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# Stereo Vision – Correspondence

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# Problem Definition

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- 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

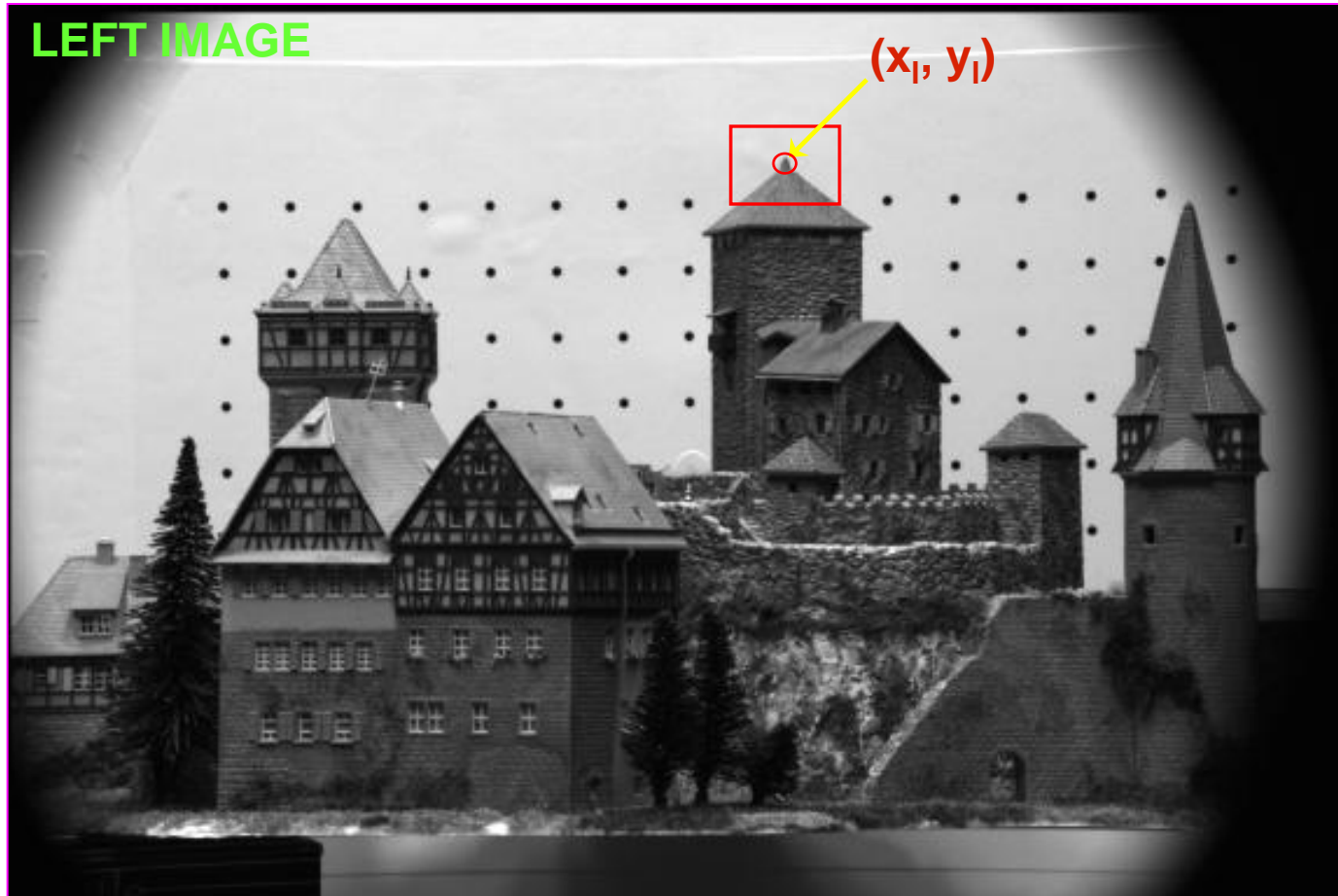
# Correspondence and Feature Methods

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- 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

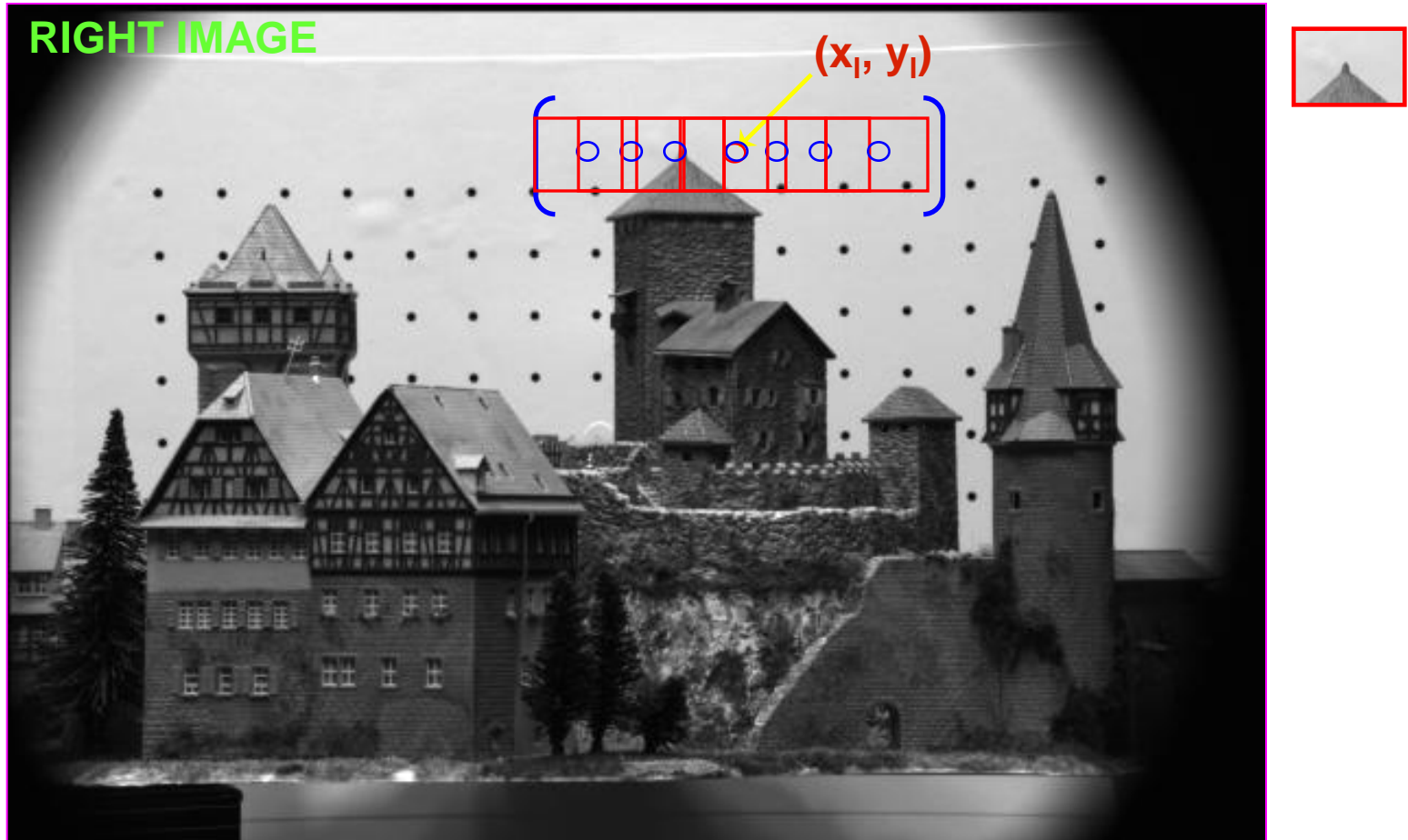
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For Each point  $(x_l, y_l)$  in the left image, define a window centered at the point

# Correlation Approach

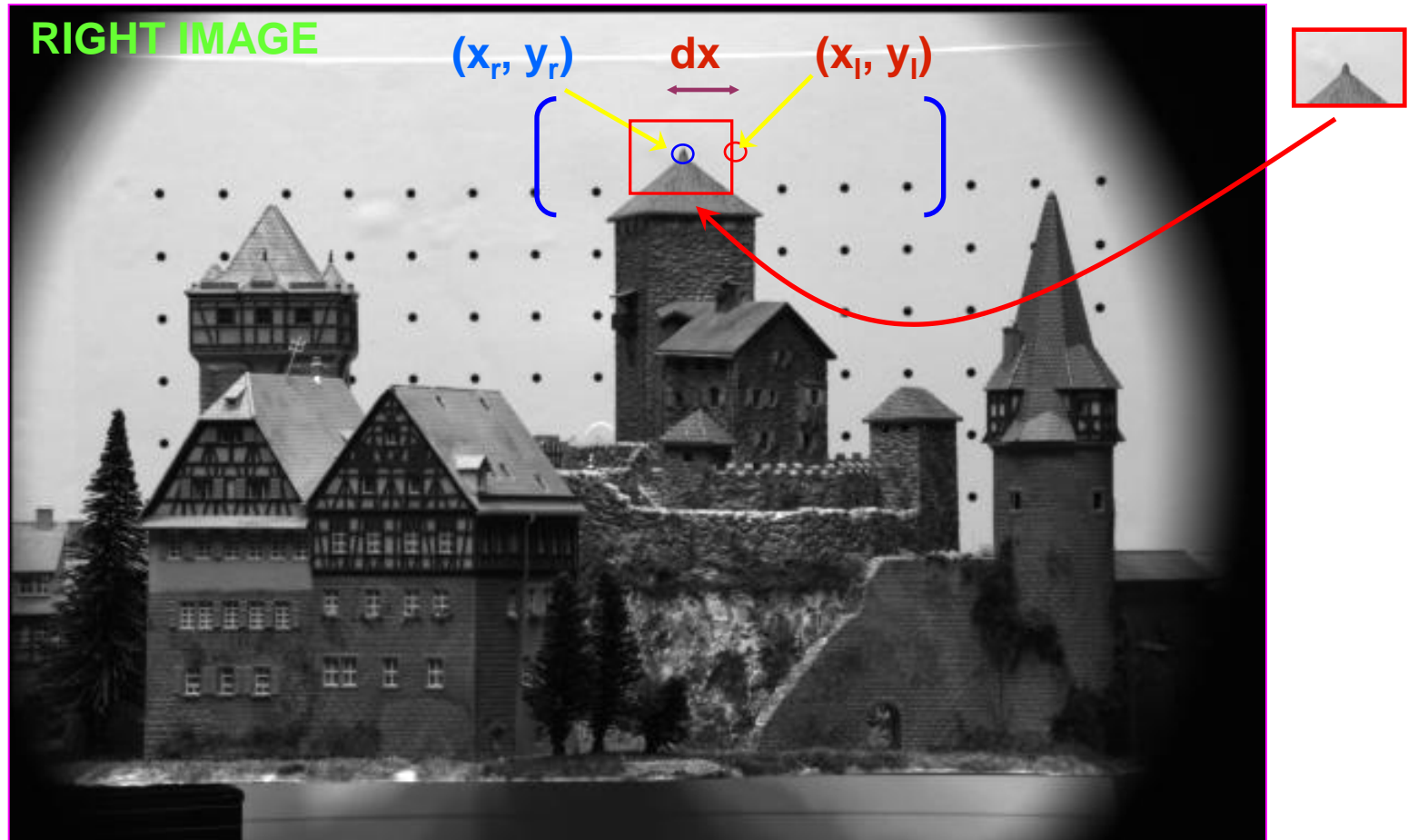
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... search its corresponding point within a search region in the right image

# Correlation Approach

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... 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  $Z_{max} = \text{infinity}$ , 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

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

## Similarity criterion

- Cross-Correlation

$$\Psi(u, v) = uv$$

- Sum of Square Difference (SSD)

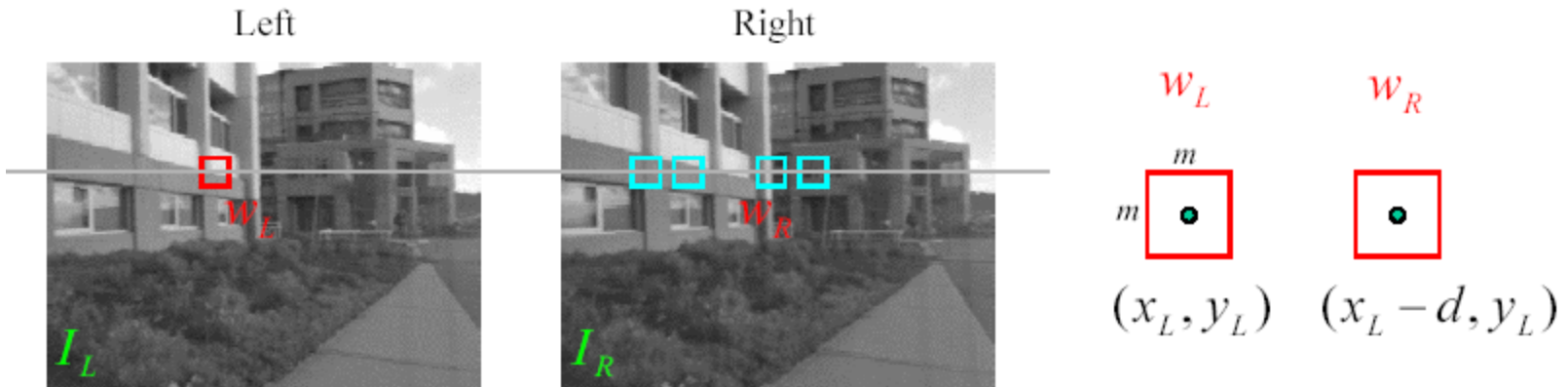
$$\Psi(u, v) = -(u - v)^2$$

- Sum of Absolute Difference (SAD)

$$\Psi(u, v) = -|u - v|$$

# Sum of Squared Differences (SSD)

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

We define the window function :

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

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

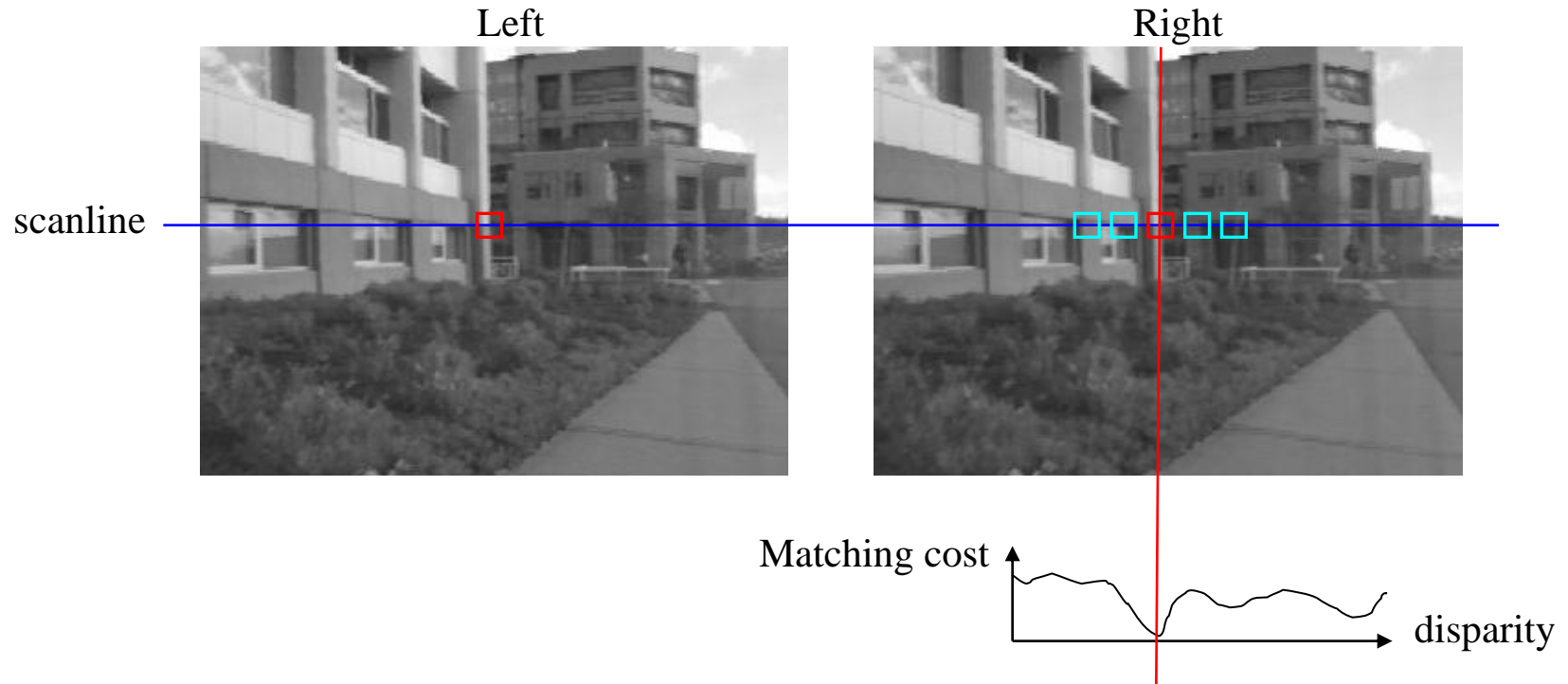
$$C_r(x, y, d) = \sum_{(u, v) \in W_m(x, y)} [I_L(u, v) - I_R(u - d, v)]^2$$

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

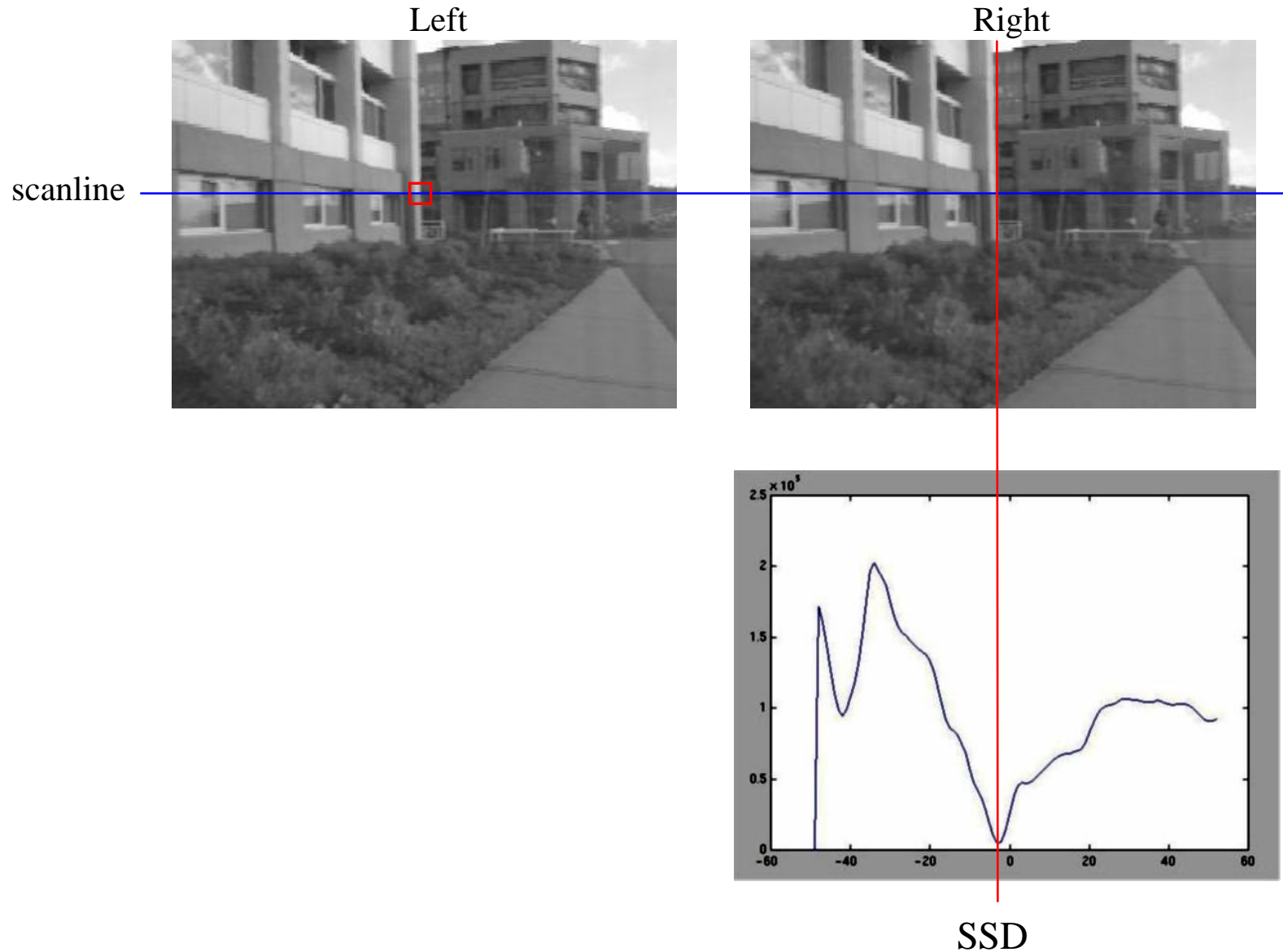
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- Slide a window along the right scanline and compare contents of that window with the reference window in the left image
- Matching cost: SSD or normalized correlation

# Correspondence search with similarity constraint

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# Correspondence search with similarity constraint

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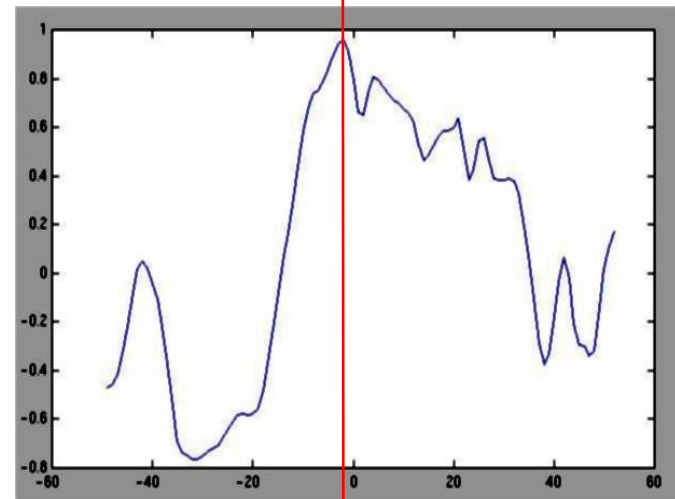
Left



Right



scanline



Norm. corr

# Correspondence Using Correlation

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Left



Disparity Map



Images courtesy of Point Grey Research

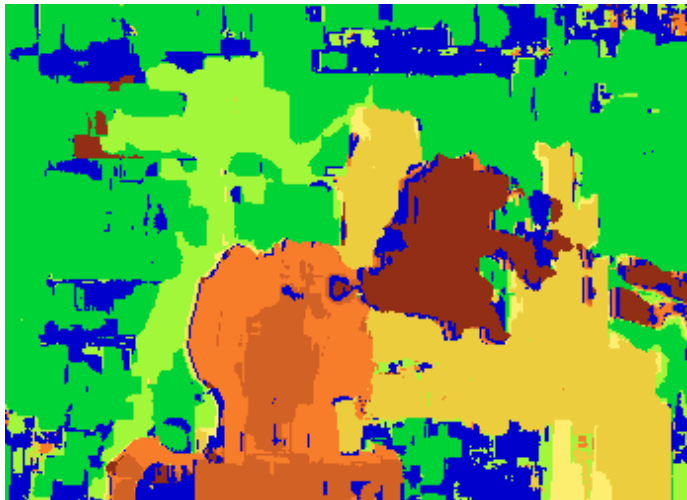
# Correspondence Using Correlation

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Data



Window-based matching



Ground truth

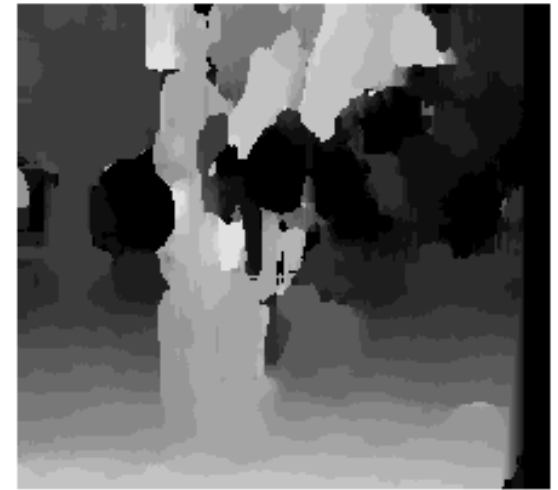


# Effect of window size

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$W = 3$

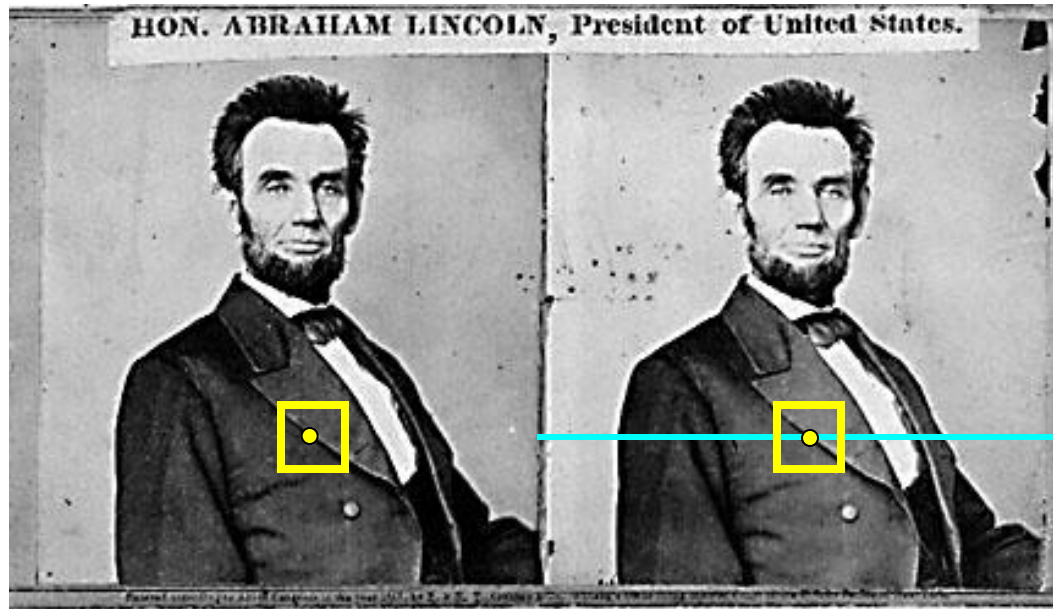


$W = 20$

- Smaller window
  - + More detail
  - More noise
- Larger window
  - + Smoother disparity maps
  - Less detail

# The similarity constraint

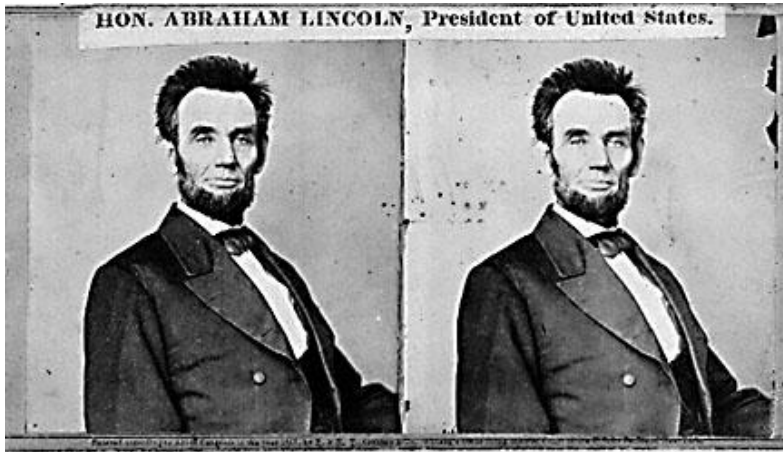
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- Corresponding regions in two images should be similar in appearance
- ...and non-corresponding regions should be different
- When will the similarity constraint fail?

# Limitations of similarity constraint

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Textureless surfaces



Occlusions, repetition



Non-Lambertian surfaces, specularities

# Problems for Similarity Constraint

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- 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

# Correspondence Difficulties

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## Photometric Distortion and Noise



## Specular Surfaces



# Correspondence Difficulties

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## Foreshortening



## Uniform / Non-textured Surfaces



# Correspondence Difficulties

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## Occlusions and Discontinuities



## Occlusions and Discontinuities



# How can we improve window-based matching?

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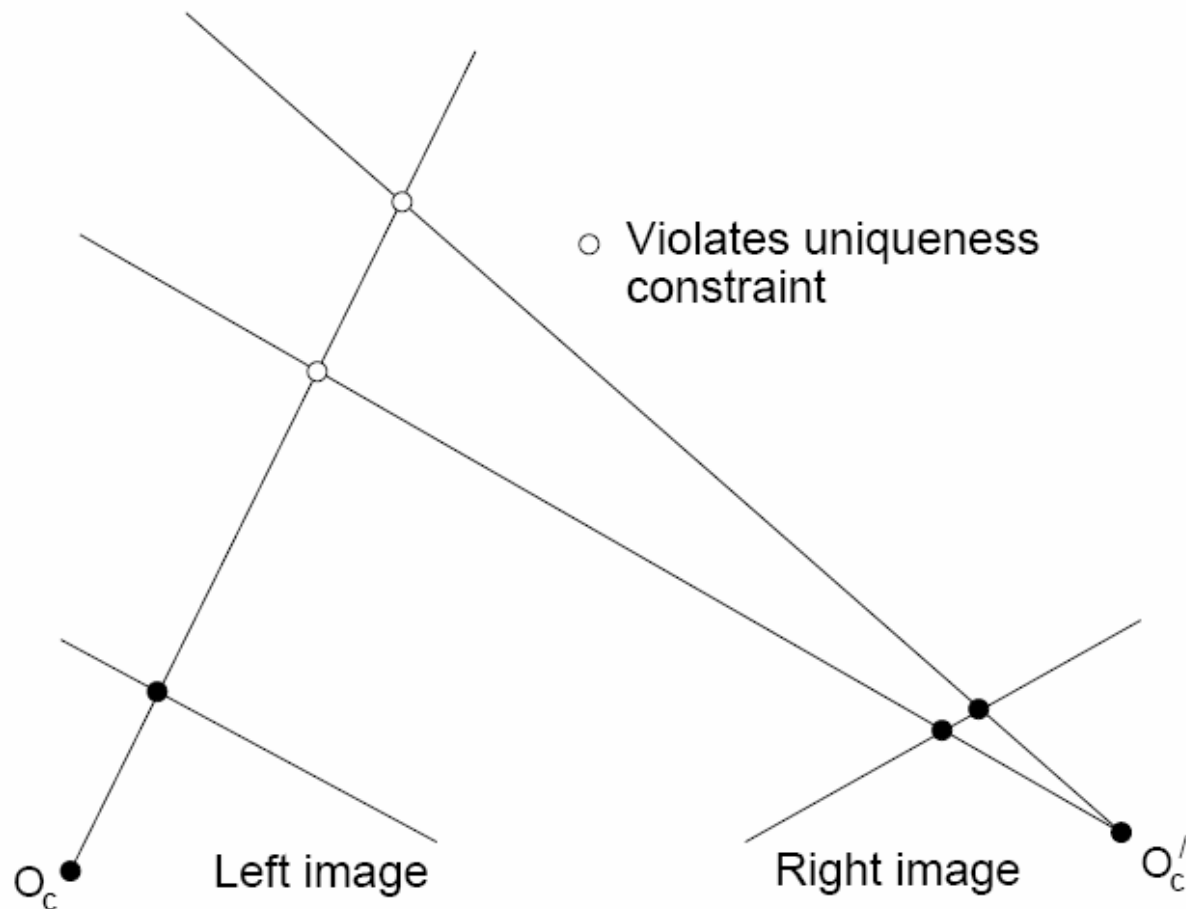
- The similarity constraint is **local** (each reference window is matched independently)
- Need to enforce **non-local** correspondence constraints
  - This means looking at the correspondences together
  - And then seeing if they make sense as a whole
- Then if correspondences are not consistent with 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 scene

# Non-local constraints

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- Uniqueness

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



# Non-local constraints

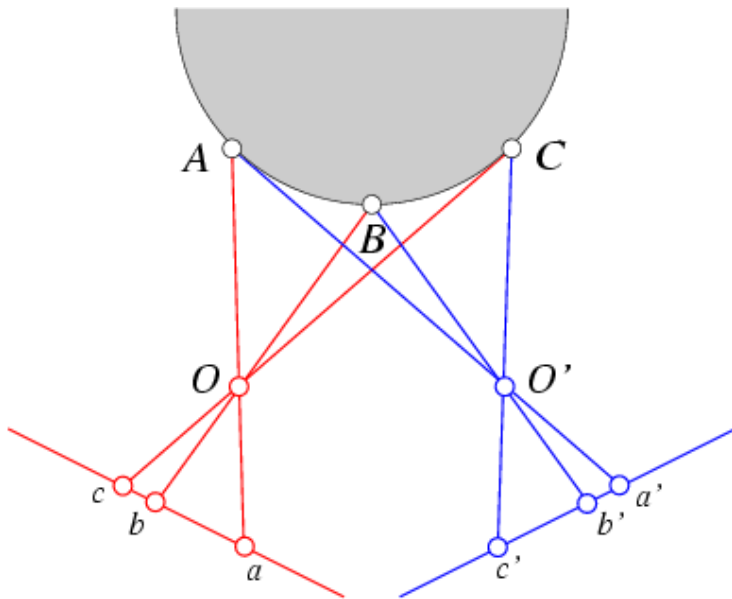
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- Uniqueness

- 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



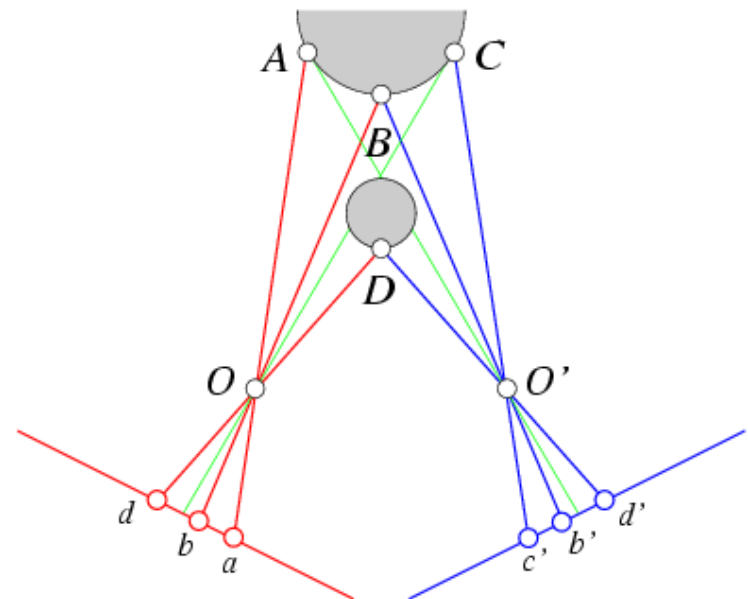
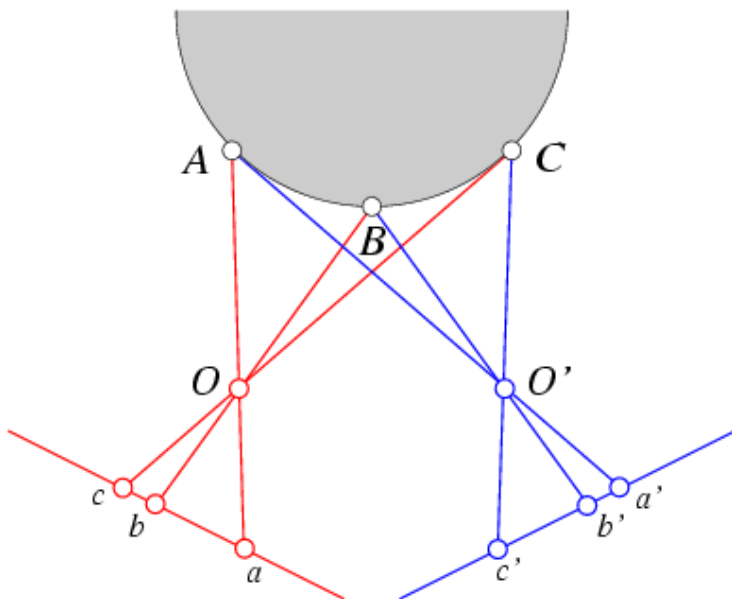
# Non-local constraints

- 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



Ordering constraint doesn't always hold

# Correlation Approach

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## 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

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## Features

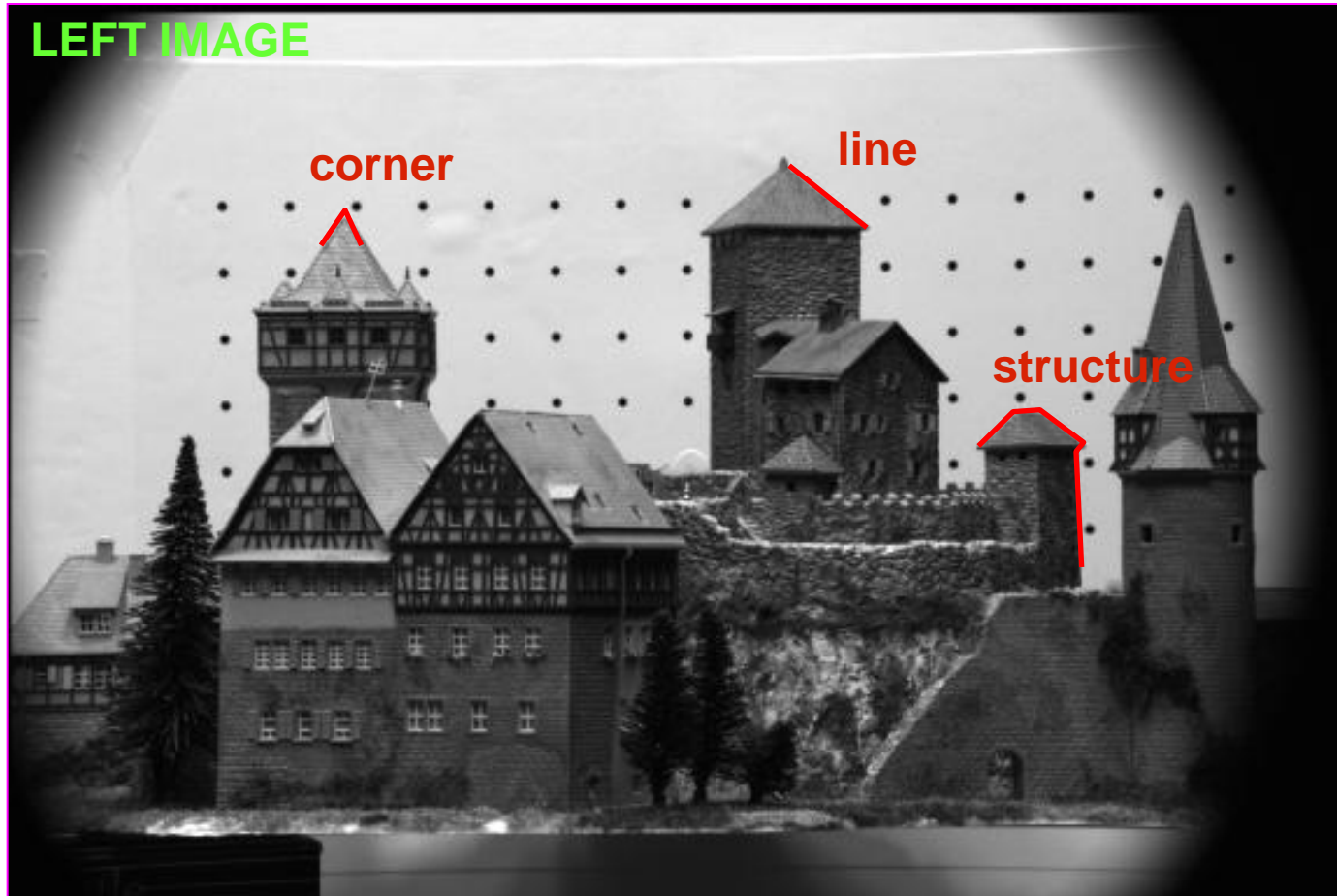
- Edge points
- Lines (length, orientation, average contrast)
- Corners (including Harris, SURF, SIFT, etc.)

## 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

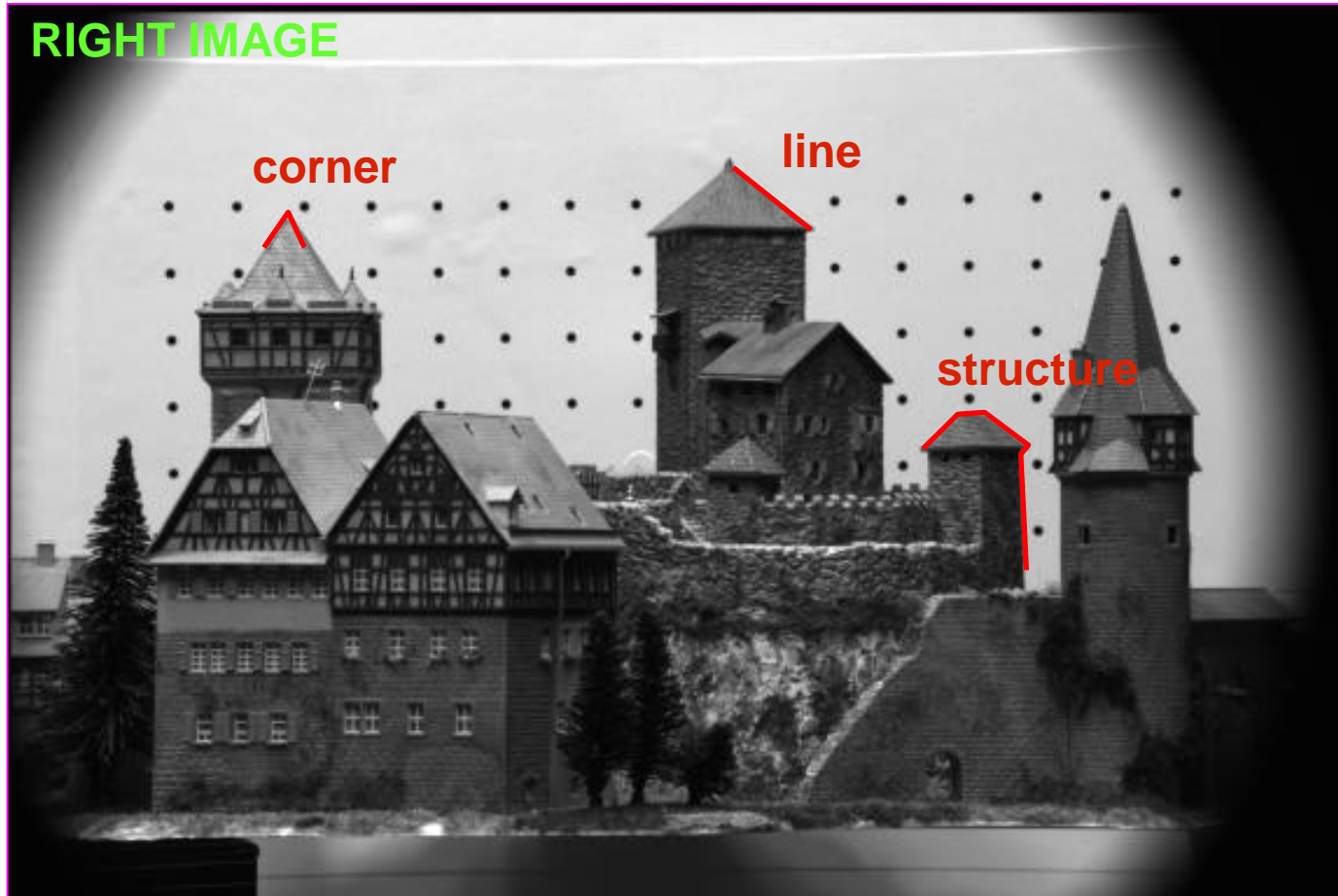
# Feature-based Approach

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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

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- 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

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## 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

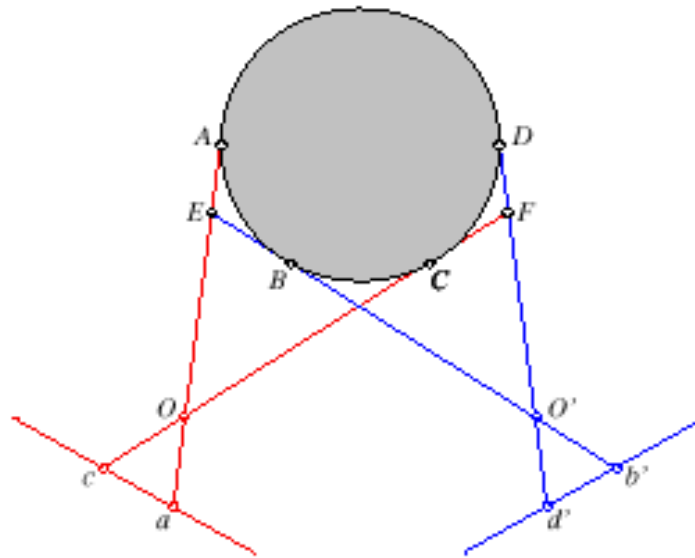
## CONS

- 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

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Correspondence fail for smooth surfaces



There is currently no good solution to the correspondence problem