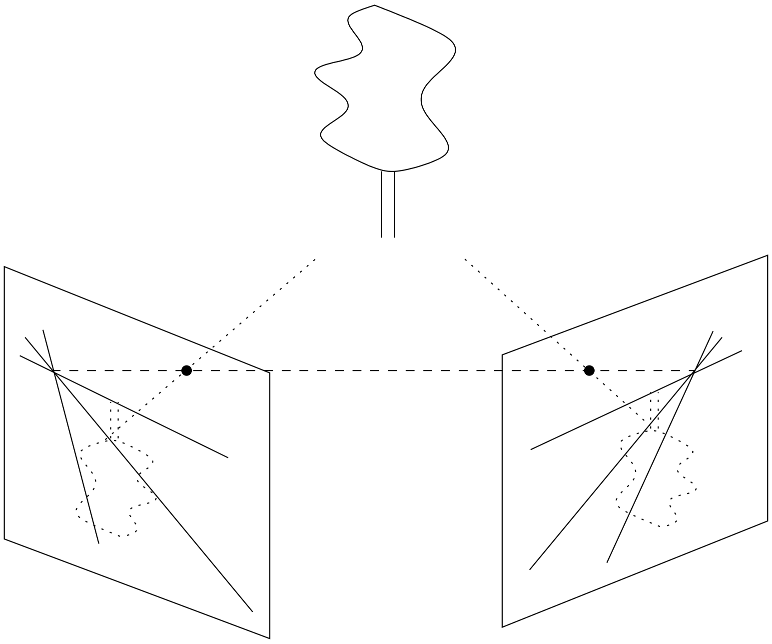
Stereovision

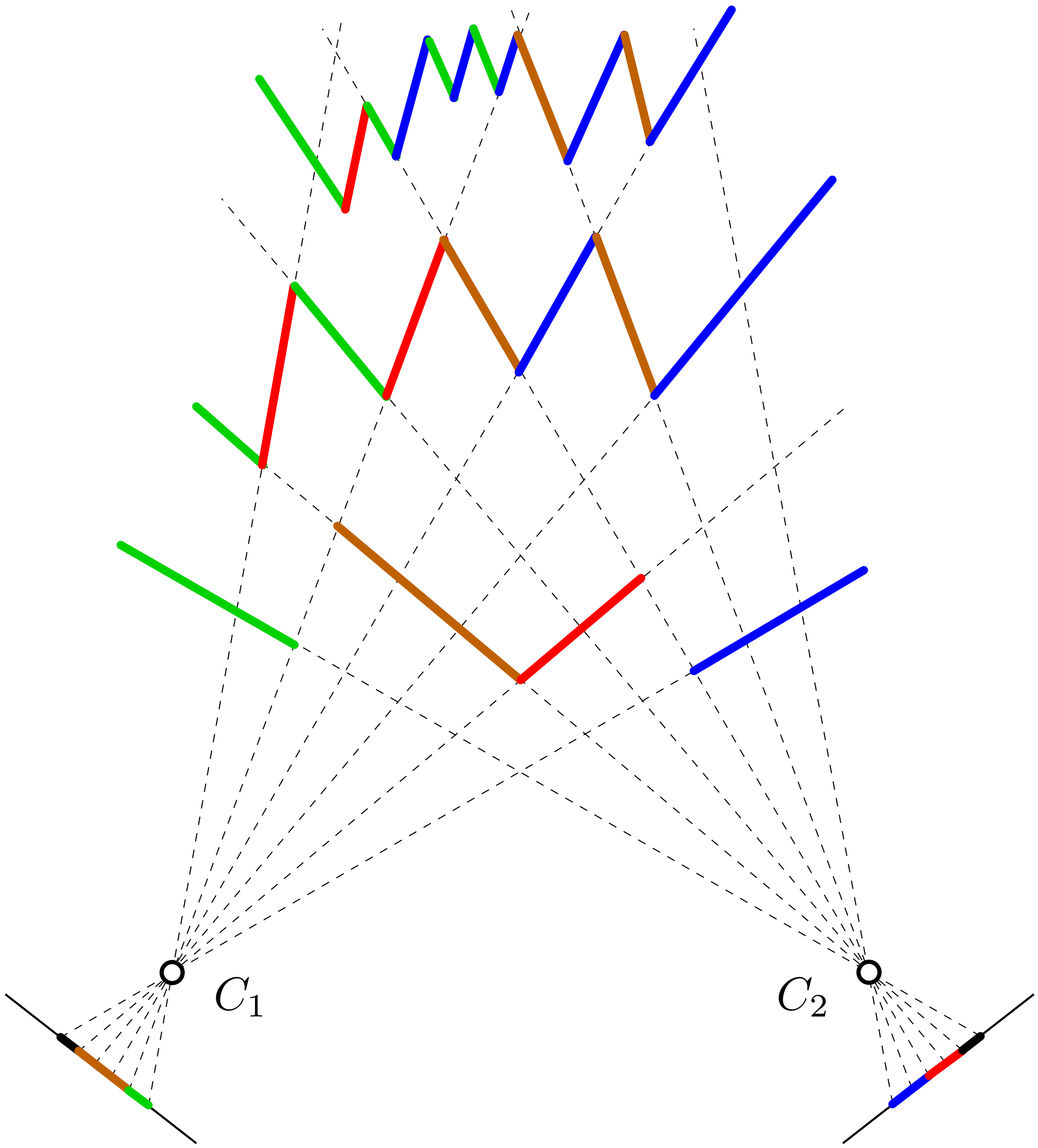


Stereo vision = dense correspondence problem

1. signatures
2. epipolar rectification
3. binocular disparity
4. disparity gradient limit
5. ordering constraint, critical depth
6. correlation table
7. stereo matching algorithms
8. sub-pixel disparity
9. Euclidean reconstruction
10. error propagation
11. disparity fusion from multiple image pairs
12. examples

How Many Scenes Correspond to This Stereoscopic Pair?

The Fundamental Ambiguity in Binocular Stereo



Infinitely many scenes give rise to the same image pair.

C1. Signature Based Stereo

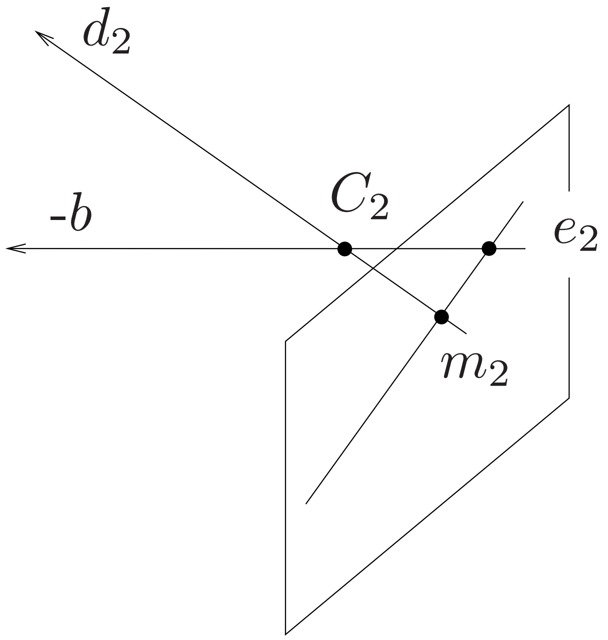
Tagging points by their (viewpoint-invariant) physical properties.

- texture window [Moravec 77]
- reflectance profile under a moving illuminant [? 98]
- photometric ratios [Wolff & Angelopoulou 93–94]
- dual photometric stereo [Ikeuchi 87]
- polarization signature

C2. Epipolar Rectification

Epipolar constraint:

$$0 = |d_1, b,\, d_2| = (Q_2\, Q_1^{-1} \underline{m}_1,\, \underline{e}_2 \times \underline{m}_2)$$



$$Q_2\, Q_1^{-1} = K_2 R K_1^{-1}$$

Special case: $R = E,\ K_1 = K_2$

(coplanar, equal cameras $\longrightarrow$ common image plane)

$$|d_1, b,\, d_2| = (\underline{m}_1,\, \underline{e}_2 \times \underline{m}_2) = (\underline{e}_2,\, \underline{m}_2 \times \underline{m}_1) = 0$$
$$= (\underline{e}_1,\, \underline{m}_1 \times \underline{m}_2) = 0$$

Observations

- **all epipolar lines are parallel**
- epipoles are at infinity

Rectification Example

Images from four cameras in a general position

1

2

3

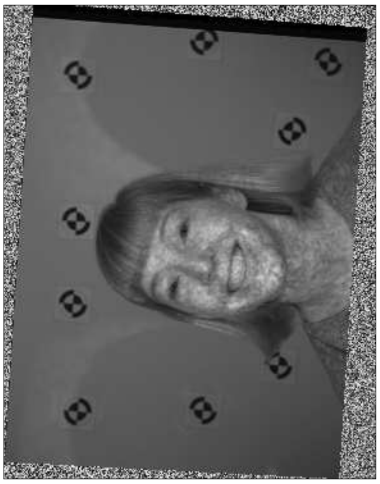
4

Rectified pairs 1–2, 2–4, 1–4

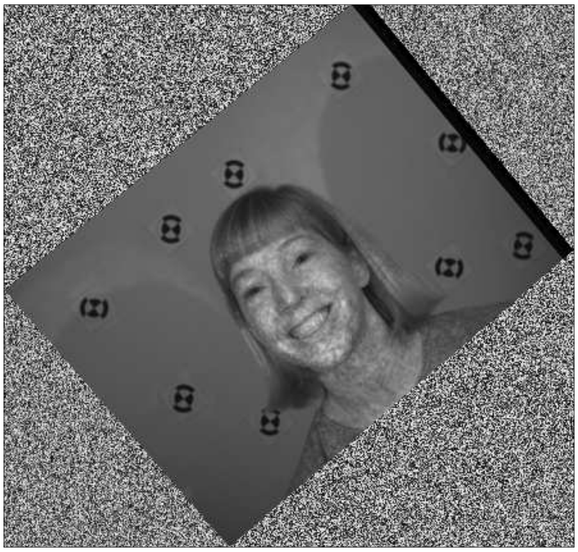

1


2


2


4


1


4

Rectification Collineation

Cameras are rectified by collineation H:

$$P_i^* = H_i^\top P_i = H_i^\top K_i R_i [E, -C_i], \quad i = 1, 2$$

such that corresponding epipolar lines are equivalent and parallel to image rows.

Necessary (insufficient) condition for rectification:

$$F^* \simeq \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 0 \\ -1 & 0 & 0 \end{bmatrix}.$$

both epipoles $e_1 \simeq e_2 \simeq [0, 1, 0]^\top$

3 steps

1. Send epipoles to infinity in both images.
2. Unify epipolar lines to get a pair of *primitive rectification* homographies.
3. Select pair of optimal rectification homographies from the class preserving F^*.

Step 1:

Let $\underline{e} = \begin{bmatrix} e_1 & e_2 & 1 \end{bmatrix}$ be the epipole such that $e_1^2 + e_2^2 \neq 0$. We map it to $\underline{e}' \simeq \begin{bmatrix} 0 & 1 & 0 \end{bmatrix}$ by homography

$$\hat{H}^\top = \begin{bmatrix} e_2 & -e_1 & 0 \\ e_1 & e_2 & 0 \\ -e_1 & -e_2 & e_1^2 + e_2^2 \end{bmatrix}.$$

i.e.

$$\hat{H}^{-\top} = \begin{bmatrix} e_2 & e_1 & 0 \\ -e_1 & e_2 & 0 \\ 0 & 1 & 1 \end{bmatrix}.$$

Step 2:

The modified fundamental matrix becomes

$$\hat{F} = \hat{H}^{-1} F \hat{H}^{-\top} = \begin{bmatrix} a & 0 & b \\ 0 & 0 & 0 \\ c & 0 & d \end{bmatrix}$$

we choose *primitive rectification homographies*

$$\hat{H}_l^\top = H_s^\top \hat{H}^\top, \qquad \hat{H}_r^\top = \hat{H}^\top,$$

where

$$H_s^\top = \begin{bmatrix} -b & 0 & -d \\ 0 & 1 & 0 \\ a & 0 & c \end{bmatrix}$$

Step 3:

Let $\hat{H}_l$ and $\hat{H}_r$ be (primitive or other) rectification homographies. Then H_l and H_r are also rectification homographies if

$$H_l^\top = \begin{bmatrix} s & 0 & u_0 \\ l_1 & l_2 & l_3 \\ q & 0 & 1 \end{bmatrix} \hat{H}_l^\top,$$

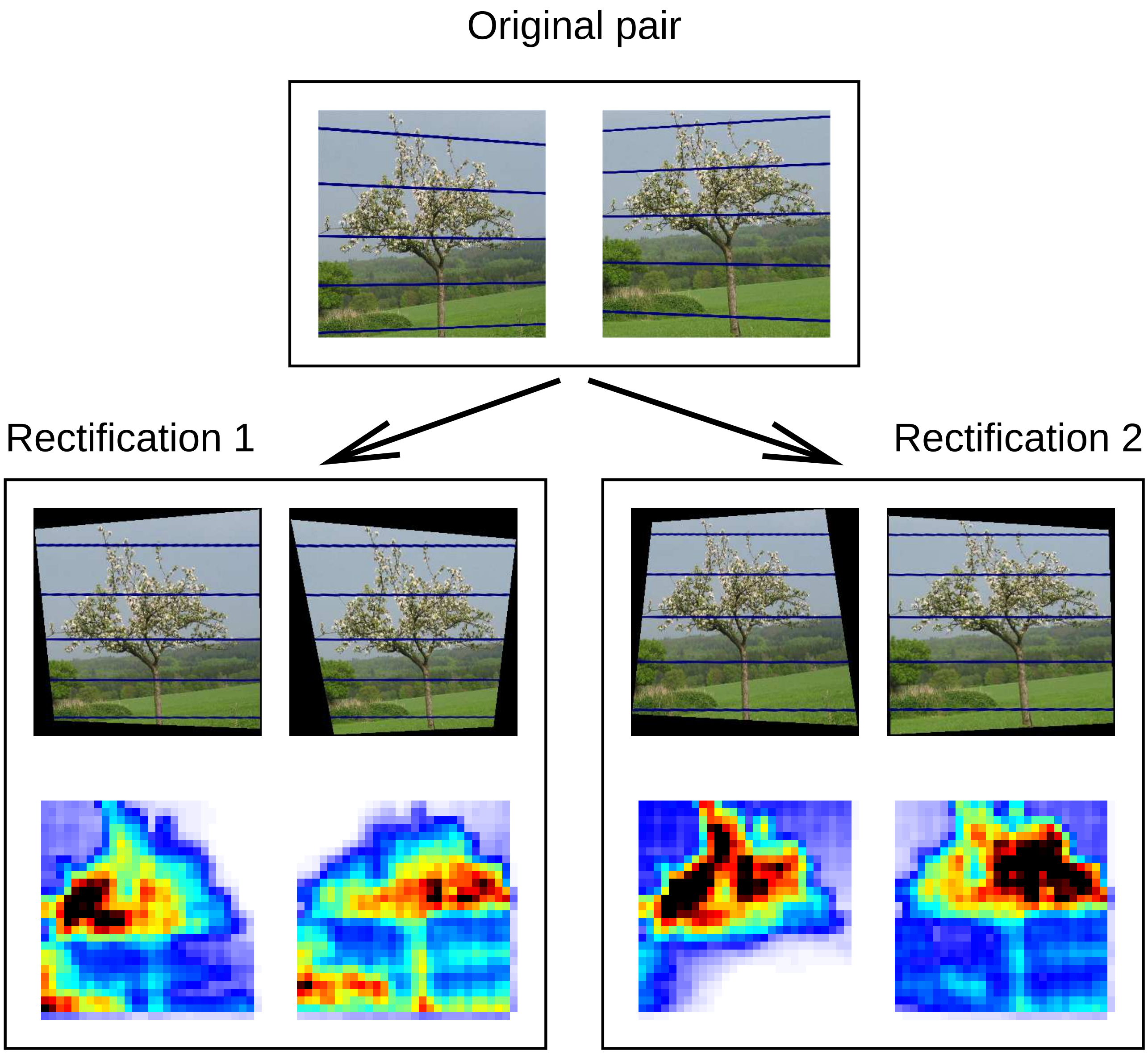
$$H_r^\top = \begin{bmatrix} s & 0 & u_0 \\ r_1 & r_2 & r_3 \\ q & 0 & 1 \end{bmatrix} \hat{H}_r^\top,$$

$s \neq 0$, u_0, l_1, $l_2 \neq 0$, l_3 r_1, $r_2 \neq 0$, r_3, q are free parameters.

Optimal choice of these parameters:

- minimizing residual image distortion
  [Gluckman & Nayar, CVPR 2001]
  [Loop & Zhang CVPR 1999]
- minimizing information loss
  [Matoušek & Šára, ICIG 2004]

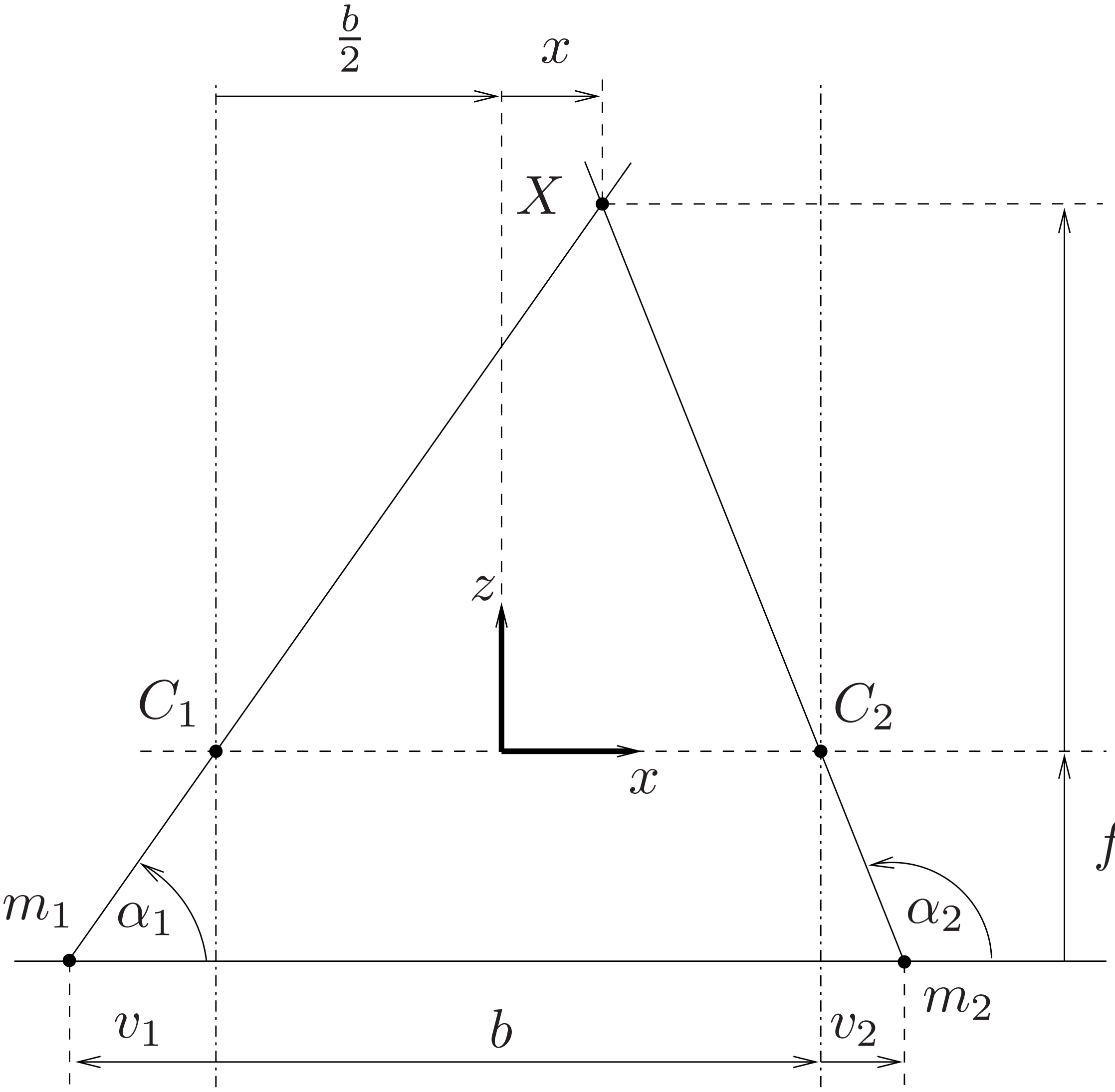
Rectification Minimizing Information Loss



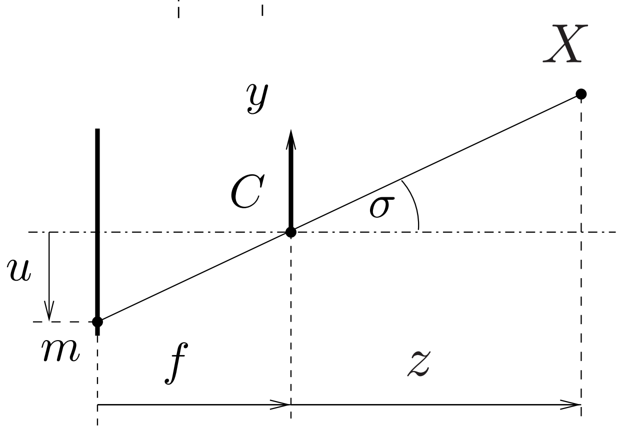
Local data loss

C3. Binocular Disparity

An image line in a rectified camera, top view



$$
\begin{aligned}
-v_1 + b + v_2 &= (z + f)\cot\alpha_1 \\
&\quad + (z + f)\cot\alpha_2 \\
-v_1 &= f\cot\alpha_1 \\
v_2 &= f\cot\alpha_2
\end{aligned}
$$



side view

Relation between disparity $d = v_2 - v_1$ and point $X = (x, z)$ coordinates

$$z = \frac{b\,f}{d}, \quad x = -\frac{b}{d}\,\frac{v_1 + v_2}{2}, \quad y = \frac{b\,u}{d}$$

Observations

- constant disparity surface is a plane

$$z = \frac{b\,f}{d} = \text{const.}$$

(in this canonical setup only; it is a quadric in general)

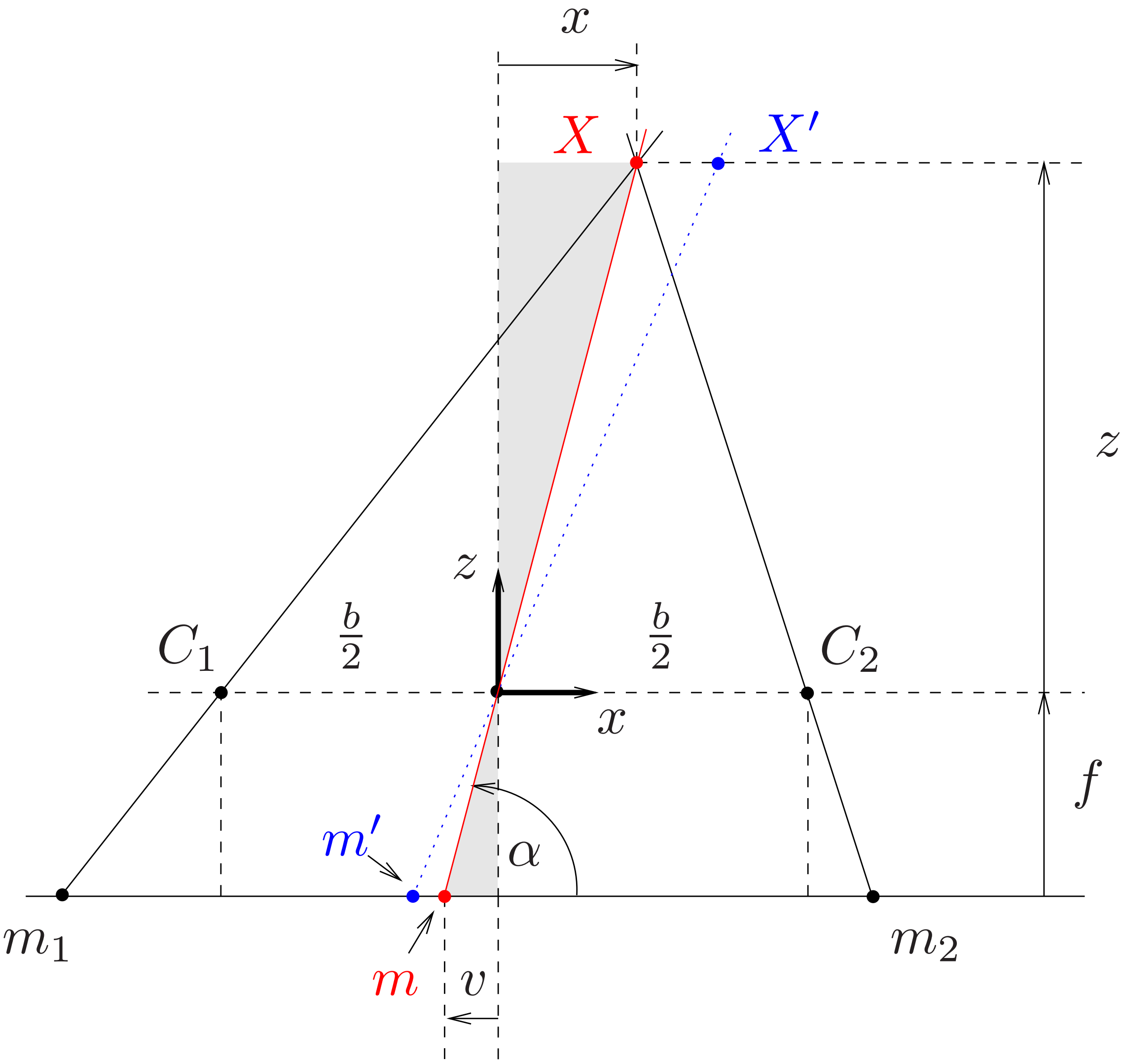
- distant points have small disparity
- relative error in z is large for small disparity

$$\frac{1}{z}\frac{dz}{dd} = \frac{1}{d}$$

- wide baseline reduces relative error in z

(increase in b is compensated by an increase in d)

C4. Cyclopean Camera



Cyclopean coordinate [Julesz 1971]

$$v = f\,\frac{x}{z}, \quad d = f\,\frac{b}{z} \;\Rightarrow\; v = \frac{v_1 + v_2}{2}$$

Disparity gradient [Pollard, Mayhew, Frisby 1985]

$$DG = \frac{|d - d'|}{|v - v'|} = b\,\frac{|z' - z|}{|xz' - x'z|}$$

Disparity Gradient Limit

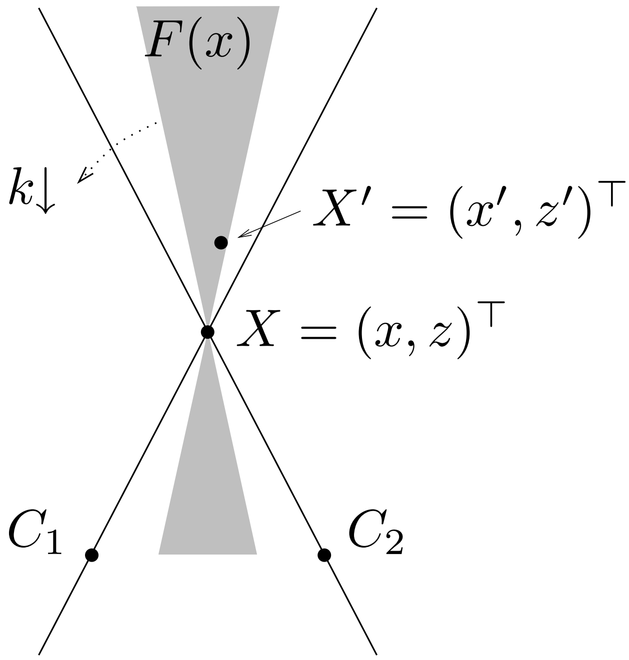
Forbidden zone $F(X)$

$$DG > k$$

with boundary

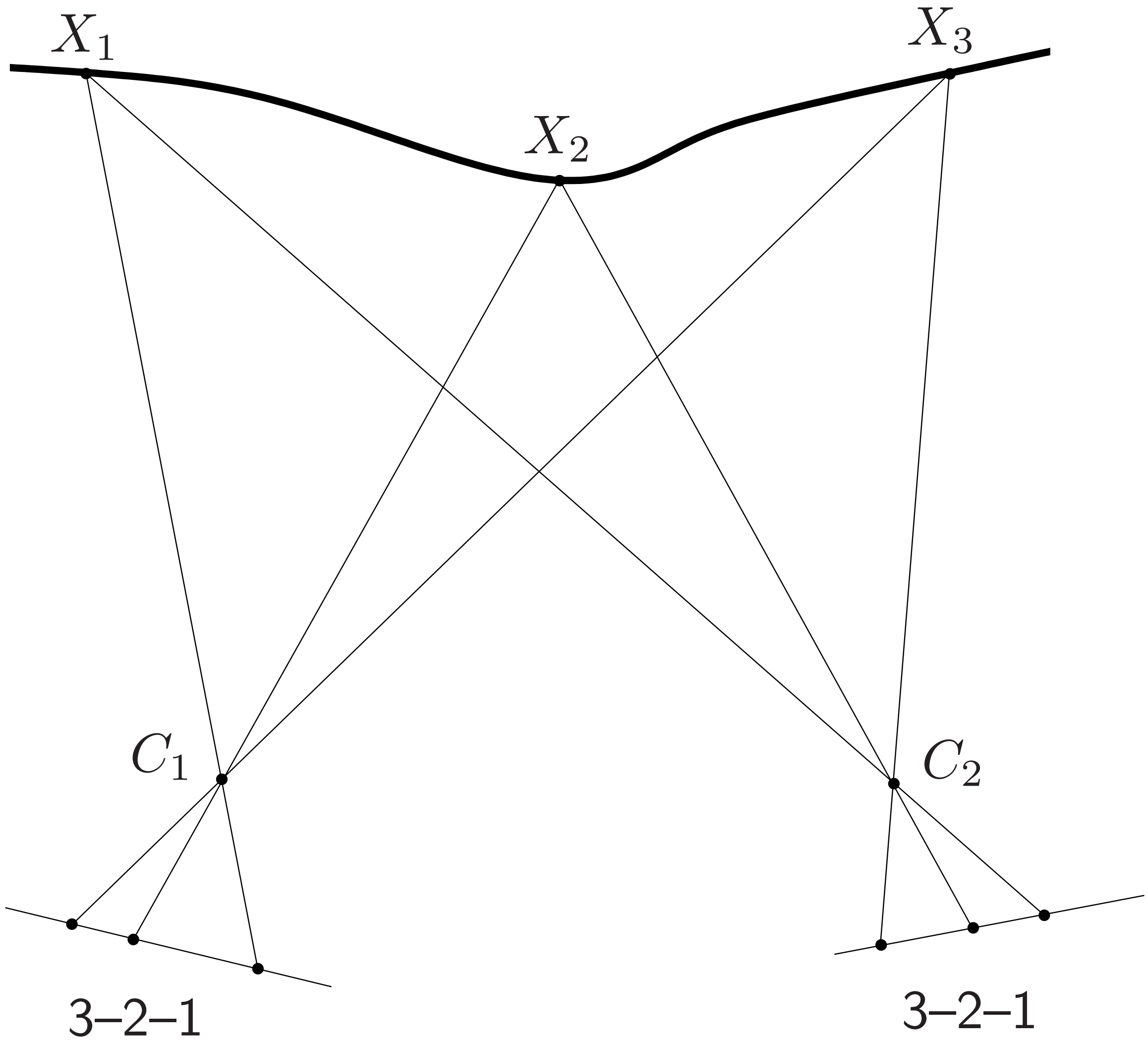
$$b\,(z' - z) = \pm k\,(xz' - x'z)$$

- boundary: a pair of lines (a degenerate conic)
- point $x = x'$, $z = z'$ lies on the boundary
- coincides with optical rays for $k = 2$
- small k means wide F



Human stereovision fails when disparity gradient limit is exceeded.

C5. Ordering Constraint

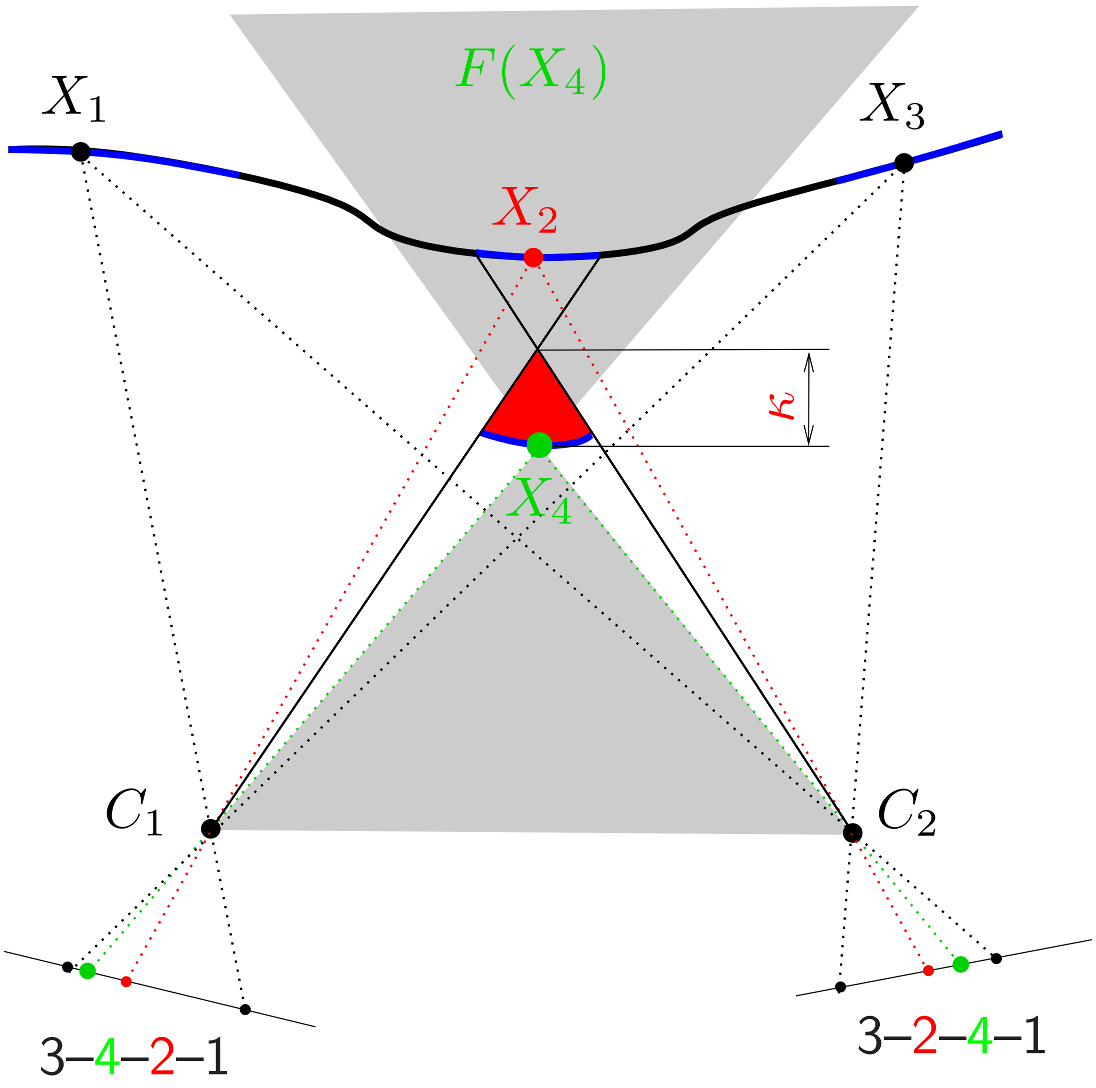


- in *some* scenes point ordering is preserved in images

Real Scenes Often Preserve Ordering

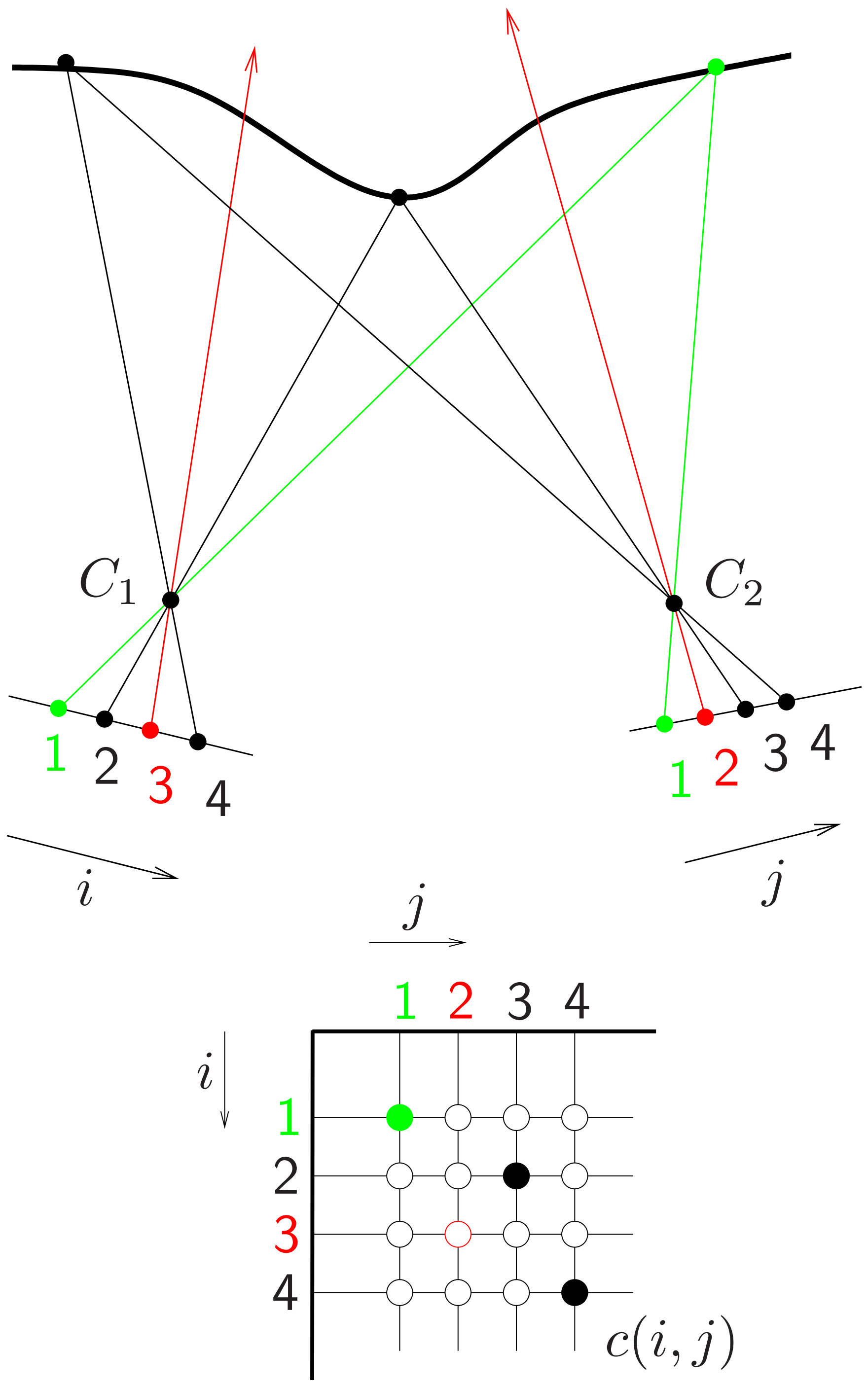
ordering holds except for a small twig growing from the foreground tree

Critical Distance κ



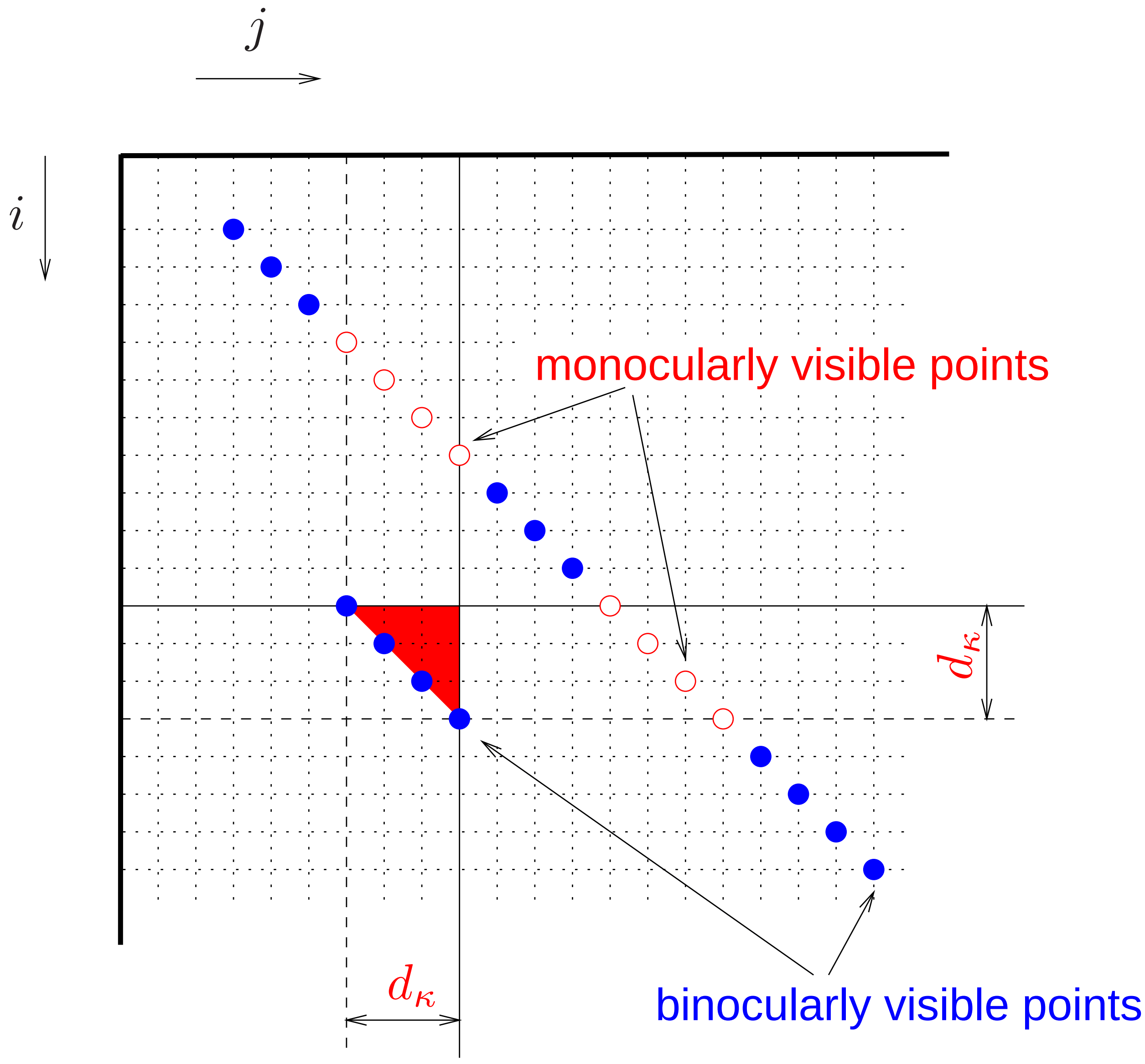
- ordering is violated iff for X_i, X_j *visible in both cameras* $X_i \in F(X_j)$
- symmetry: $X_i \in F(X_j) \Leftrightarrow X_j \in F(X_i)$
- ordering is preserved for scenes where critical distances κ are not exceeded
- smaller objects (wider baseline) require flatter scenes to preserve ordering

C6. Correlation Table



- rows and columns represent optical rays
- high-correlation structures correspond to scene objects
- sites: candidates to correspondence pairs

Critical Disparity



correlation table

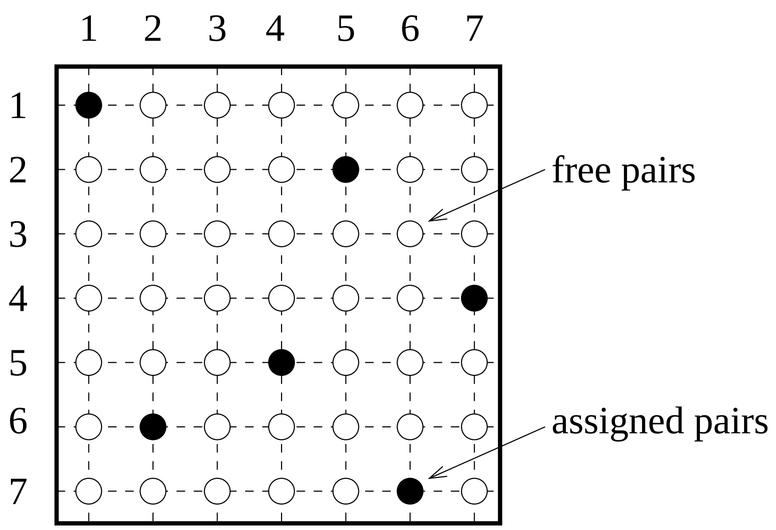
C7. Stereo Matching Problem

Task:

Find matching M in correlation table $I \times J$.
I, J – index sets

Matching

A subset M of $I \times J$ in which each $i \in I$ and each $j \in J$ is represented at most once. (uniqueness constraint)



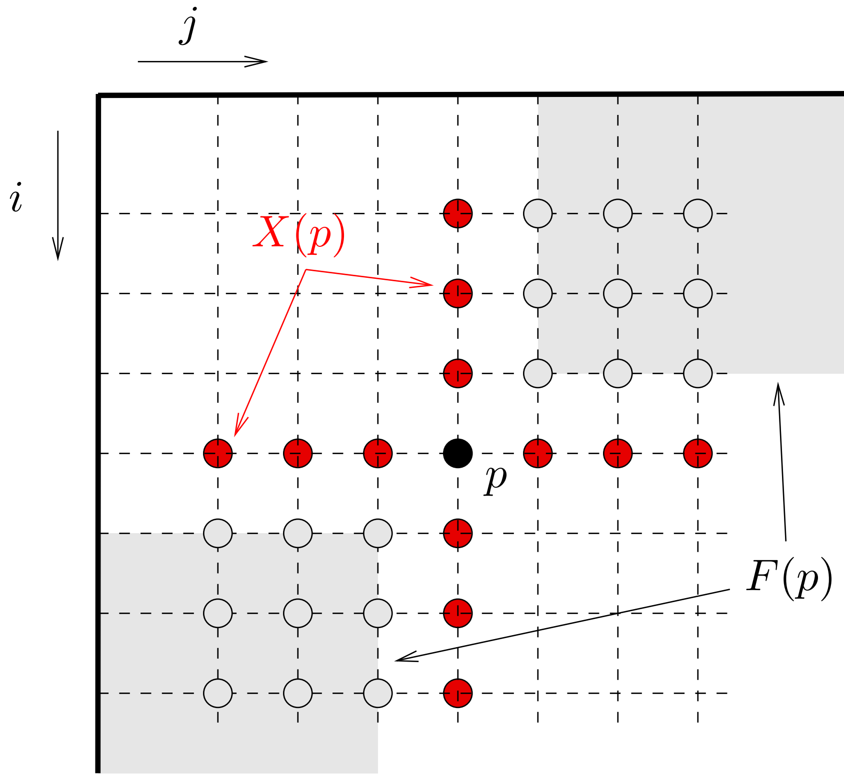
$$I = J = \{1, 2, \ldots, 7\}$$

Additional requirements

1. Maximum cardinality $|M|$
2. (optional) Monotonicity:

$$\text{For all } (i,j) \in M, (k,l) \in M, \quad k > i \Rightarrow l > j$$

F-zone and X-zone in Correlation Table



$$p \notin X(p), \qquad p \notin F(p)$$

- **Uniqueness Constraint:**

  A set of pairs $M = \{p_i\}_{i=1}^{N}$ is a matching iff $\forall p_i, p_j \in M, i \neq j: \; p_j \notin X(p_i)$.

- **Monotonicity Constraint:**

  Bipartite matching M is monotonic iff $\forall p_i, p_j \in M: \; p_j \notin F(p_i)$.

  - **occlusion model**
  - concordance, discordance
  - line graph $\mathcal{G} = L(G)$ of the matching graph G

1. Maximum/Minimum-Cost Perfect Matching

$$\sum_{p_i \in M} c(p_i) \to \text{max/min}$$

$$\forall p_i, p_j \in M : \; p_j \notin X(p_i)$$

Equivalent to 'maximum/minimum-cost flow' problem:

$$\sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij}\, x_{ij} \to \text{max/min}$$

$$\sum_{j=1}^{n} x_{ij} = \sum_{i=1}^{n} x_{ij} = 1$$

$$0 \le c_{ij} \le C, \qquad \text{integer costs}$$

selection variable $x_{ij} \in \{0, 1\}$:

$$x_{ij} = \begin{cases} 1 & \text{if } p = (i, j) \in M \\ 0 & \text{otherwise} \end{cases}$$

$O(n^2 \sqrt{n}\, \log(n\, C))$ cost scaling algorithm

[Gabow & Tarjan 1989]

Stereo Matching Example

A scene with critical distances

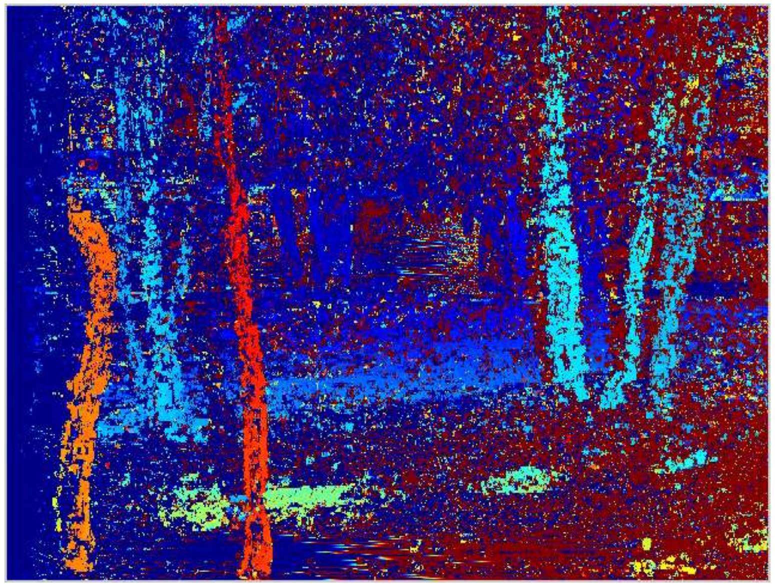
Right Image

right

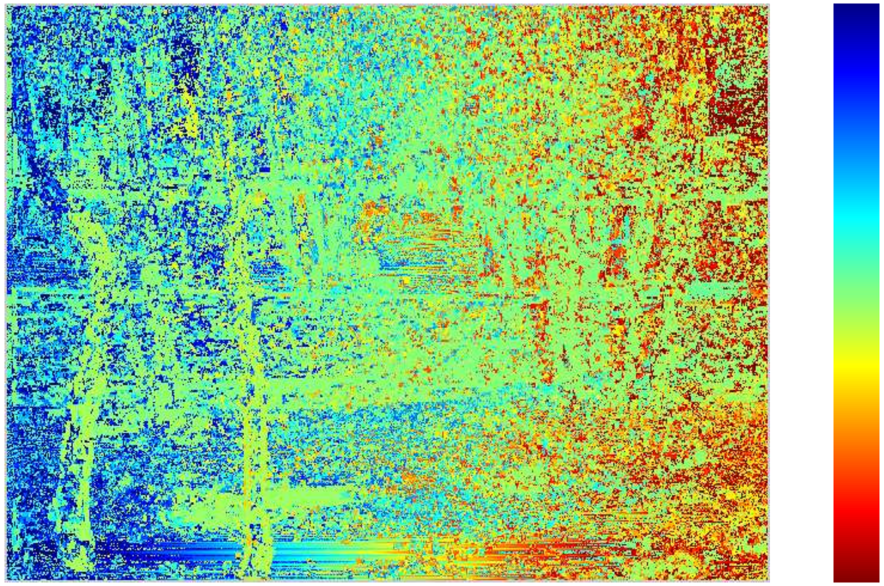
Left Image

left

Maximum-Cost Perfect Matching: Example



solution shown within true disparity range



within full range

- half-occluded pixels always matched
- many mismatches (false positives)
- objects are not missed (!)

$$c(X,Y) = \frac{2\ \mathrm{cov}(X,Y)}{\mathrm{var}\, X + \mathrm{var}\, Y}$$

2. Maximum-Cost Monotonic Matching

$$\sum_{p_i \in M} c(p_i) \longrightarrow \max$$

$\forall p_i, p_j \in M:\; p_j \notin F(p_i) \cup X(p_i)$ stronger occlusion model

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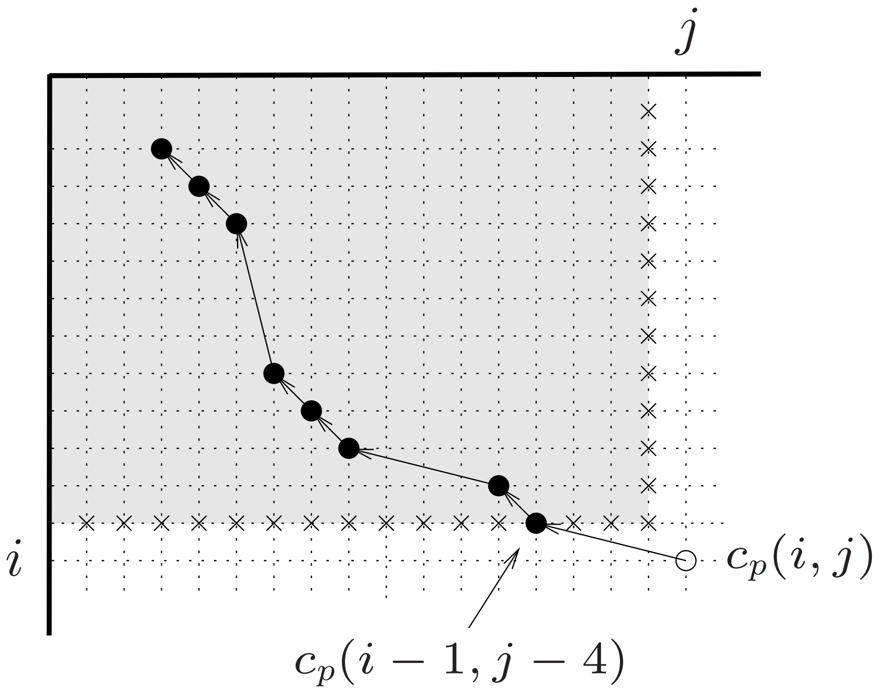
Equivalent to maximum-cost path problem on acyclic oriented graph if $c(p) > 0$.

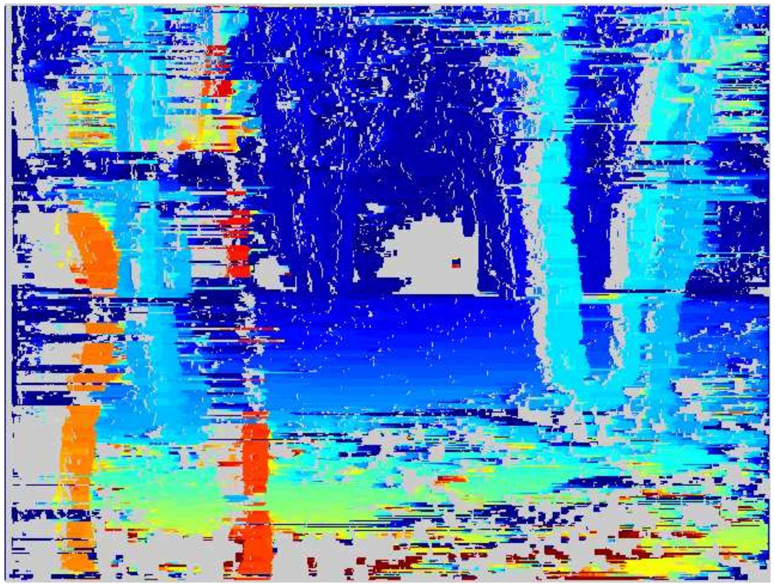


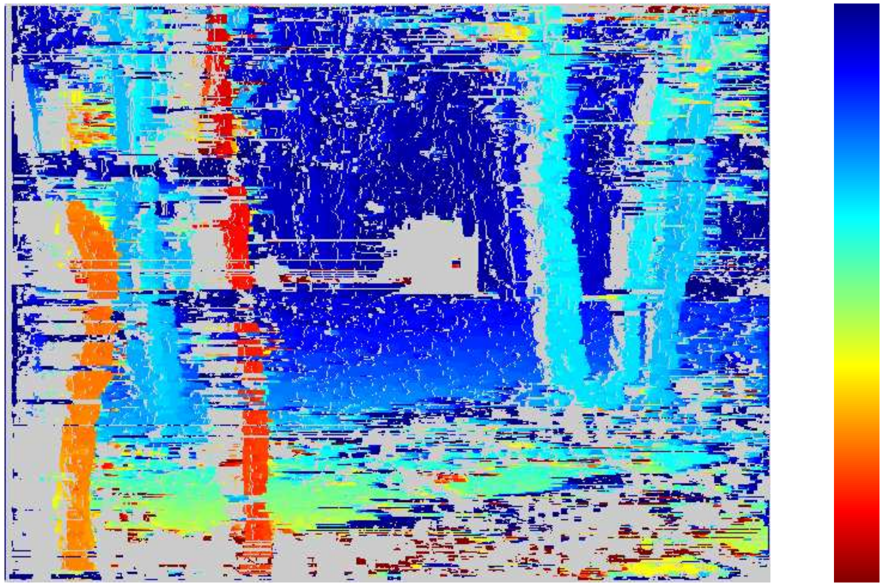
$$c_p(i-1, j-4) = \max\big(c_p(i-1, 1:j-1),\; c_p(1:i-1, j-1)\big)$$

$$c_p(i, j) = c_p(i-1, j-4) + c(i, j)$$

$O(n^2)$ dynamic programming with free ends

Maximum-Cost Monotonic Matching: Example





$$c_1(X,Y) = \frac{2\,\mathrm{cov}(X,Y)}{\mathrm{var}\,X + \mathrm{var}\,Y} \qquad c_2(X,Y) = \frac{c_1(X,Y)}{1 - c_1(X,Y)}$$

- Monotonic re-mapping of $c_1(X,Y) \Rightarrow$ different results.

2a. Minimum-Cost Monotonic Matching

MAP Estimate

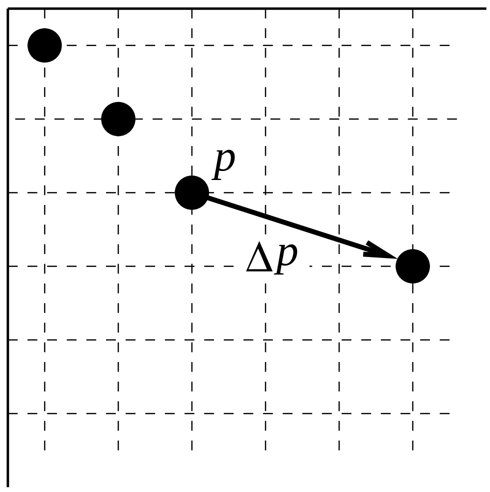
M – matching, I_L, I_R – images

$$P(M \mid I_L, I_R) = \frac{P(I_L, I_R \mid M)\, P(M)}{P(I_L, I_R)}$$

$$\hat{M} = \arg\max_M P(M \mid I_L, I_R) = \boxed{\arg\min_M E(G)}$$

$$E(G) = -\log P(I_L, I_R \mid M) - \log P(M) =$$

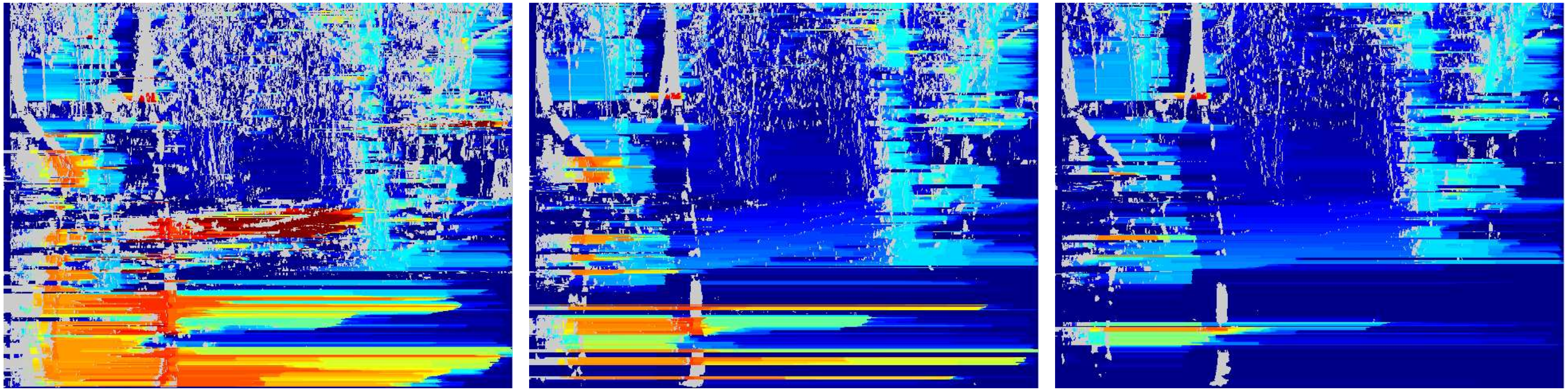
$$= \underbrace{\sum_{p=(i,j)\in M} \big(I_L(i) - I_R(j)\big)^2}_{\text{data term}} + \alpha \underbrace{\sum_{p\in M} \|\Delta p\|^2}_{\text{prior term}}$$



Algorithm: Dynamic programming with fixed ends

MAP Disparity Estimate: Example

[Cox 1992] modified for 5×5 correlation mask



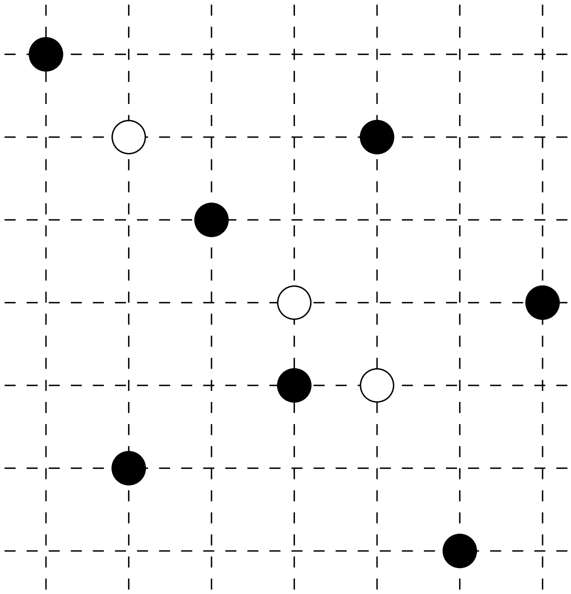
$\alpha = 150$ $\quad$ $\alpha = 500$ (opt.) $\quad$ $\alpha = 1000$

- How to choose α (discontinuity penalty)? To get non-trivial solution, $\alpha > 0$.
- Strong artifacts when continuity model breaks.
- Two competing processes: data conformance vs. smooth result

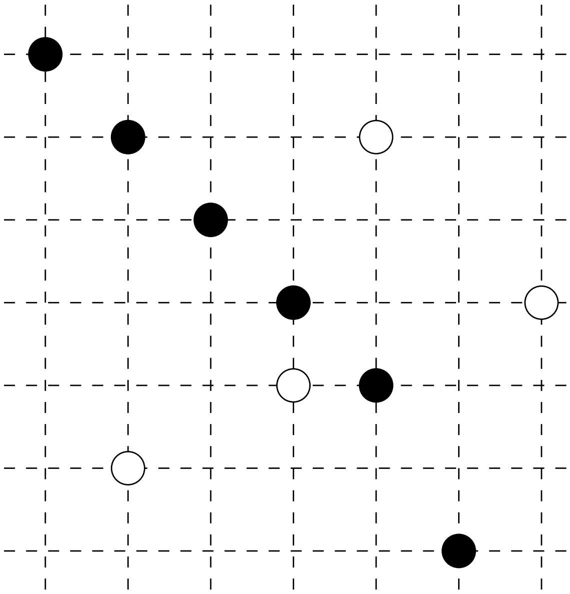
The Coherence Principle [Prazdny 85]

Traditional recipe:

- matches preserving disparity *continuity* are favored [PMF 85]



discontinuous



continuous = better

- Years of research: [Matthies92; Cox92–94; Chang&Chatterjee92; Robert&Deriche92; Geiger,Ladendorf&Yuille92–95; Belhumeur93–98; Scharstein&Szeliski96; Birchfield&Tomasi97; Boykov,Veksler&Zabih97–99; Roy&Cox98; Ishikawa&Geiger98; Gennert98; Szeliski99;. . .]

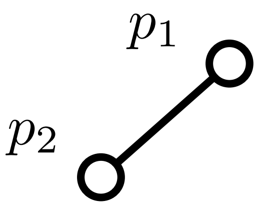
3. Confidently Stable Matching

Given:

1. Putative correspondences $p \in P$ (matching table entries)
2. Symmetric occlusion E relation on pairs $p, q \in P$
3. Interval statistic $I(p) = [\underline{c}(p), \overline{c}(p)]$

Construct:

- simple graph $\mathcal{G} = (P, E)$



$$p_1 \in M \Rightarrow p_2 \notin M$$
$$p_2 \in M \Rightarrow p_1 \notin M$$

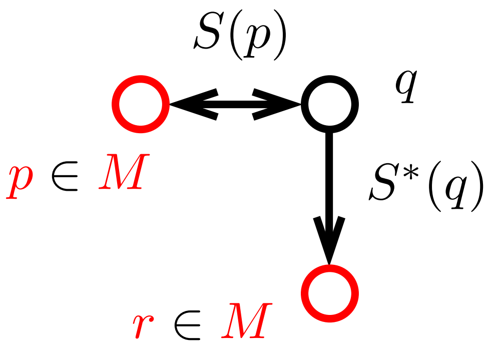
Obs: Independent vertex sets in $\mathcal{G}$ are matchings.

- graph orientation:

  $I(p) \cap I(q) \neq \emptyset$ oriented both ways $\quad p \longleftrightarrow q$

  $I(q) > I(p)$ oriented strictly $\quad p \longrightarrow q$

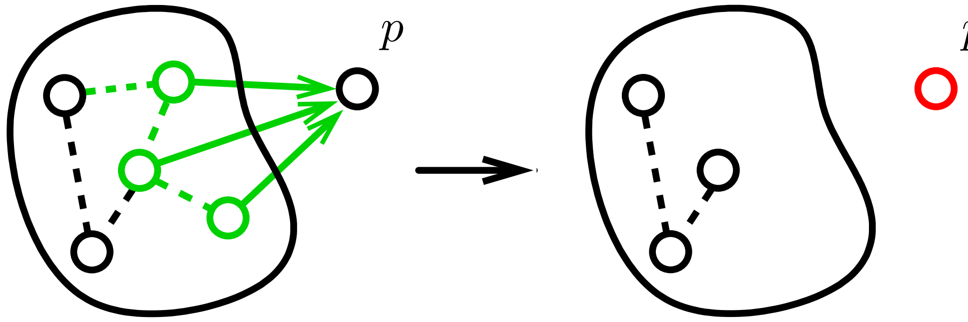
Def. *Vertex subset M is a strict sub-kernel of $\mathcal{G}$ if for every $p \in M$ it holds: every successor $S(p)$ is followed by a strict successor $S^*(q)$ back to M.*



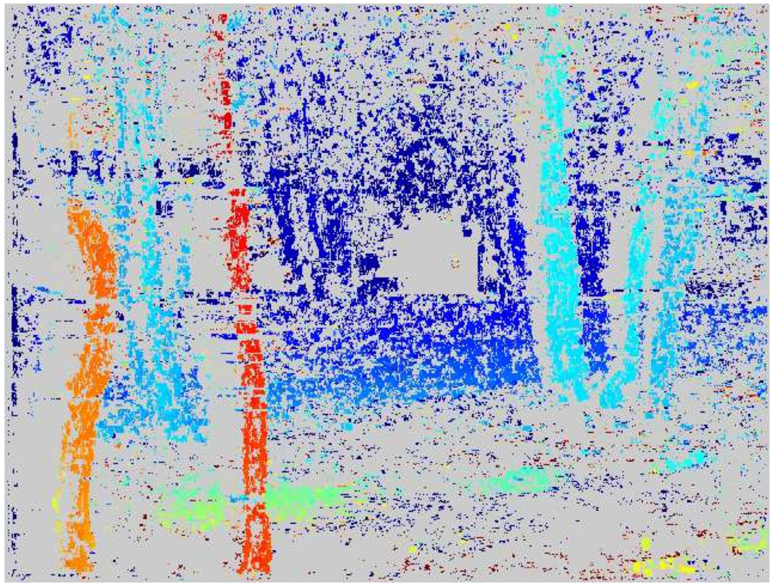
Proposition: Let $\mathcal{G}^*$ be graph $\mathcal{G}$ oriented by the interval overlap relation. Then (1) there is a unique maximum strict sub-kernel of $\mathcal{G}^*$ for any graph $\mathcal{G}$ and (2) it can be found in polynomial time.

Algorithm

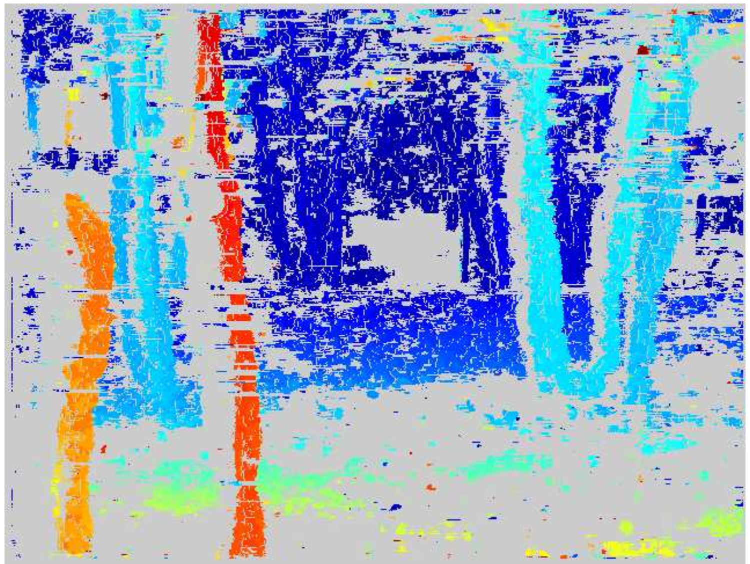
1. Initialize $M := \emptyset$.
2. Find a sink $s \in V(\mathcal{G}^*)$.
3. If there is no sink in $\mathcal{G}^*$, terminate and return M.
4. Add s to M.
5. Remove s and all its predecessors $P(s)$ from $\mathcal{G}^*$.
6. Go to Step 2.



Confidently Stable Monotonic Matching: Example



ordinary stable



confidently stable + disparity components

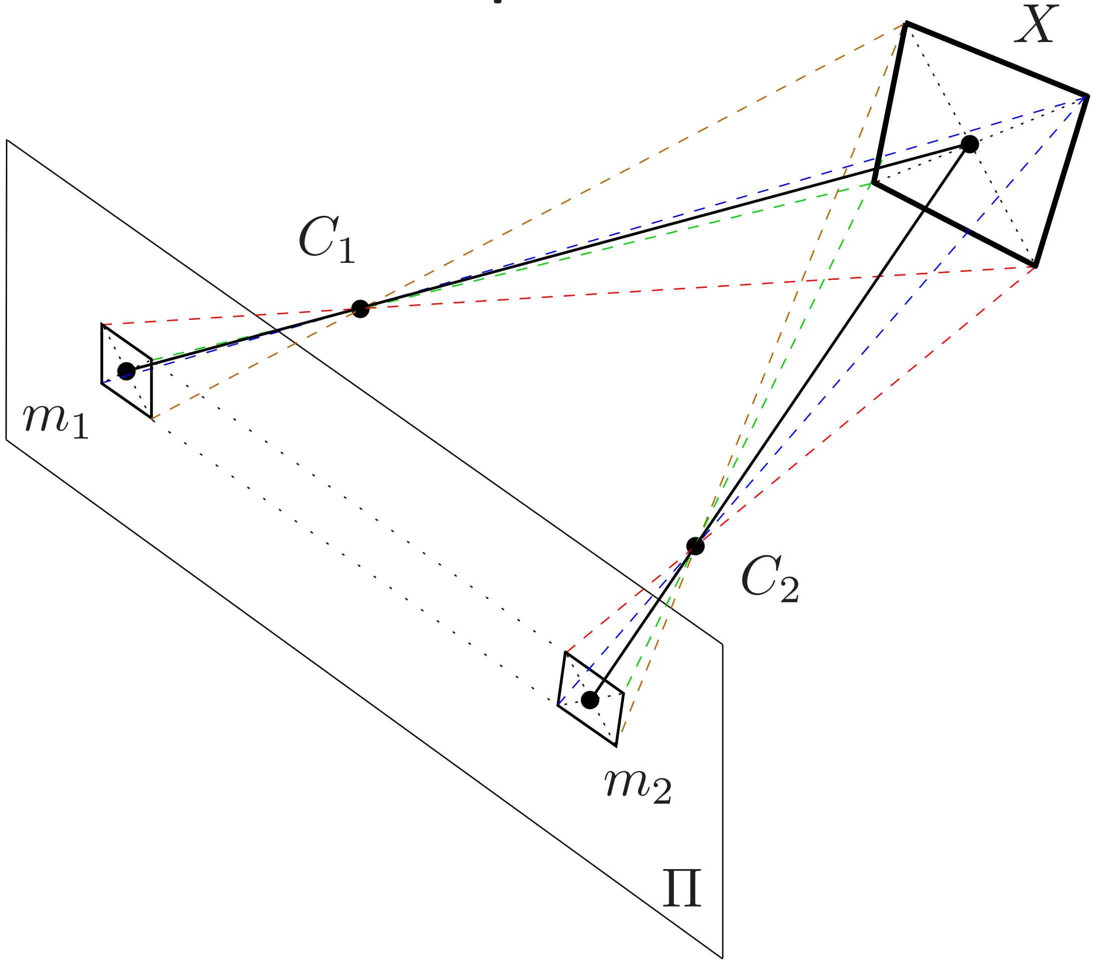
- Stable monotonic matching: few mismatches, many ‘holes’
- $\alpha = 10$, $\beta = 0.02$, 5×5 window, $X(1)$ preselection [BMVC 2003]

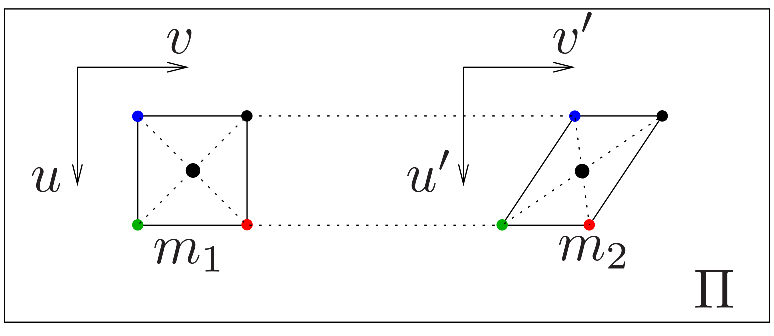
Four Classes of Stereo Matching Algorithms Using Correlation Table

	functional optimality	stability
preserves ordering	Maximum Monotonic Matching + good if ordering holds − fails badly if it does not	Stable Monotonic Matching + very few mismatches − not dense
ignores ordering	Maximum Perfect Matching + best for supercritical scenes − slow	Stable Matching + good if texture is strong − sensitive to noise

C8. Sub-pixel Disparity

Relative Perspective Distortion





$$u' = u$$
$$v' = p_0 u + p_1 v + p_2$$

Proof: looking for collineation A:

$$\underline{m}_2 = A^\top \underline{m}_1$$

such that epipolar constraint holds:

$$\underline{m}_2^\top F \, \underline{m}_1 = 0$$

---

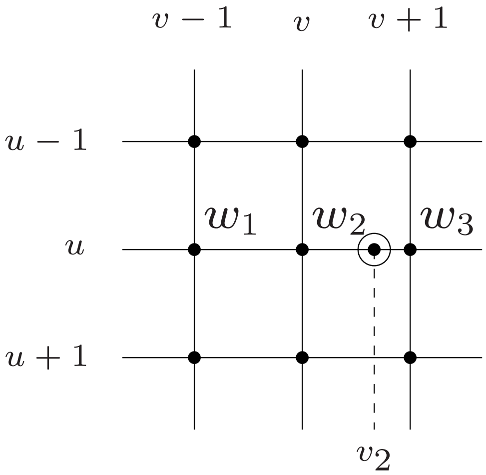
1. $F = K_2^{-T} R S K_1^{-1}$
2. Rectified cameras:

$$R = E, \; S = \begin{bmatrix} 0 & 0 & b \\ 0 & 0 & 0 \\ -b & 0 & 0 \end{bmatrix}, \; K = \begin{bmatrix} k_{11} & 0 & k_{13} \\ 0 & k_{22} & k_{23} \\ 0 & 0 & k_{33} \end{bmatrix}$$

3. $\underline{m}_1^\top AF \, \underline{m}_1 = [u \;\; v \;\; 1] \; AF \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} \equiv 0$
4. $a_{13} + (a_{11} - a_{33}) \, u + a_{12} \, v - a_{32} \, u \, v - a_{31} \, u^2 \equiv 0$
5. $A^\top = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & a_{23} \\ 0 & 0 & a_{11} \end{bmatrix}$

Image Interpolation at a Point

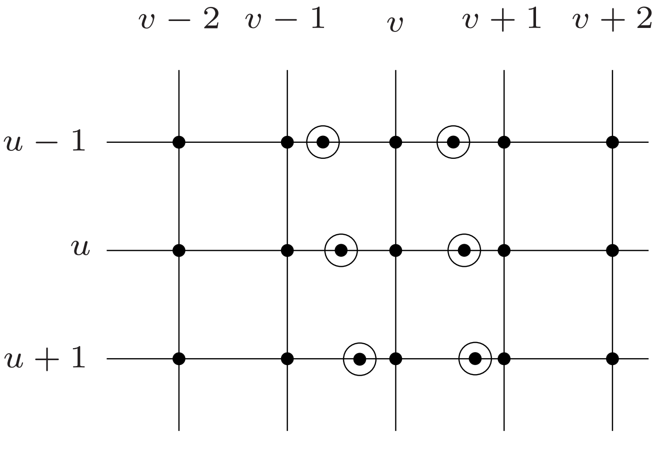
Single pixel:



$$I(u, v_2) = w_1 I(u, v-1) + w_2 I(u, v) + w_3 I(u, v+1)$$

$$I^*(u, v_2) = \begin{bmatrix} w_1, & w_2, & w_3 \end{bmatrix} \begin{bmatrix} I(u, v-1) \\ I(u, v) \\ I(u, v+1) \end{bmatrix}$$

Entire neighborhood:



$$I^* = W(u,\ p_0 u + p_1 v + p_2)\, I$$

$$I \sim [\, N \times 1\,]$$

$$W \sim [\, N \times N\,]$$

Sub-pixel Disparity Estimation Problem

1. sub-pixel disparity p_2
2. relative perspective distortion p_0, p_1
3. radiometric distortion p_3, p_4

- Constraint equation $c(p, I_1, I_2) = 0$ interpolated with kernel W:

$$I_1(u,v) - p_3\, W(u,\; p_0\, u + p_1\, v + p_2)\, I_2(u,v) - p_4 = 0$$

- Image noise is i.i.d. Gaussian additive:

$$I_i = I_{oi} + \Delta I_i, \;\; \Delta I_i \sim N(0,\, \sigma_I^2), \;\; i = 1,2$$

- Error vector and covariance matrix:

$$e = \left[\Delta I_1,\;\; W \Delta I_2\right]^\top, \;\; \Sigma_e = \sigma_i^2 \left(E + p_3^2\, W W^\top\right)$$

observation: errors not independent (interpolation kernel!)

- Least-Squares Cost Function:

$$J(p) = \underbrace{e^\top \Sigma_e^{-1} e}_{\text{minimum error}} + 2\lambda^\top \Big(\underbrace{c(p, I_{o1}, I_{o2}) + e}_{\text{error definition}}\Big) \to \min$$

variables: e, p, λ

The Constraint Linearization

$$c(p + \Delta p, I_{o1}, I_{o2}) = c(p, I_{o1}, I_{o2}) + c_p \Delta p$$

where

$$\begin{aligned}
c(\cdot,\cdot,\cdot) &\sim [\,N \times 1] \\
I_{oi} &\sim [\,N \times 1\,] \\
\Delta p &\sim [\,5 \times 1\,] \\
c_p &= \left[\frac{\partial c}{\partial p_0}, \frac{\partial c}{\partial p_1}, \frac{\partial c}{\partial p_2}, \frac{\partial c}{\partial p_3}, \frac{\partial c}{\partial p_4}\right] \sim [\,N \times 5\,]
\end{aligned}$$

Normal Equations:

$$\begin{aligned}
0 &= \frac{\partial J}{\partial e} = 2\, e^\top \Sigma_e^{-1} + 2\, \lambda^\top E_N \\
0 &= \frac{\partial J}{\partial \Delta p} = 2\, \lambda^\top c_p \\
0 &= \frac{\partial J}{\partial \lambda} = c + c_p \Delta p + e
\end{aligned}$$

The Estimation Procedure

Notation

$$
\begin{aligned}
W^{(k)} &= W(u,\ \hat{p}_0\, u + \hat{p}_1\, v + \hat{p}_2) \\
\dot{W}(x, y) &= \frac{\partial}{\partial y} W(x, y) \\
\dot{W}^{(k)} &= \dot{W}(u,\ \hat{p}_0\, u + \hat{p}_1\, v + \hat{p}_2) \\
M^{(k)} &= \hat{p}_3^{(k)}\, W^{(k)}\, I_{o2} \\
\dot{M}^{(k)} &= \hat{p}_3^{(k)}\, \dot{W}^{(k)}\, I_{o2} \\
U &= \operatorname{diag}(u_1, u_2, \dots, u_N) \\
V &= \operatorname{diag}(v_1, v_2, \dots, v_N)
\end{aligned}
$$

Iterative Procedure

$$
\begin{aligned}
\hat{p}^{(0)} &= [\,0,\ 1,\ 0,\ 1,\ 0\,]^\top \\
c^{(k)} &= I_{o1} - \hat{p}_3^{(k)}\, W^{(k)}\, I_{o2} - \hat{p}_4^{(k)}\, 1 \\
c_p^{(k)} &= \left[U\, \dot{M}^{(k)},\ V\, \dot{M}^{(k)},\ \dot{M}^{(k)},\ M^{(k)},\ 1\right] \\
\Delta\hat{p}^{(k)} &= \left({c_p^{(k)}}^\top c_p^{(k)}\right)^{-1} {c_p^{(k)}}^\top c^{(k)} \\
\hat{p}^{(k+1)} &= \hat{p}^{(k)} + \Delta\hat{p}^{(k)}
\end{aligned}
$$

Solution:

$$
\begin{aligned}
\hat{p} &= \hat{p}^{(k)} \\
\hat{\Sigma}_{\hat{p}}^{-1} &= \sigma_i^{-2}\, {c_p^{(k)}}^\top \left(E + \hat{p}_3^2\, W^{(k)} {W^{(k)}}^\top\right)^{-1} c_p^{(k)}
\end{aligned}
$$

(unbiased inefficient estimate)

C9. 3D Reconstruction

Rectified cameras:

$$P_i = O_i \, K^* R^* \, [\, E, \, -C_i \,] \,, \quad i = 1, 2$$

Image offset matrix

$$O_i = \begin{bmatrix} 1 & 0 & -o_u \\ 0 & 1 & -o_{vi} \\ 0 & 0 & 1 \end{bmatrix}$$

P_1, P_2 differ in the second row:

$$P_1 = \begin{bmatrix} p_1^\top \\ p_2^\top \\ p_3^\top \end{bmatrix}, \quad P_2 = \begin{bmatrix} p_1^\top \\ q_2^\top \\ p_3^\top \end{bmatrix}$$

$[\, u, \, v, \, w \,]^\top$ left-image point

$[\, u, \, v + d, \, w \,]^\top$ corresponding right-image point

Reconstruction matrix S

$$\underline{D} = \begin{bmatrix} u \\ v \\ d \\ w \end{bmatrix} = \begin{bmatrix} p_1^\top \\ p_2^\top \\ (q_2 - p_2)^\top \\ p_3^\top \end{bmatrix} \underline{X} = S^{-1}\, \underline{X}$$

3D Euclidean reconstruction mapping

$$\underline{X} = S\, \underline{D}$$

D – point in disparity space

X – point in Euclidean space

Mapping from disparity space of camera pair (i, j) to disparity space of camera pair (k, l)

$$\underline{D}_{kl} = S_{kl}^{-1} S_{ij}\, \underline{D}_{ij}$$

C10. 3D Reconstruction Error

Reconstruction matrix

$$S = \begin{bmatrix} s_1^\top \\ s_2^\top \\ s_3^\top \\ s_4^\top \end{bmatrix} = [s_{ij}]$$

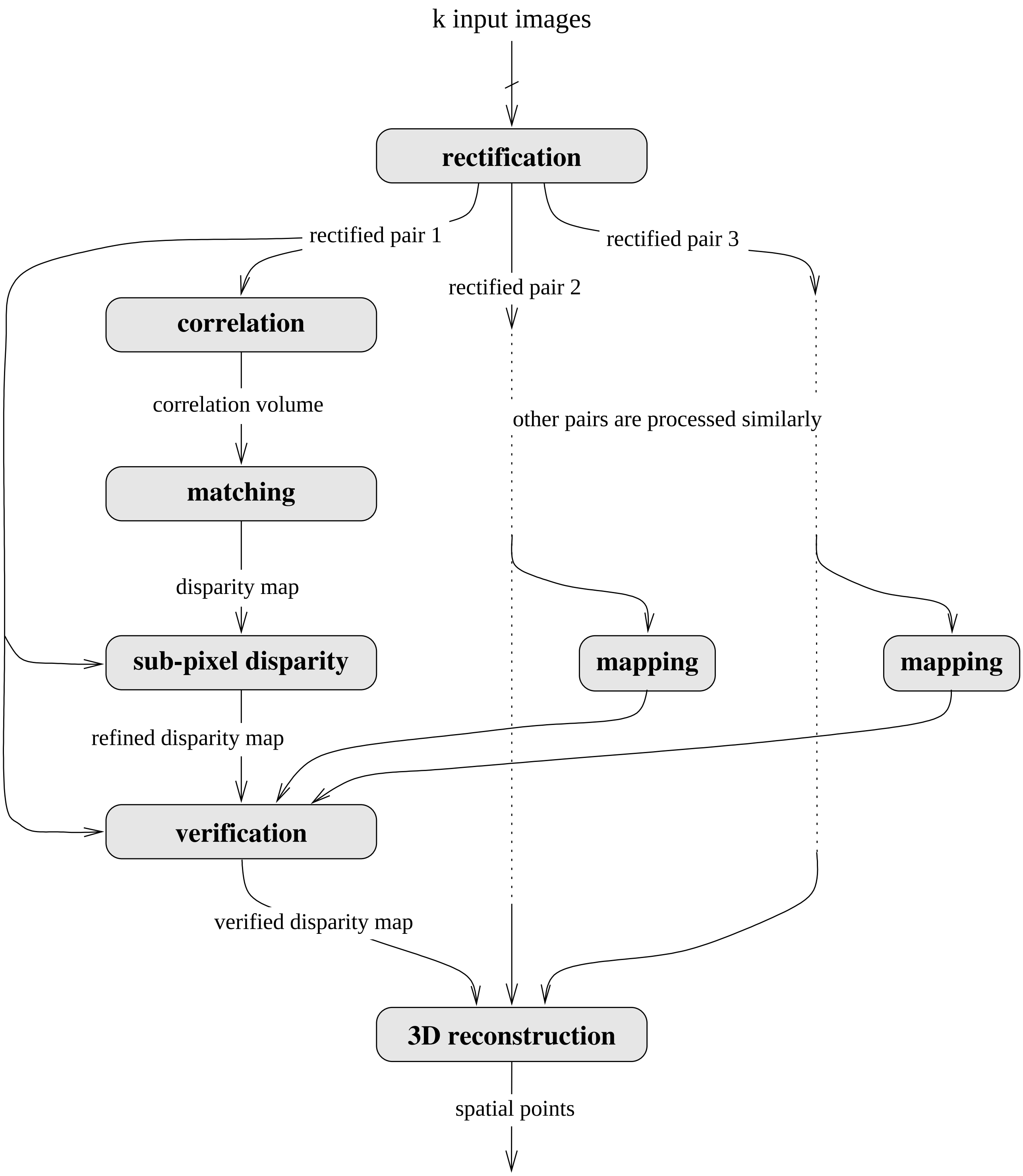
3D point $[x_1, x_2, x_3]^\top$

$$x_i = \frac{s_i^\top \underline{D}}{s_4^\top \underline{D}}, \quad i = 1, 2, 3$$

Reconstruction error δX from disparity error δD

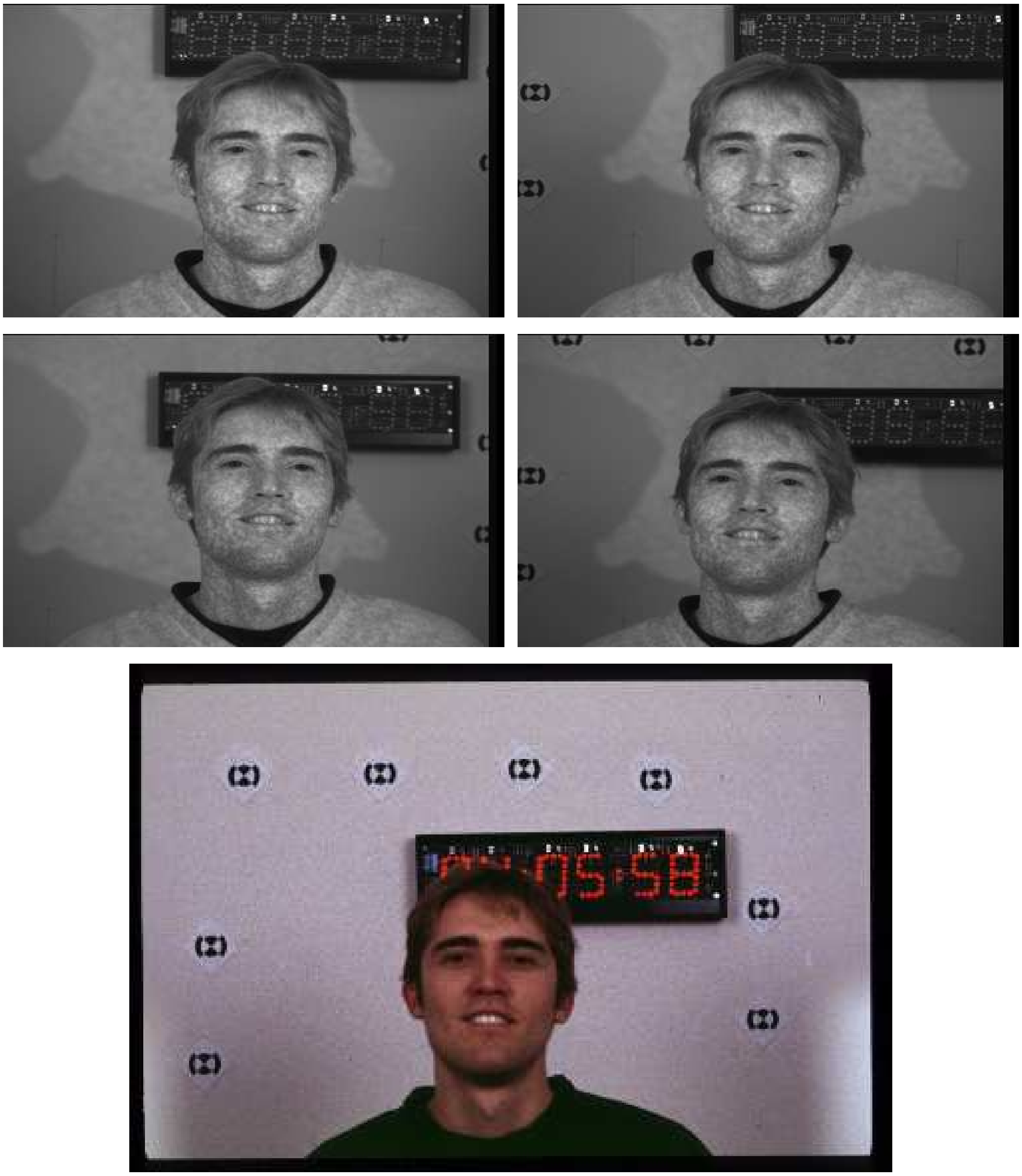
$$\delta X = \frac{\partial X}{\partial D}\,\delta D = \frac{1}{(s_4^\top \underline{D})^2} \begin{bmatrix} s_{13}\, s_4^\top - s_{43}\, s_1^\top \\ s_{23}\, s_4^\top - s_{43}\, s_2^\top \\ s_{33}\, s_4^\top - s_{43}\, s_3^\top \end{bmatrix} \delta D$$

C11. Disparity Map Fusion

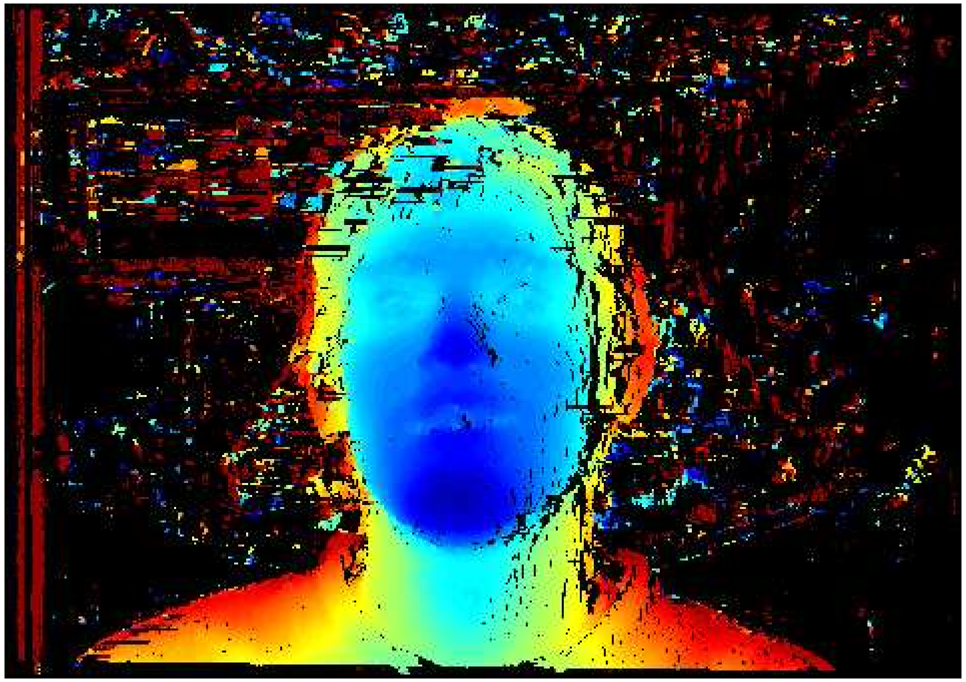


C12. Quadrinocular Stereo Example

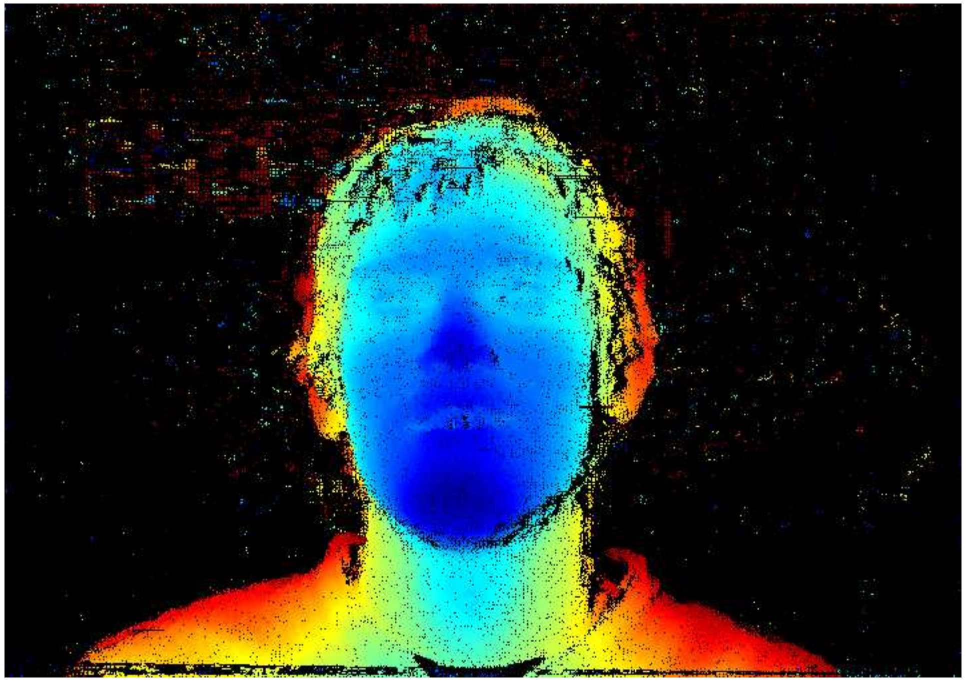
Input Images



Stereo Example: Disparity Maps



pair 3–4 raw disparity map



fused disparity map

Stereo Example: Reconstructed Points

no propagated error threshold

rejection threshold of 0.2mm