Learning State-Dependent Measurement Models to Improve Robot Localization

by

For the Ph.D. degree in Computer Science and Engineering

This dissertation proposes a novel method called state-dependent sensor measurement models (SDSMMs). Such models dynamically predict the state-dependent bias and uncertainty of sensor measurements, ultimately improving fundamental robot tasks such as localization. In our first investigation, we introduced the state-dependent sensor measurement model framework, described their properties, stated the input and output of these models, and described how to train them. We also explained how to integrate such models with an Extended Kalman Filter and a Particle Filter, two popular robot state estimation algorithms. We validated the proposed framework through a series of localization tasks. The results showed that our framework outperformed the baseline sensor measurement models. Our second investigation explored how to learn accurate state-dependent sensor measurement models with limited sensor data. This work is motivated by the difficulty of collecting large numbers of sensor data for training. To alleviate the burden of collecting large datasets, we leverage transfer learning to train models with artificially generated sensor data followed by real sensor data. We used a series of bootstrap experiments to demonstrate that the proposed transfer learning method produced sensor models that are as accurate as models learned with significantly larger datasets. These results imply that we can learn accurate sensor models with limited data quickly, which is broadly beneficial for robot systems such as autonomous vehicles.