Improving state estimation reliability

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The goal of the short-term scientific mission (STSM) was to improve the state estimation reliability. Recently developed iterative Kalman filter type algorithms, recursive update filter (RUF) [1, 2] and iterative posterior linearization filter (IPLF) [3], have been shown to improve the state estimation accuracy, but there are some estimation situations, where they do not produce reliable estimates. RUF does not produce consistent estimates in certain estimation situations [4, 5] and IPLF does not always converge.

The reliability of estimates is essential in intelligent transportation. Figure 1 shows an example of estimates, where extended Kalman filter based RUF does not produce a reliable estimate. The prior of vehicles location, shown as a dashed ellipse, is updated using a single bearings measurement. The blue ellipse, that shows the posterior estimate obtained with RUF is close to the beacon that makes the measurement (dashed line) compared to the true posterior that has a longer shape. The black line represents a border that could, for example, determine road tax zones or determine the lanes. The RUF estimate tells that the vehicle is with a high probability on the left side of the border, while such

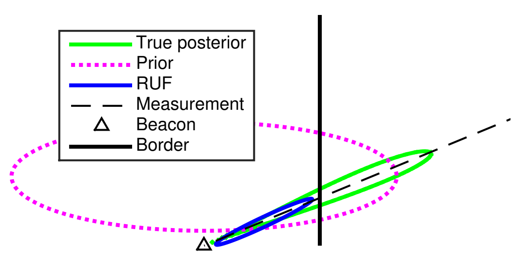

Figure 1: Posterior estimates obtained using a bearings measurement

conclusion should not be made according to the true posterior.

Also most of the previous literature has considered a special case of measurement function, where the measurement noise ε is additive and Gaussian and measurement model can be written as

$$y = h(x) + \varepsilon, \tag{1}$$

where y is the measurement value, x is the state, $h(x)$ is a measurement function, and ε is the measurement noise. For wider range of applications it would be good if the algorithm, could work with more general models of form

$$y = h(x, \varepsilon). \tag{2}$$

This form allows nonlinear transformations to the measurement noise.

During the STSM I have developed, with my host Lennart Svensson, improvements to the IPLF. The improvements are leading to an algorithm that should avoid the problems with reliability, mentioned in the first paragraph, and also work with non-additive noise models.

We have studied various different options make an algorithm that would outperform the existing algorithms. Some of details of the algorithm are still open, but we have an implementation ready that outperforms the state-of-the-art algorithms in some test situations. The goal is to submit the manuscript to a scientific journal during 2016. Figure 2 show how the new algorithm (regularized posterior linearization filter (RPLF)) produces estimate closer to the true posterior than RUF in the situation of Figure 1.

Figure 3 shows two other estimation examples, where a prior is updated using one measurement. The results are computed with the new algorithm RPLF and with the state-of-the-art algorithms IPLF and RUF. The green circle shows the prior mean, the green triangle the estimated posterior mean, the red circles means of iterations, and the red square is the mean of the true posterior. All algorithms use 10 steps and statistical linearization computed using Monte Carlo integration with 10^6 particles.

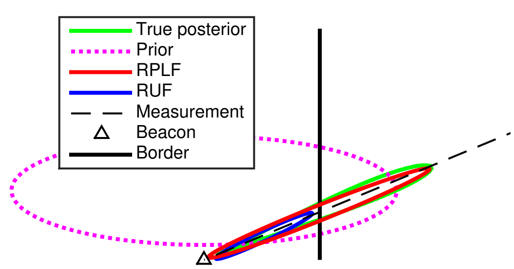

Figure 2: Posterior estimates obtained using a bearings measurement

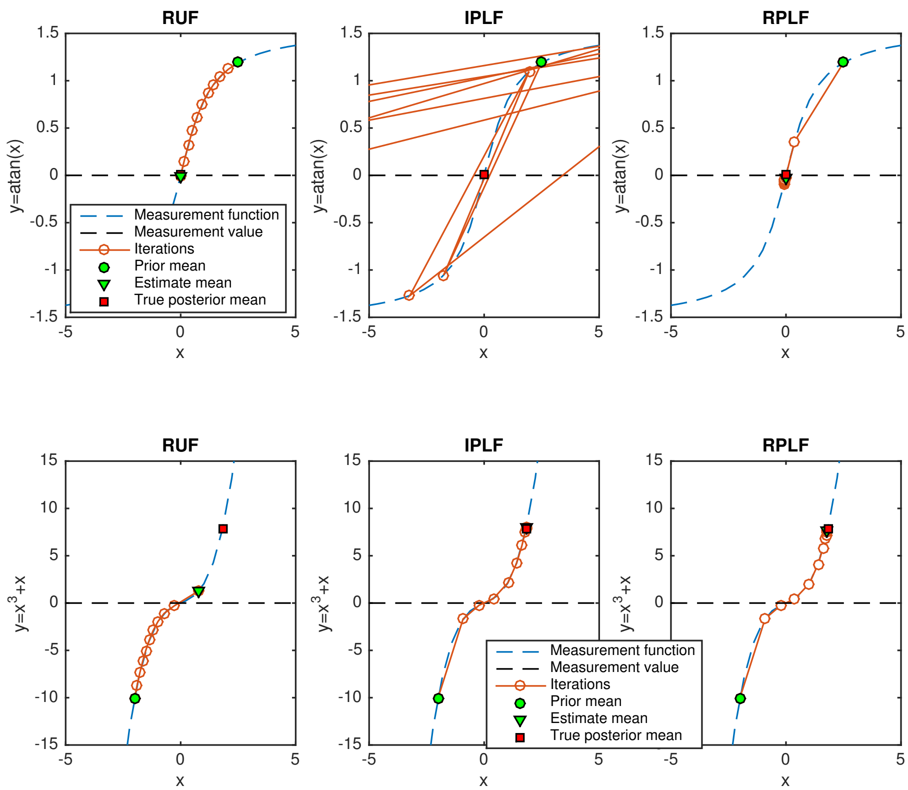

Figure 3: Estimate means computed with RUF, IPLF and RPLF

In the example in the top row, the measurement model has form

$$y = \arctan x + \varepsilon. \tag{3}$$

The prior is distributed as $\mathrm{N}(2.5, 1)$ measurement value is 0 and measurement noise variance is 10^{-4}. In this situation IPLF diverges. RUF and RPLF produce results close to the true posterior.

In the bottom row, the measurement models is

$$y = x^3 + x + \varepsilon. \tag{4}$$

The prior is distributed as $\mathrm{N}(-2, 16)$, measurement value is 8, and measurement noise variance is 1. In this situation, RUF does not produce a result close to the true posterior with 10 steps, but IPLF and RPLF produce good estimates.

In addition to the development of the RPLF, I have participated in development of an expectation propagation (EP) based inference algorithm. The algorithm seems promising and it should provide reliable estimates in some situations where Kalman filter -based algorithms may fail. The EP research probably leads to a publication.

In addition to developing algorithms, I attended a seminar where topics considered mostly algorithms that are required for development of autonomous vehicles. I learned about image segmentation algorithms and automatic mapping algorithms. In image segmentation, each pixel of an image is classified to belong to a class. The classes are selected based on the application. In automotive applications they could be car, road, pedestrian, etc. The mapping algorithms create a map of obstacles that can be used to in autonomous vehicles to navigate.

I learned a lot during the STSM and made valuable connections. I am expecting to be an author of two publications that are originated from my STSM visit. First will consider the RPLF algorithm and second the EP algorithm. I assume that my collaboration with researchers I met during my STSM will continue an lead to other publications in the future.

References

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