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TECHNICAL REPORT

A REGRESSION APPROACH TO GENERATE AIRCRAFT PREDICTOR INFORMATION

PAUL D. GALLAHER, ROGER A. HUNT, ROBERT C. WILLIGES

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A predictor display shows the human operator future consequences of his immediate control inputs. A contact analog aircraft display is described in which an airplane-like predictor symbol depicts future airplane position and orientation. The standard method for obtaining the predictor information is to use a complete, fast-time model of the controlled vehicle. An alternative approach is presented in this paper in which least-squares, first-order, linear approximations for each of the six degrees of freedom of aircraft

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AVIATION RESEARCH LABORATORY

Institute of Aviation

University of Illinois at Urbana-Champaign
Willard Airport
Savoy, Illinois
61874

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CONTEXT

The Aviation Research Laboratory of the University of Illinois is investigating methods for enhancing pilot performance through advanced integrated flight display concepts and computer-augmented flight control techniques under contract with the Office of Naval Research. Mr. Gerald S. Malecki, Assistant Director, Engineering Psychology Programs, is the ONR Scientific Officer. Professor Stanley N. Roscoe was the principal investigator during the initial phase of study and during the development of experimental apparatus. Professor Robert C. Williges served as principal investigator while Professor Roscoe was on academic leave during 1975-1976.

The research is directed toward (1) enhancing pilot performance; (2) the isolation of minimum sets of visual image cues sufficient for spatial and geographic orientation in the various ground-referenced phases of representative flight missions, (3) the generation and spatially integrated presentation of computed guidance commands and fast-time flight path predictors, and (4) the matching of the dynamic temporal relationships among these display indications for compatibility with computer-augmented flight performance control dynamics, both within each ground-referenced mission phase and during transitions between phases. The investigative program draws selectively upon past work done principally under ONR sponsorship or partial sponsorship, including the ANIP and JANAIR programs.

The work descirbed in this report represents a methodological effort directed towards more efficient techniques for generating aircraft predictor information.

Program Progress and Plans

During Phase I of the current contract, the Aviation Research Laboratory systematically investigated the relationships between the movement of the controls and the response of the airplane and demonstrated substantial improvement in pilot performance as a consequence of their reorganization. By the completion of Phase I, all planned control modifications, specifically the digital control system have been incorporated into the GAT-2 simulator. No additional work on this task is contemplated for the initial year of Phase II.

To study experimentally the effectiveness of alternate sets of visual cues, the Aviation Research Laboratory has developed a highly versatile computer-generated display system to present dynamic pictorial images either on a head-down, panel-mounted CRT or on a head-up television projection to a large screen mounted in front of the pilot's windshield on the Link GAT-2 simulator. Due to the great flexibility of the pictorial display, visual cues and flight status information can be manipulated experimentally. Experimentation to isolate the visual cues sufficient for approach and landing is in progress.

The incorporation of predictive indications of successive future states is currently under investigation during Phase II. Experiments will be conducted to determine the number and temporal spacing of flight path predictors to be integrated into the forward-looking flight view. Determination and software implementation of command guidance symbology compatible with the synthetic forward-looking contact analog and predictive flight path presentations will also be undertaken. It is the ultimate objective of this program to develop, during the second year of Phase II, a reconfigured cockpit with integrated sensor and computer-generated imaging displays and computer-augmented controls.

A REGRESSION APPROACH TO GENERATE AIRCRAFT PREDICTOR INFORMATION

By Paul D. Gallaher, Roger A. Hunt, and Robert C. Williges

University of Illinois at Urbana-Champaign

SUMMARY

A predictor display shows the human operator future consequences of his immediate control inputs. A contact analog aircraft display is described in which an airplane-like predictor symbol depicts future airplane position and orientation. The standard method for obtaining the predictor information is to use a complete, fast-time model of the controlled vehicle. An alternative approach is presented in this paper in which least-squares, first-order, linear approximations for each of the six degrees of freedom of aircraft motion were calculated. Thirteen variables representing changes in positions and rate of change of positions were selected as parameters for the prediction equations. Separate sets of equations were determined for 7, 14, and 21 seconds prediction times and continuous, 1, and 3 seconds control neutralization assumption times. The advantages and disadvantages of this regression approach are discussed.

INTRODUCTION

Predictor displays provide the operator of manually controlled systems with information about the future state of the variable being controlled. Often this information can be generated by an analog of the system to be controlled, operating repetitively in an accelerated time scale. Ideally, to generate a predictor model using such a fast-time model, the model should be a duplicate of the original plant. For example, to put a predictor display in an aircraft trainer which uses an analog computer for all flight equations and dynamics, a second analog computer just like the first with speeded-up time constants could be used. Such complexity in using an accurate fast-time model imposes a penalty of cost, computer weight, and power requirements. In fact, Kelly (1) pointed out that it may not be necessary to have the complete accuracy of a fast-time model.

Bernotat (2) used a Taylor series expansion rather than the fast-time model approach, and found that even inaccurate predictions gave improved performance over no prediction in the control of a third-order undamped system following a step input. Kelley (3) found the same effect, but he also found that the useful prediction span decreased with model accuracy while learning times for effective manual control were increased. A comprehensive study of simplified models for an automatic predictive control system for aircraft landing in two dimensional sideways looking displays was conducted by Chestnut, Sollecito, and Troutman (4). They pointed out that the model may be of either the analog or digital form, but they felt the digital approach offers more accuracy and flexibility. They also indicated that the time constants and gains of the model can be in error by two to one without excessive loss in performance.

The main effect of an inaccurate model is closely related to the predictor span. The magnitude of the errors in an inaccurate predictor can be determined analytically or experimentally if the plant can be observed directly or simulated accurately for comparison with a less accurate fast-time model. Errors farther into the future are usually compensated for by the fact that accuracy requirements on short predictions usually are greater than for long predictions. Predictor displays can also overcome the problem of accuracy when they are continuously updated. If updating is inaccurate or infrequent, the fast-time model must be that much more accurate.

This paper presents a least-squares, regression approach for determining first-order, linear approximations of accurate fast-time models used in predictor displays. Such a procedure would eliminate the need for an operational fast-time model while still providing a great deal of predictive accuracy. The accuracy of this regression approach for generating these predictor symbols is evaluated both at various prediction times and at various control input durations.

METHOD

Task

For the purpose of demonstrating the use of a regression approach to generate predictor information, an application incorporating predictor information in an aircraft system during an approach to landing was used. Because of the complexity and sluggishness of the aircraft system in the landing phase, manual performance depends heavily on the anticipatory abilities of the pilot. Under such circumstances, predictive displays might be very useful. Smith, Pence, Queen, and Wulfeck (5) demonstrated that the predictor display did improve performance in an approach to landing on an aircraft carrier. It even facilitated learning to such an extent that mean performance on transfer trials using a predictor was considerably higher than that of a control condition without the predictor.

The specific approach to landing task in this study was generated for a Singer-Link General Aviation Trainer (GAT-2) which simulates general, light, twin-engine aircraft. The predictor symbology was incorporated into a versatile computer-generated dynamic flight display developed by Artwick (6) and was part of an integrated, vertical situation display stylized in Figure 1. In addition to the situational information of runway outline, centerline, touchdown zone, and grid-line ground texture cues, three glide-slope indicators in the form of telephone-pole-shaped symbols and three discrete, airplane-like predictor symbols are shown on the display. The predictor symbols represent the position of the aircraft at three particular future points in time (7, 14, and 21 seconds as used in this study) given a specified control input by the pilot.

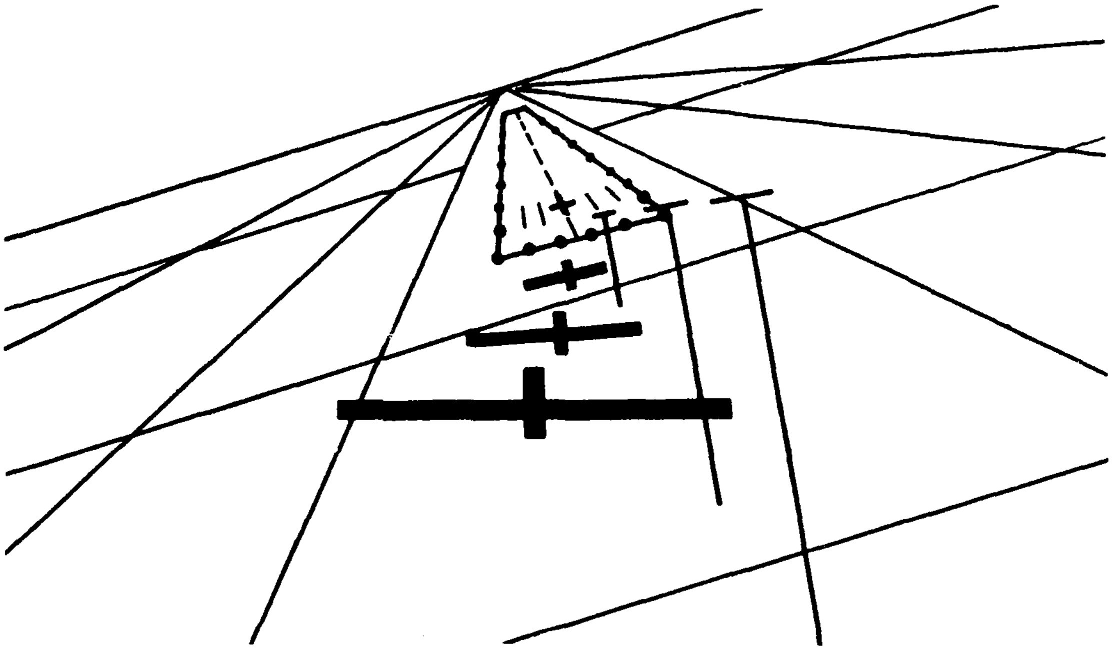

Figure 1. Stylized representation of an integrated vertical situation display showing three aircraft-like predictor symbols.

Regression Procedure

To generate the predictor symbols shown in Figure 1, one must specify the changes in the six degrees of freedom of aircraft motion as listed in Table 1. Each of these six degrees of freedom are determined by the specific flight dynamics of the aircraft. These dynamics are specified in terms of complex, higher-order differential equations which represent position, change in position, and rate of change of position as shown in Table 2. (These values are all accessible as millivolts in the GAT-2 analog computer.)

Rather than use the complete set of complex flight equations, a first-order linear approximation may suffice particularly in the limited range of variables encountered in a final approach to landing situation. A standard, least-squares, multiple linear regression analysis (Tatsuoka, 7) can be used to estimate a raw-score, linear approximation of the general form,

$$Y = \beta_o + \beta_1 X_1 + \ldots + \beta_m X_m \tag{1}$$

TABLE 1

Changes in Six Degrees of Freedom of Aircraft Motion Required to Specify Aircraft Predictor Symbology

Degrees of Freedom
Change in Bank ($\Delta\theta_B$)
Change in Yaw ($\Delta\theta_Y$)
Change in Pitch ($\Delta\theta_P$)
Change in Lateral Position (Δ_X)
Change in Vertical Position (Δ_Y)
Change in Longitudinal Position (Δ_Z)

TABLE 2

Initial Variables Used to Predict Changes in Six Degrees of Freedom of Aircraft Motion

Predictor Variables
Aileron Position (α)
Rudder Position (ρ)
Elevator Position (ε)
Throttle Position (τ)
Bank Angle (θ_B)
Yaw Angle (θ_Y)
Pitch Angle (θ_P)
Cosine Bank ($\cos \theta_B$)
Rate of Roll ($\dot{\theta}_B$)
Rate of Pitch ($\dot{\theta}_P$)
Rate of Yaw ($\dot{\theta}_Y$)
Rate of Climb (R/C)
Velocity (v)

where Y represents the dependent variable, X_1 through X_m the independent variables, and β_o through β_m the partial regression coefficients. Specifically, the general form of the Equation 1 for the predictor symbology case is,

$$\begin{aligned}\Delta \text{ degree of freedom } = \; & \beta_o + \beta_1 \alpha + \beta_2 \rho + \beta_3 \varepsilon + \beta_4 \theta_B \\ & + \beta_5 \theta_Y + \beta_6 \theta_P + \beta_7 \cos \theta_B + \beta_8 \dot{\theta}_B \\ & \beta_9 \dot{\theta}_P + \beta_{10} \dot{\theta}_Y + \beta_{11} R/C \end{aligned} \qquad (2)$$

where Y is replaced by the particular change in degree of freedom of interest the X's are replaced by selected variables in Table 2, and the β's represent the raw-score, partial regression weights which are empirically determined.

All the independent variables except velocity and throttle can take on both positive and negative values. Velocity and throttle are always zero or some positive value, so their contribution to the predictor equation would always be positive. Furthermore, velocity and throttle changes should amplify the effects produced by control surface position and airplane position changes. Consequently, the independent variables of aileron, rudder, and elevator position as well as the current bank, yaw, and pitch angles shown in Equation 2 are multiplied by the velocity and throttle values of the GAT-2. The remaining four variables in Equation 2 already contain velocity and throttle information, because they are rates of change in position.

Data Collection Procedure

Of the thirteen independent variables shown in Table 2, only the changes in position of the three control surfaces (rudder, aileron, and elevator position) and the throttle position can be directly affected by the pilot. The remaining nine variables are non-linear, interacting functions of these as well as outside disturbances. For each of the four variables under direct pilot control, three levels of change in millivolts (zero, one positive, and one negative) were directly manipulated by the experimenter to obtain the necessary data for generating the regression equations. A one-third replication of the factorial combination of these four variables was observed twice resulting in 54 data collection flights. The remaining nine variables were considered to be approximately random and were not manipulated through experimenter control.

During each of these 54 data collection cycles the GAT-2 was flown in an approach to landing configuration. The landing gear was down and the proper airspeed, flap setting, manifold pressure, etc. was maintained. When the GAT-2 was flown by the pilot to the proper landing configuration, the Raytheon 704 computer maintained the control surfaces at the appropriate level, recorded the initial values of all thirteen independent variables shown in Table 2, and measured the changes in the six degrees of freedom of motion (dependent variables) after 7, 14, and 21 seconds. These latter values provided the three prediction times represented by the successive discrete predictor symbols shown in Figure 1.

To simulate the four designated control surface positions over different flights, the Raytheon 704 computer was used. The analog signals from the GAT-2 representing control surface positions were intercepted prior to their use in the GAT-2 analog computer flight equations. An analog-to-digital converter made these signals available in the form of a 12-bit word. Thus, 0 to 10 volts was converted to 0 to 2048 binary. The software routines then generated changes in these signals as dictated by the one-third replicate of the factorial design. These new signals were sent through the digital-to-analog converter and into the GAT-2 computer to maintain precisely a given set of control movements.

As shown in Table 3, the factorial design of this study also allowed for the calculation of six prediction equations for each of three control assumption times at the 7, 14, and 21 second prediction times. The length of time these control surface changes were maintained prior to neutralization determined the control assumption times. When the control changes were maintained continuously over the 21 second prediction span, this produced the continuous or on-line predictor model (Warner 8). If the control changes were not maintained throughout the data collection phase, an off-line predictor model is used. Two off-line models using control assumption times of 1 and 3 seconds were also investigated in this study. A different set of 54 approaches to landing were required for each control assumption time. Consequently, a total of 162 approaches were measured.

TABLE 3

Factorial Design of Control Assumptions and Prediction Times Used to Generate the Six Regression Equations Predicting the Degrees of Freedom of Motion of the Predictor Symbol

Control Assumptions (Seconds)	Prediction Times (Seconds)		
	7	14	21
Continuous (21)	(6 Regression Equations)	(6 Regression Equations)	(6 Regression Equations)
1	(6 Regression Equations)	(6 Regression Equations)	(6 Regression Equations)
3	(6 Regression Equations)	(6 Regression Equations)	(6 Regression Equations)

RESULTS

A multiple, linear regression analysis was conducted on all 11 independent variables shown in Equation 2 for each dependent variable to determine the appropriate partial-regression coefficient values. Table 3 shows that there were six equations for each predictor time and the associated control assumptions. These six equations determined the changes in the six degrees of freedom of motion for a particular predictor symbol. Because each prediction equation required a separate regression analysis, a total of 54 regression equations were solved.

For example, Table 4 shows the general form of the six prediction equations needed to represent the airplane predictor symbol at seven seconds in the future for a three second control assumption time. Although this regression analysis was conducted on all 11 of the independent variables shown in Equation 2, only the statistically significant ($p < .05$) predictors are shown in Table 4. Similar sets of prediction equations were derived for the other treatment conditions summarized in Table 3. In each case, however, the specific set of statistically reliable partial-regression weights varied somewhat.

TABLE 4

Prediction Equations with Significant ($p < .05$) Independent Variables Used to Determine Changes in the Six Degrees of Freedom of Aircraft Motion for Seven-Second Prediction Span and Three-Second Neutralization Assumption.

$$\Delta\theta_\beta = \beta_o + \beta_1\,\alpha + \beta_2\,\rho + \beta_3\,\theta_B + \beta_4\,\dot{\theta}_B + \beta_5\,\dot{\theta}_Y + \beta_6\,\dot{\theta}_P$$

$$\Delta\theta_Y = \beta_o + \beta_1\,\alpha + \beta_2\,\theta_B + \beta_3\,\dot{\theta}_B + \beta_4\,\dot{\theta}_Y + \beta_5\,\dot{\theta}_P$$

$$\Delta\theta_P = \beta_o + \beta_1\,\varepsilon + \beta_2\,\theta_B + \beta_3\,\theta_Y + \beta_4\,\theta_P + \beta_5\,\dot{\theta}_P + \beta_6\,R/C$$

$$\Delta X = \beta_o + \beta_1\,\alpha + \beta_2\,\rho + \beta_3\,\theta_B + \beta_4\,\theta_Y + \beta_5\,\dot{\theta}_B + \beta_6\,\dot{\theta}_Y + \beta_7\,\dot{\theta}_P$$

$$\Delta Y = \beta_o + \beta_1\,\alpha + \beta_2\,\varepsilon + \beta_3\cos\theta_B + \beta_4\,\dot{\theta}_B + \beta_5\,\dot{\theta}_P + \beta_6\,R/C$$

$$\Delta Z = \beta_o + \beta_1\,\alpha + \beta_2\,\varepsilon + \beta_3\cos\theta_B + \beta_4\,\dot{\theta}_B + \beta_5\,\dot{\theta}_P + \beta_6\,R/C$$

One convenient way of assessing the goodness of fit of each of these regression equations is to calculate the multiple correlation coefficient. The square of this value represents the percent of variance accounted for by the regression equation. Table 5 summarizes the multiple correlation coefficients for each of the 54 prediction equations of this study. (For example, the multiple correlation coefficients for the six prediction equations presented in Table 4 are .96, .98, .84, .94, .79, and .85, respectively.) Note that the change in altitude (Y) is the degree of freedom of aircraft motion which resulted in the lowest multiple correlation coefficients. Generally, the one-second control assumption time and the seven-second prediction time also produced regression equations with lower predictive accuracy.

TABLE 5

Multiple Correlation Coefficients for Each Predictor Equation

Prediction Times	Bank	Yaw	Pitch	X	Y	Z
			Continuous (21 Second) Control Assumption			
7	.98	.95	.97	.87	.78	.77
14	.98	.98	.98	.95	.85	.94
21	.99	.98	.97	.97	.92	.96
			1 Second Control Assumption			
7	.96	.96	.87	.88	.66	.66
14	.97	.95	.94	.92	.71	.61
21	.97	.91	.94	.93	.75	.64
			3 Second Control Assumption			
7	.96	.98	.84	.94	.79	.85
14	.98	.98	.91	.98	.83	.92
21	.98	.98	.95	.98	.85	.92

DISCUSSION

The overall consistently high multiple correlation coefficients obtained in this study indicate that the regression approach yields very accurate prediction equations and is a viable alternative to using the complete, fast-time model. The lower multiple correlation coefficients for the one-second control assumption is probably reflective of the fact that a one-second control input is simply too brief to account for any significant movement of the GAT-2 over the prediction interval. Likewise, the lower predictive power of the 7 second prediction times as compared to 14 and 21 seconds merely shows that the GAT-2 dynamics are such that the simulator has not completed a response to the control force inputs. The longer prediction times represent a more complete simulator response.

A simplification of this approach for application to actual aircraft would be to remove the variables representing rates of change of motion which are not normally available. Undoubtedly, this simplification would reduce the predictive accuracy of the regression equations, because rate parameters provided significant weightings in the prediction equations. From a behavioral point of view, however, these less precise equations may not affect the pilot's performance in flying the aircraft. Additional research is needed to determine the role of predictor symbol accuracy in determining operator control inputs before the allowable degree of predictor simplification can be specified.

This approach to generating predictor symbology offers the advantages of ease of implementation, low cost, and conformity to a digitally-generated display. In fact, this method may be better than an accurate, fast-time model in the sense that time lags are no longer proportional to prediction span because of increased computations being required further into the future. Furthermore, the prediction span need not be compromised by repetition rate, updating frequency, or computing power available because any discrete prediction is as easy to make as any other.

It should be remembered that the specific prediction equations of this study pertain only to the control dynamics of the GAT-2 at the three prediction times and control assumption times varied. In other words, the regression equations are always specific to the device from which the data are collected. The approach and procedure for generating these regression equations, however, are general and can be applied to generating predictor symbology for any specific device. Obviously, there probably are situations in which a multiple linear regression may not provide an adequate representation of the true underlying system dynamics. In such instances a regression approach is still appropriate, because it can be easily extended to higher-order, polynomial regression representations of these complex functions.

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Operational Psychology Branch
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Mr. Gail J. Borden
Human Factors Research, Inc.
Santa Barbara Research Park
6780 Cortona Drive
Goleta, CA 93017

Dr. Gordon H. Robinson
University of Wisconsin - Madison
Department of Industrial Engineering
1513 University Avenue
Madison, WI 53706

Dr. W. S. Vaughan
Oceanautics, Inc.
3308 Dodge Park Road
Landover, MD 20785

Director, Human Factors Wing
Defense & Civil Institute of
Environmental Medicine
Post Office Box 2000
Downsville, Toronto, Ontario
CANADA

Dr. Malcolm L. Ritchie
Professor, Human Factors Engineering
Wright State Universtiy
Dayton, OH 45431

Dr. Lloyd Hitchcock
Human Factors Engineering Branch
Crew Systems Department
Naval Air Development Center
Warminster, PA 18974