Real Time Video Surveillance of Human Activity

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Recognition of facial expressions

- Black and Yacoob
- Recognize expressions based on nonrigid motions of facial features
  - separate head “flow” into rigid head motion and facial feature motion
  - applied to real video (Amadeus, 2001, …)
Recognizing facial expressions

LEYE   CLOCKWISE ROTATION
RBROW  ANTI-CLOCKWISE ROTATION
LBROW  CURVING UPWARD
Multi-camera recovery of 3-D body pose

- Gavrila and Davis
- Match articulated body part model to 4-7 views of a person in motion
3-D Body Articulation Recovery
Visual Surveillance-Goals

- Detection of moving and fixed objects
- Classification as people, animals, vehicles
- Recognition of specific individuals and vehicles
- Recognition of actions and interactions
  - between people
  - between people and objects
W4

- Detects and tracks people and their body parts
  - Real Time (~15-30 fps)
  - Monochromatic video camera (visible or infrared)
  - Stationary camera with pan/tilt/zoom
  - People can appear in a variety of poses and in small groups
  - Tracks people, recognizes people carrying and exchanging objects
  - No special hardware - dual 450 MHz PC
Detection: Background Modeling

- Model of background variation while the scene contains no people
- Updated during tracking

Sources of Difficulty
- Camera jitter
- Motion of background objects
Background Subtraction Example
Classification of people using periodic motion

1. Track objects
2. Align and scale objects
3. Compute similarity matrix $S$
4. Autocorrelate $S$
5. Template fit peaks of $S$
Periodic Motion: People
Person Classification

![Image of similarity matrices and autocorrelation plots]
Motion Symmetry of Running Dogs

![Motion Symmetry of Running Dogs](image)

**Similarity of Image $T_1$ and $T_2$**

**Autocorrelation of Similarity**
No Periodic Motion: Vehicle
AVS example:

*Periodic motion detection*
Tracking examples
Analyzing small groups
Detailed example
Recognizing interactions between people and objects - carrying and exchanging
Backpack
Active tracker
Active tracker
An object detection and tracking framework

Initialization

Model ↔ Initial State estimation

Regions of Interest

Shape cues ↔ Motion cues ↔ Depth cues

Tracking

State accepted

Prediction

State estimation

Model

Synthesis

Image analysis
DT based matching
Extensions

- use of **multiple feature types**
- matching **multiple** templates using a **template hierarchy**
- automatically **grouping** templates to construct the hierarchy
Multiple feature types

Original Image (Scene)
- Feature Image type 1
  - DT Image type 1
  - Correlation results type 1
- Feature Image type 2
  - DT Image type 2
  - Correlation results type 2
- Feature Image type M
  - DT Image type M
  - Correlation results type M

Template
- Feature Image type 1
- Feature Image type 2
- Feature Image type M

Correlation results
- Correlation results type 1
- Correlation results type 2
- Correlation results type M

Summation

Thresholds → Comparison → Detection Results
Multiple templates and template hierarchy

Factors determining the appropriate distance thresholds during matching

- size search grid
- distance of parent template to its children templates
- segmentation errors
- object variability
Grouping of templates into a hierarchy

- K-means like clustering algorithm
- Input - Number of clusters K and a set of templates
- Output - K partitions and prototypes for each group
- Compute distance matrix
- Minimize \( E = \sum_{k=1}^{K} \sum_{t_i \in S_k} D(t_i, p_k^*) \)
- Two passes at every iteration
  - k-means pass
  - forcing pass
- Simulated annealing
Results - Traffic sign detection

- detection rate > 90% (single frame)
- false positives < 2 per image
- speed-up factor 200-400 compared to brute-force approach (not including the SIMD implementation)
- 400% increase in speed over standard optimized C code due to SIMD implementation
- processing speed > 11 Hz on dual-Pentium II 333 MHz
Detection results
Pedestrian Detection
People detection from static shape models
Detecting people from a moving camera
Tracking

- Condensation algorithm
  - Pdf represented by a set of random samples (Monte Carlo approach)
  - Propagate samples (using a motion model as a predictor) and resample
  - Update sample probabilities based on measurements
The Condensation algorithm

\[ p(X_{t-1} \mid Z_{t-1}) \]

\[ p(X_t \mid Z_{t-1}) \]

\[ p(Z_t \mid X_t) \]

\[ p(X_t \mid Z_t) \]

\[ s_{t-1}, \pi_{t-1} \]

predict

measure

\[ s_t, \pi_t \]
Difficulties

- Learned motion model must be accurate for robust tracking
- Unknown motion model
- High-dimensional state space (4 Euclidean + 8 deformation)
- Sub-optimal and inaccurate sampling
  - Sampling error for N points for a ‘perfect’ pseudo-random generator decreases only as $O(N^{-1/2})$
  - Rand() is not free of sequential correlation on successive calls
  - Modulus operator – least significant bits less random
Proposed Extensions

- Quasi-Random sequences
  - Want to pick sample points “at random”, yet spread out in some self-avoiding way
  - Sequences of k-tuples that fill k-space more uniformly than pseudo-random points
  - Improve asymptotic complexity of search and well spread in multiple dimensions
  - Sampling error decreases as $O(N^{-1})$ as opposed to $O(N^{-1/2})$ for pseudo-random

- Zero-order motion model with large process noise
  - Sample more densely in the gaussian neighborhood of high probability samples from the previous time step
Pseudo-random vs. Quasi-random points

Gaps left by pseudo-random points are filled in by the quasi-random points
Learning a linear pedestrian model

- Extract a training set of pedestrian contours
- NURB fit to point data \( \{Q_k\}, \ k=0, \ldots, n \) using least squares
  - Parameterize the curve using the centripetal method
    \[
    \bar{u}_k = \bar{u}_{k-1} + \frac{\sqrt{|Q_k - Q_{k-1}|}}{\sum_{k=1}^{n} \sqrt{|Q_k - Q_{k-1}|}} \quad k = 1, \ldots, n-1
    \]
  - Solve for the control points \( P_i \) from \( Q_k = \sum_{i=0}^{n} N_{i,p}(\bar{u}_k)P_i \)
- Represent each shape by the shape vector consisting of the control points \( P_i \) (“landmark” points in PDM)
- Align the training shapes using Weighted Generalized Procrustes Analysis (more significance to stable landmark points)
- Use PCA to find the modes of variation
Pedestrian tracking

Sample with maximum probability
Mean estimate of the posterior
Surveillance

Modal state (maximum probability)
Mean estimate of the posterior
Probabilistic Framework for Segmenting People Under Occlusion
**Motivation:**

- What people do while they are interacting is essential for surveillance systems.
- Do not want to lose targets when they are partially occluded by other people.

**Objective:**

- Build representation of different people when they are isolated that enables the *segmentation of foreground regions* when people are interacting as a group.
Assumptions:
- People are isolated before the occlusion (so can a representation can be created for each one).
- Foreground regions are detected.

Approach:
- Model the color of the major parts of the body (torso, bottom, head).
- Localize the color features with respect to the person.
Model the person as a vertical set of blobs.

\[ M = \{ A_i \} \]

Each blob has the same color distribution everywhere inside the blob. (color distribution is independent of the location within the blob) i.e.,

\[ h_A(c \mid x,y) = h_A(c) \]
The vertical location of each blob w.r.t. the person is independent of the horizontal location.

\[ g_A(y \mid x) = g_A(y) \]

⇒ The joint distribution within the blob:

\[ P_A(x, y, c) = f_A(x) \cdot g_A(y) \cdot h_A(c) \]
Given $M$, the probability of color $c$ at location $x,y$ is:

$$P(x, y, c|M) = \frac{f(x)}{C(y)} \sum_i g_{A_i}(y) \cdot h_{A_i}(c)$$

Where $C(y) = \sum_i g_{A_i}(y)$

If the Model origin moves to $(x_o,y_o)$, then

$$P(x, y, c|M(x_o, y_o)) = \frac{f(x-x_o)}{C(y-y_o)} \sum_i g_{A_i}(y-y_o) \cdot h_{A_i}(c)$$
Three blobs: Head, Torso & Bottom.

\[ M = \{ H, T, B \} \Rightarrow \]

\[ P(x, y, u|M) = \frac{f(x)}{C(y)} (g_H(y) \cdot h_H(c) + g_T(y) \cdot h_T(c) + g_B(y) \cdot h_B(c)) \]

To discriminate between blobs:

\[ P(x, y, u|H) \propto (g_H(y) \cdot h_H(c)) \]
\[ P(x, y, u|T) \propto (g_T(y) \cdot h_T(c)) \]
\[ P(x, y, u|B) \propto (g_B(y) \cdot h_B(c)) \]
Segmentation under Occlusion

- Given 2 Models $M_1, M_2$
- Hypothesis:
  - Person 1 origin $(x_1, y_1)$
  - Person 2 origin $(x_2, y_2)$

For each Foreground pixel $X_i = (x_i, y_i, c_i)$ use maximum Likelihood classification:

$$X_i \in M_k \text{ s.t. } k = \arg_k \max P(X_i | M_k)$$
Segmentation under Occlusion

- Each choice \((x_1,y_1,x_2,y_2)\) represents a classification surface between two classes.
- Optimal solution: minimize Bayes error
- Generally, for \(N\) persons we have a search problem in \(2N\) dim
- Exhaustive search will require \(O(w^{2N})\)
  \(\Rightarrow\) Not Practical...
Practical Solution

- Look for a good choice for \((x_1,y_1,x_2,y_2)\)
- Use an origin that is always detectable in a robust way. (e.g. Top of the head)

For each new frame \(t\)

1. Given origin location \((x_{i,t-1},y_{i,t-1})\) at frame \(t-1\)
2. Classify each pixel using \(P(X|M (x_{i,t-1},y_{i,t-1}))\)
3. Detect new origin location \((x_{i,t},y_{i,t})\)

Iterations through 2,3 might lead to a better solution.
Labeling

- Misclassifications are common at very low likelihood probabilities.
- Consider only strong probabilities:
  \[ X_i \in M_k \text{ s.t. } k = \arg_k \max \ P(X_i|M_k) > th \]
- Fill in with lower probability pixels.
  (Spatial localization constraint)
Learning

Learning Color distribution $h_A(c)$
- Initialize blob model with regions at relative locations of the person.
- Classify the whole FG area accordingly.
- Determine blob separators that minimize the misclassifications.
- Recapture blob models.
- Re-segment at each new frame to determine blob separators.
Learning

- **Learning Vertical Density** $g_A(y)$
  - For each new frame find the histogram of detected blob pixels $H_t(y)$
  - Update density: $g_t(y) = (1-\alpha) g_{t-1}(y) + \alpha H_t(y)$
  - Align densities using a robust feature (we use torso-bottom separator)

- **Horizontal Density** $f(x)$
  - Assume Normal density.
  - Fit $N(\mu, \sigma)$ to the person detected pixels
Results
Results
Results
Results
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