

Calibration of laser-triangulation based vision systems under motion

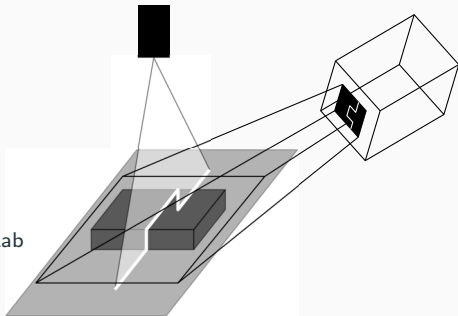
An automated method using rigid sloped artifacts fabricated through additive manufacturing

G.J.J. van Houtum

July 3, 2019

Control systems technology
Eindhoven University of Technology
Supervisor: Dr.ir. L.F.P. Etman

Multi-Scale Additive Manufacturing Lab
University of Waterloo
Supervisor: M. Vlasea, PhD



Outline

- ① Introduction
- ② Methods
- ③ Results
- ④ Conclusions

Introduction

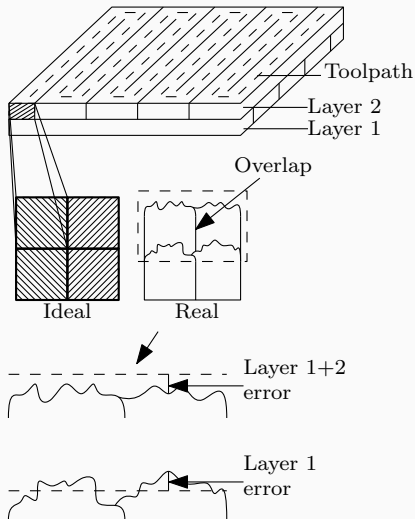
Process control in additive manufacturing

Challenges in AM

- Dimensional accuracy
- Repeatability
- Production time

Solution

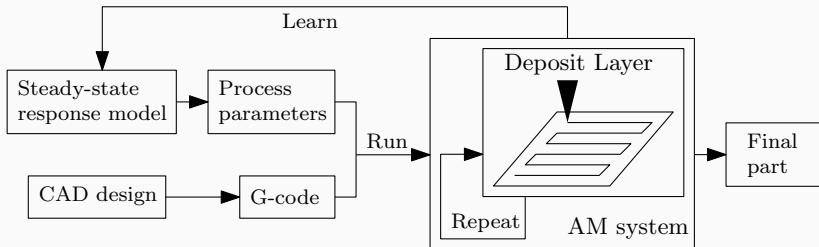
- Deposition geometry control



Process control in additive manufacturing

Deposition control strategies:

- Inter-part feedback control
- Intra-layer feedback control
- Inter-layer feedback control
- **Open-loop control**



Laser triangulation based vision

Solution

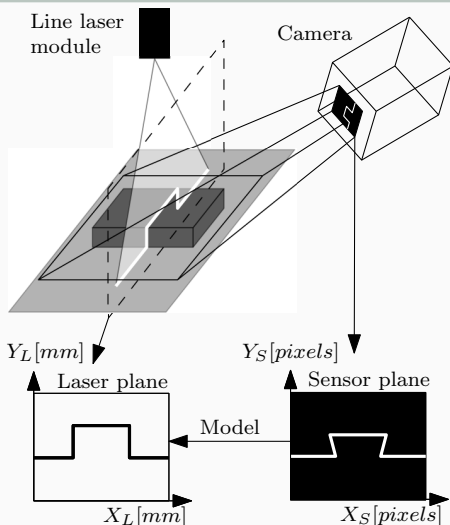
- Laser triangulation

Challenges:

- Perspective view
- Lens distortion
- Line extraction

Required developments

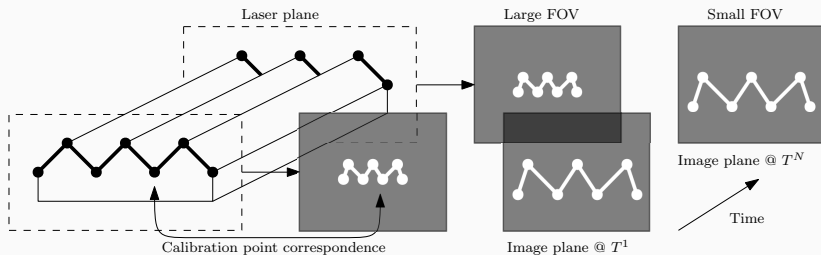
- Projection models
- Calibration method
- Laser line extraction algorithm



Problem statements

Calibration artifact problems

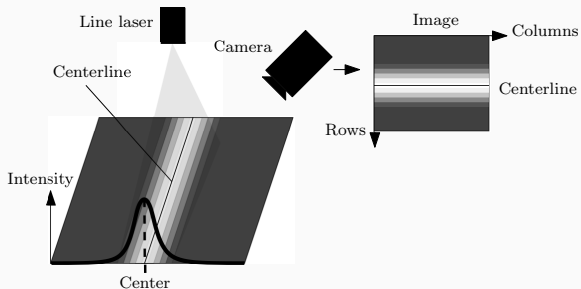
- Flat artifact → lack of point spread → reduced accuracy
- Expensive
- Artifact material not representative of printed material
- Specific artifact needed for each field-of-view (level of zoom)



Problem statements

Line/point extraction problems

- Often algorithms tailored for specific use case
- Use fixed parameters
- Not adaptive to changing reflectivity in material



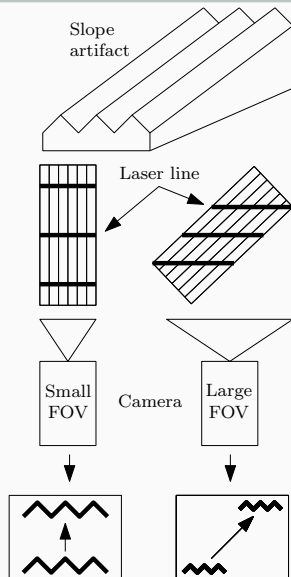
Proposed solutions

Sloped artifact:

- Slope \rightarrow vertical point spread
- Large FOV \rightarrow angular orientation for horizontal spread
- Use timing and velocity to determine slope and orientation
- Manufactured by AM machine itself.

Adaptive line/point extraction

- No fixed parameters
- Operate under changing reflectivity, pixel saturation and over/under-filling



Methods

Projection model

Pinhole camera model:

Projection of 3D camera (\mathbf{x}_c) to 2D sensor plane (\mathbf{x}_s) coordinates

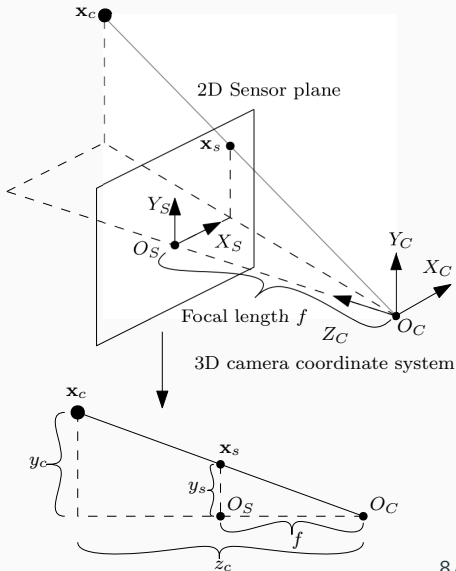
$$\mathbf{x}_s = \begin{pmatrix} x_s \\ y_s \end{pmatrix} = \frac{f}{z_c} \begin{pmatrix} x_c \\ y_c \end{pmatrix} \equiv \begin{pmatrix} f x_c \\ f y_c \\ z_c \end{pmatrix} = \hat{\mathbf{x}}_s$$

In homogenous coordinates:

$$\underbrace{\begin{pmatrix} f x_c \\ f y_c \\ z_c \end{pmatrix}}_{\hat{\mathbf{x}}_s} = \underbrace{\begin{pmatrix} f & 0 & 0 & 0 \\ 0 & f & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix}}_{\mathbf{M}_f} \underbrace{\begin{pmatrix} x_c \\ y_c \\ z_c \\ 1 \end{pmatrix}}_{\hat{\mathbf{x}}_c}$$

Combined with operator \mathcal{H} :

$$\mathbf{x}_s = \mathcal{H}^{-1}[\mathbf{M}_f \cdot \mathcal{H}[\mathbf{x}_c]]$$

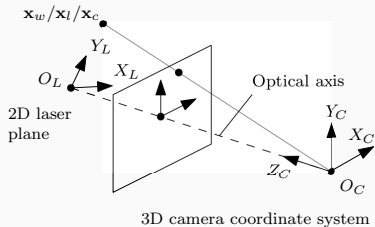


Projection model

Extrinsic view:

2D laser plane (\mathbf{x}_l) to 3D camera (\mathbf{x}_c) coordinates

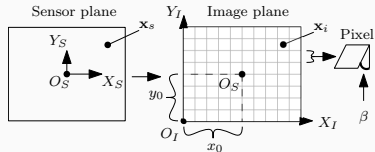
$$\mathbf{x}_c = \underbrace{\mathcal{H}^{-1} \begin{bmatrix} r_1 & r_4 & 0 \\ r_2 & r_5 & 0 \\ r_3 & r_6 & t_z \\ 0 & 0 & 1 \end{bmatrix}}_{\mathbf{M}_e} \mathcal{H}[\mathbf{x}_l]$$



Sensor intrinsics:

2D sensor (\mathbf{x}_s) to 2D image (\mathbf{x}_i) plane coordinates

$$\mathbf{x}_i = \mathcal{H}^{-1} \left[\underbrace{\begin{pmatrix} s_x & \beta & x_0 \\ 0 & s_y & y_0 \\ 0 & 0 & 1 \end{pmatrix}}_{\mathbf{M}_i} \mathcal{H}[\mathbf{x}_s] \right]$$



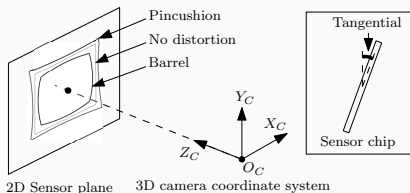
Projection model

Lens distortion compensation:

- Radial distortion (\mathbf{k})
- Tangential distortion (\mathbf{p})

Distorted 2D image (\mathbf{x}_{di}) to undistorted 2D image (\mathbf{x}_i) coordinates

$$\mathbf{x}_i = \mathbf{D}^{-1}(\mathbf{k}, \mathbf{p}, \mathbf{x}_{di})$$



Projection chain:

2D laser (\mathbf{x}_l) to 2D (undistorted) image (\mathbf{x}_i) coordinates with $\mathbf{M}_h = \mathbf{M}_i \cdot \mathbf{M}_f \cdot \mathbf{M}_e$.

$$\mathbf{x}_i = \mathcal{H}^{-1}[\mathbf{M}_h \cdot \mathcal{H}[\mathbf{x}_l]]$$

Backward projection with lens distortion compensation

$$\mathbf{x}_l = \mathcal{H}^{-1}[\mathbf{M}_h^{-1} \cdot \mathcal{H}[\mathbf{D}^{-1}(\mathbf{k}, \mathbf{p}, \mathbf{x}_{di})]]$$

Or written as a function of parameters:

$$\mathbf{x}_l = ILP(\mathbf{h}, \mathbf{k}, \mathbf{p}, \mathbf{x}_{di})$$

Calibration artifact

Sloped artifact:

2D artifact cross section pattern (\mathbf{x}_a) to 2D parallel to laser plane pattern (\mathbf{x}_p) coordinates

$$\mathbf{x}_p = \underbrace{\mathcal{H}^{-1} \begin{bmatrix} a & 0 & 0 \\ bc & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \mathcal{H}[\mathbf{x}_a]}_{\mathbf{M}_r}$$

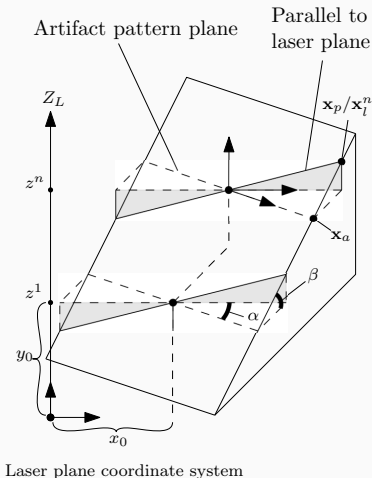
2D parallel pattern (\mathbf{x}_a) to 2D laser plane (\mathbf{x}_l) coordinates dependent on image n

$$\mathbf{x}_l^n = \underbrace{\mathcal{H}^{-1} \begin{bmatrix} 1 & 0 & x_0 + c\Delta z^n \\ 0 & 1 & y_0 + ab\Delta z^n \\ 0 & 0 & 1 \end{bmatrix} \mathcal{H}[\mathbf{x}_p]}_{\mathbf{M}_t^n}$$

Combined this leads to the

$$\mathbf{x}_l^n = \mathcal{H}^{-1} \left[\mathbf{M}_t^n \mathbf{M}_r \mathcal{H}[\mathbf{x}_a] \right] = ALP(\alpha, \beta, \Delta z^n, \mathbf{x}_0, \mathbf{x}_a)$$

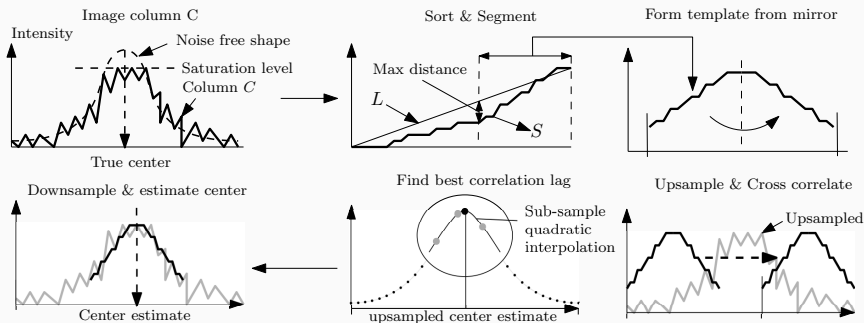
$$a = \cos(\alpha)^{-1}, b = \tan(\beta), c = \tan(\alpha), \Delta z^n = V(T^n - T^1)$$



Calibration artifact

Column-wise laser centerline extraction:

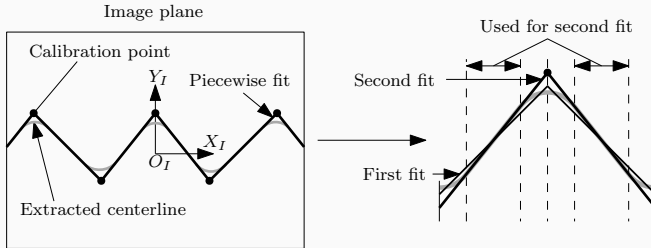
- filtering through sorting \rightarrow no parameters needed
- laser segmentation from background without differencing
- Saturation does not influence operation
- Every column new template \rightarrow reflectivity changes allowed
- Relies on symmetry of laser cross section profile



Calibration artifact

Extraction of calibration points:

- Piecewise linear regression
- First fit using all data points \rightarrow biased through over/under-filling
- Second fit using unbiased sections between points from first fit
- Intersection of coordinates are calibration points in images
- Real relative coordinates in artifact cross section are known.
- Correspondence pairs are used for calibration.



Complete projection model:

$$\mathbf{D}^{-1}(\mathbf{k}, \mathbf{p}, \mathbf{x}_{di}^n) = \mathcal{H}^{-1}[\mathbf{M}_h \cdot \mathbf{M}_t^n \cdot \mathbf{M}_r \cdot \mathcal{H}[\mathbf{x}_a]]$$

Training data:

- N images at constant velocity V time-stamped with time (T^1, T^2, \dots, T^N) .
- K known calibration points $(\mathbf{x}_a^1, \mathbf{x}_a^2, \dots, \mathbf{x}_a^K)$ in artifact cross section pattern
- $K \cdot N$ corresponding points estimated (using line & point extraction algorithms) in all N images $(\mathbf{x}_{di}^{11}, \mathbf{x}_{di}^{12}, \dots, \mathbf{x}_{di}^{NK})$

Initialisation::

Assumed no lens distortion and no artifact rotation ($\mathbf{M}_r = \mathbf{I}$) such that:

$$\mathbf{x}_i^{nk} = \mathbf{x}_{di}^{nk}, \quad \mathbf{x}_p^k = \mathbf{x}_a^k \quad \forall (n, k) \in S_1$$

where $S_1 = \{(n, k) \in \mathbb{Z}^+ \times \mathbb{Z}^+ | n \leq N \wedge k \leq K\}$

Multi-image direct linear transform:

Perspective projection (homography) where last column is dependent on image n

$$\mathbf{x}_i^{nk} = \mathcal{H}^{-1}[\mathbf{M}_h \mathbf{M}_t^n \mathcal{H}[\mathbf{x}_p^k]] = \mathcal{H}^{-1} \left[\begin{pmatrix} h_1 & h_4 & h_7^n \\ h_2 & h_5 & h_8^n \\ h_3 & h_6 & h_9^n \end{pmatrix} \mathcal{H}[\mathbf{x}_p^k] \right] \quad \forall (n, k) \in S_1$$

Is rewritten as two non-linear equations, linear in parameters

$$x_i^{nk} = \frac{h_1 x_p^k + h_4 y_p^k + h_7^n}{h_3 x_p^k + h_6 y_p^k + h_9^n}, \quad y_i^{nk} = \frac{h_2 x_p^k + h_5 y_p^k + h_8^n}{h_3 x_p^k + h_6 y_p^k + h_9^n} \quad \forall (n, k) \in S_1$$

Combining all equations leads to the following set of homogenous linear equations:

$$\mathbf{A}\mathbf{h} = \mathbf{0}$$

SVD \rightarrow minimizes $\|\mathbf{A}\mathbf{h}\|^2$ which is an algebraic error \rightarrow not geometrical meaningful.

Artifact slope and orientation estimation: Estimated image dependent parameters are defined as:

$$h_7^n = h_1(x_0 + c\Delta z^n) + h_4(y_0 + ab\Delta z^n)$$

$$h_8^n = h_2(x_0 + c\Delta z^n) + h_5(y_0 + ab\Delta z^n)$$

$$h_9^n = h_3(x_0 + c\Delta z^n) + h_6(y_0 + ab\Delta z^n) + h_9$$

which can be rewritten as a system (for all images) of linear equations as:

$$\mathbf{L}\mathbf{b} = \mathbf{k}$$

which is solved using the SVD resulting in estimated parameters

$\mathbf{b} = (h_9, x_0, y_0, x_1, y_1)$ and

$$x_1 = c = \tan(\alpha)$$

$$y_1 = ab = \cos(\alpha)^{-1} \tan(\beta)$$

An estimate for artifact rotation angle α can now be determined by:

$$\alpha = \tan^{-1}(x_1)$$

which can be used to estimate the artifact slope angle β as:

$$\beta = \tan^{-1}(y_1 \cos(\alpha))$$

Iterative linear parameter optimization:

Use estimated angles α and β to update all \mathbf{x}_p . Then loop and break if converged.

$$\mathbf{x}_p^k = \mathcal{H} \left[\underbrace{\begin{pmatrix} \cos(\alpha)^{-1} & 0 & 0 \\ \tan(\beta) \tan(\alpha) & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}}_{\mathbf{M}_r} \mathcal{H}[\mathbf{x}_a^k] \right] \quad \forall k \in S_3$$

Lens distortion

Estimate (undistorted) image points using the estimated parameters

$$\mathbf{x}_i^{nk} = \mathcal{H}^{-1}[\mathbf{M}_h \mathbf{M}_t^n \mathcal{H}[\mathbf{x}_p^k]] \quad \forall (n, k) \in S_1$$

Use (distorted) points \mathbf{x}_{di}^{nk} and (undistorted) points to estimate distortion

Non-linear refinement

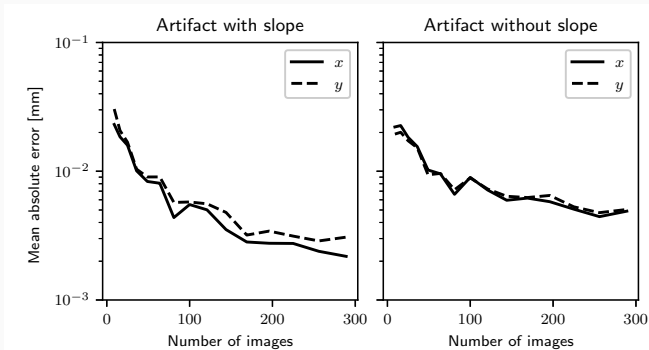
Minimize difference $\overleftarrow{\mathbf{x}}_l^{nk} = ILP(\mathbf{h}, \mathbf{k}, \mathbf{p}, \mathbf{x}_{di}^{nk})$ and $\overrightarrow{\mathbf{x}}_l^{nk} = ALP(\alpha, \beta, \Delta z^n, \mathbf{x}_0, \mathbf{x}_a)$

$$E(\mathbf{h}, \mathbf{k}, \mathbf{p}, \alpha, \beta) = \sum_{n=1}^N \sum_{k=1}^K \|\overrightarrow{\mathbf{x}}_l^{nk} - \overleftarrow{\mathbf{x}}_l^{nk}\|^2$$

Results

Simulated artifact with and without slope

- larger number of point/images \rightarrow better estimation
- More spread of points \rightarrow better estimation
- > 200 images best result \rightarrow used for experiment



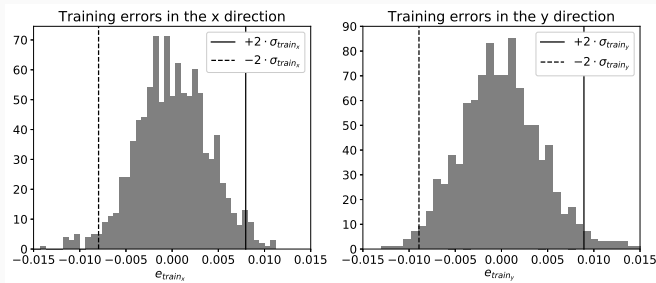
Experiment

Printed sloped artifact errors

Training errors are normally distributed \rightarrow 95% confidence interval:

$$e_{train_x} = 0.0002 \pm 0.008[mm], \quad e_{train_y} = 0.0001 \pm 0.009[mm]$$

Training errors form upperbound (conservative) on real estimation error.



Conclusions

Conclusions:

- Fully automated calibration → no human interaction
- Sloped artifact → improved calibration accuracy
- Calibrates with unknown slope and orientation
- Robust adaptive line and point extraction algorithms
- Iterative method for linear parameter estimation
- Possible to calibrate on AM printed artifact.

Questions?