Assessment of Air-to-Air Missile Guidance and Control Technology

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ABSTRACT: This paper provides an assessment of current air-to-air missile guidance and control technology. Areas explored include target state estimation, advanced guidance laws, and bank-to-turn autopilots. The assumptions, benefits, and limitations of recent applications of nonlinear filtering, adaptive filtering, modern control, adaptive control, dual control, differential game theory, and modern control design techniques to the air-to-air missile problem are discussed.

Introduction

Perhaps the most challenging of all guidance and control problems is that of a modern tactical air-to-air missile in pursuit of a highly maneuverable aircraft. The problem consists of the estimation of target motion, the generation of guidance commands to optimally steer the missile toward target intercept, and the control of the coupled, nonlinear, multivariable, uncertain dynamics of the air-to-air missile. Each portion of the problem, i.e., estimation, guidance, and control, is inherently nonlinear and time varying, and all three combine to form a highly complex integrated system.

A simplified block diagram of an advanced air-to-air missile system is given in Fig. 1. Target information obtained from a seeker is processed by a modern estimation filter, such as an extended Kalman filter, to obtain estimates of relative missile-to-target position, velocity, and acceleration. These filtered estimates are heavily dependent on an assumed target acceleration model. A guidance law based on modern control theory uses the state estimates and an estimate of time to go until intercept to produce a commanded acceleration. The autopilot converts this commanded input into fin commands for the actuators based on airframe aerodynamic characteristics and sensed missile body angular rates and linear accelerations. The resulting motion produces new missile dynamics, which close the three feedback loops.

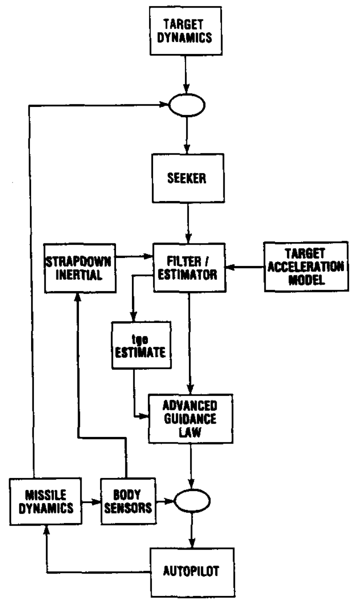

Fig. 1. Air-to-air missile block diagram.

Over the past 15 years, a significant amount of basic research has been conducted, with the intent of improving air-to-air missile guidance and control performance. This research has covered various aspects of the problem, including target state estimation, target acceleration modeling, target tracking, target maneuver detection, guidance-law development, and bank-to-turn (BTT) autopilot design. Numerous estimation and control techniques have been investigated and expanded upon. These include: adaptive filtering, nonlinear filtering, parameter identification, modern control formulation, adaptive control, dual control, robust adaptive control, and differential game theory.

The purpose of this paper is to review the progress that has been made over the years in air-to-air missile guidance and control technology, to point out those concepts which, in our opinion, hold the most promise, and to identify those areas still worthy of research. In the following sections, first we review target state estimation with special emphasis on target acceleration modeling and filtering techniques. We then consider advanced guidance laws and cover the three aspects of guidance—midcourse, terminal, and endgame. Finally, we address bank-to-turn autopilots for asymmetrical airframes and current state-of-the-art autopilot design methodologies.

Target State Estimation

Target state estimation involves stochastic filtering based on target acceleration modeling for the purpose of target maneuver detection and target tracking. In this context, the term "tracking" has often been used to mean accurate estimation of target states, without consideration for the antenna pointing/control aspect of the problem. In the next two subsections, we review the historical development of target acceleration models and the various filtering techniques that have been used in conjunction with these models to form effective trackers.

Target Acceleration Modeling

In [1], Moose et al. gave a short exposition on the evolution of one facet of target acceleration modeling: its relationship to stochastic processes. This evolutionary development is depicted graphically in Fig. 2. Initially, as shown in Fig. 2(a), target acceleration was simply accounted for with white noise (depicted by a correlated process whose spectrum is flat over the system bandwidth). This resulted in estimators with serious drawbacks. Tracking could be maintained only for those maneuvers remaining within the envelope of the white noise; even then, performance was poor due to the erroneous assumption of uncorrelated acceleration. A correlated acceleration process, Fig. 2(b), can be achieved using Gauss-Markov models [2]–[5]. The well-known Singer model [2], in spite of its simplicity, has been used with various Kalman-type filters to achieve excellent tracking characteristics over a broad class of large-scale maneuvers. Its primary drawbacks are the need to specify a priori both the acceleration time constant and power of the driving noise and the inability of a model-based filter to track target

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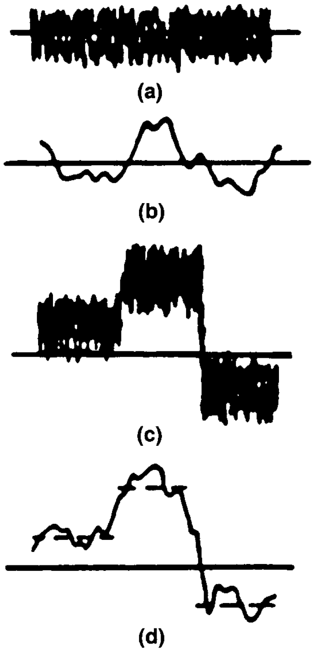

Fig. 2. Historical development of maneuvering-target acceleration models: (a) zero-mean white Gaussian process; (b) zero-mean correlated Gaussian process; (c) white Gaussian process with randomly switching mean; (d) correlated Gaussian process with randomly switching mean.

motion resulting from abrupt changes (jumps) in the acceleration process. Gholson and Moose [6] modeled rapid, major changes in target motion as a semi-Markov process. The mean of their process, Fig. 2(c), randomly switched to a finite number of states according to a Markov transition probability matrix, with the time duration in each state itself being a random variable. Such a method requires a large number of preselected states for successful tracking and also erroneously assumes uncorrelated acceleration. Moose et al. [1] extended this work by employing the Singer model to represent correlated acceleration within each of the states, Fig. 2(d). Larimore and Lebow [7] developed a similar model based on a parameterized Gauss-Markov process with the parameters changing according to a point process. Lin and Shafroth [8] concluded that one of the most versatile representations of target acceleration is that of the sum of a continuous-time Gaussian process and a finite basis/jump process. The continuous-time process can be obtained by means of a classical shaping filter, whereas the jump process, which is characterized by its basis, jump-size distribution, and interjump time distribution, can be obtained by driving a shaping filter with a white sequence.

A second facet of target acceleration modeling is that of its relationship to the aerodynamic characteristics of the target. A winged aircraft accelerates predominantly orthogonal to its velocity vector and, more specifically, orthogonal to the plane of its wings. The magnitude of the acceleration also has asymmetric bounds (positive- and negative-g) set by pilot and/or aircraft limitations. Modeling based solely on target point mass motion obviously does not take these characteristics into account. Such characteristics are embedded, to various extents, in the models developed in [9]–[11] and also in [7]. Kendrick et al. [9] modeled normal load acceleration with a random variable whose probability density function (pdf) was asymmetrically distributed between small negative-g and large positive-g. Nonnormal accelerations were modeled as first-order Gauss-Markov. It was assumed that the orientation of the three-dimensional target could be obtained by means of an electro-optical seeker in conjunction with pattern recognition. Bullock and Sangsuk-Iam [10] developed a nonlinear Cartesian model of target dynamics based on a polar coordinates submodel, which considers planar, circular turns under the assumption of constant velocity magnitude. Similarly, Hull et al. [11] implicitly used a polar coordinates submodel, which represents both acceleration magnitude and angle as random processes. This led to a Cartesian model characterized by state-dependent noise. Finally, Larimore and Lebow [7] employed aerodynamic parameters such as bank angle, lift force, and thrust minus drag in their parameterized Gauss-Markov model. A given set of the parameters corresponds to a specific maneuver, and an abrupt change in the parameters corresponds to the initiation of a new maneuver.

Merging a point process, or jump process, with a continuous-time Gaussian process, either additively as recommended in [8] or through parametric embedding as performed in [7], is an excellent way to model the acceleration of a highly maneuverable target. However, of the models of this type developed to date, only one [7] has given any consideration to the aerodynamic characteristics of the target. The natural next step in this technology area is to merge the concepts of those models based on aircraft flying characteristics with those symbolized by Fig. 2(d).

Estimation Techniques

Various types of nonadaptive stochastic filters have been employed to estimate target motion. These include the Kalman filter [2], [3], extended Kalman filter [9]–[15], modified-gain extended Kalman filter [16], Gaussian second-order filter [17], recursive nonlinear filter [18], recursive maximum likelihood filter [7], and assumed density filter [19]. However, since no single set of model statistics can accurately represent the huge set of diverse maneuvers capable of being performed by a modern tactical fighter, some type of adaptive filtering is required for best tracking performance. This may be in the form of either a single-model adaptive filter [10], [20]–[31] or a multimodel adaptive filter [1], [6], [32]–[36].

Single-model adaptive Kalman filters can be split into two groups—classical and reinitializing. Classical adaptive filters (e.g., [25]) provide continuous adaptation based on the innovations process. When applied to the air-to-air problem, this amounts to a continuous modulation of the filter bandwidth in response to target maneuvers (implicit maneuver detection).

Reinitializing-type filters are based on explicit target maneuver detection. When target motion differs from that assumed in the model, a bias appears in the innovations process. This bias is detected by employing statistical hypothesis testing. During the detection process, the filter is in a nonadaptive mode. Once detection occurs, the filter's biased state estimates are instantaneously adjusted according to the estimated input, and the filter is reinitialized. Bullock and Sangsuk-Iam [10], Chan et al. [26], and Bogler [27] assumed constant acceleration over small time intervals in developing reinitializing filters. Tang et al. [28], Haessig and Friedland [29], and Dowdle et al. [30] assumed constant velocity. Lin and Shafroth [31] avoided input estimation by developing a reinitializing filter based on concatenated measurements. Their sequential tracker employs batched measurements and is reinitialized by a local estimate whenever the difference between the two exceeds some predetermined value.

Both types of single-model adaptive Kalman filters have weaknesses. The major deficiency in the classical adaptive filter is its inherent lag, which is significant enough to produce less than desired performance. Specifically, by the time the filter bandwidth expands, the target may have transitioned into nonmaneuvering flight. The primary difficulty in the reinitializing filter is the setting of the detection threshold. The desire to have the filter respond rapidly to maneuvers conflicts with the goal of a low probability of false detection.

The multimodel adaptive Kalman filter

consists of a bank of filters and is ideally suited for the estimation of systems with parametric variations. Each individual filter from the bank is designed optimally for a discrete parameter level. The adaptive state estimate is obtained either from the conditioned probability/weighted average of the bank members or from the single member, which displays maximum a posteriori likelihood. In the case of semi-Markov modeling, switching within the bank occurs according to a Markov transition. Although swift adaptation can be achieved with the multimodel filter, its exponentially expanding memory requirements must be limited for implementation purposes. This can be done in a variety of ways. Maybeck and Hentz [33] employed a moving bank technique and recommended decision logic for moving the bank. In a nonlinear application, Verriest and Haddad [34], [35] used a consistency test based on the original linear regions of the nonlinear system. Gholson and Moose [6] made certain statistical assumptions concerning the individual filters that reduced the bank to a single Kalman filter structure augmented by a recursive learning term. Bar-Shalom et al. [36] employed a hypothesis merging technique in which the mixture of assumed Gaussian pdfs is approximated by a single Gaussian pdf via moment matching.

In the highly dynamic environment of the air-to-air encounter, the adaptive tracking filter must be able to respond quickly to rapidly changing target motion. In this regard, the multimodel adaptive Kalman filter, if designed properly, should outperform its single-model counterpart, although at the expense of filter complexity. This performance superiority was demonstrated by Lin and Shafroth [37] in a comparison of several advanced tracking filters. In addition, Bar-Shalom et al. [36] have shown that, in an interacting-type multimodel, superior performance can be achieved with as few as two or three filters.

With regard to tracking filter design, the air-to-air dynamics/measurements structure is a major consideration. Actual target dynamics are nonlinear and, thus, are modeled most accurately by Euler's rigid-body force and moment equations. Yet, for several reasons, most target state-estimation models consist only of linear kinematic equations. First, since it is impossible to predict a pilot's evasive response, it is more rational to erroneously estimate target acceleration with a linear model than with a nonlinear model. Second, in the small time interval between seeker updates, a linear acceleration model produces approximately the same target motion as a nonlinear model derived from similar assumptions. Seeker measurements, on the other hand, are spherical in nature (range and angle) and are, therefore, nonlinear functions of the state in Cartesian coordinates. Thus, in either coordinate system—Cartesian or spherical—a nonlinear structure exists. Its form is that of linear dynamics/nonlinear measurements in Cartesian coordinates, Fig. 3(a), or that of nonlinear dynamics/linear measurements in spherical coordinates, Fig. 3(b), where the nonlinear dynamics arise from the nonlinear transformation of Cartesian linear dynamics to the spherical frame. The coordinate systems in Fig. 3 are being observed from below the x-y plane and from the right of the y-z plane.

Using Cartesian coordinates, researchers have addressed the preceding nonlinear structure in various ways. In [4], [8], [28], and [30], the nonlinear measurements were transformed into linear pseudomeasurements. Speyer and Song compared pseudomeasurement and extended Kalman observers in [38] and found that the former was biased. They later confronted the nonlinear measurements by developing the modified-gain extended Kalman filter [16]. In this extended filter, the total variation of the nonlinear measurement function is not approximated by its first variation, but rather identically replaced by a linear structure that is a function of both the state estimate and the actual measurement. Verriest and Haddad [35] approximated the nonlinear measurement function with a piecewise linear function and, based on the linear segments, developed a semi-Markov multimodel Kalman filter. Sammons et al. [17] and Balakrishnan and Speyer [39] have developed hybrid filters that exploit the linearity in both coordinate systems. Propagation is performed in the Cartesian coordinate frame, whereas updating is performed in the spherical (or polar) coordinate frame. For these filters, the state statistics must be transformed nonlinearly into the second coordinate frame prior to the update and inversely transformed immediately thereafter.

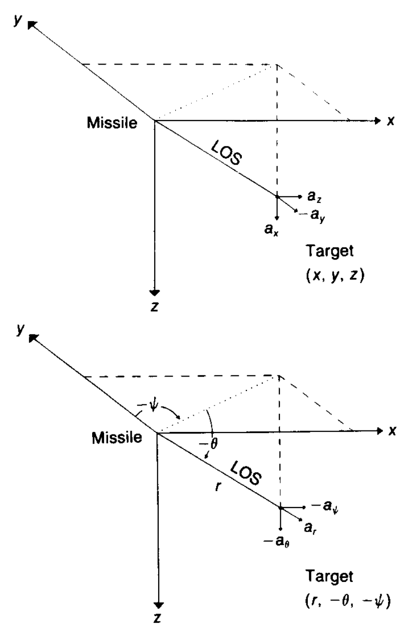

Fig. 3. Air-to-air dynamics/measurement models: (a) Cartesian coordinates; (b) spherical coordinates.

There are several reasons why spherical implementations merit further consideration in air-to-air tracking filters. First, we are aware of only two such spherical implementations [1], [6], and both produced simpler and more accurate trackers than their Cartesian counterparts. Second, it is easy to forget that, in reality, the problem structure in Cartesian coordinates is nonlinear dynamics/nonlinear measurements. Linear dynamics appear only due to modeling. Researchers apparently disdain spherical implementations, in spite of linear measurements, because such implementations transform the linearly modeled, Cartesian dynamics into nonlinear spherical dynamics. A more balanced viewpoint is that target dynamics are nonlinear in any coordinate system. Such a viewpoint suggests that linearizing nonlinearly modeled spherical dynamics is no more detrimental than linearly modeling Cartesian dynamics. This conjecture was borne out in [1] and [6]. Third, there is no compelling reason to model target acceleration in Cartesian coordinates. Linear models of inertial radial and angular acceleration could be developed directly in spherical coordinates. In this way, the entire filtering problem could be performed linearly in that frame. This would require the nonlinear transformation of inertial strapdown outputs to spherical coordinates and the inverse nonlinear transformation of the filter's output to Cartesian coordinates. In dual-control applications, the nonlinear transformation of state statistics could be avoided if the guidance law were formulated in spherical coordinates. Such filtering could inspire a whole new research effort concerning the best way to model radial and angular acceleration and the simplest way to incorporate target flying characteristics into such a model.

Advanced Guidance Laws

Air-to-air guidance consists of three phases: midcourse, terminal, and endgame.

Midcourse guidance is, in effect, from the time of launch until seeker acquisition. During this phase, an onboard inertial navigation system provides estimates of missile position, velocity, and acceleration. Periodic estimates of target position and velocity from the launch aircraft may also be available. After the seeker acquires the target, terminal guidance is initiated. Noisy measurements of line-of-sight (LOS) angles, and, perhaps, range and range rate, are provided by the seeker. The last second of terminal guidance is referred to as the endgame. It is worth treating as a separate guidance phase since target maneuvers are most effective at that time. The reasons for this include the finite missile airframe time response (typically, 0.25–0.50 sec) as well as the target state-estimator time response (on the order of 0.50 sec for a typical extended Kalman filter). The implication of this is that a well-timed target evasive maneuver has a good probability of defeating the integrated guidance and control system.

Both linear quadratic (LQ) guidance laws [40] and various nonlinear guidance laws [41]–[45] have been proposed for the midcourse phase. Glasson and Mealy [40] constructed an approximately optimal midcourse guidance law in which the kinetic-energy loss is minimized by time scheduling the guidance-navigation ratio. Cheng and Gupta [41] and Menon and Briggs [42] used singular-perturbation theory to develop implementable closed-loop guidance laws, the former based on minimum time, the latter on both flight time and terminal specific energy. Lin and Tsai [43] derived analytic solutions of a closed-loop, nonlinear optimal guidance law for both the midcourse and terminal phases. Their algorithm responds rapidly to target direction changes during midcourse so that zero heading error is achieved at midcourse-terminal transition. As these examples indicate, research on midcourse guidance has focused on deterministic optimal control formulations.

Optimal midcourse guidance using pulse rocket motors is an area worthy of research and has been addressed recently by Cheng et al. [44] and Katzir et al. [45]. On the other hand, the fundamental theoretic problems associated with boost-sustain midcourse guidance appear to have been solved. The remaining issues involve algorithm implementation and problem formulation/solution. The former involves software design methodology selection, high-order-language run-time characteristics, cross-compiler efficiencies, and hardware throughput/memory limitations [46]. The latter issue involves a choice between a closed-form solution to an approximate optimal formulation [linear quadratic Gaussian (LQG), linear quadratic regulator (LQR)] or an approximate solution to an exact nonlinear optimal formulation. An analytic solution to the nonlinear problem is unknown due to the complexity of the nonlinear two-point boundary-value problem. Furthermore, a numerical solution of the exact nonlinear problem is impractical for implementation reasons.

With regard to terminal guidance, Pastrick et al. [47] performed a survey of short-range terminal guidance laws developed up to 1979. Since then, additional guidance laws, both deterministic and stochastic, have been proposed. Deterministic formulations were developed in [48], [49]. Kim et al. [48] derived a guidance law that relies on Pronav correction to a predicted collision course. Anderson [49] compared differential game and LQ optimal guidance laws, concluding that differential game formulations are less sensitive to target acceleration estimation errors than are optimal control algorithms.

In [25] and [50]–[57], stochastic control theory was applied to the terminal guidance problem. Greenwell et al. [25] used a linear exponential Gaussian formulation in conjunction with an adaptive state estimator to produce an adaptive guidance law. The gains in this law depend on both the state estimates and covariance. The adaptive guidance algorithm reduces the tails in the miss-distance distribution when compared to an LQG guidance law. A number of guidance laws based on conventional LQG control principles were compared by Riggs and Vergez in [50]. They found improved performance of the LQG algorithms over classical Pronav, especially when improved time-to-intercept estimates were available.

For the angle-only measurement case, application of the separation principle yields guidance laws that show poor miss-distance performance. This is due to the fact that Pronav and its LQG variant produce a homing collision course in which LOS rates are zeroed by the controller. On such a course, target position and velocity are unobservable from the angle-only measurements.

Anderson [51] enhanced the estimation process by including the trace of the relative position covariance matrix in the guidance performance index. Hull et al. [52] and Tseng et al. [53] reported on a similar guidance approach. In those studies, the inverse of the estimation error covariance matrix (the Fisher information matrix) was used as an observability weighting term in a minimum control effort formulation. In the design phase, a weighting term is adjusted iteratively until the desired information-enhancing effect is achieved. Later, Speyer et al. [54] and Hull et al. [55] used the position terms of the Fisher information matrix to form a scalar observability weighting term in the performance index, yielding a less complex version of the maximum information guidance algorithm. Finally, Balakrishnan [56] and Hull et al. [57] combined these concepts with LQG theory to produce dual-control algorithms. Balakrishnan included the partial derivative of the trace of the estimation error covariance matrix with respect to the control in his performance index. Hull et al. allowed individual terms of the observability Grammian to be weighted separately and, as a further modification of [55], added a factor to enhance estimation during the earlier stages of the trajectory.

As mentioned previously, homing guidance reduces the information available from the measurements. The improved performance of guidance laws that are formulated to enhance the estimation process suggests that dual-control techniques warrant further research. Again, however, the conflicting choice between exact solution of an approximate problem formulation versus approximate solution of an exact formulation has no clear resolution. An example of the latter approach is that of Speyer and Hahn [58] in their development of a new adaptive control structure.

Several researchers have developed guidance algorithms which, in some way, attempt to deal with autopilot/airframe performance constraints. Yueh and Lin [59] derived a modified Pronav algorithm, which adjusts the autopilot gains to minimize a penalty function on control effort and time to go. Aggarwal and Moore [60], Shin [61], Stallard [62], and Caughlin and Bullock [63] derived guidance laws to deal specifically with the problems of bank-to-turn control. In [64], Caughlin and Bullock applied reachable set theory to the design of guidance laws that deal explicitly with hard limits on airframe achievable acceleration.

Additional work on guidance-law/autopilot interactions, especially with respect to the acceleration limits of the airframe and the autopilot's finite time response, should be pursued. Embedding the autopilot models in the guidance algorithm derivation would be one possibly rewarding approach. Another is the integrated system design approach taken by Williams et al. in [65].

The endgame part of the intercept has received only limited attention in the guidance and control literature. Dowdle et al. [30], [66] generalized the LQG regulator and, after appropriate model linearization via pseudo-measurements, estimated the target state with a reinitializing Kalman filter. A generalized likelihood ratio approach was applied to the innovations process as a target maneuver detector. In a more fundamental look at the endgame, Looze et al. [67] used Cramer-Rao lower-bound analysis to investigate the quality of target acceleration information available from the seeker measurements. They found that target acceleration was estimated accurately for the maneuver considered, but such estimates were poorly utilized by the modified Pronav guidance law. The guidance law was altered subsequently with lead compensation of the roll command to yield improved miss-distance performance. These results suggest that guidance-law/estimator interactions merit further study. Finally, in a departure from these approaches, Forte and Shinar [68] formulated a planar air-to-air intercept problem as a mixed-strategy, zero-sum, stochastic differential game. The cost functional of the min-max problem was single-shot-kill-probability, which is the genuine performance measure of interest in tactical air warfare. The optimal pursuer's strategy is in the form of a parametric guidance-law/target state estimator, which demonstrates increased single-shot-kill-probability against any frequency of target maneuvers when compared with any single-strategy guidance algorithm. This approach has been expanded recently to a three-dimensional encounter [69].

It is disappointing that the endgame phase of guidance has not received more attention since the deficiencies in missile kill effectiveness are associated primarily with this portion of the intercept. Here target state estimation degrades due to lack of target information, which results from increasingly noisy seeker measurements and the extremely high dynamics of the endgame evasive maneuver. For these reasons, a stochastic game approach, such as that in [68], [69], is most appropriate in deriving endgame guidance strategies.

Bank-to-Turn Autopilots

Although the design of autopilots for skid-to-turn missiles is relatively mature, recent interest in asymmetrical airframes has stimulated activity in bank-to-turn autopilot design [70]. An airframe with a noncircular cross section improves the aerodynamic efficiency of both the missile and the host aircraft. The characteristics of such a missile complicate its control in three major ways. First, its asymmetrical cross section gives the missile large acceleration capability in its pitch plane but only limited capability in the yaw plane. Hence, rolling or banking is required to maximize maneuverability. Second, other constraints, such as engine performance, often require that the angle of attack remain positive and the sideslip angle be kept small. Third, the missile shape produces significant nonlinear dynamic interaction among the roll, pitch, and yaw axes.

BTT autopilots have been designed using classical control, LQG regulator control, generalized singular LQ control, and eigenstructure assignment. Representative implementations of these techniques are described subsequently.

Classical Design

The vast majority of autopilots, both missile and airplane, have been designed using classical methods. This approach to BTT autopilot design is typified by Kovach et al. [71]. They follow the usual approach of basing the design on a linear missile model, which is assumed valid in the neighborhood of a specified operating point. An initial design is performed by ignoring the dynamic interaction among the roll, pitch, and yaw axes. This allows individual single-input/single-output (SISO) controllers to be designed for each axis. Initial control system parameters are selected so that missile response time requirements are met by the roll and pitch axes, with the yaw axis response being at least as fast as the roll axis response. BTT control is achieved by directing pitch and roll axis acceleration commands from the guidance system to the corresponding controller channel and by operating the yaw channel in a regulator mode to minimize sideslip angle. System performance is enhanced in an ad hoc way by feeding back estimated pitch and yaw accelerations in their corresponding control channels while simultaneously feeding a roll rate signal from the roll channel to the pitch and yaw channels. System gains are varied as a function of dynamic pressure to account for parametric variations over the desired operating range of the autopilot. Bode methods are used to assess stability margins and overall performance. Final gain settings are determined during six-degree-of-freedom nonlinear computer simulation analyses.

Although classical designs are based on SISO control theory, they can be enhanced through multivariable analyses. Wise [72] used multivariable singular-value techniques to maximize performance and stability robustness of an existing roll-yaw autopilot designed with classical methods. Gain parameters were adjusted to minimize the infinity norm of the sensitivity function. The resulting design is equivalent to H-infinity control techniques except for the a priori fixed compensator structure.

Nonadaptive (Gain-Scheduled) Modern Control Designs

One recent example of the modern, state-space approach to autopilot design is given by Williams et al. [73]. Their design is based on a tenth-order nonlinear model of the missile dynamics. The model is decoupled into separate roll and pitch/yaw subsystems by treating roll rate as an exogenous input to the pitch/yaw equations. The models are linearized over the specified operating region, and gains are scheduled on dynamic pressure and roll rate. Unmeasured states are estimated using a constant-gain, reduced-order Kalman observer, and the separation principle is invoked to compute controller gains. The desired roll channel time response is obtained using a pole-placement controller design procedure. Robust pitch/yaw channel gains are determined using LQG theory with loop transfer recovery (LQG/LTR). The sideslip angle is minimized by a heavy weighting in the performance index. Integral control action is obtained by treating the commanded accelerations from the guidance system as state variables.

Other examples of the modern linear regulator approach are given in [74]–[77]. Wise [74] eliminated the steady-state command errors, which are inherent in LQR error state-equation formulations by incorporating integral control into an LQG/LTR design. Shepherd and Valavani [75] gained insight from an LQG/LTR design and made recommendations for airframe improvements. Bossi et al. [76] used a design approach that included a way of methodically specifying the cost-function weighting matrices. Nonlinear simulation results of the design, presented by Langehough and Simons [77], indicate good performance when compared with a classically designed autopilot.

The generalized singular linear quadratic (GSLQ) control problem is that of minimizing the performance index

$$J = \frac{1}{2} \int_0^{t_f} (y - y_r)^T Q (y - y_r)\, dt \quad (1)$$

subject to the general constraints

$$x(t) = Ax(t) + Bu(t) + B_f f(t) \quad (2)$$

and

$$y(t) = Cx(t) + h(t) \quad (3)$$

The forcing function, $f(t)$, can be used to account for system nonlinearities and/or an estimated disturbance. Similarly, $h(t)$ can be used to account for measurement nonlinearities and uncertainties. The absence of a control penalty term in the performance index means that the control $u(t)$ is not explicitly present in the partial of the Hamiltonian with respect to $u(t)$. This causes normal solution procedures to fail, and, hence, the problem is labeled "singular." Lack of the control penalty term has its merits, however. Tracking may require a nonzero control input, and penalizing a nonzero input may lead to undesirable trade-offs in the performance index minimization, resulting in a tracking error throughout the trajectory. Lin and Lee [78] applied GSLQ control to BTT autopilot design. Control constraints were imposed by a pole-placement technique. Good stability margins were obtained at each of the outputs, and excellent command tracking was achieved in the presence of sinusoidal disturbances and roll, pitch, and yaw nonlinear couplings.

Eigenstructure assignment is a state-variable multi-input/multi-output (MIMO) design method that allows placement of system eigenvectors as well as their corresponding eigenvalues. A good description of this technique is given in [79]. It has been used in a number of aircraft control applications; see, for example, [80]. This approach is characterized by its ability to decouple interacting control, a feature that could be useful in the tightly coupled BTT autopilot problem. A recent extension [81] of the method incorporates the synthesis of dynamic compensation and sensitivity reduction. Few applications of this method to BTT missile control have been published. However, one recent study [82] of eigenstructure assignment with a command generator tracking feature resulted in the design of a responsive, stable, robust system with significant reduction in control interaction.

Comparative Comments

The LQG approach offers the advantage of direct influence on state and control effort in the time domain through performance index weighting factors. Eigenstructure assignment allows direct influence of frequency-domain parameters, such as damping and natural frequency, through eigenvalue placement. Robustness is achieved in the LQG design through LTR, and in the eigenstructure assignment method through mode decoupling by eigenvector selection. More work is required to bring these time- and frequency-domain techniques together to form a useful, unified design procedure.

A noteworthy comparison of a classical [71] and a modern [73] design was made in [83]. Not surprisingly, an extensive computer simulation study indicates that both designs perform well. It appears, however, that MIMO problems of this type tax the classical design methods to their limits, whereas modern designs are constrained more by available implementation hardware than by available design theories. For example, a number of simplifying assumptions (low-order model, constant roll rate, reduced-order/constant-gain estimators, and simplified controller gain scheduling) were made in [73] in order to produce a control algorithm that would comfortably "fit" in a current-generation, tactical missile microprocessor. It is difficult, if not impossible, to access a priori the effects of these assumptions on the control of a highly nonlinear dynamic system such as a BTT missile. It would be interesting to compare the simulated performance of a modern control autopilot designed without regard to present implementation considerations with the autopilots considered earlier.

Adaptive Control Designs

Although adaptive control techniques have been used for autopilot designs in the past, robustness remains a critical issue. Recently, this has been addressed in [84] and [85]. Krause and Stein [84] proposed a general adaptive control structure within which an autopilot design was accomplished with tuned system performance and robustness guarantees.

Kamen et al. [85] applied an indirect adaptive control technique developed in [87] to a BTT missile autopilot design. Although errors in estimation of the rapidly time-varying parameters of the autopilot were substantial, autopilot tracking performance was good. Reference [86] also gives assumptions that yield global asymptotic stability of the controller.

Promising New Techniques

Two control design techniques not detailed earlier are worthy of mention. Tahk et al. [87] describe an application of a feedback linearizing transformation technique for BTT autopilot designs. The technique greatly simplified the design process and resulted in very robust performance with minimal gain-scheduling requirements. The next step in the development of this promising approach is to study its stability properties when a parameter estimator is included in the loop.

Finally, an interesting computer-aided design method for the design of robust linear controllers is described by Boyd et al. [88]. The method is based on the Q-parameterization technique and yields high-order controllers with guaranteed stability margins. It is argued that the high-order controller is not a problem since it can be hardware implemented using MIMO finite-response filters. Application of the Q-parameterization technique to BTT autopilot design is presently under way [89].

Summary

As discussed herein, much work remains to be done on the individual missile control subsystems. The form of the nonlinear model, subsequent model order reduction and/or linearization, and control design approach determine the robustness and sensitivity of the resulting subsystem. The relationships between the design phase and resulting subsystem are only beginning to be deciphered. The effects of digital implementation and computer architecture on control system performance, likewise, are not completely understood. The roles of adaptive control and new control design techniques in the tactical missile environment are, of course, yet to be defined.

In conjunction with research on subsystem properties, a new emphasis on the interrelationships of the various subsystems, and their impact on control design, needs to develop in the controls community. Ideally, the missile flight control system (estimator, guidance law, autopilot, sensors, and actuators, as integrated in the final system) should be designed as an entity for optimum performance/stability. Since this is not possible, control methods that yield a subsystem explicitly designed to work with the specifications of another subsystem should be pursued. These include areas such as dual control, constrained control, H-infinity control, and intelligent control, among others. The authors also encourage exploration of methods used in other application areas, such as artificial intelligence, neutral networks, and sensor fusion to meet the challenges of the tactical missile flight control problem.

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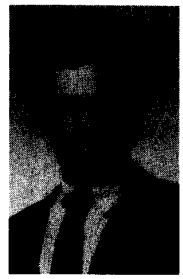

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