Consistency and SLAM

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As this summer school attests, SLAM is a vibrant research topic which is both practically important and theoretically challenging. The ability to place a robot in an arbitrary environment and have it "just work" is extremely important in many industrial, scientific, military and safety applications. However, many difficulties including the choice of appropriate landmarks and determination of methods for keeping computational costs must be derived.

Many approaches to SLAM utilise a Bayesian formulation of the problem: the vehicle and the beacons are random variables whose values are to be estimated jointly. However, implementing full optimal nonlinear filters is notoriously difficult and so many SLAM systems approximate it using the Kalman filter (KF). The KF is attractive for many reasons. It is the best linear unbiased estimator: given a linear update rule, it calculates the estimate with the smallest expected mean squared error. It only requires a description of the first two moments of the distributions[1] which limit the computational and storage requirements which are needed. Finally, the uniquely specialised structure of SLAM introduces many properties which can be readily exploited to optimise SLAM. For example, in the prediction step large portions of the covariance matrix remain the same and do not have to be explicitly calculated.

For these reasons Full Covariance Kalman Filter (FCKF) SLAM is often viewed as "the gold standard": other algorithms are derived from it and benchmarked relative to it. However, theoretical analyses and empirical tests within the past five years have raised troubling questions about the validity of FCFK-SLAM. To be more precise, FCKF-SLAM does not appear to be covariance consistent: it underestimates the true mean squared error in its estimates. To be more blunt, FCKF-SLAM doesn't work.

The purpose of this tutorial is to draw together and summarise the theoretical work which has been carried out to assess the consistency of SLAM, and to survey some of the techniques which have been proposed to overcome these difficulties. We consider two questions:

1. **How do modelling errors affect the consistency of SLAM?** *No* system is modelled perfectly. Any practical implementation of SLAM uses approximate process and observation models. Although the impacts of modelling errors are well-known in normal tracking examples, the impact on SLAM has not been thoroughly documented.

2. **How do linearisation errors affect the consistency of SLAM?** Most systems are nonlinear. It is well-known that propagating probability distributions through arbitrary nonlinear systems is extremely difficult and so approximations, such as linearisation or expansions based off of truncated Taylors Series expansions, must be used. In regular tracking examples, these can be compensated for through stabilising noise. However, the same does not apply to SLAM.

Although this tutorial is geared specifically towards Kalman filter formulations, we believe that many of the issues raised have relevance in other formulations as well.

[1]It does *not* rely on the oft-quoted and overly restrictive assumption that the distributions are zero-mean Gaussians.