9.913 Pattern Recognition for Vision

Class 8-2 – An Application of Clustering

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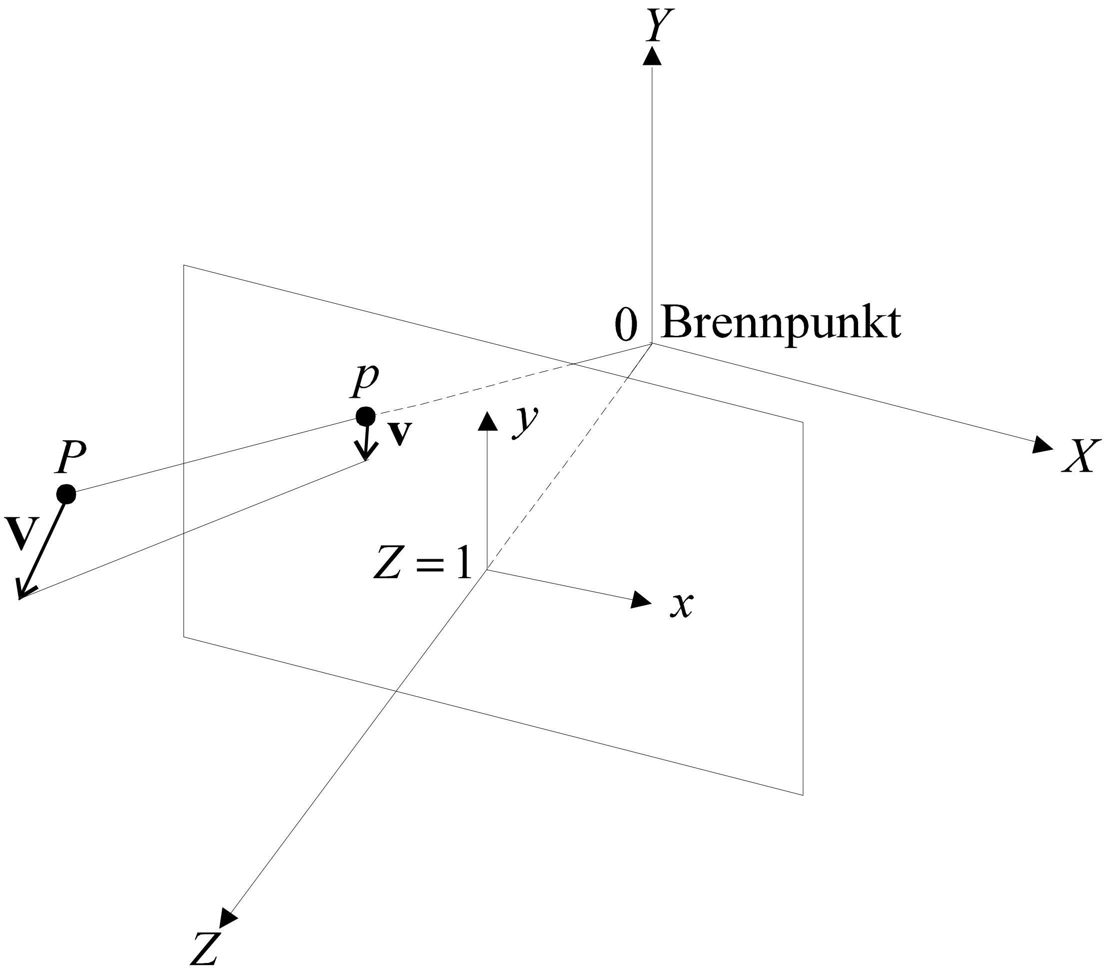
Overview

- Problem
- Background
- Clustering for Tracking
- Examples
- Literature
- Homework

Problem

Detect objects on the road:
Cars, trucks, motorbikes, pedestrians.

Image Motion



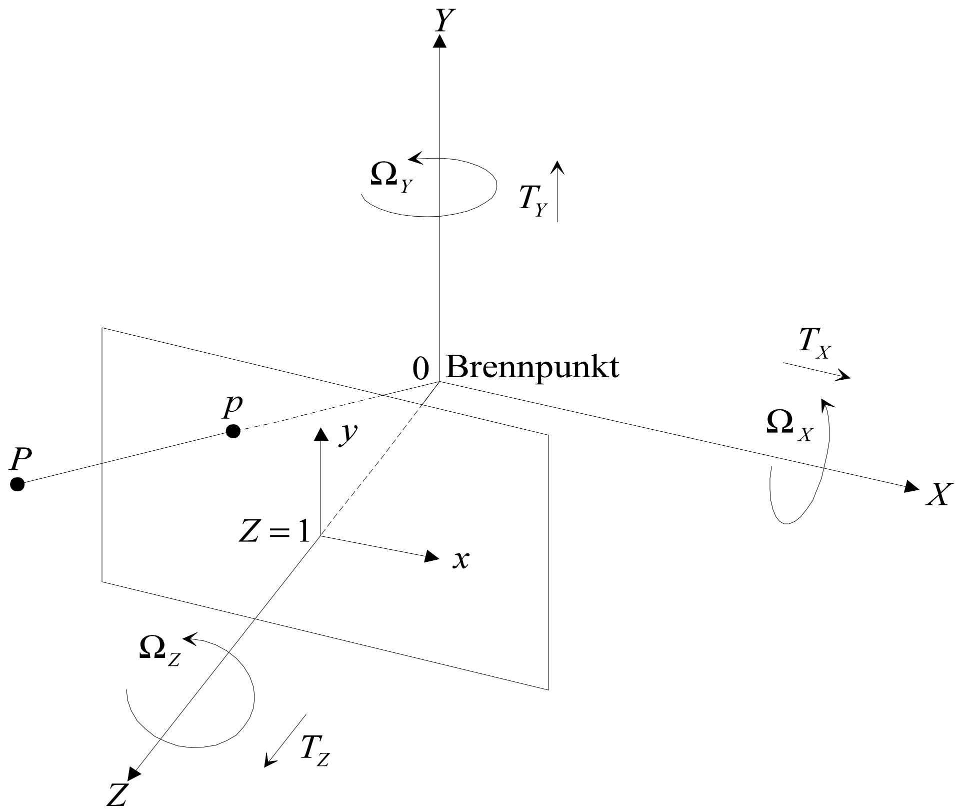
Determine the image motion (vector field)

$$\mathbf{v}(x,y) = \left(u(x,y), v(x,y)\right)^T .$$

Object Segmentation using Image Motion

Motion-based segmentation

Image Motion—Equations for Rigid Motion



$$u = -\Omega_X xy + \Omega_Y (1 + x^2) - \Omega_Z y + (V_X - V_Z x) / Z$$

$$v = -\Omega_X (1 + y^2) + \Omega_Y xy + \Omega_Z x + (V_Y - V_Z y) / Z$$

Image Motion—Estimation Optical Flow

Image intensity over time is $f(x, y, t)$

The intensity of a point over time is given by:

$g(t) = f(x(t), y(t), t)$, where $x(t), y(t)$ is the trajectory of the point in the image plane.

Assume the intensity of the point does not change over time:

$$\frac{dg(t)}{dt} = 0 \Rightarrow \frac{\partial f}{\partial x}\frac{\partial x}{\partial t} + \frac{\partial f}{\partial y}\frac{\partial y}{\partial t} + \frac{\partial f}{\partial t} = 0$$

$$\left(\frac{\partial x}{\partial t}, \frac{\partial y}{\partial t}\right) = (u, v), \quad (u, v)\nabla f + f_t = 0$$

Image Motion—Estimation Optical Flow

Gradient equation of optical flow:

$$\frac{\partial f}{\partial x}u + \frac{\partial f}{\partial y}v + \frac{\partial f}{\partial t} = 0$$

$$\frac{\Delta f(x)}{\Delta x} = -\frac{\Delta f(t)}{u\Delta t}, \quad \frac{\Delta f(x)}{\Delta x}u = -\frac{\Delta f(t)}{\Delta t}$$

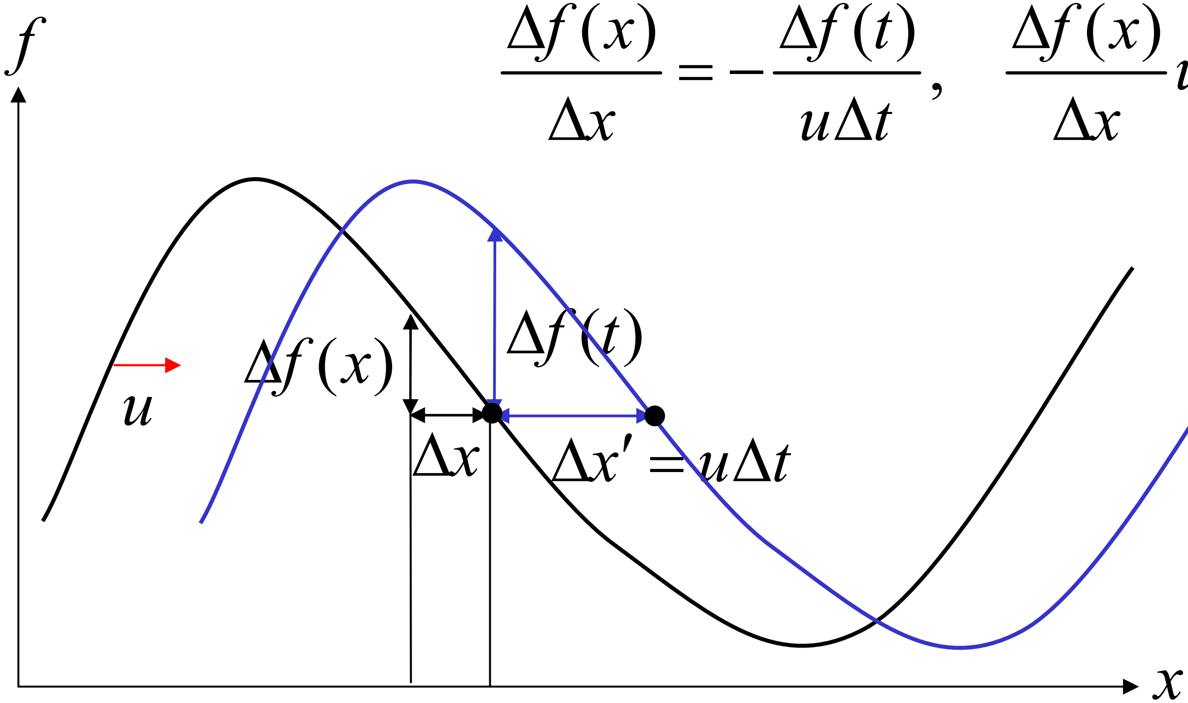
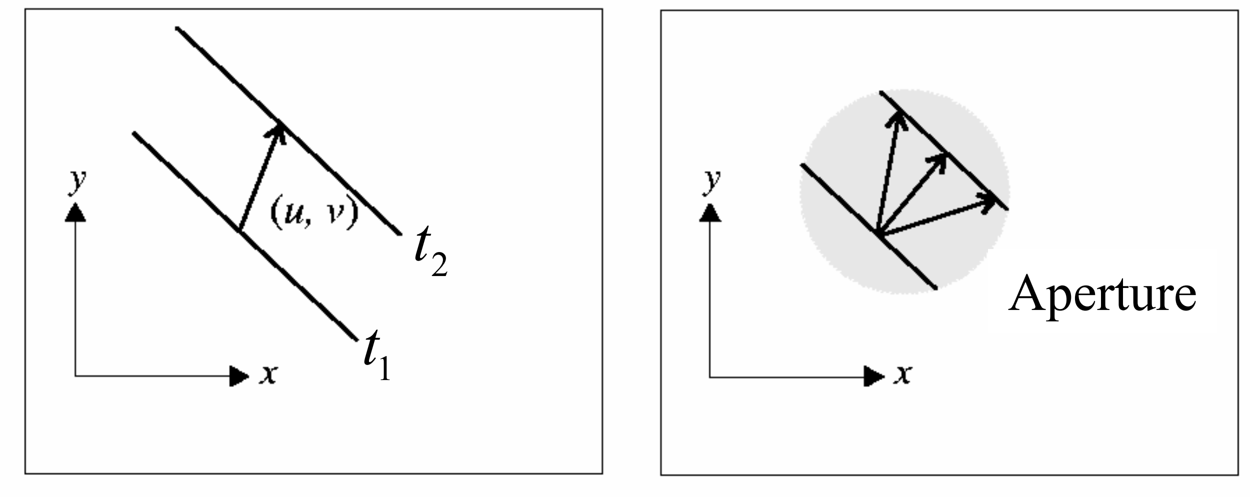
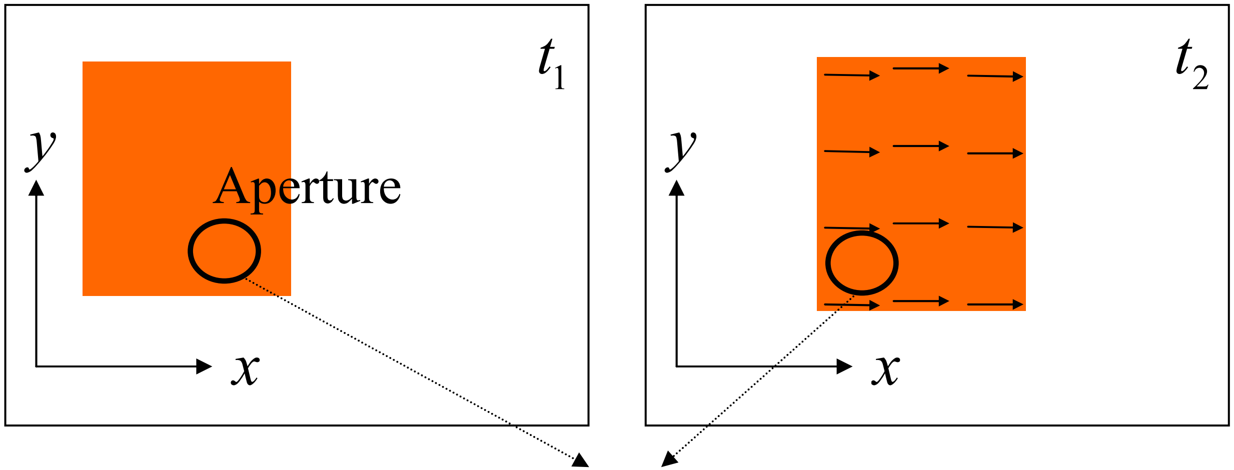


Image Motion—Estimation problems

Aperture Problem

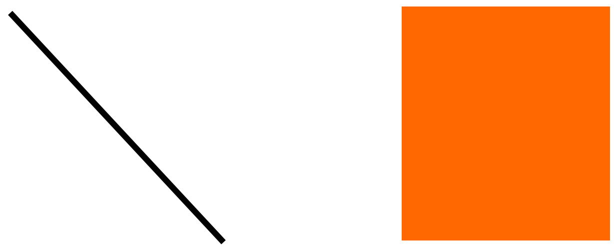




No change over time, optical flow=?

Object Segmentation Problem

Objects:



To determine the image motion we have to know what the objects are, i.e. which points belong together.

However, we can't extract objects without motion.

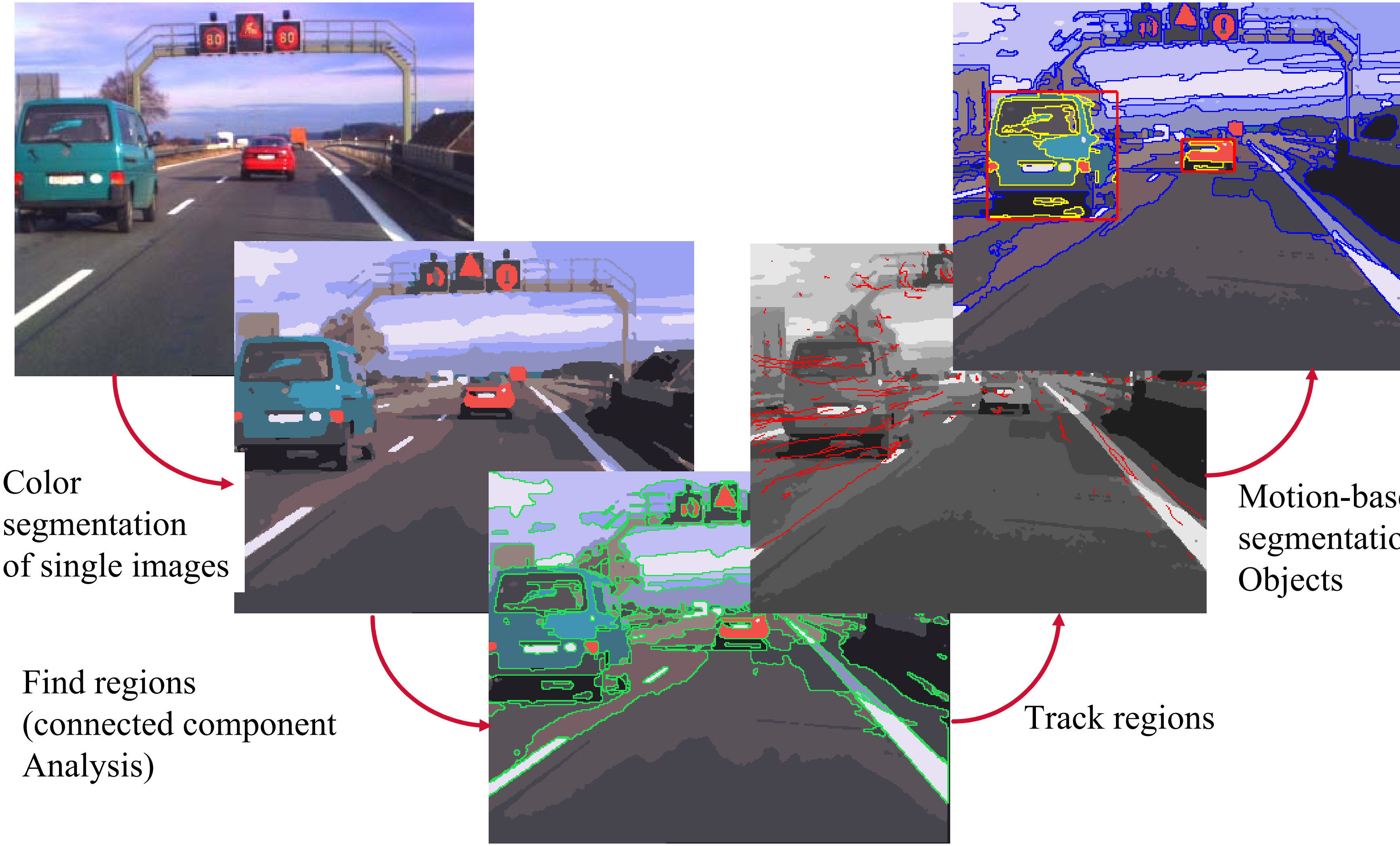
An Idea

Are there methods that help us to determine the image motion (avoid the aperture problem)?

Neighbored pixels of similar color belong to the same object $\Rightarrow$ color segmentation.

Objects usually consist of several regions of different color $\Rightarrow$ color segmentation alone does not solve the problem, we still need motion.

Color Segmentation & Motion



Color segmentation of single images

Find regions (connected component Analysis)

Track regions

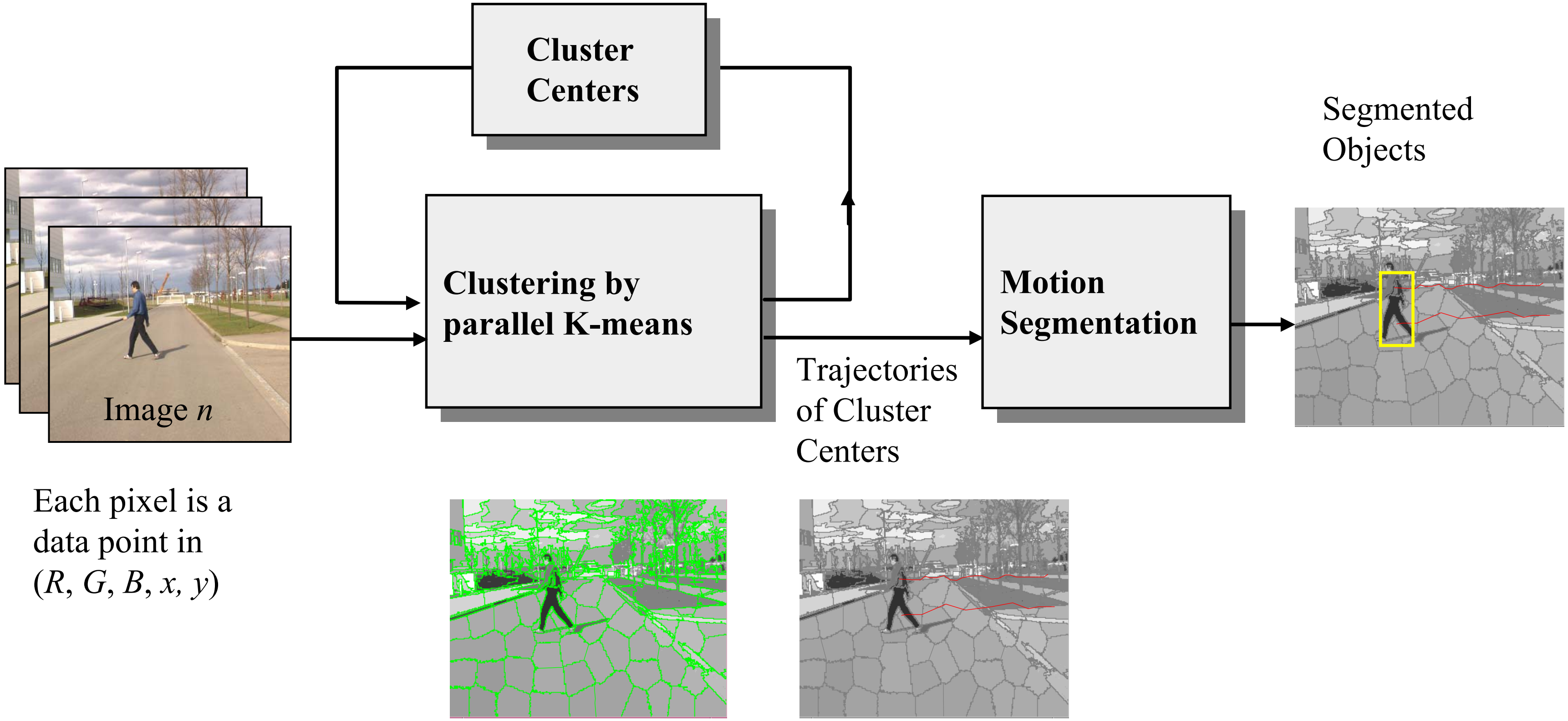
Motion-based segmentation: Objects

Color Segmentation & Motion, why it did not work

Color regions are not stable over time, they merge & break apart which makes tracking extremely difficult.

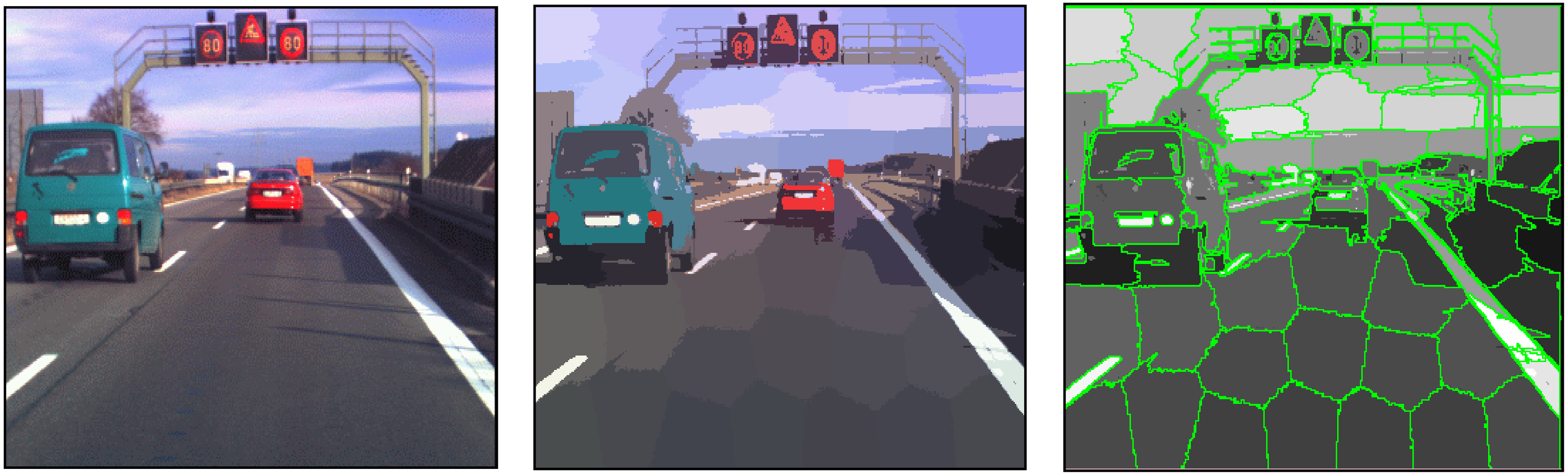
Need consistent color segmentation over time!

Color Cluster Flow



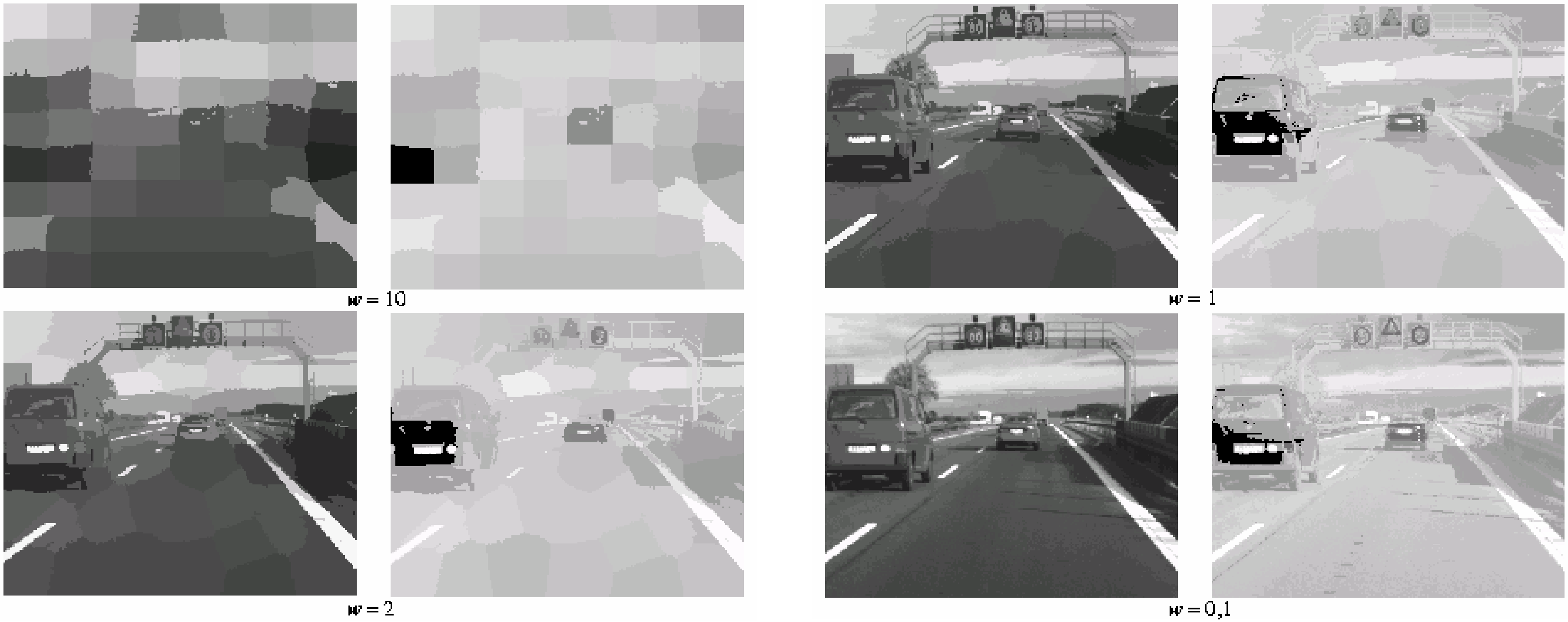
Color/Position Clustering

Original Image | Clustered Image | Boundaries of Clusters



Each pixel is represented by a its color/positoin features (R, G, B, wx, wy), where w is a constant. Clustering is applied to group pixels with similar color and position.

Color versus Position



Cluserting in (*R*, *G*, *B*, *wx, wy*)

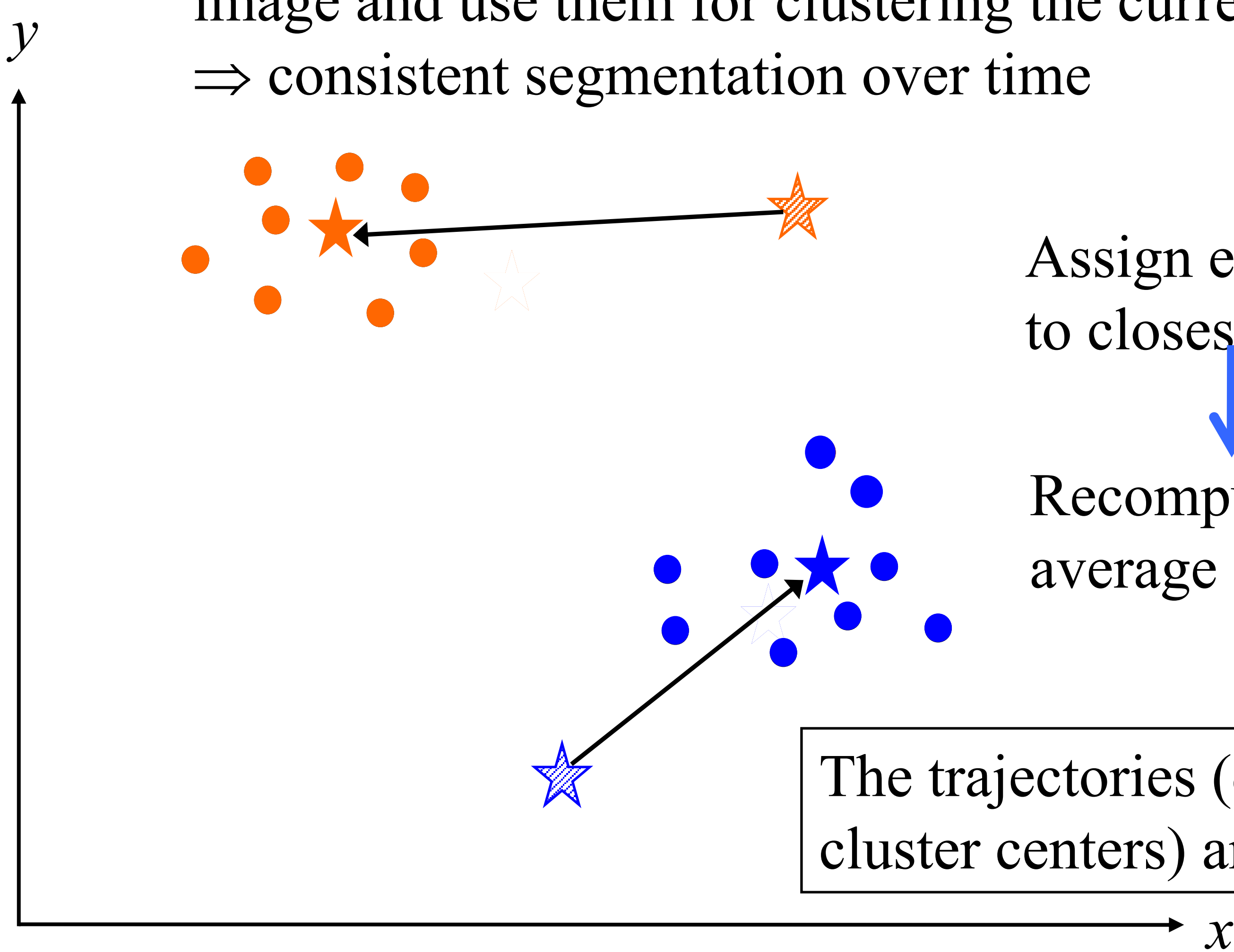
For large *w* the clusters are compact (Voronoi tesselation).

For small *w* the color dominates and the clusters lose their spatial connectivity.

Clustering of Consecutive Images with *k*-means

We know the cluster centers of the previous image and use them for clustering the current image

$\Rightarrow$ consistent segmentation over time



Assign each data point to closest center

↓

Recompute center as average of data points

The trajectories (displacemets of cluster centers) are for free.

Parallel k-means Clustering

1. Partitioning step in iteration k:

$$C_q(k) = \left\{ \mathbf{s}_n \mid \left\| \mathbf{s}_n - \mathbf{r}_q(k-1) \right\|^2 \le \left\| \mathbf{s}_n - \mathbf{r}_i(k-1) \right\|^2 \ \forall i \ne q \right\}$$

C_q: cluster q, $\mathbf{s}_n$: data point n, $\mathbf{r}_q$: prototype of cluster q

2. Computing prototypes in iteration k:

$$\mathbf{r}_q(k) = \frac{1}{S_q(k)} \sum_{\mathbf{s}_i \in C_q(k)} \mathbf{s}_i \quad S_q\text{: data points in cluster } q$$

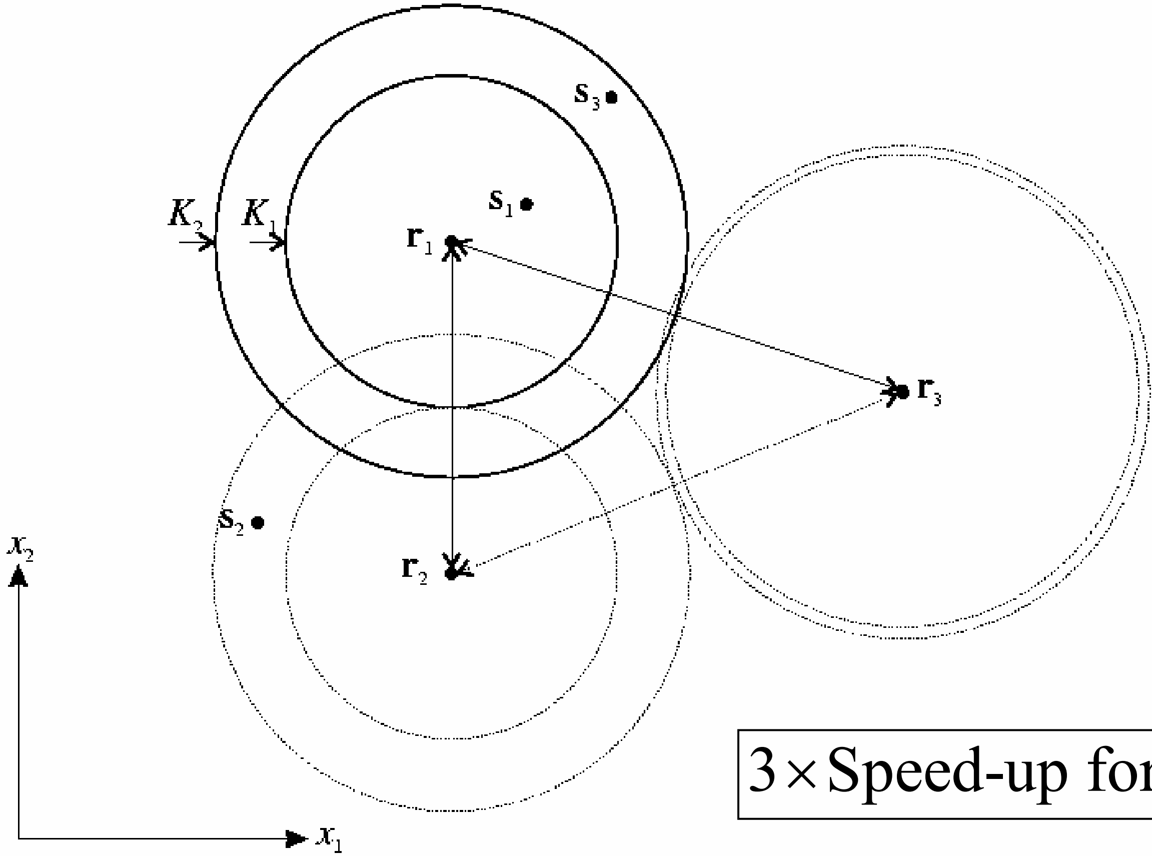
k-means leads to a local minimum of the quantization error

$$mse = \frac{1}{N} \sum_{i=1}^{N} \left\| \mathbf{s}_i - \mathbf{r}_{q(i)} \right\|^2, \quad \mathbf{r}_{q(i)} = \arg\min_{1 \le n \le Q} \left\| \mathbf{s}_i - \mathbf{r}_n \right\|^2$$

Fast parallel k-means Clustering

$Q-1$ circles around each $\mathbf{r}_m$ with diameters $d_n = \|\mathbf{r}_m - \mathbf{r}_n\|$

check if $\mathbf{s}_i$ are inside the circles.



3× Speed-up for one iteration

Initial Clustering

Clustering of the first image of a sequence

K-means is not a good choice for the first image because we don't know a good initialization of the cluster centers.

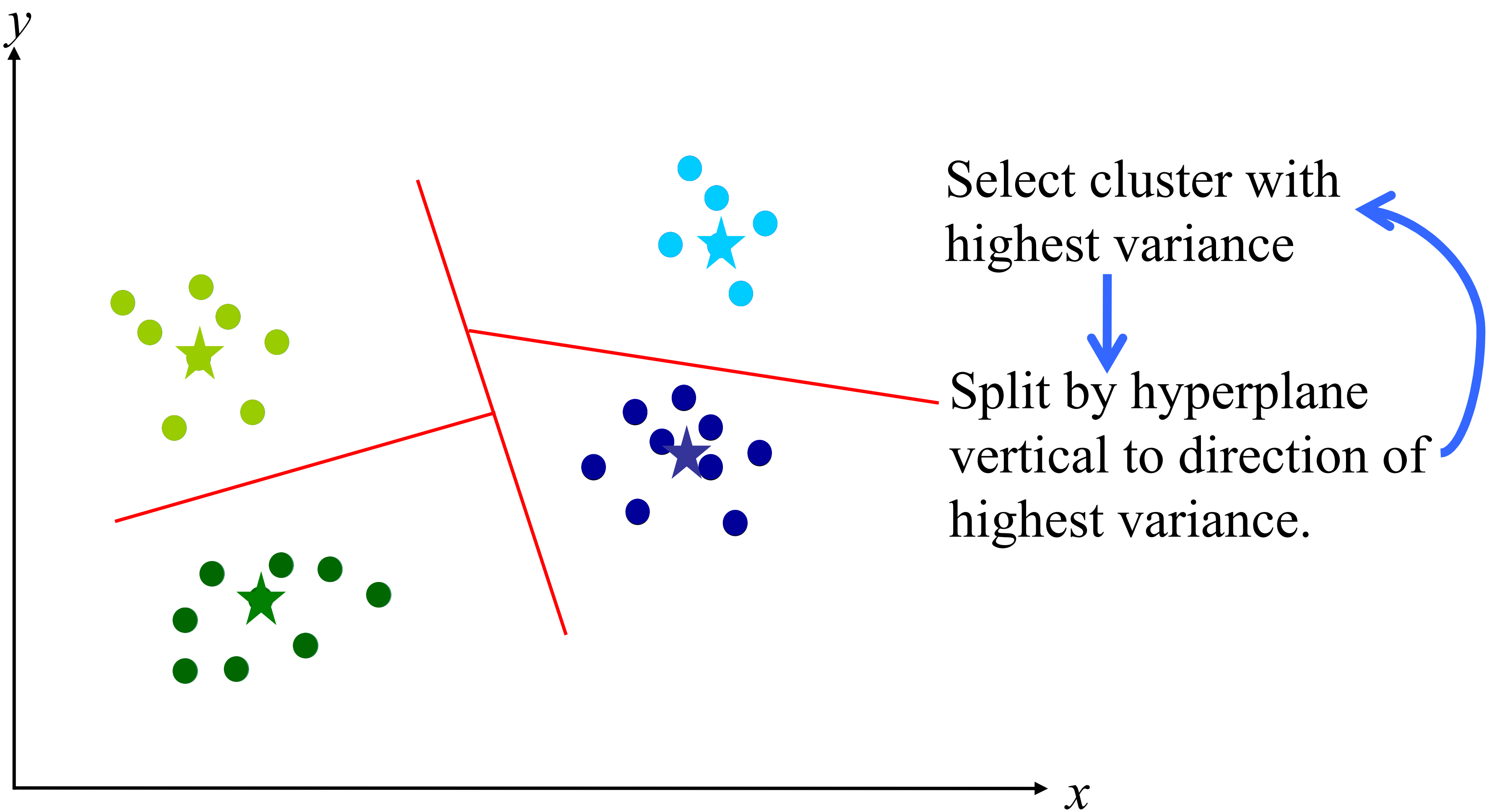
- many iterations required (slow)
- could lead to a 'bad' local minimum (large *mse*)

We need a fast algorithm which doesn't require initialization.

Divisive clustering (tree-based clustering)

Initial Clustering

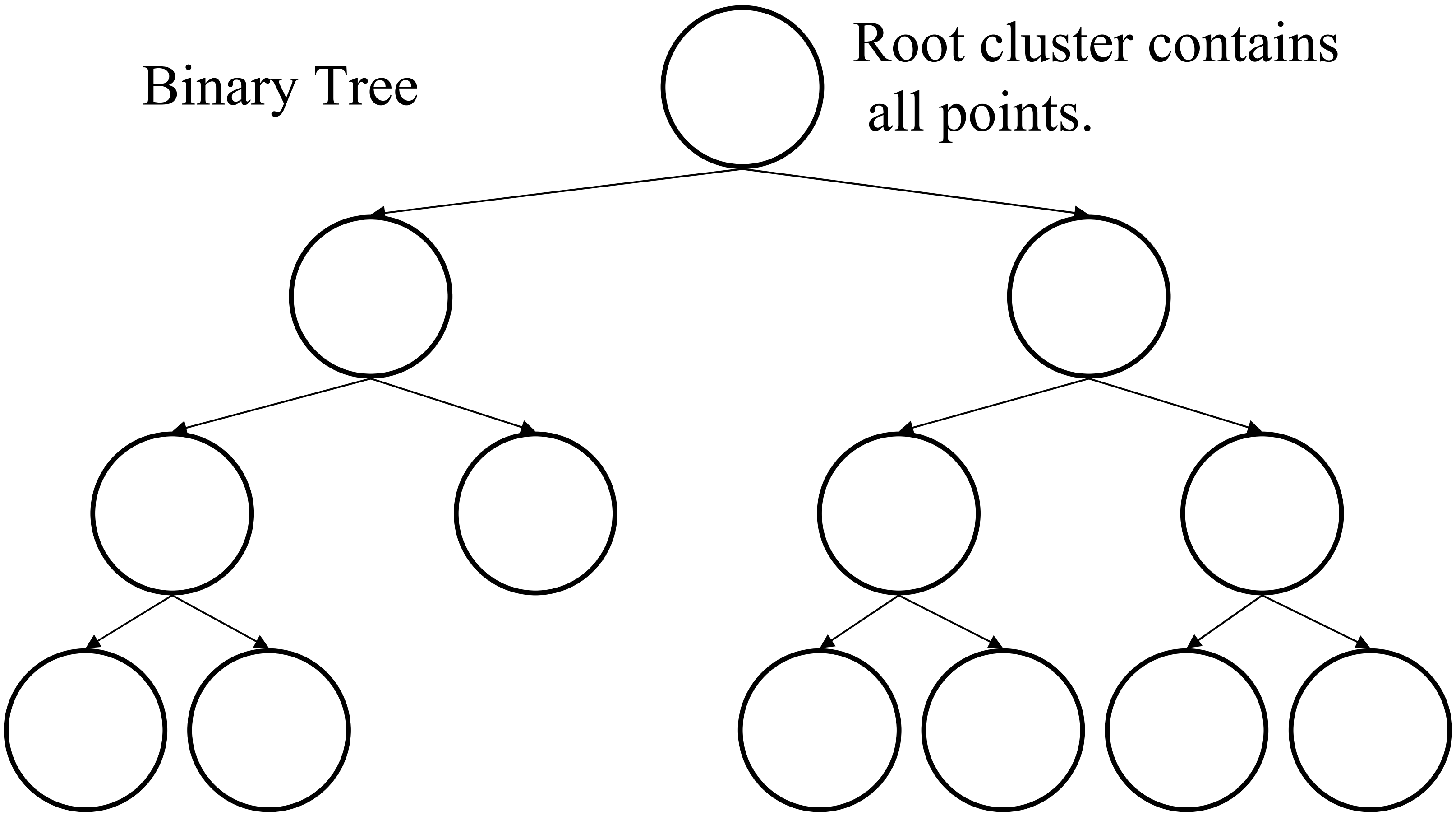
No prior knowledge about color clusters.



Select cluster with highest variance

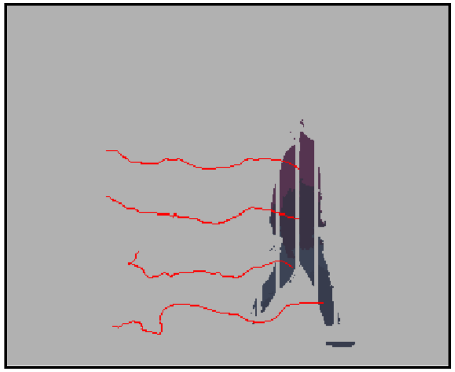
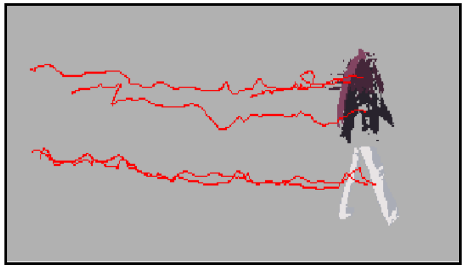
Split by hyperplane vertical to direction of highest variance.

Initial Clustering



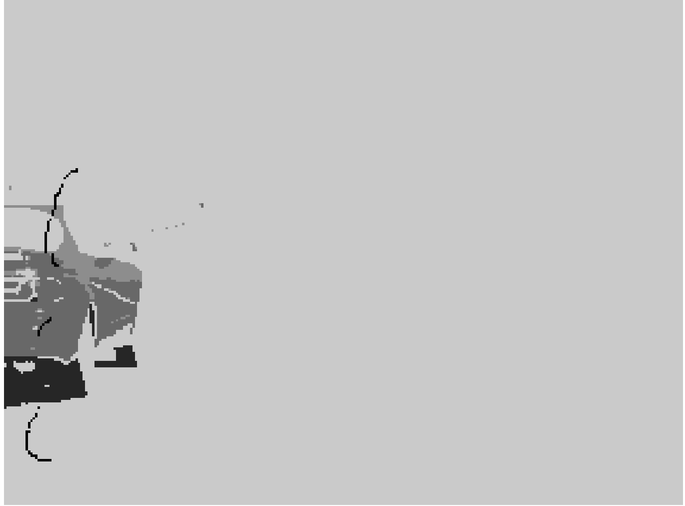
-Use *mse* bound or max. number of clusters as stop criteria.
-The cluster centers of the leafs initialize *k*-means of the next image.

Examples

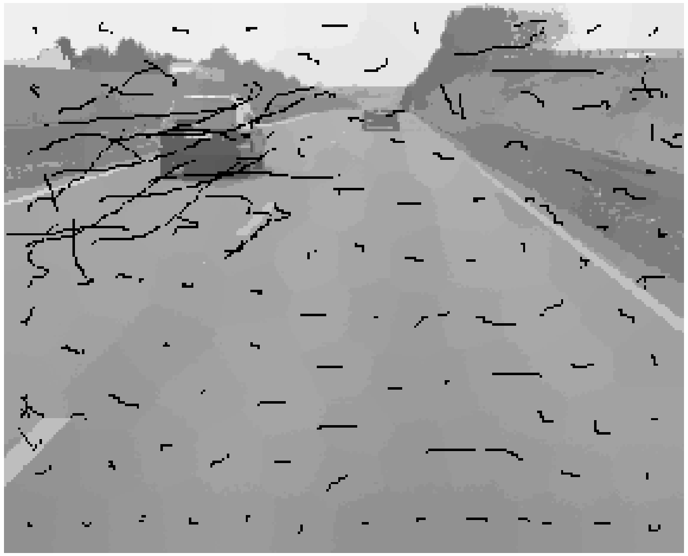
First Image of Sequence	Last Image of Sequence	Trajectories of Cluster Centroids
		
		

Not Perfect

Clusters 'jump' when objects appear or leave the scene. (Number of clusters if fixed)



Over-segmentation and spurious motion in homogenous regions



Literature

B. Heisele, U. Kressel, and W. Ritter.
Tracking non-rigid, moving objects based on color cluster flow.
Proc. Computer Vision and Pattern Recognition (CVPR),
pp. 253-257, San Juan, 1997.

Clustering Classics:

J. MacQueen.
Some methods for classification and analysis of multivariate observations. Proc. 5th Berkeley Symp. Mathematics, Statistics and Probablility, pp. 281-297, 1967.

Y. Linde, A. Buzo, and R. Gray.
An algorithm for vector quantizer design.
IEEE Transactions on Communications, COM-28/1,
pp. 84-95, 1980.

Homework

No homework!