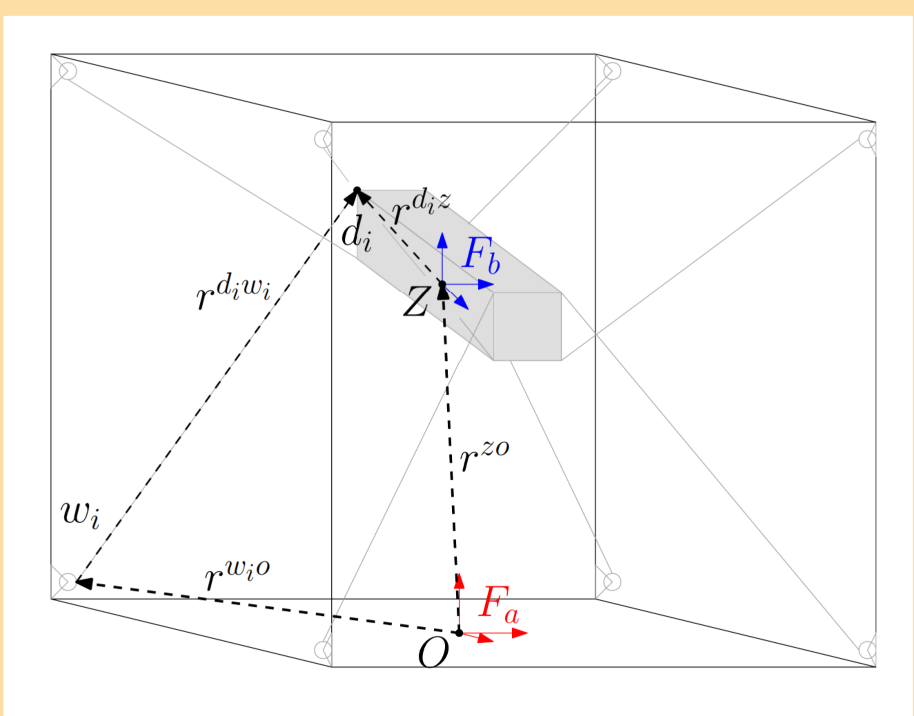
Kalman Filter Based Pose Estimation for CDPRs (Cable Driven Parallel Robots)

Neel Puri and Ryan Caverly

University of Minnesota

Abstract

This work extends previous work by taking the novel a novel extended Kalman filter (EKF) approach for the pose estimation of a cable driven parallel robot (CDPR) and comparing it with a novel Unscented Kalman Filter (UKF) based approach. Both filters fuse accelerometer, rate gyroscope, and winch encoder data together to create a more accurate covariance pose estimate. Both filters are tested on experimental data collected by a six degree-of-freedom CDPR test bed. The current results show minimal difference between the two filters but offer promising possibilities for future work.



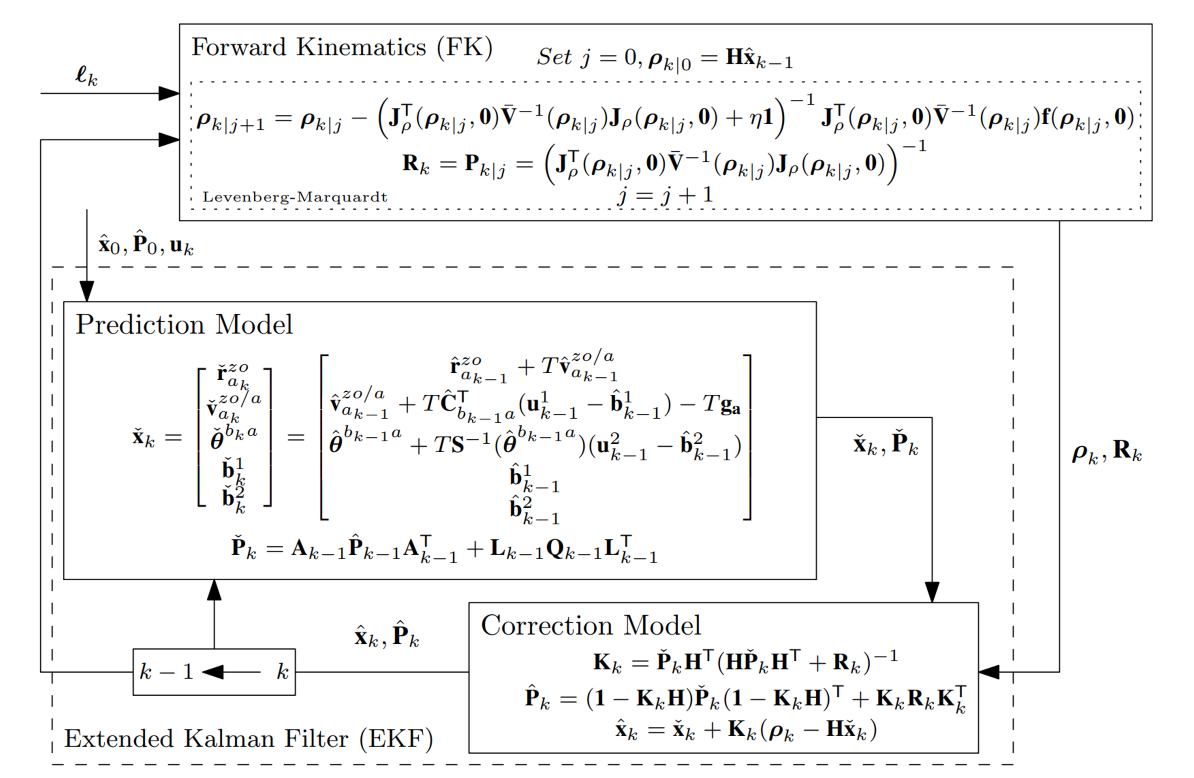
Introduction

Cable Driven Parallel Robots are an interesting class of robots that consist of an array of independent cable winches that come together to manipulate a payload or end-effector. As with most robots, accurate CDPR usage is highly dependent on how accurate the information about its payload's position and orientation is. This state is called the payload's pose. The most common method of estimating the pose is forward kinematics. This is a process of taking measurements of the cable lengths and then solving something called loop closure equations to calculate the position of the payload. You can think of it as taking the length of the cable, creating a sphere of that defined radius around each winch, and then finding which orientation and attitude the payload can be such that each corner touches the surface of only one sphere each.

This process is highly nonlinear, however, and requires much iteration and lots of uncertainty. A common way to account for this is Kalman filtering. For this method, it is incredibly common to simply have the covariances on the forward kinematics be a tuning parameter. The pervious work changed that by calculating it at each time step and using that in an EKF. This work compares that to an Unscented Kalman Filter which removes the need for the forward kinematics and operates on the nonlinear equations themselves through the use of Sigma Points.

Methodology

EKF General Formulation



State: $\mathbf{x}^\mathsf{T} = \begin{bmatrix} \mathbf{r}^{zo\mathsf{T}}_a & \mathbf{v}^{zo/a\mathsf{T}}_a & \boldsymbol{\theta}^{ba\mathsf{T}} & \mathbf{b}^{1\mathsf{T}} & \mathbf{b}^{2\mathsf{T}} \end{bmatrix}$

Jacobians:

$$\mathbf{A}_{k-1} = \begin{bmatrix} \mathbf{1} & T\mathbf{1} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{1} & -T\hat{\mathbf{C}}^\mathsf{T}_{b_{k-1}a}(\mathbf{u}^1_{k-1} - \hat{\mathbf{b}}^1_{k-1})^\times\hat{\mathbf{S}}_{k-1} & -T\hat{\mathbf{C}}^\mathsf{T}_{b_{k-1}a} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{1} + T * \frac{\partial\hat{\mathbf{S}}^{-1}_{k-1}(\mathbf{u}^2_{k-1} - \hat{\mathbf{b}}^2_{k-1})}{\partial\boldsymbol{\theta}^{b_{k-1}a}} & \mathbf{0} & -T\hat{\mathbf{S}}^{-1}_{k-1} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{1} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{1} \end{bmatrix}$$

$$\mathbf{L}_{k-1} = \begin{bmatrix} \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ T\hat{\mathbf{C}}^\mathsf{T}_{b_{k-1}a} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & T\hat{\mathbf{S}}^{-1}_{k-1} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & -\mathbf{1} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & -\mathbf{1} \end{bmatrix}$$

UKF General Formulation

Prediction:

$$\chi_k^0 = \hat{x}_k^+$$
$$\chi_k^i = \begin{cases} \hat{x}_k^+ + (\sqrt{n+\lambda}) \cdot S_k^{j,T}, \text{ for } i = 1, ..., n, \text{ and } j = 1, ..., n \\ \hat{x}_k^+ - (\sqrt{n+\lambda}) \cdot S_k^{j,T}, \text{ for } i = n+1, ..., 2n, \text{ and } j = 1, ..., n \end{cases}$$

Propagate each χ_k^i through nonlinear dynamics

$$\hat{x}_{k+1}^- \approx \sum_{i=0}^{2n} w_m^i \cdot \bar{\chi}_{k+1}^i, \qquad P_{k+1}^- \approx \sum_{i=0}^{2n} w_c^i \cdot (\bar{\chi}_{k+1}^i - \hat{x}_{k+1}^-)(\bar{\chi}_{k+1}^i - \hat{x}_{k+1}^-)^T + Q_k$$

Measurement:

$$\chi_{k+1}^0 = \hat{x}_{k+1}^-$$
$$\chi_{k+1}^i = \begin{cases} \hat{x}_{k+1}^- + (\sqrt{n+\lambda}) \cdot \bar{S}_{k+1}^{j,T}, \text{ for } i = 1, ..., n, \text{ and } j = 1, ..., n \\ \hat{x}_{k+1}^- - (\sqrt{n+\lambda}) \cdot \bar{S}_{k+1}^{j,T}, \text{ for } i = n+1, ..., 2n, \text{ and } j = 1, ..., n \end{cases}$$

Propagate each χ_{k+1}^i through nonlinear measurement

$$\hat{y}_{k+1}^- \approx \sum_{i=0}^{2n} w_m^i \cdot \gamma_{k+1}^i, \qquad P_{yy,k+1} \approx \sum_{i=0}^{2n} w_c^i \cdot (\gamma_{k+1}^i - \hat{y}_{k+1}^-)(\gamma_{k+1}^i - \hat{y}_{k+1}^-)^T + R_{k+1}$$

$$P_{xy,k+1} \approx \sum_{i=0}^{2n} w_c^i \cdot (\chi_{k+1}^i - \hat{x}_{k+1}^-)(\gamma_{k+1}^i - \hat{y}_{k+1}^-)^T$$

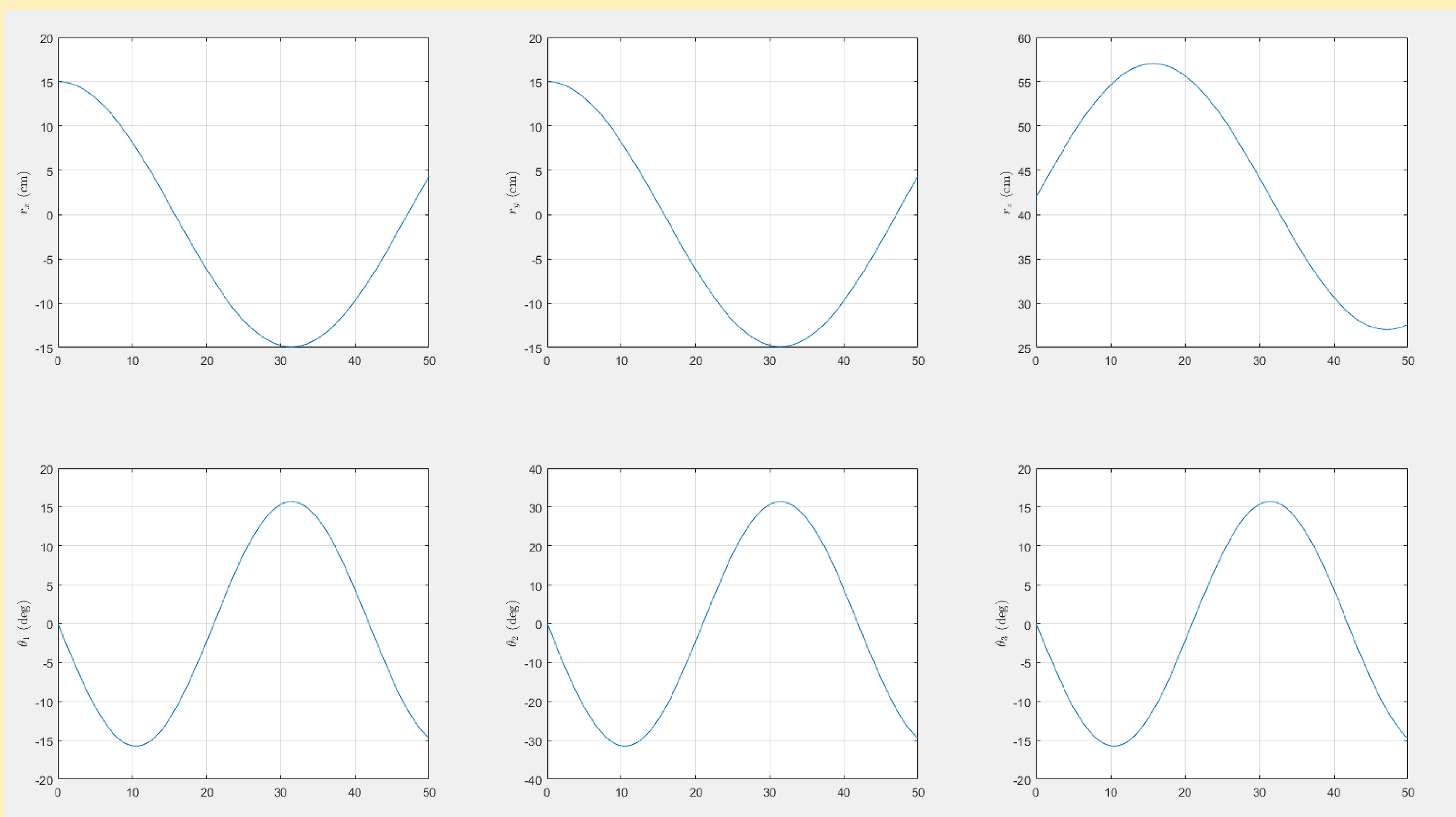
$$K_{k+1} \approx P_{xy,k+1} \cdot [P_{yy,k+1}]^{-1}$$

State Update:

$$\hat{x}_{k+1}^+ = \hat{x}_{k+1}^- + K_{k+1}(y_{k+1} - \hat{y}_{k+1}^-)$$
$$P_{k+1}^+ = P_{k+1}^- - K_{k+1}P_{yy,k+1}K_{k+1}^T$$
$$= P_{k+1}^- - P_{xy,k+1}[P_{yy,k+1}]^{-1}P_{xy,k+1}^T$$

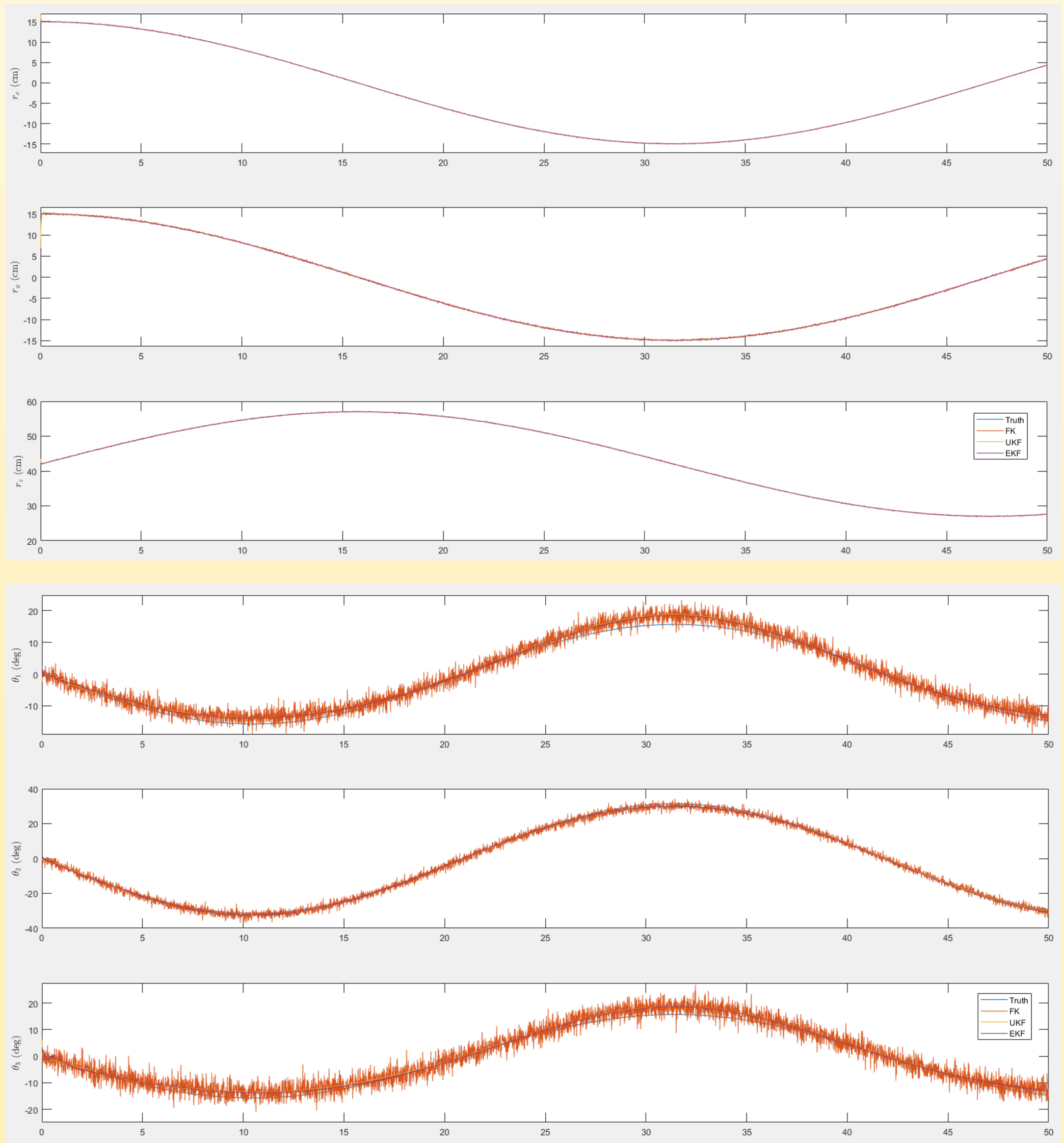
The novel contribution of this work is the comparison of Extended Kalman Filter (EKF) formulation from this work's previous version with a novel Sigma Point Filter (Unscented Kalman Filter or UKF). This involves propagating a different measurement through the nonlinear model. Namely, the UKF uses the eight cable measurements where as the EKF uses a direct measurement of the angular velocity and acceleration of the payload. The equations for both formulations are given in the sets above.

Both algorithms were run on the same simulated data set and then compared. The expected trajectory is shown below. The resulting estimates and covariances were compared to each other to determine which of the two algorithms was better.

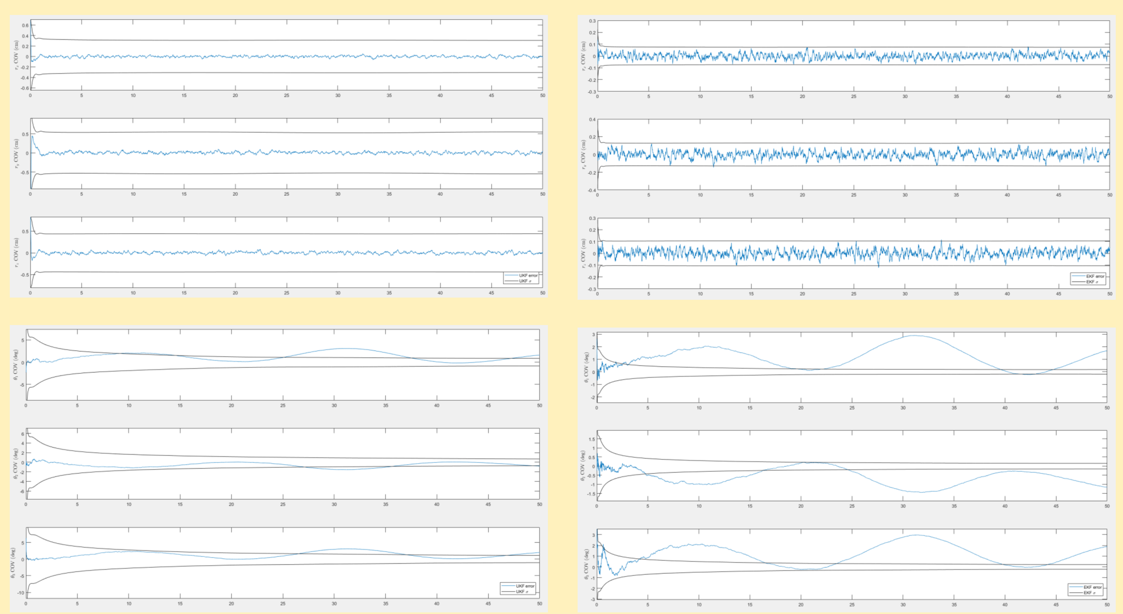


Results

Estimates:



Covariances:



Conclusion

The result of this work so far has been inconclusive. Despite numerous efforts, the UKF covariances seem to be significantly larger than what might be expected. As such it is currently estimated that there is something incorrect in the calculation of the UKF covariances. Further, the EKF and UKF both seem to have incredibly odd oscillatory behavior in the attitude covariances. The issue with this is that there seems to be no discernable cause of the issue in either of the algorithms. The estimation for both algorithms is incredibly consistent but still incorrect. An odd pattern emerges that both algorithms seem to be off the expected result in the same way but with no tangible difference in error. The authors of this work intend to continue exploring this difference as well as attempt to fish out the issues in the simulations in order to find if a UKF is truly a viable or even preferable replacement for the EKF formulated in the previous work.