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Robocup: Cooperative estimation and prediction of player and ball movement

Group Project

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ABSTRACT

Abstract

Hier kommt das Abstract ...

Contents

| | |
|--|-----------|
| 1. Introduction | 5 |
| 2. Simulation | 6 |
| 2.1. Playing Field, Robots and Ball | 6 |
| 2.2. Random Simulation | 6 |
| 3. Kalman Filtering | 7 |
| 3.1. Linear Kalman Filter | 7 |
| 3.2. Extended Kalman Filter (EKF) | 7 |
| 4. Estimation | 9 |
| 4.1. Estimate of the Ball | 9 |
| 4.2. Estimate of the Robots | 9 |
| A. Examples | 10 |
| A.1. Kalman Filtering of Linear System | 10 |
| Literatur | 12 |

List of Figures

| | |
|---|---|
| 3.1. Example: Linear electrical circuit. | 8 |
| 3.2. Example: Input signal, output signal, noisy output, and filtered ouptut. . | 8 |

1. Introduction

2. Simulation

2.1. Playing Field, Robots and Ball

2.2. Random Simulation

3. Kalman Filtering

3.1. Linear Kalman Filter

There exists a recursive Kalman filter algorithm for discrete time systems.[1] This ongoing Kalman filter cycle can be divided into two groups of equations:

1. Time update equations

$$\begin{aligned}\hat{x}_k^- &= A\hat{x}_{k-1} + Bu_{k-1} \\ P_k^- &= AP_{k-1}A^T + Q\end{aligned}\tag{3.1}$$

2. Measurement update equations

$$\begin{aligned}K_k &= P_k^- H^T (HP_k^- H^T + R)^{-1} \\ \hat{x}_k &= A\hat{x}_{k-1}^- + K_k(z_k - H\hat{x}_k^-) \\ P_k &= (I - K_k H)P_k^-\end{aligned}\tag{3.2}$$

To test this algorithm and to learn something about applying the Kalman filter on linear system we created an example. A detailed description of the following example can be found in appendix A.1.

We consider a linear, timeinvariant model, given by the following circuit diagram in Figure 3.1. First we added process noise and measurement noise to the system output. The aim is to get an estimation of the noisy output. Therefore we applied the Kalman filter algorithm based on the equations 3.1. In the figure 3.2, above we can see the input signal and the ideal measurement of the output signal. That ideal measurement includes process noise, which can obviously not be filtered by the Kalman filtering algorithm. Below one can see the noisy measurement on the left side and the filtered output on the right side.

3.2. Extended Kalman Filter (EKF)

3. Kalman Filtering

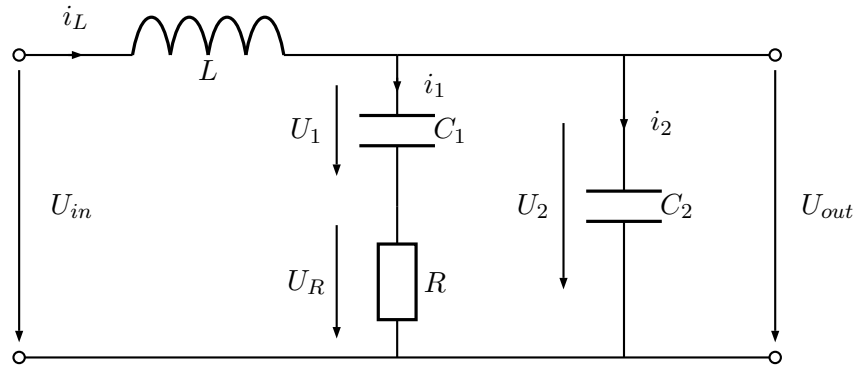


Figure 3.1.: Example: Linear electrical circuit.

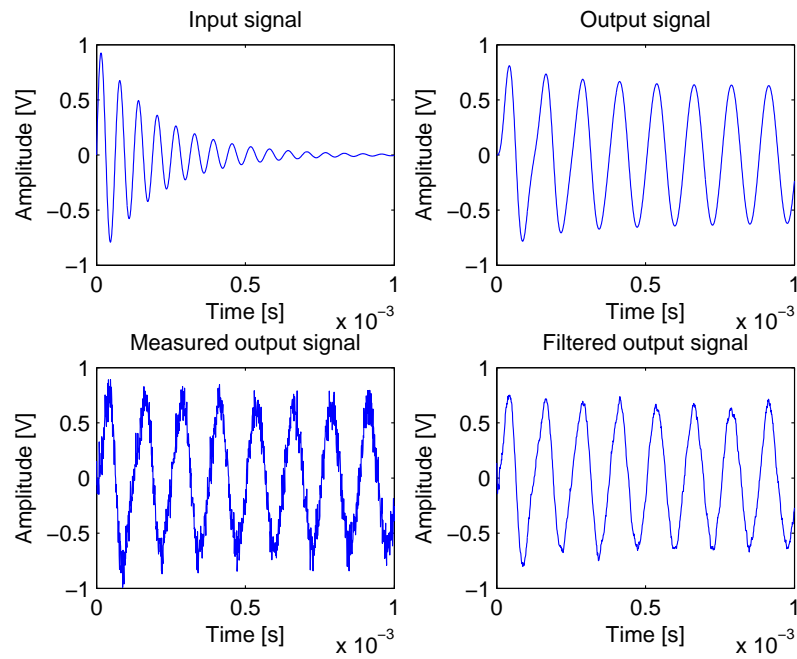


Figure 3.2.: Example: Input signal, output signal, noisy output, and filtered output.

4. Estimation

4.1. Estimate of the Ball

4.2. Estimate of the Robots

A. Examples

A.1. Kalman Filtering of Linear System

Bibliography

- [1] G. Welch and G. Bishop, “An Introduction to the Kalman Filter,” UNC-Chapel Hill, 2006.
- [2] RoboCup Technical Committee, “RoboCup Standard Platform League (Nao) Rule Book,” RoboCup, 2011.