Real Time Vehicle Tracking

Using Background Subtraction and Kalman Filters

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Overview

- **Introduction**
  - Object Tracking
  - Vehicle Tracking
- **Theory & Implementation**
  - Segmentation
  - Tracking
- **Results**
- **Q & A**

Introduction – Object Tracking

- **Object Tracking**
  - Object representation
  - Feature Selection
  - Object Detection
  - Tracking

Introduction – Object Tracking

- **Object Representation**

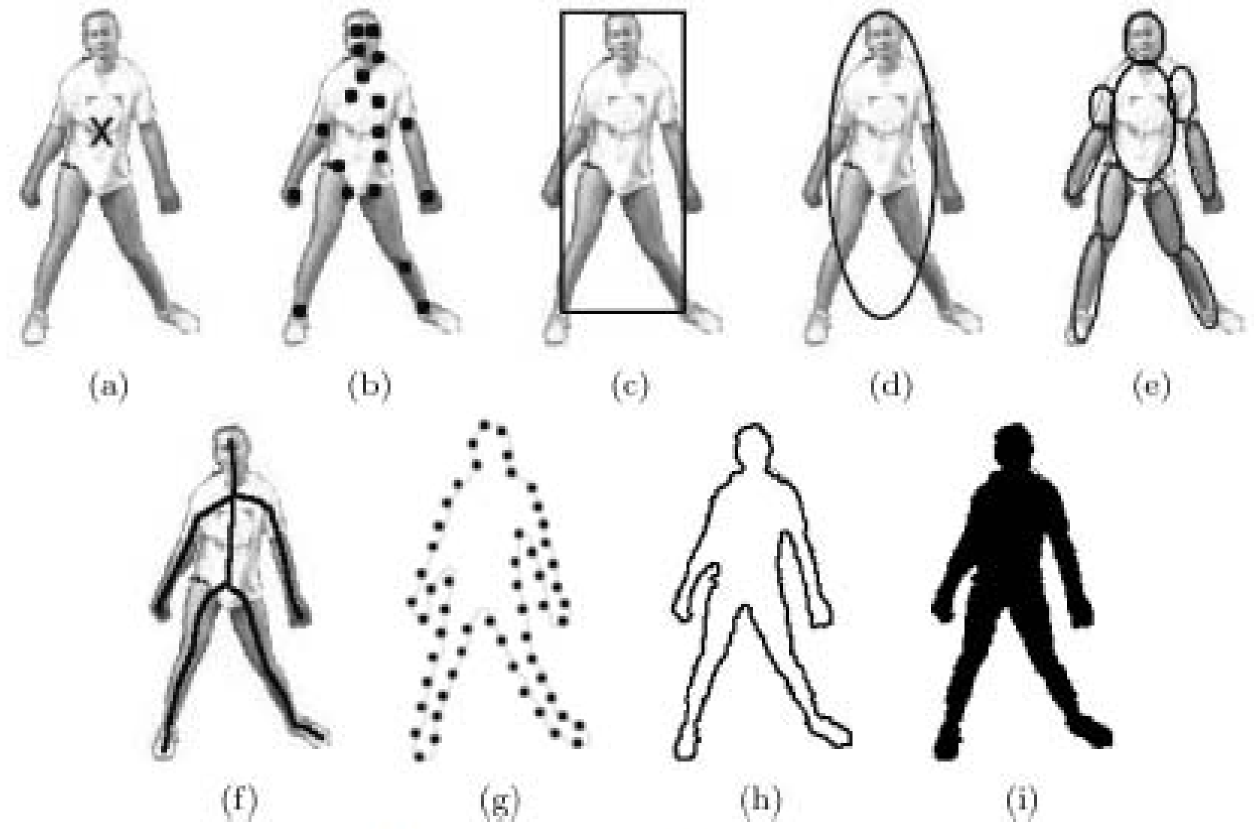


Fig. 1. Object representations. (a) Centroid, (b) multiple points, (c) rectangular patch, (d) elliptical patch, (e) part-based multiple patches, (f) object skeleton, (g) control points on object contour, (h) complete object contour, (i) object silhouette.

Introduction – Object Tracking

- **Feature Selection for Tracking**
  - Colour
  - Edges
  - Optical Flow
  - Texture

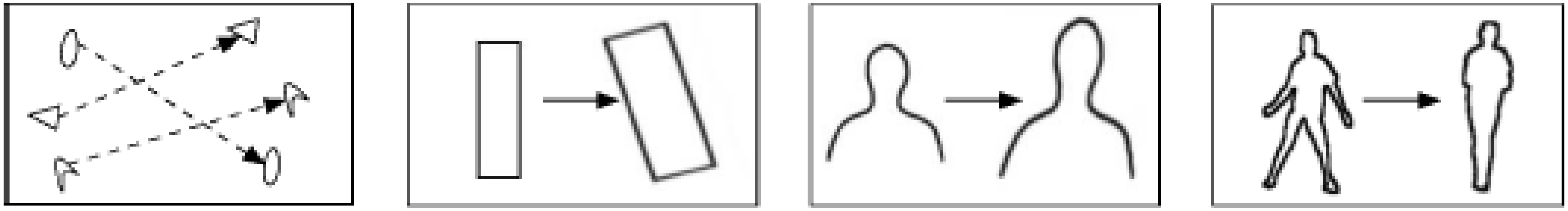
Introduction – Object Tracking

- **Object Detection**

Point detectors	Moravec's Detector Harris Detector Scale Invariant Feature Transform Affine Invariant Point Detector
Segmentation	Mean-Shift Graph-Cut Active Contours
Background Modeling	Mixture of Gaussians Eigenbackground Wall Flower Dynamic Texture Background
Supervised Classifiers	Support Vector Machines Neural Networks Adaptive Boosting

Introduction – Object Tracking

- **Tracking**
  - Point Tracking (a)
  - Kernel Tracking (b)
  - Silhouette Tracking (c) & (d)



(a) (b) (c) (d)

Introduction – Object Tracking

- **Tracking Challenges**
  - Correspondence
  - Occlusion

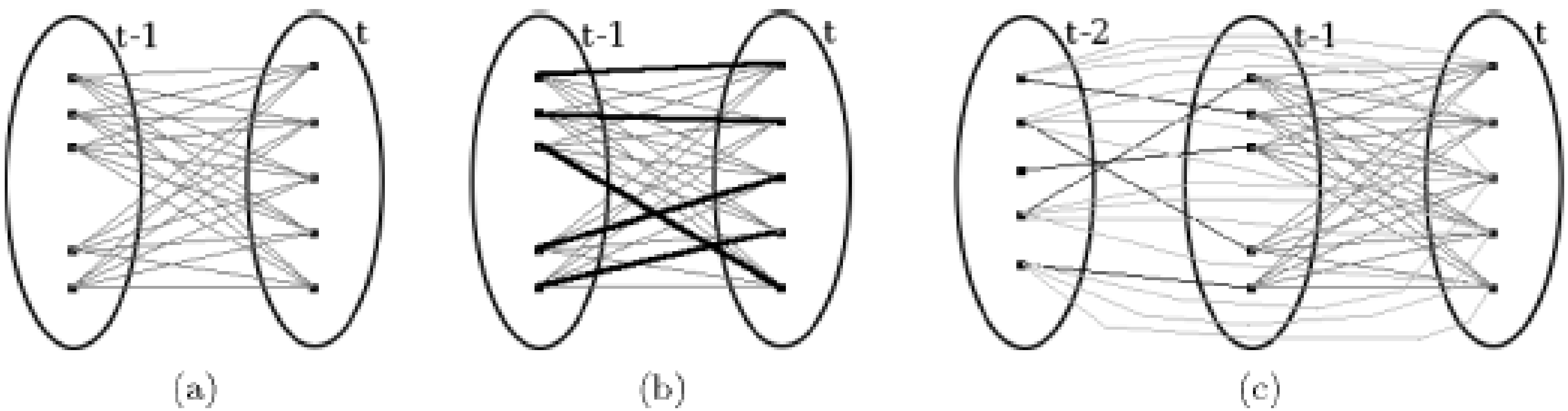


Fig. Point correspondence. (a) All possible associations of a point (object) in frame $t-1$ with points (objects) in frame t, (b) unique set of associations plotted with bold lines, (c) multiframe correspondences.

Introduction – Vehicle Tracking

Vehicle Tracking

- **Motivation**
  - Traffic information
    - **Reduce urban transportation industry costs**
    - Future: Develop “intelligent” transportation system
  - Surveillance (I’d rather not mention)
    - Public Sector
    - Private Sector

Introduction – Vehicle Tracking

- **Object**
  - Track vehicles on a highway
  - Count them
- **Implementation**
  - Real-time
  - OpenCV & C++

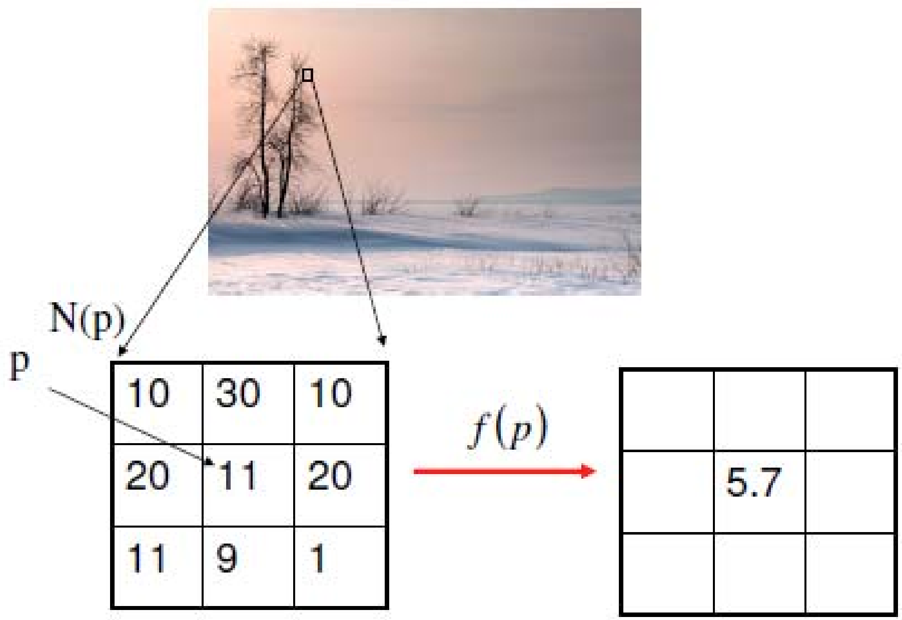
Theory Overview

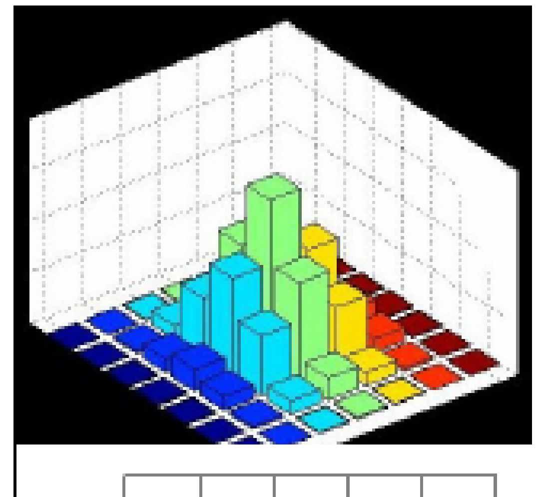
- **Segmentation**
  - Noise removal (minimization)
  - Background subtraction
  - Contour isolation
  - Rectangle fitting
- **Tracking**
  - Correspondence
  - Adding & removing vehicles
  - Persistence
  - Prediction

Theory – Segmentation

Noise minimization

- **Gaussian Blur**
  - Linear Convolution Filter





$$* \ \frac{1}{273} \begin{bmatrix} 1 & 4 & 7 & 4 & 1 \\ 4 & 16 & 26 & 16 & 4 \\ 7 & 26 & 41 & 26 & 7 \\ 4 & 16 & 26 & 16 & 4 \\ 1 & 4 & 7 & 4 & 1 \end{bmatrix}$$

$$\sigma = 1$$

Theory – Segmentation

- **Convolution**

$$I_A(i,j) = I * A = \sum_{h=-m/2}^{m/2} \sum_{k=-m/2}^{m/2} A(h,k) I(i-h, j-k)$$

where A (and G) is the kernel and I is the image

- **Gaussian Kernel is Separable**

$$I_G = I * G =$$

$$= \sum_{h=-m/2}^{m/2} \sum_{k=-m/2}^{m/2} G(h,k) I(i-h, j-k) =$$

$$= \sum_{h=-m/2}^{m/2} \sum_{k=-m/2}^{m/2} e^{-\frac{h^2+k^2}{2\sigma^2}} I(i-h, j-k) =$$

$$= \sum_{h=-m/2}^{m/2} e^{-\frac{h^2}{2\sigma^2}} \sum_{k=-m/2}^{m/2} e^{-\frac{k^2}{2\sigma^2}} I(i-h, j-k)$$

since $\quad e^{-\frac{h^2+k^2}{2\sigma^2}} = e^{-\frac{h^2}{2\sigma^2}} e^{-\frac{k^2}{2\sigma^2}}$

Theory – Segmentation

- **Gaussian Kernel is Separable**

Convolving rows and then columns with a 1-D Gaussian kernel.

$$\boxed{\;I\;} * \frac{1}{38}\begin{bmatrix} 1 & 9 & 18 & 9 & 1 \end{bmatrix} = \boxed{\;I_r\;}$$

$$\boxed{\;I_r\;} * \frac{1}{38}\begin{bmatrix} 1 \\ 9 \\ 18 \\ 9 \\ 1 \end{bmatrix} = \boxed{\text{result}}$$

The complexity increases linearly with m instead of with m^2.

Theory – Segmentation

Background Subtraction

- KaewTraKulPong, P. and Bowden, R. (2001). “An Improved Adaptive Background Mixture Model for Real-time Tracking with Shadow Detection”
- OpenCV implementation (without shadow detection)

Theory – Segmentation

Background Subtraction (continued)

- **Adaptive Gaussian Mixture Model**
  - Each pixel is modelled by a mixture of K Gaussian distributions
  - BG Pixel <= T stdev
  - FG Pixel > T stdev

where T is the threshold

Theory – Segmentation

Background Subtraction (continued)

- **Online Expectation-Maximization (EM)**
  - Iterative parameter estimation
  - Benefits
  - Mathematica demonstration

Theory – Segmentation

- **Finding Outside Contours**
- **Find Enclosed box**
- **Classification** (simple for vehicles)
  - Keep boxes with size > Threshold

    (prevents noise from being detected as a car)

Theory – Vehicle Tracking

- **Correspondence**
  - Compare each new segmented object to each tracked object with the distance cost function:

$$d^{i} = (a_x^{i} - b_x^{i})^2 + (a_y^{i} - b_y^{i})^2$$

where a^{i} is the new object and b^{i} is the tracked object

  - Add each comparison that is less than *T* to a list
  - Order list (lowest cost first)
  - Match first and remove all match with a^{i} and b^{i}

Theory – Vehicle Tracking

- **Adding Vehicles**
  - Mark all detected unmatched vehicles as potential
  - If found in next *g* frames then add
- **Subtracting Vehicles**
  - All vehicles not found in *h*

$$g, h \in [1, 2, \ldots, 10]$$

- **Persistence**
  - Object not found within *h* then not updated but still considered tracked
  - Occlusion

Theory – Vehicle Tracking

Prediction

- **Kalman Filter**
  - Estimates a system's state (optimal)
  - Maximizes a posteriori probability
- Assumptions:
  - system's dynamics are linear
  - noise is additive, white, and Gaussian

Theory – Vehicle Tracking

Kalman Filter (continued)

- Current state vector x_k

$$x_k = Fx_{k-1} + Bu_k + w_k$$

  - F : transfer matrix
  - B : relates the controls to x_k
  - u_k : control vector
  - w_k : the process noise vector
    - noise in state of the system.
    - w_k : random variable $N(0;Q_k)$.

Theory – Vehicle Tracking

Kalman Filter (continued)

- Measurement states z_k

$$z_k = H_k x_k + v_k$$

- H_k : relates x_k to z_k
- v_k : measurement noise
  - random variable with N(0; R_k).

Theory – Vehicle Tracking

Kalman Filter (continued)

- Predict

$$x_k^- = Fx_{k-1} + Bu_{k-1} + w_k$$

$$P_k^- = FP_{k-1}F^T + Q_{k-1}$$

- P_k : error covariance

Theory – Vehicle Tracking

Kalman Filter (continued)

- Update

$$K_k = P_k^- H_k^- \left(H_k P_k^- H_k^T + R_k \right)^{-1}$$

$$x_k = x_k^- + K_k (z_k^- - H_k x_k^-)$$

$$P_k = (I - K_k H_k) P_k^-$$

- K_k : Kalman gain
  - weight to assign to new information

Theory – Vehicle Tracking

Kalman Filter Implementation Details

$$x = \begin{bmatrix} x \\ y \\ v_x \\ v_y \end{bmatrix}, \quad F = \begin{bmatrix} 1 & 0 & dt & 0 \\ 0 & 1 & 0 & dt \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$z = \begin{bmatrix} z_x \\ z_y \end{bmatrix}, \quad H = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

Results

Questions and Discussion