Autonomous Flight: State-of-the-art Estimation and Guidance Systems

By Dany Dionne[1] and Camille A. Rabbath[2]

[1]Dept. of Mechanical Engineering, Concordia University, Montreal

[2]Defence R&D Canada-Valcartier, QC, and Dept. of Mechanical Eng., McGill University, Montreal.

Abstract

Unmanned aerial vehicles (UAVs) are rapidly becoming a strategic asset of today's military forces and an enabler of transformation for the civilian airspace community.

In autonomous flight, accuracy from the guidance system is necessary for performance and safety reasons. Increased accuracy can be achieved by improving the information processing and by accounting for the uncertainties. With the ever increasing on-board computational capabilities, a growing number of sophisticated estimation and guidance algorithms are becoming feasible. However, along with the new possibilities offered by these algorithms, new challenges are also encountered. This article describes some of these possibilities and challenges and presents some of the investigated solutions to optimize their application. Of particular interest is the selection of the estimation algorithm with respect to the uncertainties and the dynamics, and the coupling between the estimation and guidance systems.

Sommaire

Les drones, ou avions sans pilote, sont maintenant devenus des atouts stratégiques des forces militaires et sont en voie de transformer l'espace aérien civil. En vol autonome, un guidage de précision est nécessaire pour des raisons de performance et de sécurité. Un guidage de précision accrue peut être obtenu en améliorant le traitement de l'information et en tenant compte des incertitudes. Avec les capacités de calcul embarquées sans cesse croissantes, un nombre accru d'algorithmes d'estimation et de guidage sophistiqués deviennent accessibles. Toutefois, de nouveaux défis accompagnent les nouvelles possibilités offertes par ces algorithmes. Cet article décrit certaines de ces possibilités et des défis associés et présentes certaines des solutions étudiées pour optimiser leur application. La sélection de l'algorithme d'estimation par rapport aux incertitudes et à la dynamique est ici d'un intérêt particulier, de même que les interactions entre les systèmes d'estimation et de guidage.

1.0 Introduction

Unmanned aerial vehicles (UAVs) are encountered in an increasing number of civilian and military applications like: surveillance, communication relay, target designation, and payload delivery [1]. Such applications require the UAVs to be equipped with a guidance system. What is most often termed as "guidance" is the combination of a noise filter/estimator with a guidance policy or guidance law [2]. The objective of this guidance system is to deliver a control command that will steer the UAV toward a desired state (or location) that can vary in time. This guidance command is calculated online from a feedback signal involving the current state of the UAV and the desired state. Whenever the full feedback signal is available to measurements, the guidance law is in the form of an output feedback controller; there is no estimation system required (although one could still be beneficial to filter the noises). Otherwise, the feedback signal is only partially subject to measurements and the full feedback signal must be reconstructed by introducing an estimation system prior to the guidance law, see Fig.1.

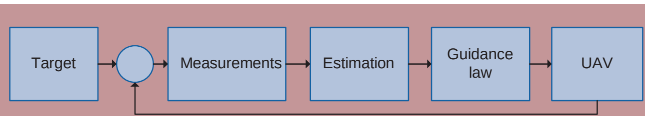


Figure 1: A control loop example

The estimation system has for objective to reconstruct online a full feedback signal based on: (i) partial measurements, (ii) some assumptions about the dynamics, and (iii) some assumptions about the measurement and dynamical uncertainties.

The dynamical uncertainty is the difference between the true dynamics and that of the dynamical model assumed by the estimation and guidance system. Examples of uncertainties are the noise in the instruments and the unmodeled phenomena like unknown aerodynamic coefficients or unknown inputs (e.g., a gust of wind that displaces the UAV or a bias in an actuator). The assumptions (ii)-(iii) about the uncertainties may be time-varying.

This article discusses some of the interactions between the estimation systems and the guidance law, and presents possible state-of-the-art solutions currently investigated. An effective selection of estimation and guidance systems should provide close-to optimal closed-loop flight performance, while allowing for a real-time implementation on-board a UAV. The selection of a Kalman filter in the estimation system is specifically discussed with respect to other most advanced estimators. Finally, the article illustrates some of the effects encountered in the control loop when employing advanced estimators.

2. The Control Loop

Fig. 1 shows a typical feedback control system enabling a UAV to reach a target. In this example, an estimation system reconstructs the feedback signal from the measurements. Whenever the uncertainties are represented using a stochastic description (like a Gaussian uncertainty), the estimation system involves a sequence of two components illustrated in Fig. 2. The first component is an estimator whose output is a probability density function (p.d.f.), this p.d.f. associates a domain of candidate feedback signals to the probability of being the exact signal (i.e., the signal if there was no uncertainties). An example p.d.f. is shown in Fig. 3 in which two neighborhoods of most probable candidate signals are indicated by the peaks. A physical interpretation of such p.d.f. is that due to noises and other uncertainties, the exact location of a target is never exactly known. Thus, engineers and scientists have to find ways to best use this uncertain information on the target state, such as its location, and that involves stochastic considerations.

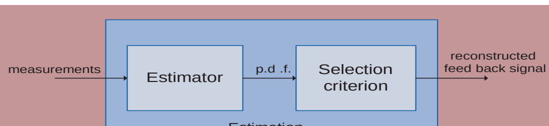


Figure 2: Estimation system with stochastic uncertainties

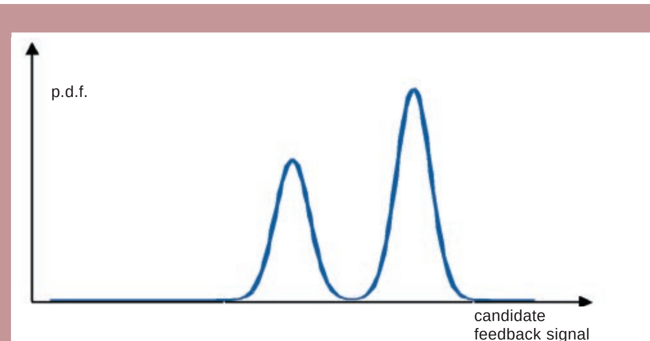


Figure 3: An example P.D.F. Each point of the x-axis is a candidate feedback signal

The second component of the estimation system is a selection criterion to choose a specific candidate feedback signal from the domain of admissible candidate feedback signals. The chosen signal becomes the reconstructed feedback signal. The selection process is conditioned by the p.d.f. Two common selection criteria are: (i) the adoption of the point at the mean of the p.d.f., the so-called minimum mean square estimate (MMSE), and (ii) selecting the point at the maximum of the p.d.f., the so-called maximum a posteriori probability (MAP) estimate [3].

After reconstruction of the feedback signal, the guidance system issues a control command. This control command is implemented by the UAV through an autopilot. The choice of the estimation system with respect to the guidance system is discussed in the following sections.

3. The Kalman Filter

The Kalman filter (KF) is a commonly encountered estimator that describes the dynamics and the measurements by a linear model, while the measurements and the dynamical uncertainties are represented by Gaussian distributions. The output of the KF is always a Gaussian p.d.f. This KF can be calculated in recursive form (see Fig. 4) allowing for real-time implementation.

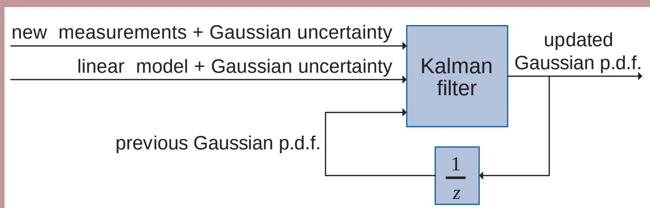


Figure 4: Recursive Kalman filter

In nonlinear systems, the Kalman filter can be applied by linearization of the nonlinear equations to which a sufficient Gaussian uncertainty is added to represent the linearization error. Whenever the linearization is state-dependent, the estimator is called an extended Kalman filter (EKF). Historically, the KF and the EKF are distinguished as many of the KF related proofs do not carry over to state-dependent linearizations. However, recent advances have now proven the convergence of the EKF [4].

A significant shortcoming of the KF is the necessity of describing the uncertainties by Gaussian distributions. In au tonomous flight applications, important uncertainties are not accurately represented by Gaussian distributions, like those that are correlated in time (e.g., flight maneuvers). In the next section, more advanced estimators applicable to broader classes of uncertainties are discussed.

4. More Advanced Estimators

Several recursive estimators with manageable computational requirements have the ability to calculate non-Gaussian p.d.f., such as the p.d.f. illustrated in Fig. 3. One class of such estimators delivers a non-Gaussian p.d.f. by running a bank of KF in parallel, each KF assumes a different model for the system. The p.d.f. is obtained as a weighted sum of Gaussian p.d.f.; each Gaussian p.d.f. being calculated by its own KF, see Fig. 5.

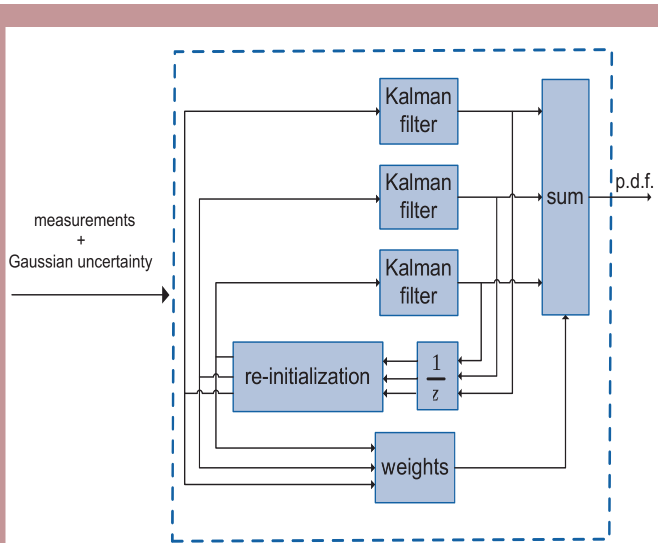


Figure 5: Example of a multiple model estimator with three models

From this approach, several different algorithms can be derived depending on which procedures are selected to calculate the weights and to re-initialize the bank of KF. A common algorithm in this class is the so-called interacting multiple model (IMM) estimator; the last is known to deliver an advantageous ratio computation/performance [3]. The IMM estimator applies to hybrid systems and it assumes that: (i) there are several behavioral modes for the system, and (ii) the system transitions between these modes according to a Markov chain. The assumption (i) is accounted for by the bank of KF: the model adopted by each KF is one of the admissible behavioral modes. The assumption (ii) is accounted for by the selected re-initialization procedure. In autonomous flight applications, each behavioral mode can represent a different flight regime. The IMM is found more suitable than the KF for tracking of uncooperative targets whose flight regime are uncertain [5].

Another class of estimators called particle filters (PF) applies to general nonlinear systems with non-Gaussian uncertainties. The PF is based on the fact that a p.d.f. can be expressed as the solution of an integral equation [6]. In few systems, this integral can be solved analytically. Such is the case when the system is linear with Gaussian uncertainties; the analytical solution is then the KF. In the case of the PF, an approximate numerical solution of the integral equation is sought instead of an exact analytical solution. In essence, the PF employs the exact model but approximates the calculation of the p.d.f.; the KF approximates the model and calculates an exact p.d.f. with respect to the approximated model.

The PF obtains the numerical solution by recursive Monte Carlo integration involving a set of so-called particles. At each iteration, the particles are evolved using the nonlinear model with non-Gaussian uncertainties. Each particle is assigned a weight based on the received measurements. From these weights, a p.d.f. is calculated and the set of particles is decimated and re-sampled. Different techniques can be employed for the decimation and re-sampling of particles, and for the calculation of the weights. The PF algorithm is depicted in Fig. 6. The algorithm is recursive and requires a large number of particles to deliver an accurate solution; the latter may involve large computational requirements.

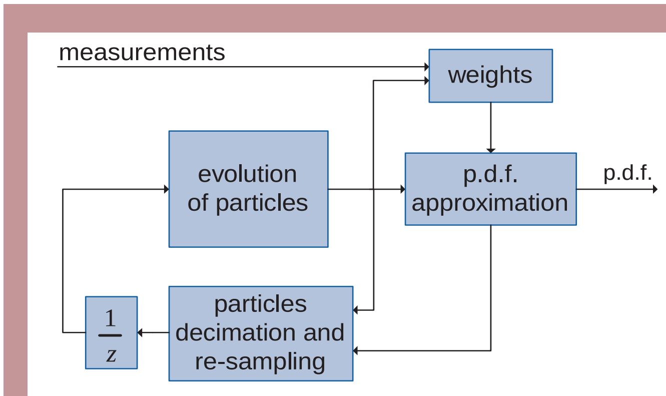


Figure 6: An example PF algorithm

The PF is of interest in autonomous flight applications in situations where the nonlinear dynamics is poorly approximated by linearization, or when significant uncertainties are poorly represented by Gaussian approximations.

5. Selection Criterion and Guidance Law

The guidance law requires a feedback signal to be reconstructed from the measurements. By employing an estimator to process the measurements, the reconstructed feedback signal is delivered by applying a selection criterion to the calculated p.d.f. When the estimation system employs the KF to calculate the p.d.f., the selection criteria MMSE and MAP deliver the same reconstructed feedback signal; that is, the average point of the p.d.f. coincides with the unique maximum of the p.d.f. Essentially, the tuning of the estimation and guidance system is limited to the optimization of the KF and of the guidance law. By comparison, when the estimation system employs a more advanced estimator like the IMM or the PF, the reconstructed feedback signals varies with the selection criterion; this provides an additional level for optimization.

The most common approach for optimization of the estimation system and guidance law in the control loop is to optimize them independently and to employ the MMSE criterion to reconstruct the feedback signal from the p.d.f. Although the couplings are then neglected, such an approach is optimal in linear quadratic Gaussian systems by virtue of the separation principle [7]. In broader classes of nonlinear systems with non-Gaussian uncertainties, the separate optimization of the estimator was shown to be still optimal, but it was also demonstrated that the optimization of the selection criterion and of the guidance system should then be coupled with the employed estimator [8]. The latter argument means that a modification to the estimator may call for modifications in the selection criterion and in the guidance law.

Several state-of-the-art optimizations in the control loop accounts for the coupling between the estimation system and the guidance law. One simple approach is to optimize the guidance law by assuming that the estimation system introduces a delay (or a lag) in the feedback signal. In autonomous flight applications, the approximation by a delay of the closed-loop dynamics introduced by the estimator was reported successful [9]. A second class of state-of-the-art approaches attempts to optimize the guidance law in such a way as to steer the UAV on a trajectory that will increase the information contained in the measurements, while preserving the satisfaction of the guidance objective [10]. Unfortunately, both requirements can be contradictory in autonomous flight applications and a trade-off may be necessary.

Another class of state-of-the-art approaches attempts to op timize the selection criterion and the guidance law with respect to both the p.d.f. and the control effort capabilities [11], [12]. For example, an alternative adaptive selection criterion (called HPI) is presented in [11] where it is shown to deliver better performance than the MMSE and MAP criteria with a non-Gaussian p.d.f. Simulation results illustrating this phenomenon are displayed in Fig. 7.

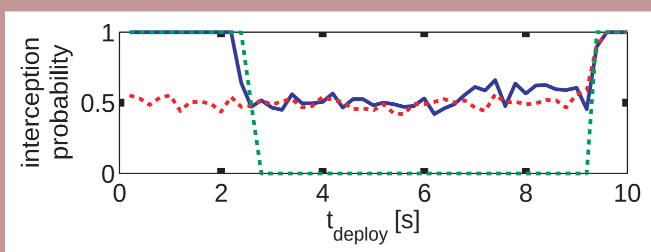


Figure 7: Example of closed-loop performance when modifying the selection criterion. The scenario is that of a moving target to be intercepted. To evade, the target deploys a decoy. The x-axis is the deployment time instant of the decoy. The whole engagement last 10 [s]. The estimator and guidance systems are the same in all the curves; the estimator delivers a non-Gaussian p.d.f. Three selection criteria are considered: MMSE (green line), MAP (red line), and HPI (blue line).

In the figure, the same estimator (with non-Gaussian p.d.f.) and guidance law are common to all the curves, only the selection criterion for the reconstructed feedback signal changes from one curve to another.

6. Concluding Remarks

The paper described some of the issues and challenges involved in the selection of the estimation system and guidance law in autonomous flight applications. The coupling of the estimation system with the guidance law was of particular interest. For instance, it was pointed out that advanced estimators capable of delivering non-Gaussian p.d.f. provide for new freedom and new challenges in optimizing the closed-loop system. With the ever increasing on-board computational capabilities, it is believed that many of these advanced estimators and control techniques will be feasible in a growing number of applications.

REFERENCES

[1] U. O. of the Secretary of Defense, Unmanned Aerial Vehicles Roadmap 2000-2025, April 2001.

[2] A. Spencer and W. Moore, “Design trade-offs for homing missiles,” in Proceedings of the AIAA SDIO Annual Interceptor Technology Conference, Huntsville, Alabama, May 1992, AIAA paper 92-2755.

[3] Y. BarShalom and X. R. Li, Estimation and Tracking: Principles, Techniques and Software. Boston, U.S.: Artech House, Inc., 1993.

[4] A. J. Krener, “The convergence of the extended Kalman filter,” in Directions in Mathematical Systems Theory and Optimization, ser. LNCIS, A. Rantzer and C. I. Byrnes, Eds., vol. 286. Berlin: Springer-Verlag, 2003, pp. 173–182.

[5] Kirubarajan, T. and Bar-Shalom, Y., “Kalman filter versus IMM estimator: when do we need the latter?” IEEE Transactions on Aerospace and Electronic Systems, vol. 39, no. 4, pp. 1452–1457, 2003.

[6] B. Ristic, A. Sanjeev, and N. Gordon, Beyond the Kalman Filter. Artech House, 2004, ISBN: 1-58053-631-x.

[7] H. S. Witsenhausen, “Separation of estimation and control for discrete time systems,” in Proceedings of the IEEE, vol. 69, 1971, pp. 1557– 1566.

[8] C. Striebel, “Sufficient statistics in the optimum control of stochastic systems,” Journal of Mathematical Analysis and Applications, vol. 12, pp. 576–592, 1965.

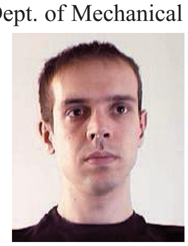
[9] J. Shinar and T. Shima, “Non-orthodox guidance law development approach for intercepting maneuvering targets,” Journal of Guidance, Control, and Dynamics, vol. 25, no. 4, pp. 658–666, 2002.

[10] H. I. Lee, M. J. Tahk, and B. C. Sun, “Practical dual control guidance using adaptive intermittent maneuver strategy,” Journal of Guidance, Control, and Dynamics, vol. 24, no. 5, pp. 1009–1015, 2001.

[11] D. Dionne and C. A. Rabbath, “Predictive guidance for pursuit-evasion engagements involving decoys,” in Proceedings of the AIAA Guidance, Navigation, and Control Conference, Keystone, Colorado, August 2006, AIAA-2006-6214.

[12] I. G. Shaviv and Y. Oshman, “Fusion of estimation and guidance using sequential Monte Carlo methods,” in Proceedings of the IEEE Conference on Control Applications, Toronto, Canada, August 2005, pp. 1361–1366.

About the Authors



Dr. Dany Dionne is a postdoctoral fellow at the Dept. of Mechanical Engineering, Concordia University. He has earn his Ph.D. degree in electrical engineering from McGill University, Montreal, in 2005. He has worked on multi-UAVs task allocation, predictive control, estimation and guidance in autonomous flight, and on the robust control of an experimental car suspension. In 2005, Dr. Dionne was a recipient of a Japan Society for the Promotion of Sciences fellowship and acted as an invited researcher in Dept. of Computer Sciences, Kyushu Institute of Technology, Japan.

Dr. Camille A. Rabbath is a Defence Scientist at DRDC Valcartier and Adjunct Professor at McGill University. He has worked for three years in industry in the areas of control systems design and distributed simulations of aerospace and robotic systems. During that period, he has implemented real-time gas-turbine engine control systems, he has developed and implemented an environment for the real-time distributed simulations of combustion engine control and has lead a research project for the Canadian Space Agency that resulted in the development of an efficient algorithm for the automatic parallelization, scheduling and load balancing of electromechanical systems. His current research interests include realtime cooperative control algorithms for teams of multiple UAVs, and robust multi-rate digital guidance and control of aerial systems.