Change Detection

Main Points

- Detect pixels which are changing due to motion of objects.
- Not necessarily measure motion (optical flow), only detect motion.
- A set of connected pixels which are changing may correspond to moving object.

Picture Difference

$$D_i(x,y) = \begin{cases} 1 & if \quad DP(x,y) > T \\ 0 & \ldots\ldots otherwise \end{cases}$$

$$DP(x,y) = | f_i(x,y) - f_{i-1}(x,y) |$$

$$DP(x,y) = \sum_{i=-m}^{m} \sum_{j=-m}^{m} | f_i(x+i, y+j) - f_{i-1}(x+i, y+j) |$$

$$DP(x,y) = \sum_{i=-m}^{m} \sum_{i=-m}^{m} \sum_{k=-m}^{m} | f_i(x+i, y+j) - f_{i+k}(x+i, y+j) |$$

Background Image

• The first image of a sequence without any moving objects, is background image.

• Median filter

$$B(x,y) = median(f_1(x,y), \ldots, f_n(x,y))$$

PFINDER

Pentland

Pfinder

- Segment a human from an arbitrary complex background.
- It only works for single person situations.
- All approaches based on background modeling work only for fixed cameras.

Algorithm

- Learn background model by watching 30 second video
- Detect moving object by measuring deviations from background model
- Segment moving blob into smaller blobs by minimizing covariance of a blob
- Predict position of a blob in the next frame using Kalman filter
- Assign each pixel in the new frame to a class with max likelihood.
- Update background and blob statistics

Learning Background Image

- Each pixel in the background has associated mean color value and a covariance matrix.
- The color distribution for each pixel is described by Gaussian.
- YUV color space is used.

Detecting Moving Objects

- After background model has been learned, Pfinder watches for large deviations from the model.
- Deviations are measured in terms of Mahalanobis distance in color.
- If the distance is sufficient then the process of building a blob model is started.

Detecting Moving Objects

• For each of k blob in the image, log-likelihood is computed

$$d_k = -.5(y - m_k)^T K_k^{-1}(y - m_k) - .5\ln|K_k| - .5m\ln(2\lambda)$$

• Log likelihood values are used to classify pixels

$$s(x, y) = \arg\max_k (d_k(x, y))$$

Updating

•The statistical model for the background is updated.

$$K^t = E[(y-m^t)(y-m^t)^T]$$
$$m^t = (1-a)m^{t-1} + ay$$

• The statistics of each blob (mean and covariance) are re-computed.

Mixture of Gaussians

Grimson

Algorithm

- Learn background model by watching 30 second video
- Detect moving object by measuring deviations from background model, and applying connected component to foreground pixels.
- Predict position of a region in the next frame using Kalman filter
- Update background and blob statistics

Summary

- Each pixel is an independent statistical process, which may be combination of several processes.
  - Swaying branches of tree result in a bimodal behavior of pixel intensity.
- The intensity is fit with a mixture of K Gaussians.

$$\Pr(X_t) = \sum_{j=1}^{K} \frac{w_j}{(2p)^{\frac{m}{2}} |\Sigma_j|^{\frac{1}{2}}} e^{-\frac{1}{2}(X_t - m_j)^T \Sigma_j^{-1} (X_t - m_j)}$$

Mixture of Gaussians

• The K distributions are stored in descending order of the term $\frac{w_j}{s_j}$

• Out of "k" distributions, the first B are selected

$$B = \arg\min{}_b \left[\frac{\sum_{j=1}^{b} w_j}{\sum_{j=1}^{K} w_j} > T \right]$$

Learning Background Model

• Every new pixel is checked against all existing distributions. The match is the first distribution such that the pixel value lies within 2 standard deviations of mean.

•If no match, introduce new distribution.

Updating

• The mean and s.d. of unmatched distributions remain unchanged. For the matched distributions they are updated as:

$$m_{j,t} = (1 - r)m_{j,t-1} + rX_t$$

$$s_{j,t} = (1 - r)s^{2}_{j,t-1} + r(X_t - m_{j,t})^T (X_t - m_{j,t})$$

• The weights are adjusted:

$$w_{j,t} = (1 - a)w_{j,t-1} + a(M_{j,t})$$

Segmenting Background

- Any pixel that is more than 2 sd from all the distributions is marked as a part of foreground-moving object.
- Such pixels are then clustered into connected components.

Kanade

Summary

- Very similar to k-Gaussian with following differences:
  - – uses only single Gaussian
  - – uses gray level images, the mean and variance are scalar values

Algorithm

- Learn background model by watching 30 second video
- Detect moving object by measuring deviations from background model, and applying connected component to foreground pixels.
- Update background and region statistics

Detection

- During detection if intensity value is more than two sigma away from the background it is considered foreground:
  - keep original mean and variance
  - track the object with new mean and variance
  - if new mean and variance persists for sometime, then substitute the new mean and variance as the background model
  - If object is no longer visible, it is incorporated as part of background

W4 (Who, When, Where, What)

Davis

W4

- Compute “minimum”(M(x)), “maximum” (N(x)), and “largest absolute difference” (L(x)).

$$D_i(x,y) = \left\{ \begin{array}{c} 1 \quad if \quad |M(x,y) - f_i(x,y)| > L(x,y) or \\ |N(x,y) - f_i(x,y)| > L(x,y) \\ 0 \quad \ldots \quad otherwise \end{array} \right\}$$

- Theoretically, the performance of this tracker should be worse than others.
- Even if one value is far away from the mean, then that value will result in an abnormally high value of L.
- Having short training time is better for this tracker.

Limitations

- Multiple people
- Occlusion
- Shadows
- Slow moving people
- Multiple processes (swaying of trees..)

Webpage

- Http://www.cs.cmu.edu/~vsam

Skin Detection

Kjeldsen and Kender

Training

- Crop skin regions in the training images.
- Build histogram of training images.
- Ideally this histogram should be bi-modal, one peak corresponding to the skin pixels, other to the non-skin pixels.
- Practically there may be several peaks corresponding to skin, and non-skin pixels.

Training

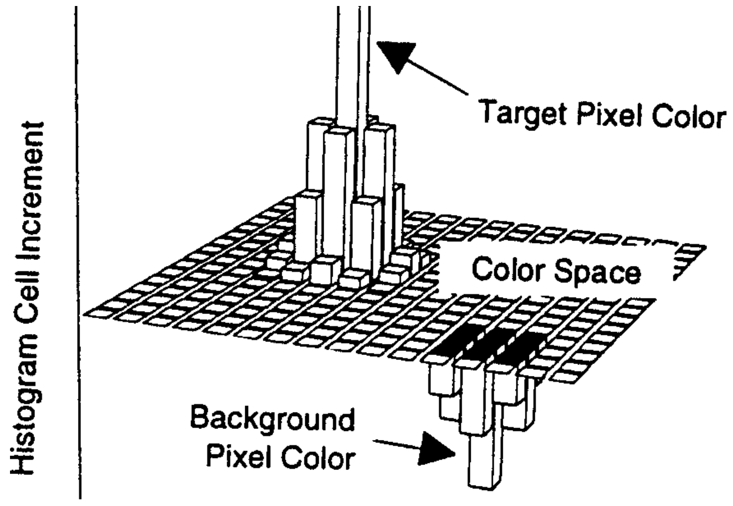
- Apply threshold to skin peaks to remove small peaks.
- Label all gray levels (colors) under skin peaks as “skin”, and the remaining gray levels as “non-skin”.
- Generate a look-up table for all possible colors in the image, and assign “skin” or “non-skin” label.

Detection

- For each pixel in the image, determine its label from the “look-up table” generated during training.

Building Histogram

- Instead of incrementing the pixel counts in a particular histogram bin:
  - for skin pixel increment the bins centered around the given value by a Gaussian function.
  - For non-skin pixels decrement the bins centered around the given value by a smaller Gaussian function.



Tracking People Using Color

Fieguth and Terzopoulos

• Computer mean color vector for each sub region.

$$(r_i, g_i, b_i) = \frac{1}{|R_i|} \sum_{(x,y)\in R_i} (r(x,y), g(x,y), b(x,y))$$

Fieguth and Terzopoulos

• Compute goodness of fit.

$$\Psi_i = \frac{\max\left\{\frac{r_i}{\bar{r}_i}, \frac{g_i}{\bar{g}_i}, \frac{b_i}{\bar{b}_i}\right\}}{\min\left\{\frac{r_i}{\bar{r}_i}, \frac{g_i}{\bar{g}_i}, \frac{b_i}{\bar{b}_i}\right\}}$$

Target Measurement

Fieguth and Terzopoulos

- Tracking

$$\Psi(x_H, y_H) = \sum_{i=1}^{N} \frac{\Psi_i(x_H + x_i, y_H + y_i)}{N}$$

$$(\hat{x}, \hat{y}) = \arg_{(x_H, y_H)} \min\{\Psi(x_H, y_H)\}$$

Fieguth and Terzopoulos

- Non-linear velocity estimator

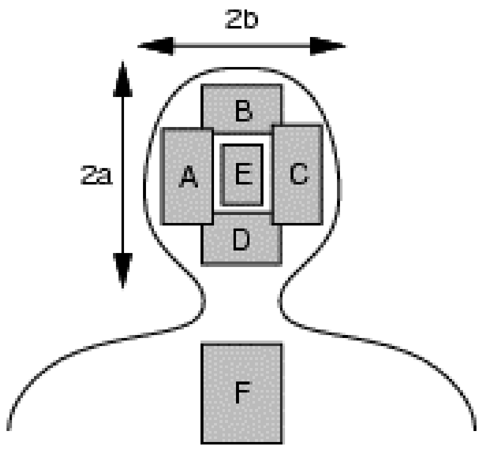
$$v(f) = v(f-1)$$

$$if \quad (r(f).r(f-1) > 0) \quad v(f) \quad += \quad d\,\frac{\text{sgn}(r(f))}{\Delta t}$$

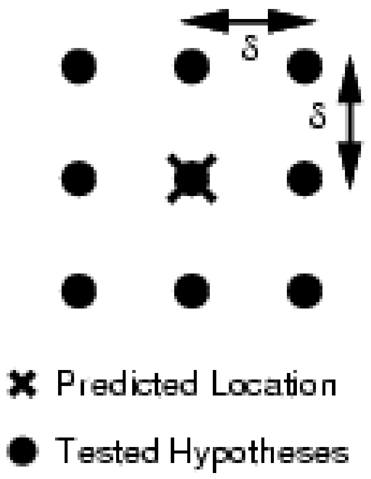
$$if \quad (r(f).v(f-1) < 0) \quad v(f) \quad += \quad d\,\frac{\text{sgn}(r(f))}{\Delta t}$$

$$if \quad (r(f) = 0) \quad v(f) \quad -= \quad d\,\frac{\text{sgn}(v(f))}{2\Delta t}$$

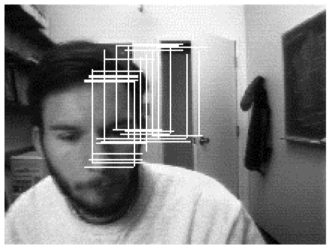
Fieguth and Terzopoulos



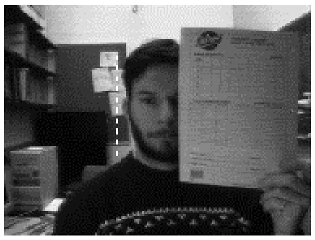
Fieguth and Terzopoulos

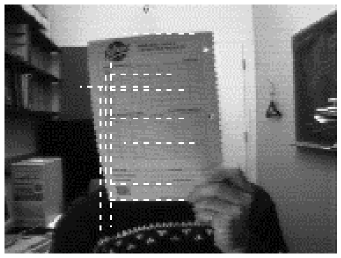
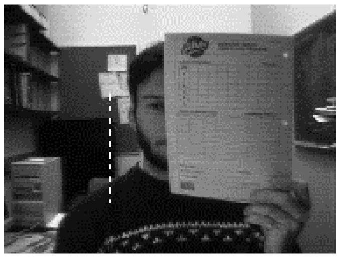


Fieguth and Terzopoulos



Fieguth and Terzopoulos



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Monitoring Human Behavior In an Office Environment

Goals of the System

- Recognize human actions in a room for which **prior knowledge** is available.
- Handle multiple people
- Provide a textual description of each action
- Extract “key frames” for each action

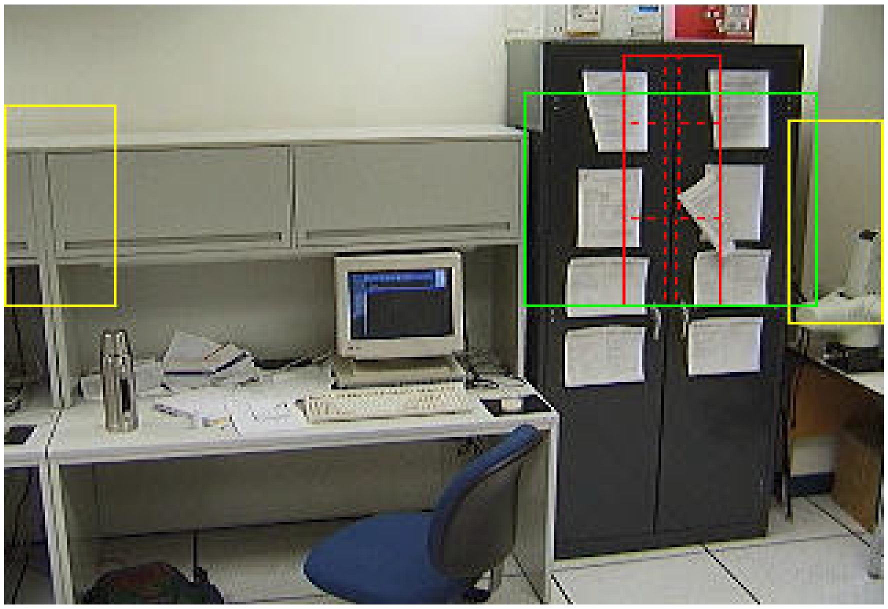
Possible Actions

- **Enter**
- **Leave**
- **Sitting** or **Standing**
- **Picking Up Object**
- **Put Down Object**
- **…..**

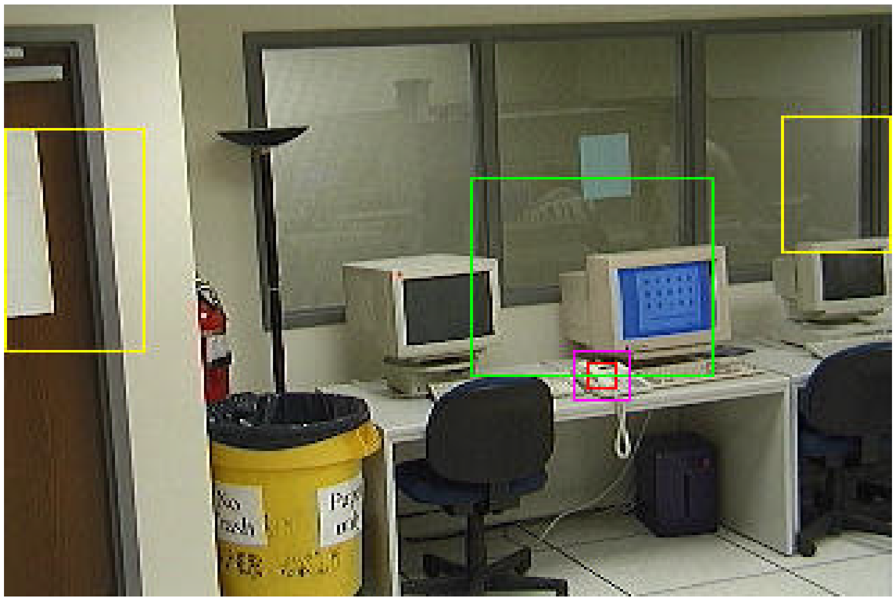
Prior Knowledge

- Spatial layout of the scene:
  - Location of **entrances** and **exits**
  - Location of **objects** and some information about how they are use
- Context can then be used to improve recognition and save computation

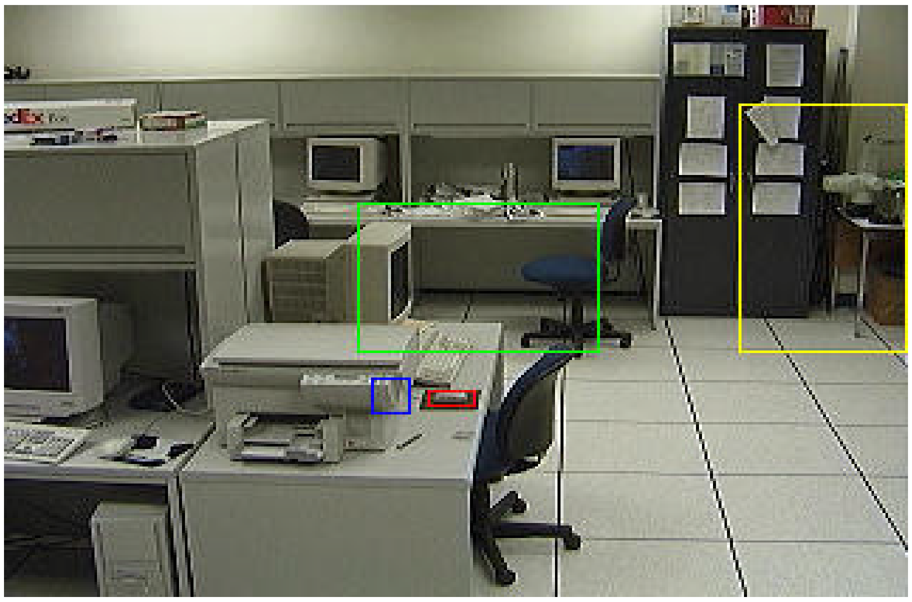
Layout of Scene 1



Layout of Scene 2



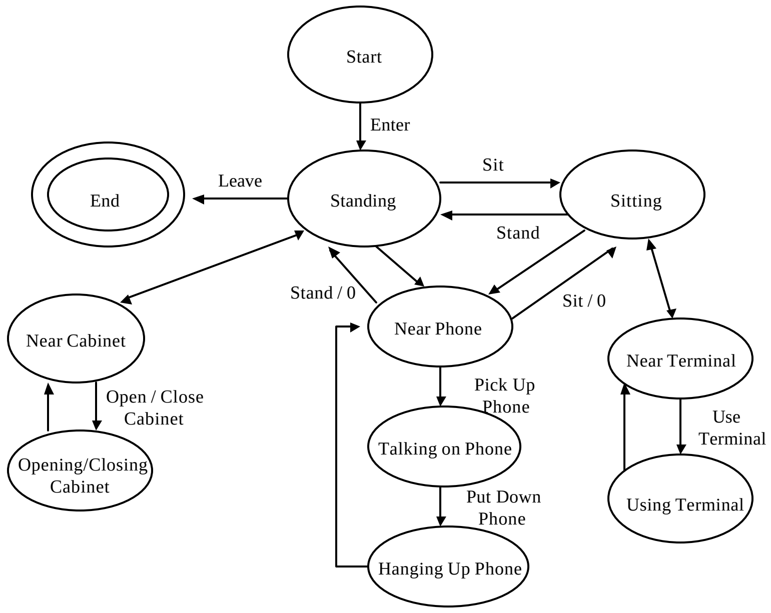
Layout of Scene 4



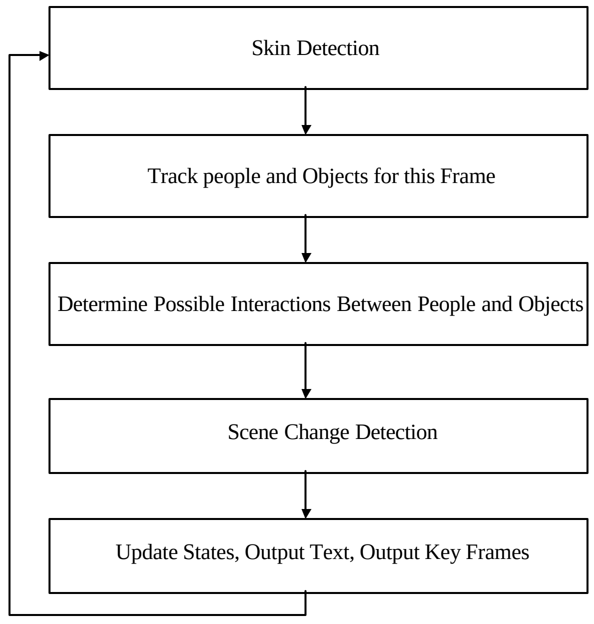
Major Components

- Skin Detection
- Tracking
- Scene Change Detection
- Action Recognition

State Model For Action Recognition



Flow of the System


Skin Detection
Track people and Objects for this Frame
Determine Possible Interactions Between People and Objects
Scene Change Detection
Update States, Output Text, Output Key Frames

Key Frames

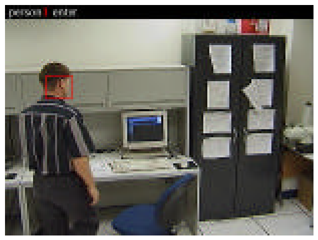
- Why get key frames?
  - Key frames take less space to store
  - Key frames take less time to transmit
  - Key frames can be viewed more quickly
- We use heuristics to determine when key frames are taken
  - Some are taken before the action occurs
  - Some are taken after the action occurs

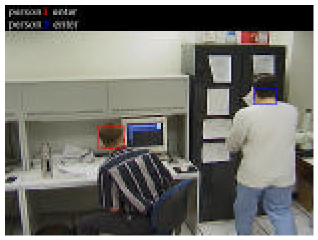
Key Frames

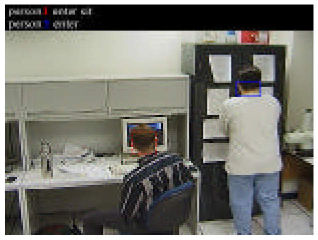
- “Enter” key frames: as the person leaves the entrance/exit area
- “Leave” key frames: as the person enters the entrance/exit area
- “Standing/Sitting” key frames: after the tracking box has stopped moving up or down respectively
- “Open/Close” key frames: when the % of changed pixels stabilizes

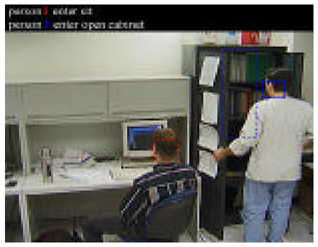
Results

Key Frames Sequence 1 (350 frames), Part 1

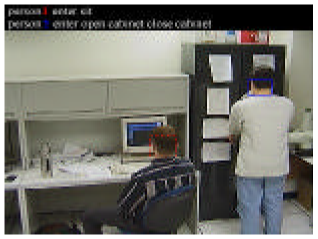


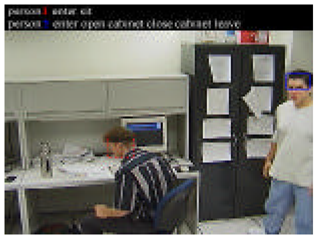


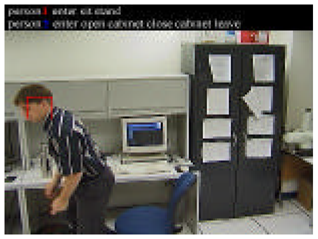


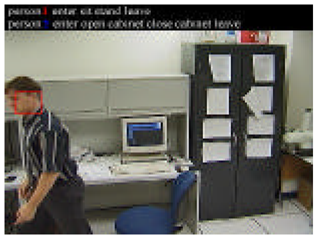


Key Frames Sequence 1 (350 frames), Part 2

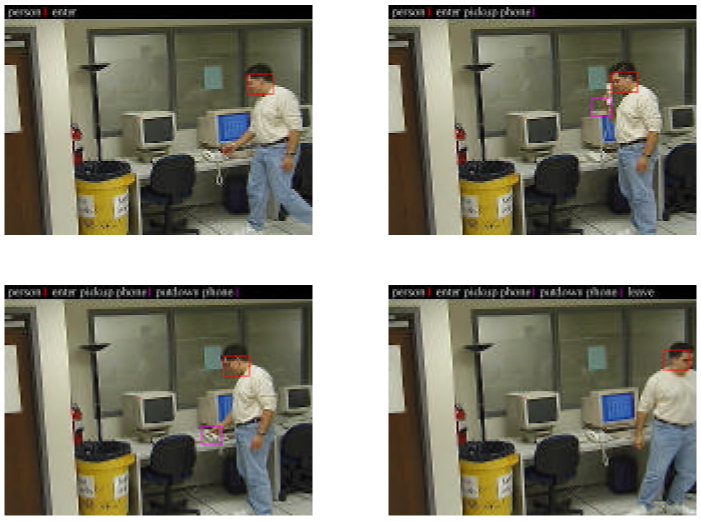




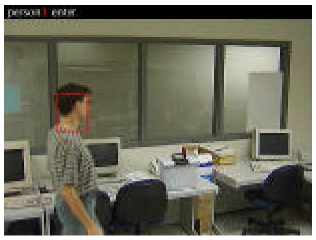


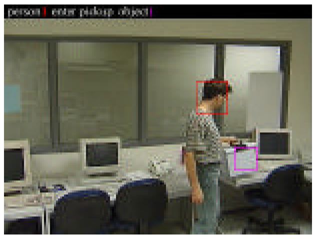

person 1 enter sit stand leave
person 2 enter open cabinet close cabinet leave

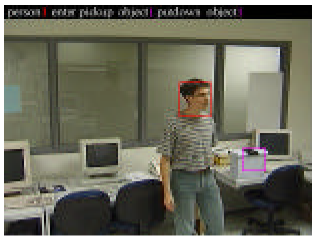
Key Frames Sequence 2 (200 frames)

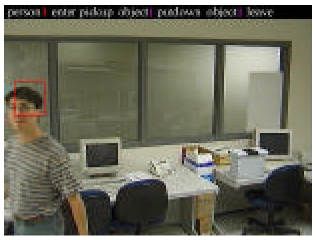

person | enter
person | enter pickup phone |
person | enter pickup phone | putdown phone |
person | enter pickup phone | putdown phone | leave

Key Frames Sequence 3 (200 frames)

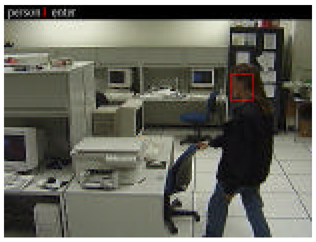


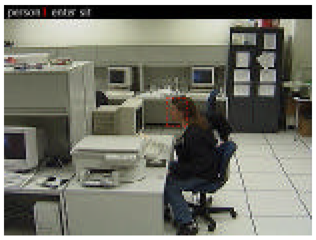


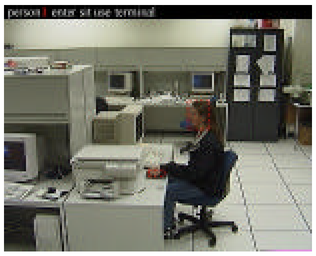


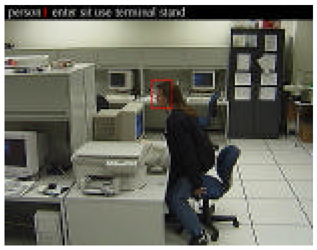


Key Frames Sequence 4 (399 frames), Part 1









Key Frames Sequence 4 (399 frames), Part 2