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Locality-Sensitive Non-Linear Kalman Filter for Target Tracking

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ABSTRACT

Target tracking (TT) with non-linear kalman filtering (NLKF) has recently become a very popular research area, particularly in the field of marine engineering and air traffic control. Contemporary NLKF algorithms have been very effective, in particular, with extensions and merging with a reduced root mean square error (RMSE) value. However, there are a number of issues that confront NLKF approaches, notably weakness in robustness, convergence speed, and tracking accuracy due to large initial error and weak observability. Furthermore, NLKF algorithms significantly results in error for high non-linear systems (NLS) because of the propagation of uncertainty. Again, there is a problem of estimating future states as a result of white noise. To handle these issues, the authors propose a novel non-linear filtering algorithm, called locality-sensitive NLKF (LSNLKF) that incorporates locality-sensitive adaptors into the structure of an integrated NLKF. They are the extended kalman filter (EKF) and the unscented kalman filter (UKF) for TT.

KEYWORDS

Extended Kalman Filter, Locality Sensitive Adaptor, Non-Linear Systems, Target Tracking, Unscented Kalman Filter

1. INTRODUCTION

Current proliferation of Digital and ubiquitous devices with its attendant advancement in Technology have contributed immensely, to the upsurge in the study of Non-linear Kalman Filtering (NLKF) and its application in surveillance networks and Military intelligence systems for tracking of objects. This complements the advancement in the life style of social beings (Humans). NLKF is a filtering algorithm that is used in linearizing NLS for effective tracking of objects in dynamic environments which is significantly better than any strictly linear filter. Frankly speaking, Ohm's law is only linear up to a certain threshold, however, many systems are more close to been linear since they give a satisfactory result (Akram, Liu, Tahir, Ali, & Wang, 2019; Julier & Uhlmann, 1997). More so, the most effective applications of KF has been in circumstances of non-linear dynamics or measurements, hence the objective is to linearize the system first and then apply the normal Kalman Filter (KF) to obtain the current state of the system addressed in (Musoff & Zarchan, 2005).

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Furthermore, there are two types of linearization carried out with respect to NLS, namely the linearization of trajectory or solution of stochastic system (i.e. continuously with state estimates resulting from measurement) and linearization with a set of chosen sample points respectively referred to as EKF by (Gao, Zhang, & Petersen, 2017) and UKF by (Wan & Van Der Merwe, 2000) as well as the normal KF in (Faragher, 2012), where the trajectories are linearized independent of measurement data. When both models (state transition and observation model) are highly non- linear, EKF give poor performance because the covariance is propagated through linearization of the underlying nonlinear model. But in case of UKF, a deterministic sampling technique is used known as *unscented transform* to pick a set of sample points around the mean known as *sigma points*. The Sigma points are propagated through non-linear functions, from which estimate of mean and covariance are calculated. More so, EKF is used to linearize all non-linear models in order to could apply linear KF (Julier & Uhlmann, 1997). Further, there is a challenge in applying KF to realistically map signals in high dimensional space into a low space and also how to obtain an appropriate approximation model. Hence, incorporating locality-sensitive with KF seems to be the most practical way to address the issue for effective target tracking. TT, which is the prediction of the future location of a dynamic object based on its estimates and measurements.

Moving objects are monitored and detected by sensor nodes and their trajectories further predicted by sensor nodes based on their observations on movements of the target. Signals that are transmitted are usually opposed by some form of inertial and these signals need to be subjected to some form of filtering. This is done digitally through an algorithm that discriminates, defined based on the traits of signals. The filters used to achieve this purpose of NLKF are the UKF and the EKF, both of which could be implemented in addressing the issues of white noise and other signal defects in NKL. TT, the estimation of the future trajectory of a targeted object calculated on its past events or states. NLKF has been widely used as tracking filter to estimate the position, the acceleration and the velocity of a target object, whose performance in the situation of maneuver could be challenging. As a result, to alleviate the issues discussed so far, different methods have been employed over the years by past studies the resolve the challenges with NLKF approaches for TT. A robust and fast tracking algorithm was developed in (Zhan & Wan, 2007), named iterated UKF (IUKF). The IUKF algorithm could obtain more accurate state and covariance estimation. the proposed method has potential advantages in tracking accuracy, convergence speed, and robustness when compared with the conventional nonlinear methods such as EKF and UKF as established through arithmetical simulation and experiment results. (Di, Joo, & Beng, 2009) iterated the relevance of TT for wireless sensor networks and also highlighted that KF and its variants are amongst the most popular algorithms in addressing signal tracking issues.

More recently, a dynamic waveform selection algorithm for radar target tracking was proposed in (Wang, Sun, Zhang, & Yang, 2017). The covariance of target range and range rate estimations is utilized to describe the statistic characteristics of the measurement noises in tracking. Then the relationship between waveform parameters and tracking performance is established. The CRLB of target estimations corresponding to a certain waveform is obtained through the ambiguity function. The UKF is used as the tracker and a secondary UKF is used to predict the tracking MSE. Minimizing the tracking MSE is chosen as the criterion of the dynamic waveform selection. At every time step of tracking, optimal transmitted waveform parameters are selected to track the nonlinear 2D target. Simulation results show the algorithm can improve the tracking performance when target states and measurements are nonlinear. In (Majumder & Sadhu, 2017), a robust EKF for state estimation of a surface-to-air object was presented with nonlinear dynamics. Outliers in the dimension can utterly vitiate the estimation performance of conventional nonlinear filters. The method resists the effect of outliers to provide improved estimation and outperforms its conventional versions. proposed, a weighted optimization-based distributed KF algorithm (WODKF) to handle the issues of nonlinearity and coupling was introduced in (Jie, Li, Yang, & Fang, 2016). The technique amplifies the data size of each sensor by the received measurements and state estimates from its connected sensors instead