Image-Based Situation Awareness Audit 28.2.2018

Sakari Lampola

Previous Audit 11.1.2018

Previous Audit

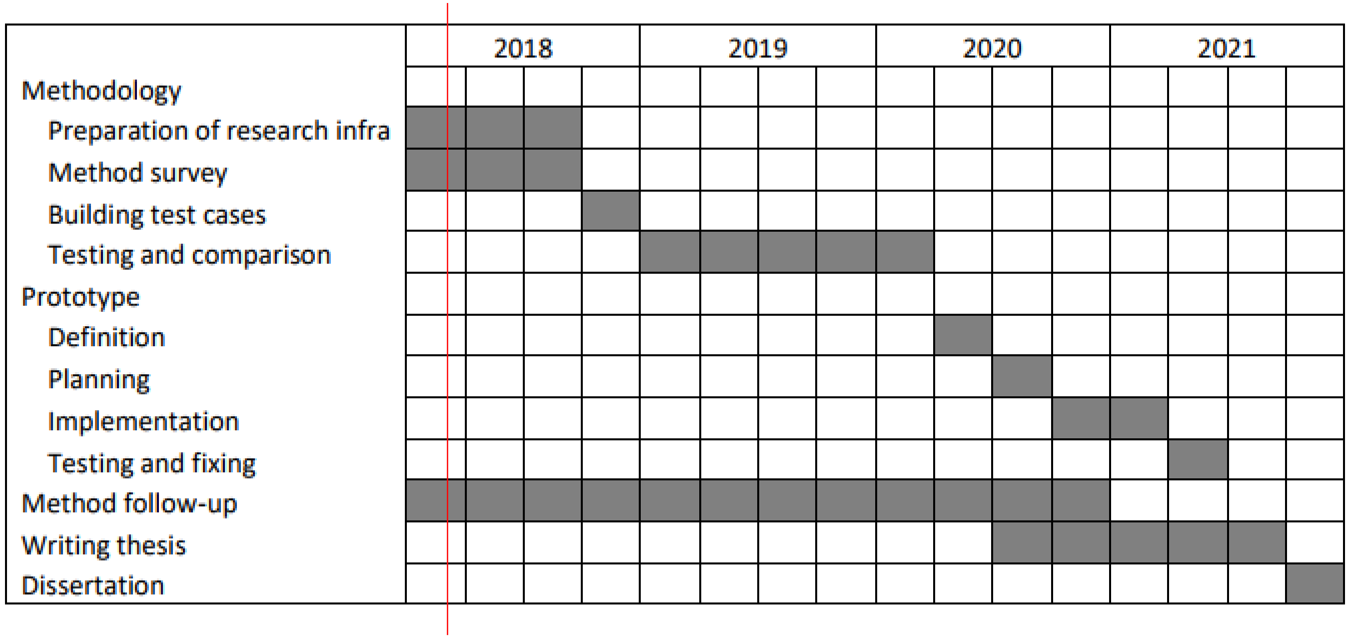
Open questions:
- Role of classical object tracking alrorithms?
- What to do with multiple bounding boxes around one object?
- Appropriate minimum confidence level?
- What to do with false detections inside other objects?
- What to do with false detections from the background?
- How to set Kalman filter parameters for image object filtering?
- Hungarian algorithm, special case for hidden objects

To do:
- Close open questions
- Image object status
- Image object velocity estimation
- Probabilistic approach for matching detected and image objects
- 2d -> 3d transformation
- World object state estimation

Other:
- Semantic segmentation
- Organisations to follow: ICCV, ICRA, NIPS, IROS, arXiv
- Camera motion (yaw, pitch,roll)
- Grid or continuous presentation?
- Class specific attributes
- Object history

Project Plan

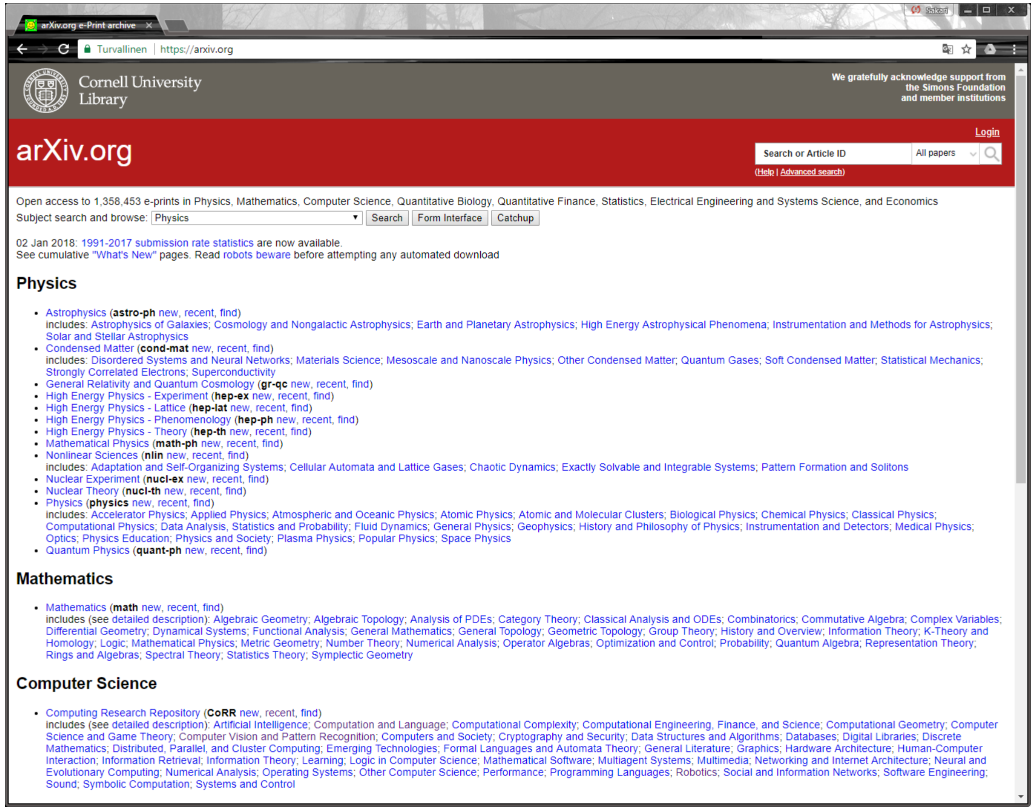
Project Plan

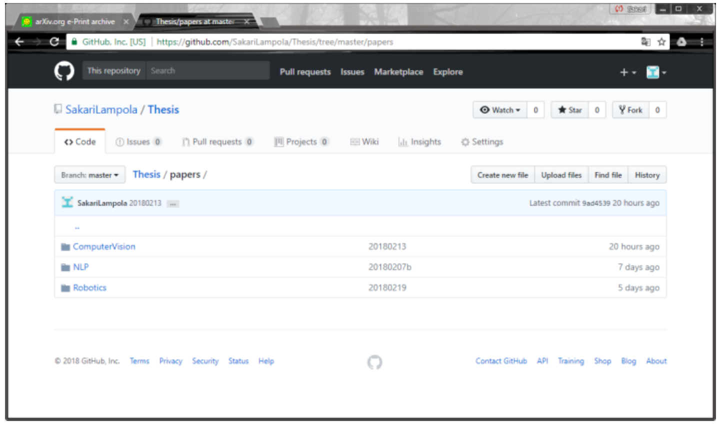


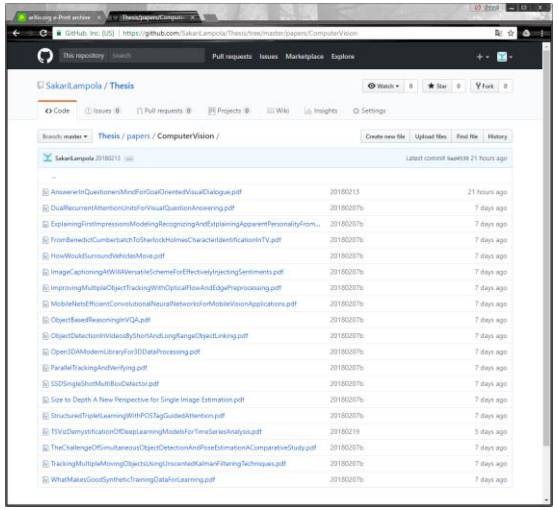
1. Methodology / Preparation of research infra
   a. Software platforms are constructed and tested
   b. Off-the-shelf models are acquired and tested
   c. Necessary skills on platforms are learned
2. Methodology / Method survey
   a. Current state-of-art methods are studied
   b. Methods are constructed and tested on the software platforms
3. Method follow-up
   a. Screening of conference papers related to the subject
   b. Possibly integrating new methods to the project

Work Done

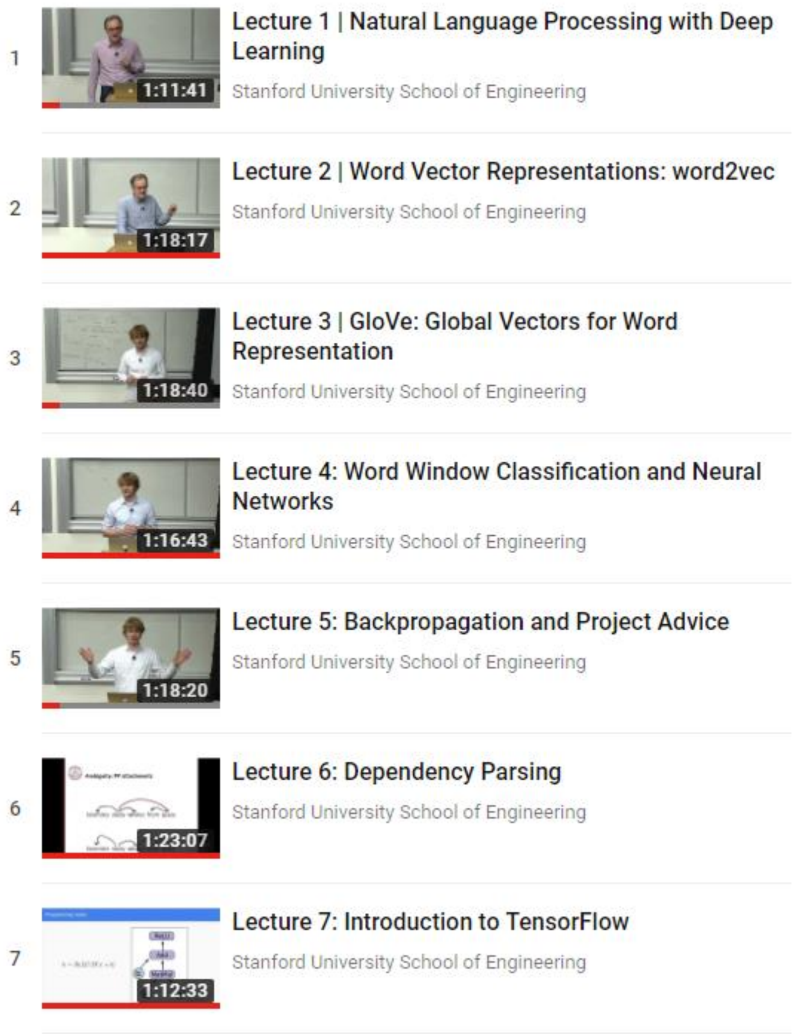
Method Follow-Up







Method Survey



Christoffer Manning & Richard Socher

Method Survey

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Lecture 8: Recurrent Neural Networks and Language Models
Stanford University School of Engineering

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Lecture 9: Machine Translation and Advanced Recurrent LSTMs and GRUs
Stanford University School of Engineering

10


Review Session: Midterm Review
Stanford University School of Engineering

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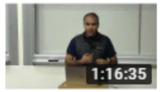
Lecture 10: Neural Machine Translation and Models with Attention
Stanford University School of Engineering

12


Lecture 11: Gated Recurrent Units and Further Topics in NMT
Stanford University School of Engineering

13


Lecture 12: End-to-End Models for Speech Processing
Stanford University School of Engineering

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Lecture 13: Convolutional Neural Networks
Stanford University School of Engineering

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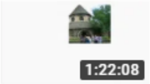

Lecture 14: Tree Recursive Neural Networks and Constituency Parsing
Stanford University School of Engineering

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Lecture 15: Coreference Resolution
Stanford University School of Engineering

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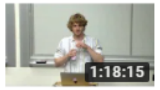

Lecture 16: Dynamic Neural Networks for Question Answering
Stanford University School of Engineering

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Lecture 17: Issues in NLP and Possible Architectures for NLP
Stanford University School of Engineering

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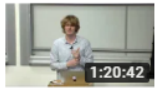


Lecture 18: Tackling the Limits of Deep Learning for NLP
Stanford University School of Engineering

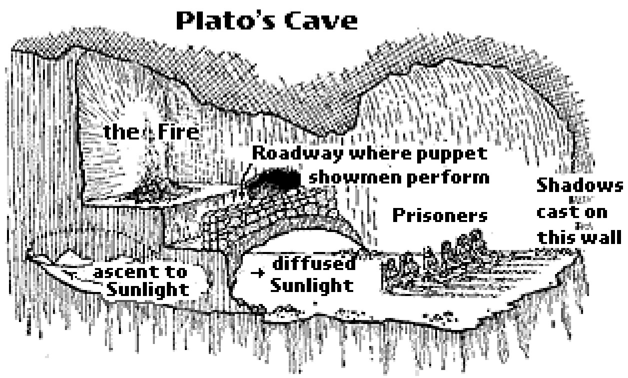
Goodfellow, Bengio, Courville: Deep Learning

Software Version 2.0

V2.0 Goal

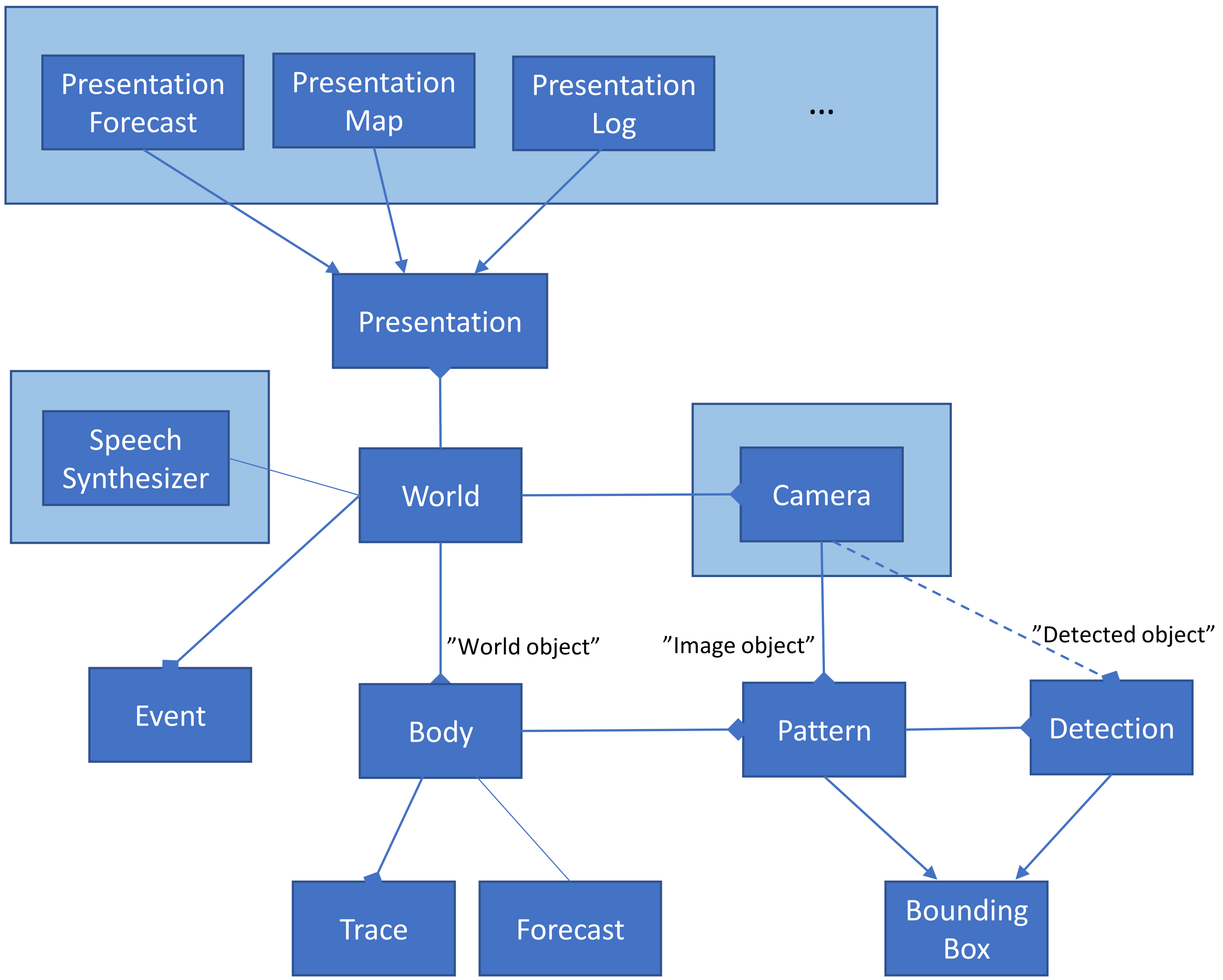
- Detected classes not hardcoded
- Object class may change
- Support for many cameras , rotations, movement
- Names less awkward, terminology fixed
- Cleaning
- Python style guide followed, excluding line length
- Code optimization
- One package
- Speech synthesizer

Name of the software package: ShadowWorld
(Plato: Allegory of the Cave)



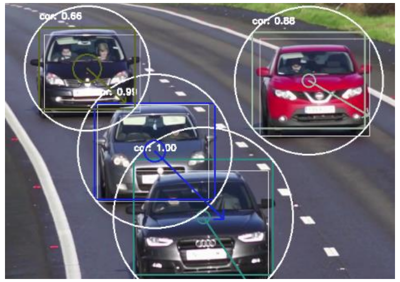
Software Version 2.0

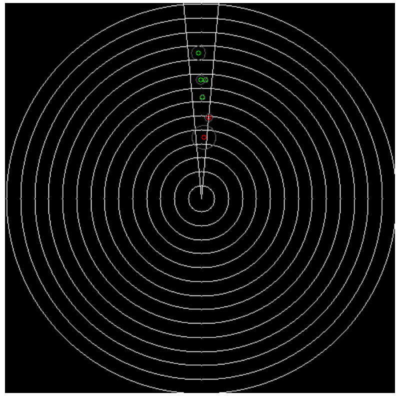
Class Diagram

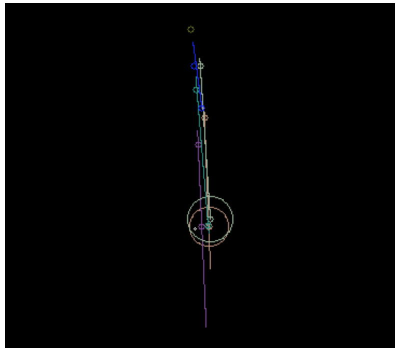


Software Version 2.0

Detection
↓
Matching
↓
Pattern Filtering
↓
Distance Estimation
↓
3D Projection
↓
Body Filtering
↓
Body Prediction
↓
Collision Detection

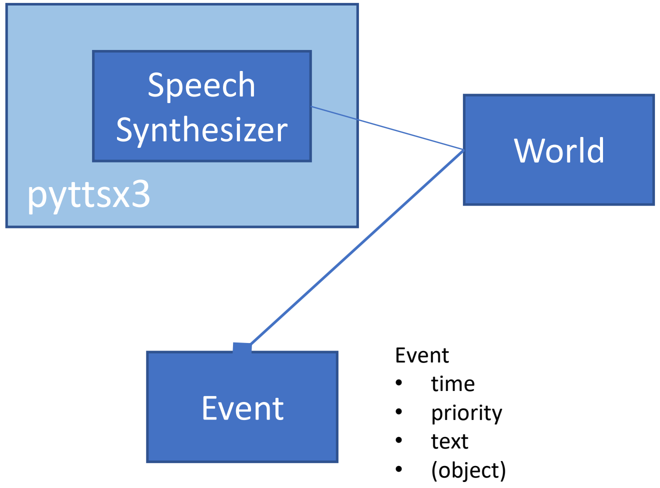






Software Version 2.0

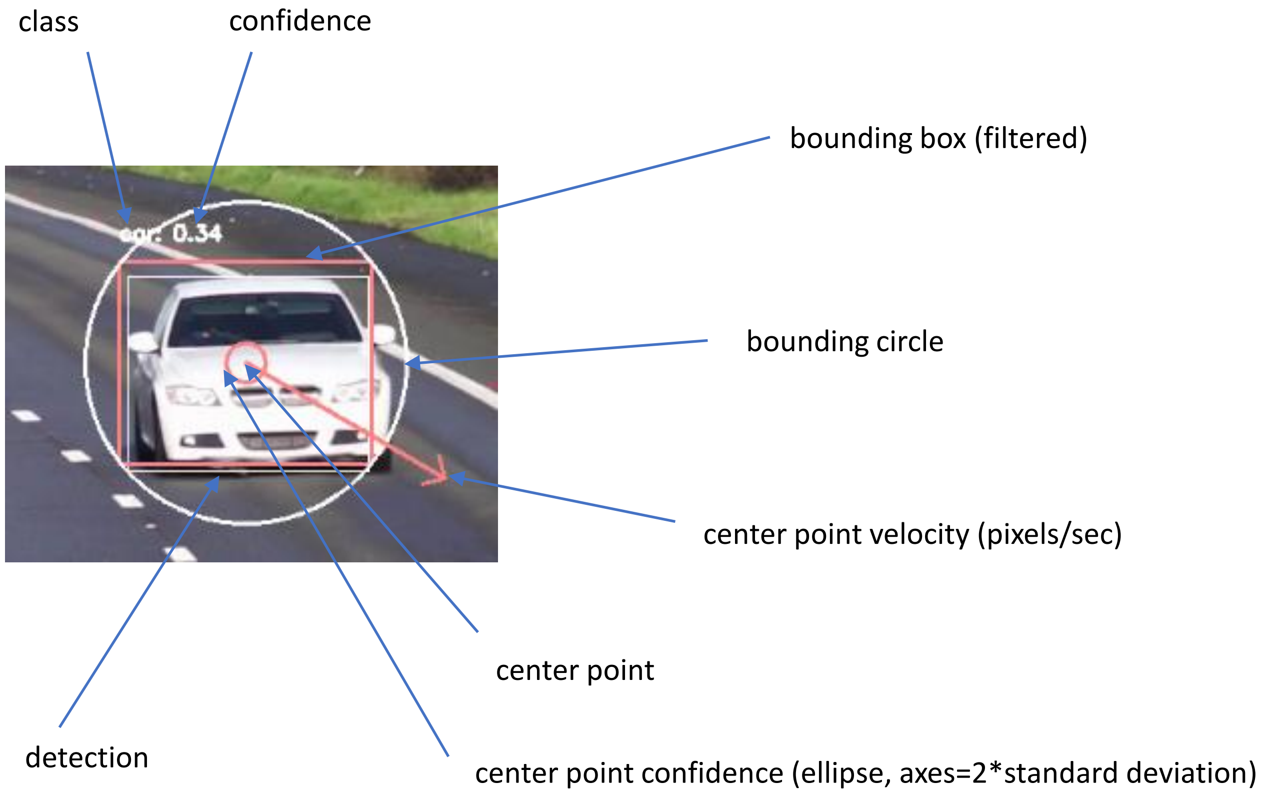
Speech Synthesizer



- Speech synthesizer based on pyttsx3 package
- Event is spelled out if priority <= 0
- Event will pause video for the duration of speech (to be changed later by using separate thread)
- Example events:
  - Body observed (1 sec after created)
  - Collision warning

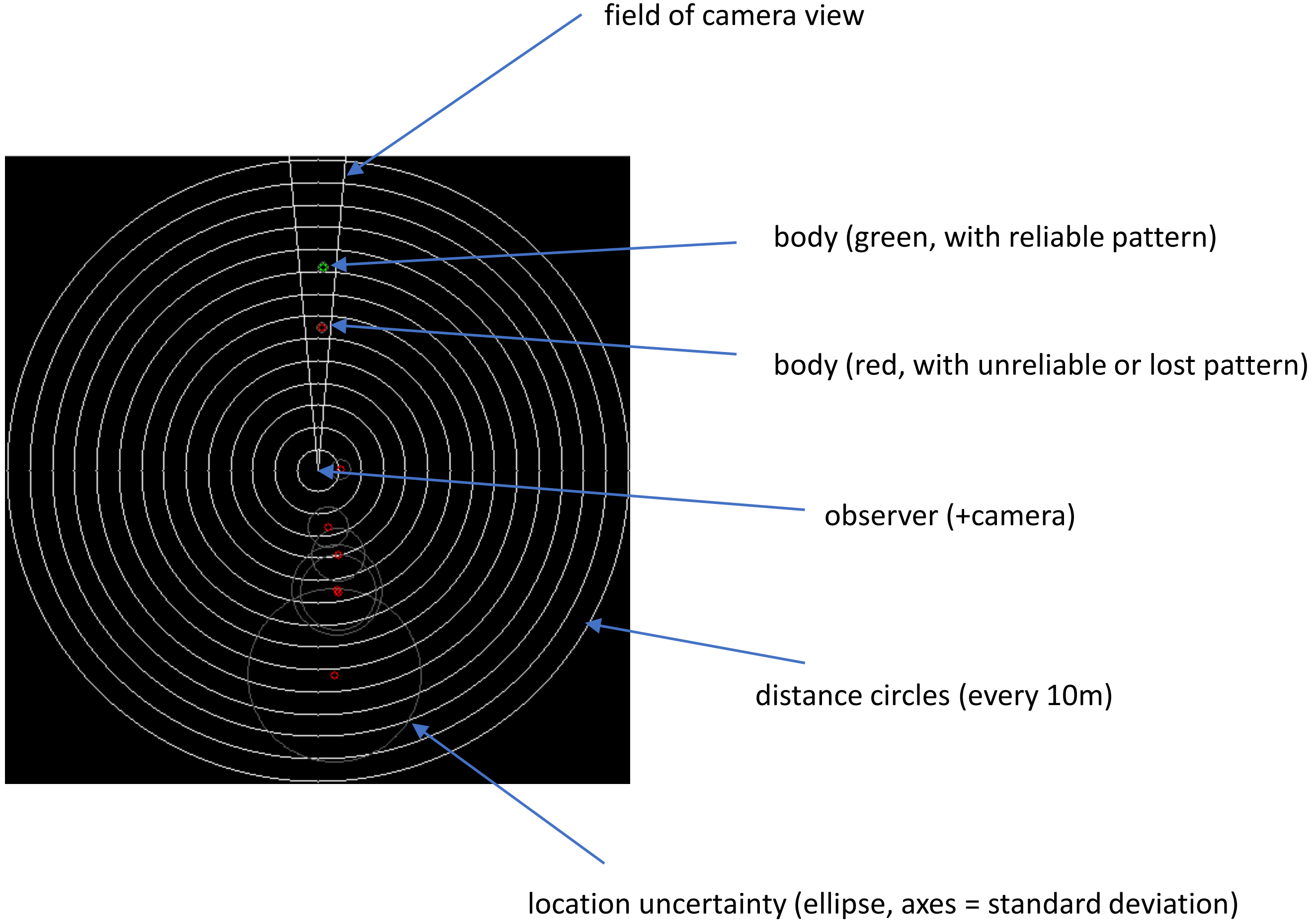
Software Version 2.0

Visual Presentation (pattern)



Software Version 2.0

Visual Presentation (body)



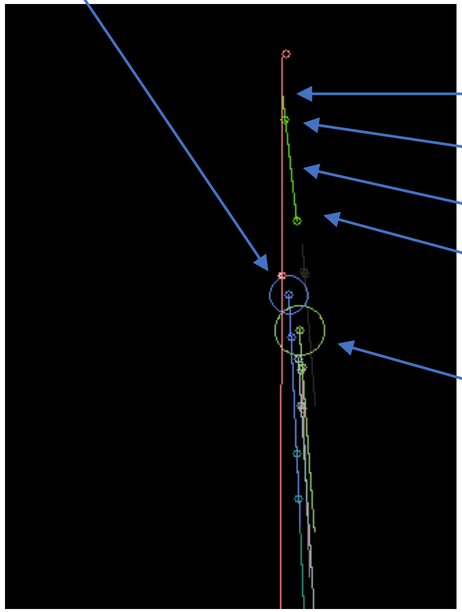
body size (circle, radius = mean class specific radius)

Software Version 2.0

Visual Presentation (forecast)

Forecast made every FORECAST_INTERVAL (=1.0) seconds

observer



body location, when forecast was made

body location, current

body location predicted path

body location after FORECAST_COUNT*FORECAST_DELTA seconds

collision probability > 1

body size (circle, radius = mean class specific radius)

Software Version 2.0

Logging

Body.txt Detection.txt Event.txt Pattern.txt

```
time,id,class_id,x,y,z,vx,vy,vz,sigma_00,sigma_01,sigma_02,sigma_03,sigma_04,sigma_05,sigma_10
0.000,2061579034864,7,3.452,-0.145,-96.541,0.000,0.000,0.000,199.601,0.000,0.000,7.971,0.000,0
0.000,2061579035088,7,-0.226,-1.349,-89.454,0.000,0.000,0.000,199.601,0.000,0.000,7.971,0.000,
0.040,2061579034864,7,3.507,-0.183,-96.872,0.612,-0.426,-3.685,128.569,0.000,0.000,1429.181,0.
0.040,2061579035088,7,-0.209,-1.372,-88.698,0.182,-0.255,8.404,128.569,0.000,0.000,1429.181,0.
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0.080,2061579035088,7,-0.193,-1.397,-88.220,0.289,-0.429,10.111,128.173,0.000,0.000,1536.731,0
0.080,2061579036712,7,0.591,2.067,-118.685,0.000,0.000,0.000,199.601,0.000,0.000,7.971,0.000,0
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```

Software Version 2.0

How to use?

```
def run_application():
    """
    Example application
    """
    test_video = 5

    world = World()

    world.add_camera(Camera(world, focal_length=TEST_FOCAL_LENGTHS[test_video],
                            sensor_width=0.0359, sensor_height=0.0240,
                            x=0.0, y=0.0, z=0.0,
                            yaw=0.0, pitch=0.0, roll=0.0,
                            videofile=TEST_VIDEOS[test_video]))

    world.add_presentation(PresentationMap(world, map_id=1, height_pixels=500,
                                           width_pixels=500,
                                           extent=TEST_EXTENTS[test_video]))

    world.add_presentation(PresentationForecast(world, map_id=2,
                                                height_pixels=500,
                                                width_pixels=500,
                                                extent=TEST_EXTENTS[test_video]))

    world.add_presentation(PresentationLog(world, "Detection", "Detection.txt"))
    world.add_presentation(PresentationLog(world, "Pattern", "Pattern.txt"))
    world.add_presentation(PresentationLog(world, "Body", "Body.txt"))
    world.add_presentation(PresentationLog(world, "Event", "Event.txt"))

    world.run()

if __name__ == "__main__":
    run_application()
```

Demo

- 3-5 videos
- Short program code review

Pattern Filtering

Why pattern filtering?

- Reduces object detection noise (bounding box)
- Provides prediction for pattern location in the next frame - matching easier
- Predicts pattern location when detection is missing

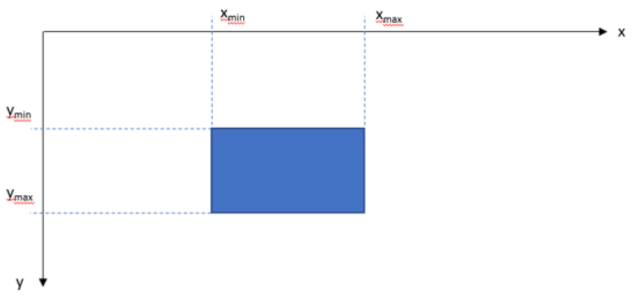
Hyperparameters:

```
#
PATTERN_ALFA = 200.0 # Pattern initial location error variance
PATTERN_BETA = 10000.0 # Pattern initial velocity error variance
PATTERN_C = np.array([[1.0, 0.0]]) # Pattern measurement matrix
PATTERN_Q = np.array([200.0]) # Pattern measurement variance
PATTERN_R = np.array([[0.1, 0.0],
                      [0.0, 1.0]]) # Pattern state equation covariance
#
```

Pattern Filtering

Pattern Kalman Filtering

Bounding box edge coordinates



Pattern location (bounding box) is determined by four edge coordinates: x_{min}, x_{max}, y_{min} and y_{max}. vx_{min}, vx_{max}, vy_{min} and vy_{max} are corresponding velocities.

Each edge coordinate is filtered separately and identically. x_{min} is used here as an example.

State equation in differential form:

$$\frac{d}{dt}\begin{bmatrix} x_{min}(t) \\ vx_{min}(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} * \begin{bmatrix} x_{min}(t) \\ vx_{min}(t) \end{bmatrix} + \epsilon(t)$$

State equation in difference form:

$$\begin{bmatrix} x_{min}(k+1) \\ vx_{min}(k+1) \end{bmatrix} = A * \begin{bmatrix} x_{min}(k) \\ vx_{min}(k) \end{bmatrix} + \varepsilon(k)$$

$$A = \begin{bmatrix} 1 & \Delta \\ 0 & 1 \end{bmatrix}$$

where Δ is the time increment and ε Gaussian noise with covariance R:

$$R = \begin{bmatrix} 0.1 & 0 \\ 0 & 1.0 \end{bmatrix}$$

Measurement equation

$$z(k) = C * \begin{bmatrix} x_{min}(k) \\ vx_{min}(k) \end{bmatrix} + \delta(k)$$

$$C = [1 \quad 0]$$

where δ is Gaussian noise with covariance matrix Q:

$$Q = [200.0]$$

Kalman filter initialization:

$$\mu(0) = \begin{bmatrix} x_{min}(0) \\ 0 \end{bmatrix}$$

where x_{min} (0) is the first location measurement.

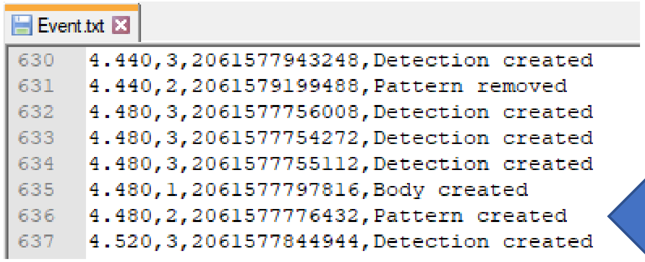
$$\Sigma(0) = \begin{bmatrix} 200.0 & 0 \\ 0 & 10\,000.0 \end{bmatrix}$$

Kalman filter update:

$$\mu_1(k) = A * \mu(k-1)$$
$$\Sigma_1(k) = A * \Sigma(k-1) * A^T + R$$
$$K(k) = \Sigma_1(k) * C^T * (C * \Sigma_1(k) * C^T + Q)^{-1}$$
$$\mu(k) = \mu_1(k) + K(k) * (z(k) - C * \mu_1(k))$$
$$\Sigma(k) = (I - K(k) * C) * \Sigma_1(k)$$

Pattern Filtering

Example:

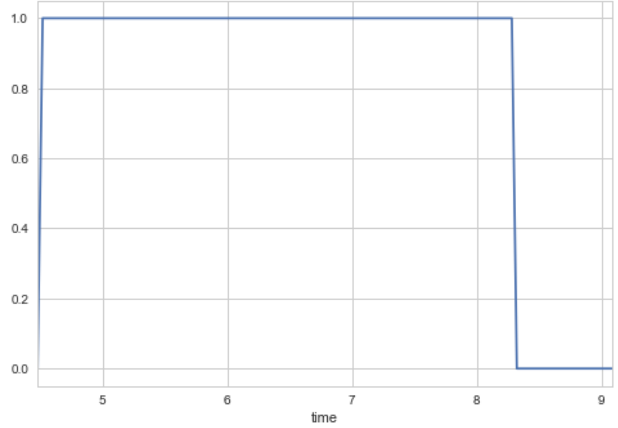



```
4.440,3,2061577943248,Detection created
4.440,2,2061579199488,Pattern removed
4.480,3,2061577756008,Detection created
4.480,3,2061577754272,Detection created
4.480,3,2061577755112,Detection created
4.480,1,2061577797816,Body created
4.480,2,2061577776432,Pattern created
4.520,3,2061577844944,Detection created
```

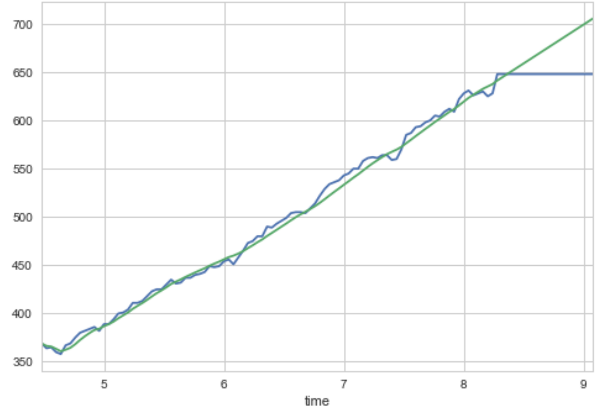
Pattern Filtering

Matched status, coordinate and velocity

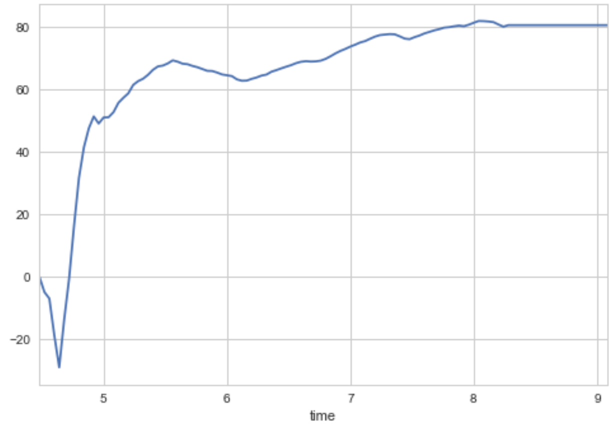
In [9]:
```
data_one['matched'].plot()
```
Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x1b3759afe80>



In [10]:
```
data_one['x_min_d'].plot() # blue, measurement
data_one['x_min'].plot() # green, filtered + predicted
```
Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x1b376ccbe48>



In [11]:
```
data_one['vx_min'].plot()
```
Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x1b376e50f98>

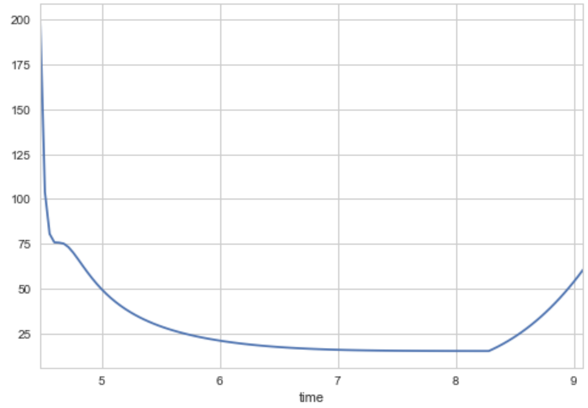


Pattern Filtering

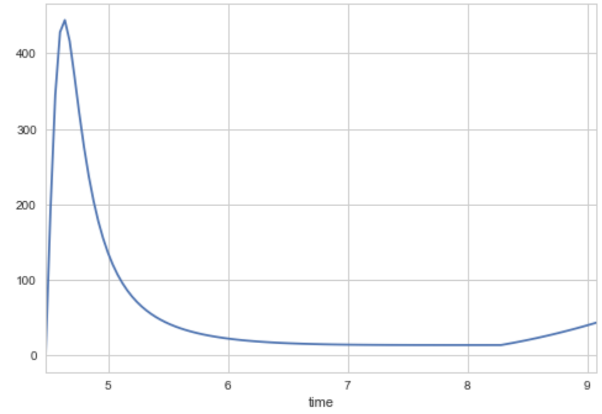
Covariance matrix

0=location, 1=velocity

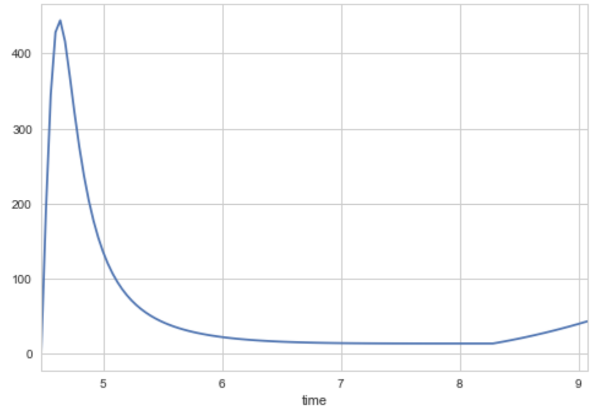
```
In [16]: data_one['sigma_x_min_00'].plot()
Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x1b3771859b0>
```



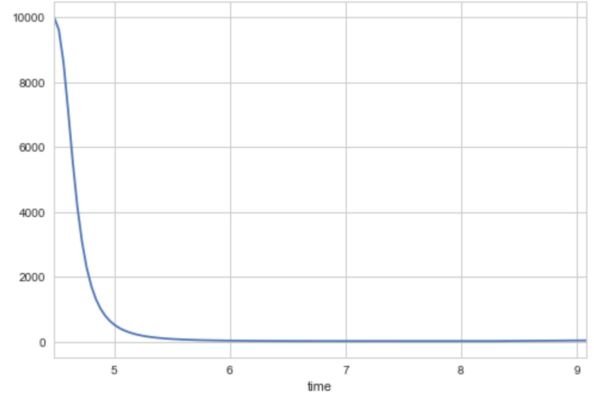

```
In [17]: data_one['sigma_x_min_01'].plot()
Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x1b37726b5c0>
```




```
In [18]: data_one['sigma_x_min_10'].plot()
Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x1b3772b9da0>
```




```
In [19]: data_one['sigma_x_min_11'].plot()
Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x1b377347358>
```



Matching / Confidence Level

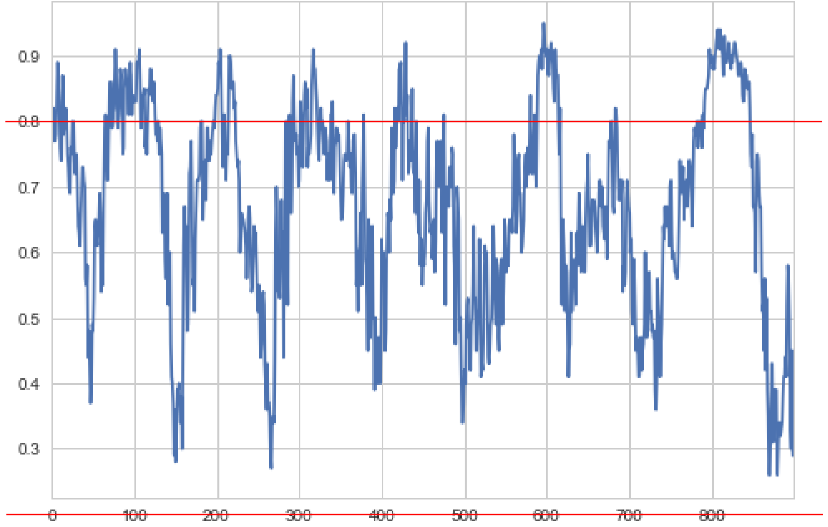
Minimum confidence level to create a pattern (and body) was varied between 0 and 1. The number of bodies created was compared to the true number of objects in the video.

Objects detected		Confidence level							
Video	Correct	0,00	0,20	0,40	0,60	0,80	0,90	0,95	1,00
CarsOnHighway001.mpg	39	49	49	39	36	34	32	32	0
Calf-2679.mp4	1	2	2	2	2	1	1	1	0
Dunes-7238.mp4	1	7	7	6	5	2	2	2	0
Sofa-11294.mp4	1	2	2	1	1	1	1	1	0
Cars133.mp4	5	9	9	6	5	5	5	5	0
BlueTit2975.mp4	1	3	3	2	1	1	1	1	0
Railway-4106.mp4	1	10	10	5	3	3	1	1	0
Hiker1010.mp4	1	4	4	0	0	0	0	0	0
Cat-3740.mp4	1	3	3	2	2	1	1	1	0
SailingBoat6415.mp4	1	1	1	1	1	1	1	1	0
AWomanStandsOnTheSeashore-10058.mp4	1	1	1	1	1	1	1	1	0
Dog-4028.mp4	1	4	4	2	1	1	1	1	0
Boat-10876.mp4	1	2	2	1	1	1	1	0	0
Horse-2980.mp4	1	3	3	3	2	2	1	1	0
Sheep-12727.mp4	1	1	1	1	1	1	1	1	1

Good value for creating a new pattern is between 0.8 and 0.9.

Matching / Confidence Level

Confidence level has dynamics



create

update

ignore

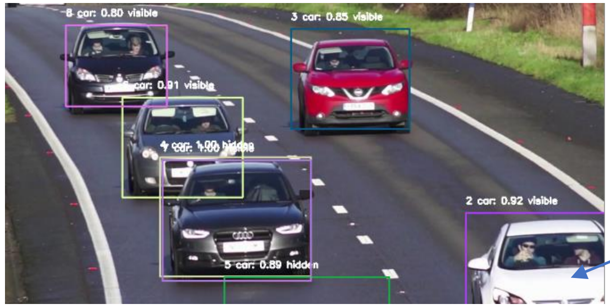
Different levels for creating and updating image object.

Hyperparameters:

- CONFIDENCE_LEVEL_CREATE (0.8)
- CONFIDENCE_LEVEL_UPDATE (0.2)

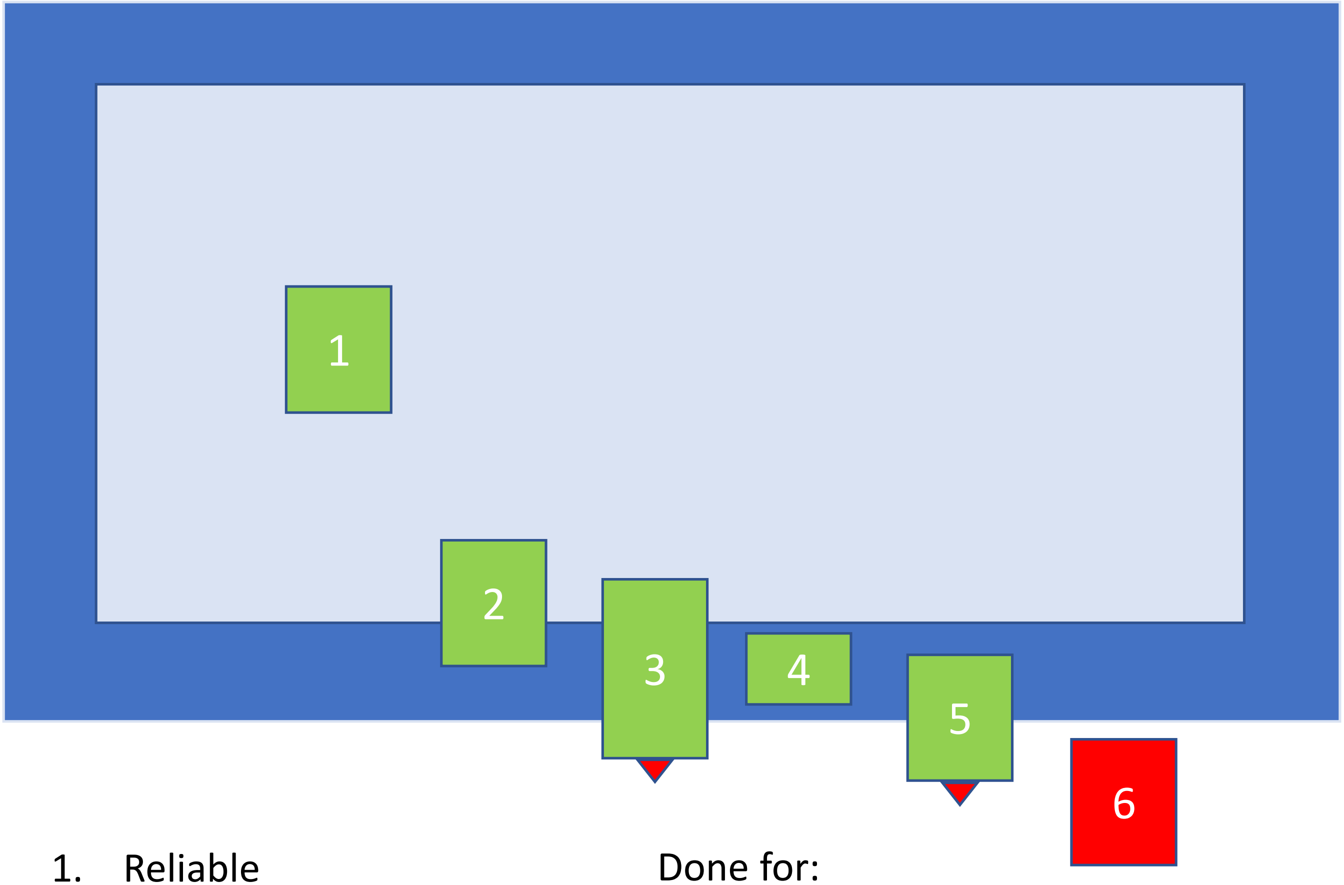
Matching / Border Behaviour

The problem:
Bounding box size and form are distorded near edges



Hyperparameter BORDER_WIDTH (30)

Matching / Border Behaviour



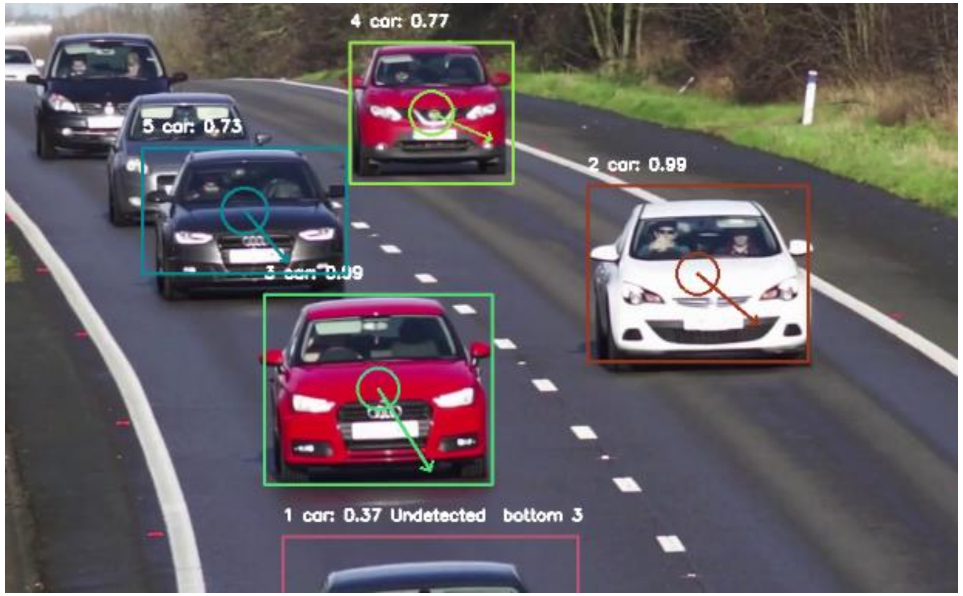
1. Reliable
2. Reliable
3. Unreliable, not created
4. Reliable, not created
5. Unreliable, not created
6. Unreliable, removed

Done for:

- left
- right
- top
- bottom

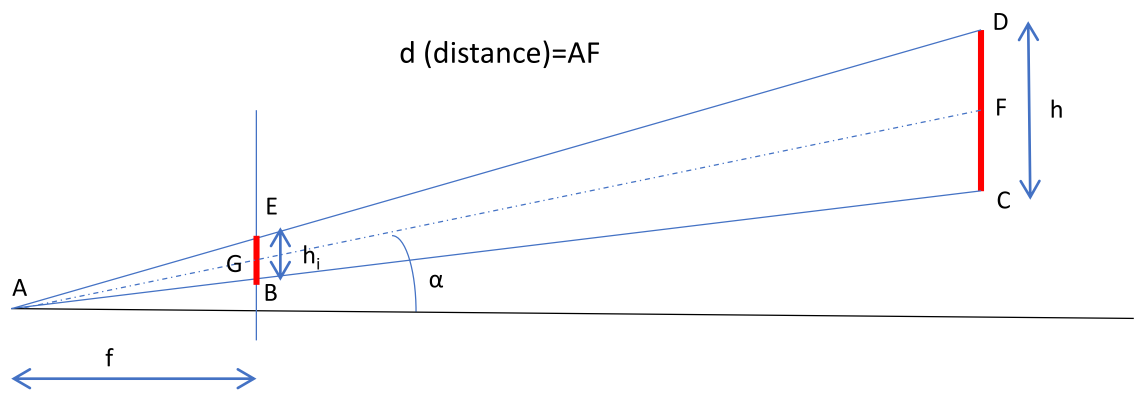
If a pattern touches 3 borders, it is removed
Reliable = body information updated

Matching / Pattern Retention



Patterns are removed if not detected in RETENTION_COUNT_MAX (30) successive frames.

Distance Estimation



Similar triangles AGE and AFD:

$$\frac{0.5 * h_i}{0.5 * h} = \frac{AG}{d} = \frac{\frac{f}{\cos(\alpha)}}{d} = \frac{f}{d * \cos(\alpha)}$$

$$d = \frac{f * h}{\cos(\alpha) * h_i}$$

Distance Estimation

Similar equations for horizontal direction (β=azimuth):

$$d = \frac{f * l}{\cos(\alpha) * \cos(\beta) * l_i} = \frac{f * l}{\cos(\alpha) * \cos(\beta) * l_i * s_h/p_h}$$

s_w= *sensor width (m)*
s_h= *sensor height (m)*
p_w= *image width (pixels)*
p_h= *image height (pixels)*
l_i = *object length (pixels)*
l = *object length (m)*
f = *focal length (m)*
α = *altitude (rad)*
β = *azimuth (rad)*

Assumptions:
- *equal vertical/horizontal pixel spacing*
- *optical axis in image center*

Example (Nikon D800E):

s_w= sensor width (m) = 0.0359 m
s_h= sensor height (m) = 0.0240 m
p_w= image width (pixels) = 7360
p_h= image height (pixels) = 4912
l_i = object length (pixels) = 100
l = object length (m) = 1.0 m
f = focal length (m) = 0.050 m
α = *altitude (rad) = 0.0*
β = *azimuth (rad) = 0.0*

$$d = \frac{0.050m * 1m}{1.0*1.0*100 * 0.024m/4912} = 102.33\ m$$

Distance Estimation

Question: How to compare pattern and body sizes for distance estimation?

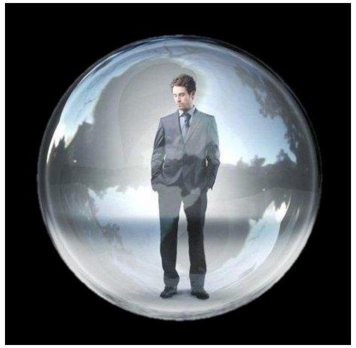
Height or width alone might be misleading.

Some form of (3D) spatial simplification is needed, like

- cube
- rectangular prism
- cylinder
- sphere (probably the easiest math)

Uncertainty should be modeled.

Solution:
pattern circle <---> body sphere



Distance Estimation

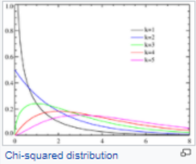
Body radius distribution

Distibution should

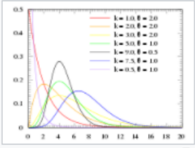
- be defined in [0,∞]
- mode > 0
- simple
- skew controllable

Supported on semi-infinite intervals, usually [0,∞) [edit]

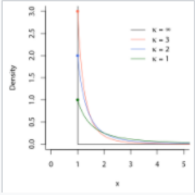
- The Beta prime distribution
- The Birnbaum–Saunders distribution, also known as the fatigue life distribution, is a probability distribution used extensively in reliability applications to model failure times.
- The chi distribution
  - The noncentral chi distribution
- The chi-squared distribution, which is the sum of the squares of *n* independent Gaussian random variables. It is a special case of the Gamma distribution, and it is used in goodness-of-fit tests in statistics.
  - The inverse-chi-squared distribution
  - The noncentral chi-squared distribution
  - The Scaled inverse chi-squared distribution
- The Dagum distribution
- The exponential distribution, which describes the time between consecutive rare random events in a process with no memory.
- The Exponential-logarithmic distribution
- The F-distribution, which is the distribution of the ratio of two (normalized) chi-squared-distributed random variables, used in the analysis of variance. It is referred to as the beta prime distribution when it is the ratio of two chi-squared variates which are not normalized by dividing them by their numbers of degrees of freedom.
  - The noncentral F-distribution
- The folded normal distribution
- The Fréchet distribution
- The Gamma distribution, which describes the time until *n* consecutive rare random events occur in a process with no memory.
  - The Erlang distribution, which is a special case of the gamma distribution with integral shape parameter, developed to predict waiting times in queuing systems
  - The inverse-gamma distribution
- The Generalized gamma distribution
- The generalized Pareto distribution
- The Gamma/Gompertz distribution
- The Gompertz distribution
- The half-normal distribution
- Hotelling's T-squared distribution
- The inverse Gaussian distribution, also known as the Wald distribution
- The Lévy distribution
- The log-Cauchy distribution
- The log-Laplace distribution
- The log-logistic distribution
- The log-normal distribution, describing variables which can be modelled as the product of many small independent positive variables.
- The Lomax distribution
- The Mittag-Leffler distribution
- The Nakagami distribution
- The Pareto distribution, or "power law" distribution, used in the analysis of financial data and critical behavior.
- The Pearson Type III distribution
- The Phase-type distribution, used in queueing theory
- The phased bi-exponential distribution is commonly used in pharmokinetics
- The phased bi-Weibull distribution
- The Rayleigh distribution
- The Rayleigh mixture distribution
- The Rice distribution
- The shifted Gompertz distribution
- The type-2 Gumbel distribution
- The Weibull distribution or Rosin Rammler distribution, of which the exponential distribution is a special case, is used to model the lifetime of technical devices and is used to describe the particle size distribution of particles generated by grinding, milling and crushing operations.



Chi-squared distribution



Gamma distribution



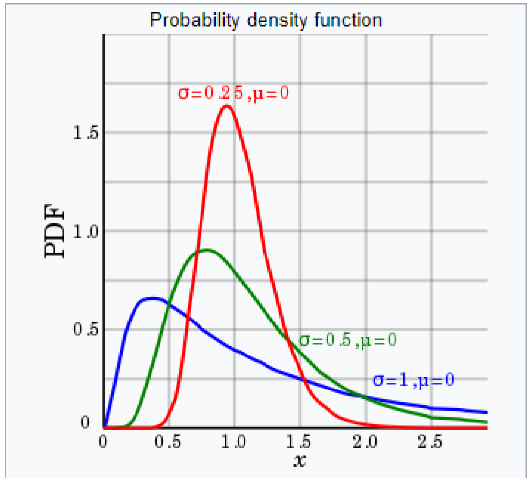
Pareto distribution

Distance Estimation

Log-normal distribution for body radius

Log-normal

Probability density function



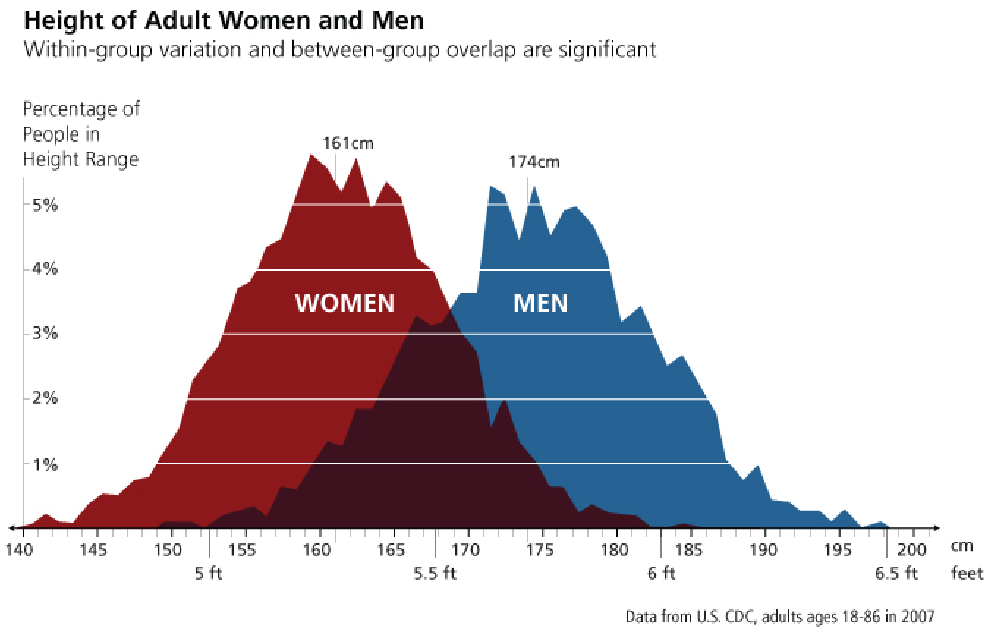
Some log-normal density functions with identical parameter μ but differing parameters σ

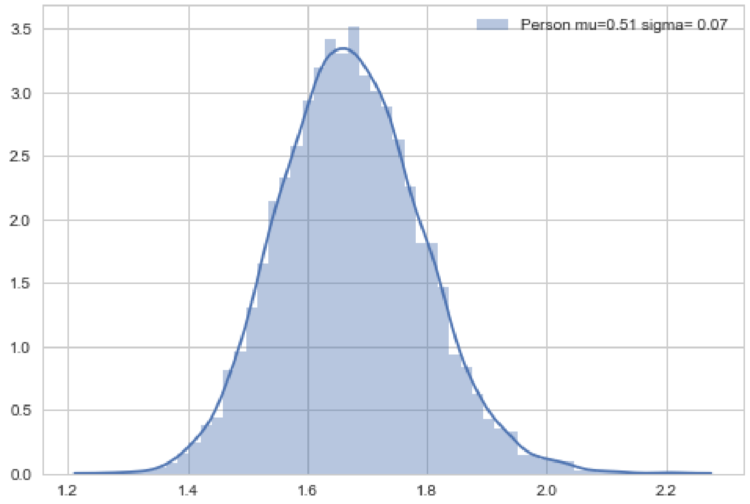
Used in the context of describing human height distribution

Notation	$\operatorname{Lognormal}(\mu,\, \sigma^2)$
Parameters	$\mu \in (-\infty, +\infty)$, $\sigma > 0$
Support	$x \in (0, +\infty)$
PDF	$\frac{1}{x\sigma\sqrt{2\pi}}\, e^{-\frac{(\ln x-\mu)^2}{2\sigma^2}}$
CDF	$\frac{1}{2} + \frac{1}{2}\operatorname{erf}\left[\frac{\ln x - \mu}{\sqrt{2}\sigma}\right]$
Mean	$\exp\left(\mu + \frac{\sigma^2}{2}\right)$
Median	$\exp(\mu)$
Mode	$\exp(\mu - \sigma^2)$
Variance	$[\exp(\sigma^2) - 1]\exp(2\mu + \sigma^2)$
Skewness	$(e^{\sigma^2} + 2)\sqrt{e^{\sigma^2} - 1}$
Ex. kurtosis	$\exp(4\sigma^2) + 2\exp(3\sigma^2) + 3\exp(2\sigma^2) - 6$
Entropy	$\log(\sigma e^{\mu+\frac{1}{2}}\sqrt{2\pi})$
MGF	defined only for numbers with a non-positive real part, see text
CF	representation $\sum_{n=0}^{\infty}\frac{(it)^n}{n!}e^{n\mu+n^2\sigma^2/2}$ is asymptotically divergent but sufficient for numerical purposes
Fisher information	$\begin{pmatrix} 1/\sigma^2 & 0 \\ 0 & 1/2\sigma^4 \end{pmatrix}$

Distance Estimation

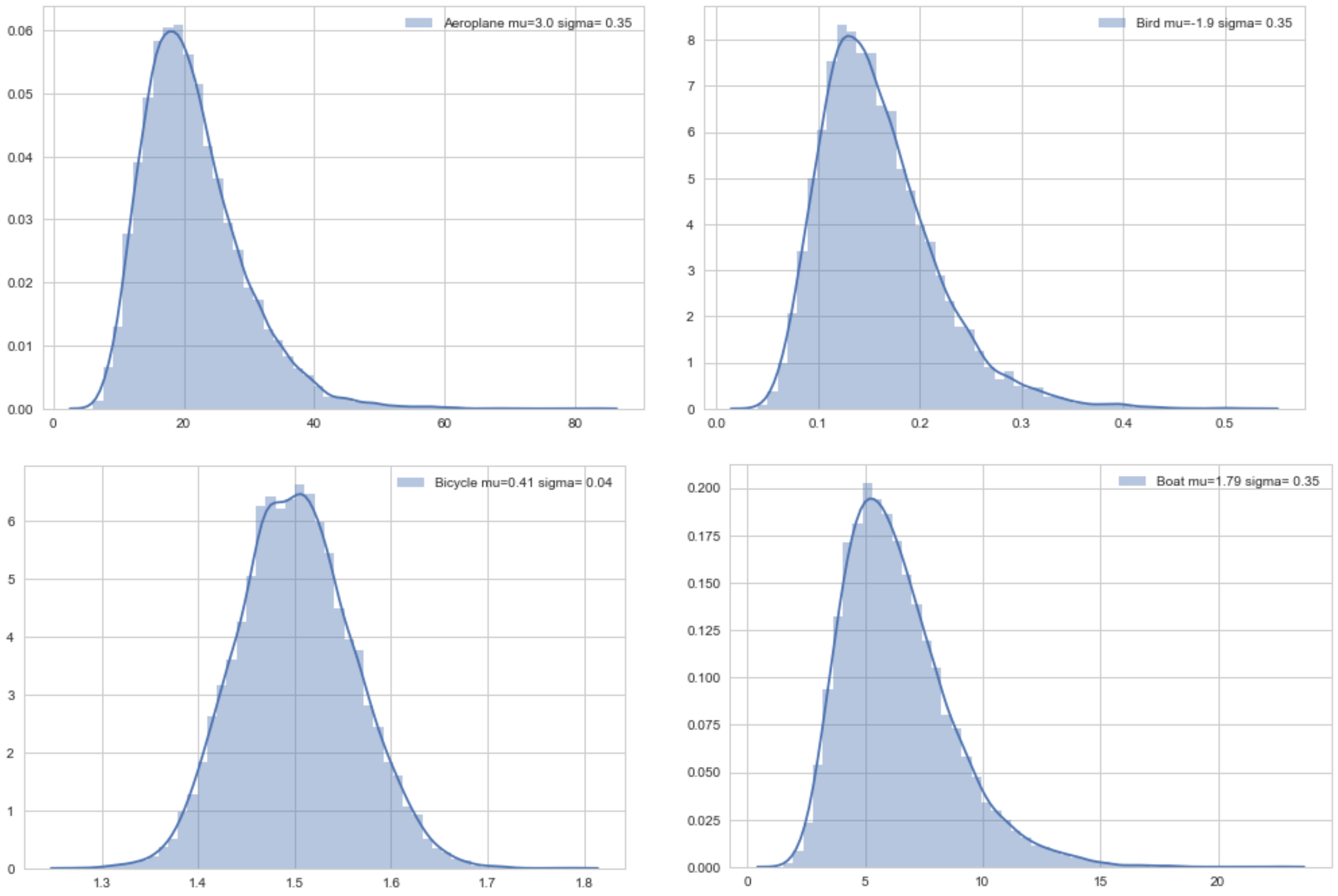
Example: Person





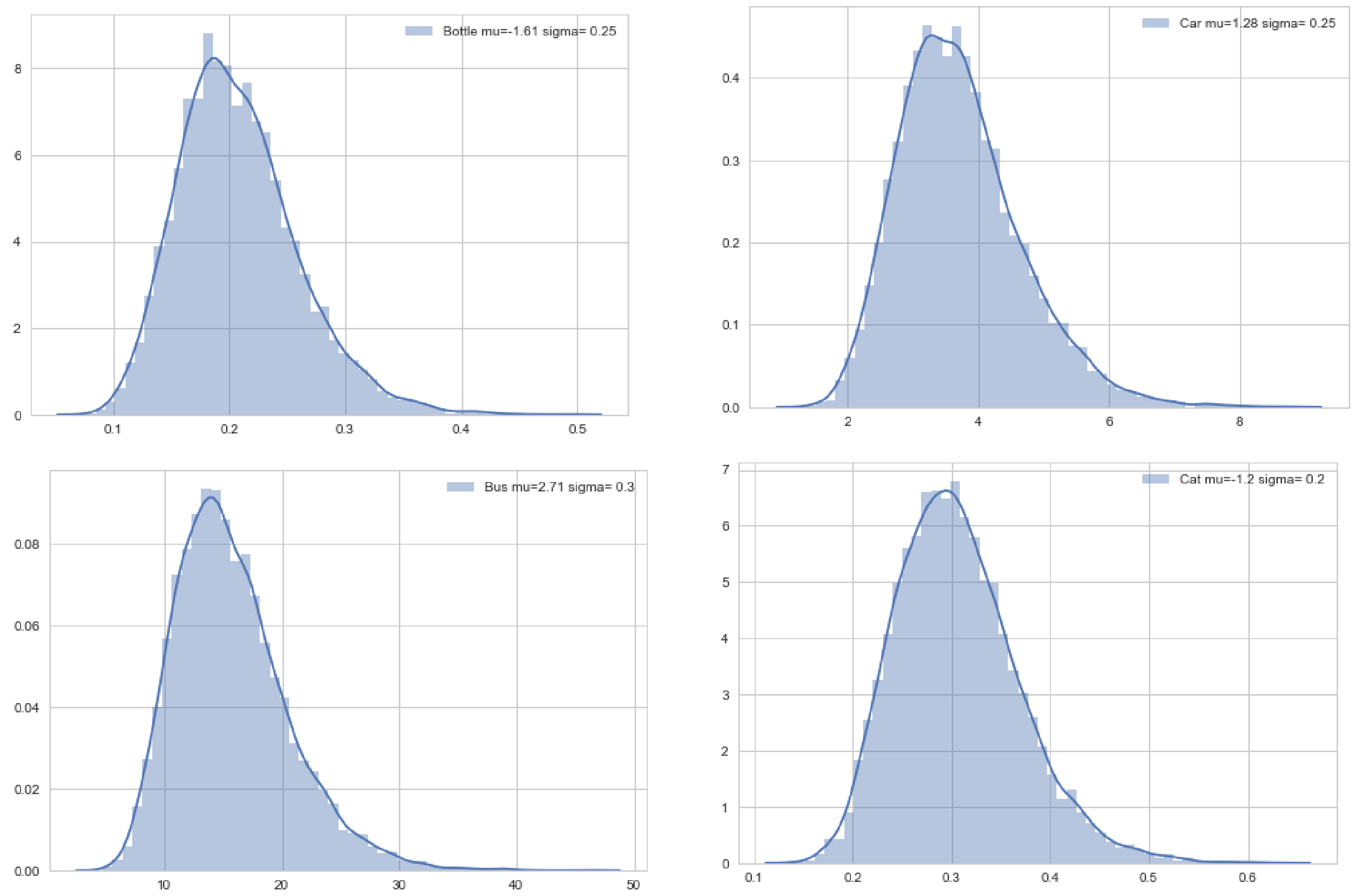
Distance Estimation

Bubble diameters (2*radius)



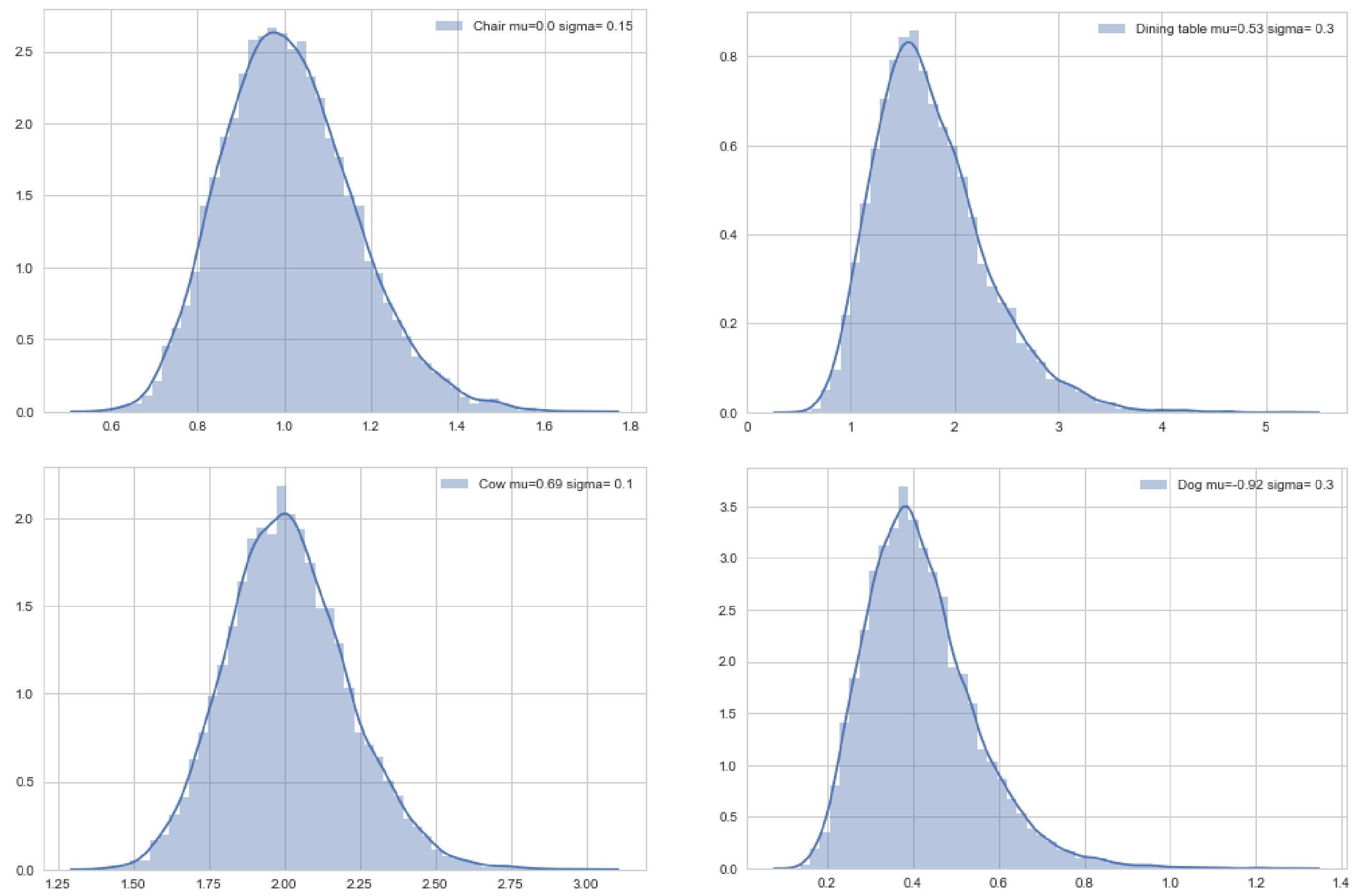
Distance Estimation

Bubble diameters (2*radius)



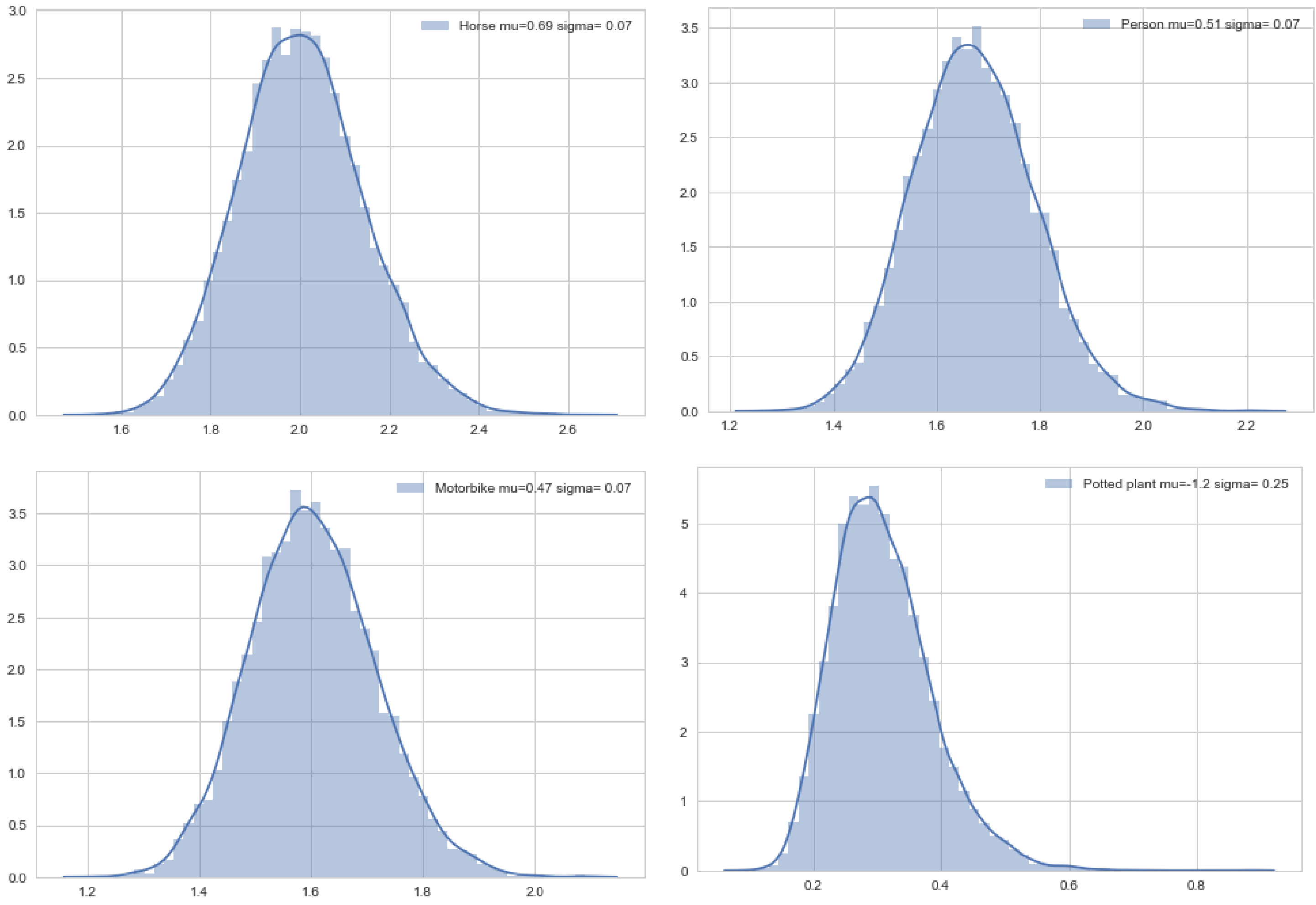
Distance Estimation

Bubble diameters (2*radius)



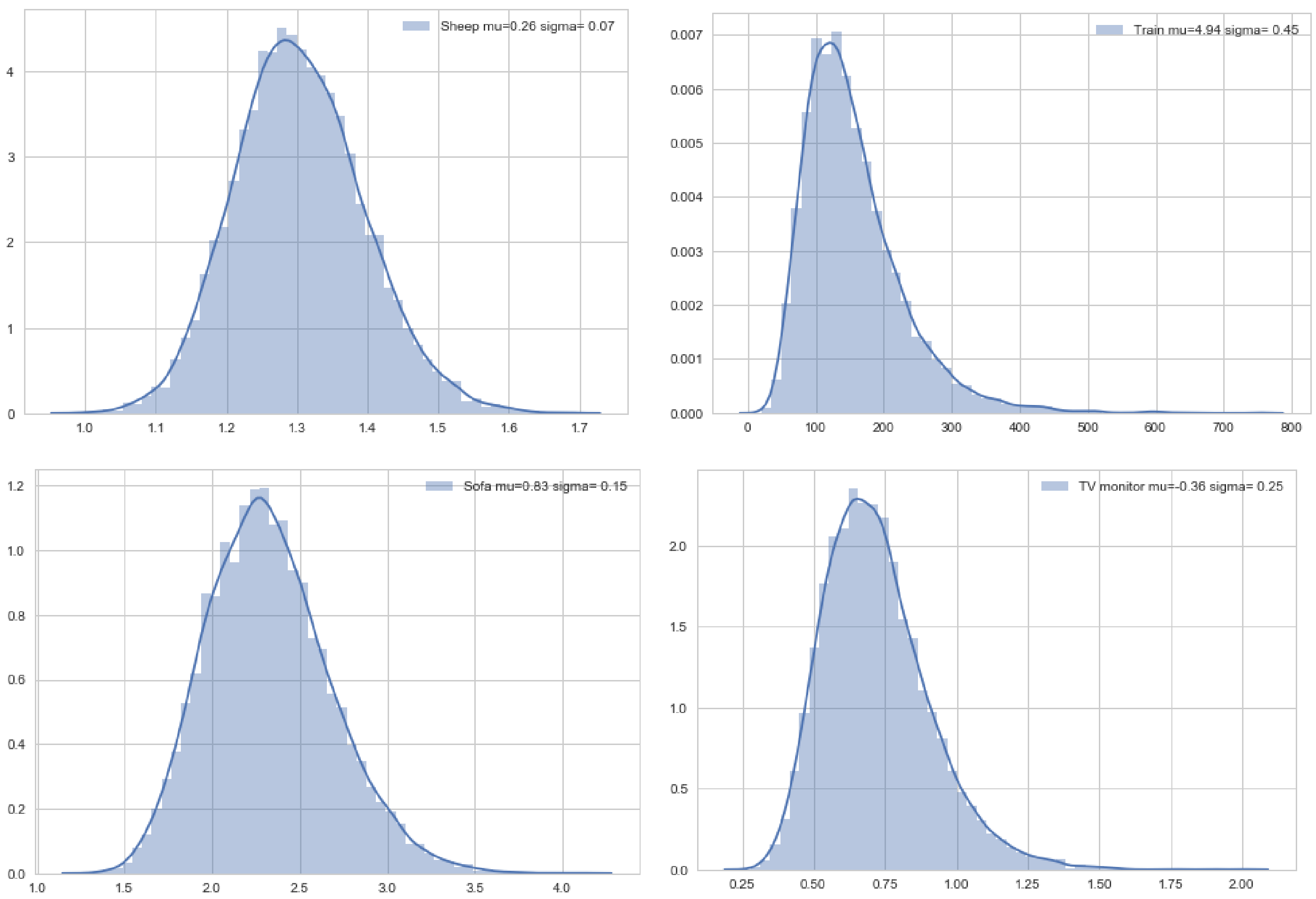
Distance Estimation

Bubble diameters (2*radius)



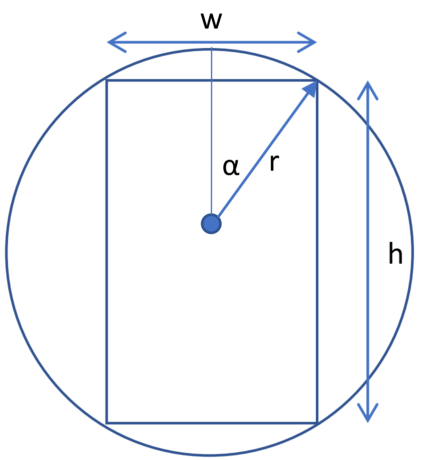
Distance Estimation

Bubble diameters (2*radius)



Distance Estimation

Radius of enclosing circle will be used for pattern



From bounding box coordinates to radius:

$$r = \sqrt{(\frac{w}{2})^2 + (\frac{h}{2})^2}$$

$$h = (ymax - ymin) \quad c_y = (ymax + ymin)/2$$

$$\mathrm{w} = (xmax - xmin) \quad c_x = (xmax + xmin)/2$$

Distance Estimation

Distance estimation using pattern circle and body sphere

$$d = \frac{f * r}{\cos(\alpha) * \cos(\beta) * r_i * s_h / p_h}$$

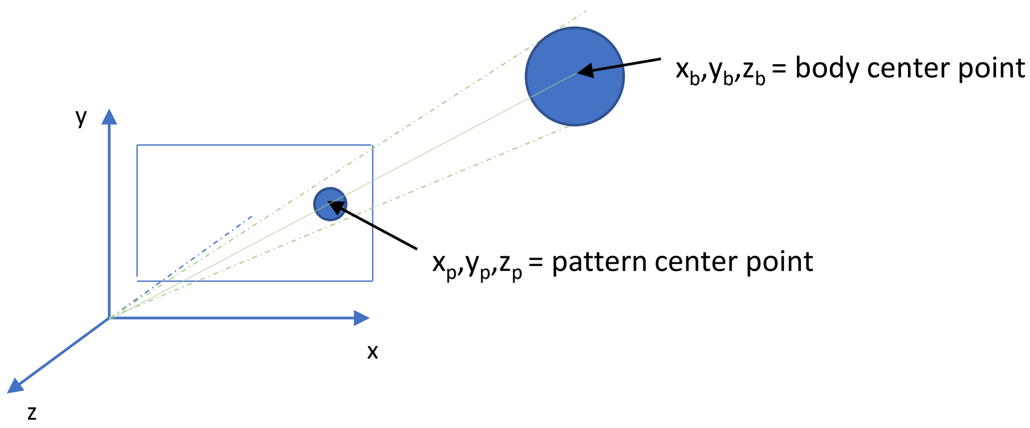
s_h = *sensor height (m)*
p_h = *image height (pixels)*
r_i = *pattern radius (pixels)*
r = body radius (m), mean from class specific distribution
f = focal length (m)
α = *altitude (rad)*
β = *azimuth (rad)*

Distance Estimation

Remarks:

- Video metadata often lacks sensor and focal parameters
- Focal length can change during shooting (zooming)

3D Projection



From pixel coordinates px_p, py_p (sensor plane) to 3d camera coordinates:

$$(x_p, y_p, z_p) = \left(-\frac{s_w}{2} + px_p * \frac{s_w}{p_w},\ \frac{s_h}{2} - py_p * \frac{s_h}{p_h},\ -f\right)$$

Body center will be on the line:

$$(x_b, y_b, z_b) = t * (x_p, y_p, z_p)$$

Distance to the body is:

$$d = \frac{f * h}{\cos(\alpha) * \cos(\beta) * h_i * s_h/p_h}$$

$$\alpha = \arctan(y_p/f)$$
$$\beta = \arctan(x_p/f)$$

s_w = sensor width (m)
s_h = sensor height (m)
p_w = image width (pixels)
p_h = image height (pixels)
h_i = object height (pixels)
h = object height (m)
f = focal length (m)
α = altitude (rad)

3D Projection

So: $t^2 * (x_p{}^2 + y_p{}^2 + z_p{}^2) = d^2$

Solving for t: $t = \frac{d}{\sqrt{x_p{}^2 + y_p{}^2 + z_p{}^2}}$

$(x_b, y_b, z_b) = t * (x_p, y_p, z_p)$

Where:

$(x_p, y_p, z_p) = \left(-\frac{s_w}{2} + xp * \frac{s_w}{p_w},\ \frac{s_h}{2} - yp * \frac{s_h}{p_h},\ -f\right)$

$$t = \frac{d}{\sqrt{x_p{}^2 + y_p{}^2 + z_p{}^2}}$$

$$d = \frac{f * h}{\cos(\alpha) * \cos(\beta) * h_i * s_h / p_h}$$

3D Projection

Example:

s_w= sensor width (m) = 0.0359 m
s_h= sensor height (m) = 0.0240 m
p_w= image width (pixels) = 7360
p_h= image height (pixels) = 4912
r_i = pattern radius (pixels) = 100
r = body radius (m) = 1.0 m
f = focal length (m) = 0.050 m
x_p = 1200
y_p = 2000

$$(x_p, y_p, z_p) = \left(-\frac{s_w}{2} + xp * \frac{s_w}{p_w},\ \frac{s_h}{2} - yp * \frac{s_h}{p_h},\ -f\right)$$

$$= \left(-\frac{0.0359}{2} + 1200 * \frac{0.0359}{7360},\ \frac{0.0240}{2} - yp * \frac{0.0240}{4912},\ -0.050\right) = (-0.0121, 0.0022, -0.0500)$$

α = arc tan(y_p/f) = 0.0445 β = arc tan(x_p/f) = -0.2374

$$d = \frac{f * h}{\cos(\alpha) * \cos(\beta) * h_i * s_h/p_h} = \frac{0.050 * 1}{\cos(0.0445) * \cos(-0.2374) * 100 * 0.0240/4912} = 105.39$$

$$t = \frac{105.39}{\sqrt{-0.0121^2 + 0.0022^2 + -0.0500^2}} = 2.0468e{+}03$$

$(x_b, y_b, z_b) = t * (x_p, y_p, z_p)$ = 2.0468e+03 * (-0.0121, 0.0022, -0.0500) = (-24.7593, 4.5602, -102.3389)

Body Filtering

- Enables prediction, including collision detection
- Second order model does not work, constant acceleration makes bodies bounce back or get enormous velocities
- In world, constant acceleration for several (tens) of seconds is not common
- First order model works! (No wonder it’s popular in robotics…)
- When measurement is lost, the body is switched into constant velocity mode

Body Filtering

Body Kalman Filtering

Body center point location

State vector s:

$$s = \begin{bmatrix} x \\ y \\ z \\ v_x \\ v_y \\ v_z \end{bmatrix}$$

where

(x, y, z) = location of the body center point

(v_x , v_y , v_z) = velocity of the body

State equation in differential form:

$$\frac{ds(t)}{dt} = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} * s(t) + \epsilon(t)$$

Body Filtering

State equation in difference form:

$$s(k+1) = \left(I + \Delta * \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \right) * s(k) + \epsilon(k) = A * s(k) + \varepsilon(k)$$

$$A = \begin{bmatrix} 1 & 0 & 0 & \Delta & 0 & 0 \\ 0 & 1 & 0 & 0 & \Delta & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

where Δ is the time increment and ε Gaussian noise with covariance R:

$$R = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Measurement equation:

$$z(k) = C * s(k) + \delta(k)$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

Where δ is Gaussian noise with covariance matrix Q:

$$Q = \begin{bmatrix} 200 & 0 & 0 \\ 0 & 200 & 0 \\ 0 & 0 & 200 \end{bmatrix}$$

Body Filtering

Kalman filter initialization:

$$\mu(0) = \begin{bmatrix} x(0) \\ y(0) \\ z(0) \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

where x(0), y(0), z(0) is the first location measurement.

$$\Sigma(0) = \begin{bmatrix} 100\,000 & 0 & 0 & 0 & 0 & 0 \\ 0 & 100\,000 & 0 & 0 & 0 & 0 \\ 0 & 0 & 100\,000 & 0 & 0 & 0 \\ 0 & 0 & 0 & 100\,000 & 0 & 0 \\ 0 & 0 & 0 & 0 & 100\,000 & 0 \\ 0 & 0 & 0 & 0 & 0 & 100\,000 \end{bmatrix}$$

Kalman filter update:

$$\mu_1(k) = A * \mu(k-1)$$

$$\Sigma_1(k) = A * \Sigma(k-1) * A^T + R$$

$$K(k) = \Sigma_1(k) * C^T (C * \Sigma_1(k) * C^T + Q)^{-1}$$

$$\mu(k) = \mu_1(k) + K(k) * (z(k) - C * \mu_1(k))$$

$$\Sigma(k) = (I - K(k) * C) * \Sigma_1(k)$$

Body Filtering

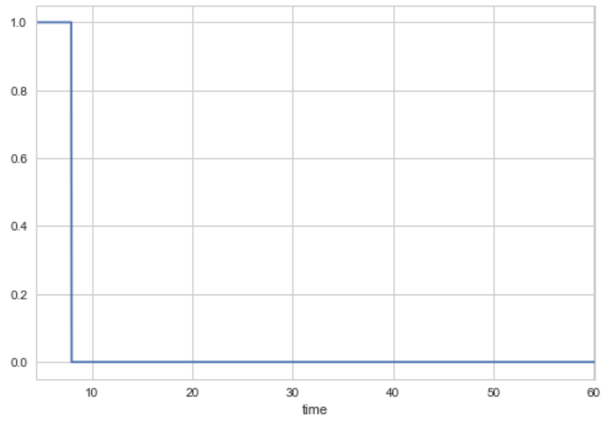
Example 1

Event.txt

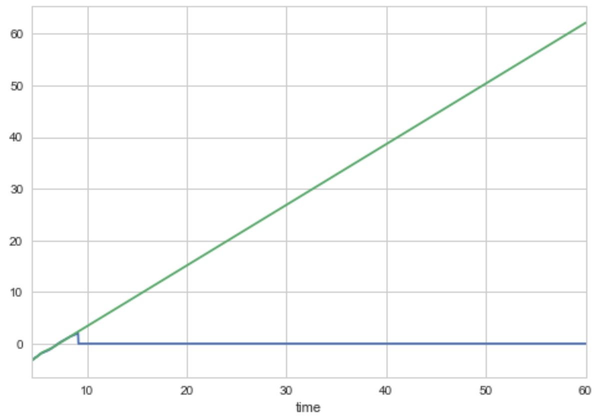
```
4.440,3,2061577943248,Detection created
4.440,2,2061579199488,Pattern removed
4.480,3,2061577756008,Detection created
4.480,3,2061577754272,Detection created
4.480,3,2061577755112,Detection create
4.480,1,2061577797816,Body created
4.480,2,2061577776432,Pattern created
4.520,3,2061577844944,Detection created
```

Body Filtering

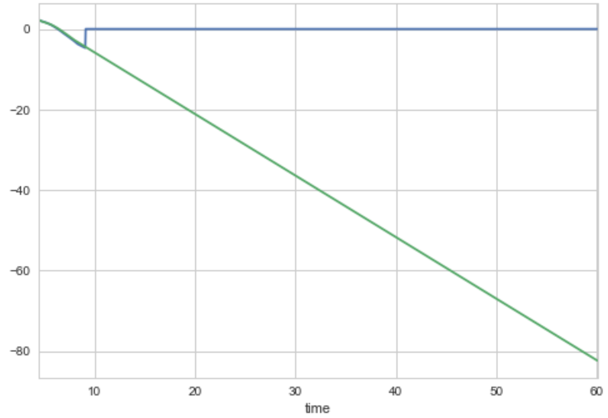
In [5]:
```
data_one['status'].plot()
```
Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x2e5b3fa4e10>



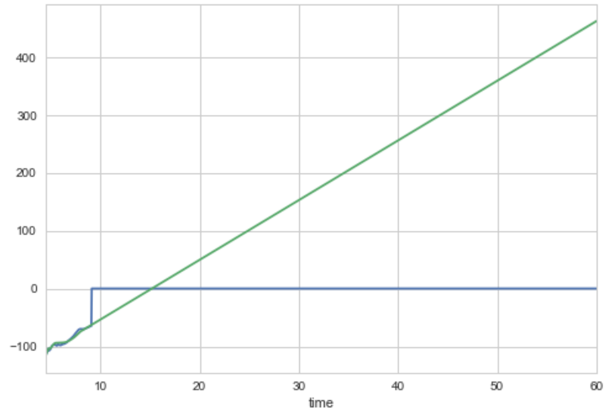
In [7]:
```
data_one['x_pattern'].plot() # blue, measurement
data_one['x'].plot() # green, filtered + predicted
```
Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x2e5b4111c50>



In [8]:
```
data_one['y_pattern'].plot() # blue, measurement
data_one['y'].plot() # green, filtered + predicted
```
Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x2e5b4125470>



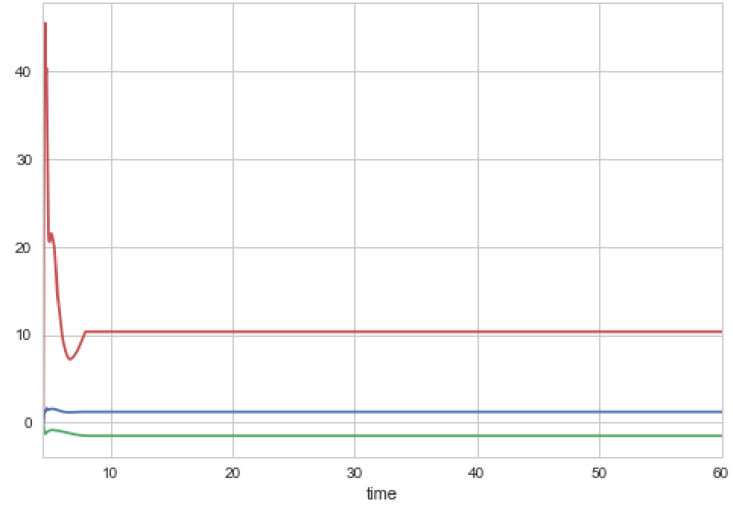
In [9]:
```
data_one['z_pattern'].plot() # blue, measurement
data_one['z'].plot() # green, filtered + predicted
```
Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x2e5b41ab6d8>



Body Filtering

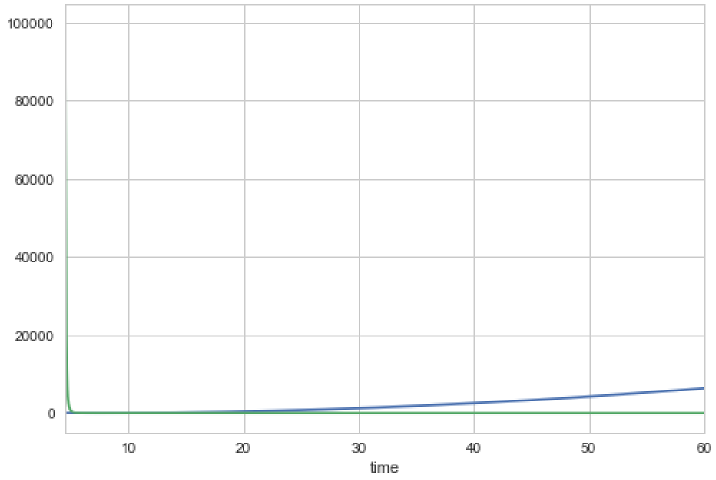
```
In [10]: data_one['vx'].plot() # blue
         data_one['vy'].plot() # green
         data_one['vz'].plot() # red
```

Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x2e5b424cac8>




```
In [11]: data_one['sigma_00'].plot() # blue, x location variance
         data_one['sigma_33'].plot() # green, x velocity variance
```

Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x2e5b55b6ac8>

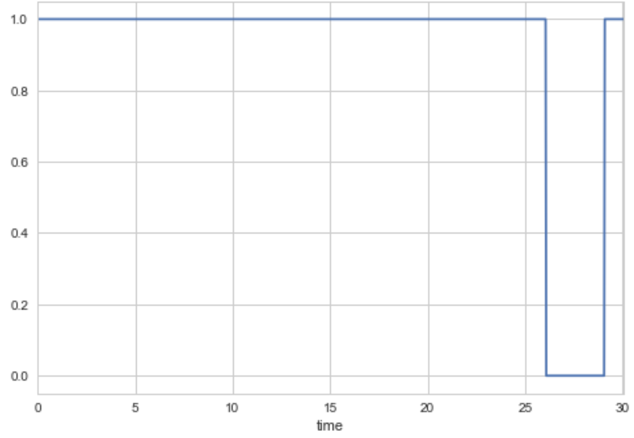


Body Filtering

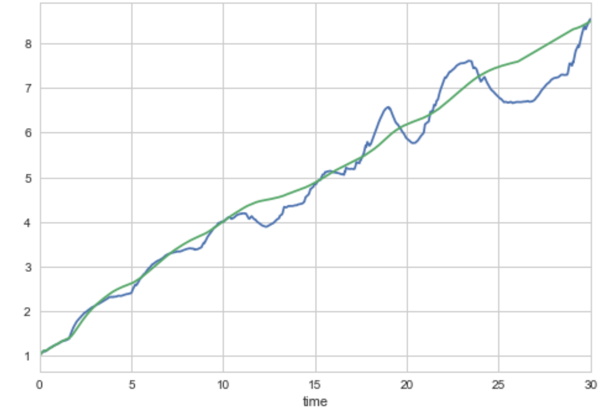
Example 2

Body Filtering

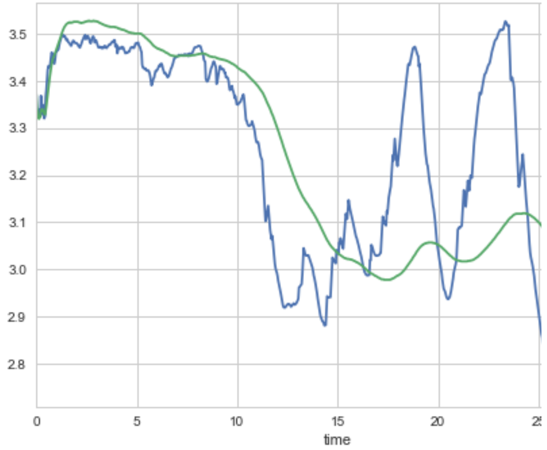
In [5]:
```
data_one['status'].plot()
```
Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x1a52aca5438>



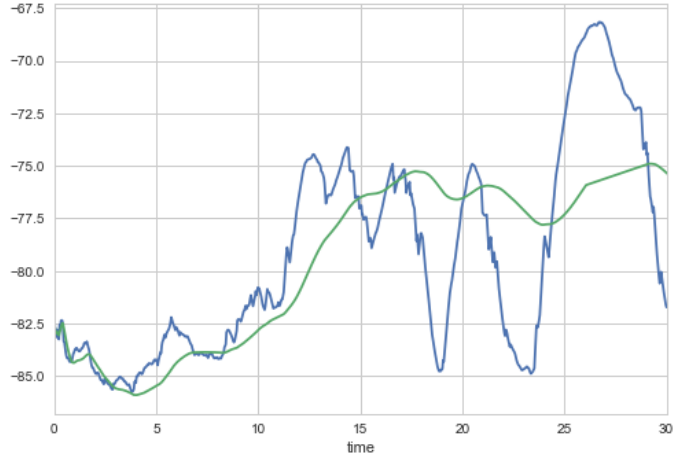
In [6]:
```
data_one['x_pattern'].plot() # blue, measurement
data_one['x'].plot() # green, filtered + predicted
```
Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x1a52bf61470>



In [7]:
```
data_one['y_pattern'].plot() # blue, measurement
data_one['y'].plot() # green, filtered + predicted
```
Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x1a52ad49



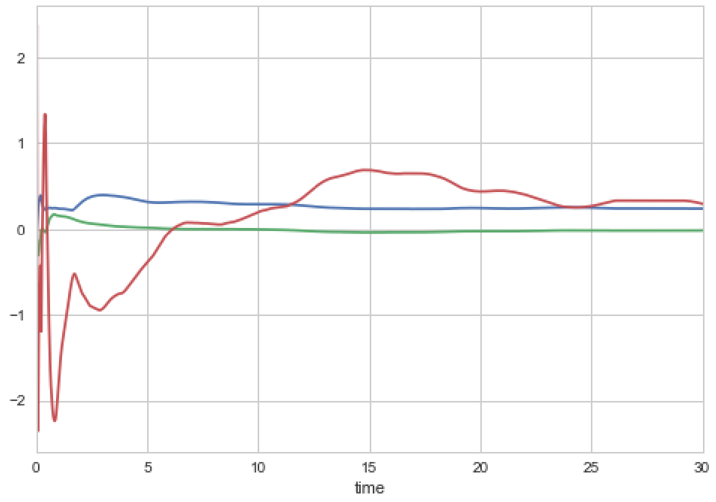
In [8]:
```
data_one['z_pattern'].plot() # blue, measurement
data_one['z'].plot() # green, filtered + predicted
```
Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x1a52c097cf8>



Body Filtering

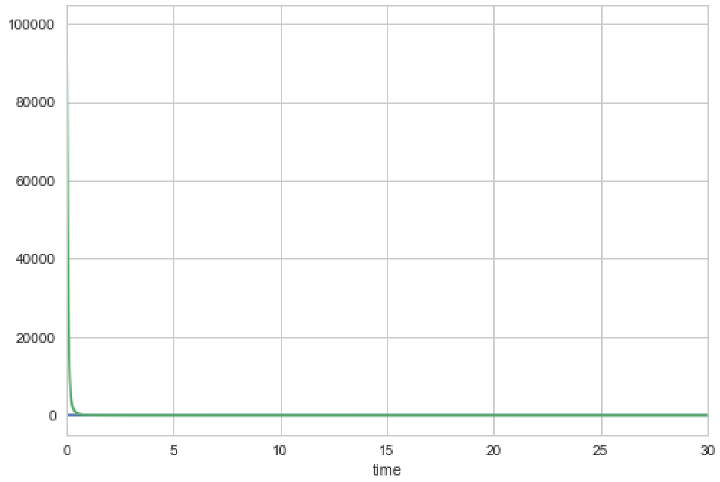
In [9]:
```
data_one['vx'].plot() # blue
data_one['vy'].plot() # green
data_one['vz'].plot() # red
```

Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x1a52708b4a8>

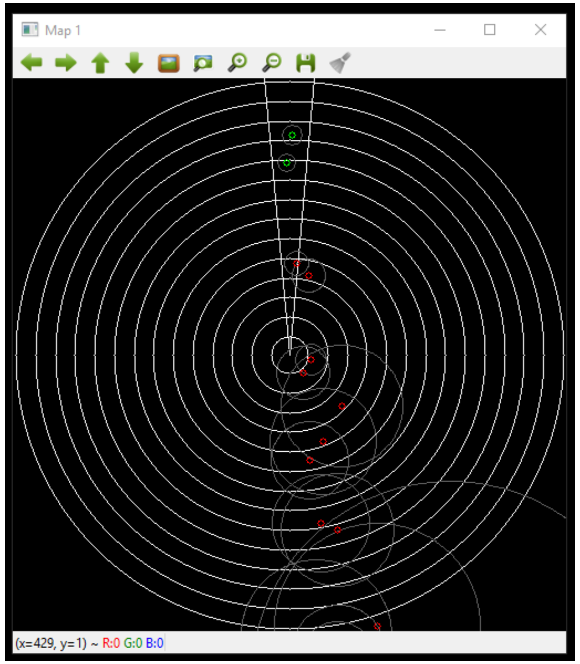


In [10]:
```
data_one['sigma_00'].plot() # blue, x location variance
data_one['sigma_33'].plot() # green, x velocity variance
```

Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x1a52c184438>



Body Prediction



Kalman filter update:

$$\mu_1(k) = A * \mu(k-1)$$

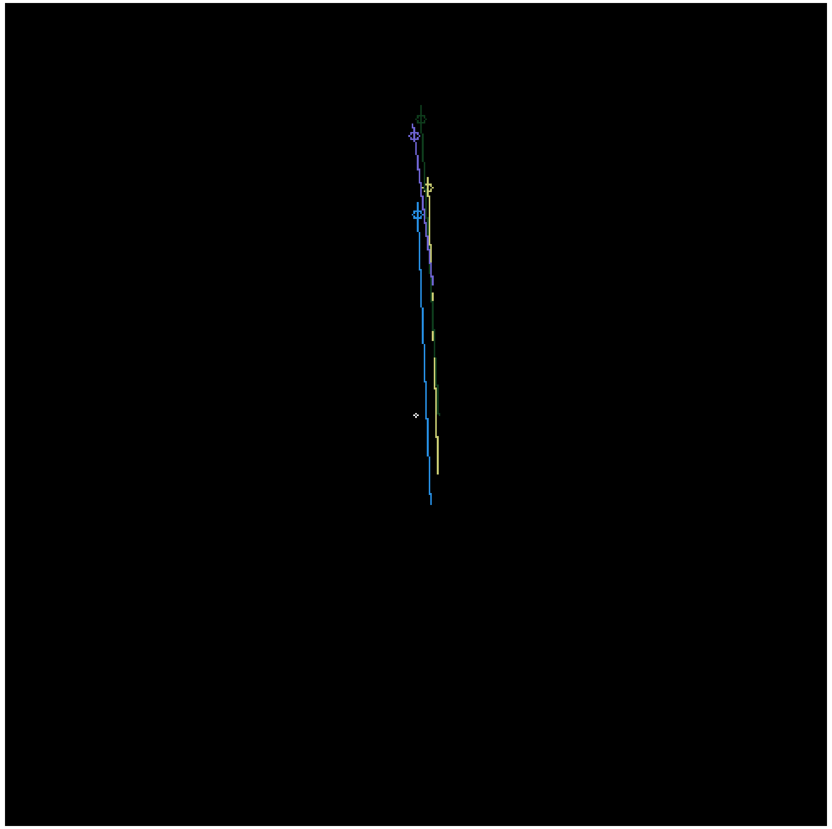
$$\Sigma_1(k) = A * \Sigma(k-1) * A^T + R$$

$$A = \begin{bmatrix} 1 & 0 & 0 & \Delta & 0 & 0 \\ 0 & 1 & 0 & 0 & \Delta & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\mu = \begin{bmatrix} x \\ y \\ z \\ v_x \\ v_y \\ v_z \end{bmatrix} \qquad R = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

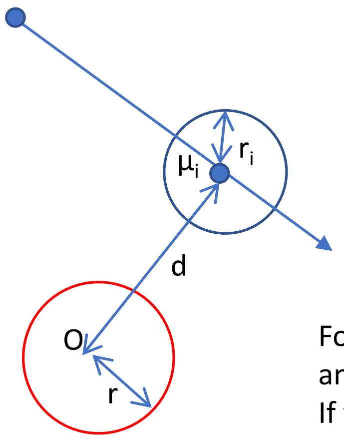
Δ has to be smaller than 1/fps. If fps=25, 1/fps = 0.04 sec. A car driving 120 km/h will proceed 1.33 meters and a collision with an observer might not be detected well enough. A value of Δ = 0.01 corresponds to the movement of 33 cm for an object moving at 120 km/h. This will generate 100 values per prediction per second predicted. Prediction is done once per second for 10 seconds horizon. This will generate 1000 values per prediction. Only the current prediction for an object is kept in memory. Objects are predicted separately.

Body Prediction



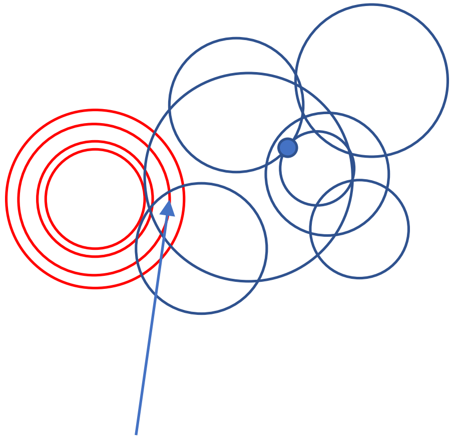
Collision Detection

Collision with the observer



nearest point μ_i on the predicted trajectory
t=t’
filter covariance estimate V_i

For each body i, a random vector t is sampled and distance to the observer calculated (center to center). If the distance is less than r_i+r, collision occurred. The proportion of collisions to all cases is the (maximum) probability estimate for the body/observer collision.



$$t = \begin{bmatrix} x_i \\ y_i \\ z_i \\ r_i \\ r \end{bmatrix} \qquad \begin{bmatrix} x_i \\ y_i \\ z_i \end{bmatrix} \sim N(\mu_i, V_i)$$

From Kalman filter

$$r_i \sim lognormal(\mu_{r,i}, \sigma_{r,i})$$

$$r \sim lognormal(\mu_{r,o}, \sigma_{r,o})$$

Class specific

$$p_i = E\{C_i\} = \sum_{k=1}^{m} \frac{\delta(C_{i,k})}{m}$$

m=1000

Note! Collision might occur earlier. This algorithm estimates the **maximum** probability on the path. Should minimum time used? Or both?

Collision Detection

Example

In [4]:
```
data['collision_p'].argmax()
```
Out[4]:
```
2885
```

In [5]:
```
data.iloc[2885].collision_p
```
Out[5]:
```
0.0080000000000000002
```

In [6]:
```
mu=np.array([data.iloc[2885].c_x, data.iloc[2885].c_y, data.iloc[2885].c_z])
mu
```
Out[6]:
```
array([ 5.978, -6.696, -0.991])
```

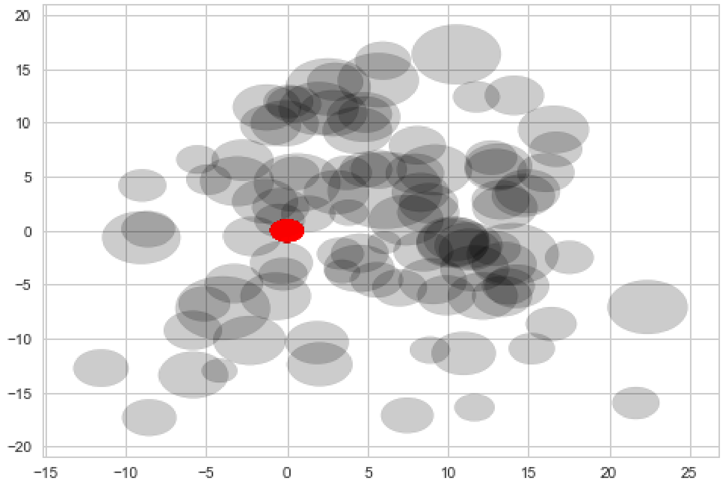
In [9]:
```
v
```
Out[9]:
```
array([[ 58.632,   0.   ,   0.   ],
       [  0.   ,  58.632,   0.   ],
       [  0.   ,   0.   ,  58.632]])
```

In [10]:
```
m=100
```

In [11]:
```
loc_samples = np.random.multivariate_normal(mu, v, m)
```

In [13]:
```
ri = np.random.lognormal(1.28, 0.25, m)/2 # car body sizes
r = np.random.lognormal(0.51, 0.07, m)/2 # observer (person) body sizes
```

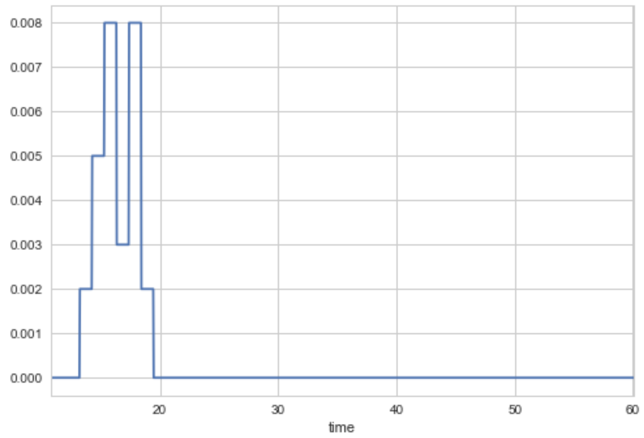
In [18]:
```
circles(loc_samples[:,0],loc_samples[:,2], s=ri[:], c='black', alpha=0.2, edgecolor='none')
circles(observer_loc[:],observer_loc[:], s=r[:], c='red', alpha=0.2, edgecolor='none')
```
Out[18]:
```
<matplotlib.collections.PatchCollection at 0x20a35820ba8>
```



Collision Detection

Example

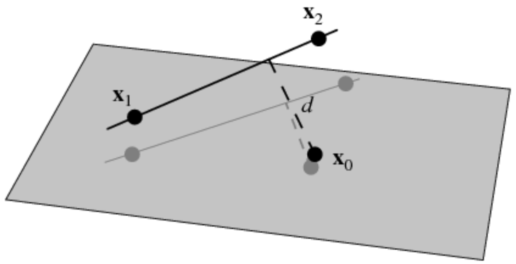
```
In [56]: data_one['collision_p'].plot()
Out[56]: <matplotlib.axes._subplots.AxesSubplot at 0x2ae866ea940>
```



Collision Detection

Open questions:

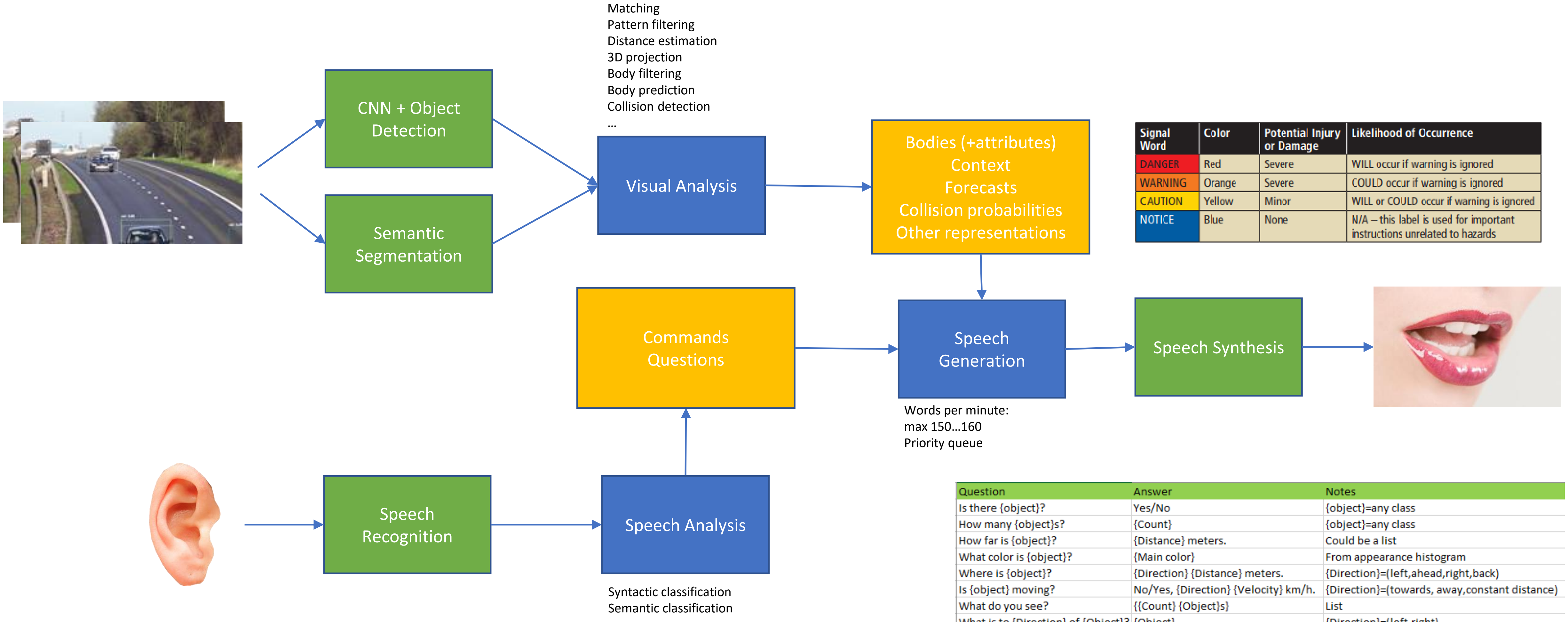
- Collisions between all bodies?
- Min time or max probability or both?
- More efficient sampling?



$$d = \frac{|(\mathbf{x}_2 - \mathbf{x}_1)\times(\mathbf{x}_1 - \mathbf{x}_0)|}{|\mathbf{x}_2 - \mathbf{x}_1|} = \frac{|(\mathbf{x}_0 - \mathbf{x}_1)\times(\mathbf{x}_0 - \mathbf{x}_2)|}{|\mathbf{x}_2 - \mathbf{x}_1|}$$

Note:
Min distance and corresponding time can be calculated without step by step prediction

The Big Picture



Signal Word	Color	Potential Injury or Damage	Likelihood of Occurrence
DANGER	Red	Severe	WILL occur if warning is ignored
WARNING	Orange	Severe	COULD occur if warning is ignored
CAUTION	Yellow	Minor	WILL or COULD occur if warning is ignored
NOTICE	Blue	None	N/A – this label is used for important instructions unrelated to hazards

Question	Answer	Notes
Is there {object}?	Yes/No	{object}=any class
How many {object}s?	{Count}	{object}=any class
How far is {object}?	{Distance} meters.	Could be a list
What color is {object}?	{Main color}	From appearance histogram
Where is {object}?	{Direction} {Distance} meters.	{Direction}=(left,ahead,right,back)
Is {object} moving?	No/Yes, {Direction} {Velocity} km/h.	{Direction}=(towards, away,constant distance)
What do you see?	{{Count} {Object}s}	List
What is to {Direction} of {Object}?	{Object}	{Direction}=(left,right)
Is {Object} {Direction} {Object}?	Yes/No	{Direction}=(left,right,above,under)
Is {Object} free?	Yes/No	For example chair with/without other objects

Command	Notes
Repeat answer	Answer to previous question is generated until stopped
Stop repeating	Stop answering
Be quiet	Output speech is off
Speak to me	Output speech is on

Signal word	Sentence	Notes
DANGER	{Object} will collide, move {Direction}.	{Object}=(bicycle,boat,bus,car,cow,horse,motorbike,person,train) {Direction}=(left,right,forward,backward)
WARNING	{Object} might collide, move {Direction}.	{Object}=(bicycle,boat,bus,car,cow,horse,motorbike,person,train) {Direction}=(left,right,forward,backward)
CAUTION	{Object} might collide, move {Direction}.	{Object}=(bird,cat,dog) {Direction}=(left,right,forward,backward)
WARNING	{Object} ahead, turn. Distance {Distance} meters.	{Object}=(chair,dining table,sofa)
NOTICE	{Object} is approaching. Distance {Distance} meters.	{Object}=(bicycle,bird,boat,bus,car,cat,cow,dog,horse,motorbike,person,train)
NOTICE	{Object} is leaving. Distance {Distance} meters.	{Object}=(bicycle,bird,boat,bus,car,cat,cow,dog,horse,motorbike,person,train)
NOTICE	{Caption}	
NOTICE	{Answer}	

Next Steps

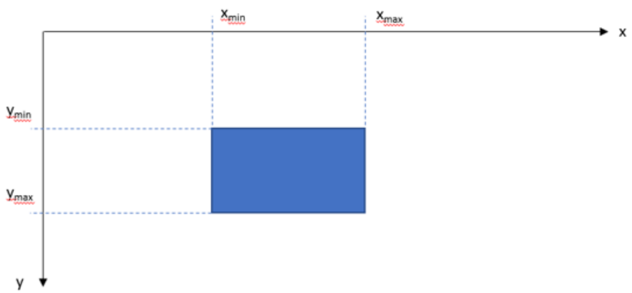
Next steps

- Kalman filter parameter adjustments
- Dataset selection
- Stereo vision
- Camera yaw, pitch, roll estimation
- Semantic segmentation
- Experiments in the wild
- Paper
- Speech recognition
- Speech analysis
- Speech generation

Kalman Filter Parameter Adjustments

Pattern Kalman Filtering

Bounding box edge coordinates



Pattern location (bounding box) is determined by four edge coordinates: x_{min}, x_{max}, y_{min} and y_{max}. vx_{min}, vx_{max}, vy_{min} and vy_{max} are corresponding velocities.

Each edge coordinate is filtered separately and identically. x_{min} is used here as an example.

State equation in differential form:

$$\frac{d}{dt}\begin{bmatrix} x_{min}(t) \\ vx_{min}(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} * \begin{bmatrix} x_{min}(t) \\ vx_{min}(t) \end{bmatrix} + \epsilon(t)$$

State equation in difference form:

$$\begin{bmatrix} x_{min}(k+1) \\ vx_{min}(k+1) \end{bmatrix} = A * \begin{bmatrix} x_{min}(k) \\ vx_{min}(k) \end{bmatrix} + \varepsilon(k)$$

$$A = \begin{bmatrix} 1 & \Delta \\ 0 & 1 \end{bmatrix}$$

where Δ is the time increment and ε Gaussian noise with covariance R:

$$R = \begin{bmatrix} 0.1 & 0 \\ 0 & 1.0 \end{bmatrix}$$

Measurement equation

$$z(k) = C * \begin{bmatrix} x_{min}(k) \\ vx_{min}(k) \end{bmatrix} + \delta(k)$$

$$C = \begin{bmatrix} 1 & 0 \end{bmatrix}$$

where δ is Gaussian noise with covariance matrix Q:

$$Q = [200.0]$$

Kalman filter initialization:

$$\mu(0) = \begin{bmatrix} x_{min}(0) \\ 0 \end{bmatrix}$$

where $x_{min}(0)$ is the first location measurement.

$$\Sigma(0) = \begin{bmatrix} 200.0 & 0 \\ 0 & 10\,000.0 \end{bmatrix}$$

Kalman filter update:

$$\mu_1(k) = A * \mu(k-1)$$

$$\Sigma_1(k) = A * \Sigma(k-1) * A^T + R$$

$$K(k) = \Sigma_1(k) * C^T * (C * \Sigma_1(k) * C^T + Q)^{-1}$$

$$\mu(k) = \mu_1(k) + K(k) * (z(k) - C * \mu_1(k))$$

$$\Sigma(k) = (I - K(k) * C) * \Sigma_1(k)$$

Kalman Filter Parameter Adjustments

Body Kalman Filtering

Body center point location

State vector s:

$$s = \begin{bmatrix} x \\ y \\ z \\ v_x \\ v_y \\ v_z \end{bmatrix}$$

where

(x, y, z) = location of the body center point

(v_x, v_y, v_z) = velocity of the body

State equation in differential form:

$$\frac{ds(t)}{dt} = \begin{bmatrix} 0&0&0&1&0&0 \\ 0&0&0&0&1&0 \\ 0&0&0&0&0&1 \\ 0&0&0&0&0&0 \\ 0&0&0&0&0&0 \\ 0&0&0&0&0&0 \end{bmatrix} * s(t) + \epsilon(t)$$

State equation in difference form:

$$s(k+1) = \left(I + \Delta * \begin{bmatrix} 0&0&0&1&0&0 \\ 0&0&0&0&1&0 \\ 0&0&0&0&0&1 \\ 0&0&0&0&0&0 \\ 0&0&0&0&0&0 \\ 0&0&0&0&0&0 \end{bmatrix} \right) * s(k) + \epsilon(k) = A * s(k) + \varepsilon(k)$$

$$A = \begin{bmatrix} 1&0&0&\Delta&0&0 \\ 0&1&0&0&\Delta&0 \\ 0&0&1&0&0&\Delta \\ 0&0&0&1&0&0 \\ 0&0&0&0&1&0 \\ 0&0&0&0&0&1 \end{bmatrix}$$

where Δ is the time increment and ε Gaussian noise with covariance R:

$$R = \begin{bmatrix} 0&0&0&0&0&0 \\ 0&0&0&0&0&0 \\ 0&0&0&0&0&0 \\ 0&0&0&0&0&0 \\ 0&0&0&0&0&0 \\ 0&0&0&0&0&0 \end{bmatrix}$$

Measurement equation:

$$z(k) = C * s(k) + \delta(k)$$

$$C = \begin{bmatrix} 1&0&0&0&0&0 \\ 0&1&0&0&0&0 \\ 0&0&1&0&0&0 \end{bmatrix}$$

Where δ is Gaussian noise with covariance matrix Q:

$$Q = \begin{bmatrix} 200&0&0 \\ 0&200&0 \\ 0&0&200 \end{bmatrix}$$

Kalman filter initialization:

$$\mu(0) = \begin{bmatrix} x(0) \\ y(0) \\ z(0) \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

where x(0), y(0), z(0) is the first location measurement.

$$\Sigma(0) = \begin{bmatrix} 100\,000&0&0&0&0&0 \\ 0&100\,000&0&0&0&0 \\ 0&0&100\,000&0&0&0 \\ 0&0&0&100\,000&0&0 \\ 0&0&0&0&100\,000&0 \\ 0&0&0&0&0&100\,000 \end{bmatrix}$$

Kalman filter update:

$$\mu_1(k) = A * \mu(k-1)$$

$$\Sigma_1(k) = A * \Sigma(k-1) * A^T + R$$

$$K(k) = \Sigma_1(k) * C^T (C * \Sigma_1(k) * C^T + Q)^{-1}$$

$$\mu(k) = \mu_1(k) + K(k) * (z(k) - C * \mu_1(k))$$

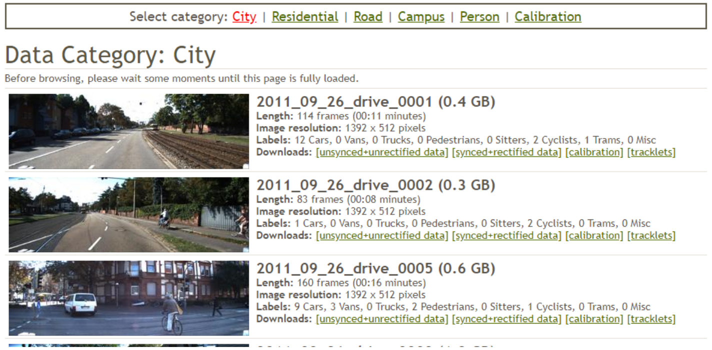
$$\Sigma(k) = (I - K(k) * C) * \Sigma_1(k)$$

Use of detection instead of pattern when pattern is “reliable”?

Dataset Selection

Specification:

- Video
- Stereo
- Distance information
- Outdoor + indoor
- Odometry



Select category: City | Residential | Road | Campus | Person | Calibration

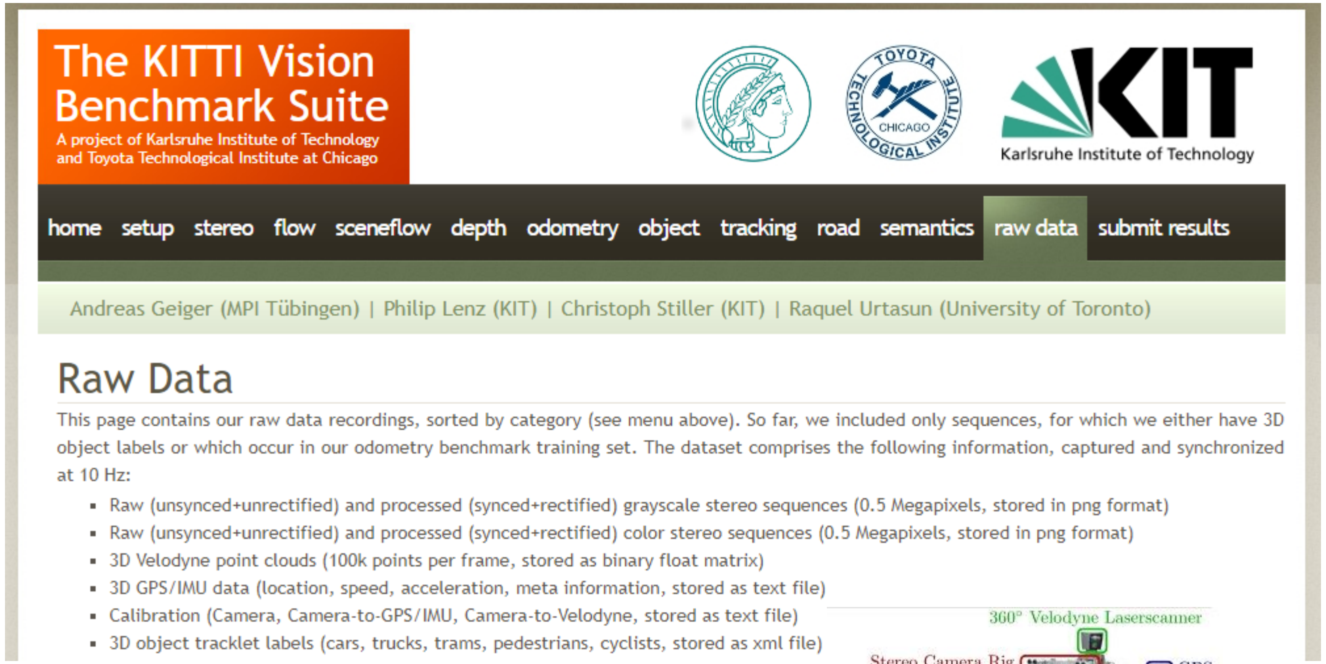
Data Category: City

Before browsing, please wait some moments until this page is fully loaded.

2011_09_26_drive_0001 (0.4 GB)
Length: 114 frames (00:11 minutes)
Image resolution: 1392 x 512 pixels
Labels: 12 Cars, 0 Vans, 0 Trucks, 0 Pedestrians, 0 Sitters, 2 Cyclists, 1 Trams, 0 Misc
Downloads: [unsynced+unrectified data] [synced+rectified data] [calibration] [tracklets]

2011_09_26_drive_0002 (0.3 GB)
Length: 83 frames (00:08 minutes)
Image resolution: 1392 x 512 pixels
Labels: 1 Cars, 0 Vans, 0 Trucks, 0 Pedestrians, 0 Sitters, 2 Cyclists, 0 Trams, 0 Misc
Downloads: [unsynced+unrectified data] [synced+rectified data] [calibration] [tracklets]

2011_09_26_drive_0005 (0.6 GB)
Length: 160 frames (00:16 minutes)
Image resolution: 1392 x 512 pixels
Labels: 9 Cars, 3 Vans, 0 Trucks, 2 Pedestrians, 0 Sitters, 1 Cyclists, 0 Trams, 0 Misc
Downloads: [unsynced+unrectified data] [synced+rectified data] [calibration] [tracklets]



The KITTI Vision Benchmark Suite

A project of Karlsruhe Institute of Technology and Toyota Technological Institute at Chicago

Karlsruhe Institute of Technology

home setup stereo flow sceneflow depth odometry object tracking road semantics raw data submit results

Andreas Geiger (MPI Tübingen) | Philip Lenz (KIT) | Christoph Stiller (KIT) | Raquel Urtasun (University of Toronto)

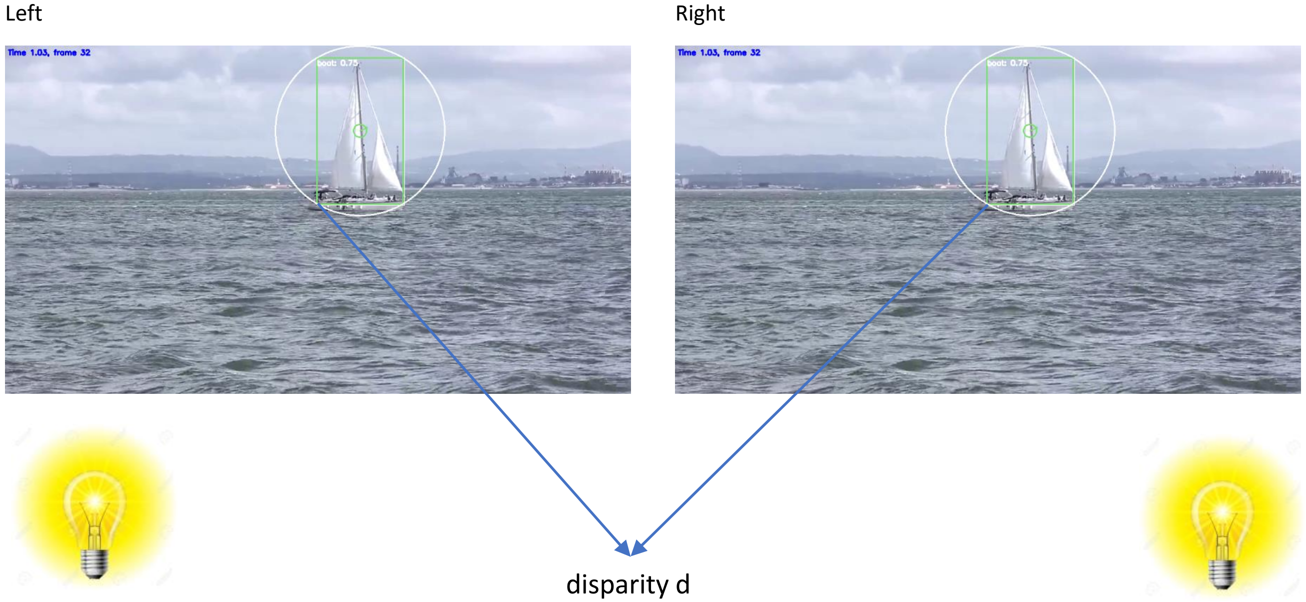
Raw Data

This page contains our raw data recordings, sorted by category (see menu above). So far, we included only sequences, for which we either have 3D object labels or which occur in our odometry benchmark training set. The dataset comprises the following information, captured and synchronized at 10 Hz:

- Raw (unsynced+unrectified) and processed (synced+rectified) grayscale stereo sequences (0.5 Megapixels, stored in png format)
- Raw (unsynced+unrectified) and processed (synced+rectified) color stereo sequences (0.5 Megapixels, stored in png format)
- 3D Velodyne point clouds (100k points per frame, stored as binary float matrix)
- 3D GPS/IMU data (location, speed, acceleration, meta information, stored as text file)
- Calibration (Camera, Camera-to-GPS/IMU, Camera-to-Velodyne, stored as text file)
- 3D object tracklet labels (cars, trucks, trams, pedestrians, cyclists, stored as xml file)

Open question: Indoor? Self generated?

Stereo Vision



Disparity for “free” using left and right bounding boxes!!!!!!!!!!

The resulting *standard rectified geometry* is employed in a lot of stereo camera setups and stereo algorithms, and leads to a very simple inverse relationship between 3D depths Z and disparities d,

$$d = f\frac{B}{Z}, \tag{11.1}$$

where f is the focal length (measured in pixels), B is the baseline, and

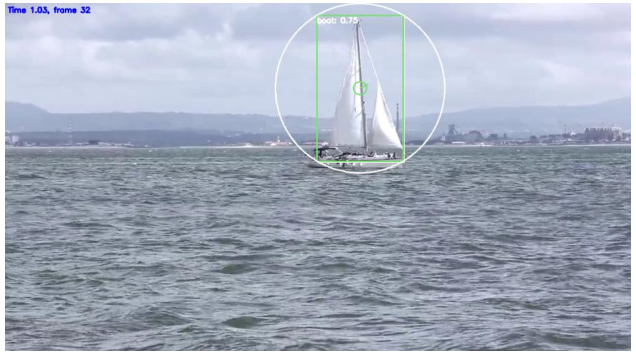
$$x' = x + d(x, y), \quad y' = y \tag{11.2}$$

describes the relationship between corresponding pixel coordinates in the left and right images (Bolles, Baker, and Marimont 1987; Okutomi and Kanade 1993; Scharstein and Szeliski

If this works, stereo algorithm will be extremely fast and easy. Paper!!!

Rectification might still be needed?

Camera yaw, pitch, roll estimation



Can be estimated from background movement (average optical flow)?

Semantic Segmentation

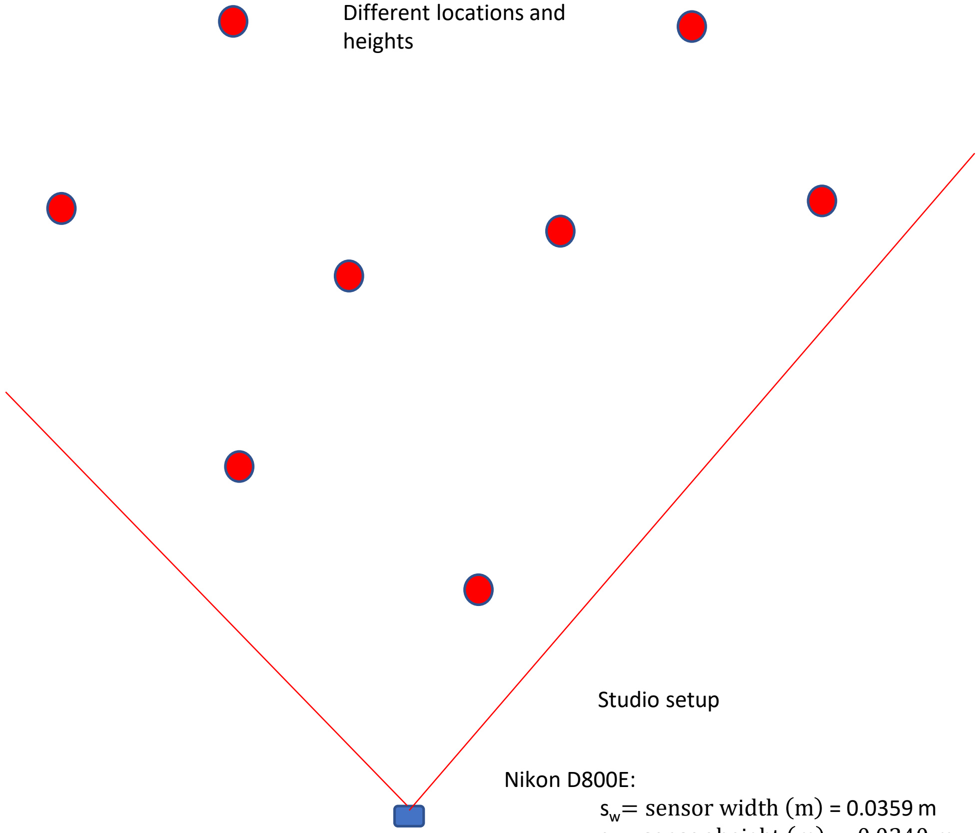
Why?

- Object context (”person on grass”)
- More exact localization for attribute extraction (”what color is person? red and white.”)

Which off-the-shelf network to use? Must be light and fast.

Experiments In Wild

Distance estimation and 3D projection

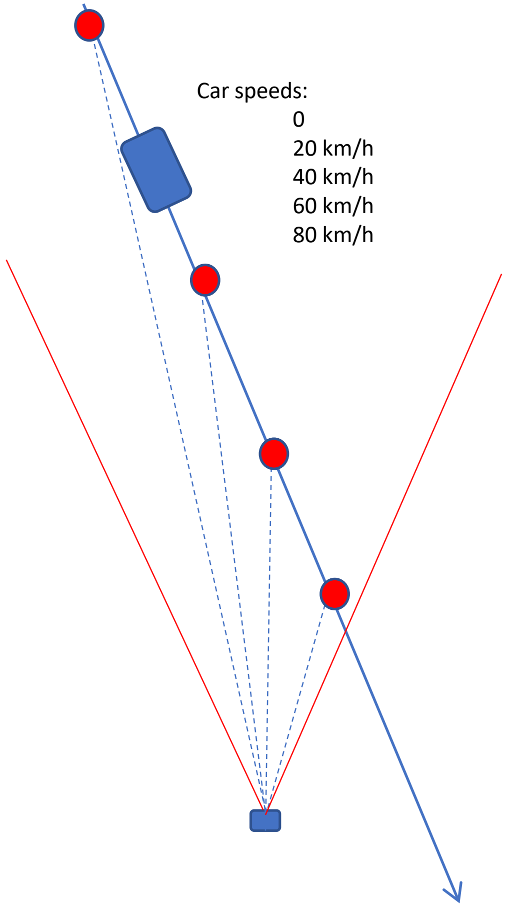


Nikon D800E:

- s_w= sensor width (m) = 0.0359 m
- s_h= sensor height (m) = 0.0240 m
- p_w= image width (pixels) = 7360
- p_h= image height (pixels) = 4912
- h = object height (m) = 1.5 m
- f = focal length (m) = 0.020 m, varied
- fov = $2 * \mathrm{atan}(\frac{s_w}{2*f})$ = 83.81 °

Experiments In Wild

Body filtering



Distances:
10 m
20 m
30 m
40 m
50 m
60 m
70 m
80 m
90 m
100 m

Outdoor setup
Laser distance measuring device would be nice…

Nikon D800E:

- s_w= sensor width (m) = 0.0359 m
- s_h= sensor height (m) = 0.0240 m
- p_w= image width (pixels) = 7360
- p_h= image height (pixels) = 4912
- h = object height (m) = 1.5 m
- f = focal length (m) = 0.050 m
- fov = $2 * \mathrm{atan}(\frac{s_w}{2*f})$ = 39.49 º

Paper

Image-Based Situation Awareness: Estimating Object Locations, Velocities and Collision Probabilities Using Object Detection

Contents:

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3. Related work
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    1. Definitions
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    9. Collision Detection
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    1. Evaluation metric
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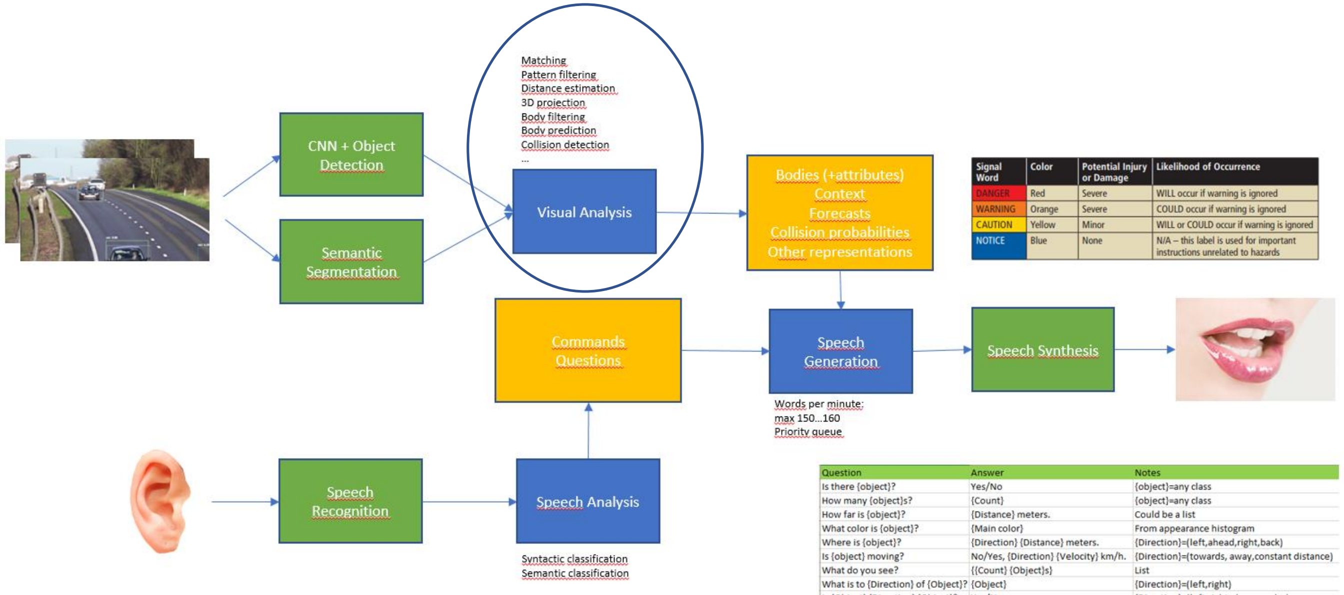
???

Paper



Signal Word	Color	Potential Injury or Damage	Likelihood of Occurrence
DANGER	Red	Severe	WILL occur if warning is ignored
WARNING	Orange	Severe	COULD occur if warning is ignored
CAUTION	Yellow	Minor	WILL or COULD occur if warning is ignored
NOTICE	Blue	None	N/A – this label is used for important instructions unrelated to hazards

Question	Answer	Notes
Is there {object}?	Yes/No	{object}=any class
How many {object}s?	{Count}	{object}=any class
How far is {object}?	{Distance} meters.	Could be a list
What color is {object}?	{Main color}	From appearance histogram
Where is {object}?	{Direction} {Distance} meters.	{Direction}=(left,ahead,right,back)
Is {object} moving?	No/Yes, {Direction} {Velocity} km/h.	{Direction}=(towards, away,constant distance)
What do you see?	{{Count} {Object}s}	List
What is to {Direction} of {Object}?	{Object}	{Direction}=(left,right)
Is {Object} {Direction} {Object}?	Yes/No	{Direction}=(left,right,above,under)
Is {Object} free?	Yes/No	For example chair with/without other objects

Command	Notes
Repeat answer	Answer to previous question is generated until stopped
Stop repeating	Stop answering
Be quiet	Output speech is off
Speak to me	Output speech is on

Signal word	Sentence	Notes
DANGER	{Object} will collide, move {Direction}.	{Object}=(bicycle,boat,bus,car,cow,horse,motorbike,person,train) {Direction}=(left,right,forward,backward)
WARNING	{Object} might collide, move {Direction}.	{Object}=(bicycle,boat,bus,car,cow,horse,motorbike,person,train) {Direction}=(left,right,forward,backward)
CAUTION	{Object} might collide, move {Direction}.	{Object}=(bird,cat,dog) {Direction}=(left,right,forward,backward)
WARNING	{Object} ahead, turn. Distance {Distance} meters.	{Object}=(chair,dining table,sofa)
NOTICE	{Object} is approaching. Distance {Distance} meters.	{Object}=(bicycle,bird,boat,bus,car,cat,cow,dog,horse,motorbike,person,train)
NOTICE	{Object} is leaving. Distance {Distance} meters.	{Object}=(bicycle,bird,boat,bus,car,cat,cow,dog,horse,motorbike,person,train)
NOTICE	{Caption}	
NOTICE	{Answer}	

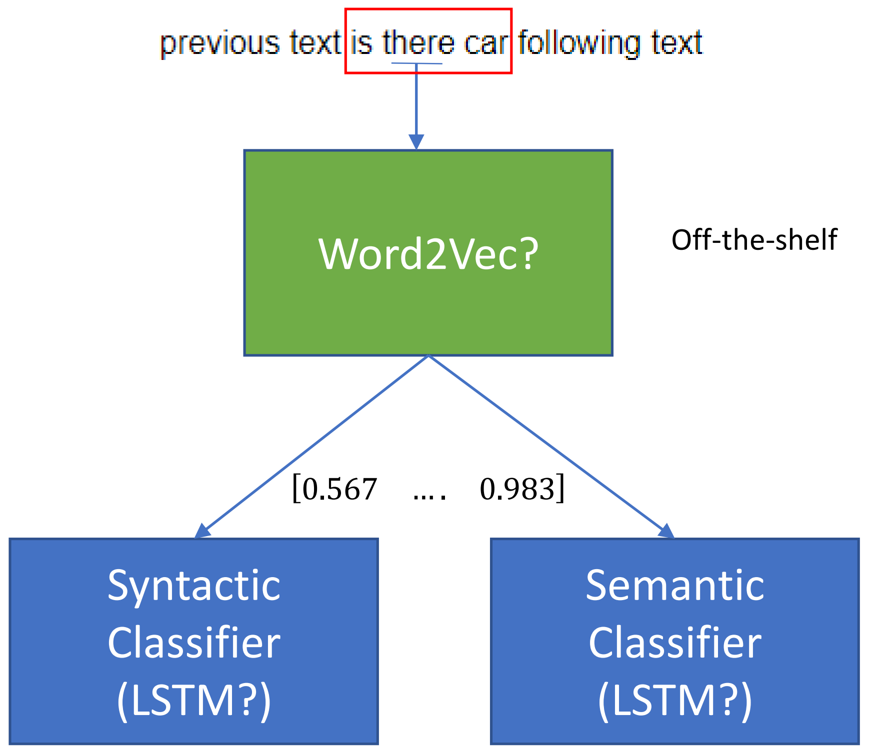
Where to publish?

- CVPR 2019 (6/2019, Long Beach, deadline 11/2018)
- ICCV 2019 (29.10.-3.11.2019, Seoul, deadline 1/2019)

Speech Recognition

Which off-the-shelf network to use? Must be light and fast.

Speech Analysis



Off-the-shelf

These two networks need to be taught, data generation required

Question
Is there {object}?
How many {object}s?
How far is {object}?
What color is {object}?
Where is {object}?
Is {object} moving?
What do you see?
What is to {Direction} of {Object}?
Is {Object} {Direction} {Object}?
Is {Object} free?

Class
Aeroplane
Bicycle
Bird
Boat
Bottle
Bus
Car
Cat
Chair
Cow
Dining table
Dog
Horse
Motorbike
Person
Potted plant
Sheep
Sofa
Train
TV monitor

Speech Generation

?

Probably mostly rule-based. ML algorithms?

Discussion

Thank you!

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https://github.com/SakariLampola/Thesis