System Identification of an Autonomous Aircraft using GPS

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BIOGRAPHY

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ABSTRACT

Stanford University's GPS Laboratory has developed and demonstrated a fully autonomous, small, unmanned airplane. Recent flight tests of the airplane have been extended to collect appropriate open-loop data to perform system identification. In previous research in the GPS Lab, the autonomous airplane, utilizing Carrier-Phase Differential GPS (CDGPS), has flown several flights of a predetermined trajectory from take-off to landing. GPS, providing position, velocity, attitude, and attitude rate, was the primary sensor for the automatic controller. No inertial sensors were used during the autonomous flights. The only additional sensors for these previous flights were indicators for wind speed and direction.

Carrier Phase Differential GPS was the enabling technology for the autonomous control. In earlier flight tests, the low noise, high bandwidth, precise positioning allowed the controller to function well with full sensor feedback. In fact, sensor performance was accurate enough to allow the controller to perform well even without an elaborate mathematical system model of the aircraft. Previous flight tests demonstrated a total system error of typically less than 0.5 m.

The same low noise, high bandwidth qualities of the GPS position and attitude system make it ideal for system identification. The multiple vehicle state information is collected and used to generate a mathematical model of the airplane. During the recent flight tests, the control surfaces are systematically disturbed to observe the aircraft modes. Several different modeling techniques are applied to the same data and results are compared. Standard aircraft modeling techniques using parameter identification and *a priori* knowledge of linearized dynamics are compared to techniques assuming no *a priori* information.

INTRODUCTION

The primary goal of this work was to experimentally demonstrate system identification of a small, unmanned airplane using CDGPS as the primary sensor for vehicle position and attitude. Air speed and direction sensors were the only additional sensors used in this experiment.

The application of GPS as a sensor for control is expanding. There are many potential uses for land, air, and sea vehicles. Stanford University has utilized the accuracy of CDGPS and demonstrated autonomous control of a small, unmanned airplane, the Stanford UAV. Additionally, CDGPS can be used, through system identification, to develop a mathematical system model to describe the dynamics of the airplane and improve the controller's performance.

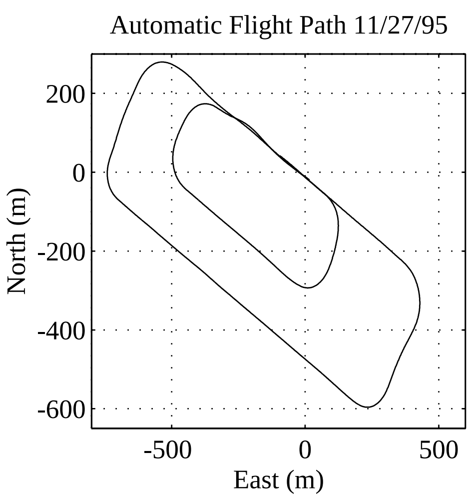
Previous research used CDGPS as the primary sensor for autonomous control of the UAV from take-off to landing [1]. The only other control sensor was for air speed and direction. Full sensor feedback was used in the controller. This was possible only because of the low noise characteristics of the GPS system, and its ability to measure all necessary airplane states of position, velocity, attitude, and attitude rate. The controller's performance, however, can be improved with the addition of an estimator into the control equations. The estimator will smooth the state measurements to lead to smaller control effort, allow for the on-line compensation of biases or noise, the optimal integration of additional sensors, and smoother performance during measurement dropouts.

The same low-noise, complete state sensor used for the autonomous flights, are ideal for system identification of the aircraft. Several open-loop flight tests have resulted in the system identification process described in the paper. The flight test data is processed with three separate system identification techniques. The newly developed state-space models are validated and compared using testing data. The new models can now be used for an expanded control system and for aircraft simulations.

BACKGROUND

The Stanford UAV is a 12-foot wing span, heavily modified, Telemaster 12 model airplane. Most of the modifications are to accommodate a large avionics bay in the front section of the airplane. In previous research, Paul Montgomery developed the Stanford UAV to take-off, fly a predetermined set of rectangular patterns, and land completely autonomously. Figure 1 shows an overhead view of a typical autonomous flight result. Several autonomous flights were flown and typical altitude, airspeed, and tracking errors were 0.21 m, 0.23 m, and 0.44 m, respectively [1].

Figure 1 – Typical Autonomous Flight Results



The control law used for the autonomous flights was based on standard LQR methods. The gains were determined in Matlab using a simulation state-space model of the airplane. This model was developed using a vortex panel method to determine aerodynamic characteristics, and combined with physical measurements of the airplane's mass and inertia's [1].

FLIGHT TEST SETUP

For the system identification, flight test data collection, several open-loop flight tests were performed. The same hardware set-up as used for the closed-loop tests was used for the open-loop tests.

In the airplane, there are two TANS Quadrex receivers, one acts as an attitude receiver with antennae at the nose, wingtips, and master at the tail. The other receiver is for position, using the tail antenna only. The receivers report data at 10 Hz to a 486 single board computer, the flight control computer. This computer also receives up-linked differential packets from the ground. The flight control computer, in a closed-loop test, generates the servo commands and passes them to another processor. This processor, a Tattletale model 7, also collects the air data information and transmits this information to the flight control computer. When the Tattletale has servo commands, it sends the commands to an RC switch. The switch passes the commands to the servos, unless, they are overridden by commands received from the remote pilot on the ground. This pilot override process is how the open-loop data was collected. Also on the ground is the reference TANS receiver with antenna, another 486 computer for display, and data-link modems [1].

For the open-loop tests, the remote RC pilot is in control of the UAV at all times. The pilot flies the airplane to altitude and trims to level flight. He then flies several passes overhead the airfield. During each overhead pass, the pilot slightly perturbs a control surface back and forth. This persistent excitation is to excite the natural modes of the airplane. The control surfaces are perturbed individually or simultaneously to ensure adequate visibility of both the lateral and longitudinal modes of the aircraft. Care was taken not to maneuver the plane so much as to lose lock on a satellite, or create a cycle slip in the receiver.

Figure 2 is a collection of two typical open-loop data passes. In first, the ailerons are perturbed, in the second, the elevator is perturbed. The figure shows the control surface commands.

SYSTEM IDENTIFICATION TECHNIQUES

Once the flight test data was collected, three different techniques were used to identify the system models. For all the techniques, we assume the airplane could be described with linear state-space equations. We also assumed the airplane dynamics were uncoupled, meaning that separate longitudinal and lateral models would be sufficient to describe the airplane motion This is a very common assumption for the symmetric airplane that we are using [2,3].

The longitudinal modes are the short period and phugoid modes, both oscillatory. These modes are observable through perturbations in forward and vertical speeds (u, w), pitch rate (q), and pitch angle (θ). These modes are controllable through elevator deflections and throttle inputs [3].

The lateral modes are the spiral, roll and Dutch roll modes. Only the Dutch roll mode is oscillatory. These modes are observable through perturbations in horizontal speed (v), heading and roll rates (r, p), and roll angle (ϕ). These modes are controllable through aileron and rudder deflections [3].

The measured states used in each system identification technique are the eight listed above. The control surface inputs are the four mentioned above. Assuming lateral and longitudinal models also made comparison with the derived simulation model from previous work much easier. The models may have given better performance if additional measured states were used, such as wind speeds.

The data sets were collected and separated as either test or training data. The training sets are used with each technique to determine the system models, while the test sets are used only to validate and compare each model. Since each state is based on perturbations from a nominal value, biases in the data are removed before processing to get a truer measured perturbation.

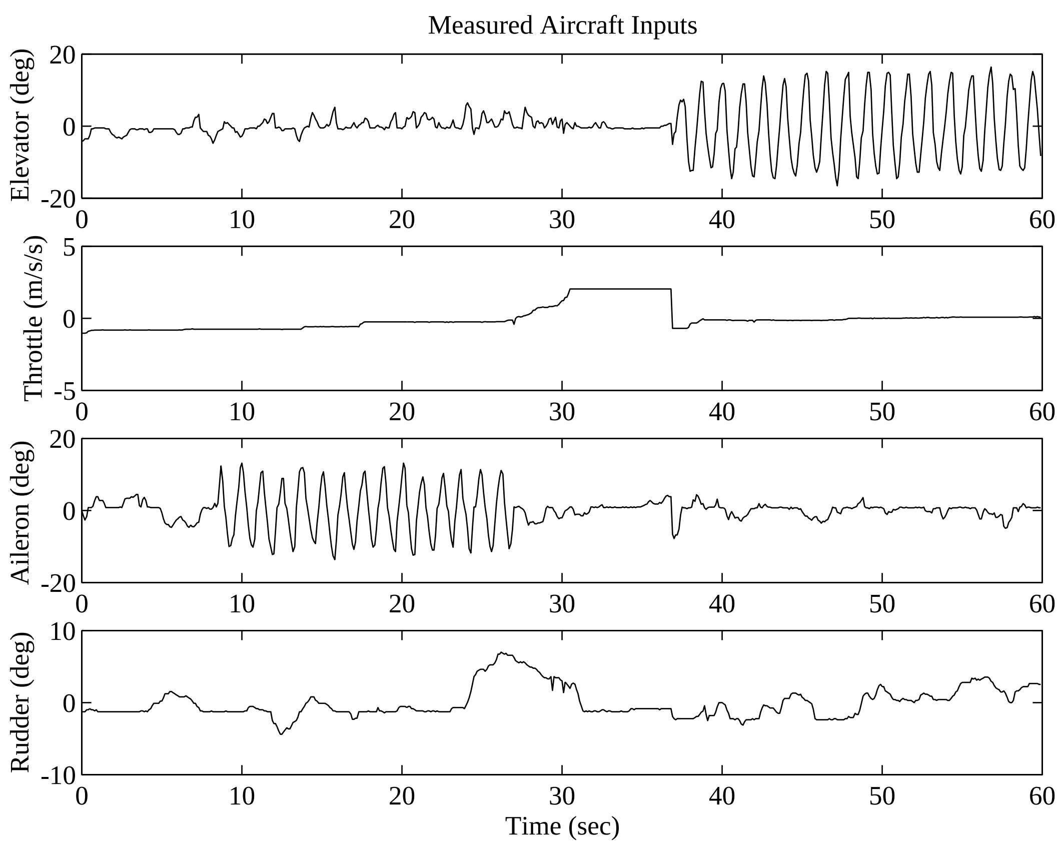
Moshe Idan

The first technique chosen for system identification is a parameter estimation technique. Parameter estimation is a commonly used technique for aircraft system identification where unknown parameters of a state-space model are identified using flight test data [4]. The model is usually derived from dynamics analysis of the system. For an airplane theses parameters are commonly known as stability derivatives. The derivatives represent the effect of forces on the airplane due to changes in the states and control surfaces [3].

A maximum likelihood approach is used in parameter estimation for a system with both process and measurement noise. There are many similar algorithms based on filtering and/or smoothing techniques. A technique described by Moshe in 1990 [4] was used here because it eliminated some of the common difficulties faced with other parameter estimation techniques.

The Idan method uses a smoothing algorithm that identifies system parameters by computing sensitivities of the loss function to changes in the parameters. It does not, however, treat the parameters as additional states of the system. This greatly simplifies the process computationally for systems with large numbers of unknown parameters. One smoothing pass through the data is sufficient to compute the gradients for any number of parameters [4].

Figure 2 – Open-Loop Control Inputs



The smoothing algorithm involves solving a linear two point boundary value problem with a forward and backward pass through the data. The performance measure $\underline{J}$ is modified by adjoint constraint variables using LaGrange multipliers. The gradient of $\underline{J}$ with respect to the parameters is next evaluated. Then the parameters are updated with a quasi-Newton gradient algorithm, where the inverse Hessian of $\underline{J}$ is estimated using a rank-two update algorithm [4].

Although the Idan method was far simpler, and performed better, than other maximum likelihood techniques, it did take much trial and error to achieve the best results. It also worked best if given a good set of initial parameters from which to start. Stability derivatives from a Cessna 172 where modified and used as the first guess of the parameters [5]. Of course, all parameter estimation techniques take a good knowledge of the system dynamics in order to determine the parameters in which to identify.

Observer/Kalman Identification Process

The second method of identifying the airplane model is the observer/Kalman filter identification method (OKID). The system uses only input and output data to construct a discrete time state space realization of the system. The method has spawned numerous extensions but the concept is essentially the same [6].

The basic idea is to identify a linear discrete time, state-space system that models the aircraft. Therefore we need to determine [A,B,C,D]. OKID begins by computing observer Markov parameters from experimental data [6] with the number of parameters specified by the user. The choice must be sufficiently large to find a solution.

The system Markov parameters are the system's response when perturbed from rest. From the observer Markov parameters, the system Markov parameters and the observer gain Markov parameters can be calculated. The system Markov parameters can then be assembled to form the generalized Hankel matrix. The Hankel matrix can be decomposed into the Observability matrix, a state transition matrix, and the Controllability matrix. The Hankel matrix (which must always be of full rank) can then be truncated using singular value decomposition (SVD) at an order that sufficiently describes the system. The truncated Hankel matrix is then used to reconstruct A,B, and C using a minimum balanced realization algorithm that ensures that the controllability and observability Grammians are equal. This is known as the Eigensystem Realization Algorithm (ERA) and a modified version with data correlation (ERA/DC) can also be used. D is recovered from the observer Markov parameters directly. The observer gain matrix can then be computed. When reduced to system order, the identified observer has to be a Kalman filter and thus the observer gain matrix G gives the steady state Kalman filter gain . [6]

Subspace

The third method used for system identification is a subspace process. Subspace identification algorithms attempt to determine a system by first estimating the (Kalman filter) states and then determining the system matrix [7]. Subspace algorithms are simple to use, fast, and robust. The only required user specified parameter is system order. They are fast when implemented correctly and there are no convergence problems [7].

A combined deterministic stochastic subspace identification algorithm was used. Again we need to determine [A,B,C,D] but in addition we will also determine [Q,S,R], the noise process and measurement covariance matrices. For our system and each model type (longitudinal and lateral), we have a set of data with k = 4 outputs, and m = 2 inputs.

The method begins by computing oblique and orthogonal projections of the modified input and output data sets to determine Z_i, Z_{i-1}, and O_i (the weighted oblique composition). An orthogonal projection is defined as the projection of the row space of a matrix A onto the row space of a matrix B and denoted by A/B. An oblique projection $A/_cB$ is the projection of the row space of a matrix A along the row space of C onto the row space of B [7].

The SVD of weighted oblique composition is calculated and a system order, n, is then chosen by inspection of the singular values. The SVD is then used to estimate the extended observability matrix Γ_i (i > n), a ki x n block observability matrix. Γ_{i-1}, a k(i-1) x n block observability matrix, is found by removing the last k rows of Γ_i. The following set of linear equations are solved for A, C and κ through least squares and then

$$\left(\frac{\boldsymbol{\Gamma^t_{i-1}.Z_{i+1}}}{\mathbf{Y_{i|i}}}\right) = \left(\frac{A}{C}\right).\Gamma^{\mathbf{t}}_{\mathbf{i}}.\mathbf{Z_i} + \kappa.U_f + \left(\frac{\rho_w}{\rho_v}\right)$$

1

where r_w and r_v are the process and measurement noise from the residuals. $Y_{i|i}$ is found directly from output data

$\bullet^t$ designates the Moore – Pensrose pseudoinverse

The least squares solution computes asymptotically unbiased estimates of the system matrix. Γ_i and Γ_{i-1} can now be recalculated and the residuals can be found. B and D are solved for through a minimization problem. Since the problem is convex, there is a unique minimum. Finally, the residuals can be used to compute the noise covariance matrices and K can be determined from Q,S, and R [7].

RESULTS

Once the data was processed and the three technique's models determined, each was validated as an estimator and also as a predictor. For these validation and comparison data runs, only the test data sets were used.

The estimator comparisons show how the system may perform in a controller. A steady state Kalman gain is determined and used in conjunction with the actual measurement outputs to determine how well the models would follow the test data if each had some knowledge of the current measurement at each epoch. The gain determines how much information about the measurement is feedback into the estimator equations. For comparisons of the different techniques, this process can be misleading if the gains are not determined in the same manner. If for one technique, the gains are too large, the system will weight the measurement output more heavily, and therefore track the measurement more than another technique model with a lower gain.

For a clearer idea of the model's performance, the techniques are compared as predictors only. The gain is zero so no knowledge of the current measured state is feedback into the predictor equations. This testing configuration determines how well the models simulate the airplane motion.

All three models, Idan, OKID, and Subspace, are compared with the derived model from previous research.

Figure 3 shows the predictor performance for all the techniques in the longitudinal modes. Figure 4 shows the predictor performance for all the techniques in the lateral modes.

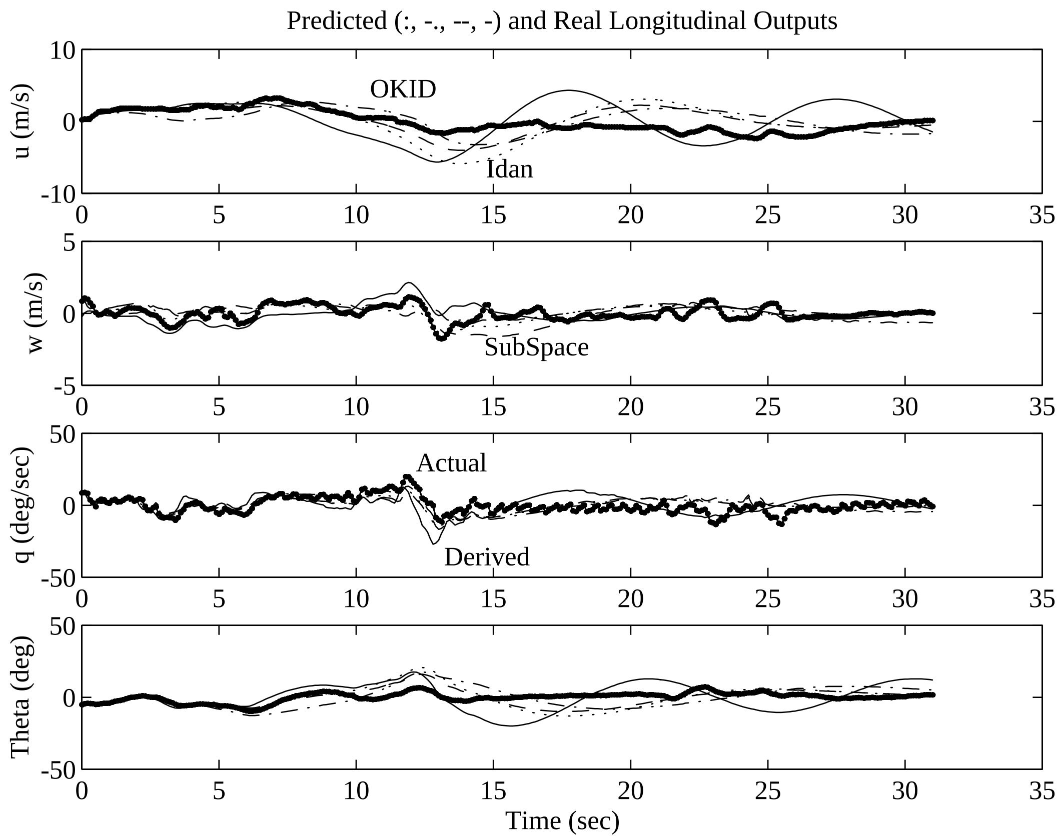


Figure 3 – Longitudinal Comparison

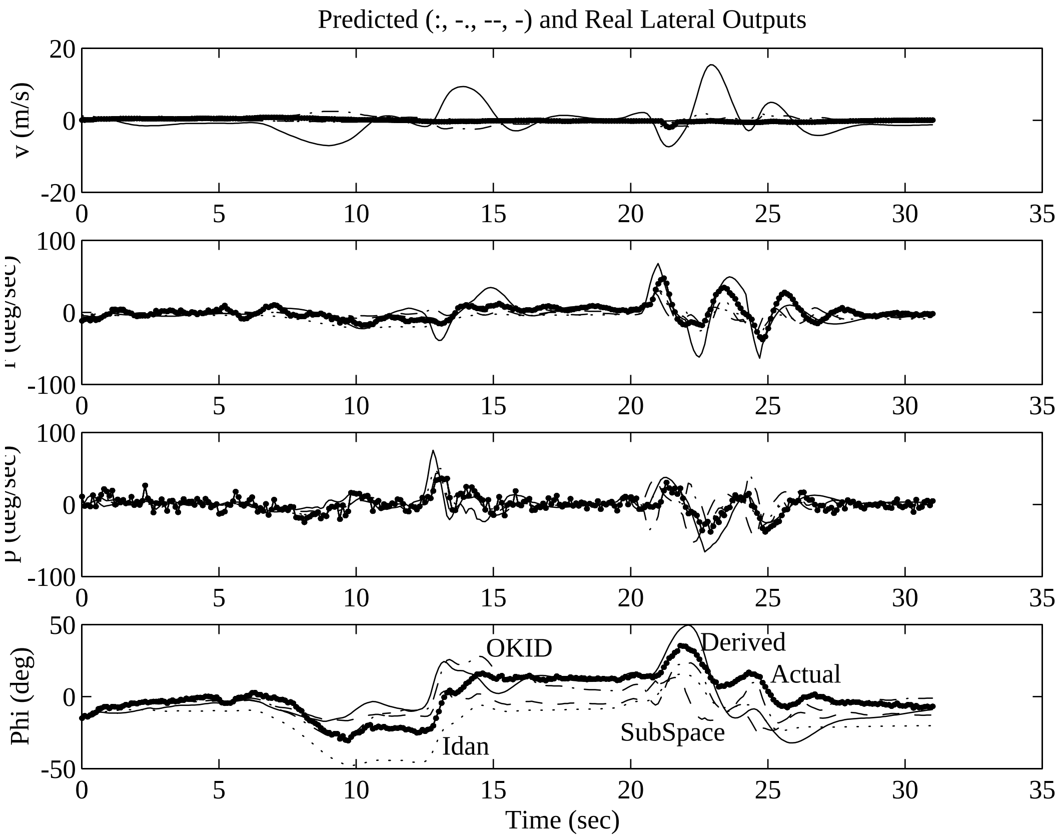


Figure 4 – Lateral Comparison

The following charts summarize by showing the percent error per output for all techniques uses as an estimator (Figure 5) and as a predictor (Figure 6) over all the test data sets. The percent error per output is the residual at each epoch normalized by the measured output at that epoch for each state. This facilitates the comparison of model performance from one state to another. The longitudinal states are show followed by the lateral states for each technique.

Figure 6 – Predictor: Percent Error per Output

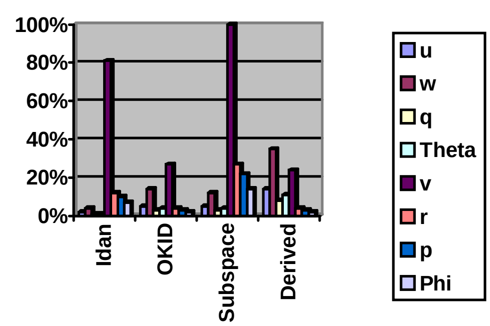
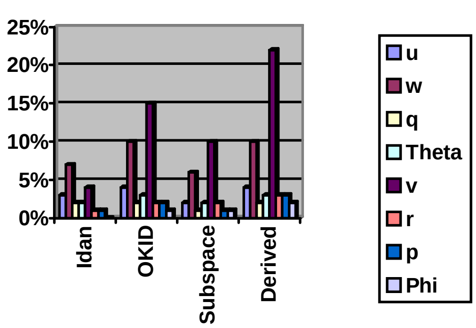


Figure 5 – Estimator: Percent Error per Output



CONCLUSIONS

The same GPS sensor set-up used for the successful demonstration of autonomous flight with the Stanford UAV is also an excellent tool for the system identification of the aircraft. From essentially one box, all necessary states are measured with little noise. This data and set-up is ideal for system identification.

The Moshe Idan technique and the OKID technique for system identification delivered very good system models for simulation and possibly control. The Idan method needed much more a priori information about the system, but both were computationally intensive and took some trial and error to use. The subspace technique was less computationally intensive and took little trial and error to achieve results comparable with the other techniques.

The ultimate test of all the techniques will be a closed-loop test using the models as estimators in the controller of the airplane.

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