

# 1€ Filter: A Simple Speed-based Low-pass Filter for Noisy Input in Interactive Systems

Géry Casiez, Nicolas Roussel, Daniel Vogel

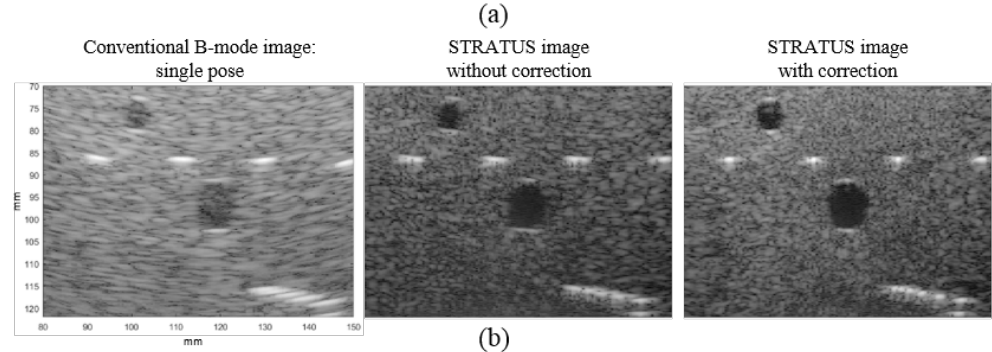
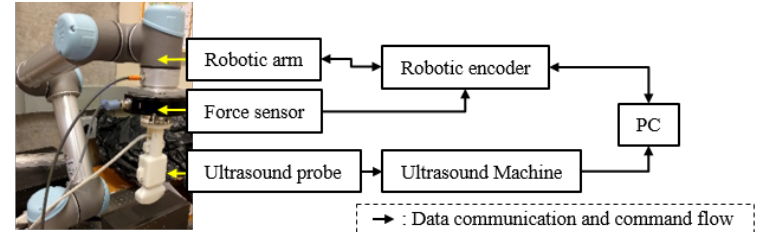
Rodolfo Finocchi

Seminar Presentation

Group 2: Synthetic Tracked Aperture Ultrasound Imaging

# Project Overview

- Aperture size of the ultrasound transducer limits image quality
- Synthetic tracked aperture imaging shows improvement
- Goal: bring system from autopilot to co-robotic freehand using virtual fixtures and force control



# Admittance Control

$$\dot{x}_{des} = Kf$$

$$\dot{q}_{des} = \underset{\dot{q}}{\min} \|\dot{x}_{des} - J\dot{q}_{des}\|$$

- Probe must be tracked accurately
- Robot movements must be predictable



# Paper Selection

Casiez, Géry, Nicolas Roussel, and Daniel Vogel. "1€ Filter: A Simple Speed-based Low-pass Filter for Noisy Input in Interactive Systems." *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 2012.

- Relevance to problem of interactive co-robotic control
- Useful comparison of different types of filters
- Ease of integration with existing admittance control framework

# Noise and Jitter

Noise reduces the accuracy and precision of a signal:

introduces jitter, leading to many different observed values for a single true one.

**What we observe can be divided into:**

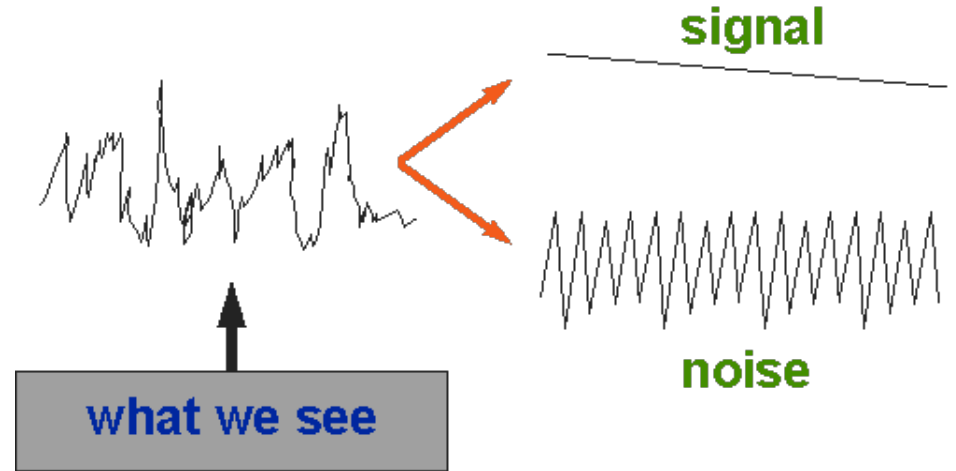
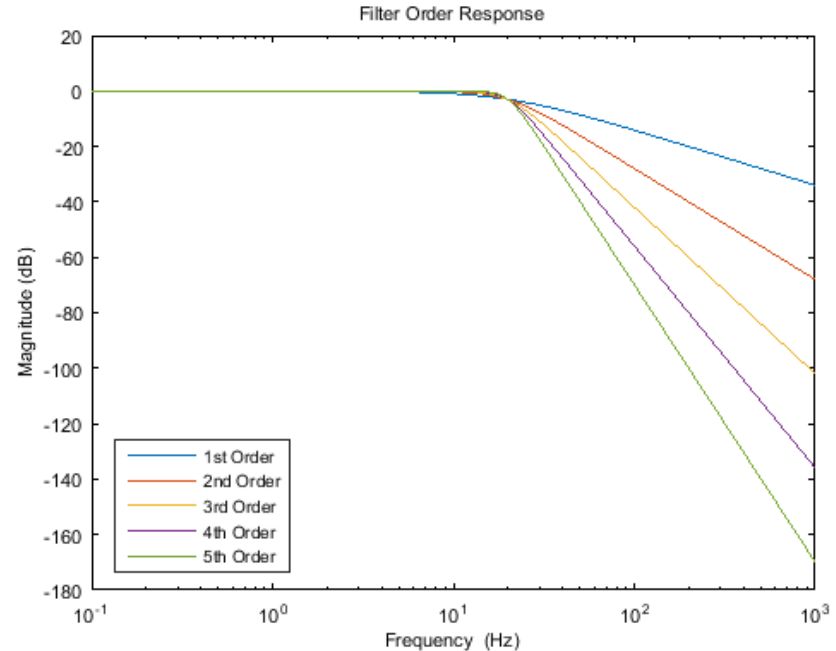


Image source: <http://www.socialresearchmethods.net/kb/expclass.php>

# Filtering and Lag

Filtering noisy signals reduces, and possibly removes, the unwanted parts of the signal.

However, it introduces time latency, or lag, which reduces system responsiveness



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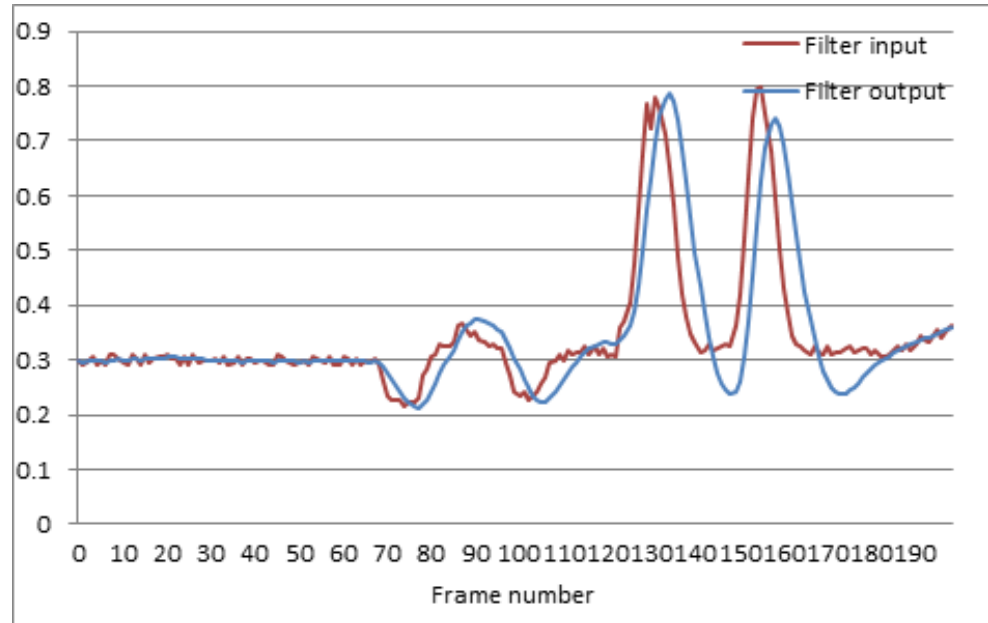


Image source: <https://i-msdn.sec.s-msft.com/dynimg/IC584344.png>

# Filter Comparisons: Moving Average Filter

By the Central Limit Theorem, averaging enough successive values of a noisy signal should produce a better estimate of the true one.

Moving average low-pass filter: average of last  $n$  data values is used to estimate current values.

Problem: creates lag of  $n$  times the sampling period

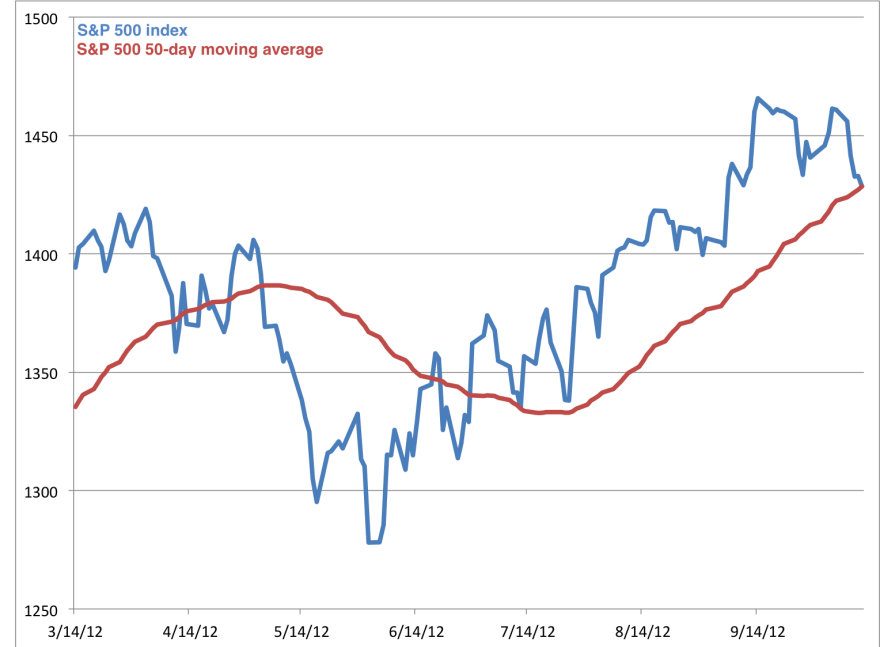


Image source: <http://static4.businessinsider.com/image/507862e2ecad04db7d000016-1502-1127/sp-500-50-day-ma.png?maxX=600>



# Filter Comparisons: Exponential Smoothing

- $\hat{X}_i = \alpha X_i + (1 - \alpha)\hat{X}_{i-1}$ 
  - First term: contribution of new input data
  - Second term: adds inertia from previous values
- As  $\alpha$  decreases, jitter is reduced, but lag increases

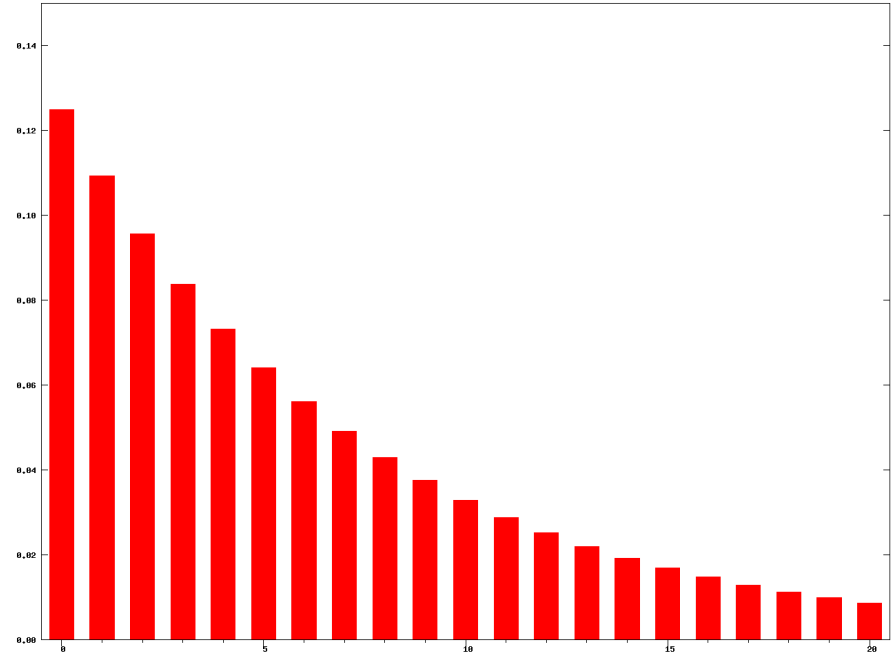


Image source:

[https://upload.wikimedia.org/wikipedia/commons/b/ba/Exponential\\_moving\\_average\\_weights\\_N%3D15.png](https://upload.wikimedia.org/wikipedia/commons/b/ba/Exponential_moving_average_weights_N%3D15.png)

# Filter Comparisons: Double Exponential Smoothing

$$\begin{aligned}\hat{X}_i &= \alpha X_i + (1 - \alpha)\hat{X}_{i-1} \\ \hat{X}_i^{[2]} &= \alpha \hat{X}_i + (1 - \alpha)\hat{X}_i^{[2]} \\ P_{t+\tau} &= \left(2 + \frac{\alpha\tau}{1 - \alpha}\right) \hat{X}_i - \left(1 + \frac{\alpha\tau}{1 - \alpha}\right) \hat{X}_i^{[2]}\end{aligned}$$

- Used by LaViola\* to predict positions  $\tau$  steps in the future
- Good Jitter-Lag balance but introduces overshoot

\*LaViola, J. J. Double exponential smoothing: an alternative to kalman filter-based predictive tracking. In Proc. of EGVE '03, ACM (2003), 199–206.

# Filter Comparisons: Kalman Filter

Commonly used in robotics for navigation and tracking: rely on a process model and measurement model

1) Start with an initial guess:

$$\hat{x}_0, \Sigma_0$$

2) Compute prior (prediction):

$$\hat{x}'_t = A\hat{x}_{t-1} + Bu_{t-1}$$
$$\Sigma'_t = A\Sigma_{t-1}A^T + Q$$

3) Compute posterior (correction):

$$K_t = \Sigma'_t H^T (H\Sigma'_t H^T + R)^{-1}$$
$$\hat{x}_t = \hat{x}'_t + K_t(z_t - H\hat{x}'_t)$$
$$\Sigma_t = (1 - K_t H)\Sigma'_t$$

4) Repeat steps 2 and 3

- An improperly tuned filter can increase and even degrade the signal.
- Considerably slower than other methods (~135 times)
- Complicated

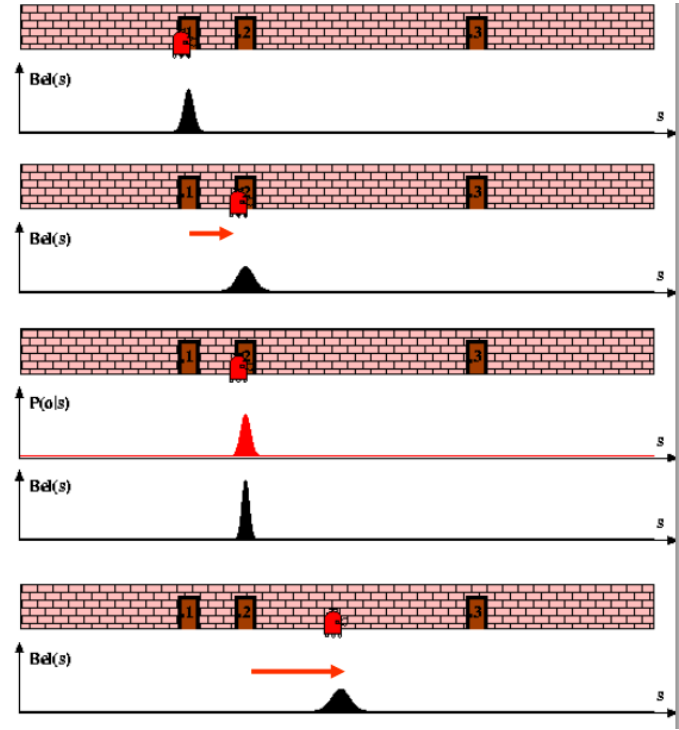


Image from: GD Hager slides

# The 1€ Filter

Adaptive 1st-order low-pass filter: cutoff frequency adapts according to an estimate of the signal's speed, or derivative

$$\alpha = \frac{1}{1 + \frac{\tau}{T_e}}$$

$$\tau = \frac{1}{2\pi f_c}$$

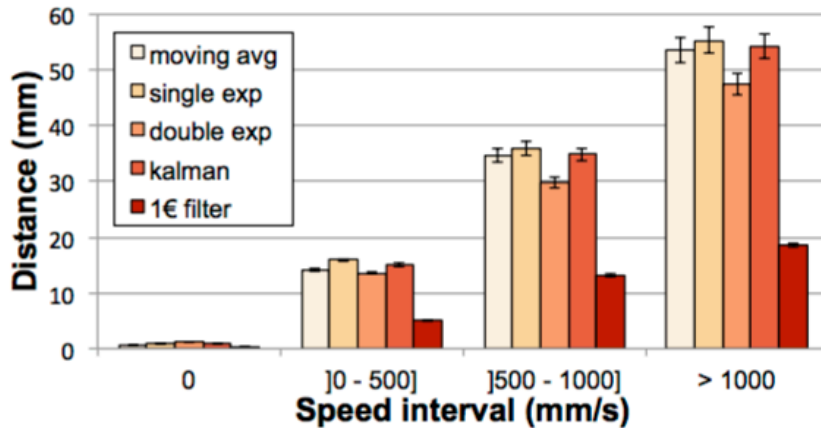
$$\hat{X}_i = \left( X_i + \frac{\tau}{T_e} \hat{X}_{i-1} \right) \frac{1}{1 + \frac{\tau}{T_e}} = \alpha X_i + (1 - \alpha) \hat{X}_{i-1}$$

$$f_c = f_{c_{min}} + \beta \left| \dot{\hat{X}}_i \right|$$

People are more sensitive to jitter at low speeds, and more sensitive to lag at high speeds. Therefore, at low rates of change in  $\hat{X}_i$ ,  $f_c$  is minimized to reduce jitter. As the rate of change of  $\hat{X}_i$  increases,  $f_c$  is increased to reduce lag.

# Interactive Demo and Results

<http://www.lifl.fr/~casiez/1euro/InteractiveDemo/>



The 1€ filter had the smallest Standard Error of the Mean (SEM) at 0.004 mm.

It was 0.013 mm for double exponential smoothing, 0.015 for the Kalman filter and moving average, and 0.016 for single exponential smoothing.

**Figure 1. Mean distance between filtered and true cursor position for each speed interval and filter. Error bars represent 95% CI.**

Image source: Casiez, Géry, Nicolas Roussel, and Daniel Vogel. "1€ Filter: A Simple Speed-based Low-pass Filter for Noisy Input in Interactive Systems." *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 2012.

# Assessment

## Pros

- Very easy to understand
- Clear comparison and explanation of various filter types
- Sample code in a number of languages
- Great website with demo and clear instructions

## Cons

- Few images or illustrations
- Failed to explain certain concepts e.g. Kalman Filtering
- Few examples of applications outside cursor tracking
- Little quantitative analysis

## APPENDIX A - 1€ FILTER

### Algorithm 1: 1€ filter

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**EXT:** First time flag: *firstTime* set to *true*  
Data update rate: *rate*  
Minimum cutoff frequency: *mincutoff*  
Cutoff slope: *beta*  
Low-pass filter: *xfilt*  
Cutoff frequency for derivate: *dcutoff*  
Low-pass filter for derivate: *dxfilt*

**IN :** Noisy sample value: *x*  
**OUT:** Filtered sample value

---

```
1 if firstTime then
2   | firstTime ← false
3   | dx ← 0
4 else
5   | dx ← (x - xfilt.hatxprev()) * rate
6 end
7 edx ← dxfilt.filter(dx, alpha(rate, dcutoff))
8 cutoff ← mincutoff + beta * ledxl
9 return xfilt.filter(x, alpha(rate, cutoff))
```

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### Algorithm 2: Filter method of Low-pass filter

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**EXT:** First time flag: *firstTime* set to *true*  
**IN :** Noisy sample value : *x*  
Alpha value : *alpha*  
**OUT:** Filtered value

---

```
1 if firstTime then
2   | firstTime ← false
3   | hatxprev ← x
4 end
5 hatx ← alpha * x + (1 - alpha) * hatxprev
6 hatxprev ← hatx
7 return hatx
```

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### Algorithm 3: Alpha computation

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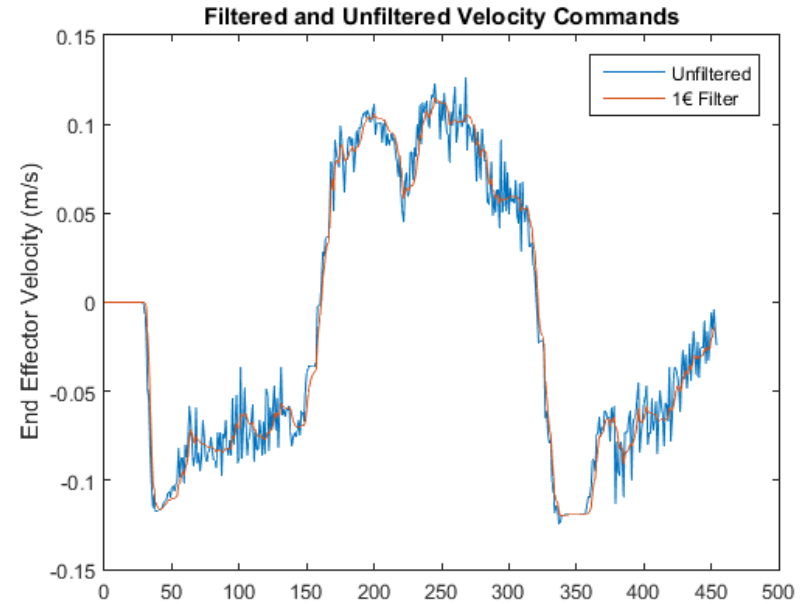
**IN :** Data update rate in Hz: *rate*  
Cutoff frequency in Hz: *cutoff*  
**OUT:** Alpha value for low-pass filter

---

```
1 tau ← 1.0 / (2* $\pi$ *cutoff)
2 te ← 1.0 / rate
3 return 1.0 / (1.0 + tau/te)
```

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# Relevance to Our Project





Questions?