

# LiDAR-to-Optical Registration

William L. Ruys

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## 1 Introduction

## 2 Methods

### 2.1 Fourier Based Registration

Suppose you have two gray-scale image functions  $I_1, I_2 : \mathbf{x} \in R^2 \mapsto [0, 255]$ . Without loss of generality assume the images have the same width and height,  $N$ . If this is not the case, they can be zero padded to meet this condition.

Let  $I_2$  be a shift of  $I_1$  such that  $I_2(\mathbf{x}) = I_1(\mathbf{x} + \mathbf{t})$ . Then this translation  $\mathbf{t}$  can be estimated as the shift that gives the maximum correlation between the two images. The naive evaluation of this takes  $O(|T|N^2)$  time to evaluate for all translations in a prospective set  $T$ . If the correlation function can be expressed as a linear combination of convolutions this calculation can be accelerated through the Fourier transform. This allows us to evaluate the correlation for  $\mathbf{t} \in T = \{[-\frac{N}{2}, \frac{N}{2}] \times [-\frac{N}{2}, \frac{N}{2}]\}$  in  $O(N^2 \log(N))$  time. We consider a few correlation functions in our Python implementation that we'll outline briefly.

Throughout this writeup, let  $\hat{f} = \mathcal{F}(f)$ , its Fourier transform. In a gross abuse of theory and notation we also overload this hat notation to mean the discrete Fourier transform in the algorithms below. Let  $\nabla I_i = \nabla_x I_i + j \nabla_y I_i$ , where  $j = \sqrt{-1}$ .

#### 2.1.1 Cross-Correlation Function $C(\tau)$

$$\begin{aligned} C(\tau) &= \int_{R^2} I_1(\mathbf{x}) I_2(\mathbf{x} + \tau) d\tau \\ &= \mathcal{F}^{-1}[\hat{I}_1(k) \hat{I}_2^*(k)] \end{aligned}$$

#### 2.1.2 Phase Correlation (Cross-Power) $PC(\tau)$

$$PC(\tau) = \mathcal{F}^{-1}\left[\frac{\hat{I}_1(k) \hat{I}_2^*(k)}{|\hat{I}_1(k)| |\hat{I}_2^*(k)|}\right]$$

### 2.1.3 Normalized Gradient Correlation NGC( $\tau$ )

$$\begin{aligned} NGC(\tau) &= \frac{\int_{R^2} \nabla I_1(\mathbf{x}) \nabla I_2(\mathbf{x} + \tau) d\tau}{\int_{R^2} |\nabla I_1(\mathbf{x})| |\nabla I_2(\mathbf{x} + \tau)| d\tau} \\ &= \frac{\mathcal{F}^{-1}[\hat{\nabla} I_1(k) \hat{\nabla} I_2^*(k)]}{\mathcal{F}^{-1}[|\hat{\nabla} I_1(k)| |\hat{\nabla} I_2^*(k)]} \end{aligned}$$

### 2.1.4 Normalized Gradient Fields NGF( $\tau$ )

Let  $n_x(I_i) = \frac{\nabla_x I_i}{|\nabla I_i|}$ ,  $n(I_i) = [n_x(I_i), n_y(I_i)]$ .

$$\begin{aligned} NGF(\tau) &= \int_{R^2} (n(I_1(\mathbf{x})) \cdot n(\nabla I_2(\mathbf{x} + \tau)))^2 d\tau \\ &= \int_{R^2} n_x^2(I_1(\mathbf{x})) n_x^2(\nabla I_2(\mathbf{x} + \tau)) d\tau + \int_{R^2} n_y^2(I_1(\mathbf{x})) n_y^2(\nabla I_2(\mathbf{x} + \tau)) d\tau \\ &\quad + \int_{R^2} (n_x \cdot n_y)(I_1(\mathbf{x})) (n_x \cdot n_y)(\nabla I_2(\mathbf{x} + \tau)) d\tau \end{aligned}$$

### 2.1.5 Log-Log Interpolation

Consider  $I_2$  as an anisotropic scaling and translation of  $I_1$  such that  $I_2(\mathbf{x}) = I_1(S\mathbf{x} + \mathbf{t})$  where  $S = \text{Diag}([s_1, s_2])$ . The translation can be separated from the scaling by taking a Fourier transformation, where the relationship between the two images is  $\hat{I}_2(\mathbf{k}) = \frac{1}{|S|} \hat{I}_1(S^{-1}\mathbf{k}) e^{j\mathbf{t} \cdot \mathbf{k}}$ . If we take the magnitude (complex modulus) the phase component is dropped and we just have a scaling (with adjusted amplitude),  $M_2(k) = \frac{1}{|S|} \hat{M}_1(S^{-1}k)$ .

We can change a scaling to a translation by performing a trick where we change the spacing of the interpolation points to a logarithmic scale (instead of linear) and view the function as if these interpolation points were linearly spaced. Under this interpolation  $\tilde{M}_2(k_1, k_2) \propto \tilde{M}_1(k_1 - \log(s_1), k_2 - \log(s_2))$ . These scaling parameters can then be found by the correlation method described above. Once the  $I_2$  has been warped to the found rescaling, only a translation remains between the two images. This can be computed via a second pass of the correlation method.

**Result:** Estimate of Affine Warping Parameters:  $(\mathbf{t}, \tilde{S}_w, \tilde{S}_h)$   
**Data:** Image fuctions:  $I_1, I_2$  related by scaling and translation  
**Data:** Oversampling parameter  $l$

- 1  $b_i = (\frac{N_i}{2})^{\frac{1}{lN_i}}, N_i = I_2.\text{shape}[i];$
- 2 Apply windowing function to  $I_1, I_2;$
- 3 Zero pad  $I_1, I_2;$
- 4 Take 2D FFT of  $\nabla I_1$  and  $\nabla I_2;$
- 5  $M_1, M_2 =$  magnitudes of  $\hat{\nabla} I_1$  and  $\hat{\nabla} I_2;$
- 6 Interpolate  $M_1$  and  $M_2$  to log-log coordinate system with bases  $(b_1, b_2);$
- 7 Apply windowing function to  $M_1, M_2;$
- 8 Zero pad  $M_1, M_2;$
- 9 Take 2D FFT of  $\nabla M_1$  and  $\nabla M_2;$
- 10 Compute element-wise product,  $\frac{\nabla M_1(k) \nabla M_2^*(k)}{|\nabla M_1(k)| |\nabla M_2^*(k)|};$
- 11 Take 2D iFFT of product to get  $PC(\tau)$ .  $O(N^2 \log(N));$
- 12  $(e_1, e_2) = \arg \max$  of  $PC(\tau);$
- 13  $\tilde{S}_w = (b_1)^{e_1}, \tilde{S}_h = (b_2)^{e_2};$
- 14 Warp & Interpolate  $I_2$  by  $(\tilde{S}_w, \tilde{S}_h);$
- 15 Take 2D FFT of  $I_1$  and  $I_2;$
- 16 Compute element-wise product,  $\frac{\nabla I_1(k) \nabla I_2^*(k)}{|\nabla I_1(k)| |\nabla I_2^*(k)|};$
- 17 Take 2D iFFT of product to get  $PC(\tau);$
- 18  $\mathbf{t} = \arg \max$  of  $PC(\tau);$
- 19 Return  $(\mathbf{t}, \tilde{S}_w, \tilde{S}_h);$

**Algorithm 1:** Log-Log Fourier Based Registration

## 2.2 Exhaustive Registration

**Result:** Estimate of Affine Warping Parameters:  $(\tilde{\theta}, \tilde{S}_w, \tilde{S}_h)$   
**Data:** Parameter Search Space:  $P = (\theta^{1:N_\theta}, S_w^{1:N_{S_w}}, S_h^{1:N_{S_h}})$   
**Data:** Downsampled Images:  $J_1, J_2$   
**Data:** nb = Maximum Batch Size (Determined by GPU Memory)

- 1  $N = |P|;$
- 2  $\text{itr} = N/\text{nb};$
- 3  $J_1 = FFT[\nabla J_1];$
- 4 **for**  $l$  in  $1:\text{itr}$  **do**
- 5      $W =$  Batch Warp  $I_2$  by subset of  $P;$
- 6     Compute  $\nabla W$  for each image;
- 7     Batch Compute  $W = FFT[\nabla W];$
- 8      $PC = (W)(J_1^*)/(|W||J_1^*|);$
- 9     Batch Compute  $PC = iFFT[PC];$
- 10     $(\tilde{\theta}, \tilde{S}_w, \tilde{S}_h) = \arg \max(PC, (\tilde{\theta}, \tilde{S}_w, \tilde{S}_h));$
- 11 **end**

**Algorithm 2:** Exhaustive Search

**Result:** Moving Image  $I_2$  aligned at maximum correlation peak

- 1 Parameter Search Space:  $P = (\theta^{1:N_\theta}, S_w^{1:N_{S_w}}, S_h^{1:N_{S_h}})$ ;
- 2 Downsampling rates:  $R = [0.1, 0.1, 0.8]$ ;
- 3 **for**  $r$  *in*  $R$  **do**
- 4      $J_1, J_2 = \text{Downsample } I_1, I_2 \text{ by } r$ ;
- 5     Pad  $I_1$  and  $I_2$  to  $(2^M, 2^N)$ , nearest containing powers of 2 ;
- 6      $(\tilde{\theta}, \tilde{S}_w, \tilde{S}_h) = \text{exhaustiveSearch}(J_1, J_2, P)$ ;
- 7     Restrict  $(\theta^{1:N_\theta}, S_w^{1:N_{S_w}}, S_h^{1:N_{S_h}})$ ;
- 8 **end**
- 9 Warp  $I_2$  by  $(\tilde{\theta}, \tilde{S}_w, \tilde{S}_h)$ ;
- 10 Perform phaseCorrelation on  $I_1, I_2$

**Algorithm 3:** Multilevel Exhaustive Search

### 3 Results

#### 3.1 Exhaustive Registration

##### 3.1.1 Image Recovery

##### 3.1.2 Failure Cases

#### 3.2 Log-Log Fourier Based Registration