Sensing for action

IAR Lecture 3

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Sensing for Action

- Sensors transduce energy from one form to another
- From the robot control point of view we have some information – a measured value – that represents some property of the world
- This relationship is rarely a direct one:

E.G. We say the IR sensor is a 'range' or 'distance' sensor:

Distance to object →
Light scattering →
Amount of light reflected →
Resistance of sensor element →
Voltage →
Analog to Digital Conversion→
Calculation →
Distance value

But note! We may not need to know the actual distance to perform the appropriate action, such as "avoid"

Describing sensors

- *Sensitivity*:
  - ratio of output change to input change
  - Usually a trade-off with *range* (min to max)
- *Resolution*:
  - Limit in resolving power of output scale
- *Precision:*
  - Repeatability of measurements (under same conditions)
- *Accuracy:*
  - (lack of) error in measurements

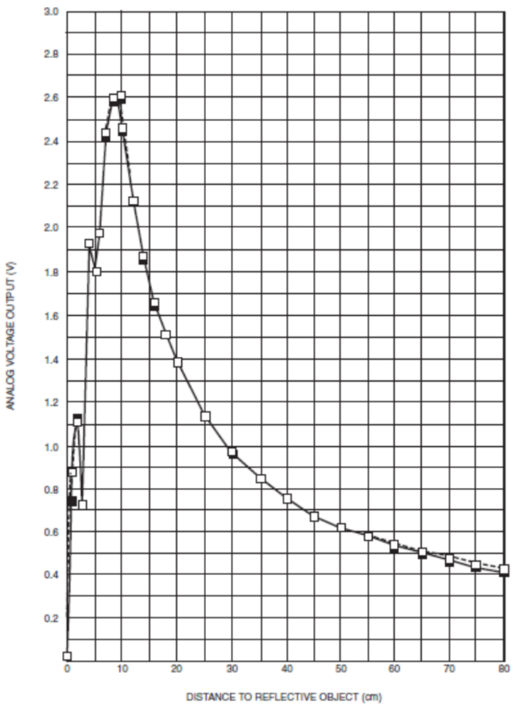
Accuracy

- Sometimes described in terms of the mean of the error (*precision* relates to the variance of error)
- Calibration can remove some but not all inaccuracy. E.g. for a linear sensor there may remain:
  - Uncertainty about the offset
  - Uncertainty about the slope (% error)
  - Uncertainty about deviations from linearity
- Combined with imprecision, inaccuracy may limit the *effective* resolution much more than the output scale

Example: IR sensors on the Khepera

Sensor data sheet

Voltage

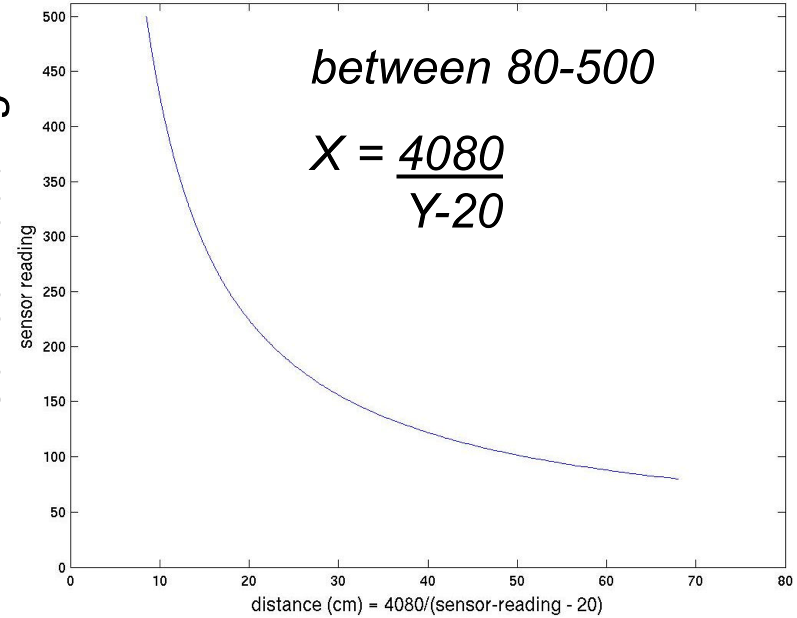


Real distance to object

10 bit Analog to Digital Conversion

Calculation of distance from reading

Sensor reading



between 80-500

$$X = \frac{4080}{Y-20}$$

Estimated distance to object

Describing sensors

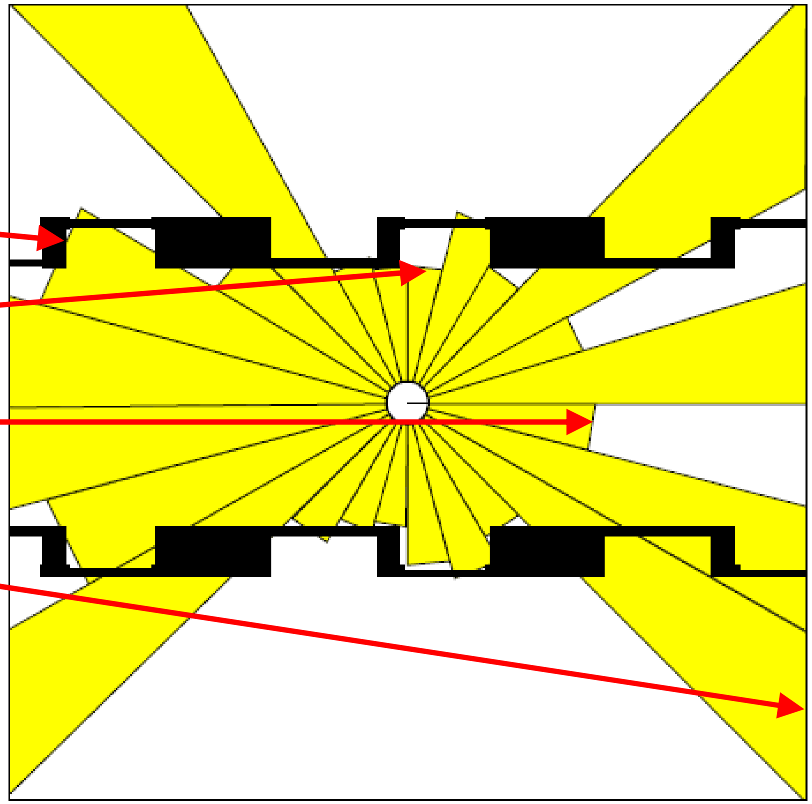
- *Selectivity*
  - Inaccuracy is often the result of *cross-sensitivity* to environmental properties *other* than the target property
  - E.g. many transducers are affected by temperature
  - For IR, reflectance of the object and ambient light will alter the ‘distance’ reading

Describing in form of a *sensor model*

- E.g. what is the probability distribution of the sensor reading from a range sensor, given the wall distance?

Possible sources of error:

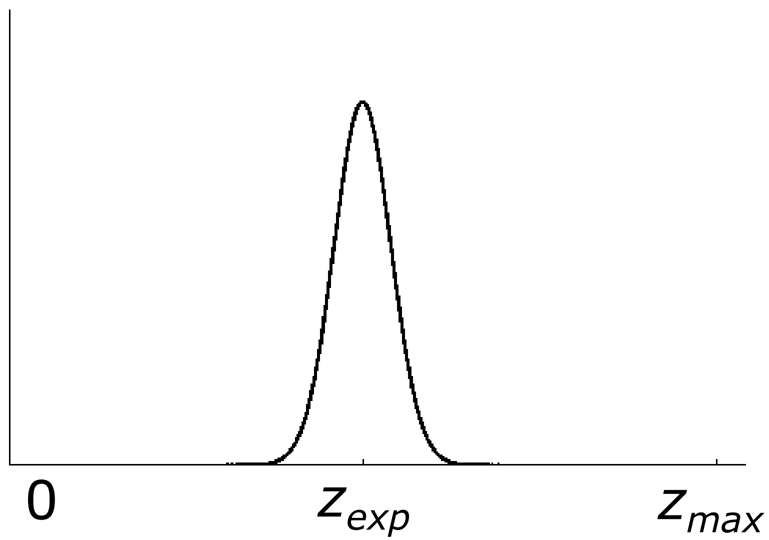
1. Noise in the actual distance measure
2. Person passing
3. Random measurements
4. Maximum range measurements



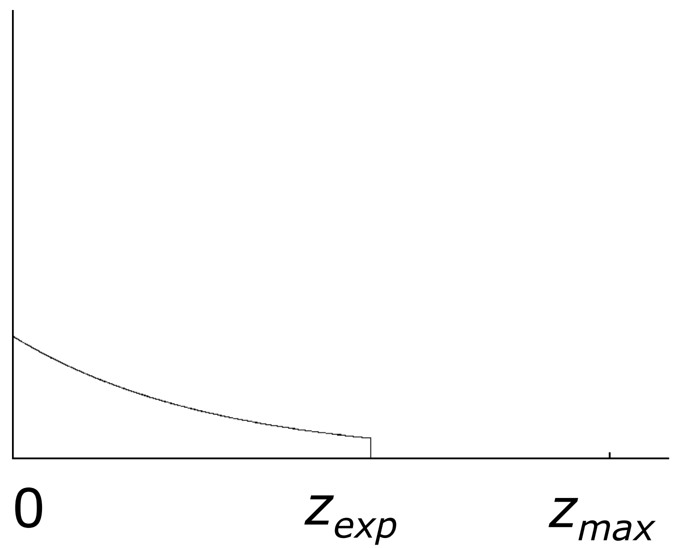
Thrun (2005)

Describe each error source as a distribution

Measurement noise



Unexpected obstacles



$$P_{hit}(z \mid x, m) = \eta \frac{1}{\sqrt{2\pi b}} e^{-\frac{1}{2}\frac{(z - z_{\exp})^2}{b}}$$

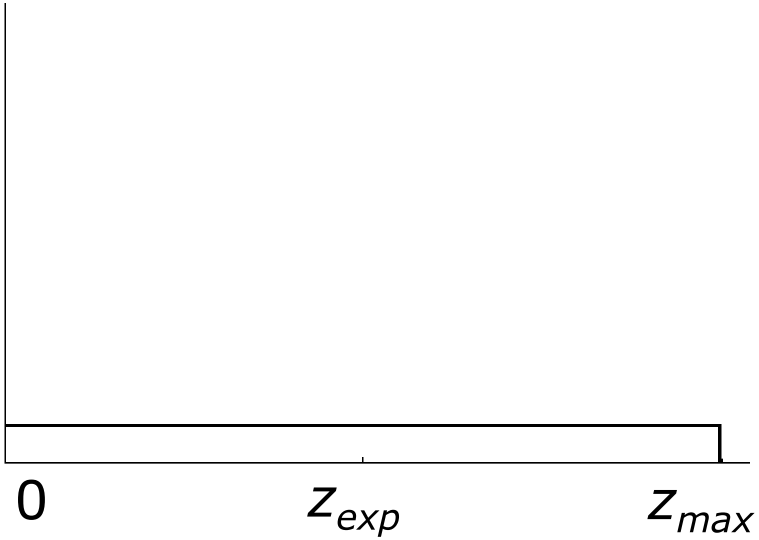
$$P_{\text{unexp}}(z \mid x, m) = \begin{cases} \eta\, \lambda\, \mathrm{e}^{-\lambda z} & z < z_{\exp} \\ 0 & otherwise \end{cases}$$

z is sensor signal, x is robot pose, m is world model, $\{x,m\}$ define expected z_{exp}

Thrun (2005)

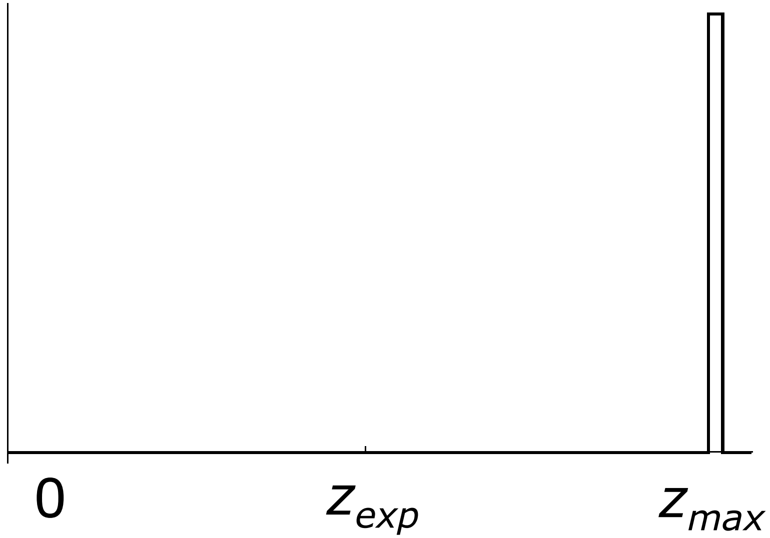
Describe each error source as a distribution

Random measurement



$$P_{rand}(z \mid x, m) = \eta \frac{1}{z_{\max}}$$

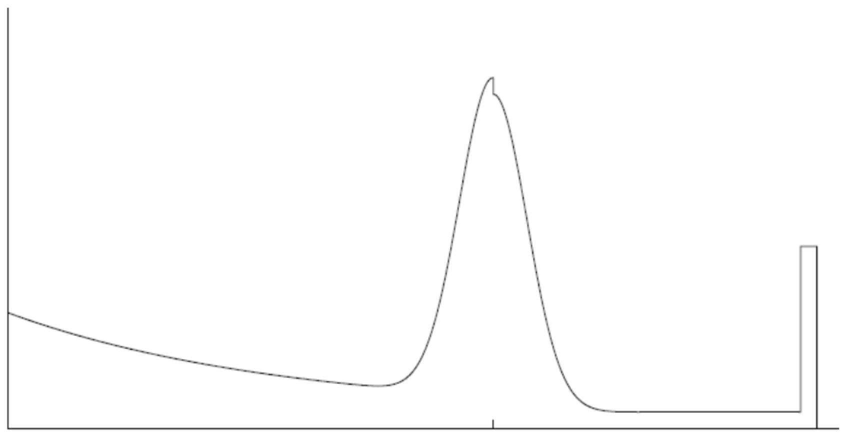
Max range



$$P_{\max}(z \mid x, m) = \begin{cases} 1 \; if \;\; z = z_{\max} \\ 0 \; otherwise \end{cases}$$

Thrun (2005)

Combine as a mixture density



$$P(z \mid x, m) = \begin{pmatrix} \alpha_{\text{hit}} \\ \alpha_{\text{unexp}} \\ \alpha_{\text{max}} \\ \alpha_{\text{rand}} \end{pmatrix}^T \cdot \begin{pmatrix} P_{\text{hit}}(z \mid x, m) \\ P_{\text{unexp}}(z \mid x, m) \\ P_{\text{max}}(z \mid x, m) \\ P_{\text{rand}}(z \mid x, m) \end{pmatrix}$$

Note, this seems to assume we know the real distance, z_{exp}

- May be in context of calibration; use to learn parameters α
- Knowing $P(z|z_{exp})$ can be applied (through Bayes theorem) to determine $P(z_{exp}|z) = P(z|z_{exp})P(z_{exp})/P(z)$ (see later lectures)

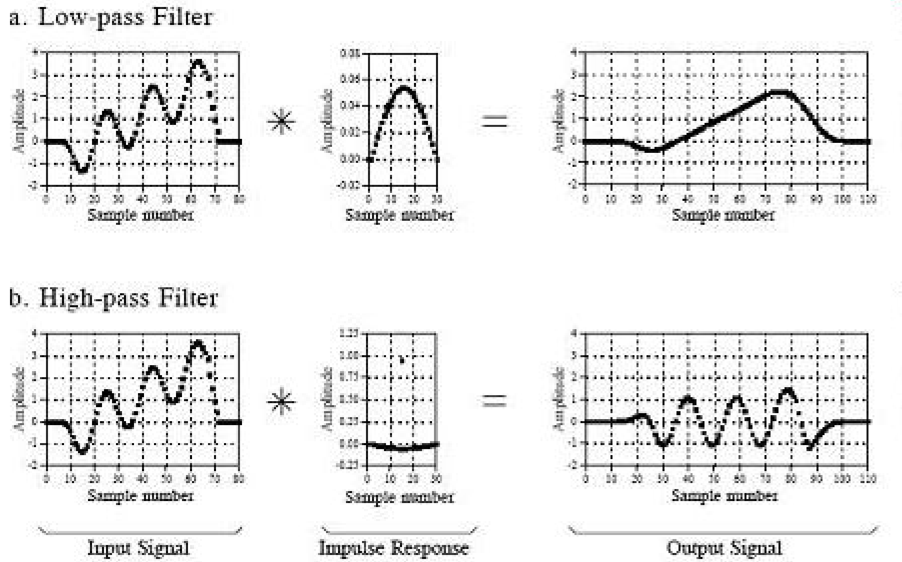
Thrun (2005)

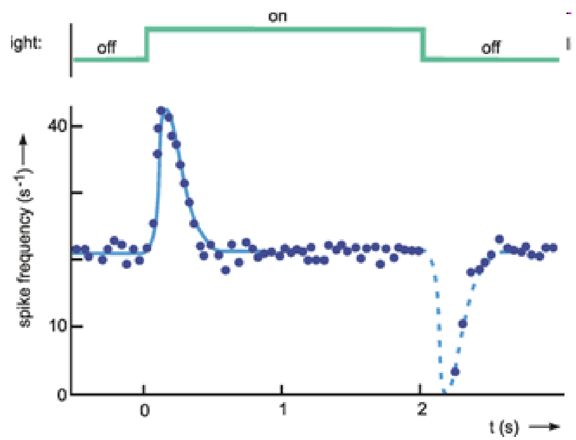
Sensor/signal conditioning

- E.g. linear transformation: $output = offset + gain \times input$
- Many signals may need non-linear transformation
- Might need to tune linear or non-linear parameters through learning methods (again, this can be action-relative)
- 'Intelligence' might be introduced at this level to make sensing adaptive, i.e., sensor/system itself detects:
  - Is the output a reasonable value (e.g. relative to previous measurements or other sensor reports)?
  - Is the full range being used?
  - Is the sensor stuck at one extreme?

Sensor/signal conditioning

- Low-pass filtering:
  - Low-pass: usually against noise or other rapid fluctuations
- Highpass filtering:
  - interested in fluctuations not background





Response of *Limulus* sensory neuron to light

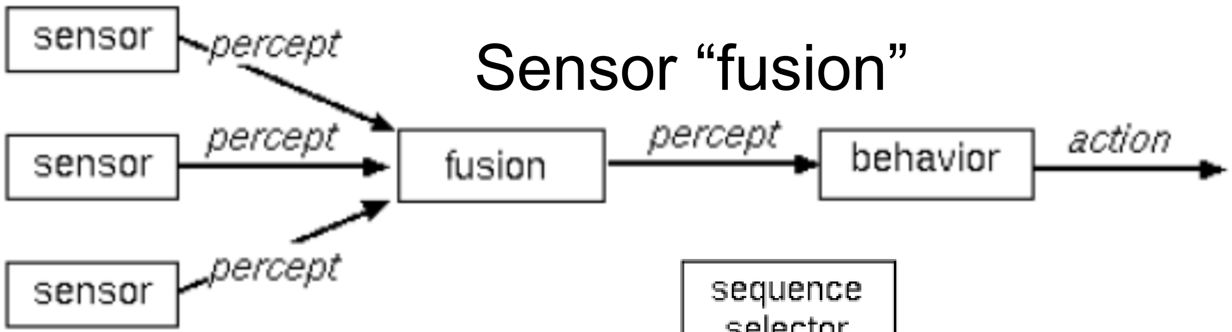
Sensor processing

Implies a more complex transformation than conditioning:

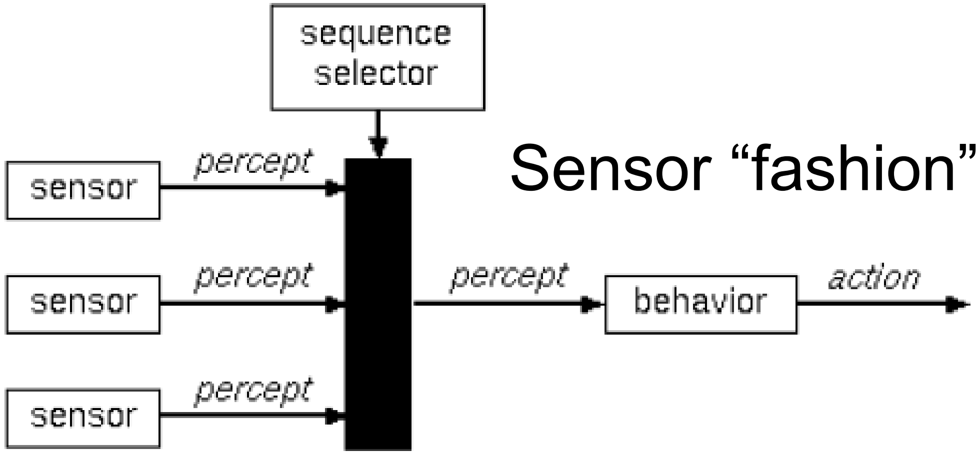
- Logic functions (e.g. triggers for action)
- Data reduction (e.g. extracting features)
- Decision making (e.g. classification)

Combining sensors

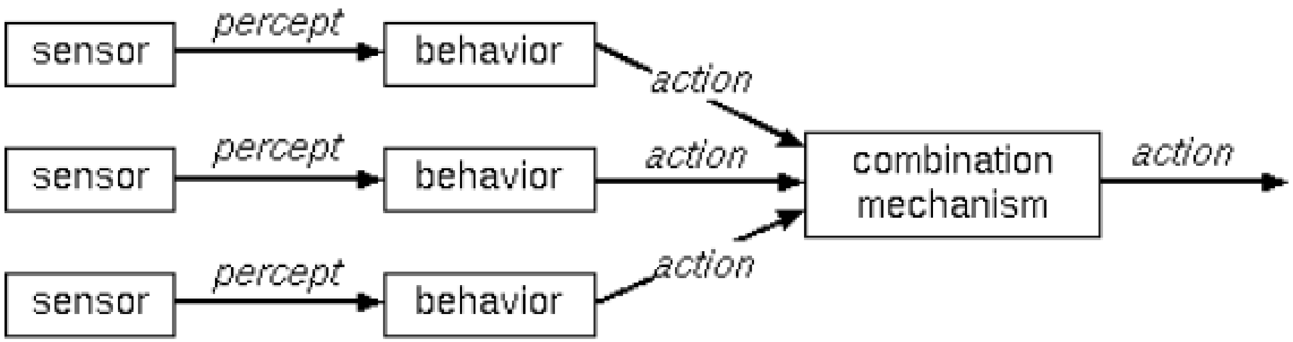
Sensor “fusion”



Sensor “fashion”



Sensor “fission”



Sensor fusion

The information provided by different sensors might be:

- Complementary: sensors that measure different attributes of same target → Fusion could provide richer description
- Co-operative: can derive new feature by combining several attributes (e.g. triangulation) → Fusion could disambiguate
- Competitive/redundant: different sensors that measure the same attribute → Fusion could provide better estimate of actual value

Sensor fusion

A standard approach is to use a weighted average.

Assume N sensors provide measurements *z* of property *x* with some Gaussian distributed noise

$$z_i = x + \varepsilon_i, \varepsilon_i \approx N(0, \sigma_i)$$

Combined estimate is weighted average:

$$\hat{x} = \sum_{i=1}^{N} w_i z_i, \quad \sum_{i=1}^{N} w_i = 1$$

Maximum likelihood estimation says optimal weighting is:

$$w_i = \frac{1/\sigma_i^2}{\sum_{j=1}^{N} 1/\sigma_j^2}$$

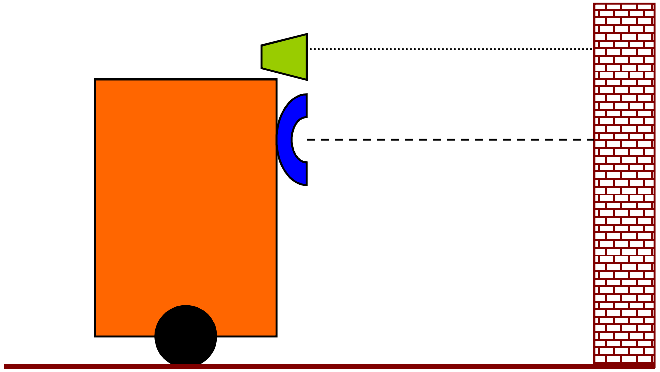
Note there are also adaptive methods that modify the weights over time, e.g. *democratic cue integration*: sensors with values near the combined estimate increase their weights, those further away decrease.

Simple example with two measurements

Robot uses two different sensors to measure distance to a wall:

z_1 with variance σ_1^2

z_2 with variance σ_2^2



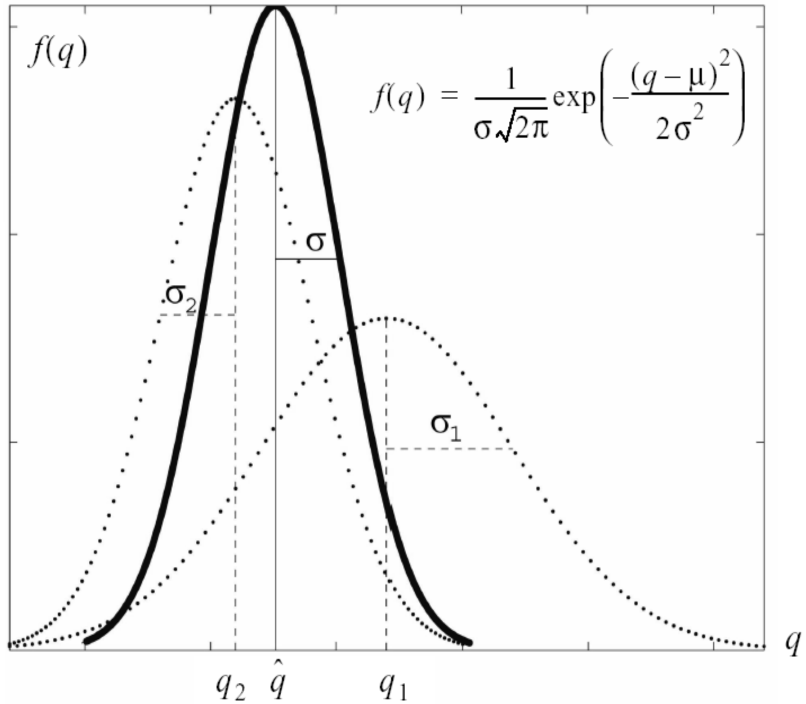
Combined estimate:

$$\hat{x} = \frac{1/\sigma_1^2}{1/\sigma_1^2 + 1/\sigma_2^2} z_1 + \frac{1/\sigma_2^2}{1/\sigma_1^2 + 1/\sigma_2^2} z_2$$

Variance of combined estimate –

$$\sigma^2 = \frac{\sigma_1^2 \sigma_2^2}{\sigma_1^2 + \sigma_2^2}$$

– will be less than that of either single measure



Seigwart & Nourbakhsh, 2004

Can rearrange in terms of successive estimates:

$$\hat{x} = \frac{1/\sigma_1^2}{1/\sigma_1^2 + 1/\sigma_2^2} z_1 + \frac{1/\sigma_2^2}{1/\sigma_1^2 + 1/\sigma_2^2} z_2$$

$$= z_1 + \frac{\sigma_1^2}{\sigma_1^2 + \sigma_2^2}(z_2 - z_1)$$

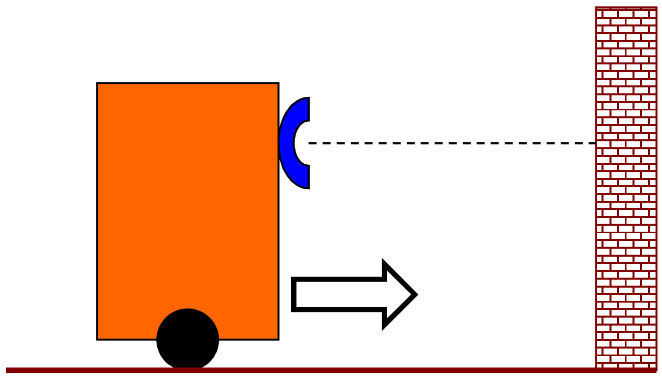
Or in general, updating estimate with the k+1th measurement:

$$\hat{x}_{k+1} = \hat{x}_k + K_{k+1}(z_{k+1} - \hat{x}_k)$$

$$\sigma_{k+1}^2 = \sigma_k^2 - K_{k+1}\sigma_k^2$$

$$K_{k+1} = \frac{\sigma_k^2}{\sigma_k^2 + \sigma_z^2} \quad ; \quad \sigma_k^2 = \sigma_1^2 \quad ; \quad \sigma_z^2 = \sigma_2^2$$

What about updating successive estimates for a moving robot?



Seigwart & Nourbakhsh, 2004

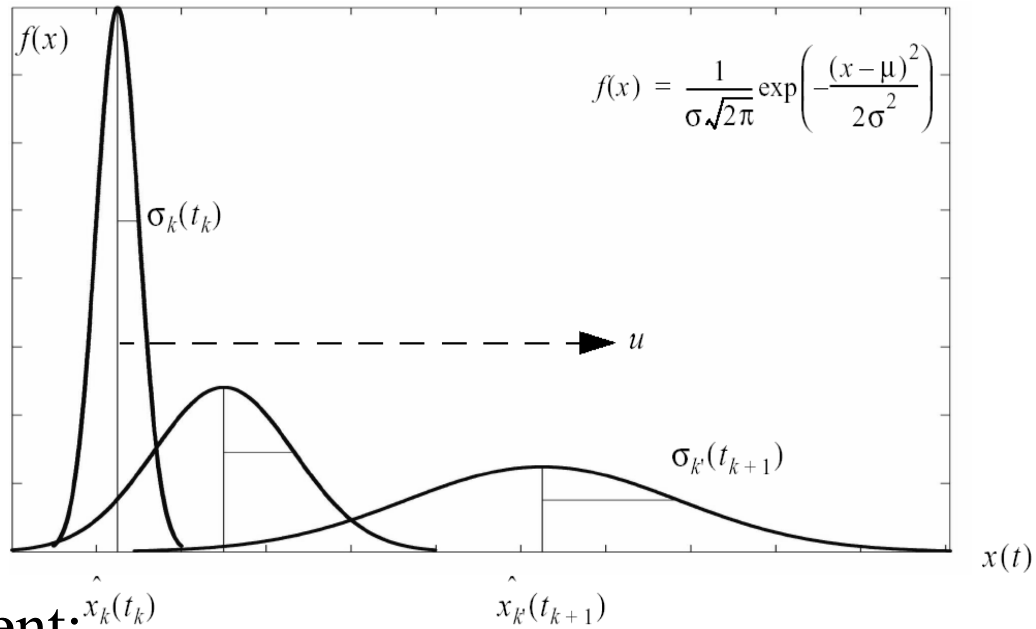
For a moving robot, can first predict the change, then combine this with the new measurement

Robot moves at velocity u, with noise w

$$\frac{dx}{dt} = u + w$$

Our estimate should incorporate the predicted change:

$$\hat{x}_{k'} = \hat{x}_k + u(t_{k+1} - t_k)$$
$$\sigma^2_{k'} = \sigma^2_k + \sigma^2_w[t_{k+1} - t_k]$$



Seigwart & Nourbakhsh, 2004

Then update with the measurement:

$$\hat{x}_{k+1} = \hat{x}_{k'} + K_{k+1}(z_{k+1} - \hat{x}_{k'})$$
$$= [\hat{x}_k + u(t_{k+1} - t_k)] + K_{k+1}[z_{k+1} - \hat{x}_k - u(t_{k+1} - t_k)]$$

$$K_{k+1} = \frac{\sigma^2_{k'}}{\sigma^2_{k'} + \sigma^2_z} = \frac{\sigma^2_k + \sigma^2_w[t_{k+1} - t_k]}{\sigma^2_k + \sigma^2_w[t_{k+1} - t_k] + \sigma^2_z}$$

Generalised form of this is the Kalman filter…

References

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