Applied Computer Vision

David Vernon
Carnegie Mellon University Africa

vernon@cmu.edu www.vernon.eu

Lecture 21

Video Image Processing

Moving Object Detection

Motion detection issues, difference images, background models: static background, running average, selective update, median, running Gaussian average, Gaussian mixture model

Motion detection

Relative motion

- Facilitates segmentation of (moving) foreground from (static) background
- Possibly also segmentation of one moving object from another

Applications

- Motion detection (e.g. security alert)
- Detection and localization of moving object
 - Detection
 - Tracking
 - Recognition
 - Prediction of likely future positions (i.e. expected trajectory)
- Determine 3D structure (so-called structure from motion ... camera or object motion)

Constraints defining objects of interest

Minimum size (in pixels)

Maximum velocity (pedestrians vs. cars)

constrains change in position between frames

Maximum acceleration

constrains change in velocity between frames

Common motion

object move in a coordinated manner

(Near) constant appearance

constrains change in colour or shape

Common problems

Illumination & appearance changes

- Gradual (e.g. time of day)
- Sudden (e.g. clouds, lights)
- Shadows
- Weather (e.g. rain, snow)

Background changes (and may need to be updated)

- Objects becoming part of the background (e.g. parked car)
- Objects leaving the background (e.g. parked car)
- Background objects oscillating slightly (e.g. trees or bushes)

Camera configuration

- Mobile or static?
- Pan, tilt, zoom?
- Time interval between frames: constrain allowable/detectable speed of objects

background: first frame

Difference Images

Image subtraction

Binary image output

$$d(i,j) = \begin{cases} 0 & \text{if } |f_k(i,j) - b(i,j)| < T \\ 1 & \text{otherwise} \end{cases}$$

Grey-level output

$$d(i,j) = |f_k(i,j) - b(i,j)|$$

Options for colour images

- · Process each channel separately
- Just process hue



Difference Images

OpenCV

absdiff(frame, background, difference);

Issues

- Threshold selection
- Sensitivity to threshold
- False positives
 - detected pixels that are not moving
- False negatives
 - undetected pixels that are moving
- May need to perform some morphological processing



Difference Images



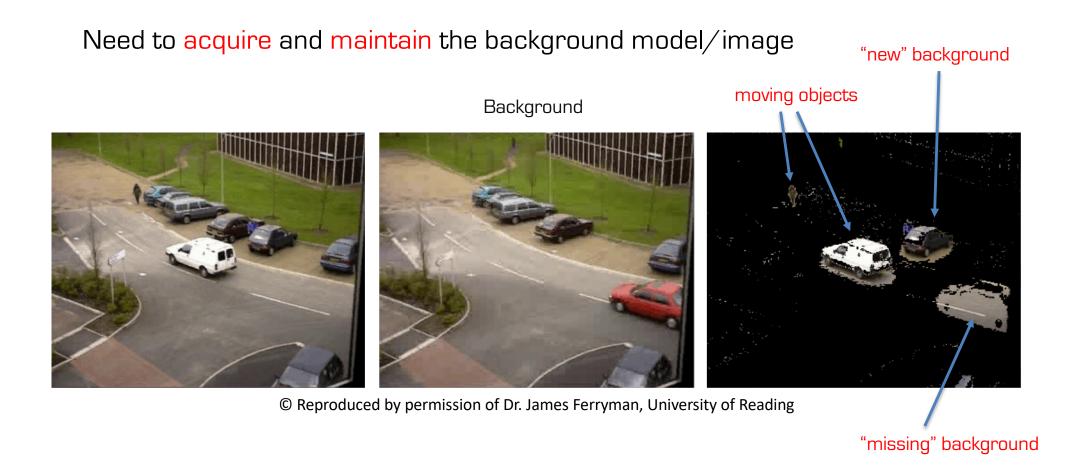
Difference Images







© Reproduced by permission of Dr. James Ferryman, University of Reading



Static background image

Acquire background image by taking a static frame of the scene

Simplest approach

Can't deal with objects being added or removed from the static scene

Cannot deal with illumination changes

Cannot deal with even minor changes in the camera pose

Frame difference

background: previous frame

Image subtraction

$$d(i, j) = |f_n(i, j) - f_{n-1}(i, j)| > \text{Threshold}$$

- Depends on the speed of the objects and the frame rate
- Sensitive to the Threshold



© Reproduced by permission of Dr. James Ferryman, University of Reading

Running Average

- Incorporate changes to the background
- Use the average of the last k frames
- Approximation to avoid storing k frames:

Learning rate

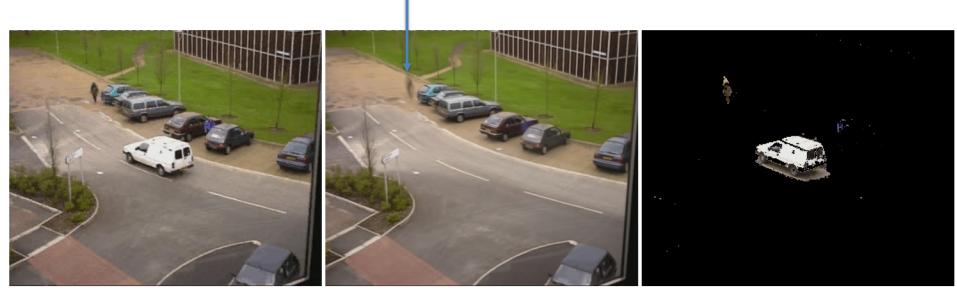
$$b_{n+1}(i,j) = \alpha \cdot f_n(i,j) + (1-\alpha) \cdot b_n(i,j)$$

OpenCV

For colour images, apply to each channel separately

Running Average

- Will adapt to changing lighting conditions
- Will also incorporate in moving objects



© Reproduced by permission of Dr. James Ferryman, University of Reading

Selective Update

 To overcome the problem of incorporating foreground object into the background model, only update pixels which are determined to be background

$$b_{n+1}(i,j) = \begin{cases} \propto f_n(i,j) + (1-\infty) \cdot b_n(i,j) \dots & \text{if } f_n(i,j) \text{ is background} \\ b_n(i,j) & \dots & \text{if } f_n(i,j) \text{ is foreground} \end{cases}$$

OpenCV

Selective Update

- objects that enter the scene and stop (e.g. a car parking) will not be incorporated into the background model
- Moving objects in the first frame are not removed



© Reproduced by permission of Dr. James Ferryman, University of Reading

Selective Update (with running average for foreground)

– Alternative: a different (lower) learning rate eta for the foreground pixels

$$b_{n+1}(i,j) = \begin{cases} \propto f_n(i,j) + (1-\infty). \, b_n(i,j) & \text{... if } f_n(i,j) \text{ is background} \\ \propto /_3. \, f_n(i,j) + \left(1 - \frac{\alpha}{3}\right). \, b_n(i,j) & \text{... if } f_n(i,j) \text{ is foreground} \end{cases}$$



© Reproduced by permission of Dr. James Ferryman, University of Reading

Running Average

Selective Update

Selective Update (with running average)



© Reproduced by permission of Dr. James Ferryman, University of Reading

Median (middle element of an ordered list or a histogram)
Sum over last m frames

Compute the median background image

Histogram bin

$$h_n(i,j,p) = \sum_{k=(n-m+1)..n} \begin{cases} 1 & ... & \text{if } (f_k(i,j) = p) \\ 0 & ... & \text{otherwise} \end{cases}$$

- Decide on the number of frames m
- Decide on the histogram quantisation, i.e. number of bins
- Computationally expensive
 - Adding, storing and removing frames
 - Change in median can be tracked inexpensively from frame to frame
 - Can be approximated using aging

$$h_n(i,j,p) = \sum_{k=1..n} \begin{cases} w_k & ... & \text{if } (f_k(i,j)=p) \\ 0 & ... & \text{otherwise} \end{cases}$$

where $w_1 = 1$ and $w_k = w_{k-1} * 1.001$ or some other value, e.g. 1.005

Can also use selective update

Median

- Not supported in openCV but relatively easily implemented
- Could use the **Mode** instead... (most common value)

$$b_n(i,j) = p$$
 where $h_n(i,j,p) \ge h_n(i,j,q)$ for all $q \ne p$

Median

```
First frame:
  total = 1
  for all pixels (i, j)
    median = f_1(i, j)
     less\_than\_median(i, j) = 0
Current frame (n):
  total = total + w_n
  for all pixels (i, j)
     if (median(i, j) > f_n(i, j))
       less\_than\_median(i, j) = less\_than\_median(i, j) + w_n
     while (less\_than\_median(i,j) + h_n(i,j,median(i,j)) < total/2)
       less\_than\_median(i,j) = less\_than\_median(i,j) + h_n(i,j,median(i,j))
       median(i,j) = median(i,j) + 1
     while (less\_than\_median(i, j) > total/2)
       median(i, j) = median(i, j) - 1
        less\_than\_median(i,j) = less\_than\_median(i,j) - h_n(i,j,median(i,j))
```

Learning Rate = 1.001

Learning Rate = 1.005

Learning Rate = 1.02

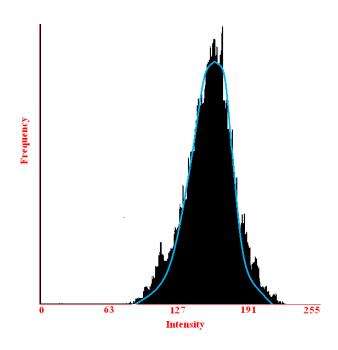


© Reproduced by permission of Dr. James Ferryman, University of Reading

Running Gaussian Average

- Pixel values change from frame to frame
 - · sampling noise
 - variations in illumination
 - ...
- Model the noise as a Gaussian distribution:
 - PDF with mean and standard deviation μ , σ
- Define a point as foreground if it is more than some multiple k of σ from the mean μ

$$|f_n(i,j) - \mu_n(i,j)| > k\sigma_n(i,j)$$



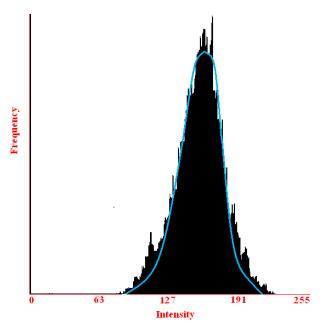
Running Gaussian Average

Update the Gaussian distribution in a manner similar to the running average

$$\mu_{n+1}(i,j) = \alpha f_n(i,j) + (1-\alpha)\mu_n(i,j)$$

$$\sigma_{n+1}^2(i,j) = \alpha (f_n(i,j) - \mu_n(i,j))^2 + (1-\alpha)\sigma_n^2(i,j)$$

 Can also use selective update if necessary so that the foreground objects don't pollute the Gaussian distribution

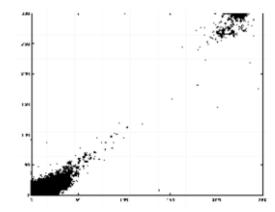


Gaussian Mixture Model

- None of the techniques so far are able to deal with background objects which move slightly
 - ripples on water
 - leaves and branches on trees,
- Stauffer & Grimson (1998) proposed to model each point of the background using a mixture of Gaussian distributions
 - Typically 3 5 distributions per pixel
 - For example
 - If a pixel corresponded to a leaf on a tree, and the leaf is moved by the wind, periodically revealing the sky, then two distributions would model the leaf and the sky respectively
 - If a pixel corresponded to a rippling water, then two distributions would model the water with and without a reflection

Gaussian Mixture Model





Bi-modal distribution of a single pixel's values resulting from specularities on the surface of water

Gaussian Mixture Model

- Fit multiple Gaussian distributions to the historical pixel data for each point
 - Model each pixel $f_n(i, j)$ using K Gaussian distributions $N_K = N(\mu_K, \sigma_K)$
- At any frame n, each Gaussian distribution k ($1 \le k \le K$) has a weight $\omega_{k,n}$ depending on how frequently the distribution been matched in past frames

Gaussian Mixture Model

When a new frame is acquired, each pixel $f_n(i, j)$ is checked against the existing K Gaussian distributions currently modelling that pixel

- If the pixel value is < 2.5 σ from mean μ , then that distribution is updated
- Otherwise, a new distribution is created:
 - The least probable distribution is replaced
 - A new distribution is initialized with
 - mean equal to the pixel value
 - high variance
 - low weight

Gaussian Mixture Model

The prior weights of the K distributions at frame n are adjusted as follows

$$\omega_{k,n} = (1 - \alpha) \omega_{k,n-1} + \alpha M_{k,n}$$

where $M_{k,n}$ = 1 for distribution that matched = 0 for all other distributions

lpha is the learning rate

After this, the weights are re-normalized

The mean μ and standard deviation σ of the unmatched distributions remain the same

Gaussian Mixture Model

The mean μ and standard deviation σ of the distribution k that matches the new observation are updated:

$$\mu_n = (1 - \rho) \mu_{n-1} + \rho f_n(i, j)$$

$$\sigma_n^2 = (1 - \rho) \sigma_{n-1}^2 + \rho (f_n(i, j) - \mu_n)^2$$

where

$$\rho = \alpha N_k(f_n(i,j))$$

The value of the Gaussian distribution for that pixel value (i.e. the probability of that value occurring)

Gaussian Mixture Model

Identify the background distributions (and label the pixel accordingly)

- Define T, a proportion of the frames in which background pixels should be visible (e.g. 70%)
- Order the distributions by value of ω_k / σ
- Choose the first B distributions as the background model where

$$B = \operatorname{argmin}_b \left(\sum_{k=1}^b \omega_k > T \right)$$

where T is a measure of the minimum portion of the data that should be accounted for by the background

e.g. 70% allows for a multi-modal model of the background

Gaussian Mixture Model







© Reproduced by permission of Dr. James Ferryman, University of Reading

Gaussian Mixture Model

openCV supports several variants of the GMM background model

GMG

Andrew B Godbehere, Akihiro Matsukawa, and Ken Goldberg. Visual tracking of human visitors under variable-lighting conditions for a responsive audio art installation. In American Control Conference (ACC), 2012, pages 4305–4312. IEEE, 2012.

MOG

Pakorn KaewTraKulPong and Richard Bowden. An improved adaptive background mixture model for real-time tracking with shadow detection. In Video-Based Surveillance Systems, pages 135–144. Springer, 2002.

MOG2

Pakorn KaewTraKulPong and Richard Bowden. An improved adaptive background mixture model for real-time tracking with shadow detection. In Video-Based Surveillance Systems, pages 135–144. Springer, 2002.

Demos

The following code is taken from the backgroundModelStatic project in the lectures directory of the ACV repository

See:

backgroundModelStatic.h
backgroundModelStaticImplementation.cpp
backgroundModelStaticApplication.cpp

```
Example use of openCV to extract the background and foreground images of a dynamic scene: static model
  (image difference between the first & current frames)
 Implementation file
 David Vernon
  27 October 2017
*/
#include "backgroundModelStatic.h"
 * function backgroundModelStatic
 * Trackbar callback - threshold user input
*/
void backgroundModelStatic(int, void*) {
  extern Mat first_frame;
  extern Mat current frame;
  extern char* input_window_name;
  extern char* background_window_name;
  extern char* foreground_window_name;
  extern int thresholdValue;
  Mat difference_frame;
  Mat binary difference;
  Mat thresholded image;
  if (thresholdValue < 1) // the trackbar has a lower value of 0 which is invalid
     thresholdValue = 1;
```

```
/*
    Adapted from code provided as part of "A Practical Introduction to Computer Vision with OpenCV"
    by Kenneth Dawson-Howe @ Wiley & Sons Inc. 2014. All rights reserved.
    */
absdiff(current_frame,first_frame,difference_frame);
cvtColor(difference_frame, thresholded_image, CV_BGR2GRAY);
threshold(thresholded_image,thresholded_image,thresholdValue,255,THRESH_BINARY);
binary_difference.setTo(Scalar(0,0,0));
current_frame.copyTo(binary_difference, thresholded_image);
/*
imshow(background_window_name, first_frame);
imshow(foreground_window_name, binary_difference);
```

The following code is taken from the backgroundModelRunningAverage project in the lectures directory of the ACV repository

See:

backgroundModelRunningAverage.h
backgroundModelRunningAverageImplementation.cpp
backgroundModelRunningAverageApplication.cpp

```
/*
  Example use of openCV to extract the background and foreground images of a dynamic scene: Running Average Model
  Implementation file
  David Vernon
  27 October 2017
#include "backgroundModelRunningAverage.h"
 * function backgroundModelRunningAverage
 * Trackbar callback - threshold user input
void backgroundModelRunningAverage(int, void*) {
   extern Mat current_frame;
   extern Mat running_average_background;
   extern char* input window name;
   extern char* background_window_name;
   extern char* foreground_window_name;
   extern int thresholdValue;
   Mat difference_frame;
   Mat binary_difference;
   Mat thresholded image;
   if (thresholdValue < 1) // the trackbar has a lower value of 0 which is invalid
      thresholdValue = 1;
```

```
* Adapted from code provided as part of "A Practical Introduction to Computer Vision with OpenCV"
 * by Kenneth Dawson-Howe @ Wiley & Sons Inc. 2014. All rights reserved.
 */
// Running Average (three channel version)
Mat temp_running_average_background;
Mat selective running average background;
Mat running average foreground mask;
Mat running average difference;
Mat running average foreground image;
double running average learning rate = 0.01;
vector<Mat> input planes(3);
split(current frame,input planes);
vector<Mat> running average planes(3);
split(running_average_background,running_average_planes);
accumulateWeighted(input planes[0], running average planes[0], running average learning rate);
accumulateWeighted(input planes[1], running average planes[1], running average learning rate);
accumulateWeighted(input_planes[2], running_average_planes[2], running_average_learning_rate);
merge(running_average_planes,running_average_background);
running average background.convertTo(temp running average background,CV 8U);
absdiff(temp_running_average_background,current_frame,running_average_difference);
split(running average difference, running average planes);
// Determine foreground points as any point with a difference of more than threshold (DV) on any one channel:
threshold(running average difference, running average foreground mask, thresholdValue, 255, THRESH BINARY); // DV replaced literal 30
split(running average foreground mask,running average planes);
bitwise or (running average planes[0], running average planes[1], running average foreground mask );
bitwise_or( running_average_planes[2], running_average_foreground_mask, running_average_foreground_mask );
running average foreground image.setTo(Scalar(0,0,0));
current frame.copyTo(running average foreground image, running average foreground mask);
/* ------*/
imshow(background window name, temp running average background);
imshow(foreground window name, running average foreground image);
```

The following code is taken from the backgroundModelSelectiveUpdate project in the lectures directory of the ACV repository

See:

backgroundModelSelectiveUpdate.h
backgroundModelSelectiveUpdateImplementation.cpp
backgroundModelSelectiveUpdateApplication.cpp

```
Example use of openCV to extract the background and foreground images of a dynamic scene: Selective Update Model
 Implementation file
  David Vernon
  27 October 2017
*/
#include "backgroundModelSelectiveUpdate.h"
 * function backgroundModelSelectiveUpdate
 * Trackbar callback - threshold user input
void backgroundModelSelectiveUpdate(int, void*) {
   extern Mat selective running average background;
   extern Mat current frame;
   extern char* input window name;
   extern char* background window name;
   extern char* foreground_window_name;
   extern int thresholdValue;
   Mat difference_frame;
   Mat binary_difference;
   Mat thresholded image;
   if (thresholdValue < 1) // the trackbar has a lower value of 0 which is invalid
     thresholdValue = 1;
```

```
* Adapted from code provided as part of "A Practical Introduction to Computer Vision with OpenCV"
* by Kenneth Dawson-Howe @ Wiley & Sons Inc. 2014. All rights reserved.
 */
// Selective Running Average
Mat temp selective running average background;
Mat selective running average foreground mask;
Mat selective running average difference;
Mat selective running average foreground image;
double running average learning rate = 0.01;
vector<Mat> input planes(3);
split(current frame,input planes);
// Running Average with selective update
vector<Mat> selective running average planes(3);
// Find Foreground mask
selective_running_average_background.convertTo(temp_selective_running_average_background,CV_8U);
absdiff(temp selective running average background, current frame, selective running average difference);
split(selective running average difference, selective running average planes);
// Determine foreground points as any point with an average difference of more than a given threshold over all channels:
Mat temp sum = (selective running average planes[0] + selective running average planes[1] +
                selective_running_average_planes[2])/3;
threshold(temp_sum,selective_running_average_foreground_mask,thresholdValue,255,THRESH_BINARY_INV); // DV replaced literal 30
                                                                                                    // with thresholdValue
```

```
// Update background
split(selective_running_average_background,selective_running_average_planes);
accumulateWeighted(input planes[0], selective running average planes[0], running average learning rate,
                  selective running average foreground mask);
accumulateWeighted(input_planes[1], selective_running_average_planes[1], running_average_learning_rate,
                  selective_running_average_foreground_mask);
accumulateWeighted(input planes[2], selective running average planes[2], running average learning rate,
                  selective_running_average_foreground_mask);
invertImage(selective running average foreground mask, selective running average foreground mask);
accumulateWeighted(input planes[0], selective running average planes[0], running average learning rate/3.0,
                  selective running average foreground mask);
accumulateWeighted(input_planes[1], selective_running_average_planes[1], running_average_learning_rate/3.0,
                  selective running average foreground mask);
accumulateWeighted(input planes[2], selective running average planes[2], running average learning rate/3.0,
                  selective running average foreground mask);
merge(selective running average planes, selective running average background);
selective_running_average_foreground_image.setTo(Scalar(0,0,0));
current frame.copyTo(selective running average foreground image, selective running average foreground mask);
       */
imshow(background window name, temp selective running average background);
imshow(foreground_window_name, selective_running_average_foreground_image);
```

The following code is taken from the backgroundModelMedian project in the lectures directory of the ACV repository

See:

backgroundModelMedian.h
backgroundModelMedianImplementation.cpp
backgroundModelMedianApplication.cpp

```
Example use of openCV to extract the background and foreground images of a dynamic scene: Median Model
  ______
 Implementation file
 David Vernon
 27 October 2017
*/
#include "backgroundModelMedian.h"
 * function backgroundModelMedian
* Trackbar callback - threshold user input
*/
void backgroundModelMedian(int, void*) {
  extern Mat current frame;
  extern char* input_window_name;
  extern char* background_window_name;
  extern char* foreground window name;
  extern int thresholdValue;
  /* Bug: there is no way to reinstantiate median background or change its properties in the event that
                                                                                                   */
  /* if the dimensions of the current frame change such as will be the case when a new video file is opened */
  /* Consequently, we only run this example with one video file
                                                                                                   */
  static MedianBackground median background( current frame, (float) 1.005, 1 );
  Mat median background image;
  Mat median_foreground_image;
  Mat median difference;
```

```
if (thresholdValue < 1) // the trackbar has a lower value of 0 which is invalid
  thresholdValue = 1;
/*
* Adapted from code provided as part of "A Practical Introduction to Computer Vision with OpenCV"
* by Kenneth Dawson-Howe @ Wiley & Sons Inc. 2014. All rights reserved.
*/
median background.UpdateBackground( current frame );
median background image = median background.GetBackgroundImage();
absdiff(median background image,current frame,median difference);
cvtColor(median_difference, median_difference, CV_BGR2GRAY);
threshold(median_difference, median_difference, thresholdValue, 255, THRESH_BINARY); // DV: replaced literal 30 with thresholdValue
median foreground image.setTo(Scalar(0,0,0));
current frame.copyTo(median foreground image, median difference);
/* -----*/
imshow(background_window_name, median_background_image);
imshow(foreground window name, median foreground image);
```

The following code is taken from the backgroundModelGMM project in the lectures directory of the ACV repository

See:

backgroundGMMStatic.h
backgroundModelGMMImplementation.cpp
backgroundModelGMMApplication.cpp

```
Example use of openCV to extract the background and foreground images of a dynamic scene: Gaussian Mixture Model (GMM)
 Implementation file
 David Vernon
 27 October 2017
#include "backgroundModelGMM.h"
void backgroundModelGMM() {
  extern Mat current frame;
  extern char* input window name;
  extern char* background_window_name;
  extern char* foreground window name;
  extern char* foreground mask window name;
  Mat thresholded_image;
  static BackgroundSubtractorMOG2 gmm;
  /* -----
   * Adapted from code provided as part of "A Practical Introduction to Computer Vision with OpenCV"
   * by Kenneth Dawson-Howe @ Wiley & Sons Inc. 2014. All rights reserved.
   */
  Mat foreground mask;
  Mat foreground image = Mat::zeros(current_frame.size(), CV_8UC3);
  // Update the Gaussian Mixture Model
  gmm(current frame, foreground mask);
```

```
threshold(foreground_mask,thresholded_image,150,255,THRESH_BINARY);
Mat moving_incl_shadows, shadow_points;
threshold(foreground_mask,moving_incl_shadows,50,255,THRESH_BINARY);
absdiff( thresholded_image, moving_incl_shadows, shadow_points);
foreground_image.setTo(Scalar(0,0,0));
current_frame.copyTo(foreground_image, thresholded_image);

// Create an average background image (just for information)
Mat mean_background_image;
gmm.getBackgroundImage(mean_background_image);

/*
imshow(background_window_name, mean_background_image);
imshow(foreground_window_name, foreground_image);
imshow(foreground_mask_window_name, foreground_mask);
```

Reading

R. Szeliski, Computer Vision: Algorithms and Applications, Springer, 2010.

Section 12.6.4 Whole body modeling and tracking