AI technology Helps Kalman Filter Performs Better

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1 Introduction

With the rapid development of Artificial intelligence (AI) technology, it has been widely used in various fields. One such field is sensor data processing and filtering techniques. Accurately estimating the system state is crucial in many real-time data processing applications, especially in tracking. The Kalman filter is a classical state estimation technique that provides an elegant and effective method for estimating the system state by fusing measurement data and system dynamic models.

The Kalman filter(KF) was initially proposed by Kalman in the 1960s[1] and has found wide applications in navigation and control systems. It is primarily based on the assumption of a linear system model and Gaussian noise, updating the state estimate and covariance matrix recursively for state estimation. Traditional Kalman filters perform well under the assumption of linear systems and Gaussian noise, but they may face challenges in certain situations. Many real-world systems are nonlinear and involve various complex noises and uncertainties. In such cases, traditional Kalman filters may fail to provide accurate estimation results and there are some variations of KF to improve the estimation results such as Extended Kalman Filter(EKF)[2], Unscented Kalman Filter(UKF). All these variations trying to linearize the system or model the non-linear parts.

AI technologies, such as deep learning and neural networks, possess powerful pattern recognition and nonlinear modeling capabilities[3]. It is an obvious idea to introduce AI techniques to the Kalman filter to improve the robustness of the algorithm to non-linear problems.

2 Existing work

For Kalman Filter, there are four important parts which will effect the estimation: transition equation, measurement equation, process noise matrix and measurement noise matrix.

KF ask the system must be linear and the noise must be Gaussion which are tough requirement for some real world system. In order to expand the application area of the KF, the EKF linearizes the system using the Jacobian matrix of the nonlinear system. EKF do expand the KF but the linearization introduces a certain prediction error, and the estimation effect is still not good enough in some cases. Another problem is that even the non-linear transition and measurement equations may not describe the system accurately because of some unknown factors or lows[4]. AI technology are good at black-box problems, which means build a model for some unknown system only using data. This makes possible to implement a EKF on some system which can't use a transition and measurement equations to describe.

Except using AI technology to model the unknown system, it also helps on tuning the parameters of KF. Sometime it is hard to directly get the process noise matrix and the measurement matrix, and it is impossible to traversal all possible value for these parameters because of the limited computing resources. The performance of KF can be consider like a function of some parameters, and AI technology can build a model ofto describe the function. With calculate the gradient of the function, the optimal parameters can be find[5].

Sukkeun Kim, et al. make a survey on KF with AI technology[6]. In the survey, they divided this topic into four parts: 1) Methods tuning parameters of KF, 2) Methods compensating errors in KF, and 3) Methods estimating pseudo-measurements of KF.

2.1 Tuning parameters of KF

In vehicle localization and navigation area, this methods are very popular because of the when vehicle is moving, the environment is changing which means the parameters of KF is changing. DJ Jwo, et al[7]. using AI to predicts the parameters of Adaptive Extended Kalman Filter(AEKF), making the filter can adapt to dynamic environments.

2.2 Compensating errors in KF

Artificial intelligence techniques such as machine learning or neural networks can learn error patterns or system dynamics and provide error compensation mechanisms. These methods aim to improve the robustness and accuracy of the Kalman filter by reducing the effects of measurement errors, model uncertainties, or non-Gaussian noise. The advantage of this method is that the model is separate with KF which means a simple framework and can be utilised in many applications. For example, L Chin propose a multi-traget tracking method which using a neural network to compensate the KF estimate errors[8].

2.3 Estimating pseudo-measurements of KF

Estimating pseudo-measurements of KF is a method to simplify the Kalman filter by introducing virtual measurements. This method can be used to improve the performance of the Kalman filter in some cases, or to deal with some special problems.

A common way to estimate spurious Measurements is to use Reconstruction Measurements. In Kalman filters, it is often necessary to measure some properties of the system state, such as position, velocity, etc. However, in some cases, these attributes may not be directly measurable or the measurement results may be inaccurate. By introducing reconstructed measurements, these properties can be estimated indirectly, thus simplifying the design of the Kalman filter.The basic idea of reconstructing measurements is to use known measurement information to infer unknown properties. For example, suppose we cannot directly measure the position of the system, but we can measure its velocity. By combining the velocity with the position information at the previous time instant, the position at the current time instant can be estimated indirectly.

Rejecting Error Measurements is another way to estimate spurious measurements. In some cases, the measurement results may contain noise or outliers, and these erroneous measurements can adversely affect the performance of the Kalman filter. By identifying and rejecting these erroneous measurements, the robustness and accuracy of the Kalman filter can be improved.

3 Simulation

In this part, I done a simulation of tuning parameters of KF.

3.1 Problem Definition

Describing certain real physical systems using a single, completely accurate system equation is often challenging. Assuming we have a physical system where a given input function $u(t)$ generates different outputs $y(t)$, and we can only obtain a series of observed values $z(t)$ corresponding to the input function through certain measurement methods. In this scenario, we are dealing with a situation where we have limited knowledge about the internal workings of the system. We have access to observed values, which are the outcomes or responses produced by the system based on the input function. However, the exact details of the input function itself remain unknown to us. What we want to do is establish an Extended Kalman Filter (EKF) to track the system's output based on multiple sets of input functions and observed values.

3.2 System Prototype

Given that the physical system is essentially an integrator, where the output is the integral of the system input, but we are unaware of this fact, we need to explore the system's state transition equation using the input functions and observed values in order to implement an EKF. We need to employ a data-driven approach to determine the system's behavior. By analyzing the input functions

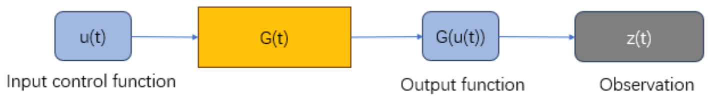

Figure 1: system prototype

and corresponding observed values, we can infer the relationship between them and formulate a state transition equation.

3.3 Methodology

To obtain the system's state transition equation, we need to find a mapping from the input functions to the output function, rather than a straightforward mapping from one vector to another. We can solve this problem using operator learning. After that, We obtain a system equation with t as the independent variables but what we need is actually a state transition equation with x_t respect to $x_t + 1$. So we shift the predict output function for one tick and using neural network to training the transition model. The nature of the neural network is a nonlinear function, so we can calculate the Jacobian matrix of the neural network, from which an EKF can be built to track the output of the system.

3.4 Results

After completing the model training, we use an input function$u(t) = sin^2(x)$, The theoretical output of the system and the output of Deep Operator Neural Network (DeepONet) are shown in figure 2. As can be seen from the figure, the predictions of DeepONet are similar to the ground truth as a whole, but there are still some errors. This same trend indicates that the deeponet model may contain certain system information.

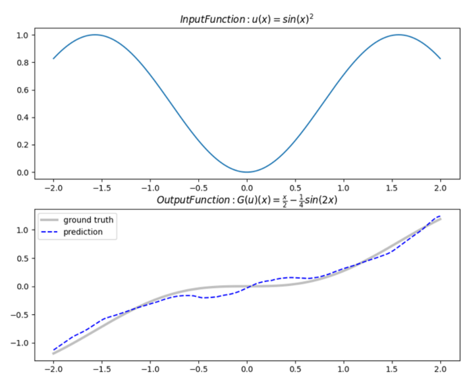

Figure 2: Test input function and DeepONet prediction

In addition to making predictions about the system output based on deeponet, the observations which shows in figure 3, are also have some information.

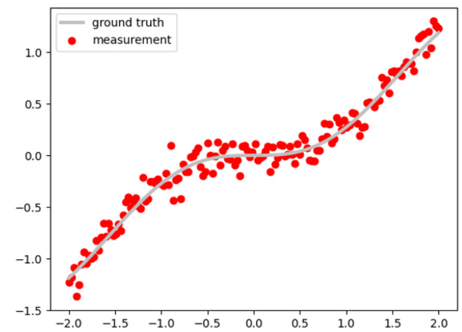

Figure 3: Observation

We used four different ways to track the output of the system. 1) Learning-based Extended Kalman Filter, 2) Nolearning Extended Kalman Filter, 3)Polynomial Regression, and 4) Partical Filter (PF). The learning-based Extended Kalman Filter means we using DeepONet model to build a transition model, according to the model, implement a EKF. Nolearning Extended Kalman Filter means in the predict step, we always assume that the next state is the same as last state. The observations looks like a function of x^3, so we using a 3 order polynomial regression to fit the observation. The prediction results of the four methods are shown in figure 4.

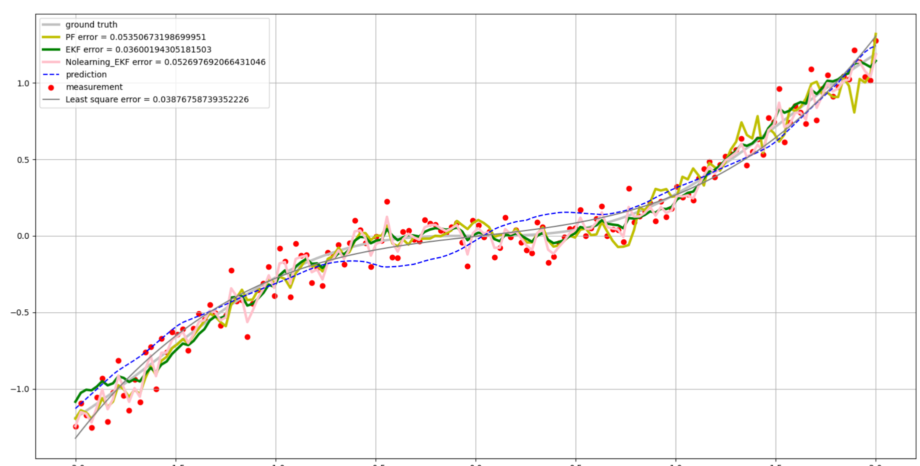

Figure 4: Different methods performance

From the results, it can be found that the EKF using the Deeponet system model has a better tracking effect and a lower mean absolute error than the

EKF without using the information of the system. The tracking performance of the learning-based EKF is similar to the mean absolute error of the third-order polynomial regression. But the advantage of learning-based EKF is that it can be tracked in real time, whereas third-order polynomial regression requires all the observations to make a prediction. It also works better than the particle filter. This shows that the method of combining neural network can extract the information of the system transfer equation to a certain extent, and help KF to achieve better prediction effect in the system prediction step, and improve the tracking effect.

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