)}_{\text{Euler angles* (3)}}\ ).$$

Robot & Camera : a spherical approach !

	Standard preconditionning	**Spherical preconditionning**
Fitness score (spheric, $\times 10^{-4}$)	1.3	**1.1**
Fitness score (standard, $\times 10^{-6}$)	7.8	**7.0**
Position error (µm)	1.3	**0.75**
Rotation error ($\times 10^{-6}$ rad)	**21**	25
Reprojection error (pixels)	20	**16**
***z*-axis rotation error ($\times 10^{-6}$ rad)**	**3.4**	9.4

$\Longrightarrow$ The identification takes benefit from the ***z*-axis (optical axis) invariability** of camera measurements !

Table of Contents

What we have done

- A **combined robot-camera** calibration procedure.
  - → A **more efficient** and **less time-consumming** calibration procedure;
  - → A 66% **position accuracy improvement** and 61% **reprojection error reduction** compared to the camera-only calibration;
- An efficient implementation of **identification preconditionning**.
  - → A direct embedding of the **sensor physical behaviour** in the identification;
  - → A 42% **position accuracy improvement** and 20% **reprojection error reduction** compared to the standard preconditionning;

What we aim to do (if we have time)

- Integrate the **intrinsic camera calibration**.
  - → Directly use the **reprojection error** as the identification fitness function.
  - → ⚠ **Redundancies** and optical **constraints** !
- Investigate **measurements configurations optimization**.
  - → What about the **geometric** and **optical** parameters **identifiability** ?
- More steps towards **meta-calibration** ?
  - → La Coupole $\Longrightarrow$ LED calibration, light calibration, 3D scanner calibration, etc.

Thank you for your time and attention !

References I

Caroline Pascal, Alexandre Chapoutot, and Olivier Doaré.
Far-field sound field estimation using robotized measurements and the boundary elements method.
In *53rd International Congress on Noise Control Engineering (Inter-Noise 2024)*, August 2024 (forthcoming).

Antoine Lucat.
Acquisition opto-numérique de vêtements asiatiques anciens.
Theses, Université de Bordeaux, February 2020.

Ihtisham Ali, Olli Suominen, Atanas Gotchev, and Emilio Ruiz Morales.
Methods for simultaneous robot-world-hand–eye calibration: A comparative study.
Sensors, 19(12), 2019.

References II

Caroline Pascal, Alexandre Chapoutot, and Olivier Doaré.
A ROS-based kinematic calibration tool for serial robots.
In *2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Detroit, Michigan, USA, October 2023.

Mili Shah.
Solving the Robot-World/Hand-Eye Calibration Problem Using the Kronecker Product.
Journal of Mechanisms and Robotics, 5(031007), June 2013.