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Title: Video Analysis in Multi-Intelligence

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Video Analysis in Multi-Intelligence

Everett Key

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Myself

- Graduated high school student.
- Intended to major in Physics/Mathematics
- Starting as a freshman at University of Washington in fall.
- No previous video analysis or Matlab experience.
- Worked 10 weeks on this project.

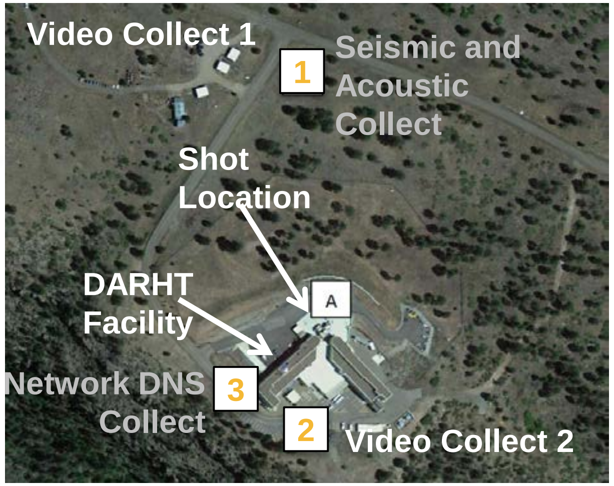
The goal of the Multi-intelligence (MINT) project is to determine the state of a facility from multiple data streams.

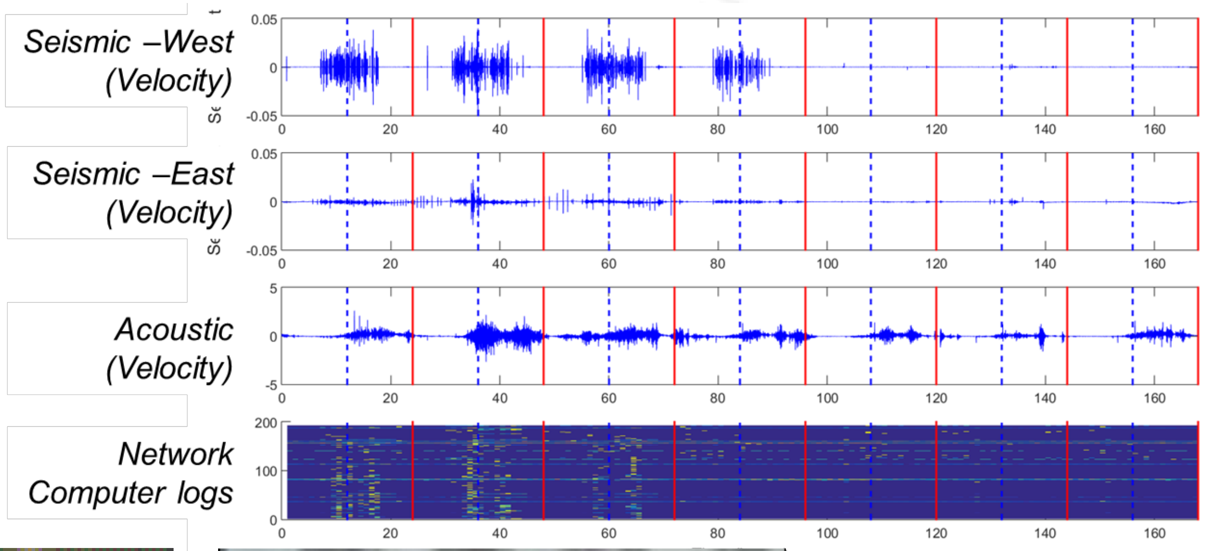
- The data streams are indirect observations.
  - Direct: A calendar log of activity.
  - Indirect: Car traffic pattern.
- Using DARHT (Dual-Axis Radiographic Hydrodynamic Test Facility) as a proof of concept.
  - Different modes include: regular work day, holiday, preparation, explosive shot experiment (shot day), tear-down.

DARHT

The MINT project works with five data streams to generate generic features. (Ex. Number of cars)

Generic feature logs





151,200,000 samples/week

151,200,000 samples/week

151,200,000 samples/week

~70,000 queries/week

Video Data

UNCLASSIFIED

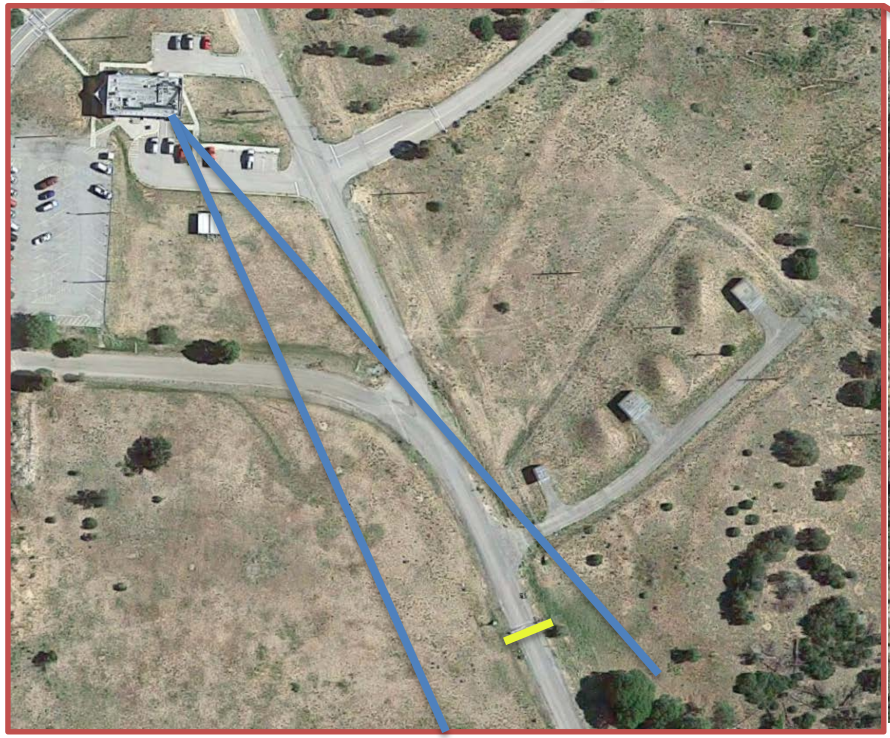
Video Data

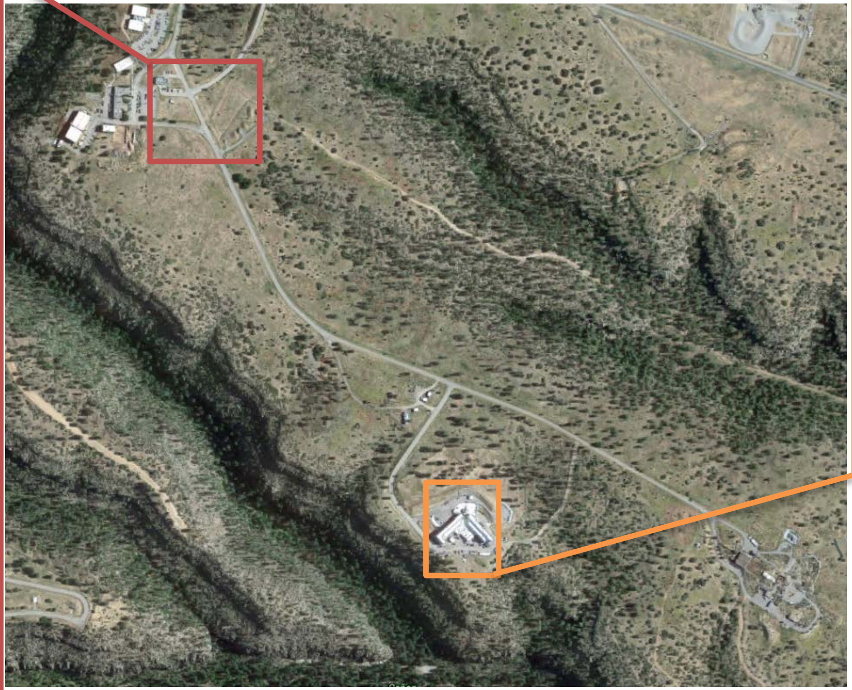
- Acquired from two security cameras on/around site.
- 6/23 ~ 9/5, 74 days of non-stop record.
- Includes two shot days, one non-weekend holiday.
- Received as down-sampled, 87 X 60 pixels videos.
- Compressed and de-compressed before video transfer.

Original Video

What I received

Camera Positions





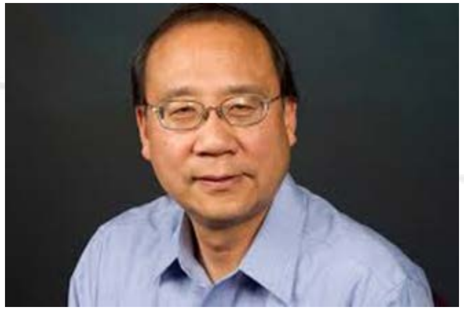
Gate

DARHT Parking Lot

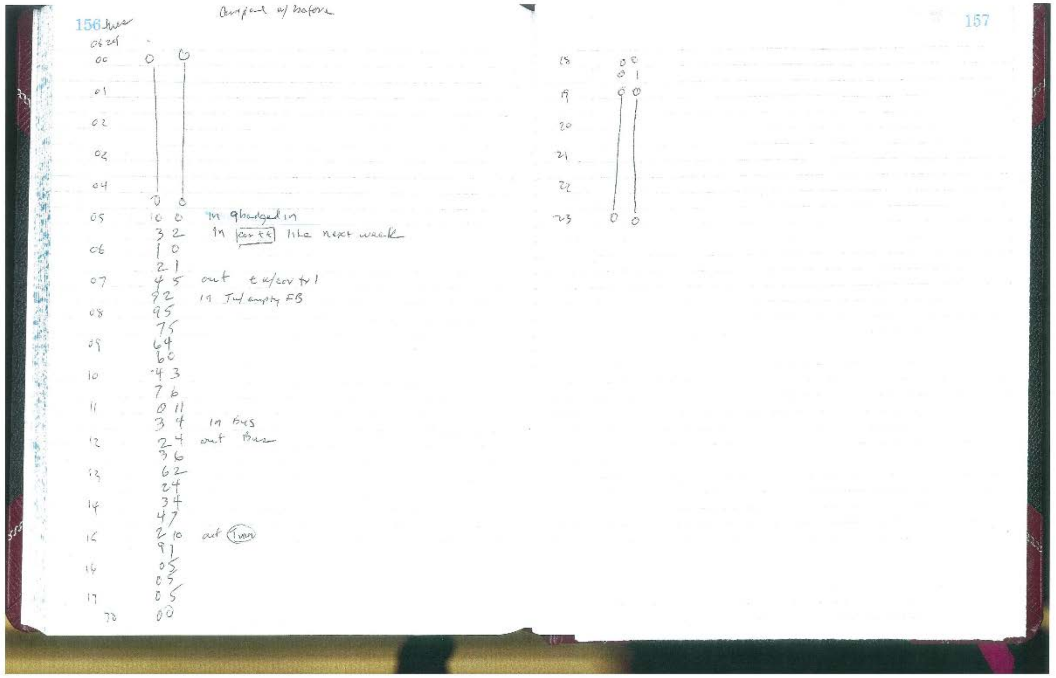
Video data contains a very rich amount of information

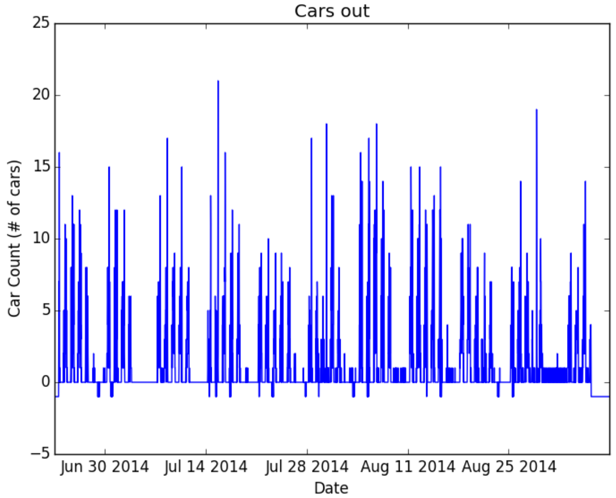
- Overall level of activity
- Weather
- Overall population on site
- Overall flux of population in the facility
- Can be correlated with other signals
- … all of these are essential to determine special events.

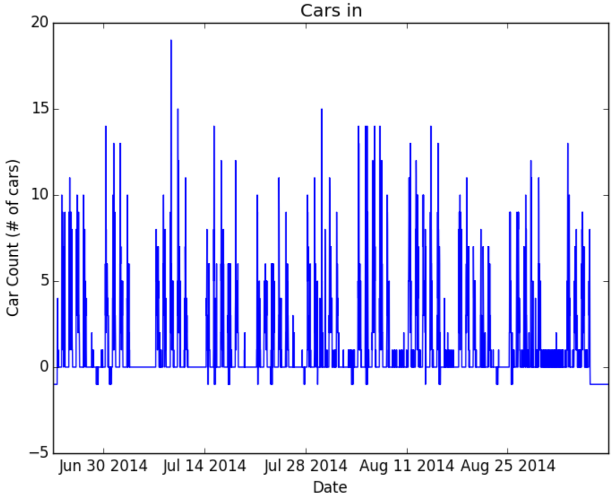
Car count development.



- Manual car count was done before the algorithm by Michael Hamada.
- An automated car counting algorithm is developed to verify manual results and look into other features.

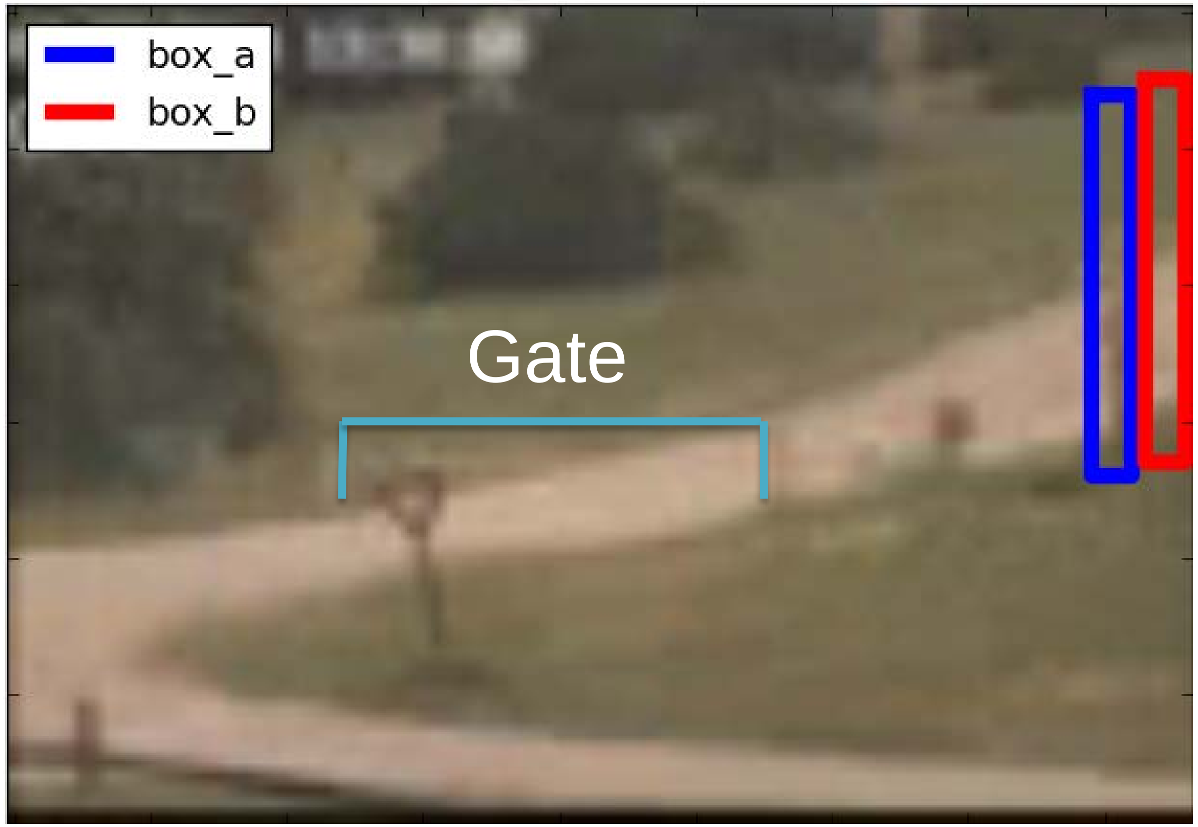






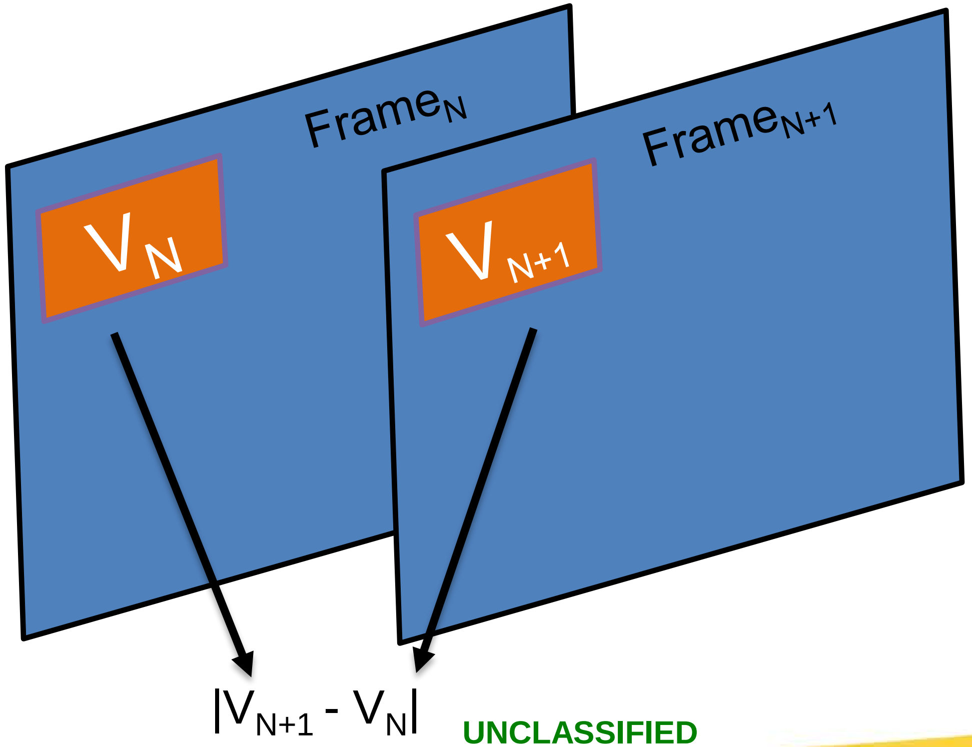
The automated car counting algorithm looks for car motion passing through two windows.

- The windows need to be where cars pass without stopping.
- Preferable that the windows are narrower than the space between two cars.
- The windows are 4X20 pixels in size.



To try to detect if a car is passing through the windows, we need to look at the change in pixels between frames.

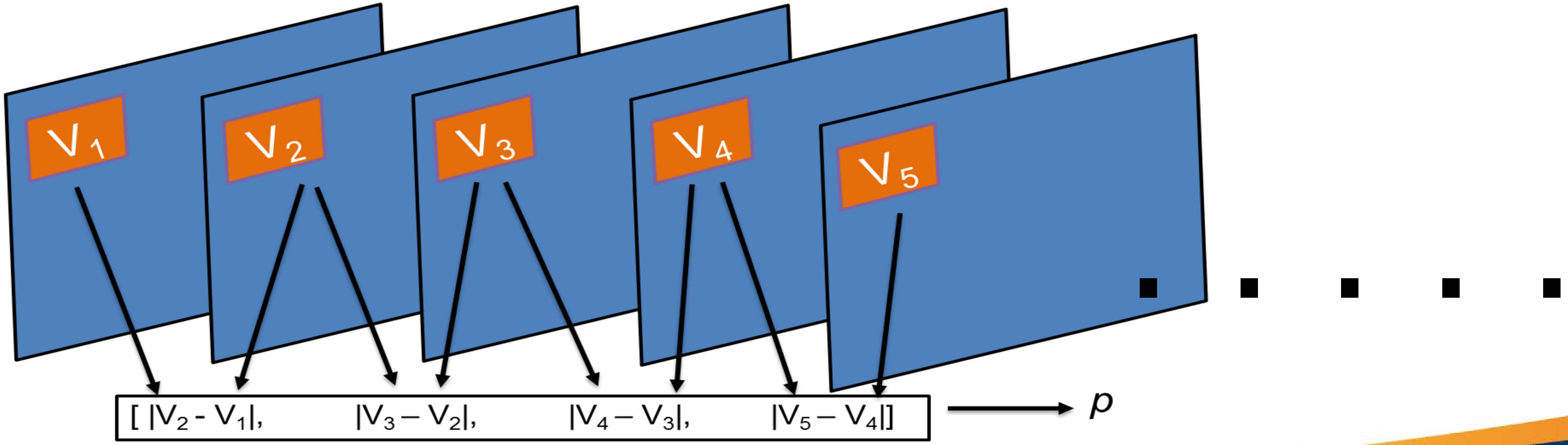
- Subtract a pixel’s value by the same pixel’s value in the previous frame.
- Average all the pixel change in the same window.



A time series of the average change in pixel values between frames is created for each video.

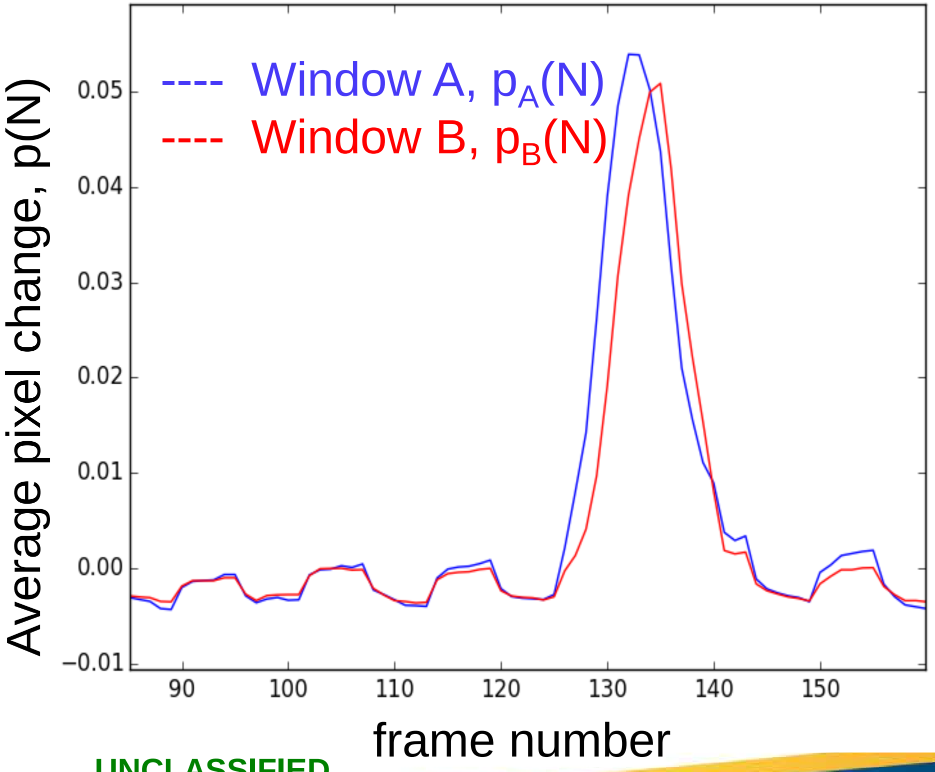
- Each step in the time series, p(N), considers all the pixels in the window.

$$\mathrm{p(N)} = \frac{\sum_{i=1}^{4}\sum_{j=1}^{20} V_{N+1}^{ij} - V_{N}^{ij}}{4 \cdot 20}$$



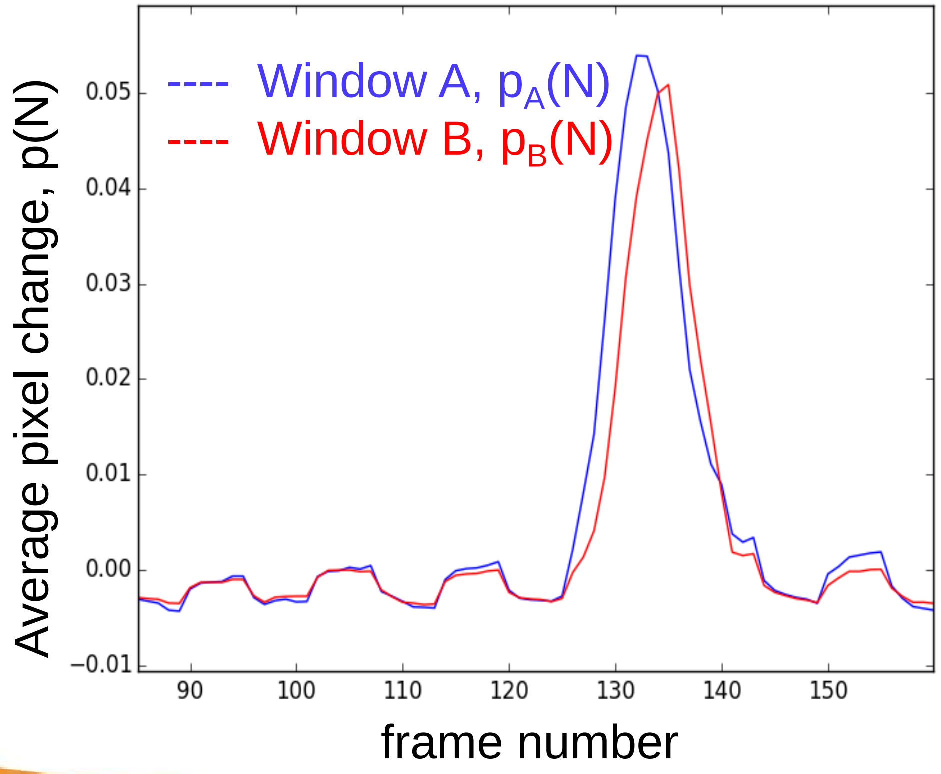
"Spikes" in the time series of average pixel change, p(N), is indicative of car movement.

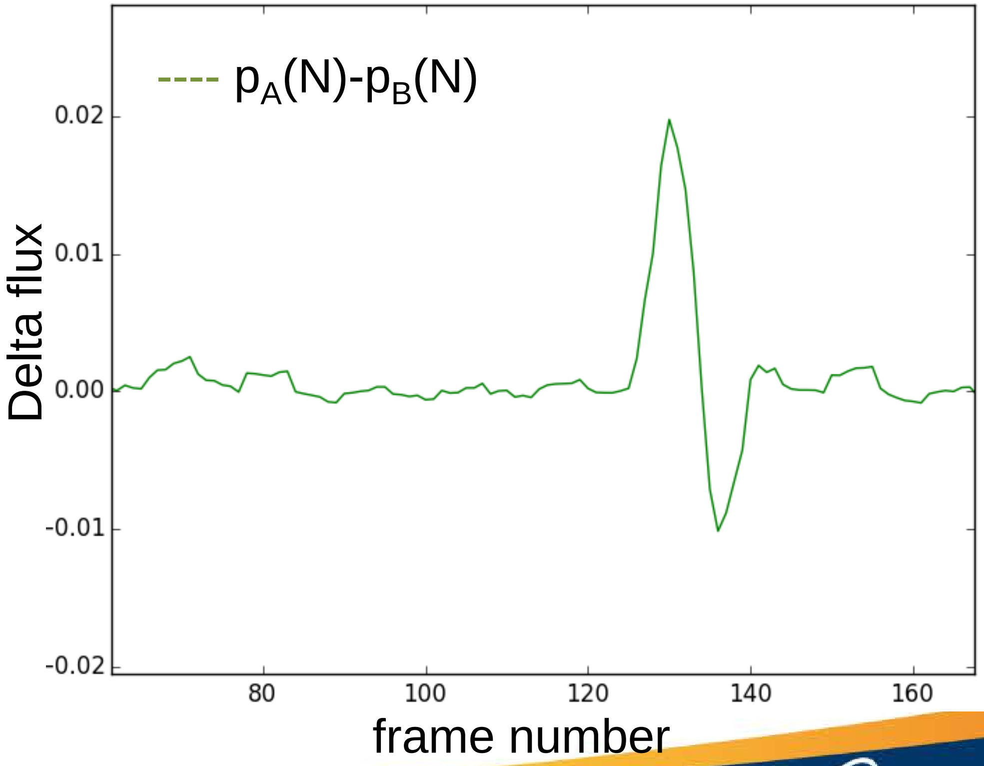
- A "spike" in the p(N) for Window A followed by a "spike" in the Window B time series suggests a car moving left to right (i.e. entering DARHT).



The pixel change values are subtracted from each other to obtain a delta flux that indicates car movement and direction.

- If there is an upward flux followed by downward flux, the car is entering DARHT. If vice versa, then the car is leaving DARHT.

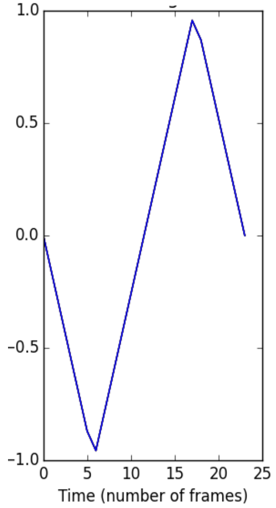




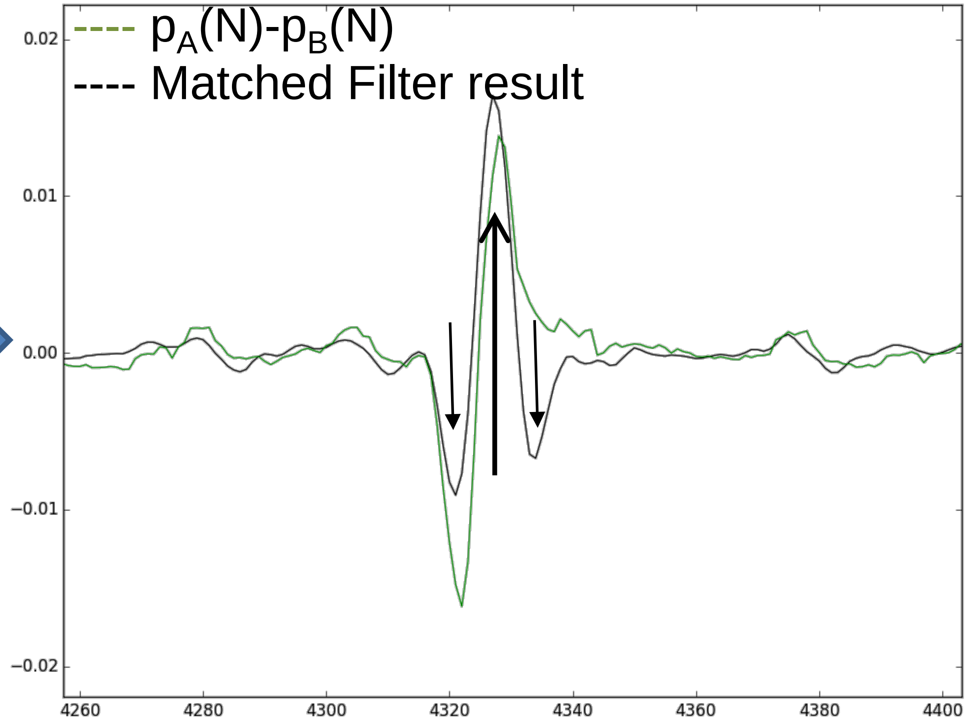
A match filter is applied to the delta flux to count the cars.

- Visually, it is obvious when a car is entering or leaving DARHT.

Ideal Signal

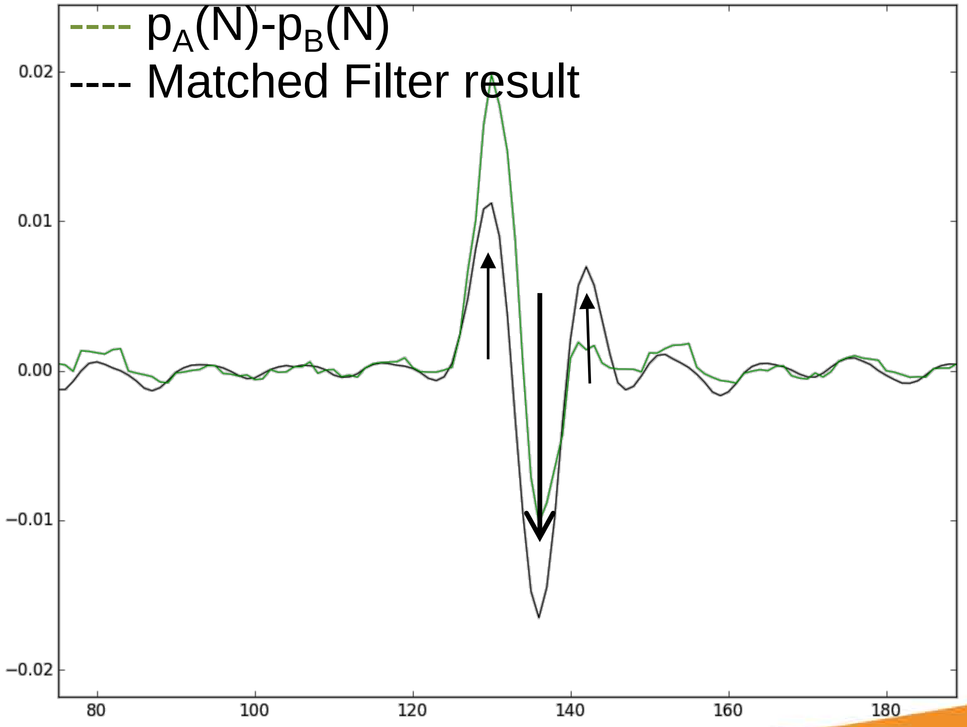


Car leaving DARHT



frame number

Car entering DARHT

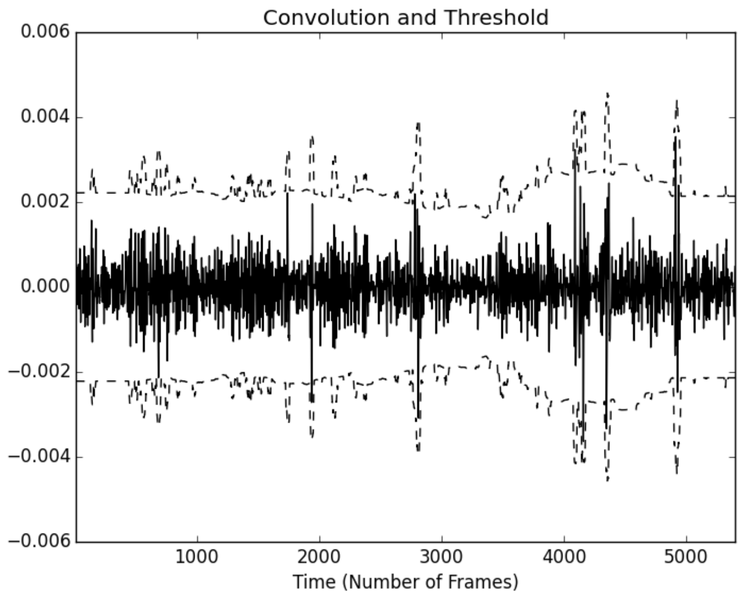


frame number

A threshold applied to the convolution of the delta flux and the “ideal signal” is used to count the number and direction of cars.

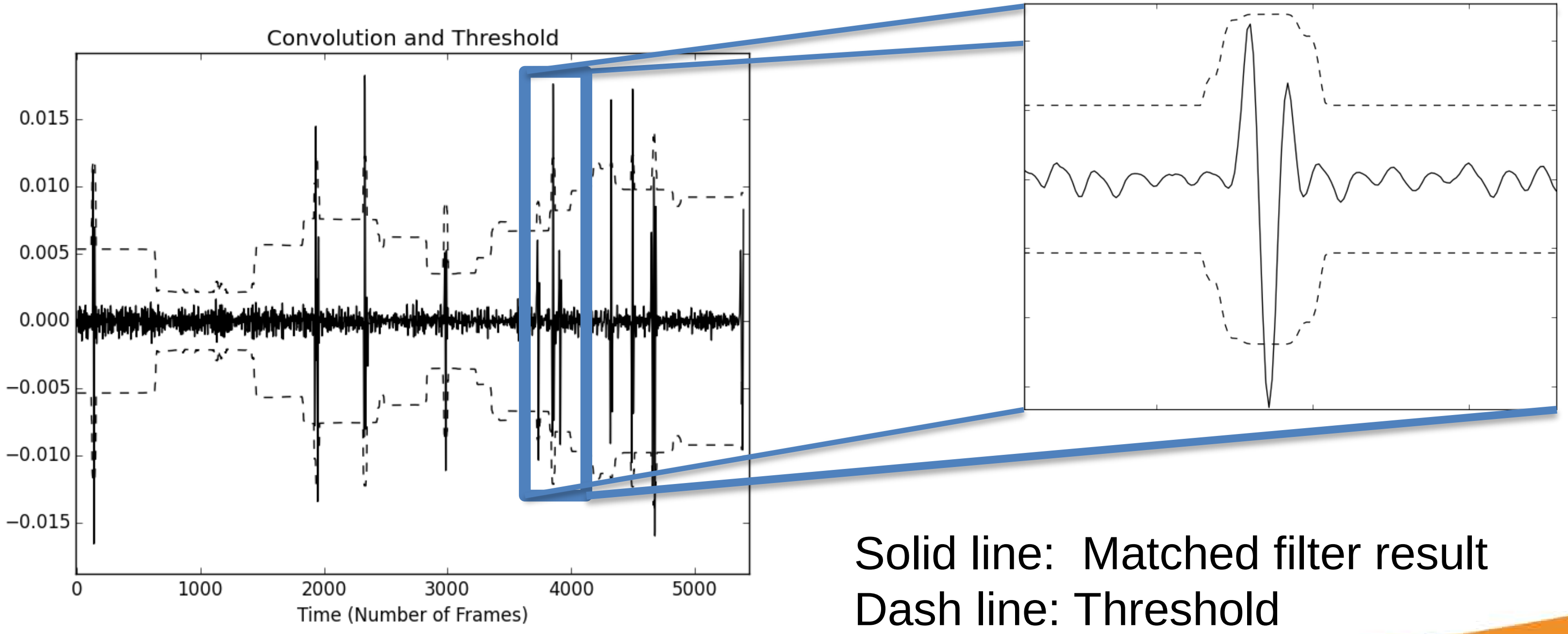
- The threshold utilizes a moving window to account for noise.

Fuzzy signal (Bigger threshold)



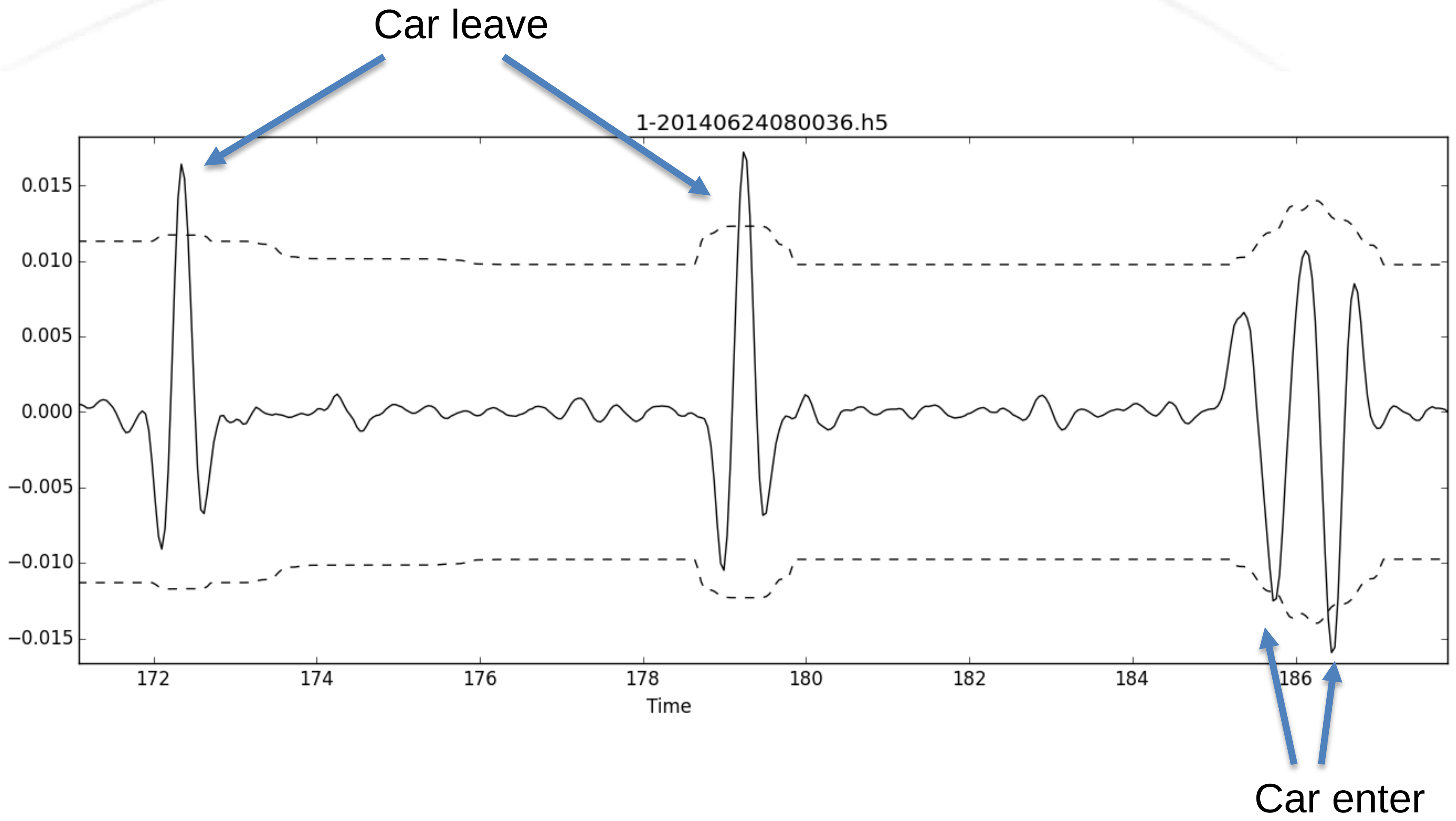
Clean signal (Smaller threshold)

Zoomed in

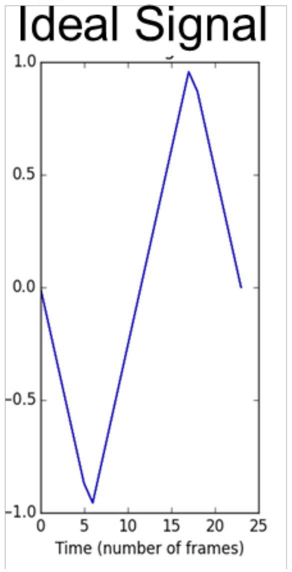


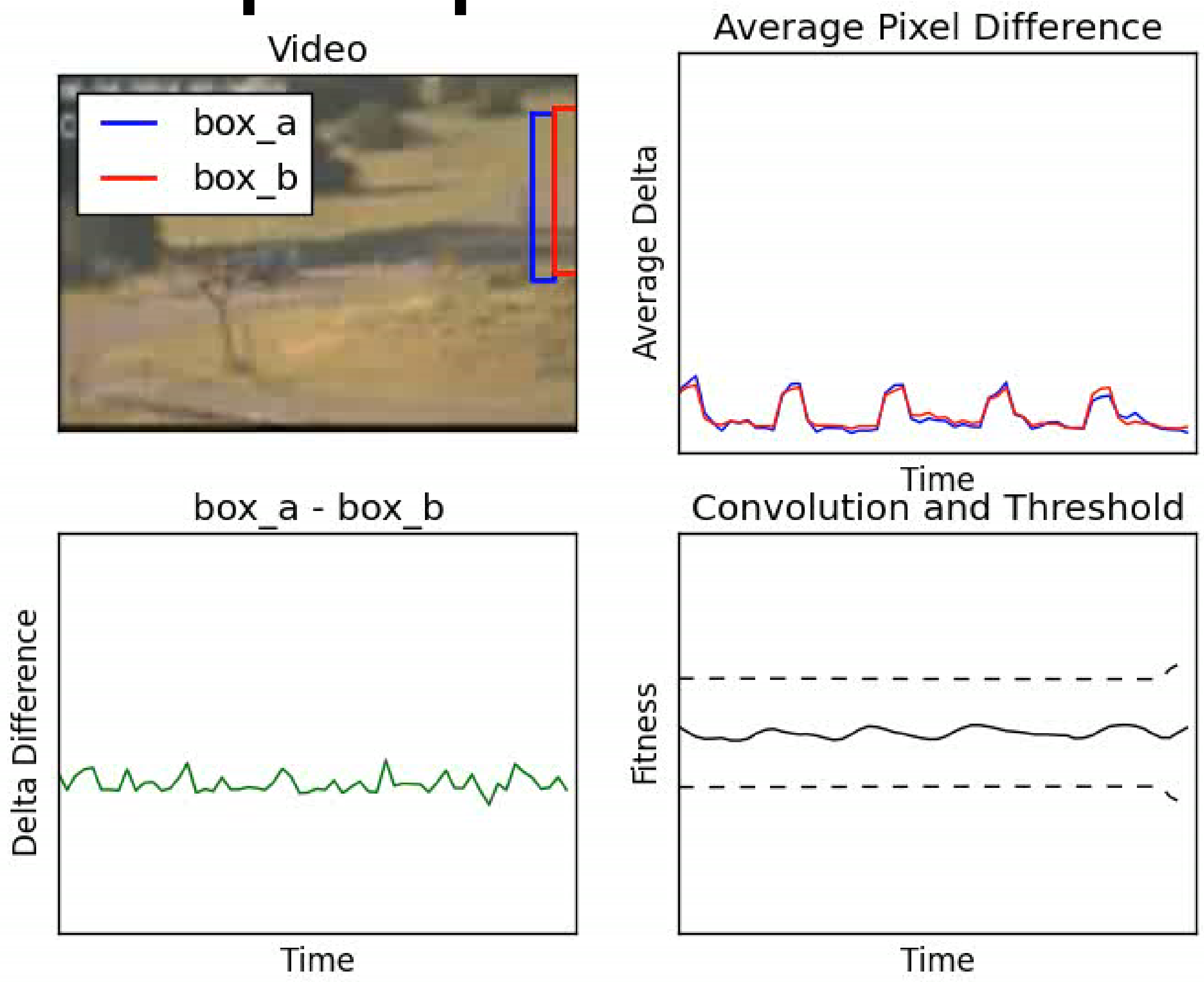
Solid line: Matched filter result
Dash line: Threshold

Counting how many times and which side the signal exceeds the threshold gives us the car count.

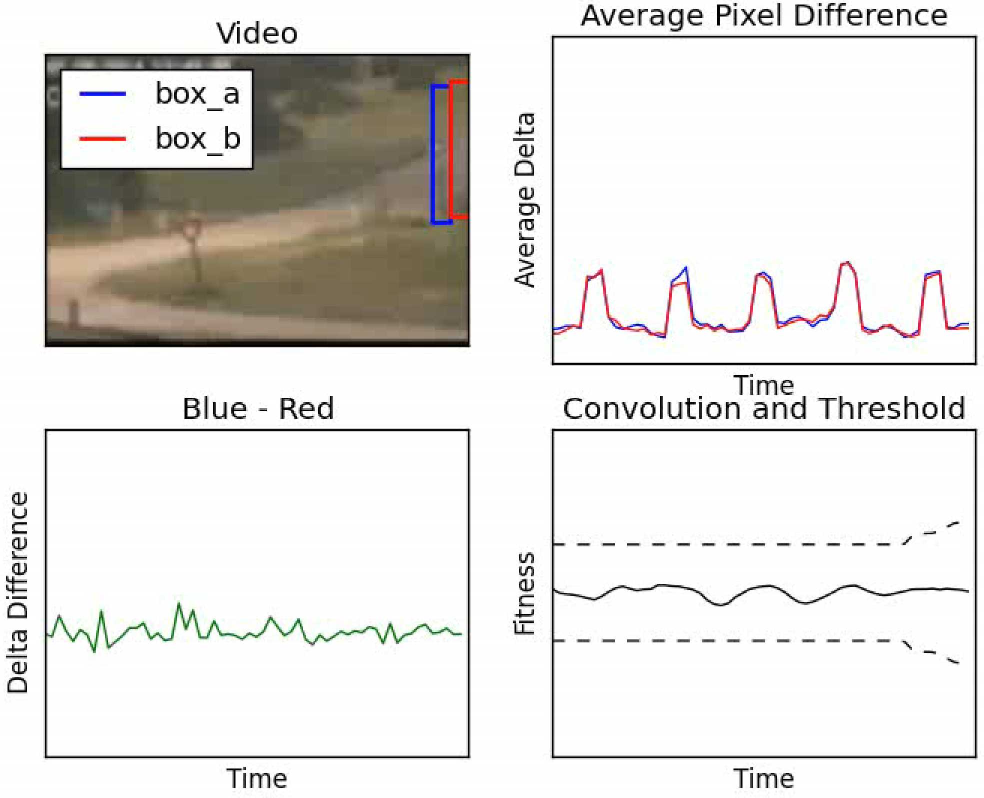


Animation of the complete process.

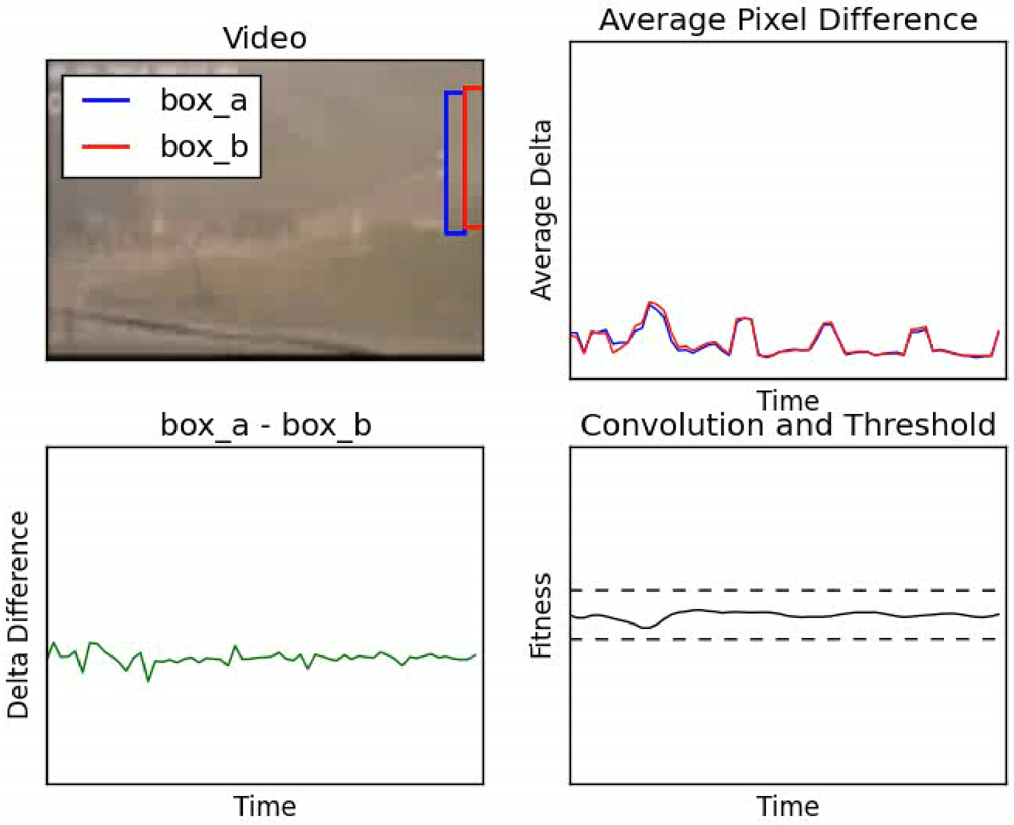




Factors that affect the algorithm.



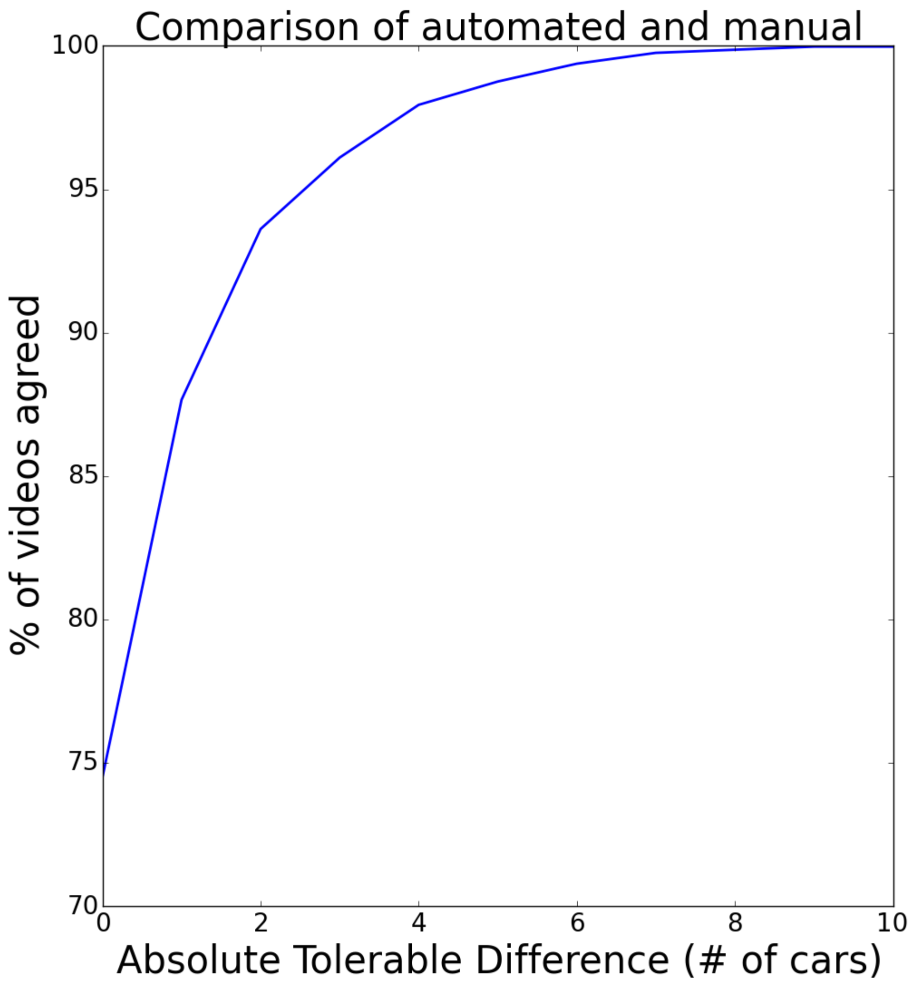
Tailgating



Fog/Sand/Rain

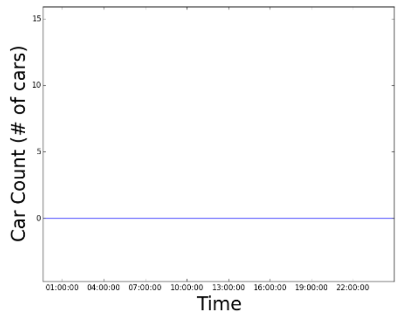
Comparison of automated car counting algorithm with the manual car count.

- Approx. 3500 videos.
- 75% of the automated car counts exactly match the manual count.
- 95% of the counts are accepted within 2 cars tolerance.
- Flaws in the manual count can be found by looking at the videos with large variation.

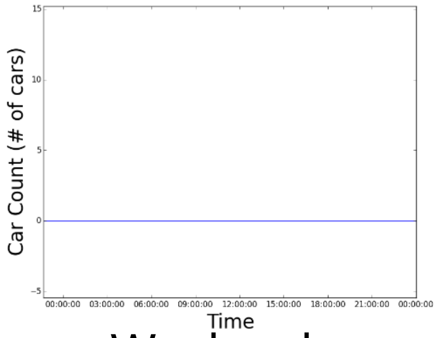


State of the facility is related more to the distribution than the number.

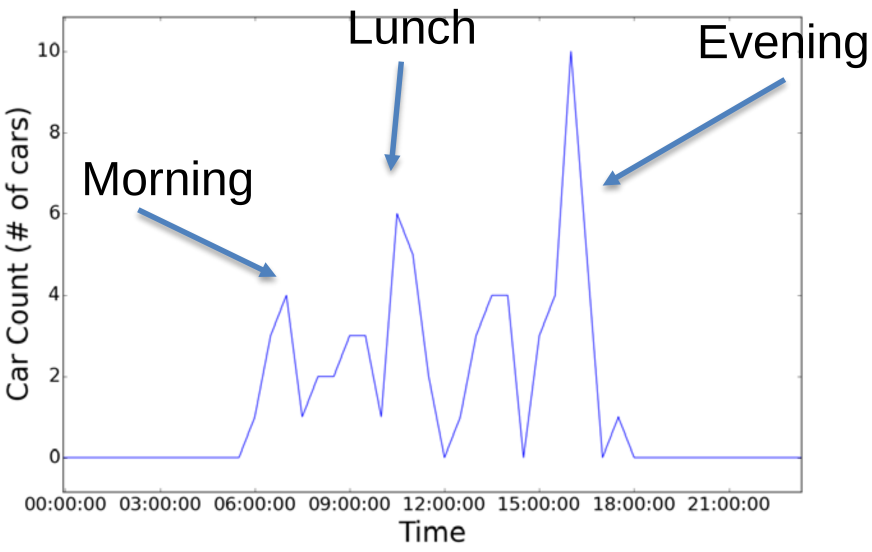
- Week days and weekends can be easily determined.
- Shape of car distribution is significantly different.



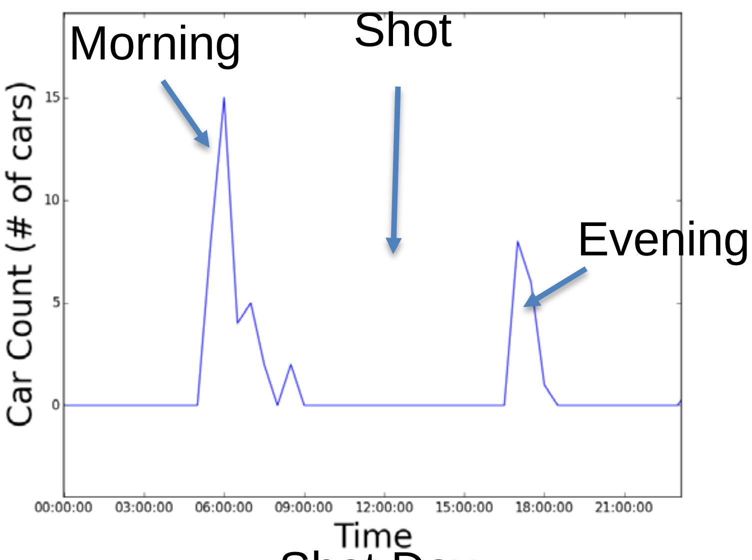
July 4th



Weekend



Regular Day



Shot Day

The algorithm is modified slightly to try to identify large vehicles such as trucks or cranes.

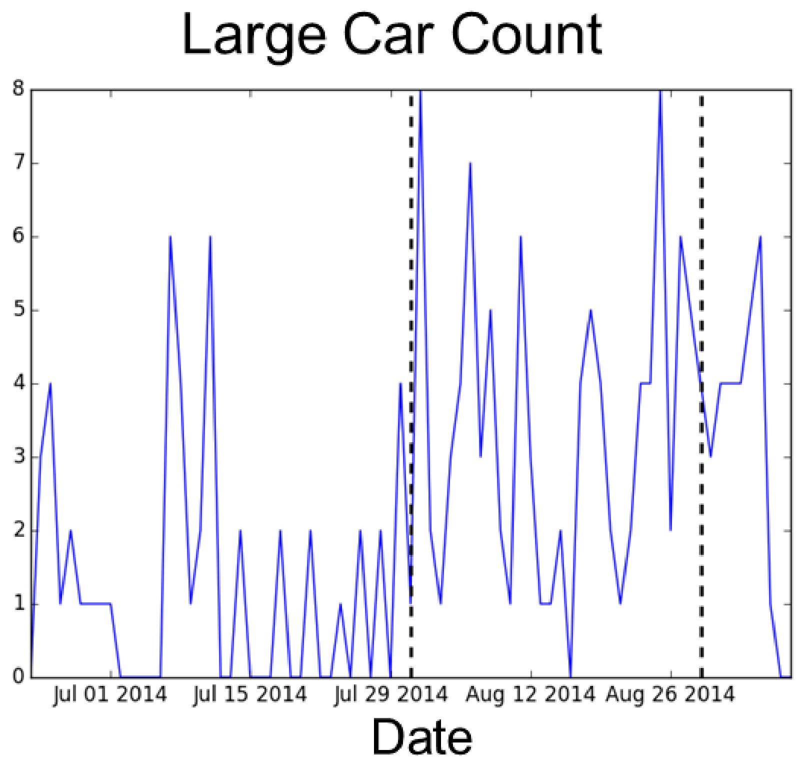
- Large vehicles may be indicative of preparation or tear-down for shot day.
- An extra window is created to differentiate small cars from large vehicles.

Large vehicle detected

Small car undetected

There is a slight correlation between the shot day and the large vehicle count.

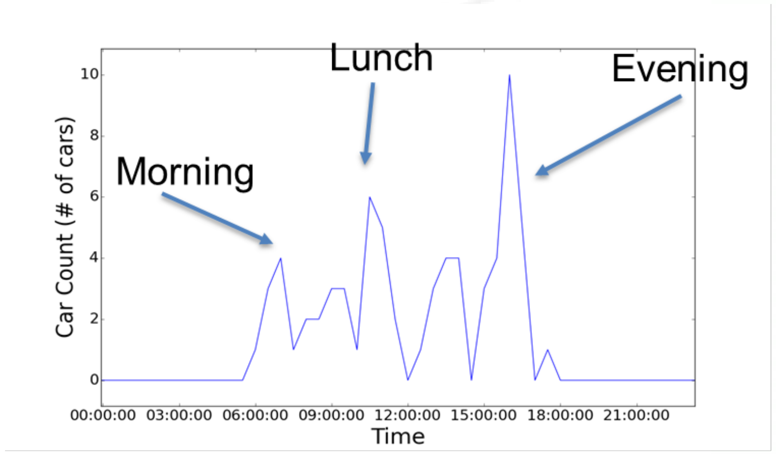
- We need more than two shot days to say anything more conclusive.



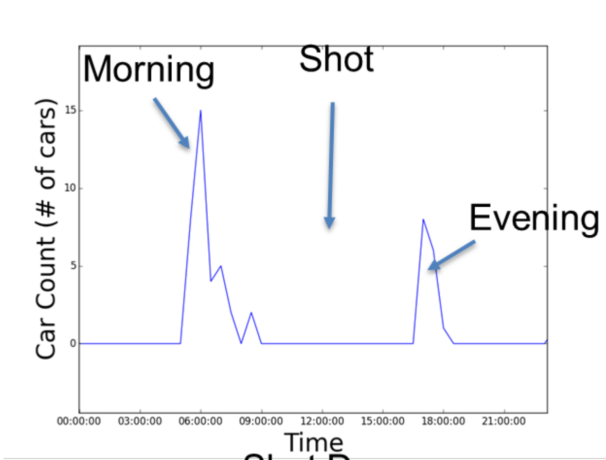
In summary, videos from the DARHT facility contain a rich amount of information.

- Distribution of car activity can inform us about the state of the facility.
- Counting large vehicles shows promise as another feature for identifying the state of operations.
- Signal processing techniques are limited by the low resolution and compression of the videos.
- We are working on integrating these features with features obtained from other data streams to contribute to the MINT project.
- Future work can pursue other observations, such as when the gate is functioning or non-functioning.

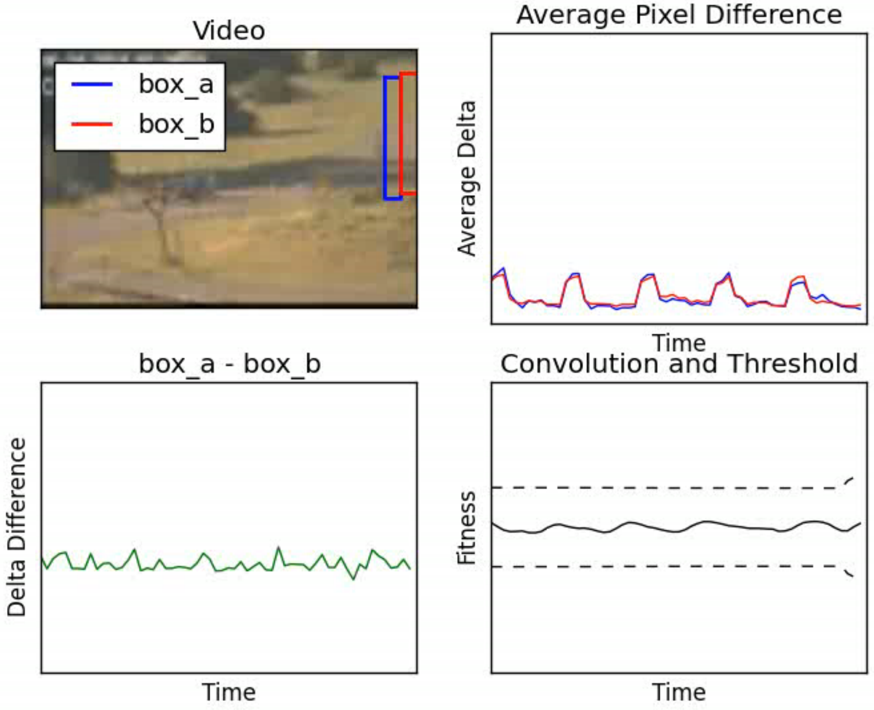
Questions?

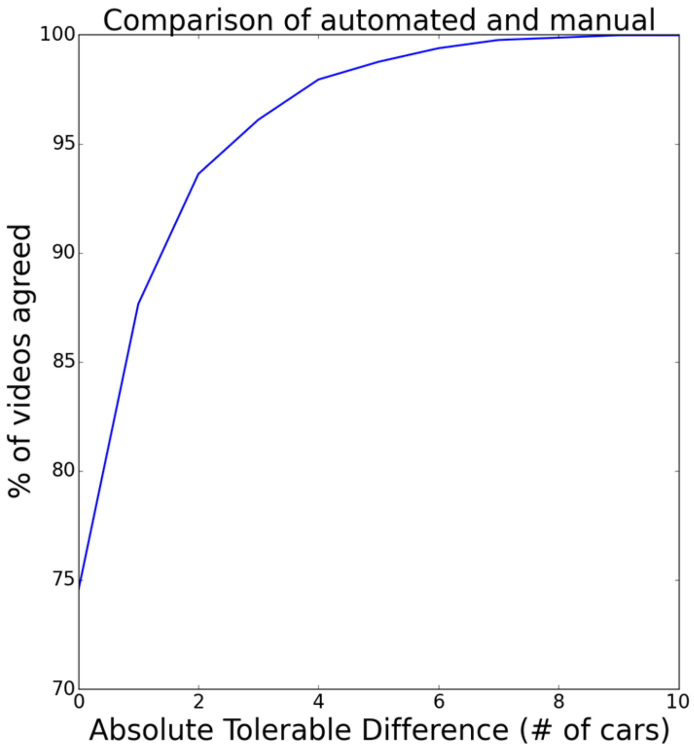


Regular Day



Shot Day





Everett Key

Reason for not using foreground & blob detection

- Foreground detection detects pixels that are not associated with a stationary background
- Blob detection detects and track clustered foreground.

- The video is in a low resolution (60 pixels X 87 pixels)
- It is hard to differentiate between cars and cloud shadow, elks and sand cloud.