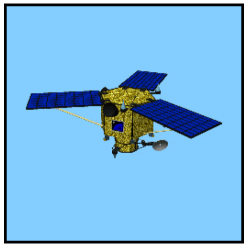


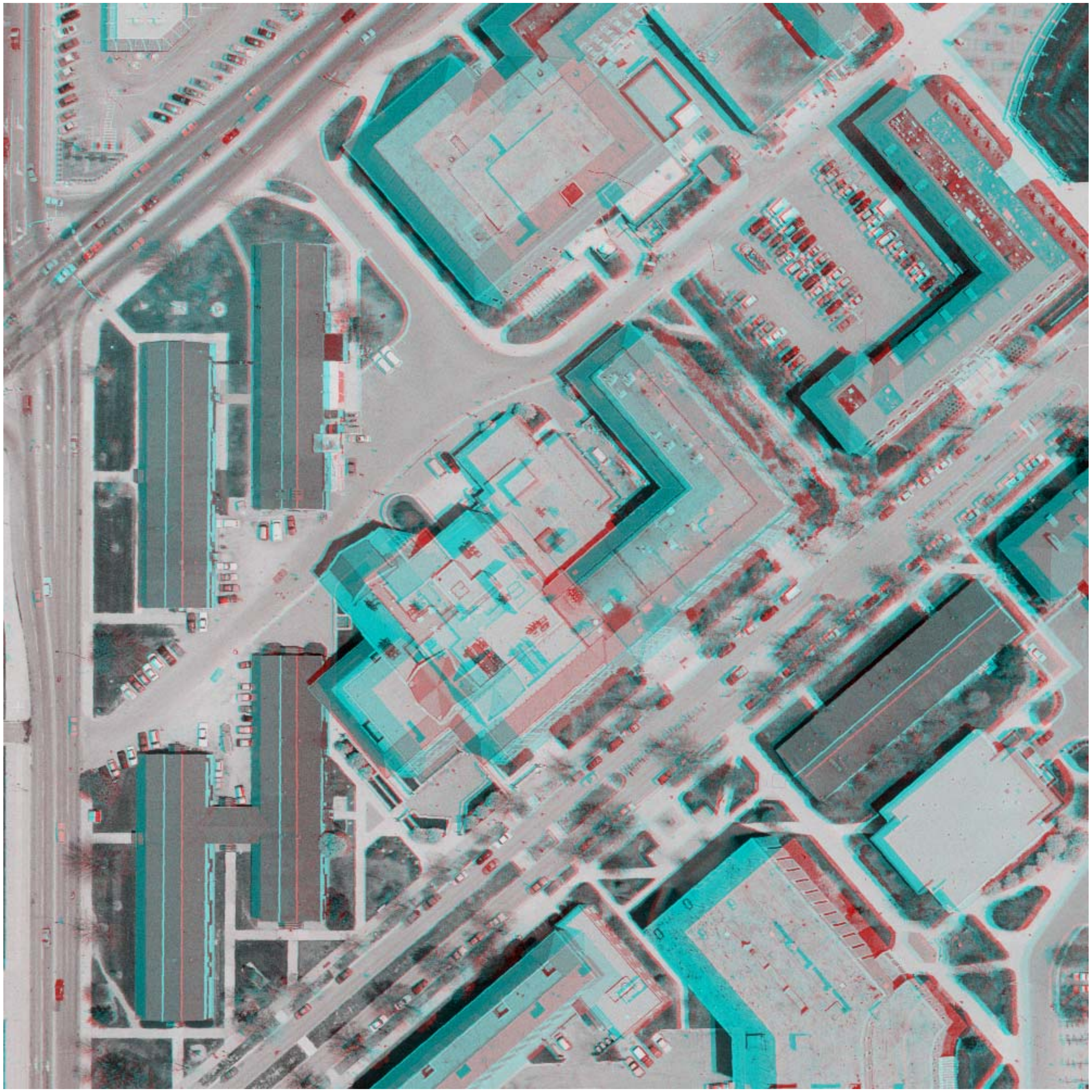
Matching: Signal & Feature

- Search
  - Limited
  - Exhaustive
  - Constrained
  - Unconstrained
  - Single Point
  - Many Points
  - 1D
  - 2D

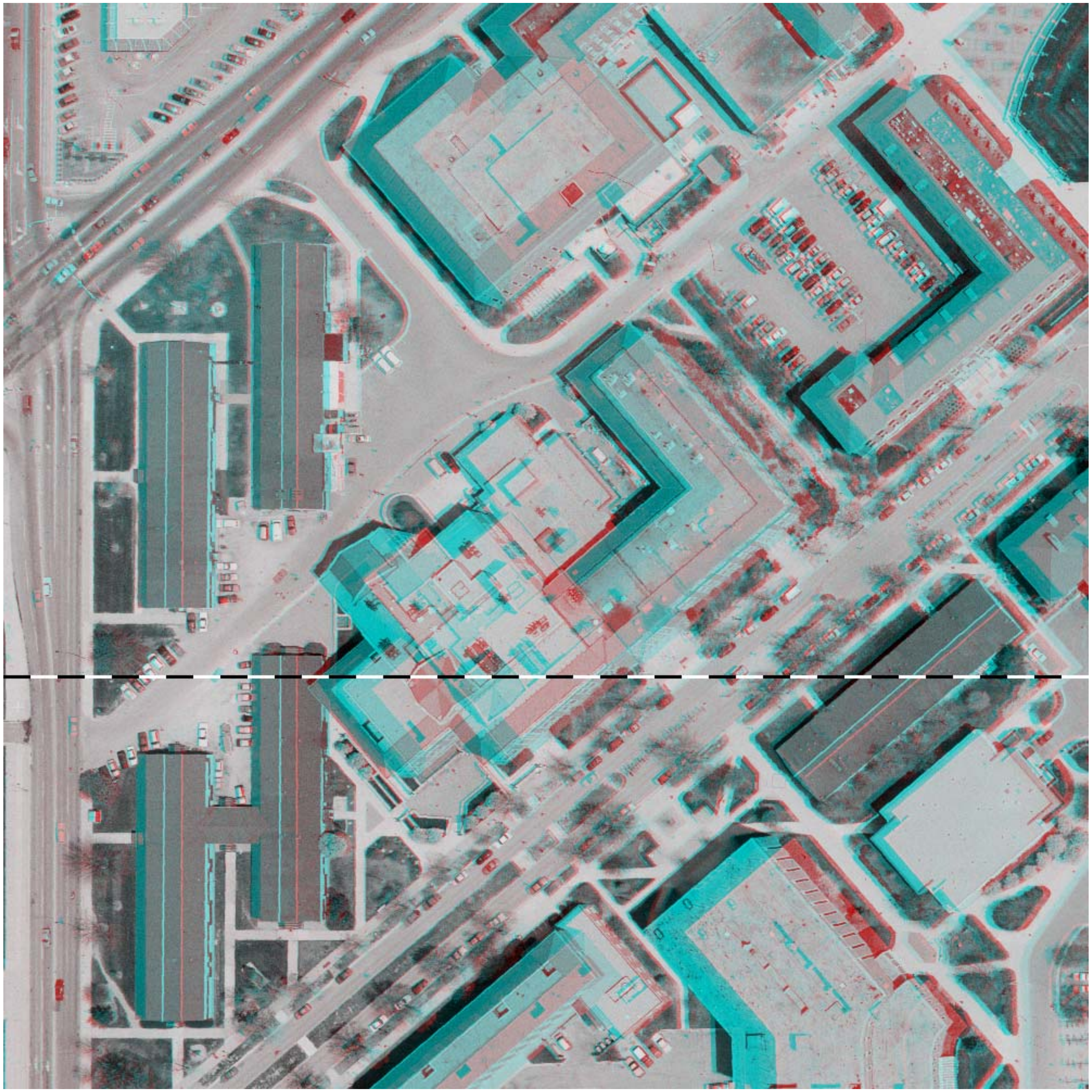
- Refinement
  - Least Squares
  - L1

Similarity Metric

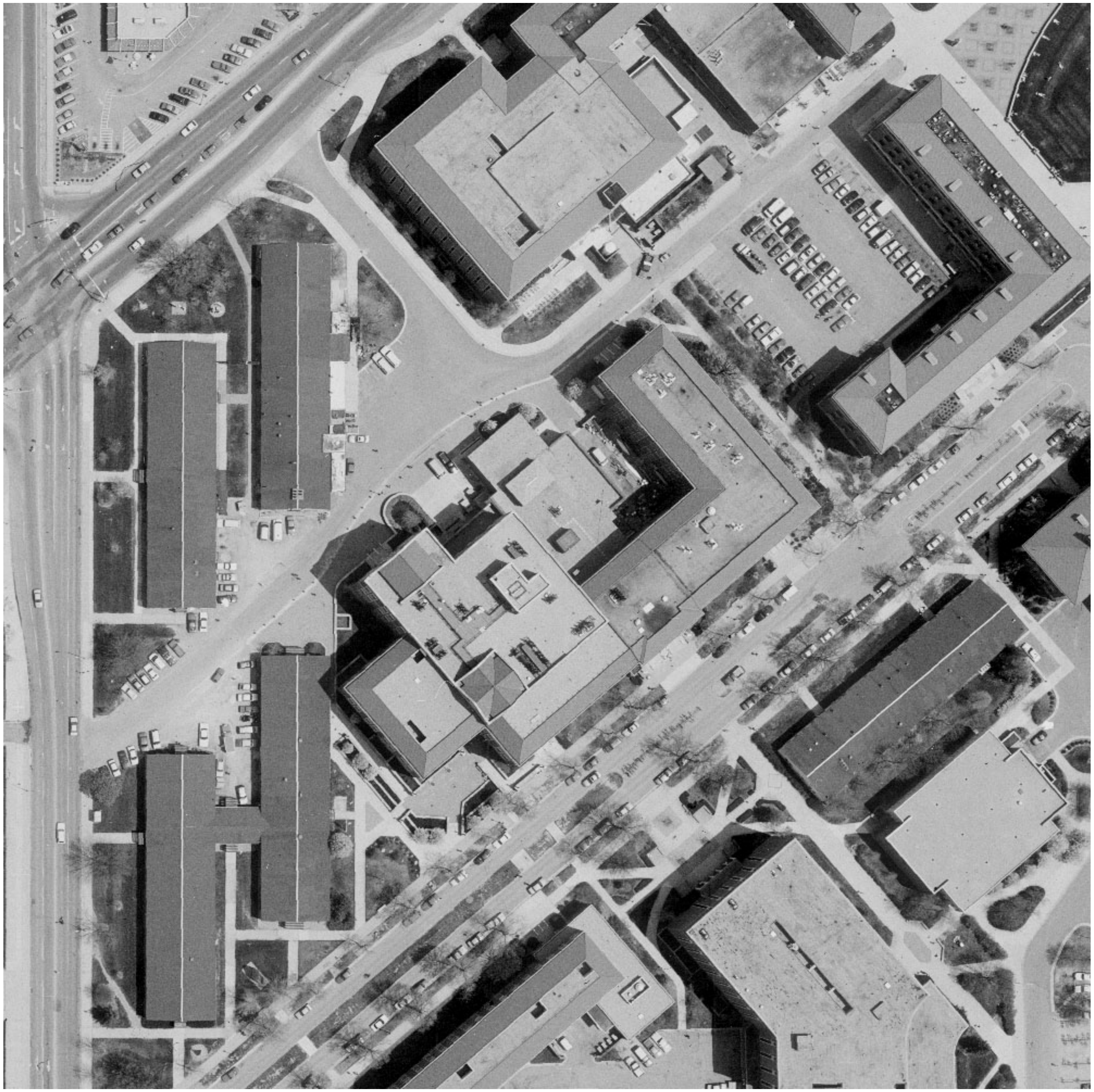
- Cross Correlation
  - Space Domain
  - Frequency Domain
- Cost Function

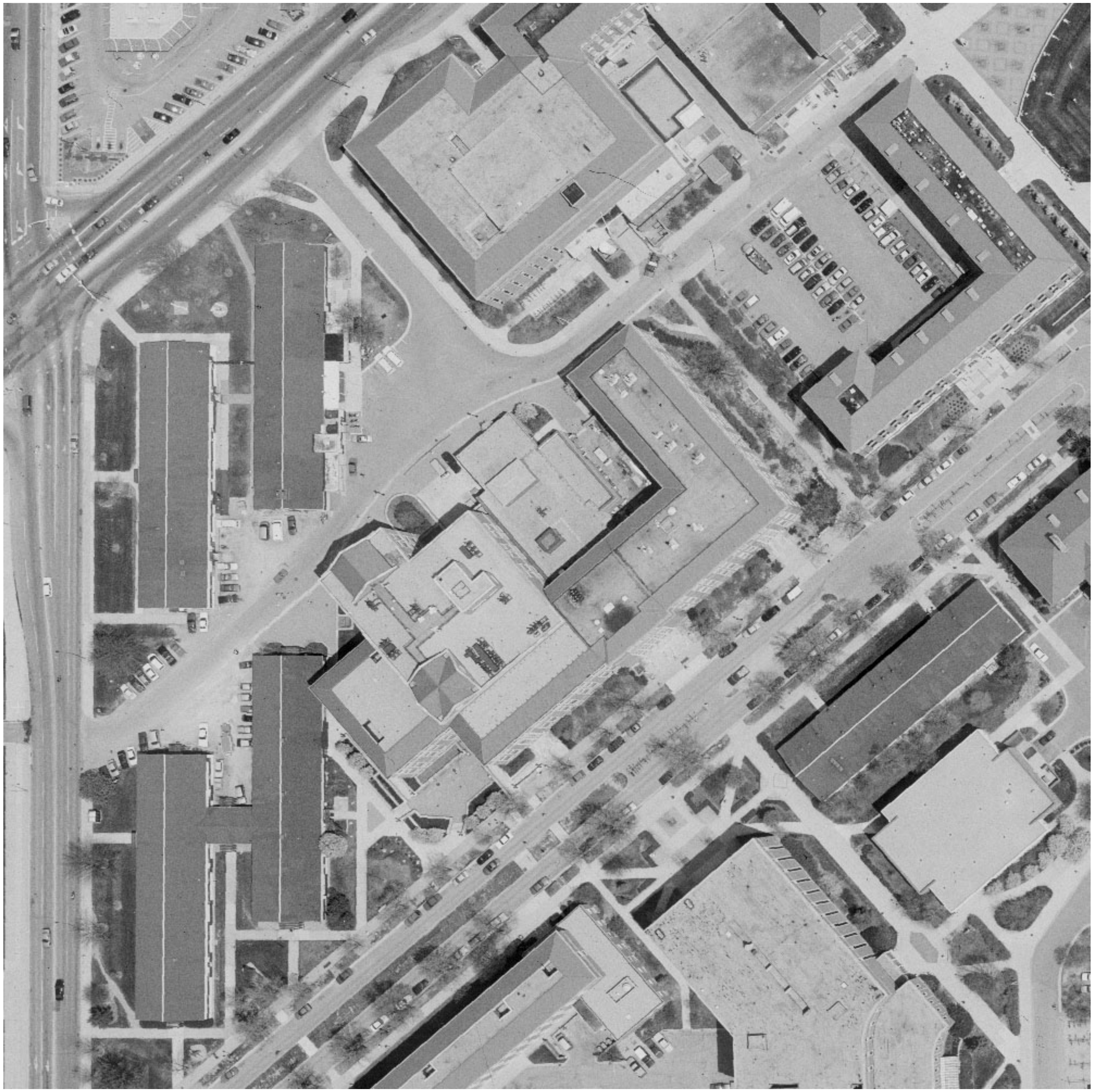


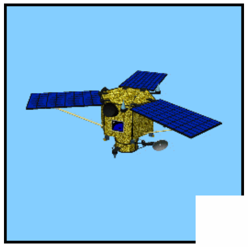
Normalized image pair presented as anaglyph. Normalization is equivalent to epipolar resampling which removes all y-parallax and leaves only x-parallax, which is directly related to height or elevation. For matching this is important – you can restrict your search to one dimension – i.e. constrained matching



As an example, let's extract the intensity profiles along a single line from the left and right normalized images (left = red, right = blue)

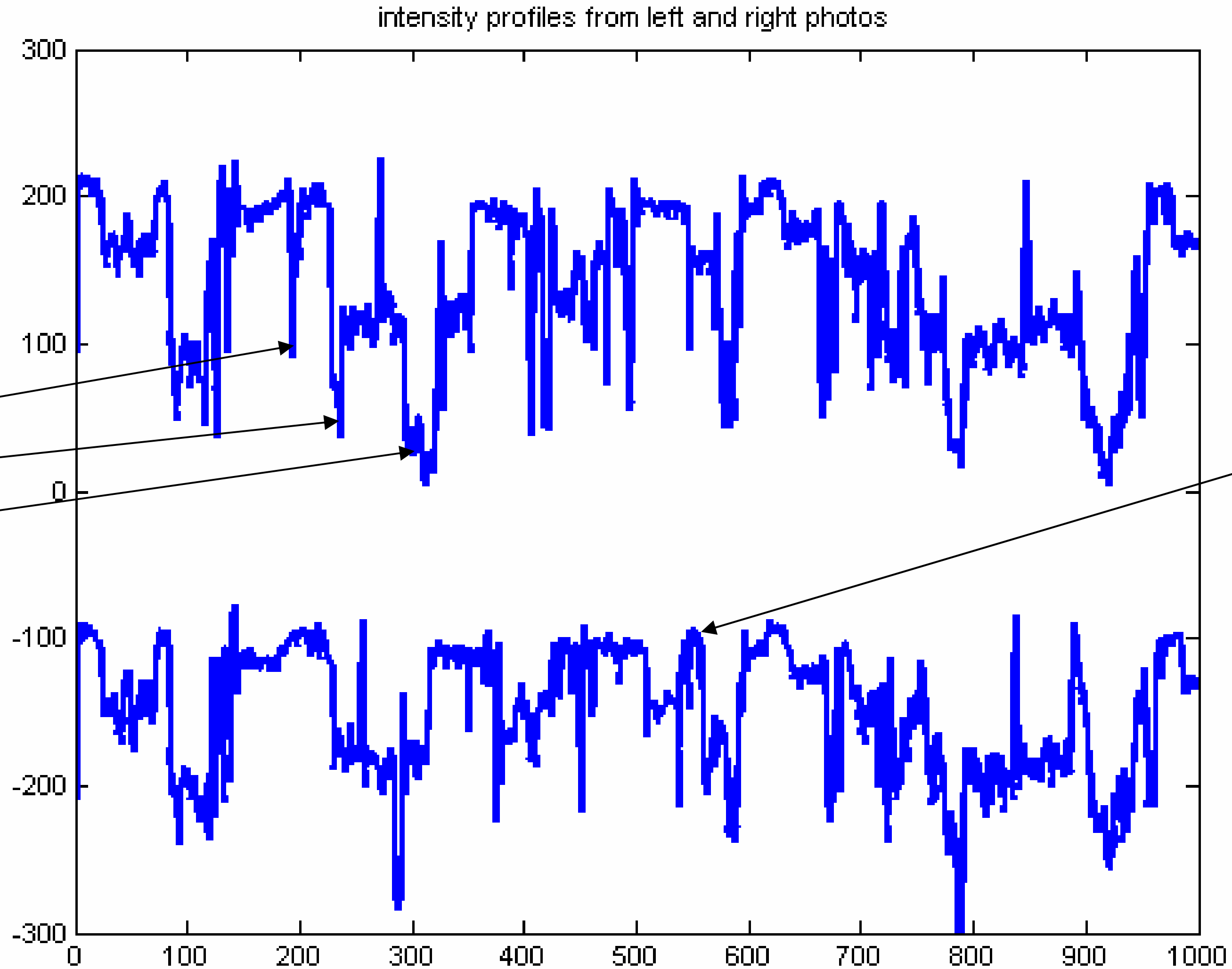






Intensity (Gray Level) Profiles from Normalized Images

Discrepancies which cause difficulties in (naïve) matching



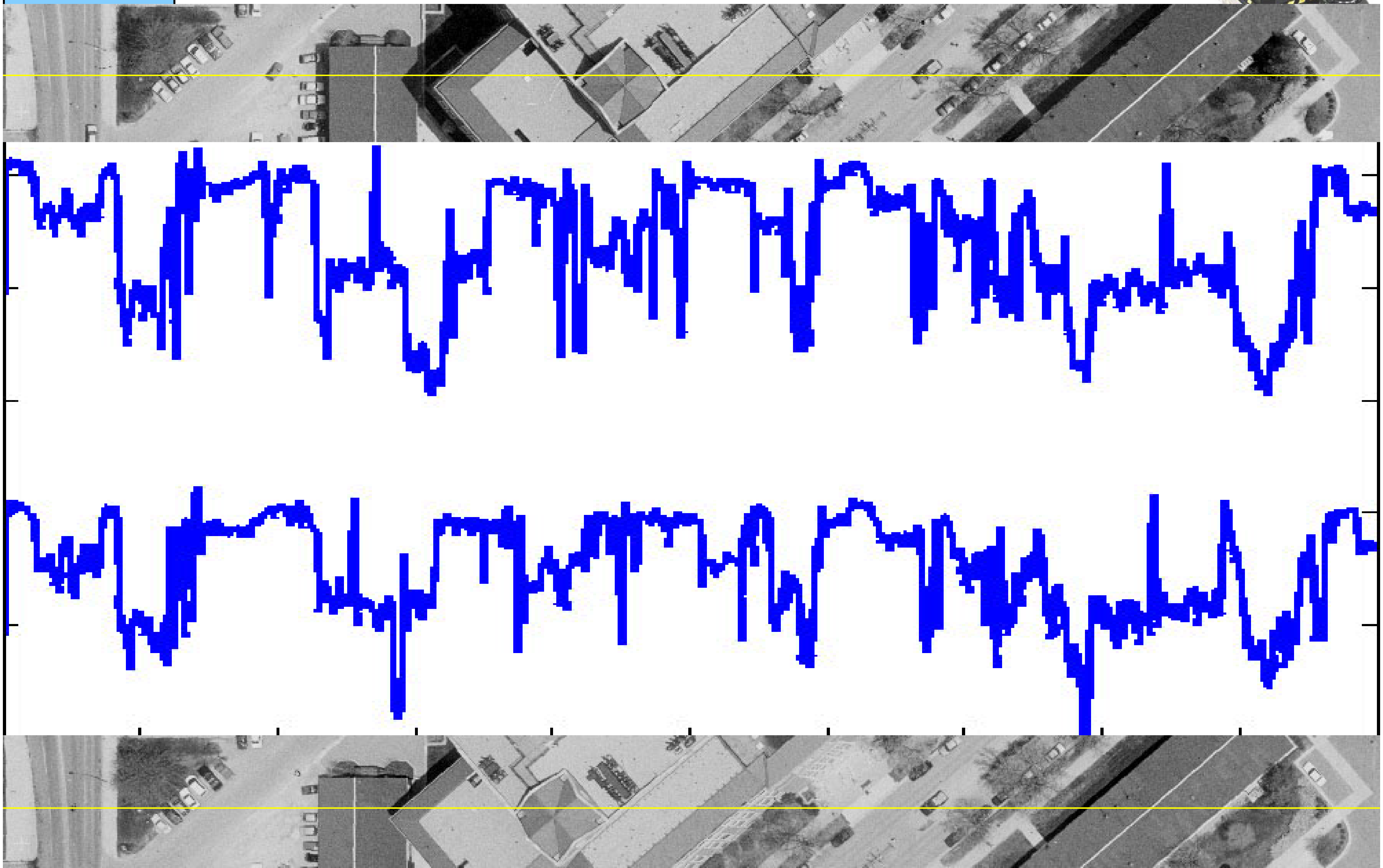
Car

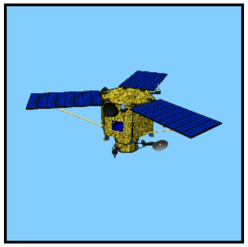
Shadow

Shadow

Front of CE Building, Occluded on Left

Correspondence between features & intensity profile





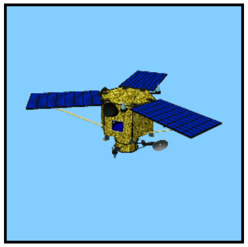
Most Common Similarity Measure for Signal Matching: Normalized Cross Correlation (Discrete Version)

$$C_{uv} = \frac{\sum (u_i - \bar{u})(v_i - \bar{v})}{\left[\sum (u_i - \bar{u})^2 \sum (v_i - \bar{v})^2\right]^{1/2}}$$

$$\bar{u} = \frac{\sum u_i}{N}$$

$$\bar{v} = \frac{\sum v_i}{N}$$

N : number of elements in u & v



Famous property of Fourier Transform: multiplication in the frequency domain equivalent to convolution in the space/time domain

You can use this to gain speed if correlating or filtering large data sets (images), transform and element wise multiplication is much faster than shift-multiply-store required by space domain correlation. For 1D, discrete form of FT and inverse are

DFT:

$$X(k) = \sum_{n=0}^{N} x(n) e^{-i2\pi kn/N}$$

IDFT:

$$x(n) = \left(\frac{1}{N}\right) \sum_{k=0}^{N} X(k) e^{i2\pi kn/N}$$

Note: there are several equivalent forms for these equations, make sure to use forward and inverse formulae that are consistent. There is a natural extension to 2D which we need for imagery

Slide intensity fragment from left along the right profile and compute correlation at every position