# A Machine Learning Approach to Hand-Eye Calibration 

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## Outline

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Stand-alone Calibration: Camera

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## Introduction



## Introduction

- pre-step to high level algorithms, e.g. object recognition or grasping
- calibrate each piece of hardware by itself
- after calibration measure relative offset between arm and camera (tricky)
- non-linearities, e.g. through distortions
- our idea: reformulation of these problems as a single problem
- simultaneously learn:
- mapping from image coordinates to world coordinates
- mapping from state vector $q$ to world coordinates
- minimize error between both mappings


## Stand-alone Calibration: Robot Arm

## Forward Kinematics

- n-dof robot arm:
- controlled via state vector $\vec{q} \in \mathbb{R}^{n}$, e.g. joint angles
- foward kinematics: given $\vec{q}$ determine world coord. $\vec{X}$ of end-effector
- ideal world: $\vec{X}=\omega(\vec{q})$, actual world: $\vec{X}_{\delta}=\omega(\vec{q}+\vec{\delta})$
- unknown $\vec{\delta}$ due to physical phenomena, e.g. cog wheels



## Stand-alone Calibration: Camera

Pinhole Camera Model

- projection matrix $P \in \mathbb{R}^{3 \times 4}$ :

$$
\begin{equation*}
P=K R[I \mid-\tilde{C}] \tag{1}
\end{equation*}
$$

- projection of world point $\vec{X}=(x, y, z, v)^{t}$ to image point $\vec{x}=(u, v, w):$

$$
\left(\begin{array}{c}
u  \tag{2}\\
v \\
w
\end{array}\right)=P \cdot\left(\begin{array}{l}
x \\
y \\
z \\
v
\end{array}\right)
$$

- intrinsics $K \in \mathbb{R}^{3 \times 3}$, extrinsics $R \in \mathbb{R}^{3 \times 3},-\tilde{C} \in \mathbb{R}^{3}$ :

$$
K=\left[\begin{array}{ccc}
\alpha_{x} & s & x_{0} \\
0 & \alpha_{y} & y_{0} \\
0 & 0 & 1
\end{array}\right]
$$

## Stand-alone Calibration: Camera

## Gold Standard algorithm ${ }^{1}$ to determine int./ext. parameters

- solvable through Direct Linear Transform(ation) (DLT)
- given: collect $n \geq 6$ point correspondances: $\vec{x}_{i} \leftrightarrow \vec{X}_{i}$
- wanted: matrix $P$, so that

$$
\vec{x}_{i}=P \vec{X}_{i} \quad \Leftrightarrow \vec{x}_{i} \times\left(P \vec{X}_{i}\right)=\overrightarrow{0} \quad \Leftrightarrow \vec{x}_{i} \times\left(\begin{array}{c}
P^{1} \vec{X}_{i}  \tag{3}\\
P^{2} \vec{X}_{i} \\
P^{3} \vec{X}_{i}
\end{array}\right)=\overrightarrow{0}
$$

- rewrite eq. (3) in matrix notation, $A \in \mathbb{R}^{12 \times 12}, p \in \mathbb{R}^{12}$ :

$$
\begin{equation*}
A \vec{p}=\overrightarrow{0} \text {, s.t. }\|\vec{p}\|=1 \tag{4}
\end{equation*}
$$

- solve with SVD: $A=U D V^{T}$
- $p=V(:$, end $)$, if diagonal values of $D$ in descending order

[^0]
## Stand-alone Calibration: Camera

Optical Aberration/Distortion

- camera with lens $\neq$ pin-hole camera model (!)
- distortion (radial, tangential, ...)
- significance increases while focal length (and price) decreases

(a) lens distortion

(b) types of (radial) distortion


## Stand-alone Calibration: Camera

## Optical Aberration/Distortion

- correction of radial distortion

$$
\begin{aligned}
x^{\prime} & =x\left(1+k_{1} r^{2}+k_{2} r^{4}+k_{3} r^{6}\right) \\
y^{\prime} & =y\left(1+k_{1} r^{2}+k_{2} r^{4}+k_{3} r^{6}\right)
\end{aligned}
$$

- correction of tangential distortion

$$
\begin{aligned}
x^{\prime} & =x+\left[2 p_{1} y+p_{2}\left(r^{2}+2 x^{2}\right)\right] \\
y^{\prime} & =y+\left[p_{1}\left(r^{2}+2 y^{2}\right)+2 p_{2} x\right]
\end{aligned}
$$

- minimizing geometric error of a calibration object (chessboard) based on deviation from linear mappings


## Stand-alone Calibration: Camera

## Stereo Calibration

- first, single-camera calibration to obtain

$$
P_{l}=K_{l} R_{l}\left[I \mid-\tilde{C}_{l}\right]
$$

and

$$
P_{r}=K_{r} R_{r}\left[I \mid-\tilde{C}_{r}\right]
$$

- then, translation matrix $R$ and translation $T$ from right to left camera coordinate system:

$$
\begin{aligned}
R & =R_{r}\left(R_{l}\right)^{T} \\
T & =\tilde{C}_{r}-R \tilde{C}_{l}
\end{aligned}
$$

## Stand-alone Calibration: Camera

## Calibration Pipeline



## Hand-Eye Calibration

General Setup


- unknown calibrations parameters: initially, hardware is uncalibrated!
- unknown rotation \& translation between robot and camera
- fiducal marker ("lolly pop") in robot's hand
- visually track lolly pop and record image coordinates $\vec{x}_{i}^{l}$ and $\vec{x}_{i}^{r}$
- record state vector $\vec{q}_{i}$ of robot
- ...


## Hand-Eye Calibration

Data Acquisition



## Hand-Eye Calibration

## Minimization Problem



- given: set of image points $\vec{x}_{i}^{l}, \vec{x}_{i}^{r}$, and state vectors $\vec{q}_{i}$
- wanted: world coordinates $\vec{X}_{i}$ from non-linear mappings, such that

$$
\begin{equation*}
\Phi\left(\vec{x}_{i}^{l}, \vec{x}_{i}^{r}\right)=\vec{X}_{i}=\psi\left(\vec{q}_{i}\right) \tag{6}
\end{equation*}
$$

## Hand-Eye Calibration

Minimization Problem

- global cost function:

$$
\begin{equation*}
L_{\mathrm{global}}=\sum_{i}\left|\psi\left(\vec{q}_{i}\right)-\Phi\left(\vec{x}_{i}^{l}, \vec{x}_{i}^{r}\right)\right|^{2} \tag{7}
\end{equation*}
$$

- hard to minimize eq. (7) directly
- local cost function for image points:

$$
\begin{equation*}
L_{\vec{x}}=\sum_{i}\left|X_{i}-\Phi\left(\vec{x}_{i}^{l}, \vec{x}_{i}^{r}\right)\right|^{2} \tag{8}
\end{equation*}
$$

- local cost function for state vector:

$$
\begin{equation*}
L_{\vec{q}}=\sum_{i}\left|X_{i}-\psi\left(\vec{q}_{i}\right)\right|^{2} \tag{9}
\end{equation*}
$$

## Hand-Eye Calibration

Suggested Algorithm

Input: image point pairs $\left(\vec{x}_{i}^{l}, \vec{x}_{i}^{r}\right)$, state vectors $\vec{q}_{i}$
Output: mappings $\psi\left(\vec{q}_{i}\right)$ and $\Phi\left(\vec{x}_{i}^{l}, \vec{x}_{i}^{r}\right)$
1: define $\psi^{\prime}(\cdot)$ as regular forward kinematics
2: repeat
3: learn $\Phi^{\prime}(\cdot)$ given $\psi^{\prime}\left(\vec{q}_{i}\right)$ (eq. (8))
4: learn $\psi^{\prime}(\cdot)$ given $\Phi^{\prime}\left(\vec{x}_{i}^{l}, \vec{x}_{i}^{r}\right)$ (eq. (9))
5: until $L_{\text {global }}<\varepsilon$
6: return $\Phi=\Phi^{\prime}, \psi=\psi^{\prime}$

## Hand-Eye Calibration

Learning Step

- SVM regression
- Gaussian Process
- Multi-layer Perceptron
- [your algorithm]
- ...


## Next steps

- Proof of concept in simulator
- Verification with actual camera and arm
- make data available to IDA members
- ...


## Conclusions

- iterative approach to the Hand-Eye calibration problem
- solving problem in "EM-fashion"
- no assumption on parameters
- no need to measure exact camera-to-robot offset
- interesting for people with algorithm but no data/problem


# $10 q$ ! <br> Questions? 


[^0]:    ${ }^{1}$ Zissermann, Multiple View Geometry

