



# Stereo Matching by Neural Networks

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May 6, 2005



# OUTLINE

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  - Comparison
- Correspondence – Matching Constraints
- Artificial Neural Network approach
  - Feature Extraction
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  - Occlusion
- Future Work



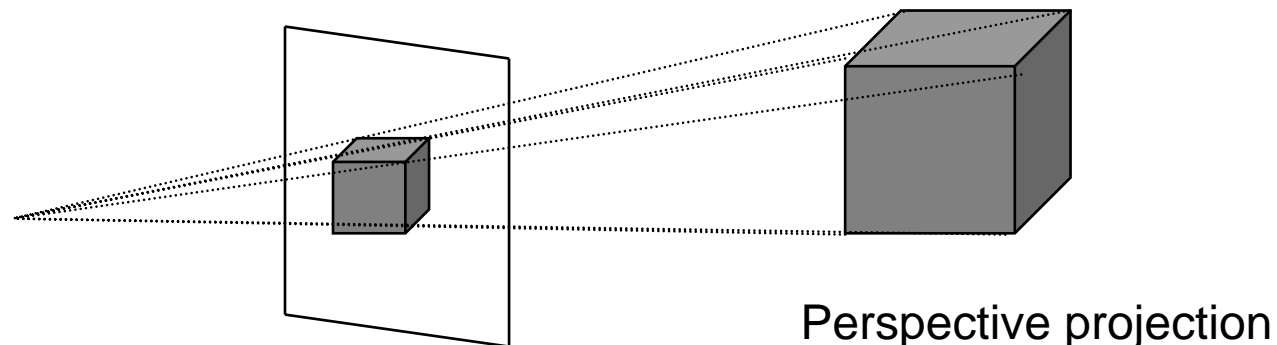
# Research Objective

- Develop a Vision System for a robotics close-range position sensing system
- In other words, develop a system that will enable the robot to “see” and interact with its environment
- The algorithm takes images of the environment as input, the output is 3D location of objects in view plus orientation -> give commands to robot to grab object
- Need a way to extract 3D information form images -> stereo vision



# Background- Image Formation

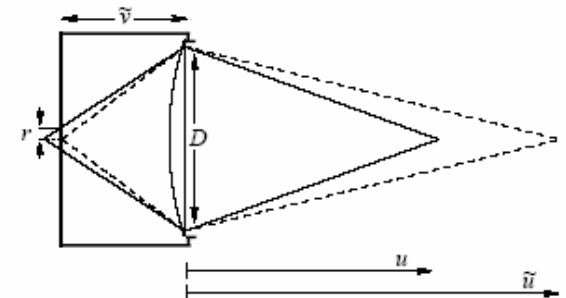
- **Image:** is a 2D projection of a 3D scene.  
Mapping from 3D to 2D, i.e., some information is getting lost
- **Computer vision problem:** recover (some or all of) that information.  
The lost dimension 2D  $\rightarrow$  3D
- **3D Vision Goals:**
  - **Reconstruction:** recover a model of the 3D scene from 2D images in order to accomplish close range position sensing





# 3D Vision

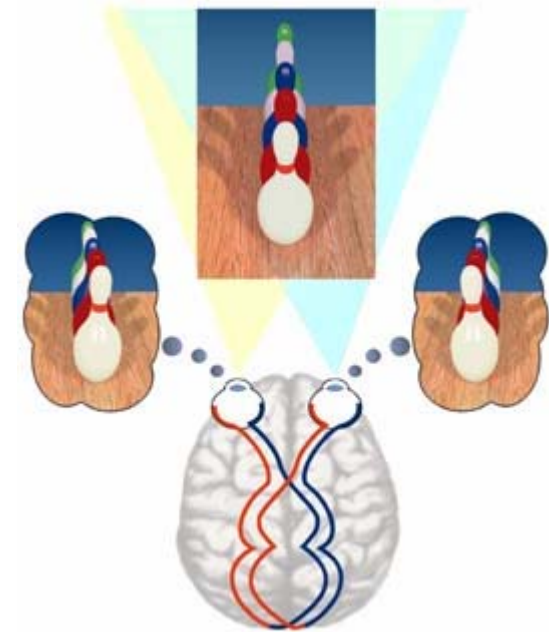
- There are different methods for recovering 3D info. From images:
  - 1- Passive Vision
    - Shape from de-focus
    - Stereo vision
  - 2- Active vision:
    - Laser
- Laser: In active vision, some type of energy such as a laser is emitted into the environment with the reflected light detected by sensors.
- Shape from de-focus: By adjusting the camera's focus, we can determine when a point is in focus and hence determine its depth.





# Stereo Vision

- The fundamental basis for stereo is the fact that a single three-dimensional physical location projects to a unique pair of image locations in two observing cameras.
- Given two camera images, if it is possible to locate the image locations that correspond to the same physical point in space, then it is possible to determine its three-dimensional location.





# Why Stereo?

- Uses basic cameras which are inexpensive compared with laser and optical scanners.
- Affordability means vision systems could be constructed using personal computers.
- Active vision drawbacks: slow scanning speed and higher cost.
- Passive sensors have the advantage over laser and radar sensors: the possibility of acquiring data in a noninvasive way and so not altering the environment.
- Biggest advantage over active: interference among sensors of the same type.
- Shape from defocus suffers from low resolution.



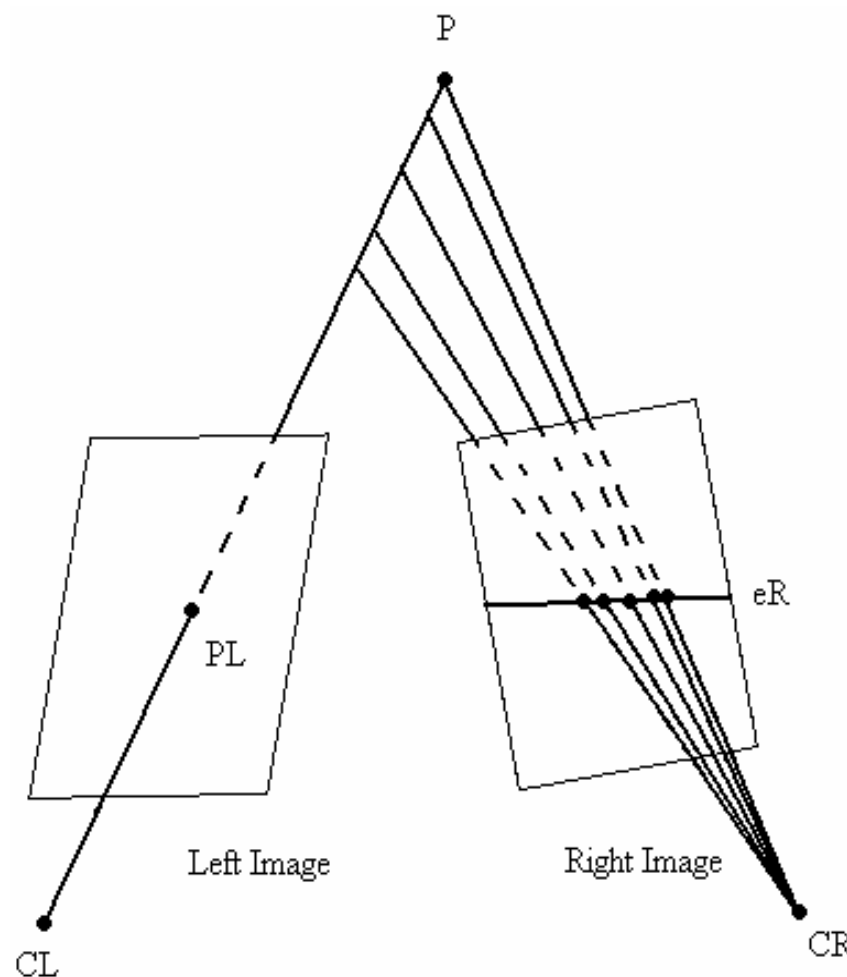
# Stereo Vision

- **Steps taken for 3D information using stereo vision systems:**

- **Calibration:** find geometrical relationship between the 3D space and the cameras.

- **Correspondence:** Identify the image point that represents the same scene point in the other image.

- **Reconstruction:** Calculate the depth of the selected location based on the location difference of the corresponding points and camera position.





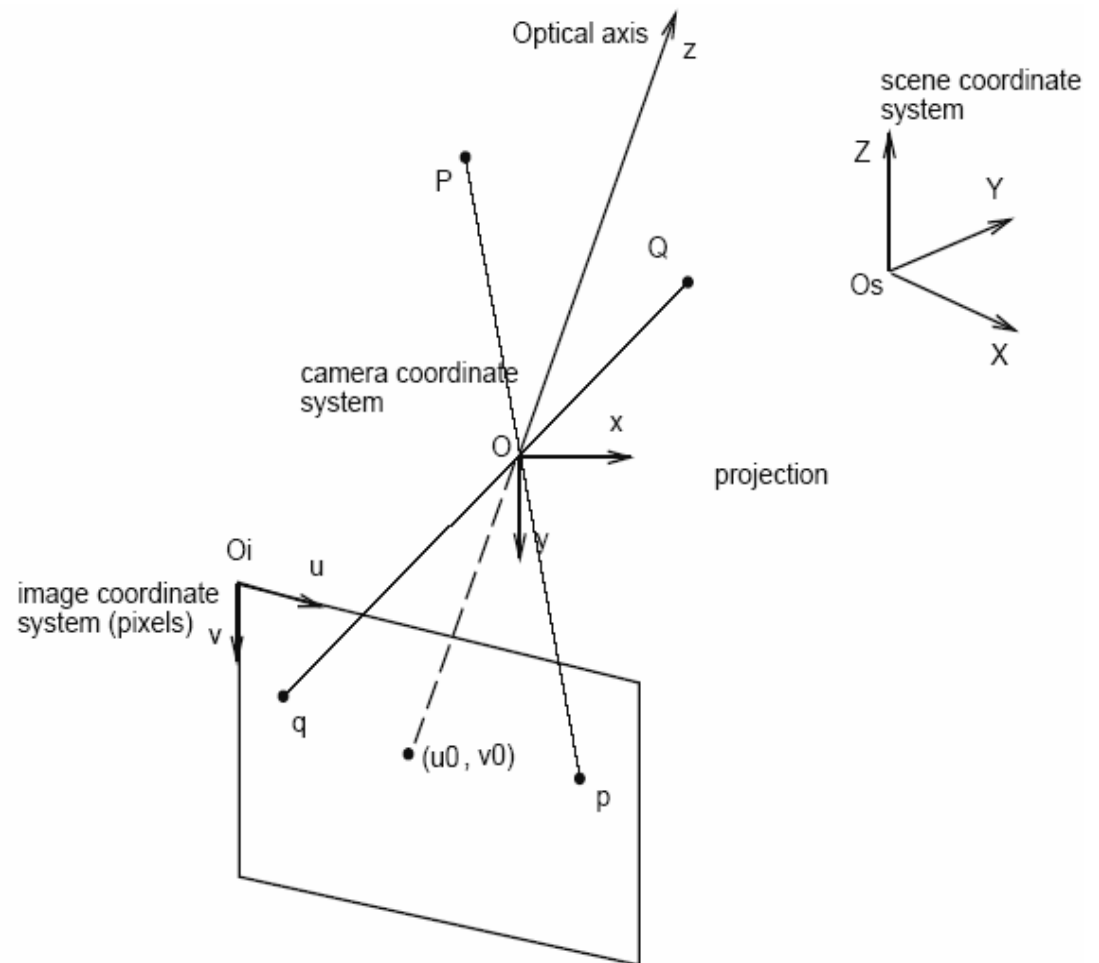


# Camera Calibration

- Projection Matrix

$$\begin{pmatrix} x \\ y \\ 1 \end{pmatrix} = \begin{pmatrix} \beta_1 & \beta_2 & \beta_3 & \beta_4 \\ \beta_5 & \beta_6 & \beta_7 & \beta_8 \\ \beta_9 & \beta_{10} & \beta_{11} & 1 \end{pmatrix} \begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix}$$

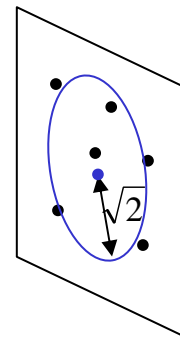
- 1- A 3D to 3D transformation: rigid camera displacement
- 2- A 3D to 2D transformation (perspective projection)
- 3- A 2D to 2D transformation: normalized camera parameters





# Calibration

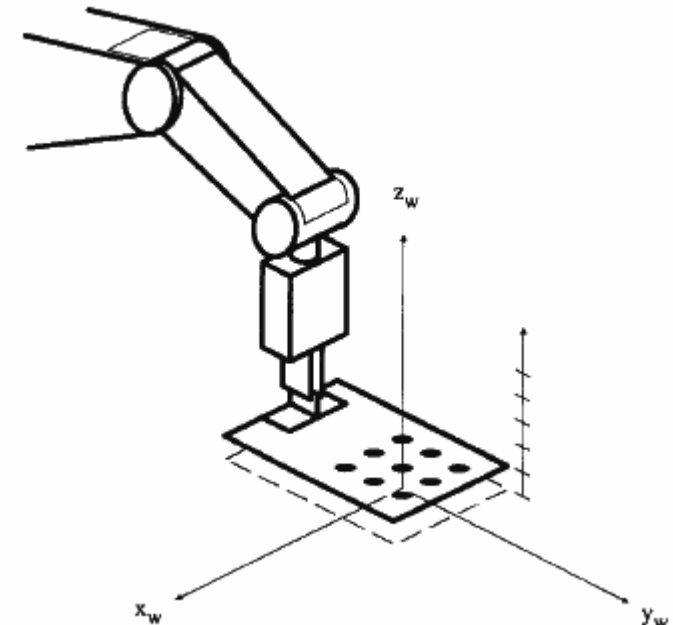
- Camera calibration is the process of estimating the extrinsic and intrinsic parameters of a camera *or* finding the projection matrix.
- The steps involved in calibrating a camera:
  - Taking images of the calibration target at known world coordinates.
  - Using the image locations of the interest points on the calibration target and the known world coordinates, calculate projection matrix.
- There are several methods to solve this numerical problems, the most popular is the SVD.
- It is important to normalize the data points for stability purposes.





# Calibration examples

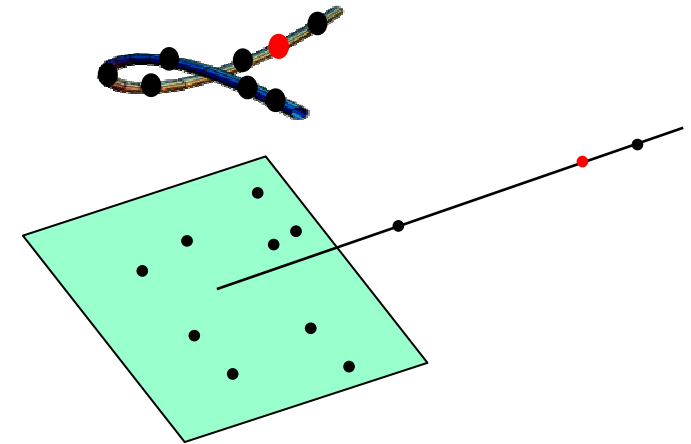
- Canny edge detection
  - Straight line fitting to the detected edges
  - Intersecting the lines to obtain the images corners
- 
- Move the target to three different heights
  - Threshold the image
  - Border follow the resulting image
  - Find centroid



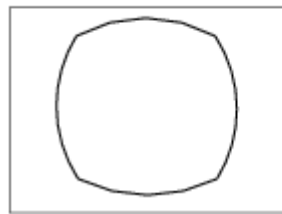


# Calibration

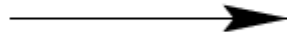
- Degenerative configurations:
  - Camera and points on a twisted cubic
  - Points lie on a plane or on a single line containing the camera centre
- Lens Distortion
  - Real lenses suffer from a number of aberrations
  - Correct image coordinates to those that would be obtained under the linearity assumption



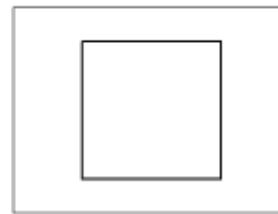
radial distortion



correction



linear image



$$p = \begin{pmatrix} 1/\lambda & 0 & 0 \\ 0 & 1/\lambda & 0 \\ 0 & 0 & 1 \end{pmatrix} MP$$

$$\lambda = 1 + \kappa_1 \hat{r}^2 + \kappa_2 \hat{r}^4 + \dots$$



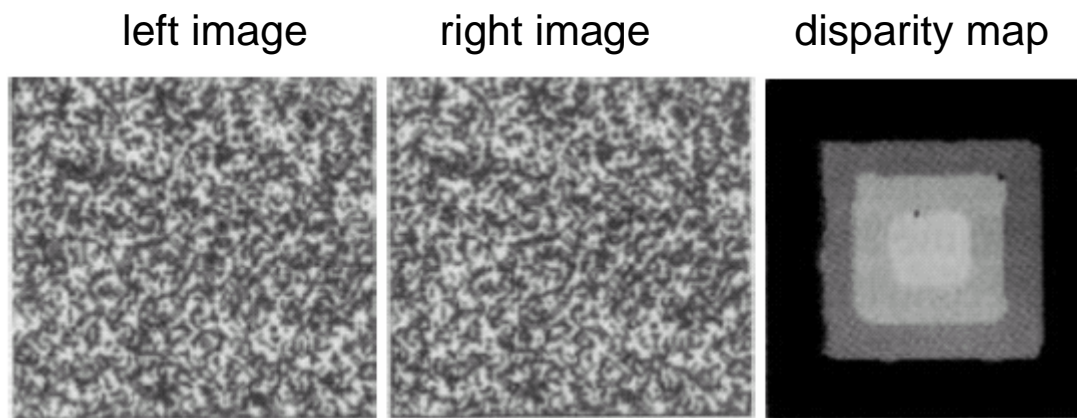
# Correspondence

- Correspondence needs to be established between points corresponding to the same scene point.
- The disparity is used to extract the 3D information.
- Disparity is the difference in location of corresponding features seen by the left and right cameras.
- Parallel cameras make matching easier: not the case in this project.
- Epipolar line computation becomes necessary, but the advantage of greater overlap of the images.
- Challenges of correspondence:
  - ambiguity (low-contrast regions)
  - missing data (occlusions)
  - intensity error (quantization, sensor error)
  - position error (camera calibration)



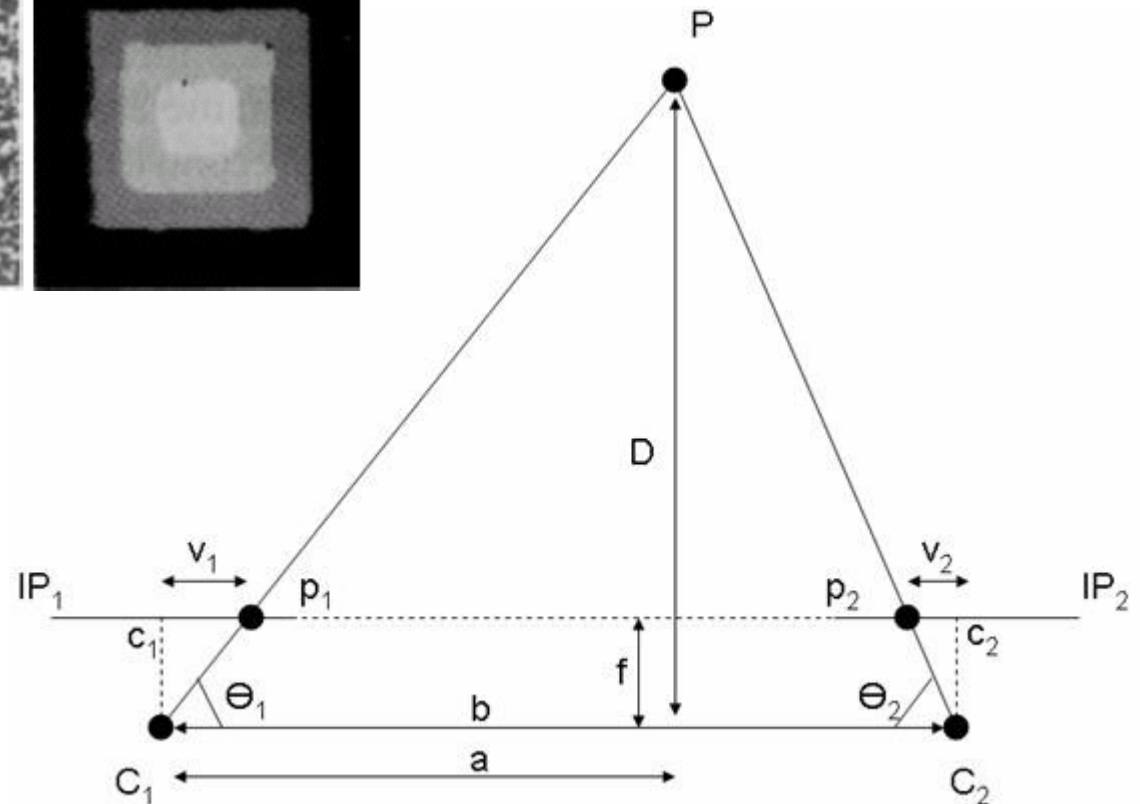
# Correspondence

- Relationship between depth and disparity



From similar triangles:

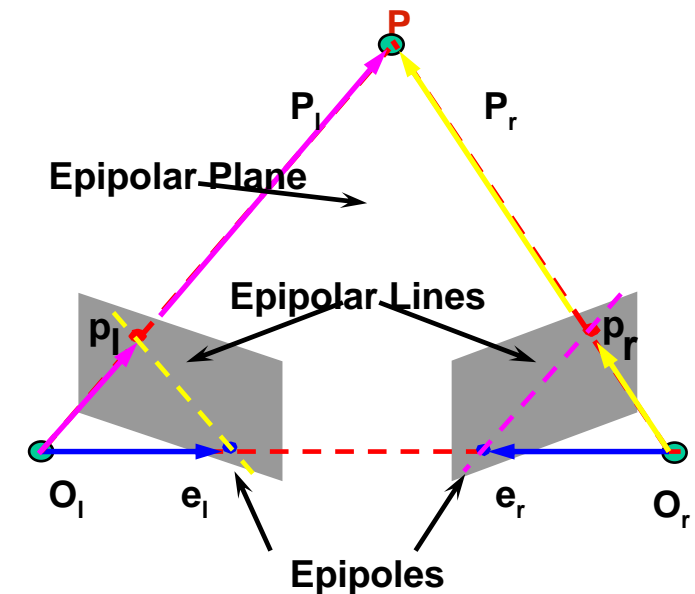
$$D = \frac{bf}{v_1 + v_2}$$





# Correspondence

- Due to the limited resolution of images, increasing the baseline distance  $b$  gives us a more precise estimate of depth.
- Large  $b$   $\rightarrow$  views will be very different  $\rightarrow$  difficult to establish correspondence.
- If a non-parallel scheme is used, it is important to determine the Fundamental Matrix during the calibration stage, this will reduce the search from 2D to 1D.
  - Computable from corresponding points
  - Simplifies matching
  - Allows to detect wrong matches
  - Related to calibration

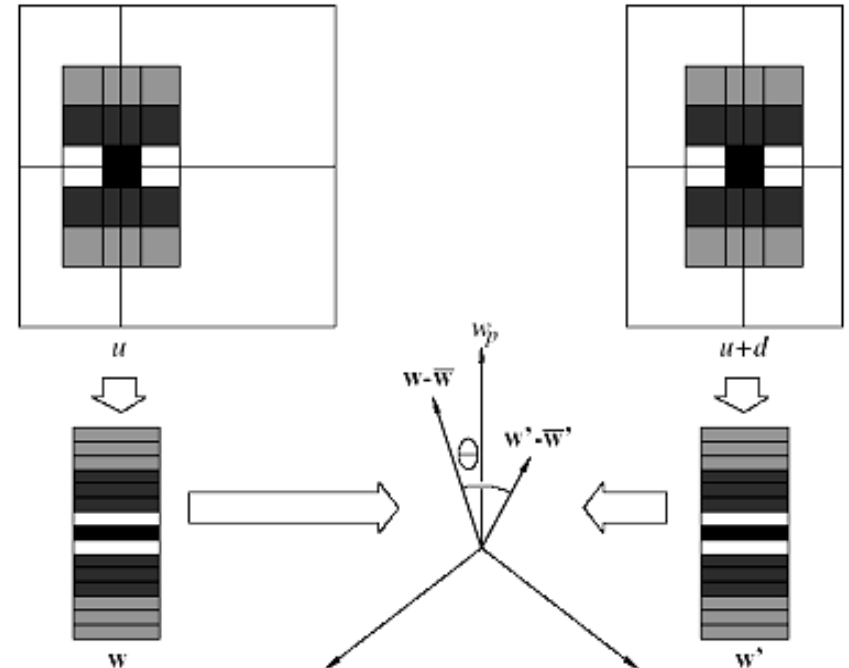




# Correspondence: Area-based algorithms

- Comparison between brightness patterns in the neighborhood of a pixel
- Use NCC, SSD, NSSD, SAD,...
- Drawbacks:
  - 1- Use intensity values directly thus sensitive to distortion.
  - 2- Occluding boundaries confuse the matching process: erroneous depth values.

$$NCC = \frac{\sum_{u,v} (I_1(u,v) - \bar{I}_1)(I_2(u+d,v) - \bar{I}_2)}{\sqrt{\sum_{u,v} (I_1(u,v) - \bar{I}_1)^2 (I_2(u+d,v) - \bar{I}_2)^2}}$$







# Correspondence: Feature-based algorithms

- Primitives that are to be matched should correspond to physical items that have identifiable physical properties.
- Various problems with area-based techniques.
- Symbolic features derived from intensity value are used instead of intensity values themselves for matching.
- Edge points or edge segments (intensity and direction) are the most commonly used features.
- Faster than area based algorithms since only the attributes of features are compared instead of intensity values.
- The system is more insensitive towards changes in contrast and ambient lighting.



# Area-based versus Feature-based

## Feature-based

- Sparse maps
- Ideal for feature-rich images
- More efficient and robust against image variation
- Needs preprocessing: feature extraction
- Need for dense maps and improvement in efficient area matching: decline in this area

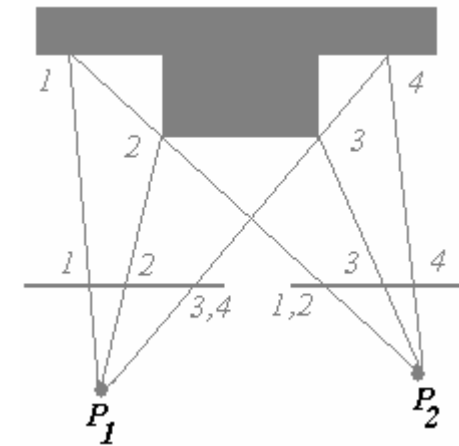
## Area-based

- Dense disparity map
- Ideal for highly textured environments
- Easy to implement
- Computation of correlation is very expensive
- Perform poorly in occluded areas



# Constrains

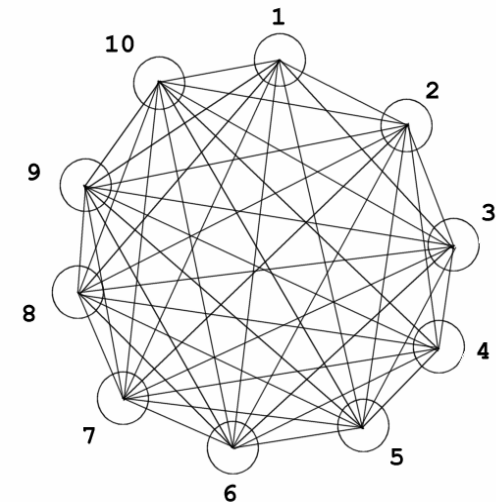
- Epipolar line: horizontal in case of parallel cameras, must be computed in nonparallel geometry
- Regional disparity continuity constraint: smooth surfaces thus smooth disparities on surfaces
- Figural continuity constraint: contours project as continuous curves in both images
- Uniqueness of a match
- Preserved ordering of matches along horizontal scanlines
- Disparity limit





# ANN Approach

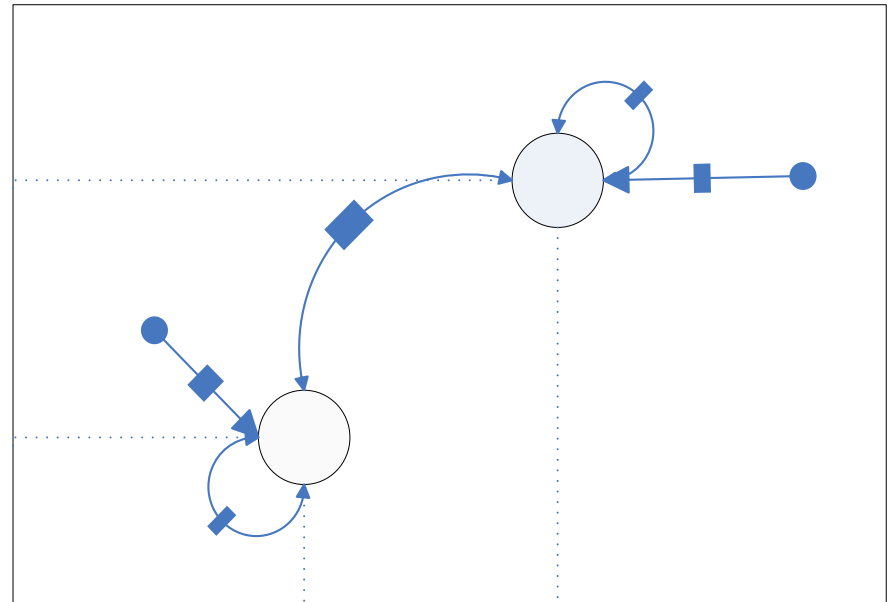
- NN used to implement cognitive mechanisms: fit for vision
- NN is an energy surface, min energy = solution to many optimization problems
- Matching problem can be formulated as minimization of a cost function, where all the constraints can explicitly be included
- 2D Hopfield Networks are good candidates, used for pattern association and optimization





# ANN Approach: Hopfield NN

- Matching = an optimization where an energy function representing the constraints will be minimized using HNN
- HNN, different from multilayer scheme
- 2D array of  $N_r \times N_l$
- No self feedback,  $T_{ijkl}=0$
- Symmetric,  $T_{ij}=T_{kl}$
- Binary network
- Random updating

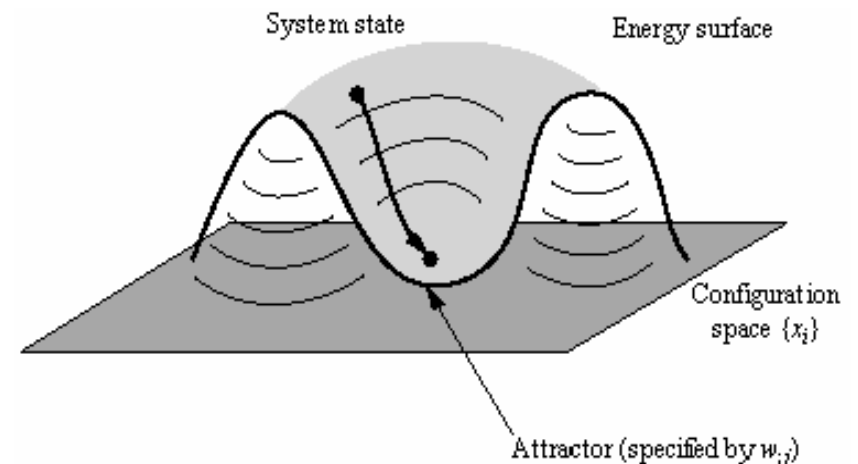


$$E = \left(-\frac{1}{2}\right) \sum_{i=1}^{N_l} \sum_{k=1}^{N_r} \sum_{j=1}^{N_l} \sum_{l=1}^{N_r} T_{ijkl} V_{ik} V_{jl} - \sum_{i=1}^{N_l} \sum_{k=1}^{N_r} I_{ik} V_{ik}$$



# ANN Approach

- The stereo constraints are the starting point for every stereo system
- Point of using the constraints: narrow the search, match selection, false match detection
- Design an energy function: associate to every constraint a term that decreases when approaching a match
- Every neuron  $n_{ik}$  represents a matching possibility between the respective elements





# ANN Approach: Feature extraction

- Choosing the right primitives: important
- Features should be:
  - General: represent majority of the useful info in a picture
  - Matchable: should be easy to match
  - Available: a convenient method for extraction should exist
- Use feature points: local maxima of the directional variance minima
- The Moravec operator is used to extract these points:

$$V(i, j) = \min_{\theta} V_{\theta}(i, j) \quad \text{with } \theta = \frac{\pi}{4}, \frac{\pi}{2}, \frac{3\pi}{4}, \pi$$

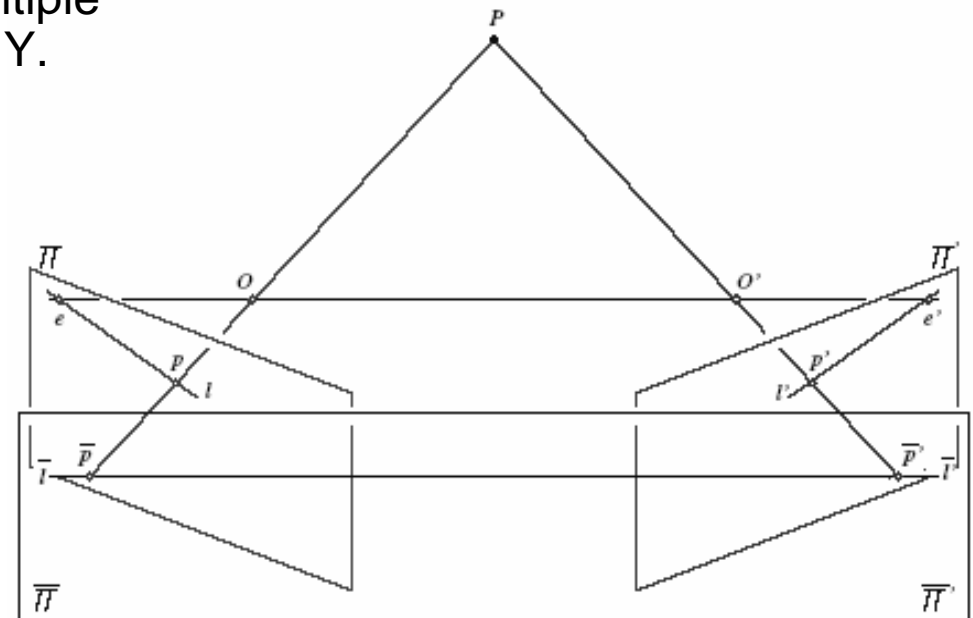
$$V(i, j)_{\frac{\pi}{2}} = [f(x, y) - f(x+1, y)]^2$$



# ANN: Occlusion

- Carry out epipolar rectification: easier to spot outliers and detect occlusion.
- ANN method: after finding all points, if multiple match, check Y disparity against average Y.
- ANN method: only feature points matched thus lower chance of error.
- Finally, use simple cross checking if too many errors due to occlusion.

## Rectified Stereo Pair







# Occlusion

- Much of the stereo research in the last decade: detecting and measuring occlusion

## 1- Detect Occlusion :

### **ANN**

Simplicity, overall good performance,  
implemented in many real-time stereo systems

## 2- Reduce Sensitivity to Occlusion:

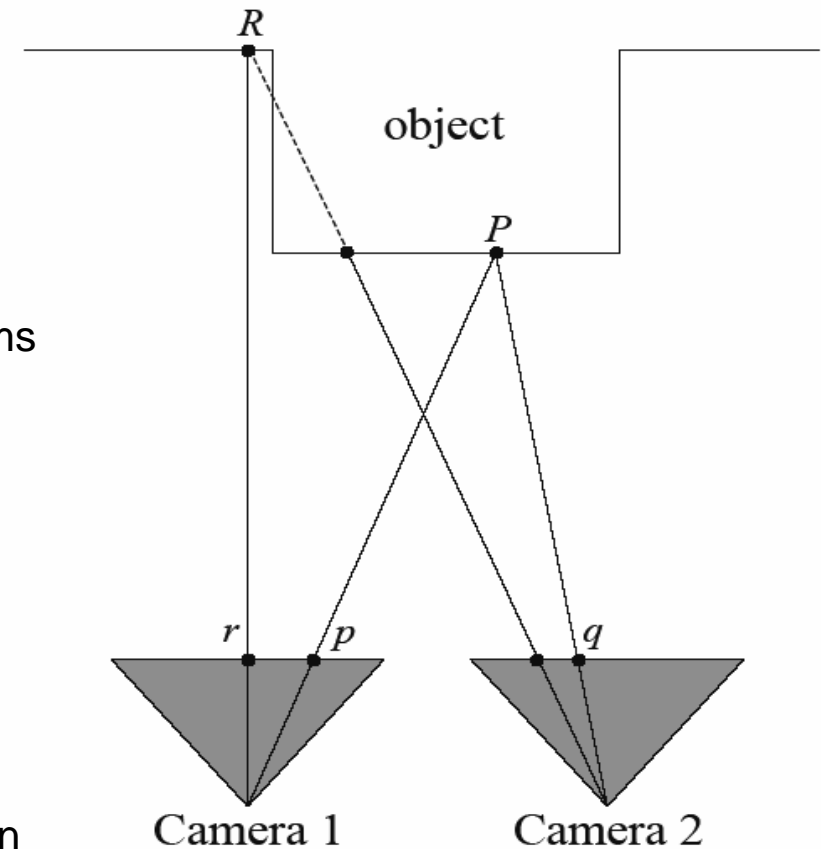
### **Adaptive Window Size for Correlation**

## 3- Model Occlusion Geometry:

### **Graph Cuts**

Integrate knowledge of the occlusion  
geometry itself into the search process

- \*Other methods: use more cameras, use active vision in addition to passive sensing





# Future Work

- Investigate the effects of using various point features, move to line matching
- Finding the number of optimal feature points that will characterize an object in space
- Incorporate epipolar constraint in the matching cost of the ANN algorithm
- Experiment with alternative calibration techniques and report on their feasibility
- Report on the robustness of the ANN method in presence of measurement noise and compare with other methods (correlation)



# References

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