# Stereo Vision – Correspondence

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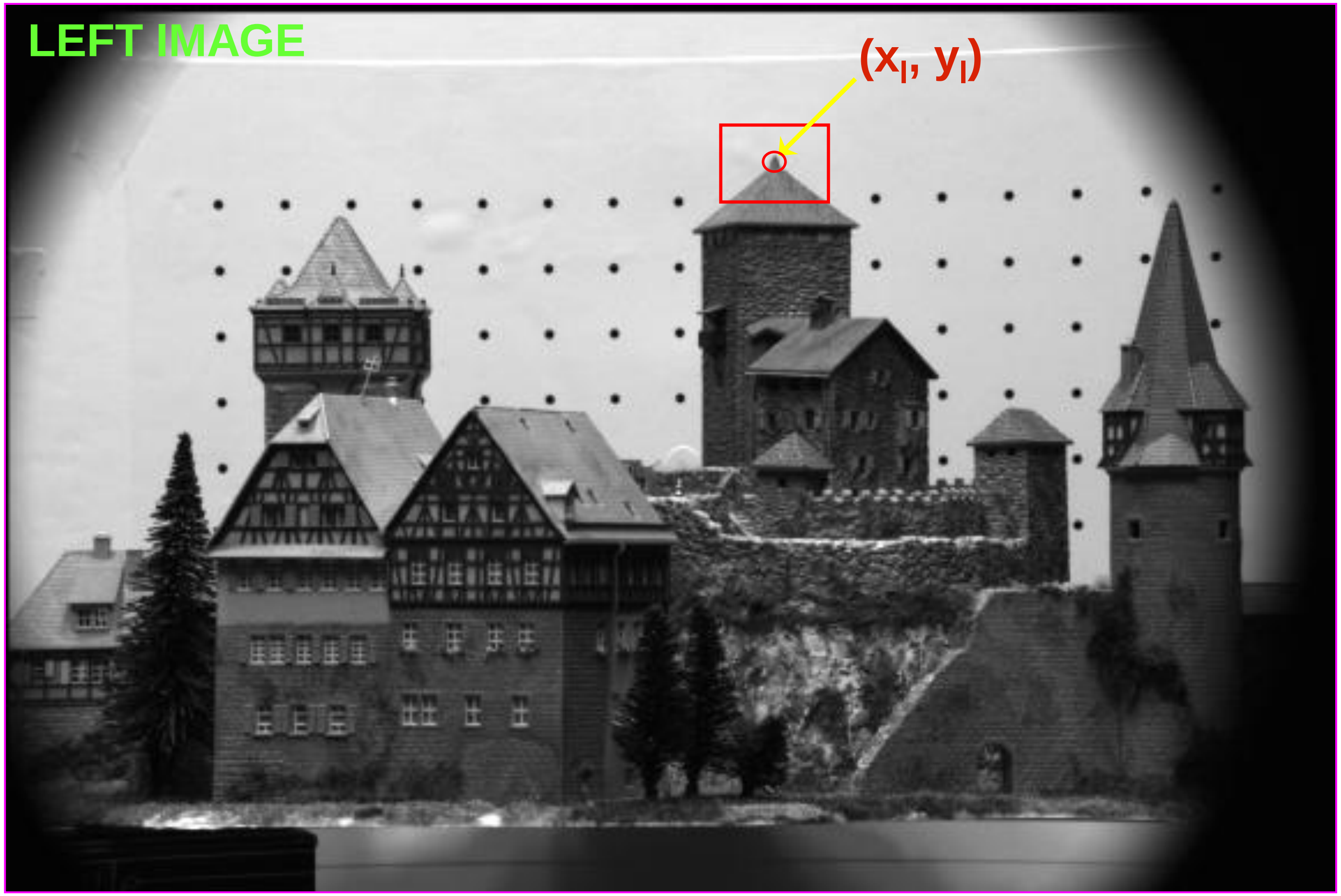
# Problem Definition

- Correspondence problem
  - What parts of the left and right image are projections of the same point in the 3D scene
- Simple stereo configuration
  - Corresponding points are on same horizontal line
- Assumptions
  - Most scene points are visible from both regions
  - Corresponding image regions are similar (called similarity constraint)
- Search problem
  - Given scene element on left image search for
  - What parts of left and right images are parts of same object?
- Two decisions
  - Which element to match
  - Which similarity measure to adopt

# Correspondence and Feature Methods

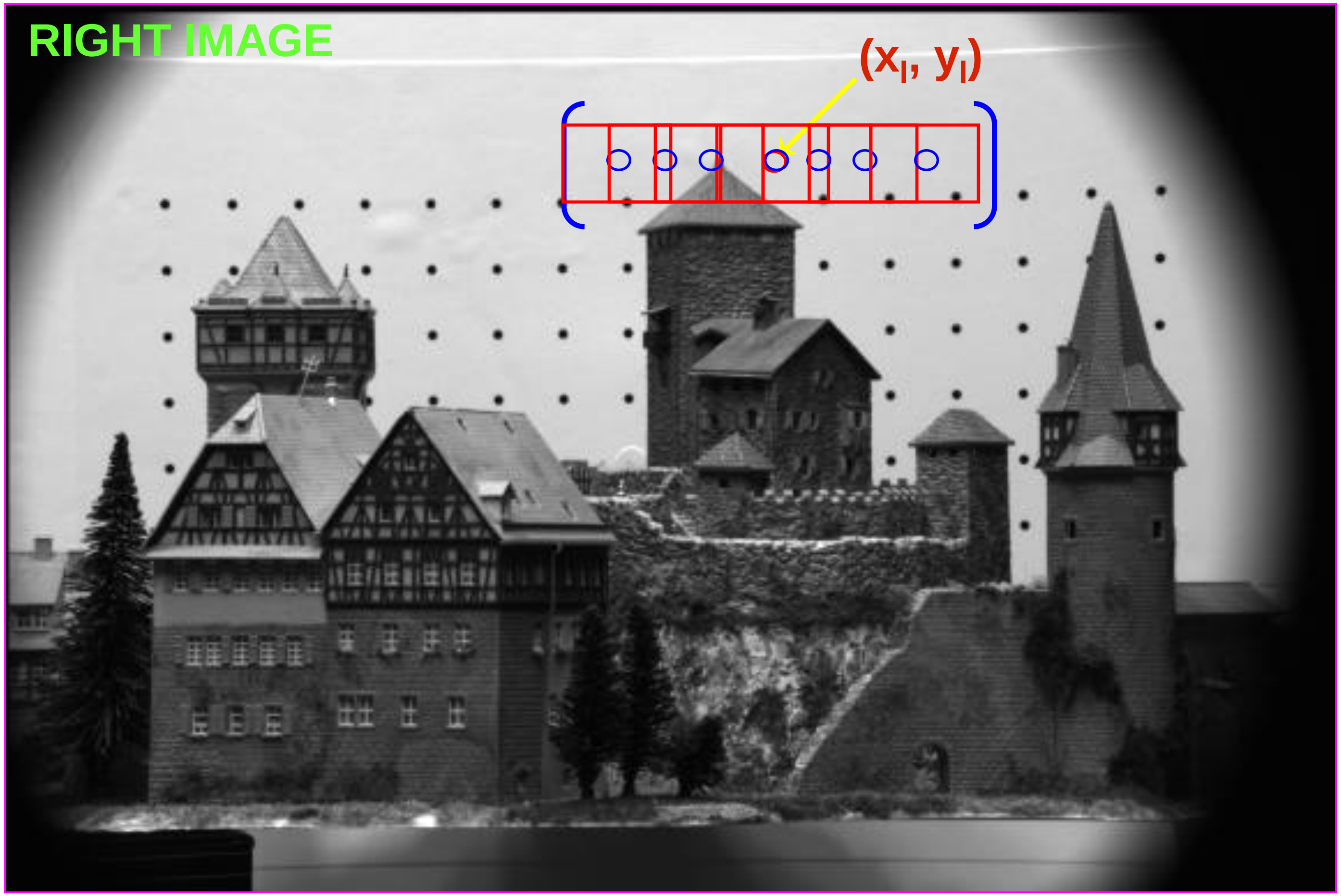
- Two basic approaches
- Correlation (Similarity) methods
  - Apply to all image points
  - Elements are image windows of fixed size
  - Similarity measure is the difference between two windows in the left and right images
  - Corresponding element is window that maximizes similarity criterion within a search window
- Feature methods
  - Apply only to a sparse set of feature points
  - Narrows down feasible matches by using constraints
  - Geometric constraints
  - Analytic constraints – uniqueness and continuity

# Correlation Approach



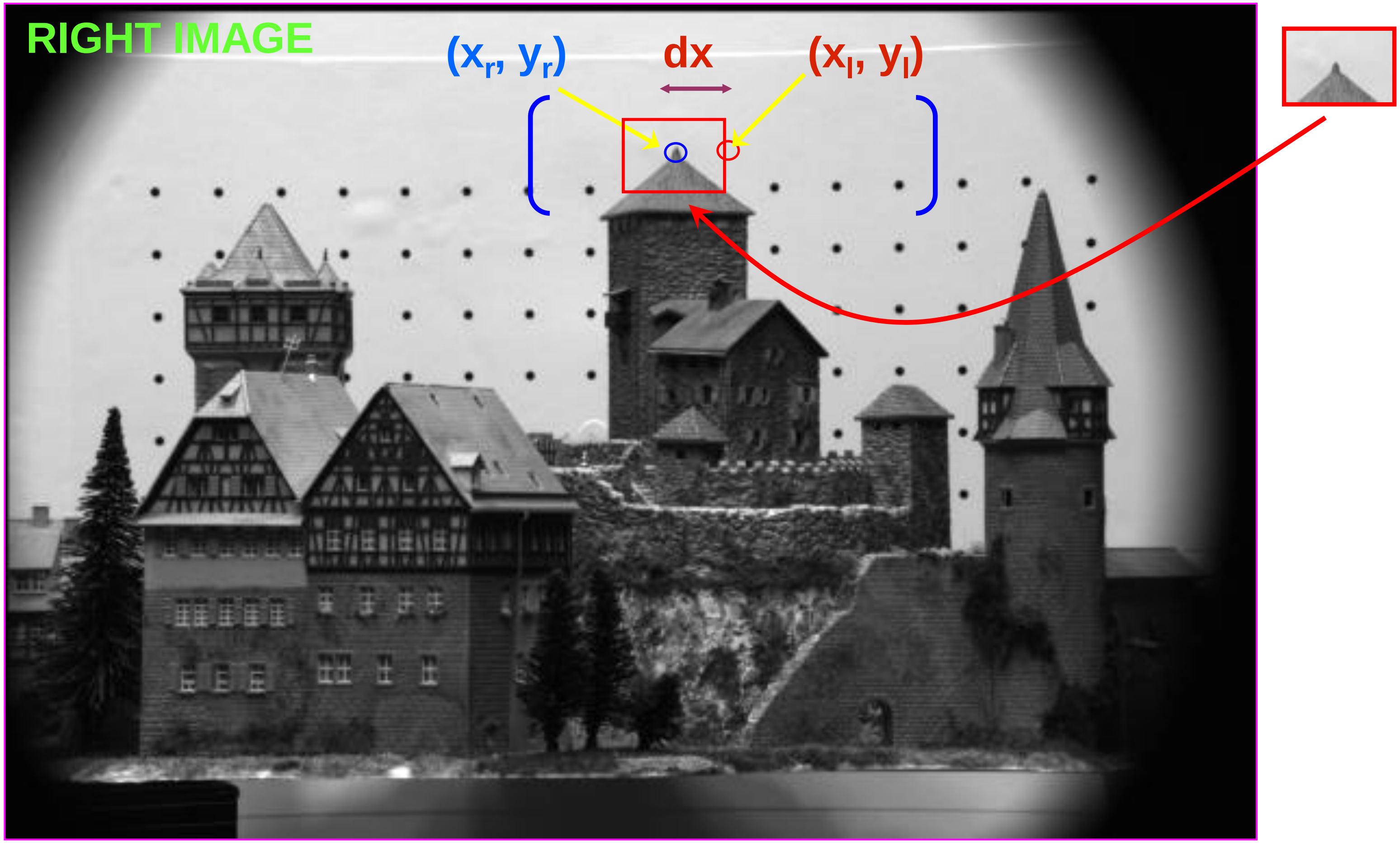
For Each point $(x_l, y_l)$ in the left image, define a window centered at the point

# Correlation Approach



… search its corresponding point within a search region in the right image

# Correlation Approach



… the disparity (dx, dy) is the displacement when the correlation is maximum

# Correlation (Similarity) Approach

## Elements to be matched

- Image window of fixed size centered at each pixel in the left image

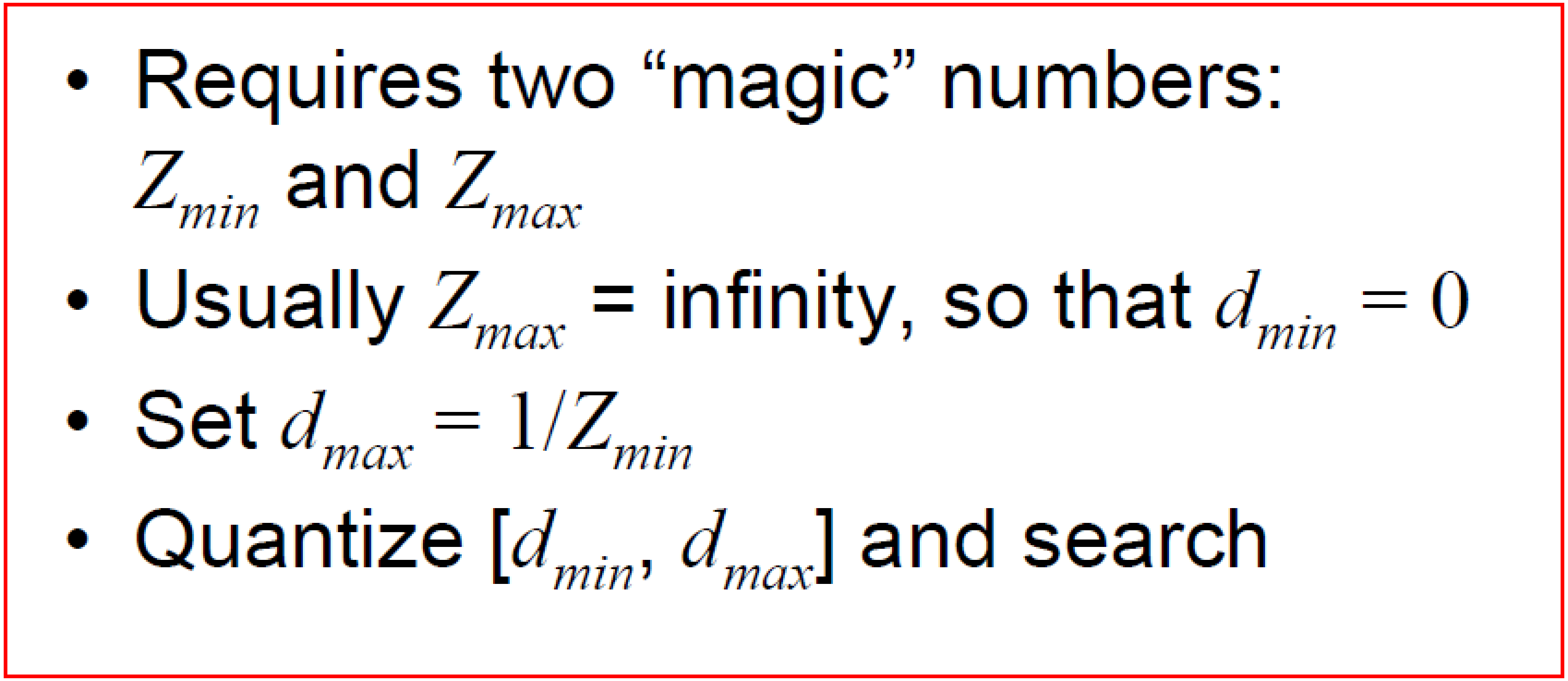
## Similarity criterion

- A measure of similarity between windows in the two images
- The corresponding element is given by window that maximizes the similarity criterion within a search region

## Search regions

- Theoretically, search region can be reduced to a 1-D segment, along the horizontal line (in future we will use term epipolar line), and within the disparity range.
- In practice, search a slightly larger region due to errors in calibration

# Search Region Size (Disparity Range)



- Requires two “magic” numbers: $Z_{min}$ and $Z_{max}$
- Usually $Z_{max}$ = infinity, so that $d_{min} = 0$
- Set $d_{max} = 1/Z_{min}$
- Quantize [$d_{min}$, $d_{max}$] and search

# Correlation Approach (general disparity)

Equations = w is the window size

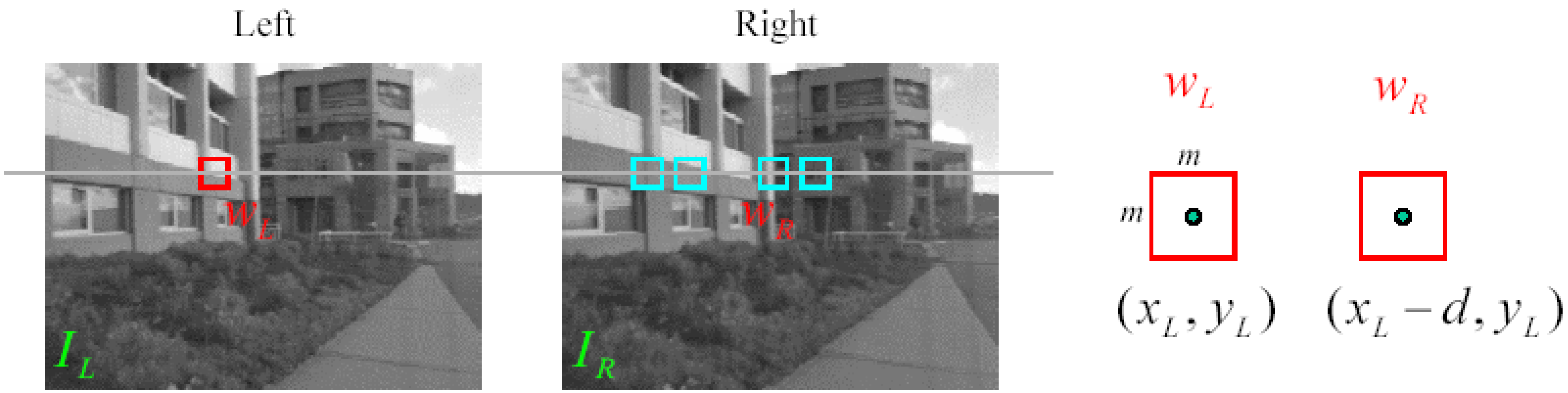
$$c(dx,dy) = \sum_{k=-W}^{W} \sum_{l=-W}^{W} \psi(I_l(x_l + k, y_l + l), I_r(x_l + dx + k, y_l + dy + l))$$

disparity $$\bar{\mathbf{d}} = (\bar{d}x, \bar{d}y) = \arg\max_{\mathbf{d}\in R}\{c(dx,dy)\}$$

Similarity criterion

- Cross-Correlation $$\Psi(u,v) = uv$$
- Sum of Square Difference (SSD) $$\Psi(u,v) = -(u-v)^2$$
- Sum of Absolute Difference(SAD) $$\Psi(u,v) = -|u-v|$$

# Sum of Squared Differences (SSD)



$w_L$ and $w_R$ are corresponding $m$ by $m$ windows of pixels.

We define the window function :

$$W_m(x, y) = \{u, v \mid x - \tfrac{m}{2} \le u \le x + \tfrac{m}{2}, y - \tfrac{m}{2} \le v \le y + \tfrac{m}{2}\}$$

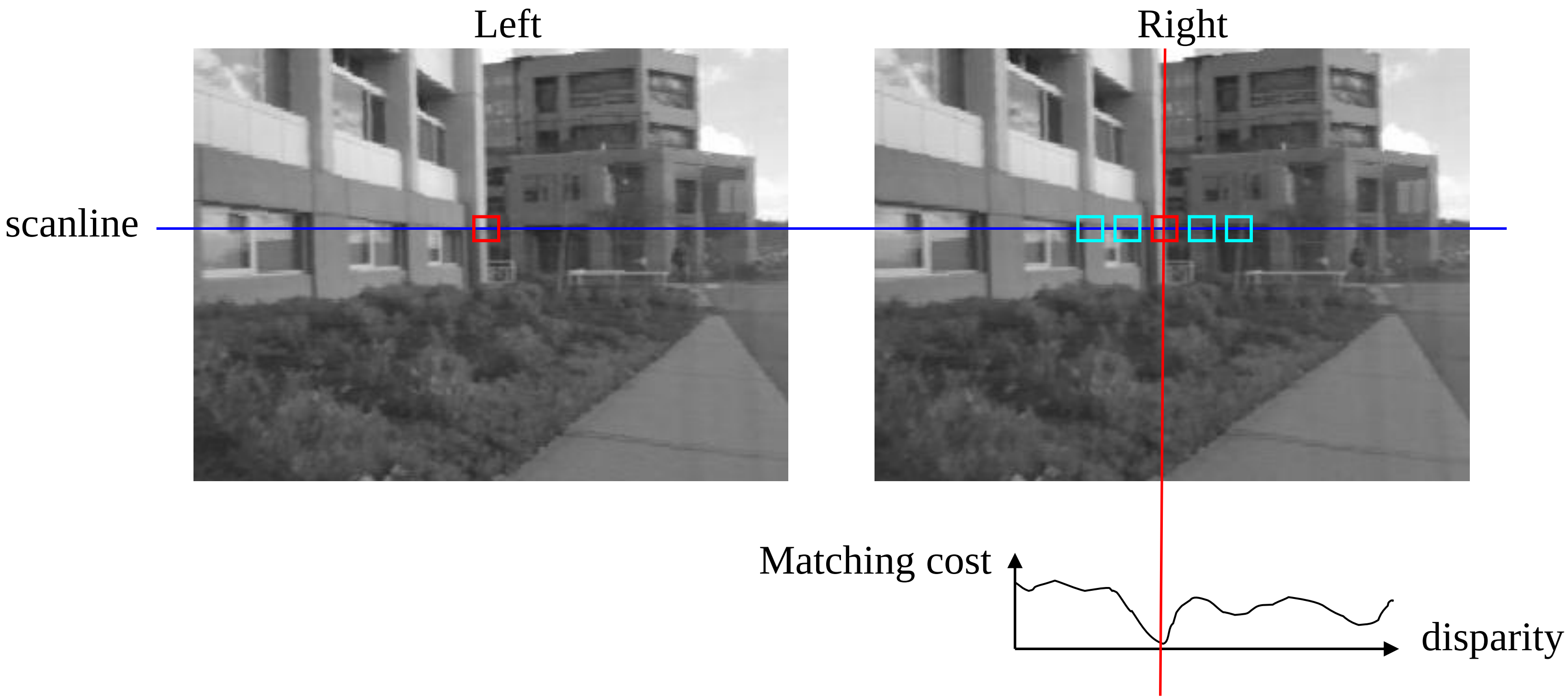
The SSD cost measures the intensity difference as a function of disparity :

$$C_r(x, y, d) = \sum_{(u,v) \in W_m(x,y)} [I_L(u, v) - I_R(u - d, v)]^2$$

For simple stereo need only move to left in rightmost image.

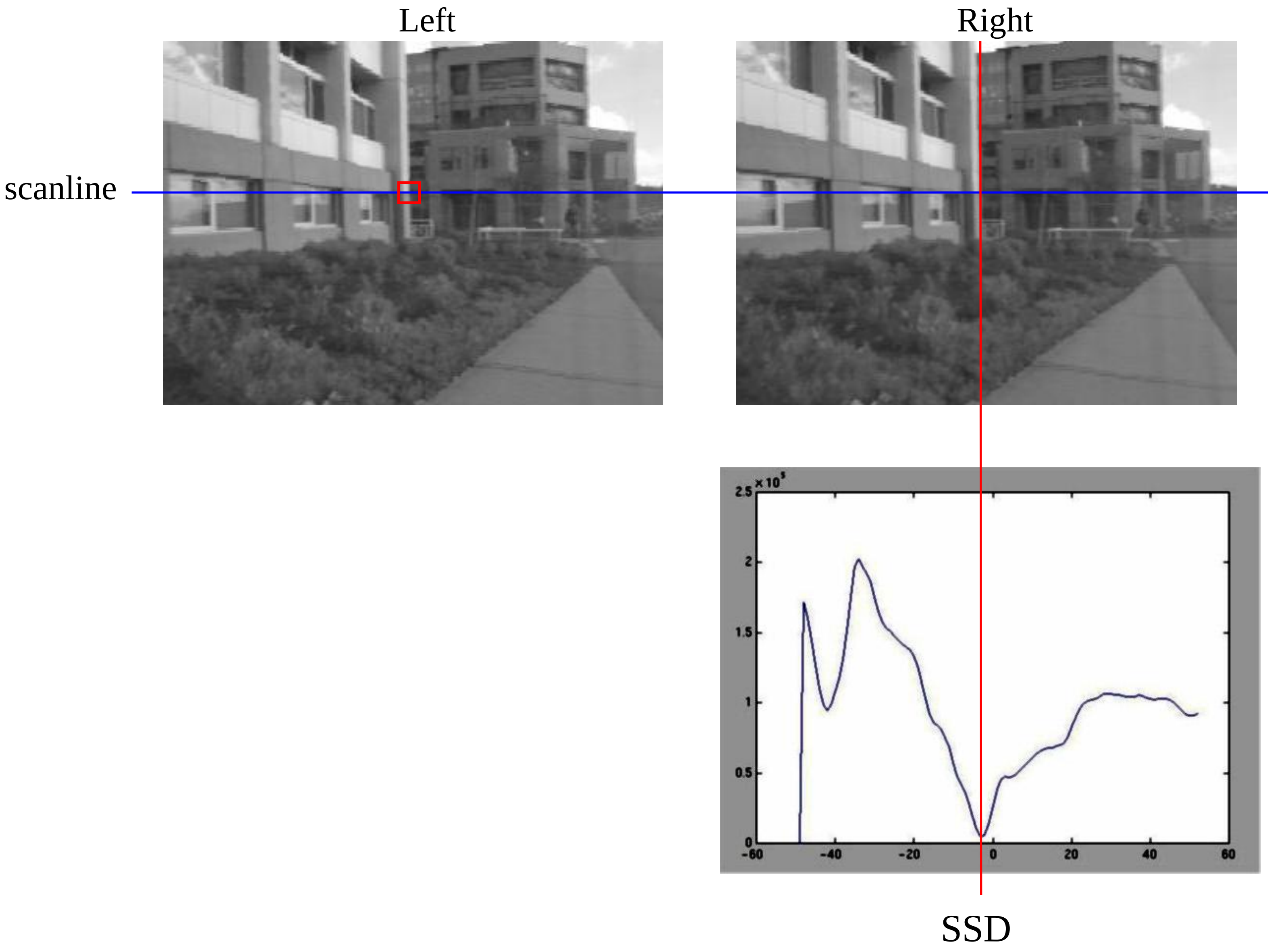
If x is zero is leftmost part of image, only look at $(x_L – d)$

# Correspondence search with similarity constraint



- Slide a window along the right scanline and compare contents of that window with the reference window in the left image
- Matching cost: SSD or normalized correlation

# Correspondence search with similarity constraint



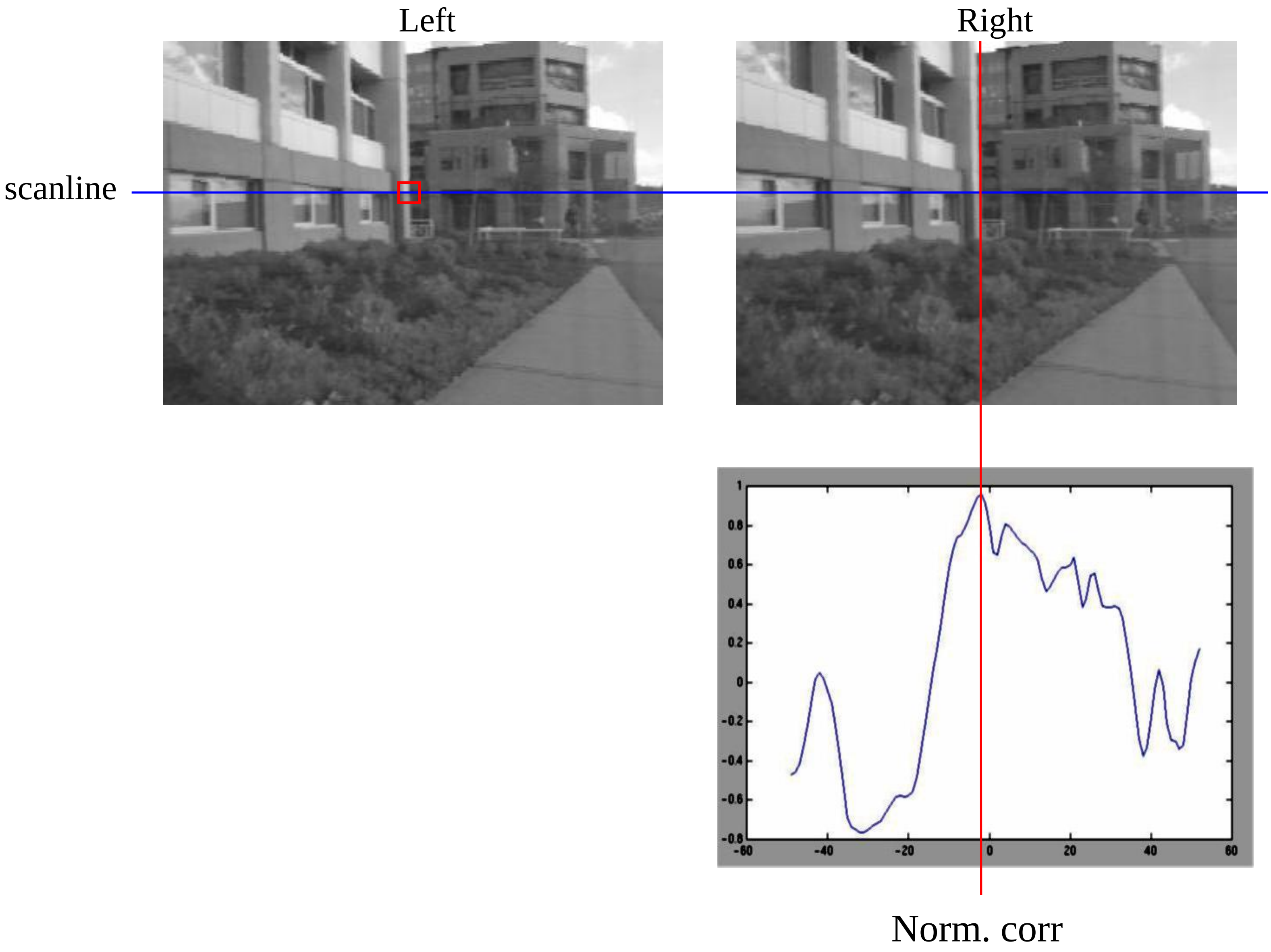
Left

Right

scanline

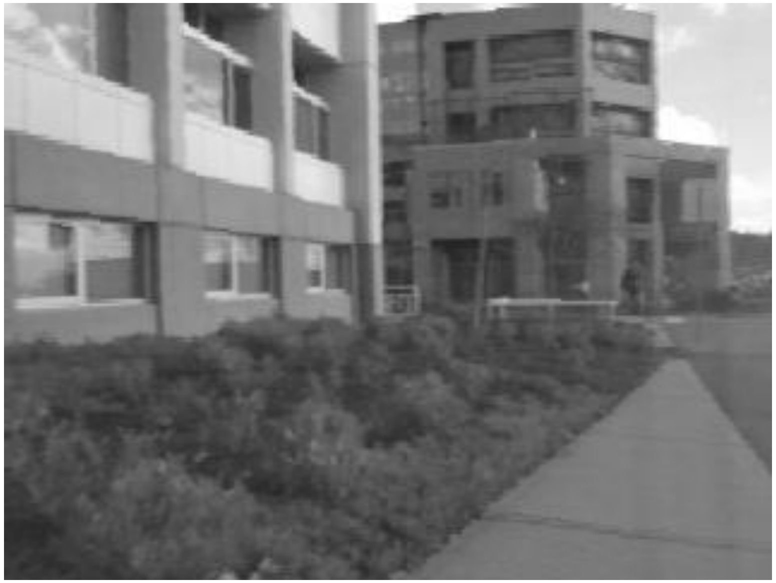
SSD

# Correspondence search with similarity constraint

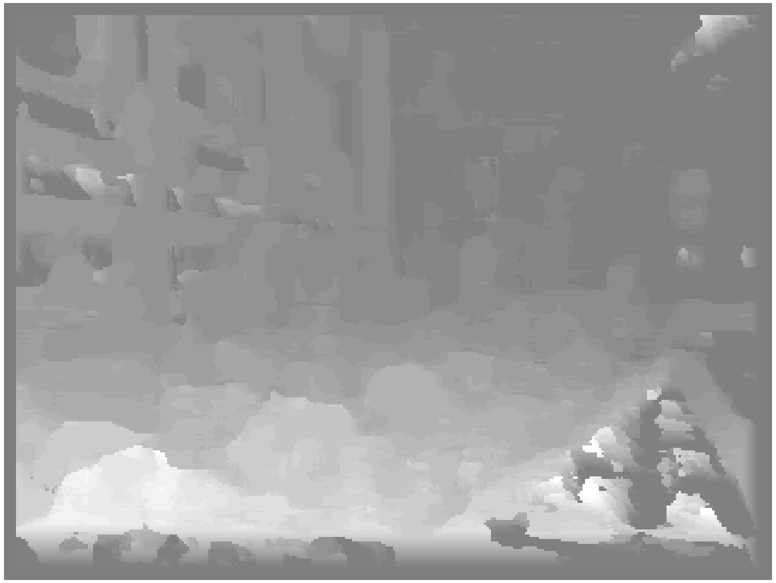


# Correspondence Using Correlation

Left



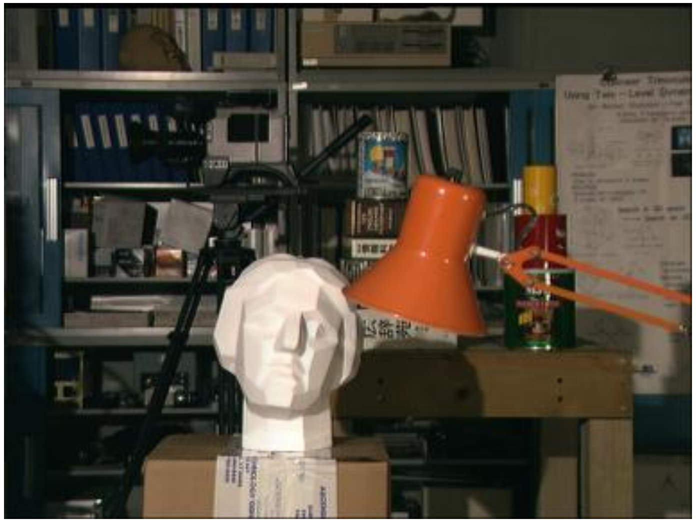
Disparity Map



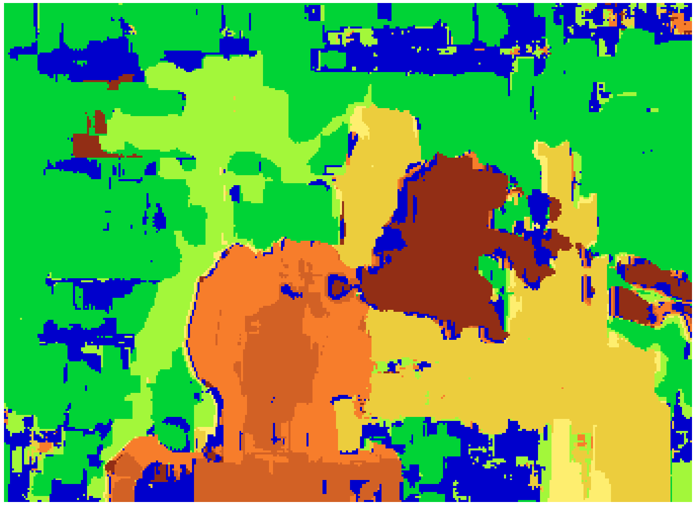
Images courtesy of Point Grey Research

# Correspondence Using Correlation

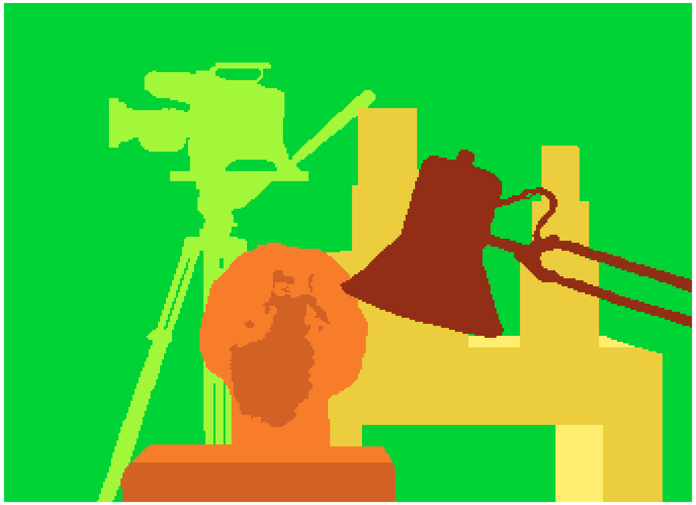
Data



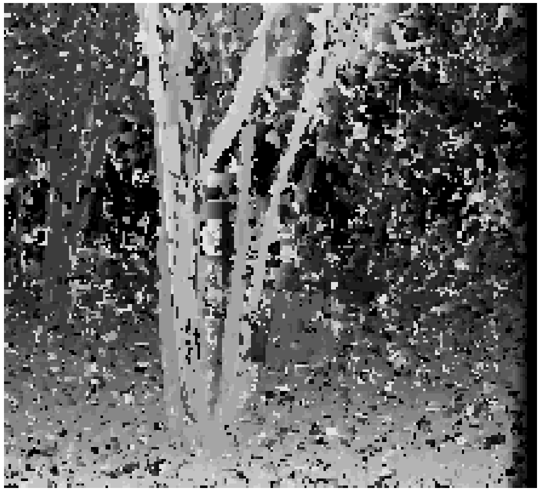
Window-based matching



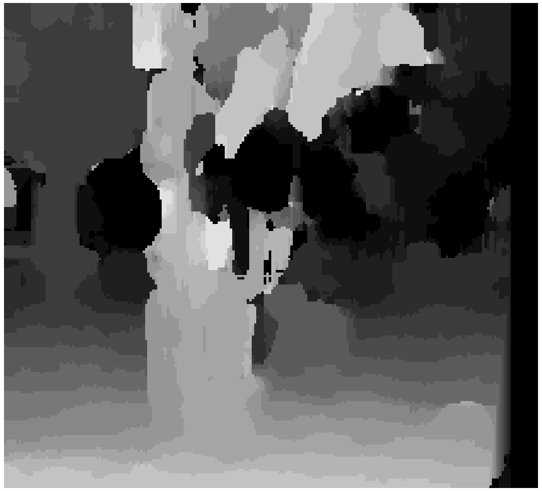
Ground truth



# Effect of window size



W = 3

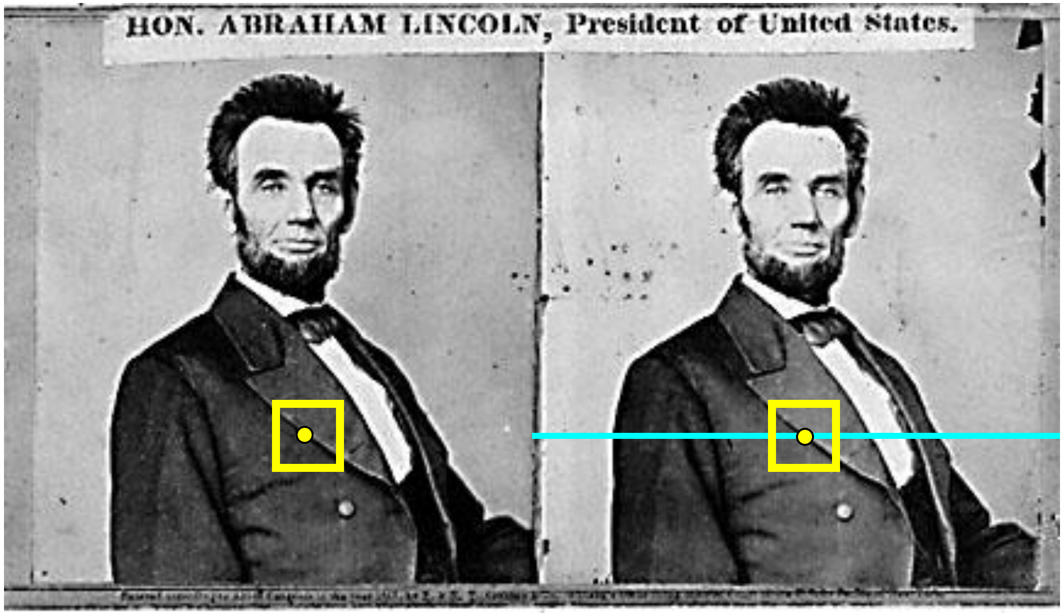


W = 20

- Smaller window
  - + More detail
  - – More noise

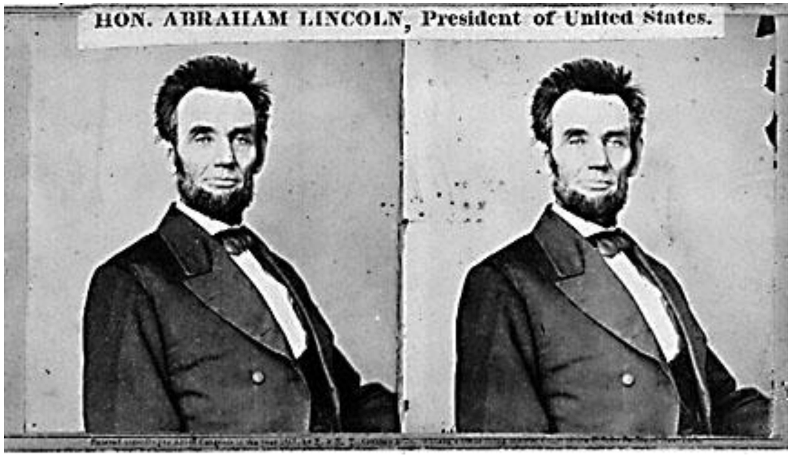
- Larger window
  - + Smoother disparity maps
  - – Less detail

# The similarity constraint

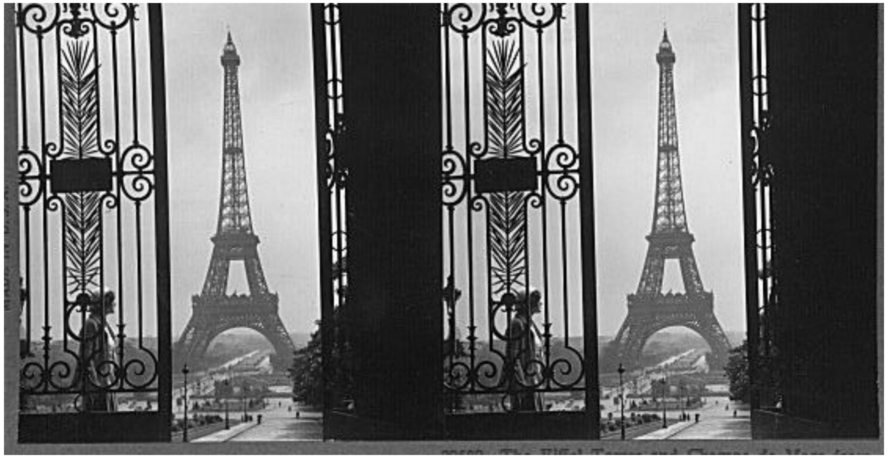


- Corresponding regions in two images should be similar in appearance
- …and non-corresponding regions should be different
- When will the similarity constraint fail?

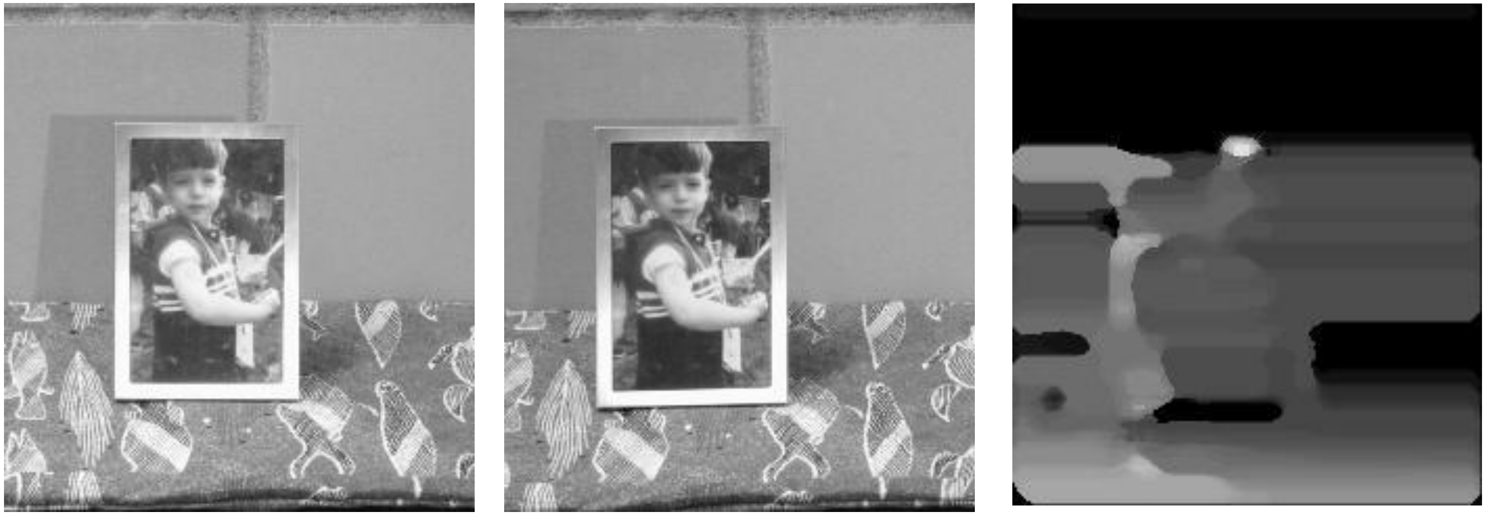
# Limitations of similarity constraint



Textureless surfaces



Occlusions, repetition



Non-Lambertian surfaces, specularities

# Problems for Similarity Constraint

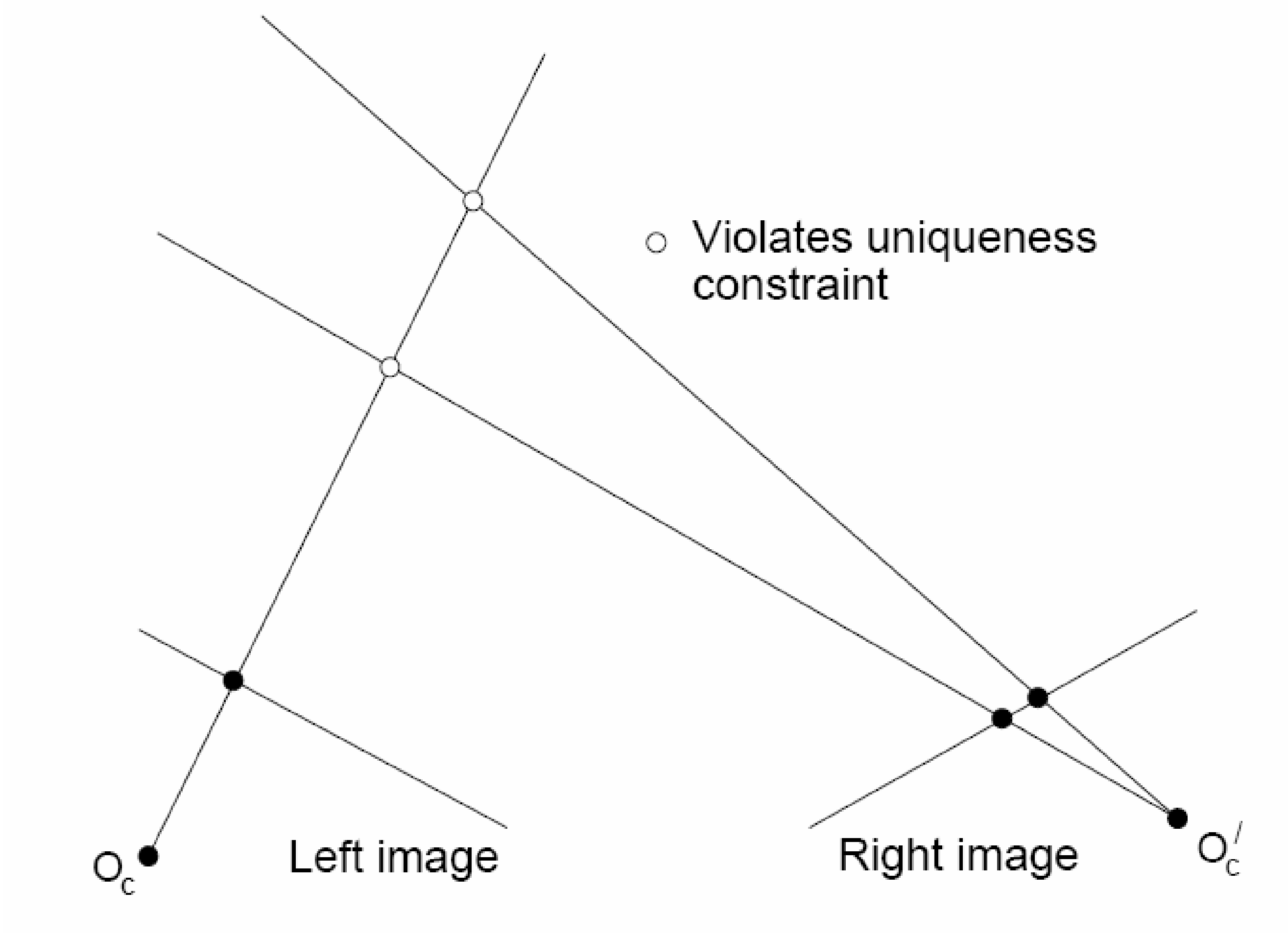
- Occlusions
  - Points with no counterpart in the other image
  - The wider the stereo baseline the more chance that there are occlusions (this should be obvious)
- Repetition
  - Elements are so similar can not tell them apart locally
- Textureless Surface
  - Nothing can be matched in these regions
- Non-Lambertian Surface – Specularities
  - Makes matching much more difficult (two views not similar)
- Such problems produce spurious matches
  - False correspondences created for the above reasons

# How can we improve window-based matching?

- The similarity constraint is **local** (each reference window is matched independently)
- Need to enforce **non-local** correspondence constraints
  - This means looking at the correspondences together
  - And then seeing if they make sense as a whole
- Then if correspondences are not consistent with each other we can make a decision
  - And likely discard some bad correspondences
- Another option is to use active sensors!
  - Project your own correspondences on the scene!
  - For example, shine a single laser beam around the scence

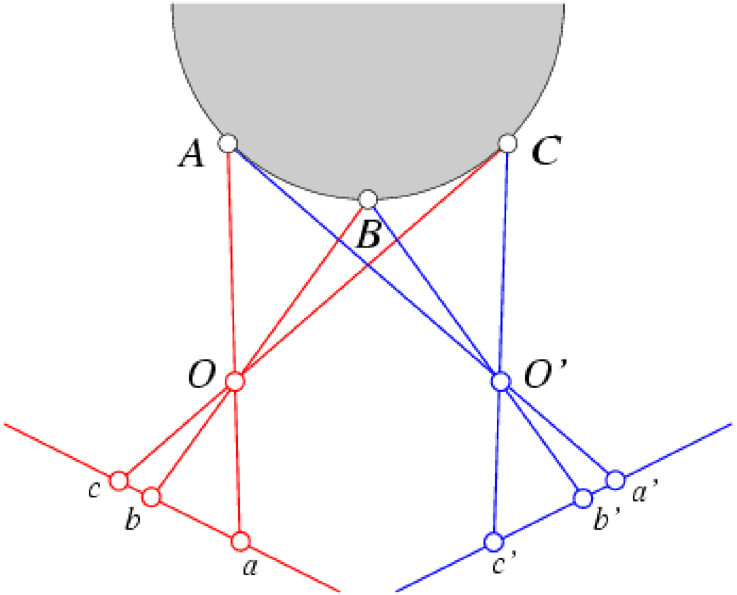
# Non-local constraints

- Uniqueness
  - For any point in one image, there should be at most one matching point in the other image



# Non-local constraints

- Uniqueness
  - For any point in one image, there should be at most one matching point in the other image
- Ordering
  - Corresponding points should be in the same order in both views



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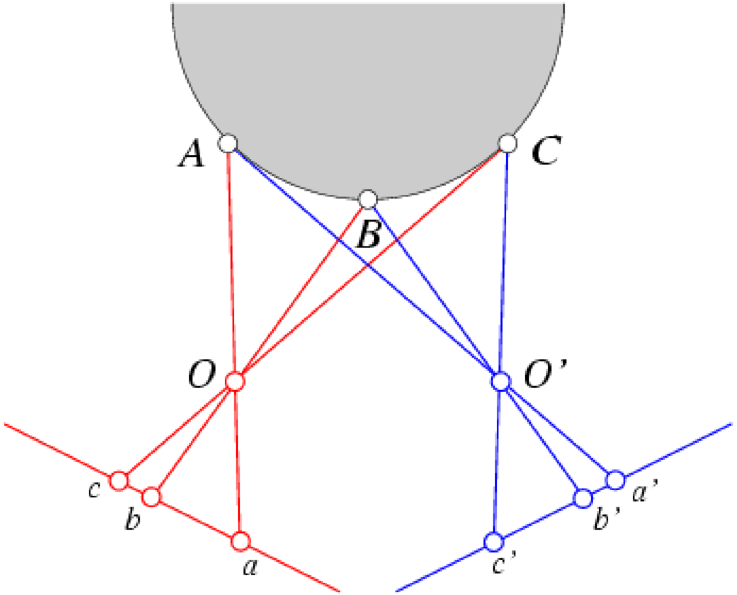
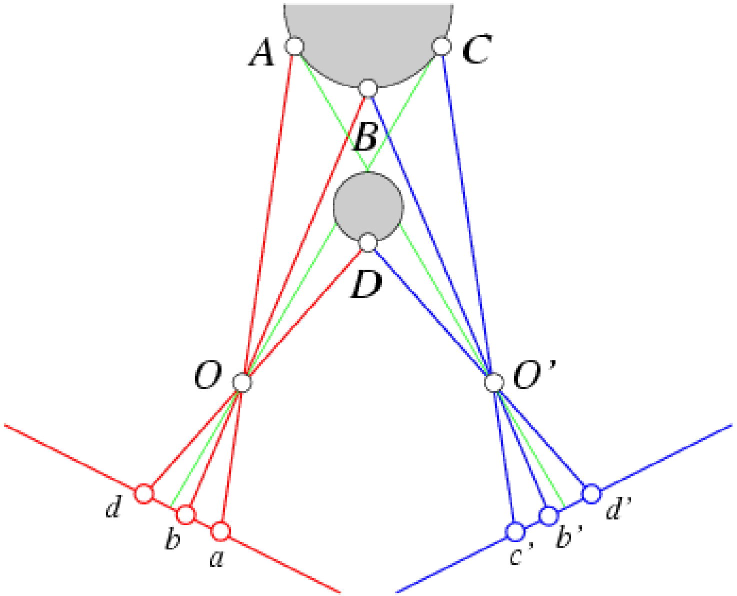




Ordering constraint doesn’t always hold

# Correlation Approach

## PROS

- Easy to implement
- Produces dense disparity map
- Can be slow if implemented poorly

## CONS

- Needs textured images to work well
- Inadequate for matching image pairs from very different viewpoints due to failure of similarity constraint
  - Poor for wide baseline matching
- Window may cover points with quite different disparities
- Inaccurate disparities on the occluding boundaries

# Feature-based Approach

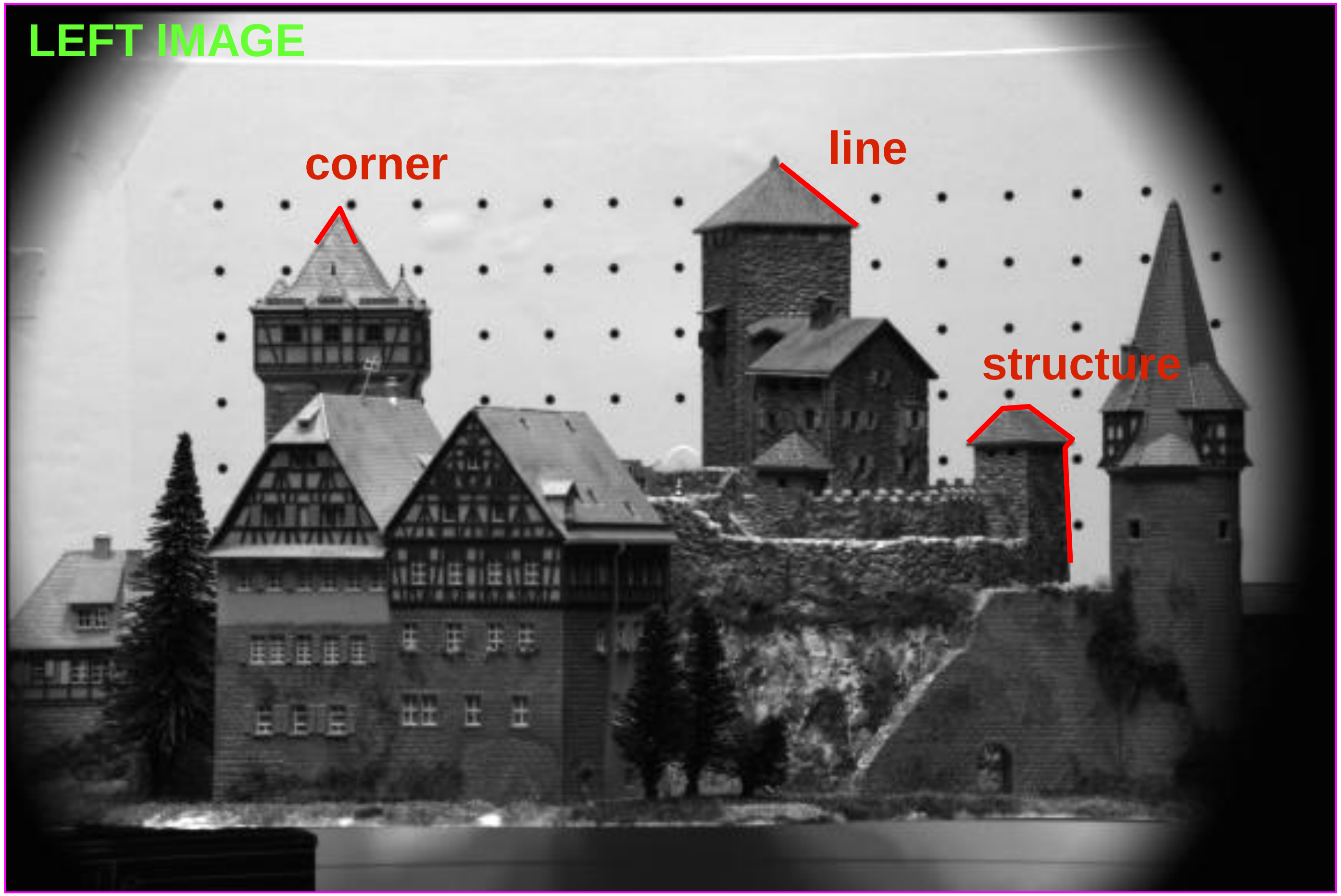
## Features

- Edge points
- Lines (length, orientation, average contrast)
- Corners (including Harris, SURF, SIFT, etc.)

## Matching algorithm

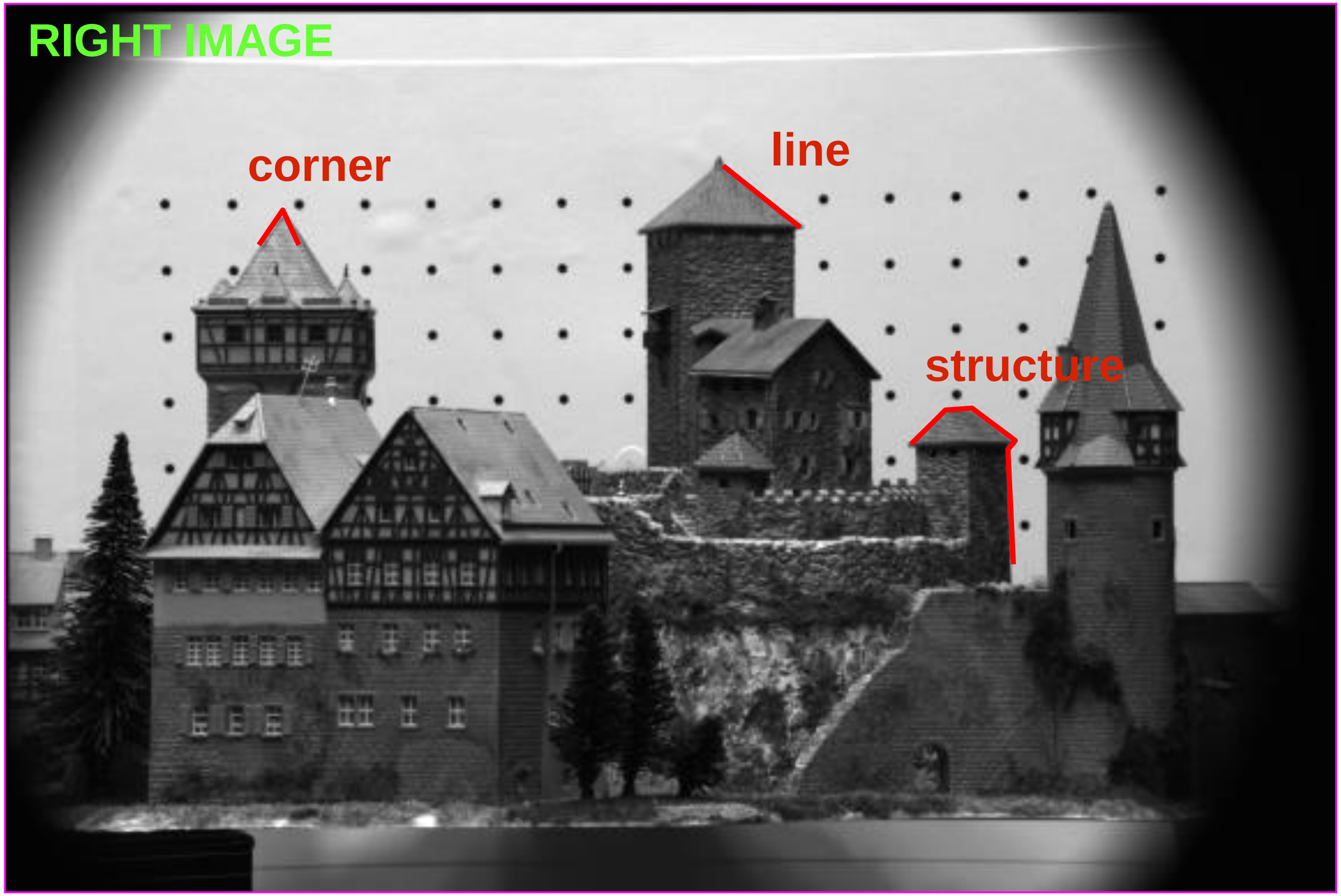
- Extract features in the stereo pair
- Define a suitable similarity measure for these features
- Use constraints to reduce number of matches
- Geometric constraints
  - Need only match features on same horizontal line
- Analytic constraints
  - Uniqueness – each feature has at most one match
  - Continuity – disparity varies continuously almost everywhere across this image

# Feature-based Approach



For each feature in the left image…

# Feature-based Approach



Search in the right image… the disparity (dx, dy) is the displacement when the similarity measure is maximum

# Matching corner features

- For Harris corners usually just match small windows around the corner (using SSD)
- But SURF/SIFT corners have much more powerful and complex descriptor
- SURF descriptor is a 64 element float
  - Choosing best match between a set of SURF descriptors is a closest point problem (find_obj.cpp in OpenCV examples)
  - For simple stereo means finds closest (in terms of 64 elements) match in left and right image
- SURF descriptors have good invariance but are slow to match (can only handle hundreds)
  - Invariance means they work well for wide baseline images

# Feature-based Approach

## PROS

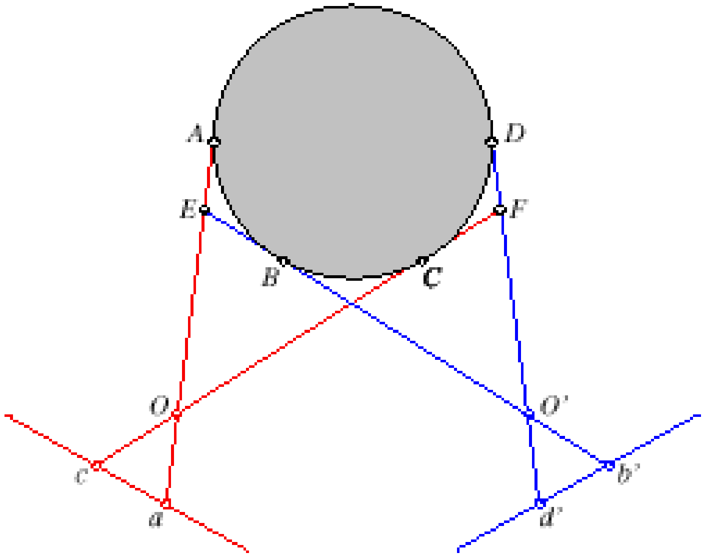
- Relatively insensitive to illumination changes
- Good for man-made scenes with strong lines but weak texture or textureless surfaces
- Work well on the occluding boundaries (edges)
- Could be faster than the correlation approach
- With SURF/SIFT features can work well for wider baseline

## CONS

- Only produces a sparse depth map (usually hundreds of pts)
- Feature extraction is slow and matching is sometimes slower
  - Finding good feature descriptors is difficult
  - Lot of work done for matching SURF/SIFT features
  - But problem still difficult; i.e. what is similarity between two lines?

# A Last Word on Correspondences

Correspondence fail for smooth surfaces



There is currently no good solution to the correspondence problem