Feature Detection

Canny

Finds edges in an image using the [Canny86] algorithm.

C++: void **Canny**(InputArray **image**, OutputArray **edges**, double **threshold1**, double **threshold2**, int **apertureSize**=3, bool **L2gradient**=false)

Python: `cv2.`**Canny**(image, threshold1, threshold2[, edges[, apertureSize[, L2gradient]]]) → edges

C: void **cvCanny**(const CvArr* **image**, CvArr* **edges**, double **threshold1**, double **threshold2**, int **aperture_size**=3)

Python: `cv.`**Canny**(image, edges, threshold1, threshold2, aperture_size=3) → None

Parameters:
- **image** – single-channel 8-bit input image.
- **edges** – output edge map; it has the same size and type as `image` .
- **threshold1** – first threshold for the hysteresis procedure.
- **threshold2** – second threshold for the hysteresis procedure.
- **apertureSize** – aperture size for the `Sobel()` operator.
- **L2gradient** – a flag, indicating whether a more accurate L_2 norm $= \sqrt{(dI/dx)^2 + (dI/dy)^2}$ should be used to calculate the image gradient magnitude (`L2gradient=true`), or whether the default L_1 norm $= |dI/dx| + |dI/dy|$ is enough (`L2gradient=false`).

The function finds edges in the input image `image` and marks them in the output map `edges` using the Canny algorithm. The smallest value between `threshold1` and `threshold2` is used for edge linking. The largest value is used to find initial segments of strong edges. See http://en.wikipedia.org/wiki/Canny_edge_detector

Note:

- An example on using the canny edge detector can be found at opencv_source_code/samples/cpp/edge.cpp
- (Python) An example on using the canny edge detector can be found at opencv_source_code/samples/python/edge.py

cornerEigenValsAndVecs

Calculates eigenvalues and eigenvectors of image blocks for corner detection.

C++: void **cornerEigenValsAndVecs**(InputArray **src**, OutputArray **dst**, int **blockSize**, int **ksize**, int **borderType**=BORDER_DEFAULT)

Python: `cv2.`**cornerEigenValsAndVecs**(src, blockSize, ksize[, dst[, borderType]]) → dst

C: void **cvCornerEigenValsAndVecs**(const CvArr* **image**, CvArr* **eigenvv**, int **block_size**, int **aperture_size**=3)

Python: `cv.`**CornerEigenValsAndVecs**(image, eigenvv, blockSize, aperture_size=3) → None

Parameters:
- **src** – Input single-channel 8-bit or floating-point image.
- **dst** – Image to store the results. It has the same size as `src` and the type `CV_32FC(6)` .
- **blockSize** – Neighborhood size (see details below).
- **ksize** – Aperture parameter for the `Sobel()` operator.
- **borderType** – Pixel extrapolation method. See `borderInterpolate()` .

For every pixel p , the function `cornerEigenValsAndVecs` considers a `blockSize` $\times$ `blockSize` neighborhood $S(p)$. It calculates the covariation matrix of derivatives over the neighborhood as:

$$M = \begin{bmatrix} \sum_{S(p)}(dI/dx)^2 & \sum_{S(p)}(dI/dx\,dI/dy) \\ \sum_{S(p)}(dI/dx\,dI/dy) & \sum_{S(p)}(dI/dy)^2 \end{bmatrix}$$

where the derivatives are computed using the `Sobel()` operator.

After that, it finds eigenvectors and eigenvalues of M and stores them in the destination image as $(\lambda_1, \lambda_2, x_1, y_1, x_2, y_2)$ where

- λ_1, λ_2 are the non-sorted eigenvalues of M
- x_1, y_1 are the eigenvectors corresponding to λ_1

- x_2, y_2 are the eigenvectors corresponding to λ_2

The output of the function can be used for robust edge or corner detection.

See also: `cornerMinEigenVal()`, `cornerHarris()`, `preCornerDetect()`

Note:

- (Python) An example on how to use eigenvectors and eigenvalues to estimate image texture flow direction can be found at opencv_source_code/samples/python2/texture_flow.py

cornerHarris

Harris edge detector.

C++: void **cornerHarris**(InputArray **src**, OutputArray **dst**, int **blockSize**, int **ksize**, double **k**, int **borderType**=BORDER_DEFAULT)

Python: cv2.**cornerHarris**(src, blockSize, ksize, k[, dst[, borderType]]) → dst

C: void **cvCornerHarris**(const CvArr* **image**, CvArr* **harris_response**, int **block_size**, int **aperture_size**=3, double **k**=0.04)

Python: cv.**CornerHarris**(image, harris_dst, blockSize, aperture_size=3, k=0.04) → None

Parameters:
- **src** – Input single-channel 8-bit or floating-point image.
- **dst** – Image to store the Harris detector responses. It has the type `CV_32FC1` and the same size as `src` .
- **blockSize** – Neighborhood size (see the details on `cornerEigenValsAndVecs()`).
- **ksize** – Aperture parameter for the `Sobel()` operator.
- **k** – Harris detector free parameter. See the formula below.
- **borderType** – Pixel extrapolation method. See `borderInterpolate()` .

The function runs the Harris edge detector on the image. Similarly to `cornerMinEigenVal()` and `cornerEigenValsAndVecs()` , for each pixel (x, y) it calculates a 2×2 gradient covariance matrix $M^{(x,y)}$ over a $\texttt{blockSize} \times \texttt{blockSize}$ neighborhood. Then, it computes the following characteristic:

$$\texttt{dst}(x,y) = \mathrm{det} M^{(x,y)} - k \cdot \left(\mathrm{tr} M^{(x,y)} \right)^2$$

Corners in the image can be found as the local maxima of this response map.

cornerMinEigenVal

Calculates the minimal eigenvalue of gradient matrices for corner detection.

C++: void **cornerMinEigenVal**(InputArray **src**, OutputArray **dst**, int **blockSize**, int **ksize**=3, int **borderType**=BORDER_DEFAULT)

Python: cv2.**cornerMinEigenVal**(src, blockSize[, dst[, ksize[, borderType]]]) → dst

C: void **cvCornerMinEigenVal**(const CvArr* **image**, CvArr* **eigenval**, int **block_size**, int **aperture_size**=3)

Python: cv.**CornerMinEigenVal**(image, eigenval, blockSize, aperture_size=3) → None

Parameters:
- **src** – Input single-channel 8-bit or floating-point image.
- **dst** – Image to store the minimal eigenvalues. It has the type `CV_32FC1` and the same size as `src` .
- **blockSize** – Neighborhood size (see the details on `cornerEigenValsAndVecs()`).
- **ksize** – Aperture parameter for the `Sobel()` operator.
- **borderType** – Pixel extrapolation method. See `borderInterpolate()` .

The function is similar to `cornerEigenValsAndVecs()` but it calculates and stores only the minimal eigenvalue of the covariance matrix of derivatives, that is, $\min(\lambda_1, \lambda_2)$ in terms of the formulae in the `cornerEigenValsAndVecs()` description.

cornerSubPix

Refines the corner locations.

C++: void **cornerSubPix**(InputArray **image**, InputOutputArray **corners**, Size **winSize**, Size **zeroZone**, TermCriteria **criteria**)

Python: `cv2.`**cornerSubPix**(image, corners, winSize, zeroZone, criteria) → None

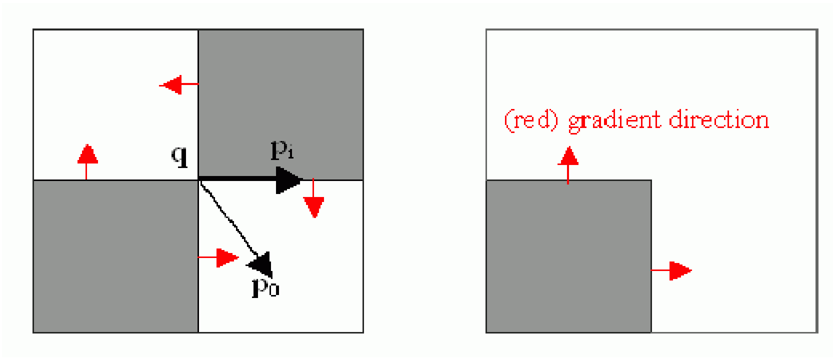
C: void **cvFindCornerSubPix**(const CvArr* **image**, CvPoint2D32f* **corners**, int **count**, CvSize **win**, CvSize **zero_zone**, CvTermCriteria **criteria**)

Python: `cv.`**FindCornerSubPix**(image, corners, win, zero_zone, criteria) → corners

Parameters:

- **image** – Input image.
- **corners** – Initial coordinates of the input corners and refined coordinates provided for output.
- **winSize** – Half of the side length of the search window. For example, if `winSize=Size(5,5)` , then a $5*2+1 \times 5*2+1 = 11 \times 11$ search window is used.
- **zeroZone** – Half of the size of the dead region in the middle of the search zone over which the summation in the formula below is not done. It is used sometimes to avoid possible singularities of the autocorrelation matrix. The value of (-1,-1) indicates that there is no such a size.
- **criteria** – Criteria for termination of the iterative process of corner refinement. That is, the process of corner position refinement stops either after `criteria.maxCount` iterations or when the corner position moves by less than `criteria.epsilon` on some iteration.

The function iterates to find the sub-pixel accurate location of corners or radial saddle points, as shown on the figure below.



Sub-pixel accurate corner locator is based on the observation that every vector from the center q to a point p located within a neighborhood of q is orthogonal to the image gradient at p subject to image and measurement noise. Consider the expression:

$$\epsilon_i = {DI_{p_i}}^T \cdot (q - p_i)$$

where DI_{p_i} is an image gradient at one of the points p_i in a neighborhood of q . The value of q is to be found so that ϵ_i is minimized. A system of equations may be set up with ϵ_i set to zero:

$$\sum_i (DI_{p_i} \cdot {DI_{p_i}}^T) - \sum_i (DI_{p_i} \cdot {DI_{p_i}}^T \cdot p_i)$$

where the gradients are summed within a neighborhood ("search window") of q . Calling the first gradient term G and the second gradient term b gives:

$$q = G^{-1} \cdot b$$

The algorithm sets the center of the neighborhood window at this new center q and then iterates until the center stays within a set threshold.

goodFeaturesToTrack

Determines strong corners on an image.

C++: void **goodFeaturesToTrack**(InputArray **image**, OutputArray **corners**, int **maxCorners**, double **qualityLevel**, double **minDistance**, InputArray **mask**=noArray(), int **blockSize**=3, bool **useHarrisDetector**=false, double **k**=0.04)

Python: `cv2.`**goodFeaturesToTrack**(image, maxCorners, qualityLevel, minDistance[, corners[, mask[, blockSize[, useHarrisDetector[, k]]]]]) → corners

C: void **cvGoodFeaturesToTrack**(const CvArr* **image**, CvArr* **eig_image**, CvArr* **temp_image**, CvPoint2D32f* **corners**, int* **corner_count**, double **quality_level**, double **min_distance**, const CvArr* **mask**=NULL, int **block_size**=3, int **use_harris**=0, double **k**=0.04)

Python: cv.**GoodFeaturesToTrack**(image, eigImage, tempImage, cornerCount, qualityLevel, minDistance, mask=None, blockSize=3, useHarris=0, k=0.04) → cornerCount

Parameters:

- **image** – Input 8-bit or floating-point 32-bit, single-channel image.
- **eig_image** – The parameter is ignored.
- **temp_image** – The parameter is ignored.
- **corners** – Output vector of detected corners.
- **maxCorners** – Maximum number of corners to return. If there are more corners than are found, the strongest of them is returned.
- **qualityLevel** – Parameter characterizing the minimal accepted quality of image corners. The parameter value is multiplied by the best corner quality measure, which is the minimal eigenvalue (see `cornerMinEigenVal()`) or the Harris function response (see `cornerHarris()`). The corners with the quality measure less than the product are rejected. For example, if the best corner has the quality measure = 1500, and the `qualityLevel=0.01` , then all the corners with the quality measure less than 15 are rejected.
- **minDistance** – Minimum possible Euclidean distance between the returned corners.
- **mask** – Optional region of interest. If the image is not empty (it needs to have the type `CV_8UC1` and the same size as `image`), it specifies the region in which the corners are detected.
- **blockSize** – Size of an average block for computing a derivative covariation matrix over each pixel neighborhood. See `cornerEigenValsAndVecs()` .
- **useHarrisDetector** – Parameter indicating whether to use a Harris detector (see `cornerHarris()`) or `cornerMinEigenVal()`.
- **k** – Free parameter of the Harris detector.

The function finds the most prominent corners in the image or in the specified image region, as described in [Shi94]:

1. Function calculates the corner quality measure at every source image pixel using the `cornerMinEigenVal()` or `cornerHarris()` .
2. Function performs a non-maximum suppression (the local maximums in *3 x 3* neighborhood are retained).
3. The corners with the minimal eigenvalue less than $\texttt{qualityLevel} \cdot \max_{x,y} qualityMeasureMap(x,y)$ are rejected.
4. The remaining corners are sorted by the quality measure in the descending order.
5. Function throws away each corner for which there is a stronger corner at a distance less than `maxDistance`.

The function can be used to initialize a point-based tracker of an object.

Note: If the function is called with different values `A` and `B` of the parameter `qualityLevel` , and `A` > {B}, the vector of returned corners with `qualityLevel=A` will be the prefix of the output vector with `qualityLevel=B` .

See also: `cornerMinEigenVal()`, `cornerHarris()`, `calcOpticalFlowPyrLK()`, `estimateRigidTransform()`,

HoughCircles

Finds circles in a grayscale image using the Hough transform.

C++: void **HoughCircles**(InputArray **image**, OutputArray **circles**, int **method**, double **dp**, double **minDist**, double **param1**=100, double **param2**=100, int **minRadius**=0, int **maxRadius**=0)

C: CvSeq* **cvHoughCircles**(CvArr* **image**, void* **circle_storage**, int **method**, double **dp**, double **min_dist**, double **param1**=100, double **param2**=100, int **min_radius**=0, int **max_radius**=0)

Python: cv2.**HoughCircles**(image, method, dp, minDist[, circles[, param1[, param2[, minRadius[, maxRadius]]]]]) → circles

Parameters:

- **image** – 8-bit, single-channel, grayscale input image.
- **circles** – Output vector of found circles. Each vector is encoded as a 3-element floating-point vector $(x, y, radius)$.
- **circle_storage** – In C function this is a memory storage that will contain the output sequence of found circles.
- **method** – Detection method to use. Currently, the only implemented method is `CV_HOUGH_GRADIENT` , which is basically *21HT* , described in [Yuen90].
- **dp** – Inverse ratio of the accumulator resolution to the image resolution. For example, if `dp=1` , the accumulator has the same resolution as the input image. If `dp=2` , the accumulator has half as big width and height.
- **minDist** – Minimum distance between the centers of the detected circles. If the parameter is too small, multiple neighbor circles may be falsely detected in addition to a true one. If it is too large, some circles may be missed.
- **param1** – First method-specific parameter. In case of `CV_HOUGH_GRADIENT` , it is the higher threshold of the two passed to the `Canny()` edge detector (the lower one is twice smaller).

- **param2** – Second method-specific parameter. In case of `CV_HOUGH_GRADIENT` , it is the accumulator threshold for the circle centers at the detection stage. The smaller it is, the more false circles may be detected. Circles, corresponding to the larger accumulator values, will be returned first.
- **minRadius** – Minimum circle radius.
- **maxRadius** – Maximum circle radius.

The function finds circles in a grayscale image using a modification of the Hough transform.

Example:

```
#include <cv.h>
#include <highgui.h>
#include <math.h>

using namespace cv;

int main(int argc, char** argv)
{
    Mat img, gray;
    if( argc != 2 && !(img=imread(argv[1], 1)).data)
        return -1;
    cvtColor(img, gray, CV_BGR2GRAY);
    // smooth it, otherwise a lot of false circles may be detected
    GaussianBlur( gray, gray, Size(9, 9), 2, 2 );
    vector<Vec3f> circles;
    HoughCircles(gray, circles, CV_HOUGH_GRADIENT,
                 2, gray->rows/4, 200, 100 );
    for( size_t i = 0; i < circles.size(); i++ )
    {
         Point center(cvRound(circles[i][0]), cvRound(circles[i][1]));
         int radius = cvRound(circles[i][2]);
         // draw the circle center
         circle( img, center, 3, Scalar(0,255,0), -1, 8, 0 );
         // draw the circle outline
         circle( img, center, radius, Scalar(0,0,255), 3, 8, 0 );
    }
    namedWindow( "circles", 1 );
    imshow( "circles", img );
    return 0;
}
```

Note: Usually the function detects the centers of circles well. However, it may fail to find correct radii. You can assist to the function by specifying the radius range (`minRadius` and `maxRadius`) if you know it. Or, you may ignore the returned radius, use only the center, and find the correct radius using an additional procedure.

See also: `fitEllipse()`, `minEnclosingCircle()`

Note:

- An example using the Hough circle detector can be found at opencv_source_code/samples/cpp/houghcircles.cpp

HoughLines

Finds lines in a binary image using the standard Hough transform.

C++: void **HoughLines**(InputArray **image**, OutputArray **lines**, double **rho**, double **theta**, int **threshold**, double **srn**=0, double **stn**=0)

Python: cv2.**HoughLines**(image, rho, theta, threshold[, lines[, srn[, stn]]]) → lines

C: CvSeq* **cvHoughLines2**(CvArr* **image**, void* **line_storage**, int **method**, double **rho**, double **theta**, int **threshold**, double **param1**=0, double **param2**=0)

Python: cv.**HoughLines2**(image, storage, method, rho, theta, threshold, param1=0, param2=0) → lines

Parameters:

- **image** – 8-bit, single-channel binary source image. The image may be modified by the function.
- **lines** – Output vector of lines. Each line is represented by a two-element vector (ρ, θ) . ρ is the distance from the coordinate origin $(0, 0)$ (top-left corner of the image). θ is the line rotation angle in radians ($0 \sim \text{vertical line}, \pi/2 \sim \text{horizontal line}$).
- **rho** – Distance resolution of the accumulator in pixels.
- **theta** – Angle resolution of the accumulator in radians.

- **threshold** – Accumulator threshold parameter. Only those lines are returned that get enough votes ($> \texttt{threshold}$).
- **srn** – For the multi-scale Hough transform, it is a divisor for the distance resolution `rho` . The coarse accumulator distance resolution is `rho` and the accurate accumulator resolution is `rho/srn` . If both `srn=0` and `stn=0` , the classical Hough transform is used. Otherwise, both these parameters should be positive.
- **stn** – For the multi-scale Hough transform, it is a divisor for the distance resolution `theta`.
- **method** –

  One of the following Hough transform variants:

  - **CV_HOUGH_STANDARD** classical or standard Hough transform. Every line is represented by two floating-point numbers (ρ, θ) , where ρ is a distance between (0,0) point and the line, and θ is the angle between x-axis and the normal to the line. Thus, the matrix must be (the created sequence will be) of `CV_32FC2` type
  - **CV_HOUGH_PROBABILISTIC** probabilistic Hough transform (more efficient in case if the picture contains a few long linear segments). It returns line segments rather than the whole line. Each segment is represented by starting and ending points, and the matrix must be (the created sequence will be) of the `CV_32SC4` type.
  - **CV_HOUGH_MULTI_SCALE** multi-scale variant of the classical Hough transform. The lines are encoded the same way as `CV_HOUGH_STANDARD`.
- **param1** –

  First method-dependent parameter:

  - For the classical Hough transform, it is not used (0).
  - For the probabilistic Hough transform, it is the minimum line length.
  - For the multi-scale Hough transform, it is `srn`.
- **param2** –

  Second method-dependent parameter:

  - For the classical Hough transform, it is not used (0).
  - For the probabilistic Hough transform, it is the maximum gap between line segments lying on the same line to treat them as a single line segment (that is, to join them).
  - For the multi-scale Hough transform, it is `stn`.

The function implements the standard or standard multi-scale Hough transform algorithm for line detection. See http://homepages.inf.ed.ac.uk/rbf/HIPR2/hough.htm for a good explanation of Hough transform. See also the example in `HoughLinesP()` description.

Note:

- An example using the Hough line detector can be found at opencv_source_code/samples/cpp/houghlines.cpp

HoughLinesP

Finds line segments in a binary image using the probabilistic Hough transform.

C++: void **HoughLinesP**(InputArray **image**, OutputArray **lines**, double **rho**, double **theta**, int **threshold**, double **minLineLength**=0, double **maxLineGap**=0)

Python: `cv2.`**HoughLinesP**(image, rho, theta, threshold[, lines[, minLineLength[, maxLineGap]]]) → lines

Parameters:

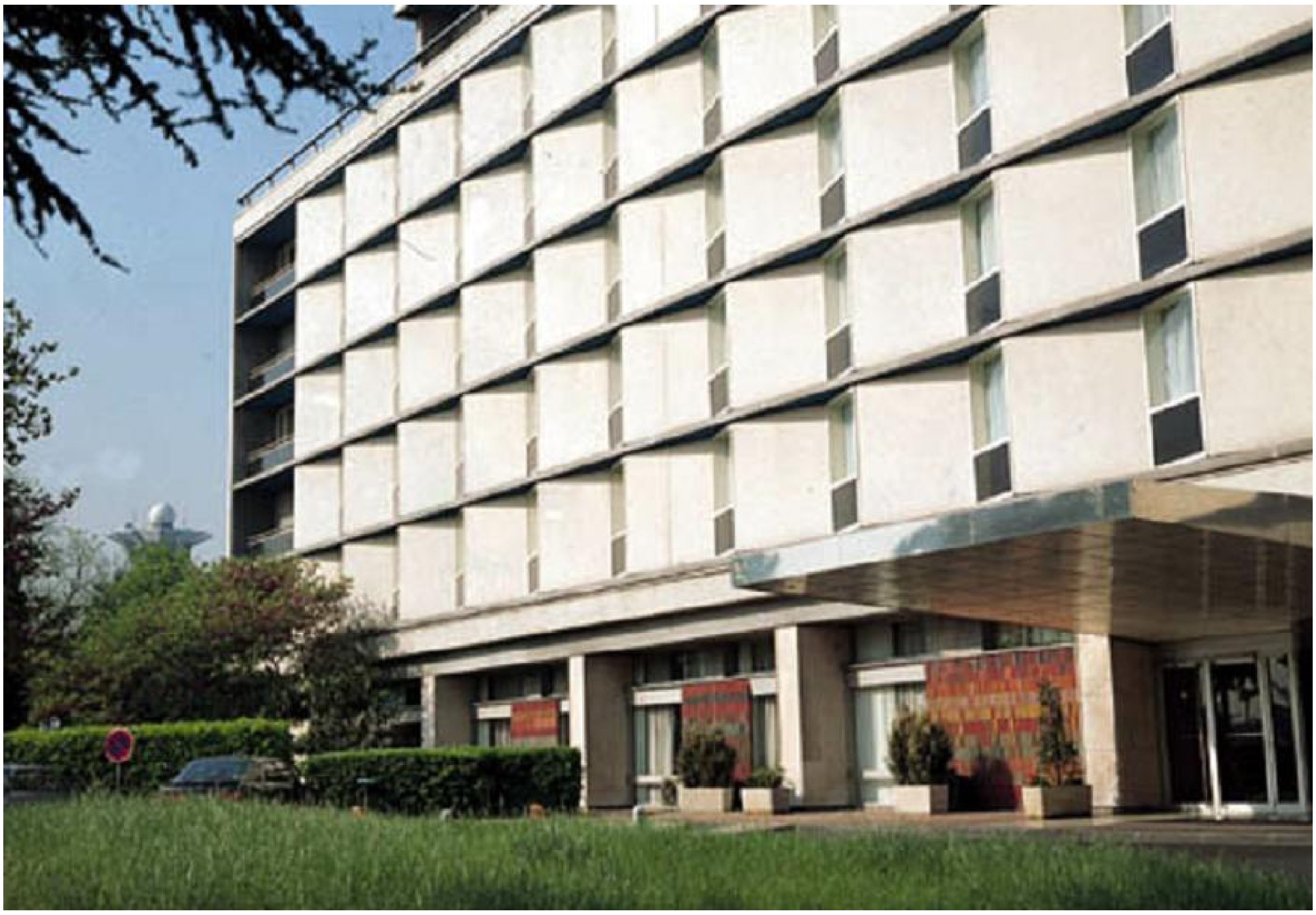
- **image** – 8-bit, single-channel binary source image. The image may be modified by the function.
- **lines** – Output vector of lines. Each line is represented by a 4-element vector (x_1, y_1, x_2, y_2) , where (x_1, y_1) and (x_2, y_2) are the ending points of each detected line segment.
- **rho** – Distance resolution of the accumulator in pixels.
- **theta** – Angle resolution of the accumulator in radians.
- **threshold** – Accumulator threshold parameter. Only those lines are returned that get enough votes ($> \texttt{threshold}$).
- **minLineLength** – Minimum line length. Line segments shorter than that are rejected.
- **maxLineGap** – Maximum allowed gap between points on the same line to link them.

The function implements the probabilistic Hough transform algorithm for line detection, described in [Matas00]. See the line detection example below:

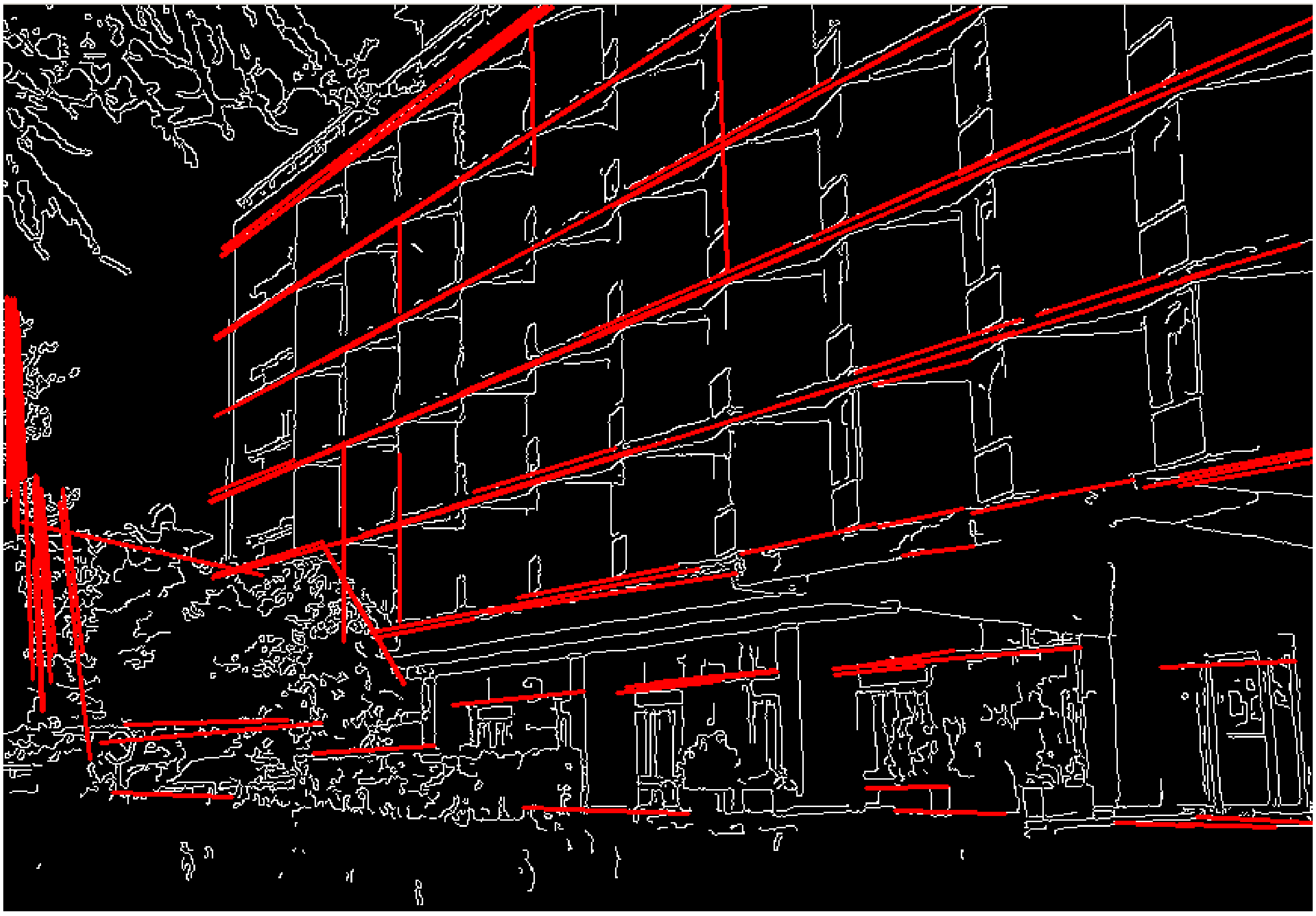
```
/* This is a standalone program. Pass an image name as the first parameter
of the program.  Switch between standard and probabilistic Hough transform
by changing "#if 1" to "#if 0" and back */
```

```
#include <cv.h>
#include <highgui.h>
#include <math.h>

using namespace cv;

int main(int argc, char** argv)
{
    Mat src, dst, color_dst;
    if( argc != 2 || !(src=imread(argv[1], 0)).data)
        return -1;

    Canny( src, dst, 50, 200, 3 );
    cvtColor( dst, color_dst, CV_GRAY2BGR );

#if 0
    vector<Vec2f> lines;
    HoughLines( dst, lines, 1, CV_PI/180, 100 );

    for( size_t i = 0; i < lines.size(); i++ )
    {
        float rho = lines[i][0];
        float theta = lines[i][1];
        double a = cos(theta), b = sin(theta);
        double x0 = a*rho, y0 = b*rho;
        Point pt1(cvRound(x0 + 1000*(-b)),
                  cvRound(y0 + 1000*(a)));
        Point pt2(cvRound(x0 - 1000*(-b)),
                  cvRound(y0 - 1000*(a)));
        line( color_dst, pt1, pt2, Scalar(0,0,255), 3, 8 );
    }
#else
    vector<Vec4i> lines;
    HoughLinesP( dst, lines, 1, CV_PI/180, 80, 30, 10 );
    for( size_t i = 0; i < lines.size(); i++ )
    {
        line( color_dst, Point(lines[i][0], lines[i][1]),
            Point(lines[i][2], lines[i][3]), Scalar(0,0,255), 3, 8 );
    }
#endif
    namedWindow( "Source", 1 );
    imshow( "Source", src );

    namedWindow( "Detected Lines", 1 );
    imshow( "Detected Lines", color_dst );

    waitKey(0);
    return 0;
}
```

This is a sample picture the function parameters have been tuned for:



And this is the output of the above program in case of the probabilistic Hough transform:



preCornerDetect

Calculates a feature map for corner detection.

C++: void **preCornerDetect**(InputArray **src**, OutputArray **dst**, int **ksize**, int **borderType**=BORDER_DEFAULT)

Python: cv2.**preCornerDetect**(src, ksize[, dst[, borderType]]) → dst

C: void **cvPreCornerDetect**(const CvArr* **image**, CvArr* **corners**, int **aperture_size**=3)

Python: cv.**PreCornerDetect**(image, corners, apertureSize=3) → None

Parameters:
- **src** – Source single-channel 8-bit of floating-point image.
- **dst** – Output image that has the type `CV_32F` and the same size as `src` .
- **ksize** – Aperture size of the `Sobel()` .
- **borderType** – Pixel extrapolation method. See `borderInterpolate()` .

The function calculates the complex spatial derivative-based function of the source image

$$\texttt{dst} = (D_x \texttt{src})^2 \cdot D_{yy} \texttt{src} + (D_y \texttt{src})^2 \cdot D_{xx} \texttt{src} - 2 D_x \texttt{src} \cdot D_y \texttt{src} \cdot D_{xy} \texttt{src}$$

where D_x,:math:*D_y* are the first image derivatives, D_{xx},:math:*D_{yy}* are the second image derivatives, and D_{xy} is the mixed derivative.

The corners can be found as local maximums of the functions, as shown below:

```
Mat corners, dilated_corners;
preCornerDetect(image, corners, 3);
// dilation with 3x3 rectangular structuring element
dilate(corners, dilated_corners, Mat(), 1);
Mat corner_mask = corners == dilated_corners;
```

[Canny86] J. Canny. *A Computational Approach to Edge Detection*, IEEE Trans. on Pattern Analysis and Machine Intelligence, 8(6), pp. 679-698 (1986).

[Matas00] Matas, J. and Galambos, C. and Kittler, J.V., *Robust Detection of Lines Using the Progressive Probabilistic Hough Transform*. CVIU 78 1, pp 119-137 (2000)

[Shi94] J. Shi and C. Tomasi. *Good Features to Track*. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 593-600, June 1994.

[Yuen90] Yuen, H. K. and Princen, J. and Illingworth, J. and Kittler, J., *Comparative study of Hough transform methods for circle finding*. Image Vision Comput. 8 1, pp 71–77 (1990)