Bayesian Methods for Identifying Faults on Robots for Planetary Exploration

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1 Introduction

In a number of application domains, such as planetary exploration, robots operate in environments where human intervention is expensive, slow, unreliable, or impossible. It is therefore essential for these robots to autonomously detect and recover from faults. This process needs to be efficient since there is limited computational power available on rovers.

Fault Detection and Identification (FDI) for robots is a complex problem. This is because the space of possible faults is very large and robot sensors, actuators, and environment models are uncertain. Probability theory provides a natural representation of the uncertainty in the rover domain, but an exact Bayesian solution to FDI is intractable. Traditional methods address this by *approximating the problem* using linear approximations of rover dynamics and/or by ignoring uncertainty. Often these approximations are unrealistic, and either faults go undetected, or an unreasonable number of false positives are triggered.

We instead prefer to *approximate the solution* using Monte Carlo methods. Classical Monte Carlo methods for dynamic systems, such as particle filters, have a high variance for small sample sets. Using large sample sets is computationally expensive and defeats the purpose.

A *fault* is defined as a deviation from expected behavior. *Fault detection* is defined as the process of determining that a fault has occurred. *Fault identification* is the process of determining exactly which exception or fault occurred. We concentrate on a class of faults that are relatively difficult to detect because they cannot be inferred from sensor values at a given instance, but require a sequence of time-varying sensor values. The faults addressed here include mechanical component failures, such as broken motors and gears; faults due to environmental interactions, such as a wheel stuck against a rock; and sensor failures, such as broken encoders.

Interpreting faults requires context sensitive interpretation of sensor data that can only be obtained by monitoring the dynamics of the system over time, which tend to differ according to operating conditions. For example, for a rover, an increase in the power required for locomotion on flat ground may be a cause for concern, but a similar increase on a slope might be perfectly acceptable. Sensors do not directly report these dynamics because they are noisy and limited, i.e., they do not have complete information about the state of the rover and the environment that it is operating in. In addition, there are a large number of components that can fail in various combinations at any instant in time and the computational resources are too limited to consider all possible combinations.

State estimation is the process of determining the sate of the system from a sequence of data. FDI has a natural representation as a state estimation problem. We represent the possible fault and operational modes of the systems as explicit discrete states. The sequence of sensor measurements are then used to determine the state of the system.

We concentrate on a discrete time, first order Markov formulation of the state estimation problem to obtain a distribution over the unobservable discrete fault and operational states of a rover from noisy measurements of continuous sensor readings. We address this problem with Bayesian filtering.

Although the mathematical structure of the optimal Bayesian solution is well understood, the computational complexity of the optimal filtering algorithm limits its practical applicability. In robotics particle filters are a popular method for computing tractable approximations to this posterior. Particle filters perform Monte Carlo integration to approximate the posterior distribution over the states with a set of samples of "particles." The particle approximation converges to the true Bayesian posterior in the limit as the number of samples go to infinity.

Particle filters have a number of characteristics that make them attractive for fault detection on robots: they are non-parametric (can represent arbitrary distributions), can handle hybrid state spaces, can handle noisy sensing and motion and can easily be extended to an anytime approach where the number of particles (and hence the estimation accuracy) can be adjusted to match available computation.

The main problem is that a large number of particles are often needed to maintain a reasonable approximation of the state probability distribution and to enable detection of rare events. Reliably tracking multiple low-probability fault states, which requires maintaining and updating large numbers of particles, is typically not practical due to limited computation. Small particle sets do not provide reasonable approximations because: (1) they are unlikely to represent low probability fault states, (2) their estimates are likely to have a high variance, particularly when there are a large number of possible state transitions.

We describe algorithms that address these issues. First, the Risk Sensitive Particle Filter [3, 1] reduces the number of particles required to track unlikely states by including cost when updating the particles. Second, the Variable Resolution Particle Filter [4] reduces the number of particles required by grouping multiple low-probability states based on similarity until differentiation is required. Third, the Variable Resolution Unscented Particle Filter [2] looks at the expected sensor measurement one step ahead in time to improve the state estimate provided by a limited number of particles. Experimental results show a significant improvement in efficiency over the classical approach.

References

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