Embedded Lucas-Kanade Tracking: How it Works, How to Implement It, and How to Use It

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October 2nd, 2013

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Understanding Motion: Sensors, Algorithms, Applications

Camera (visual)

Inertial Sensor

Range Sensor

GPS

Application Requirements
- static / moving camera
- frame rate
- motion range

Motion Field
- 2D / 3D
- dense / sparse
- resolution
- Accuracy (angular/magnitude)

Algorithms
- model fitting
- object tracking
- segmentation
- 3D reconstruction

Automotive
- cross-traffic alert
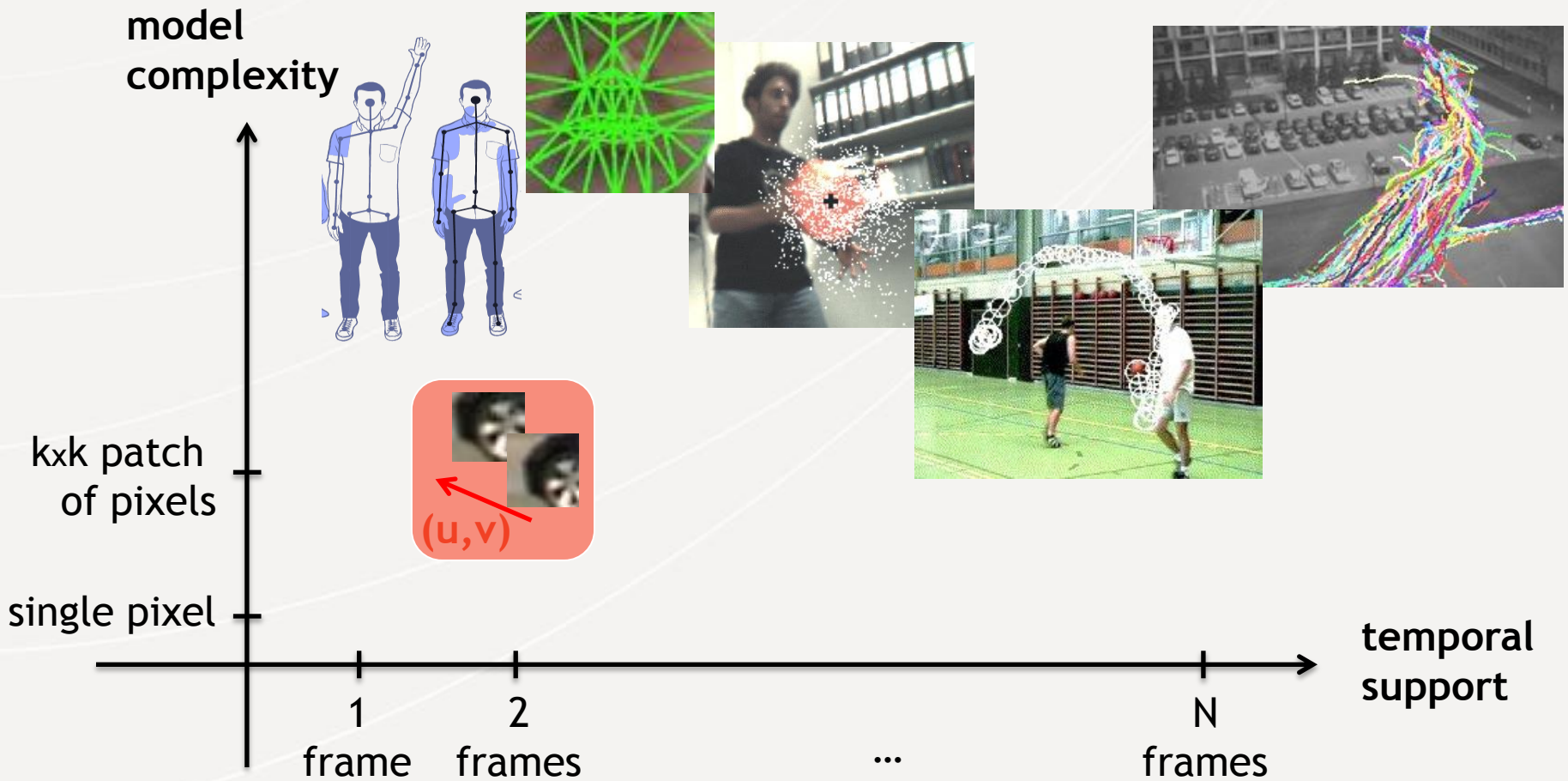- collision avoidance
- parking assist

Video Security
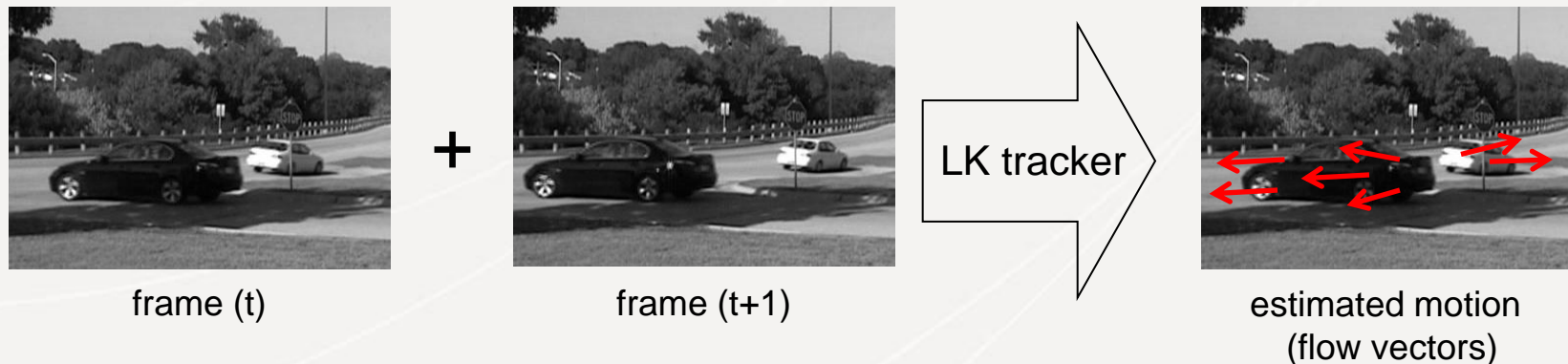- crowd analysis
- action recognition
- traffic analysis

Human-Device Interaction
- gesture recognition
- sign recognition
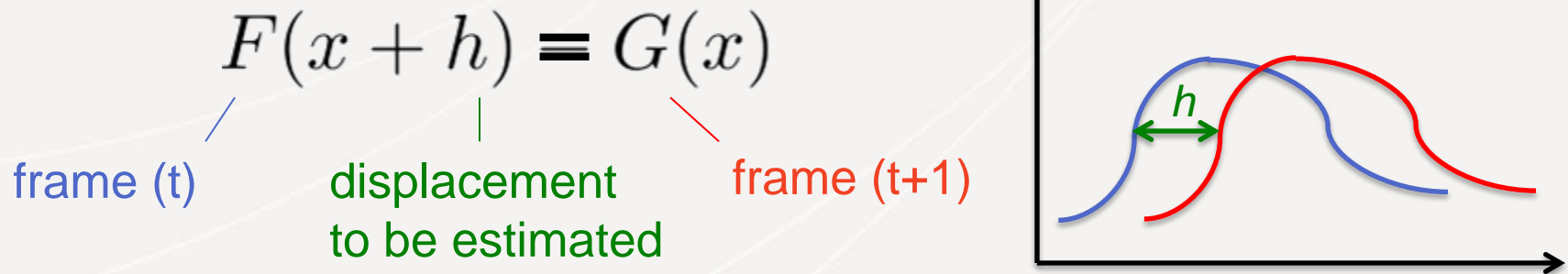- facial expression analysis

Lucas-Kanade Estimates Motion Between Consecutive Frames

frame (t)   frame (t+1)   LK tracker   estimated motion (flow vectors)

- *"An Iterative Image Registration Technique with an Application to Stereo Vision"*, Bruce Lucas and Takeo Kanade, published in 1981.
- Tested and proven over 30+ years in practical applications
  - There exist generalizations to more complex object & motion models
  - There exist much-simplified versions that work for very small displacements
- Good understanding of how & when it works well
  - "Good Features to Track", Jianbo Shi and Carlo Tomasi, published in 1994

- Assumption: brightness constancy

$$F(x + h) \equiv G(x)$$

frame (t)   displacement to be estimated   frame (t+1)

- Underdetermined system of equations; additional constraints needed.

- Assuming the flow is constant in a small neighborhood of pixels, estimate the displacement (optical flow) vector h by minimizing

$$E = \sum_{x}^{k \times k} \left[F(x + h) - G(x) \right]^2$$

1. The objective function is
$$E = \sum_{\substack{x \\ k \times k}} \left[F(x + h) - G(x) \right]^2$$

2. Linearize
$$E = \sum_{\substack{x \\ k \times k}} \left[F(x) + h\frac{\partial F}{\partial x} - G(x) \right]^2$$

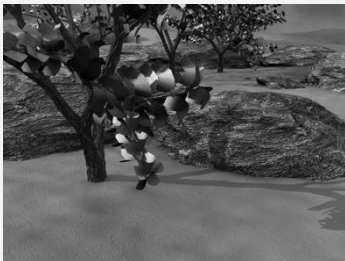3. Compute the least-squares solution for the displacement h

$$\begin{bmatrix} h_x \\ h_y \end{bmatrix} = \begin{bmatrix} \sum F_x^2 & \sum F_x F_y \\ \sum F_x F_y & \sum F_y^2 \end{bmatrix}^{-1} \begin{bmatrix} \sum F_x(G - F) \\ \sum F_y(G - F) \end{bmatrix}$$

4. Iterate until convergence!

- When image regions are "textured"

$$\begin{bmatrix} h_x \\ h_y \end{bmatrix} = \begin{bmatrix} \sum F_x^2 & \sum F_x F_y \\ \sum F_x F_y & \sum F_y^2 \end{bmatrix}^{-1} \begin{bmatrix} \sum F_x(G-F) \\ \sum F_y(G-F) \end{bmatrix}$$

- When displacements are small

  - The higher frame-rate the sensor, the better!

  - At the expense of increased computation, more robust expected with faster numerical convergence
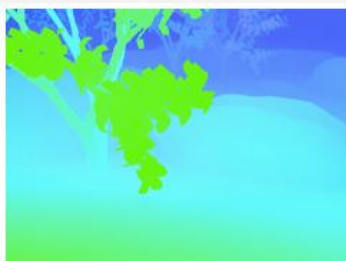
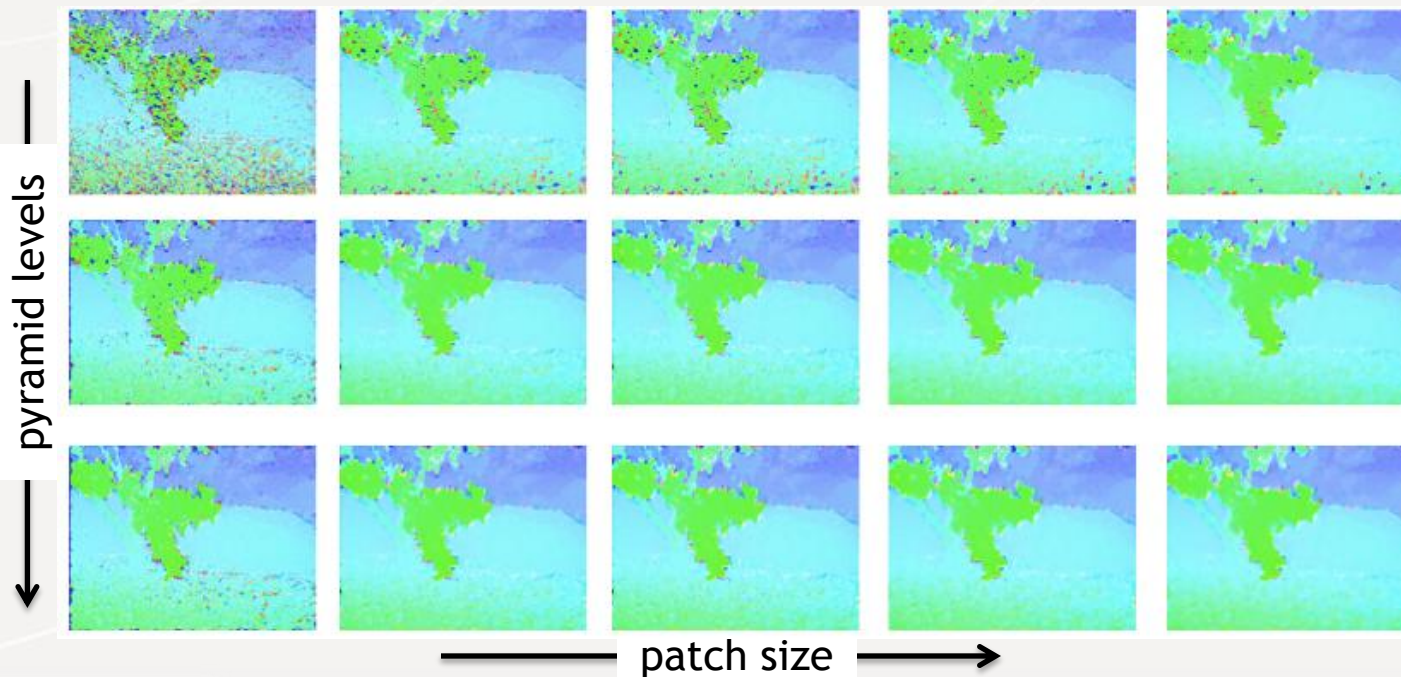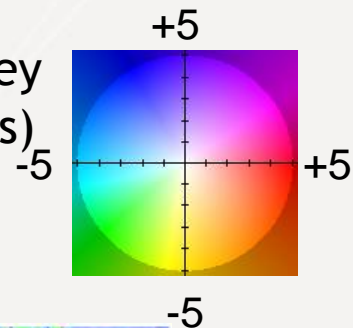 - Common remedy: multi-resolution pyramids

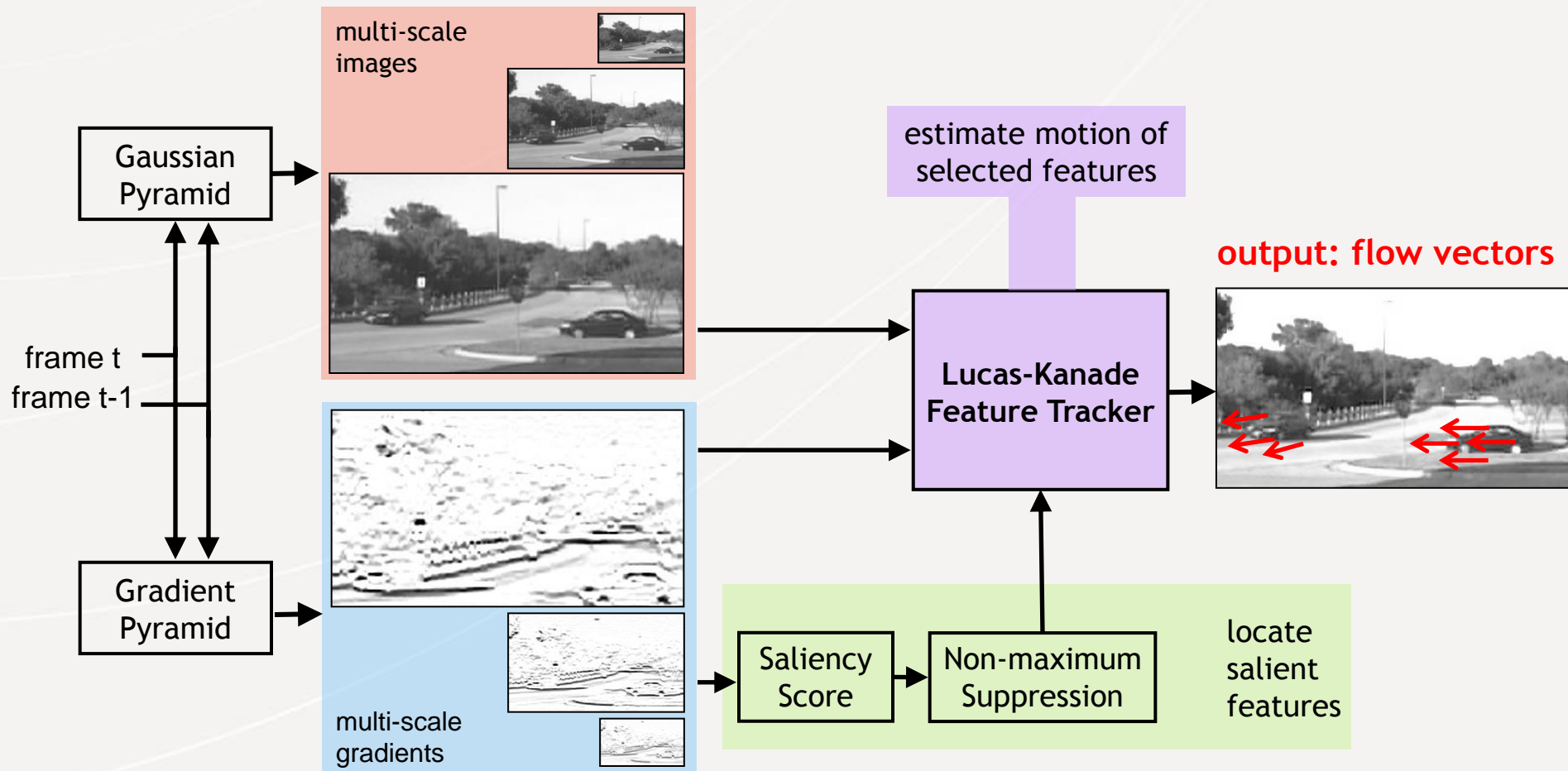# How to chose typical parameters

Scene

Ground Truth Motion

Motion Key (in pixels)

pyramid levels

patch size

multi-scale images

Gaussian Pyramid

frame t
frame t-1

Gradient Pyramid

multi-scale gradients

estimate motion of selected features

Lucas-Kanade Feature Tracker

output: flow vectors

Saliency Score

Non-maximum Suppression

locate salient features

VLIB

Gaussian Pyramid

multi-scale images

frame t
frame t-1

VLIB

Gradient Pyramid

multi-scale gradients

estimate motion of selected features

VLIB

Lucas-Kanade Feature Tracker

output: flow vectors

VLIB

Harris, FAST,ORB

VLIB

Non-maximum Suppression

locate salient features

TEXAS INSTRUMENTS
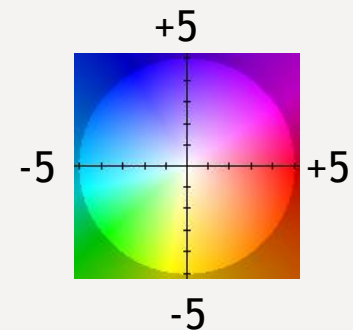
```
S32 VLIB_trackFeaturesLucasKanade_7x7_track_error(
        const U08 * restrict im1,
        const U08 * restrict im2,
        const S16 * restrict gradX,
        const S16 * restrict gradY,
        S32 width,
        S32 height,
        S32 nfeatures,
        const S16 x[],        // SQ11.4
        const S16 y[],        // SQ11.4
        S16 outx[],           // SQ11.4
        S16 outy[],           // SQ11.4
        S32 max_iters,
        const U08 * restrict scratch_klt,
        U32 track_error[],
        U08 patch)
```
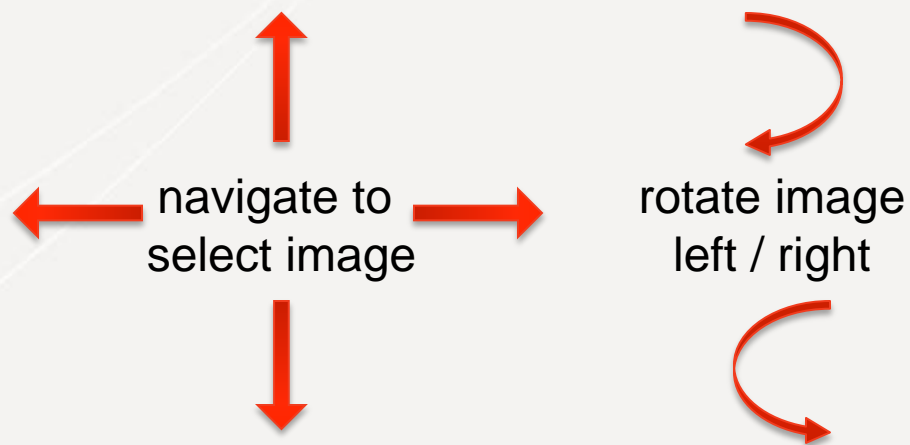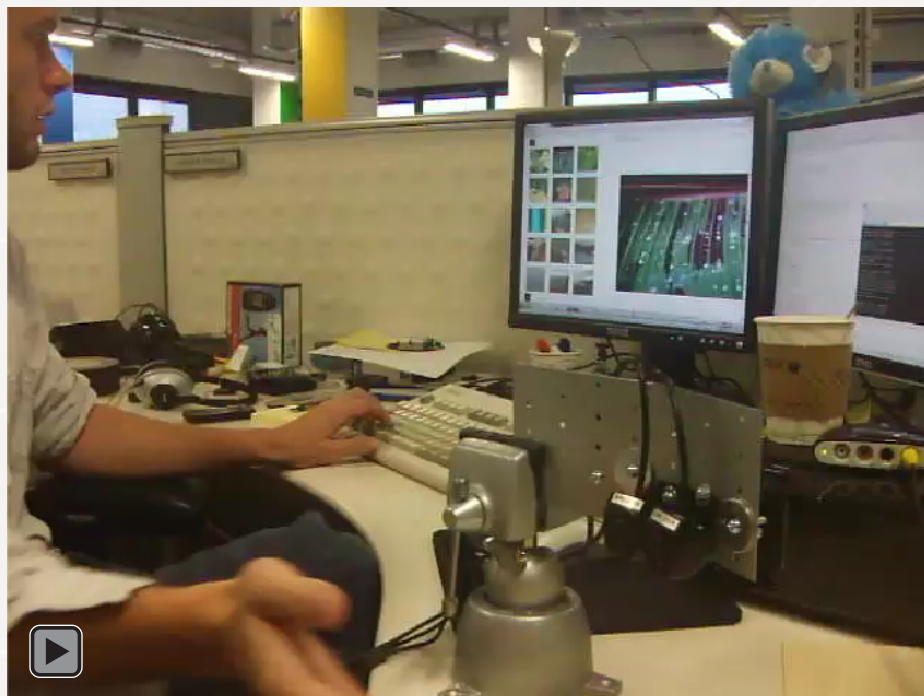
Scene

Ground
Truth Motion

Floating Point
(e.g., OpenCV)

Fixed Point
Optimized VLIB

Motion Key
(in pixels)

+5

-5   +5

-5

navigate to select image

rotate image left / right
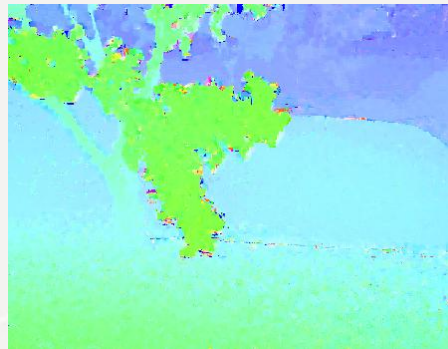
- Computer Vision is evolving, with Open Source libraries expanding fast, but with limited scrutiny & quality control. There exist two "Lucas-Kanade" optical flow functions in OpenCV:

ground truth
optical flow

calcOpticalFlowPyrLK
pyramid-based
good results
"LK-brand"

cvCalcOpticalFlowLK
single-step algorithm
can be **100x** faster
handles **very** small motion
now **obsolete**

- Embedded developers & architects beware!

Conclusions

- Lucas-Kanade is a well-understood & widely deployed method for tracking feature points

- We have implemented an <u>embedded</u> Lucas-Kanade tracker on the DaVinci DM6437 SoC; APIs are available in TI's Vision Library VLIB

- Three key messages:
    - Advantages: tested & proven over 30+ years, works reliably in textured   image regions and small motion vectors
    - Challenge: computationally demanding, algorithmic extensions continue
    - With the right <u>programmable</u> processor and careful design trade-offs, Lucas-Kanade can be implemented with cost & power consumption suitable for embedded systems.

- *"An Iterative Image Registration Technique with an Application to Stereo Vision"*, Bruce Lucas and Takeo Kanade, Proceedings of the 7th International Joint Conference on Artificial Intelligence (IJCAI '81), April, 1981, pp. 674-679. (URL)

- *"Lucas-Kanade 20 Years On"*, project lead by Simon Baker & Iain Matthews at the Robotics Institute of Carnegie Mellon University (URL)

- *"Determining Optical Flow"*, Berthold Horn and Brian Schunck, Artificial Intelligence, vol. 17, pp. 185-203, 1981.

- For related algorithms, benchmarks and datasets, see

  - Middlebury dataset: http://vision.middlebury.edu/flow

  - KITTI dataset: http://www.cvlibs.net/datasets/kitti