Temporal Video Tracking

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Overview

- Problem Statement
- Background
- General Concepts
- Solution Architecture
- Results

Problem Statement

- Track an object through a video sequence.
  - Occlusion
  - Complex Background
  - Object motion/rotation
  - Multiple targets
  - Noise artifacts
  - Changing features

Background

- Literature survey to understand existing methods
- Widely varied, examined approaches include:
  - Structured Output Tracking with Kernels (STRUCK)
  - Kernelized Correlation Filter (KCF)
  - Minimum Output Sum of Squared Error Correlation Filter (MOSSE)

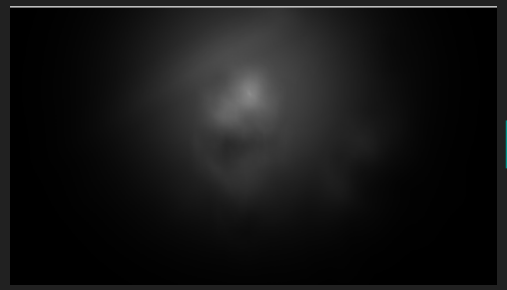
- Common ground
  - Identify features of interest
  - Predict how the features change
  - Look for the features in new frames

Solution Architecture

- Three stage approach
  - Feature Detection, Classification, and Prediction
  - An initial truth frame of the target is provided to prime the tracker
  - For subsequence frames the tracker draws a boundary box around the target
- Developed with OpenCV
  - High performance video manipulation framework

How to Build a Tracker

Input Data



Feature Detection

Classifier

Prediction

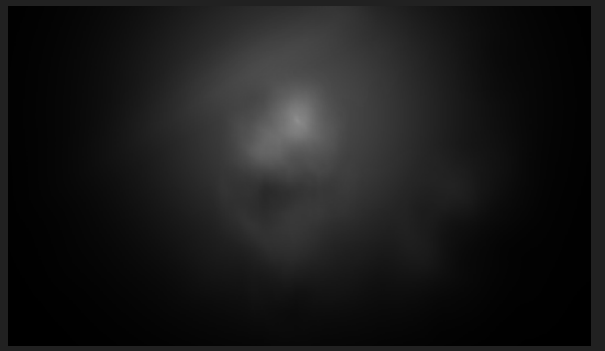
Feature Detection

- Correlation Filter
  - Detects similarity between the video frame and a “kernel”
  - Correlation in the spatial domain becomes multiplication in Fourier domain
- Two kernels are processed
  - A “positive” kernel based on last known match
  - A ”negative” kernel based on surrounding known bad tiles
  - Uses the linearity of convolution to combine both into one operation
  - The separation helps the tracker to suppress complex background clutter
- Raw correlation scores are weighted and used for classification

Feature Classification and Prediction

- The highest score is classified as the target
  - The updated position is fed into the smoother
  - The smoothed location adjust the Gaussian weights in the detector
  - Matches closer to the predicted location are weighted heavier

- Kalman Smoother
  - Estimates the state of the tracked object (position, velocity)
  - A constant acceleration two-dimensional Kalman filter was used
  - The smoother permits prediction of the target's position in the next frame
  - Tunable between smoother and more responsive tracks



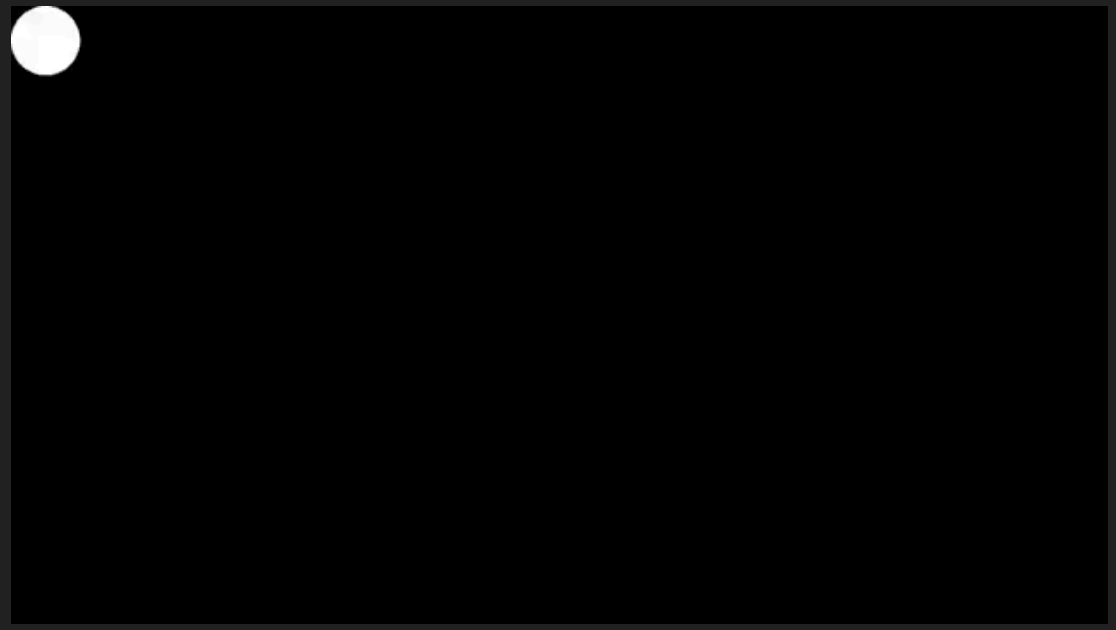
Weighted Correlation Score
(White is Higher)

Kalman Prediction

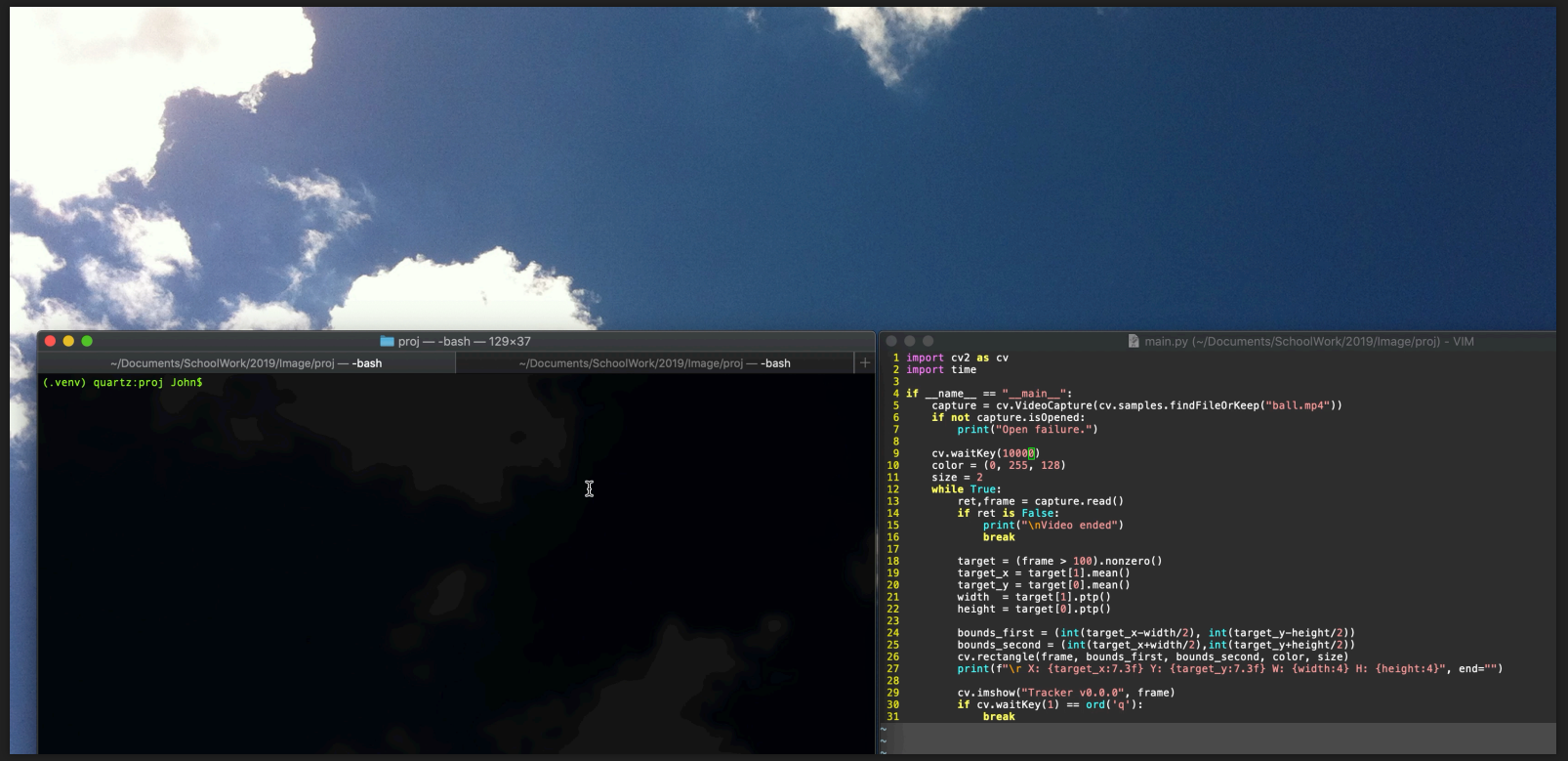
- The Kalman filter is used to smooth detected position
  - This position is used to focus in on the predicted search area helping to discern background clutter in complex environments
  - The smoother also permits coasting during track break
  - Prevents track steals when target is partially covered
- The filter is implemented in two stages
  - Predict – Uses the internal state to generate a prediction for the next frame
  - Correct – Updates the internal state based on the observed measurements
- The filter must be calibrated to the expected motion of the scene
  - If the process noise is too low the smoother will not lock
  - Too high and track steals become frequent

Verification

- Literature survey revealed a tracker testbench
- Several example clips were extracted to validate algorithm
- A set of simpler test clips were used to assist development

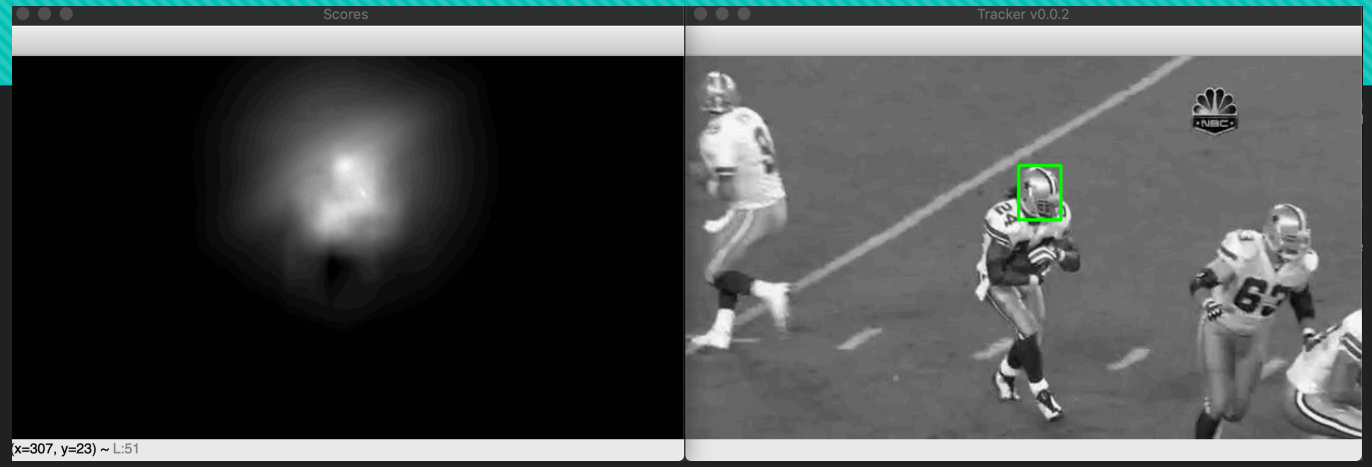


Hello Word – v0.0.0



Algorithm Refinements

- Learning Rates
  - Update kernels based on observed samples.
- Kalman Tuning
  - Calibrate process noise and weight distribution.
- Two stage focus
  - Wide area adjusting based on correlation lock.
  - Gain for predicted region.
- Lost lock fallback
  - Auto target re-acquisition

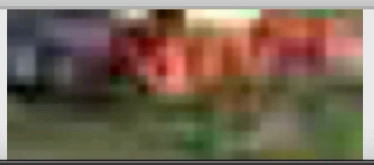


After Kalman Tuning

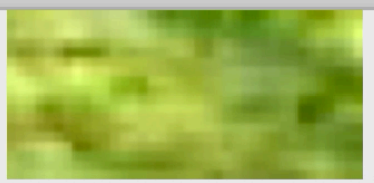
Before Kalman Tuning

Tracker v0.0.2

Positive Kernel



Negative Kernel



```
184          #start_pos = [0, 0, 40, 40]
```

proj — Python main.py — 62×23

~/Documents/Scho... | ...ython main.py | ...eam — -bash

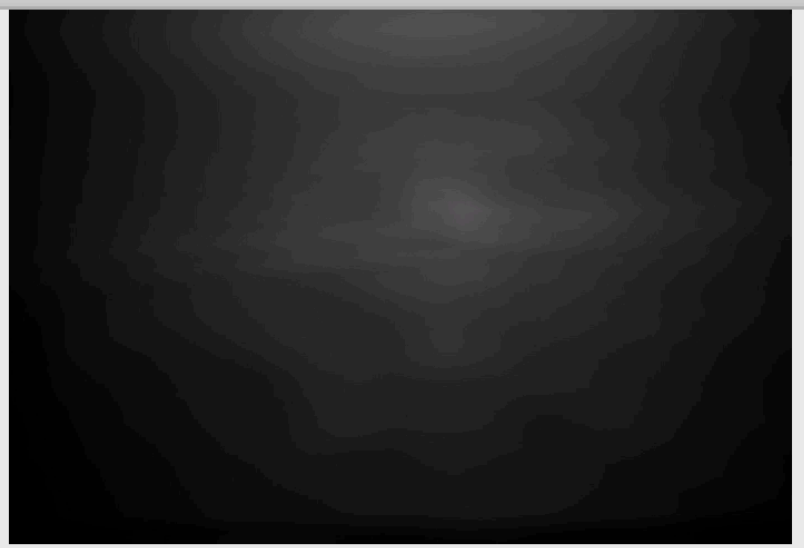
```
(.venv) quartz:proj John$ python main.py
 X: 203.000 Y:  89.000 W:   38 H:   18 score: 88.44
```

iCloud

clip_v0.0.0_small.mp4 Dec 4,

clip_v0.0.0.mp4 Dec 4,

Scores



Summary

- Successful tracking
  - Reasonable performance with common configuration
- Sensitive to camera motion
  - Affects Kalman Estimation
- Profile changes are difficult
  - Faster learning rate makes system susceptible to clutter

Questions?

- https://github.com/skhobahi/Kalman-Filter-Object-Tracking/blob/master/Object%20Tracking%20Using%20Kalman%20Filter.pdf
- https://www.opencv-srf.com/2018/03/gaussian-blur.html
- https://opencvexamples.blogspot.com/2014/01/kalman-filter-implementation-tracking.html
- http://www.robots.ox.ac.uk/~joao/publications/henriques_tpami2015.pdf
- http://setosa.io/ev/image-kernels/
- https://ieeexplore-ieee-org.proxy1.library.jhu.edu/stamp/stamp.jsp?tp=&arnumber=7360205&tag=1
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