

Deep learning Models for Image/Video

Prof. Venki Muthukumar

What is OpenCV

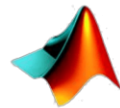


- **OpenCV: Open-Source Computer Vision & Machine Learning software library**
 - Created in 1999 by Intel
 - Supported from 2008 by Willow Garage(a SME dedicated to hardware & open-source software for personal robotics applications)
 - www.willowgarage.com/pages/software/overview
 - Willow Garage also supports the Point Cloud Library (PCL)
- **Cross-platform**
 - Windows|Linux|Android|MacOS|iOS_{*}
- **Free under BSD License**
 - Commercial & non-commercial applications

OpenCV



- **Written in C / C++**
- **Extended to Python**
- Stable source code opencv.org/releases
- Developments
 - Source code github.com/opencv
 - Wiki github.com/opencv/opencv/wiki
- **APIs available for a variety of programming languages**



MATLAB



- **Current stable version is 4.13.0**



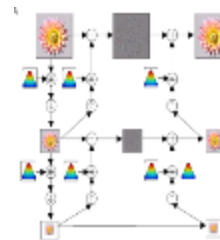
opencv.willowgarage.com

OpenCV Overview:

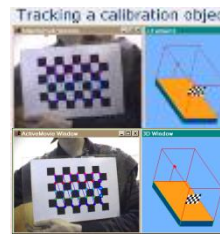
> 2000 algorithms

Robot support

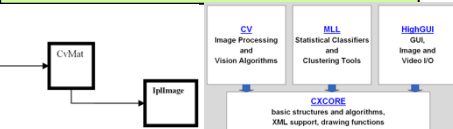
Image Pyramids



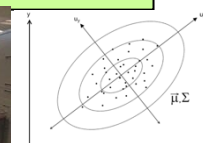
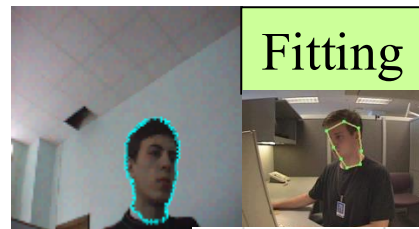
Camera calibration, Stereo, 3D



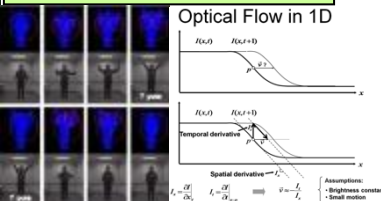
Utilities and Data Structures



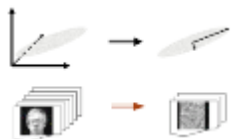
Fitting



Tracking



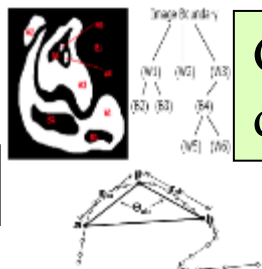
Matrix Math



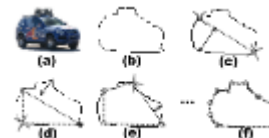
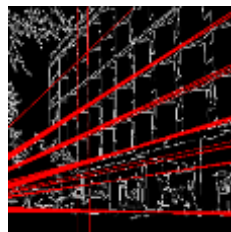
General Image Processing Functions



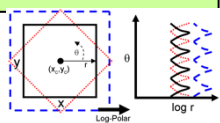
Geometric descriptors



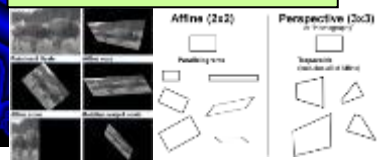
Features



Segmentation

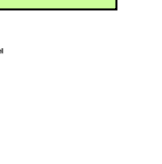
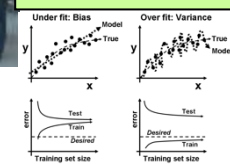


Transforms



Machine Learning:

- Detection,
- Recognition



Where is OpenCV Used?



Embedded ML

- Google Maps, Google street view, Google Earth, Books
- Academic and Industry Research
- Safety monitoring (Dam sites, mines, swimming pools)
- Security systems
- Image retrieval
- Video search
- Structure from motion in movies
- Machine vision factory production inspection systems
- Robotics



OpenCV & DL

- Tensorflow, Pytorch, Caffe, MxNet, CNTK, Keras etc. are the libraries use OpenCV to build deep learning vision models.



OpenCV Resources

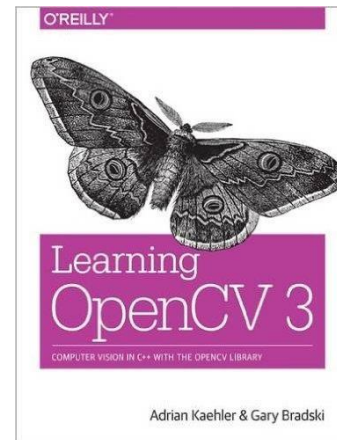
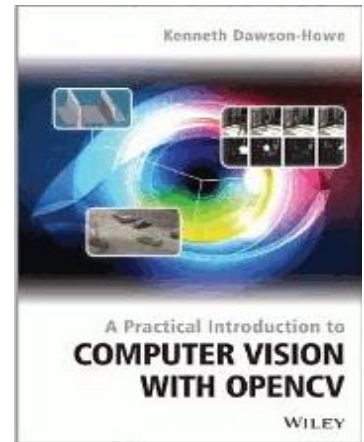
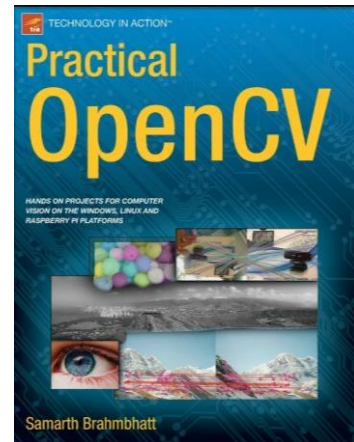
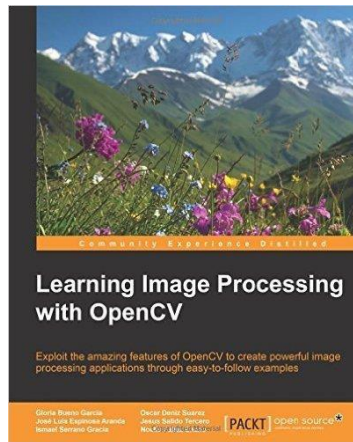
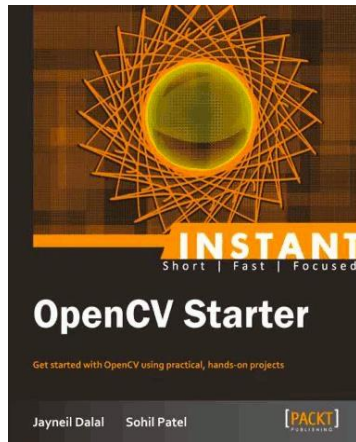
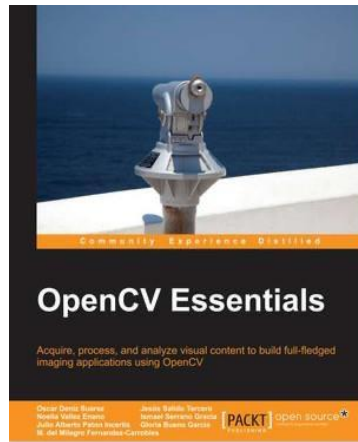


- **Online documentation** docs.opencv.org
- Reference | Tutorials | QuickStart | Examples
- **Online resources** opencv.org>Resources
- Books | Publications | Usefullinks
- **Q&A Forum** answers.opencv.org



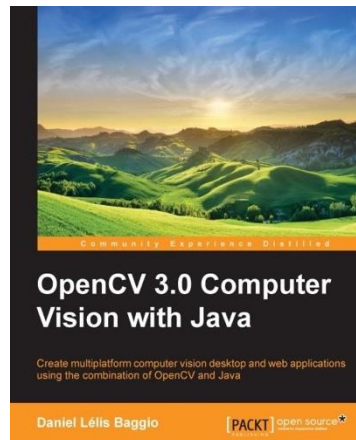
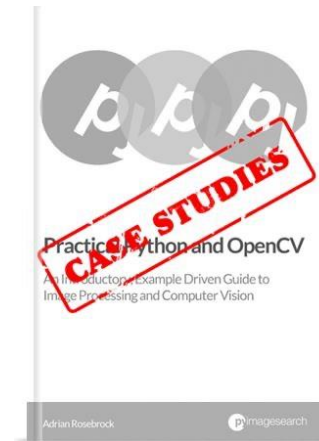
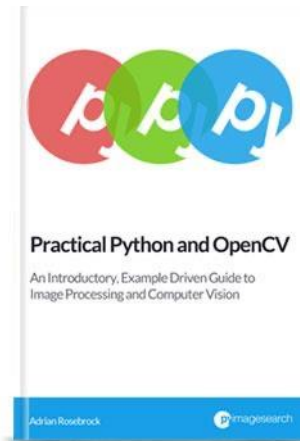
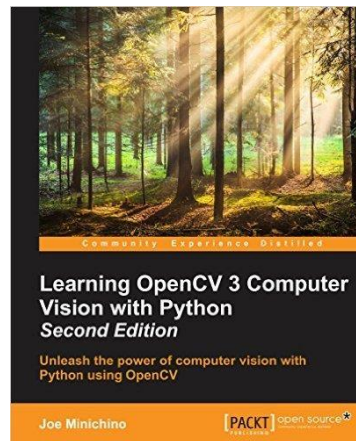
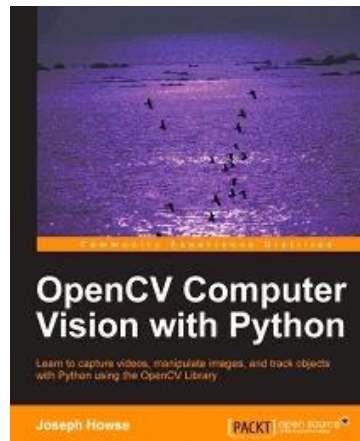
Embedded ML

Bibliography



Bibliography

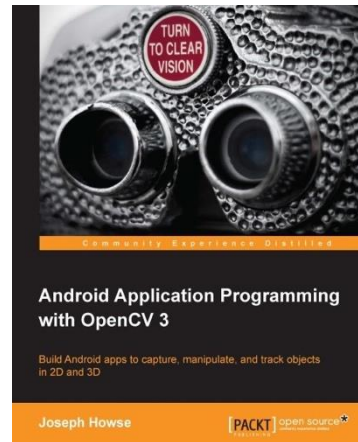
Python | Java | .NET APIs



Bibliography

Mobile & Game APIs

Android | iOS | Raspberry Pi | Unity



OpenCV Modules



- **Calib3d**
 - Calibration, stereo, homography, rectify, projection, solvePNP
- **Contrib**
 - Octree, self-similar feature, sparse L-M, bundle adj, chamfer match
- **Core**
 - Data structures, access, matrix ops, basic image operations
- **features2D**
 - Feature detectors, descriptors and matchers in one architecture
- **Flann** (Fast library for approximate nearest neighbors)
- **Gpu** – CUDA speedups
- **Highgui**
 - Gui to read, write, draw, print and interact with images
- **Imgproc** – image processing functions
- **ML** – statistical machine learning, boosting, clustering
- **Objdetect** – PASCAL VOC latent SVM and data reading
- **Traincascade** – boosted rejection cascade

Digital Image Acquisition

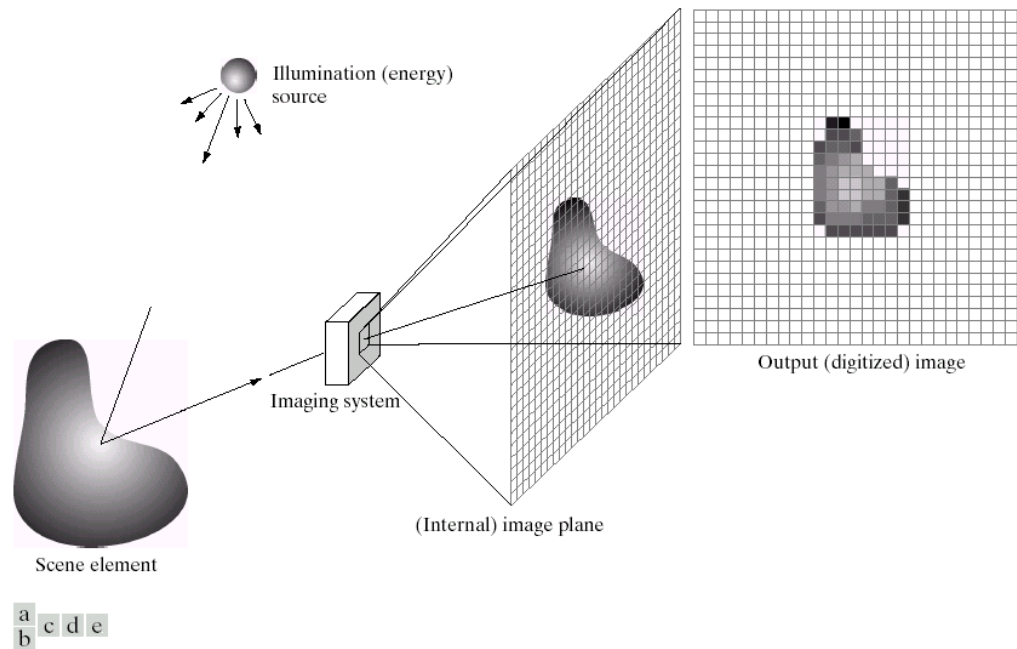


FIGURE 2.15 An example of the digital image acquisition process. (a) Energy (“illumination”) source. (b) An element of a scene. (c) Imaging system. (d) Projection of the scene onto the image plane. (e) Digitized image.

Digital Camera Issues



- Noise

- caused by low light



- Color

- color fringing (chromatic aberration) artifacts from Bayer patterns



- Blooming

- charge overflowing into neighboring pixels



- In-camera processing

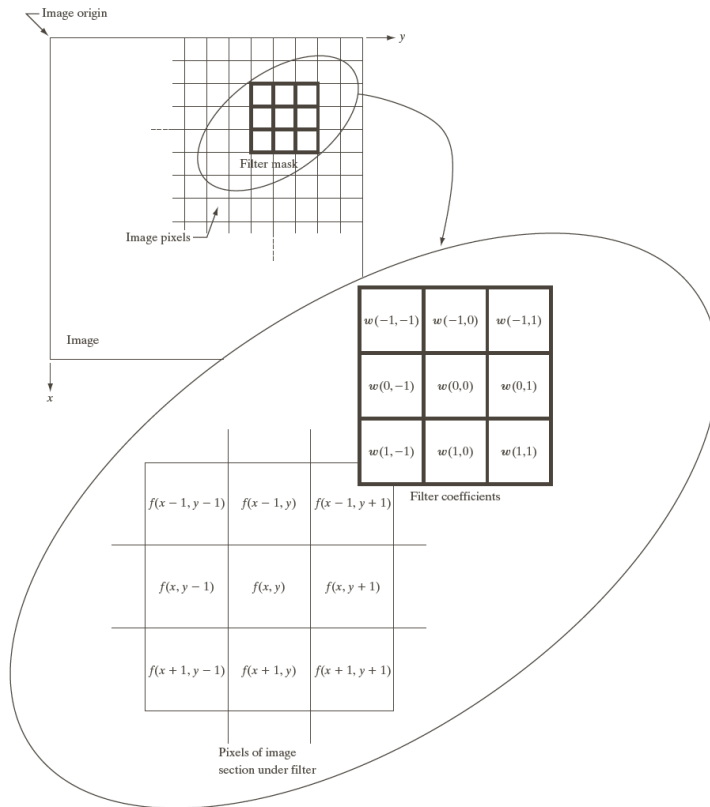
- over-sharpening can produce halos

- Compression

- creates blocking artefacts



Image Filtering



Input Image

| | | | | |
|---|---|---|---|---|
| 7 | 8 | 4 | 5 | 5 |
| 5 | 9 | 4 | 3 | 8 |
| 5 | 2 | 7 | 2 | 2 |
| 6 | 1 | 9 | 2 | 4 |
| 3 | 2 | 6 | 9 | 4 |

median

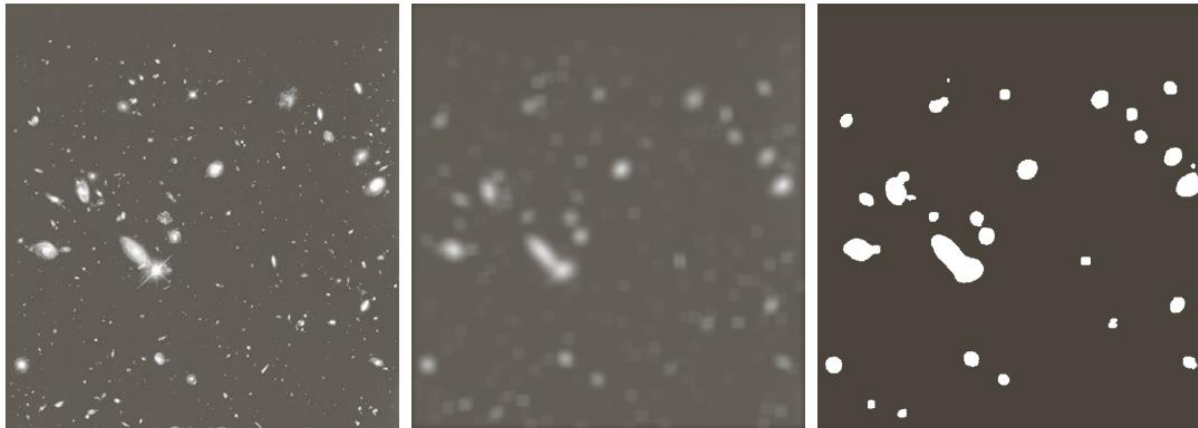
| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 2 | 2 | 2 | 2 | 4 | 4 | 4 | 9 | 9 |
|---|---|---|---|---|---|---|---|---|

Filtered Img

| | | | | |
|---|---|---|---|---|
| 8 | 5 | 4 | 4 | 5 |
| 7 | 5 | 4 | 4 | 3 |
| 5 | 5 | 3 | 4 | 2 |
| 2 | 5 | 2 | 4 | 2 |
| 2 | 6 | 2 | 4 | 4 |

FIGURE 3.28 The mechanics of linear spatial filtering using a 3×3 filter mask. The form chosen to denote the coordinates of the filter mask coefficients simplifies writing expressions for linear filtering.

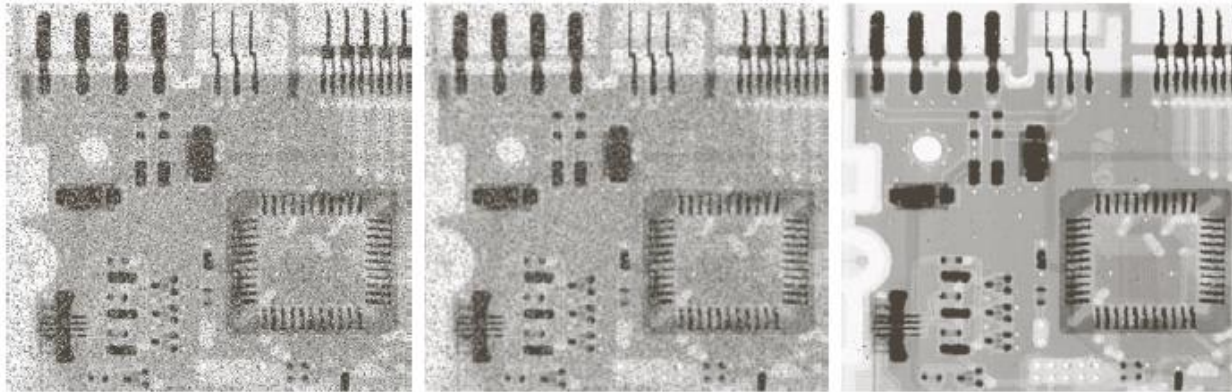
Application of Filtering



a b c

FIGURE 3.34 (a) Image of size 528×485 pixels from the Hubble Space Telescope. (b) Image filtered with a 15×15 averaging mask. (c) Result of thresholding (b). (Original image courtesy of NASA.)

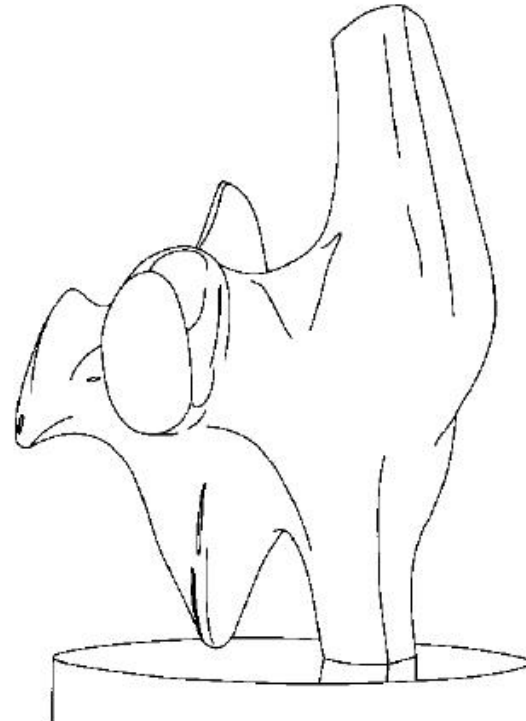
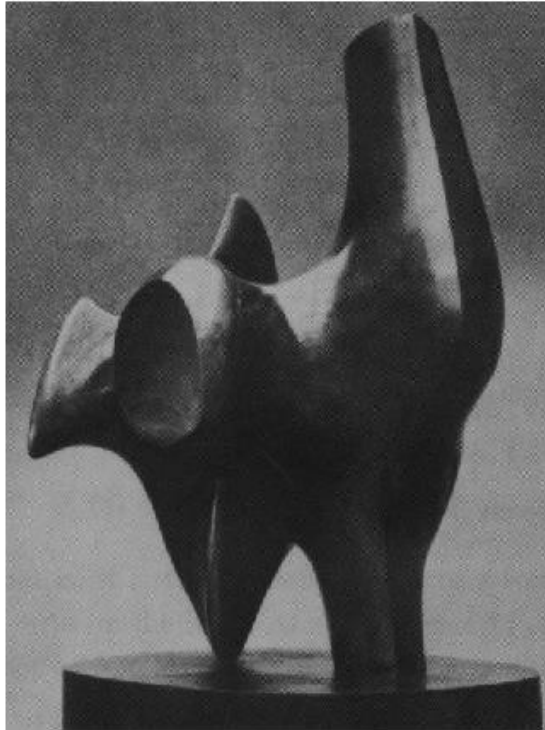
Filtering for Denoising



a b c

FIGURE 3.35 (a) X-ray image of circuit board corrupted by salt-and-pepper noise. (b) Noise reduction with a 3×3 averaging mask. (c) Noise reduction with a 3×3 median filter. (Original image courtesy of Mr. Joseph E. Pascente, Lixi, Inc.)

Edge detection



- Convert a 2D image into a set of curves
 - Extracts salient features of the scene
 - More compact than pixels

Optimal Edge Detection: Canny



- Assume:
 - Linear filtering
 - Additive Gaussian noise
- Edge detector should have:
 - Good Detection. Filter responds to edge, not noise.
 - Good Localization: detected edge near true edge.
 - Single Response: one per edge.
- Detection/Localization trade-off
 - More smoothing improves detection
 - And hurts localization.

The Canny edge detector



original image (Lena)



Norm of gradient



thresholding

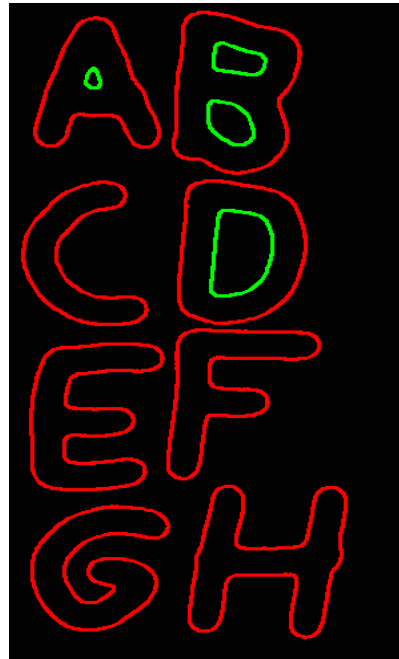


thining

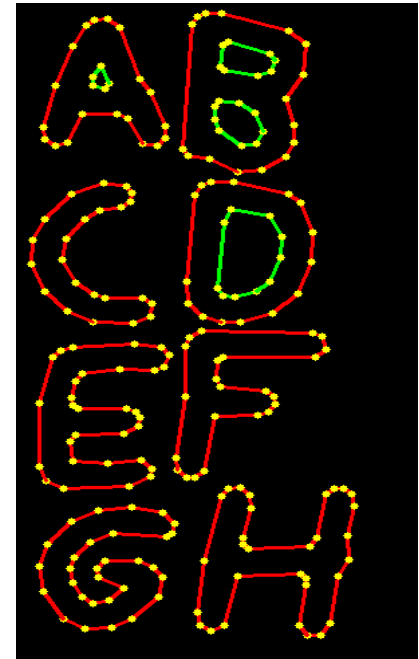
Contours Examples



Source Picture
(300x600 = 180000 pts total)



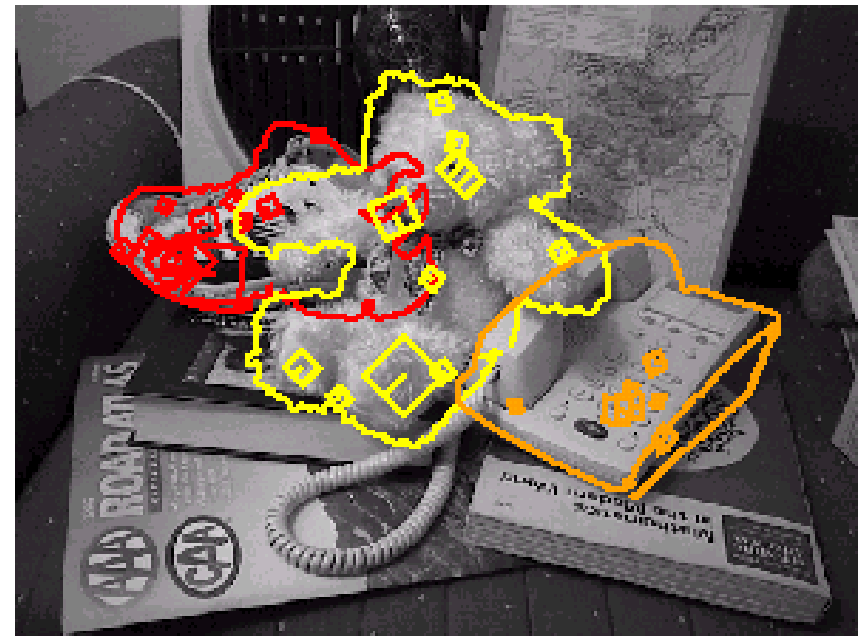
Retrieved Contours
(<1800 pts total)



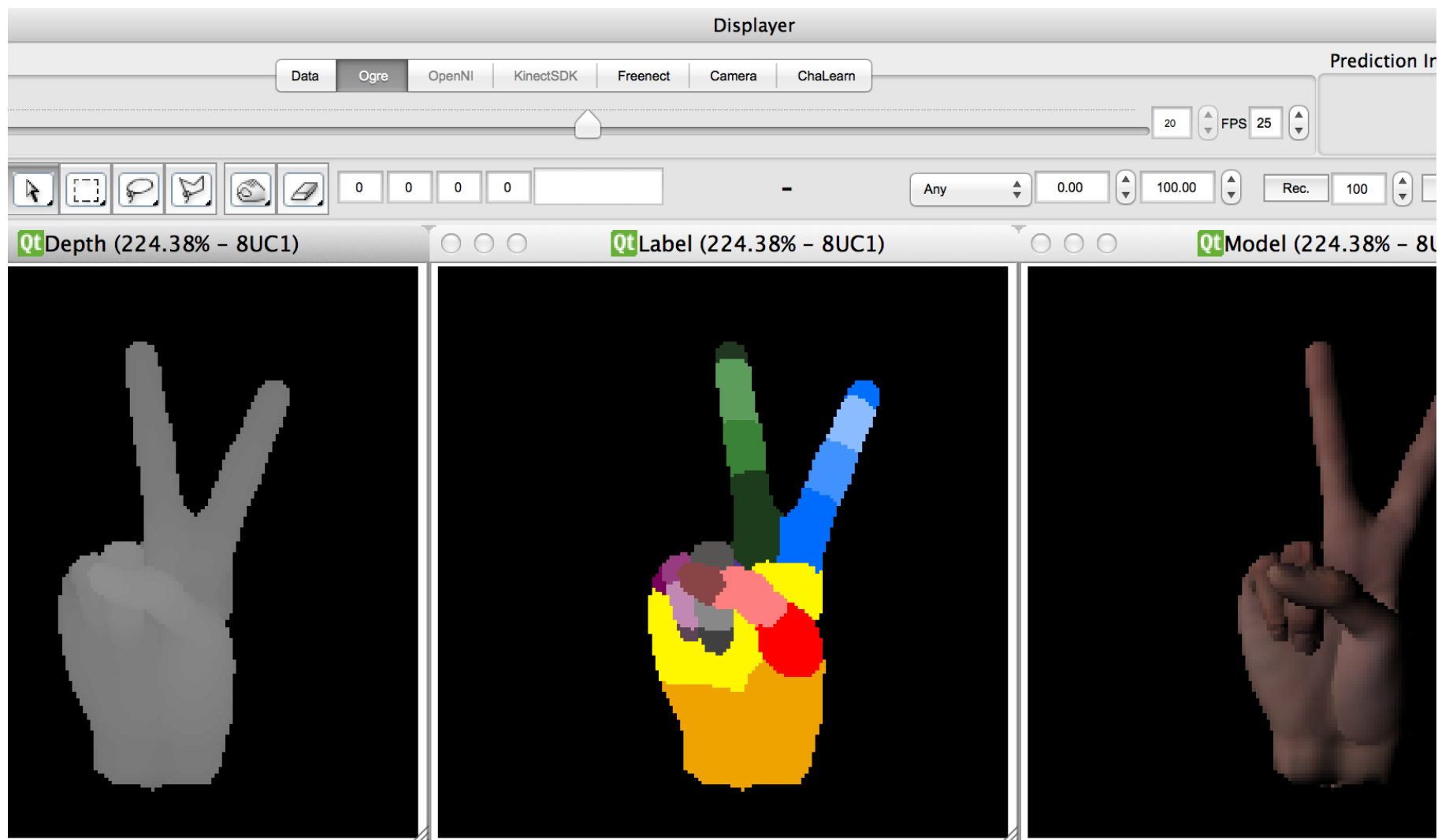
After Approximation
(<180 pts total)

And it is rather fast: ~ 70 FPS for 640x480 on complex scenes

Object Recognition



Human Pose/Sign Estimation



Motion Detection

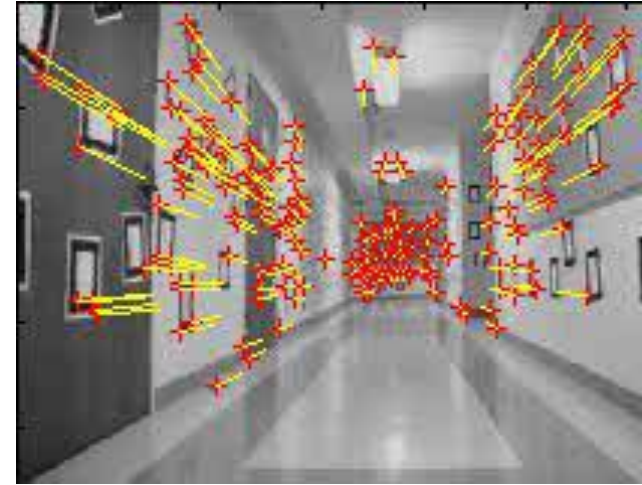


- **A. Frame Differencing (Basic)**
 - *Logic:* Subtracts the current frame from the previous one ($| \text{Frame}_t - \text{Frame}_{\{t-1\}} |$).
 - *Pros/Cons:* Extremely fast, but sensitive to noise and fails if the object stops moving.
 - *Key Function:* `cv2.absdiff(frame1, frame2)`
- **B. Background Subtraction (Intermediate)**
 - *Logic:* The system "learns" a static background model over time and isolates moving foreground objects. Adapts to lighting changes.
 - *Pros/Cons:* Robust for surveillance; handles shadows.
 - *Key Function:* `cv2.createBackgroundSubtractorMOG2()`
- **C. Optical Flow (Advanced)**
 - *Logic:* Tracks the apparent motion of brightness patterns to calculate velocity and direction vectors for every pixel.
 - *Pros/Cons:* Provides speed and direction data, but is computationally expensive.
 - *Key Function:* `cv2.calcOpticalFlowFarneback()`

Optical Flow



```
// opencv/samples/c/lkdemo.c
int main(...){
...
CvCapture* capture = <...> ?
    cvCaptureFromCAM(camera_id) :
    cvCaptureFromFile(path);
if( !capture ) return -1;
for(;;) {
    IplImage* frame=cvQueryFrame(capture);
    if(!frame) break;
    // ... copy and process image
    cvCalcOpticalFlowPyrLK( ...)
    cvShowImage( "LkDemo", result );
}
```



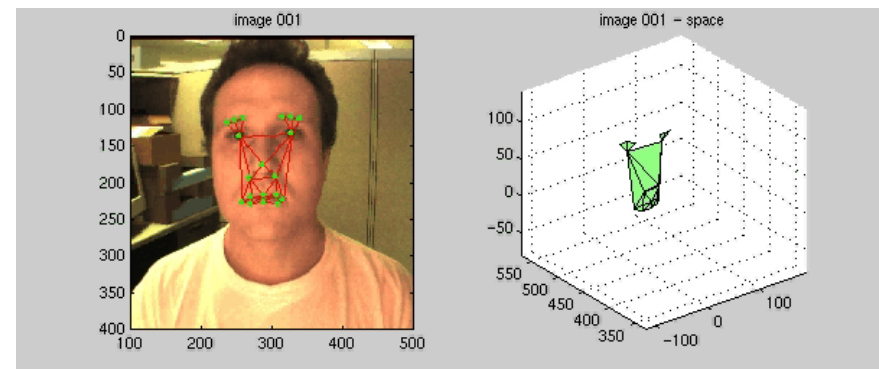
$$I(x + dx, y + dy, t + dt) = I(x, y, t);$$

$$-\partial I / \partial t = \partial I / \partial x \cdot (dx / dt) + \partial I / \partial y \cdot (dy / dt);$$

$$G \cdot \partial X = b,$$

$$\partial X = (\partial x, \partial y), G = \sum \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}, b = \sum I_t \begin{bmatrix} I_x \\ I_y \end{bmatrix}$$

calcOpticalFlowPyrLK()
 Also see *dense optical flow*:
calcOpticalFlowFarneback()



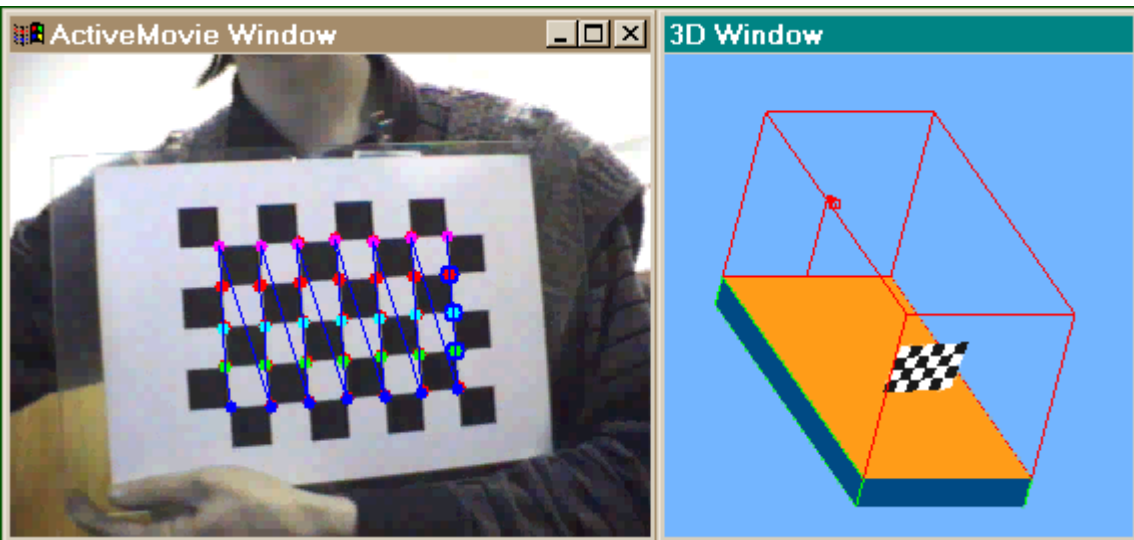
Single Camera Calibration

[See samples/cpp/calibration.cpp](#)

Now, camera calibration can be done by holding checkerboard in front of the camera for a few seconds.

And after that you'll get:

3D view of checkerboard



Un-distorted image



CLASSIFICATION / REGRESSION

(new) Fast Approximate NN (FLANN)

(new) Extremely Random Trees

(coming) LSH

CART

Naïve Bayes

MLP (Back propagation)

Statistical Boosting, 4 flavors

Random Forests

SVM

Face Detector

(Histogram matching)

(Correlation)

CLUSTERING

K-Means

EM

(Mahalanobis distance)

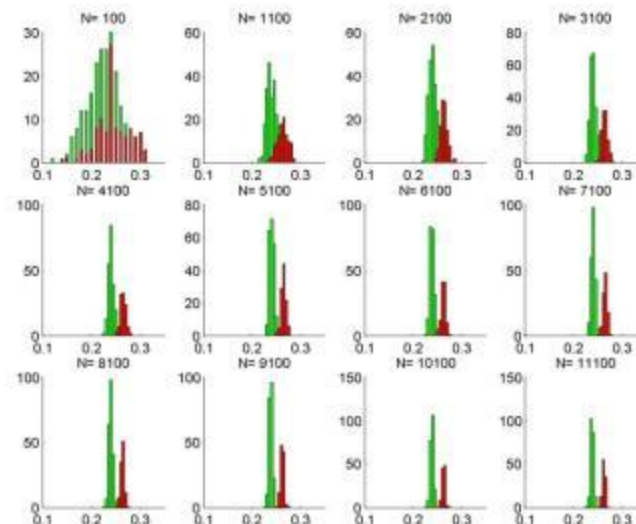
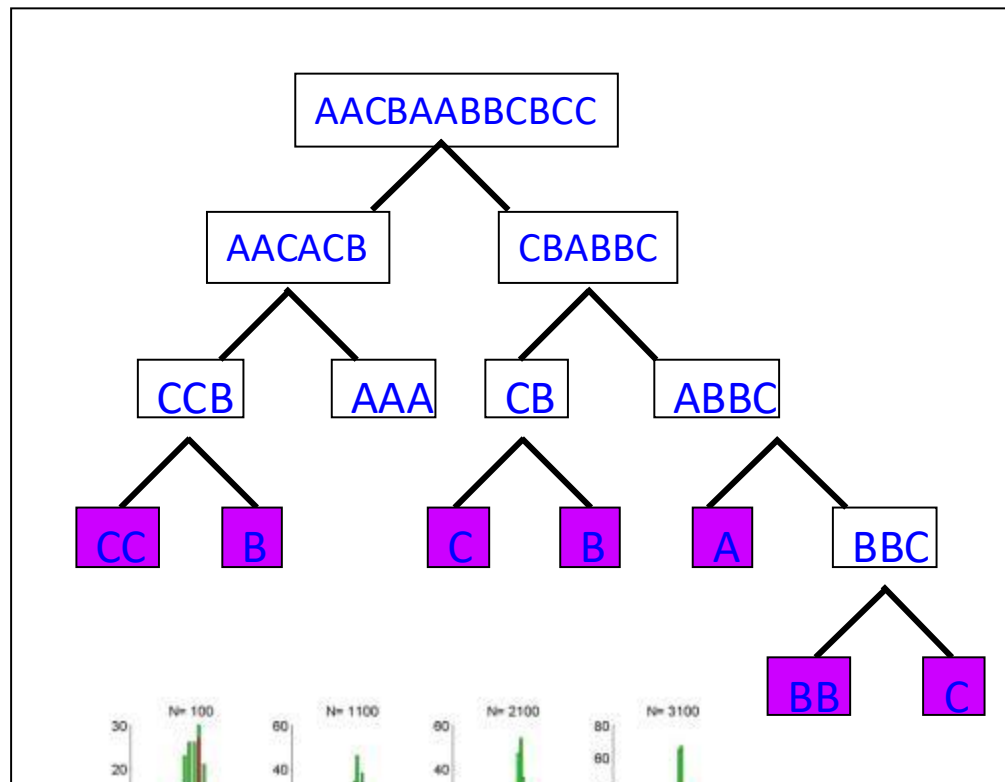
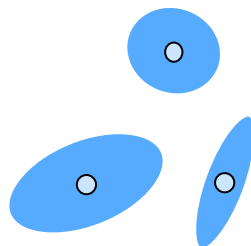
TUNING/VALIDATION

Cross validation

Bootstrapping

Variable importance

Sampling methods



YOLO



- **Definition:** YOLO is a state-of-the-art, real-time object detection system.
- **The Core Concept:** Unlike traditional classifiers that scan images step-by-step, YOLO treats object detection as a single regression problem.
- **"You Only Look Once":** The model looks at the entire image exactly once to predict:
 - What objects are present (Classification).
 - Where they are located (Localization/Bounding Boxes).
- **Key Characteristic:** Extremely fast inference speed, making it the standard for video processing and live streams.

Evolution of YOLO



- **YOLOv1 (2015):** The breakthrough. Fast but struggled with small objects.
- **YOLOv2 & v3:** Introduced "Anchor Boxes" and multi-scale detection (detecting small & big objects simultaneously).
- **YOLOv4 & v5:** Focused on speed optimizations (Mosaic augmentation) and usability (PyTorch implementation).
- **YOLOv8 (2023) & Beyond:** The current standard. Introduced "Anchor-Free" detection, simpler architecture, and native support for segmentation and pose estimation.
- **YOLO-NAS / YOLO-World:** New variants using Neural Architecture Search and open-vocabulary detection.
-

Pros & Cons of YOLO



- **Advantages:**
- **Speed:** Capable of 140+ FPS (frames per second) on modern GPUs.
- **Global Context:** Because it sees the whole image at once, it makes fewer "background errors" compared to sliding-window models.
- **Versatility:** Can perform Detection, Segmentation (masks), and Pose Estimation (skeletons) with the same API.
- **Limitations:**
- Can struggle with very small objects grouped tightly together (e.g., a flock of birds) compared to slower, two-stage detectors like Faster R-CNN.

YOLO Real-World Applications



Embedded ML

- **Autonomous Driving:** Detecting pedestrians, traffic lights, and other cars in milliseconds.
- **Security & Surveillance:** Intruder detection, face recognition, and crowd counting.
- **Retail:** Automated checkout (identifying products) and people counting in stores.
- **Healthcare:** Detecting tumors in X-rays or counting cells in microscopy.
- **Agriculture:** Weed detection and crop monitoring from drones.



Embedded ML