This post contains my self-quiz and self-answer, I had tried but hard to find a proper answer by myself.

The question 1 is focus on the unmeasured state could be get by difference with LPF.

The question 2 is discuss the model type.

The question 3 is opening question, I hope you could share your experiment that use Kalman filter in real word.

Quetion1

If the system is simple enough, is the Kalman filter a good choice instead of difference with low pass filter method?

For example, consider a DC motor.

The input voltage is known.

The position is measurable.

The acceleration is measurable. (assume)

The goal is estimate the velocity.

Method 1, take difference on position then pass through a LPF to get velocity.

Pros:

easy to implement

the bandwidth is known

cons:

the noise is large if the resolution of position sensor is low.

Trade off between the phase delay & vel noise.

Method2, Kalman filter

The model is below, p is position, v is velocity, a is acceleration measurement, w\_a is acceleration measurement noise, v\_p is position measurement noise

Pros:

The acceleration measurement could provide more information

Cons:

The bandwidth of velocity is unknown.

(I only know the poles of whole estimator)

Hard to tune the Q and R weighting.

(I had tried to use the variance of measurement noise, but that just provide a start point for tuning)

The estimated velocity might have an offset value, because the acceleration measurement has an offset value.

Quetion2

How to determine the estimator model? Use kinematic model or dynamic model?

You might think the model at quetion1 didn’t scribe the true system properly.

So, let me rewrite again.

Method3, consider the offset value on acceleration measurement.

Pros:

The estimated velocity has no offset value if the a\_offset is converged.

Cons:

It is hard to measure acceleration for DC motor.

Other comment:

the convergence of a\_offset is so wired. I gauss that is the poles of a\_offset are not on real axis and measurement is noisy.

Method4, consider the dynamic model

The u is control effort, c is viscous friction, b is gain.

This model has a big problem.

the estimated velocity has over/undershoot when u changing.

u\_offset is also not a const. value because the model is not true system and affected by nonlinear term and so on…

Method5, put everything in measurement matrix

I didn’t try this method in real system, but this is the only method that I know could include u (input value) and a (acceleration) at a same time.

Pros:

Use all available information

Estimated acc without noise

Cons:

The a\_offset and u\_offset seems mix together.

Hard to tune the weightings.

Question3,

When to use Kalman filter?

According the first question, it seems difference with LPF is more practical than Kalman Filter.

According the second question, it seems the kinematic model has better performance than dynamics model.

(But not every time could get the kinematic model. So sad.)

In addition 1, the Kalman filter mix all information. That will lead some noise affect all state.

For example, a KF based attitude estimator, the Mag disturbance will affect roll and pitch angle.

In addition 2, the Kalman filter assume noise is a zero-mean Gaussian noise. But not all noise could be treated as zero-mean Gaussian noise. Like Coulomb friction.

Those let me want to know why people like Kalman filter, when to use KF, why to use KF, how to use KF.