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MODELING THE HUMAN AS A CONTROLLER IN A MULTITASK ENVIRONMENT*

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SUMMARY

Modeling the human as a controller of slowly responding systems with preview is considered. Along with control tasks, discrete non-control tasks occur at irregular intervals. In multitask situations such as these, it has been observed that humans tend to apply piecewise constant controls. It is believed that the magnitude of controls and the durations for which they remain constant are dependent directly on the system bandwidth, preview distance, complexity of the trajectory to be followed, and nature of the non-control tasks. A simple heuristic model of human control behavior in this situation is presented. The results of a simulation study, whose purpose was determination of the sensitivity of the model to its parameters, are discussed.

INTRODUCTION

Although successful operation of an airliner is now possible from take-off to touchdown with minimum involvement of the human pilot [1] he must still perform various routine checks in the course of a normal flight. In addition, even when flying on autopilot, constant monitoring of various instruments is necessary to detect any out of tolerance signals and abnormal occurences of any events. Further, malfunctions or changes in atmospheric conditions, for example, might require that the pilot take over control and make course changes that are different from the preplanned trajectory. Thus, despite advances in automation, human control of aircraft is certainly still of interest.

When the human is controlling a plant, it has been observed that the controls applied are not always continuous. Continuous controls are necessary and are observed when the time constants involved are rather small and the deviations from some reference trajectory must be kept within some close tolerance. But when the time constants are relatively large, it is unnecessary and also difficult to apply the right amount of continuous control. For slowly responding processes it is often sufficient and desirable to apply step-like controls intermittently. This gives an opportunity to observe the actual behavior of the system, compare it with the

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predicted behavior, and take corrective action. This usually prevails in a tracking situation where a certain length of the future command trajectory is available, along with the present required position. Further, applying the step-like controls also frees the human to engage in non-control tasks. In fact, this kind of behavior is common in process control situations and also has been observed in simulations of a flight management situation [2], [3].

When preview of the command trajectory for a certain distance into the future is available, it is likely that the human would apply step-like controls so as to minimize the future trajectory deviations rather than instantaneous deviations. A model which appears reasonable is one which updates the expected deviations of the cost over the length of the previewed trajectory and uses this information along with the knowledge that it "costs" to change control values. The cost to change control reflects the fact that non-control tasks must be attended to, though they may not be of primary importance. The "cost" is thus due to the feeling that the non-control tasks would "suffer" if attention is focused away from them and on the primary task alone. This cost may manifest itself as a tolerance threshold for error below which no action is taken. A measure for the cost of not attending to the subsystem tasks is available as a function of various probabilities and costs for delay of subsystem tasks [4].

BACKGROUND

Of the available models for manual control, the optimal control model would appear to be a suitable candidate. However, this model assumes that control remains non-zero at all times whereas in an intermittent control situation, control is zero for a significant portion of the time. Hence the mean fraction of time devoted solely to control, corresponding to non-zero control intervals, cannot be calculated with the optimal control model. For a given fraction of attention, the conventional optimal control model predicts only RMS errors and RMS control actions. While recent versions of the model do yield a measure of attention that should optimally be used for monitoring subsystems that dynamically relate to the control task, subsystem tasks that only remotely relate to the aircraft's dynamic response cannot be considered. Further, in multitask situations the optimal control model's performance criterion, which minimizes mean squared deviations, may not be appropriate. Finally, these approaches do not yield any predictions of the split of attention between control and non-control tasks or about the probability that the human is involved in the control of a continuous system at any particular instant.

The human in multitask situations has been modeled by Walden and Rouse [3] as a 'server' in a queue where 'customers' are the control and non-control tasks. The customers are assumed to arrive for service with exponentially distributed inter-arrival times (Poisson arrivals.) Service times are Erlang-k distributed. Some customers have a higher priority over others (e.g., control tasks over non-control tasks.) There are a total of N customers in the population (total number of possible tasks the human may be called upon to attend), and N spaces are available in the queue (i.e., at worst all the N systems may require service simultaneously.) This situation can be modeled as a ($M/E_k/1$:PRP/N/N) queue. (See references [5] or [6] for details about the notation.) The queueing model predicts the fraction of time spent in each type of task (i.e., server utilization). The emphasis in this model is on the subsystem task performance. The control task is modeled in the sense that performing it consumes time. However, measures characterizing control performance (i.e., RMS errors) are not available.

AN INITIAL MODEL

Some success has been achieved using a heuristic model to describe control of an aircraft (with simplified dynamics) in a horizontal plane. Initial computer simulations indicate that this could be a fruitful approach. A piece-wise straight line map was created using uniformly distributed random variables for the length of straight line segments. The magnitudes for angle of turn between segments were chosen from nine values (10°-90°) with equal probability. The direction was chosen randomly. This type of map was designed because of the flexibility in determining the parameters. It is a simple matter to change the probability distributions of various parameters of the path, so that different conditions could be easily tested. It was assumed that the aircraft would be moving forward with constant speed. A point moved along the map corresponding to the desired aircraft position. A distance equivalent to two time constants ahead of the desired position on the map was shown as preview. Only lateral motion was considered. Control in the horizontal plane was achieved through use of the aileron to change the bank angle. The dynamics are shown in Figure 1.

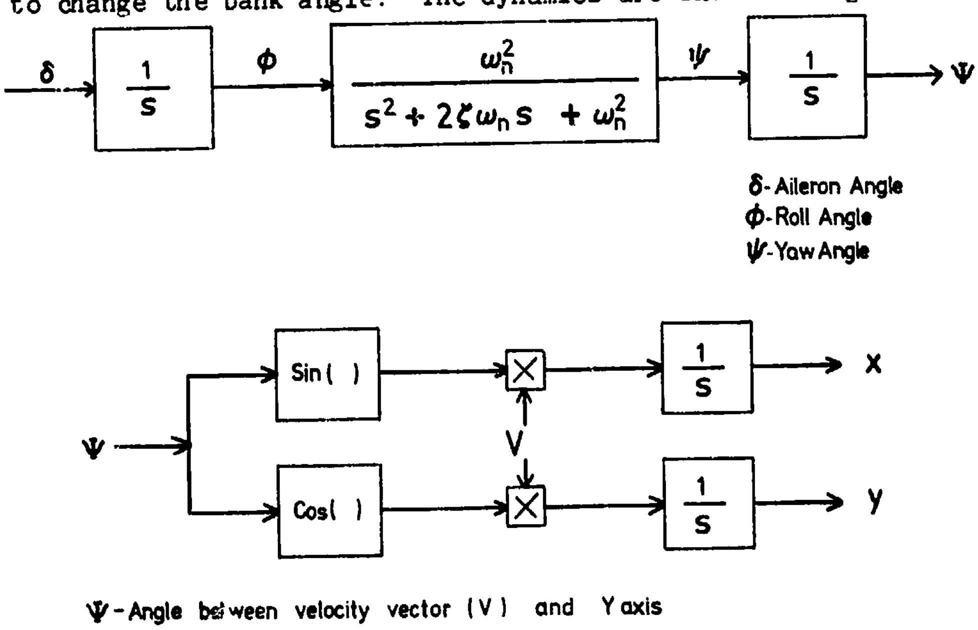
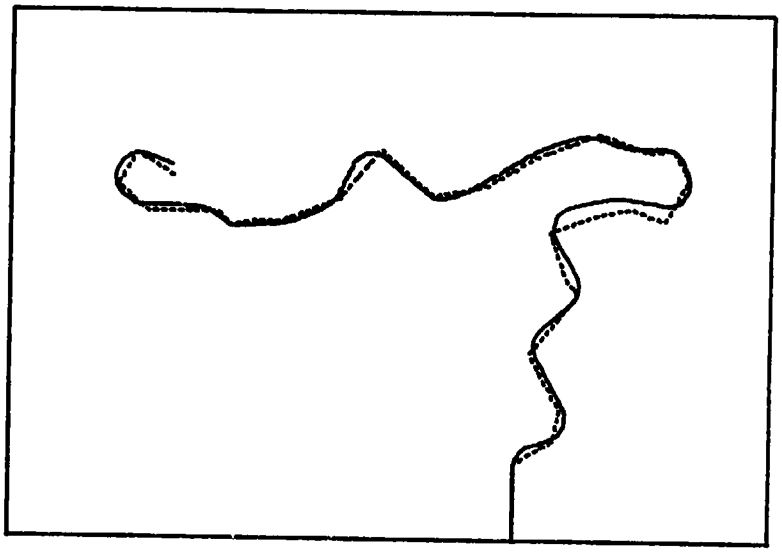


Fig. 1 Simplified Lateral Dynamics

The deviation from the desired position was constantly monitored. A perfect internal model of the aircraft was assumed. At every time instant, the model calculated the future positions for the entire preview length assuming that the roll angle would be zero. At any point, the error was calculated as the deviation from the commanded position, instead of the perpendicular distance to the map

It appears reasonable to expect that the importance given by the human operator to deviations from the desired trajectory will vary along the length of the trajectory. Deviations at the current time cannot be corrected or changed significantly due to the slow response of the system. Also, the expected deviations near the end of the previewed command trajectory need not be considered immediately, since enough time will be available in the future to correct these. Further, any changes "beyond the horizon" that would come into view soon can reasonably be ignored. Accordingly, the human might weight the mid-portion of the previewed command more than either end. So the weighting function for errors would increase to a maximum (from zero), about one time constant from the current position, and decrease again to a near zero value at the end of the trajectory.



TRAJECTORIES : ------- REFERENCE ——— MODEL

Fig. 2 Simulation Results : Heuristic Model

Weighted error is squared and summed over the preview length. If this predicted error function exceeds a certain threshold, 'aileron' is held at a maximum value until maximum bank angle is reached. If the error is within the threshold, the bank angle is made zero. Constant weights on errors were used for the simulation. The results are shown in Figures 2 and 3 and appear reasonable. The time intervals corresponding to non-zero aileron action give a direct measure of fraction of time required for control which is proposed as a correlate of workload. Although the human must continuously monitor for cumulative error, workload due to this is assumed negligible compared to the workload involved in control where he must watch the effect of his actions more carefully.

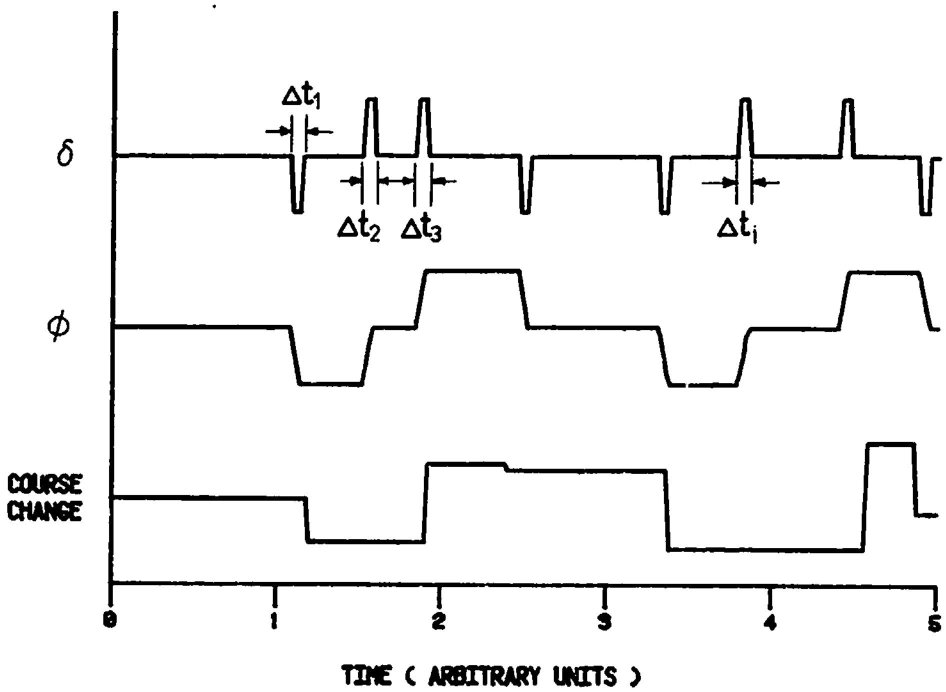


Fig. 3 Control and Roll Angle History for a Given Course Change

Simulation experiments were conducted using a fractional factorial design to find out the sensitive/relevant parameters. A resolution VI design was used so that no main effect or two factor interaction is confounded with any other main effect, two factor interaction, or three factor interactions. The following parameters were assumed to affect performance:

1. Dynamics (τ of the process),	τ = 1,5
2 Average arrival rate of turns,	$1/\mu$ = $3\tau, 6\tau$
3 Standard deviation of course changes	σ = $10^\circ, 30^\circ$
4. Amount of preview	T_p = $2\tau, 4\tau$
5. Weighting function,	Rect. Triang.
6 Threshold on cumulative weighted error.	Low High

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RMS errors and the fraction of time spent on control were used as performance measures. A constant function (rectangular) and a triangular function were used for weighting on errors. For other parameters, two extreme values were chosen, to obtain a total of 32 different conditions. Exponentially distributed segment lengths and normally distributed angles of turn were used for the map. For each condition, two replications were run. The results are shown in Tables I and II.

Table I

Analysis for RMS Error

Factor	Effect	Sum of Squares	DOF	F Ratio	
1	4.433	314.409	1	131.037	$P < 0.001$
2	-0.671	7.206	1	3.003	
3	1.477	34.887	1	14.540	$P < 0.001$
4	4.087	267.247	1	111.381	$P < 0.001$
5	-1.397	31.219	1	13.011	$P < 0.001$
6	0.622	6.188	1	2.579	
12	-0.268	1.145	1	0.477	
13	1.108	19.653	1	8.191	$P < 0.01$
14	4.174	278.726	1	116.165	$P < 0.001$
15	-0.886	12.557	1	5.233	$P < 0.05$
16	-0.250	1.004	1	0.418	
23	-0.288	1.325	1	0.552	
24	0.049	0.038	1	0.016	
25	0.335	1.794	1	0.748	
26	1.315	27.676	1	11.535	$P < 0.005$
34	0.383	2.350	1	0.979	
35	1.295	26.822	1	11.179	$P < 0.005$
36	0.197	0.619	1	0.258	
45	-0.914	13.364	1	5.570	$P < 0.025$
46	0.258	1.062	1	0.443	
56	0.124	0.246	1	0.102	
Average	4.192				
Error		100.774	42		
Total		1150.313	63		

(1-Period, 2-Segment Length, 3-Angle of Turn, 4-Preview Length, 5-Weight, 6-Threshold)

Table II

Analysis for Fraction of Attention

Factor	Effect	Sum of Squares	DOF	F Ratio	
1	0.231	0.856	1	33.221	P < 0.001
2	-0.057	0.051	1	1.999	
3	0.017	0.005	1	0.181	
4	0.144	0.331	1	12.837	P < 0.001
5	-0.117	0.218	1	8.468	P < 0.01
6	-0.139	0.311	1	12.084	P < 0.005
12	0.004	0.000	1	0.011	
13	-0.018	0.005	1	0.206	
14	0.269	1.158	1	44.963	P < 0.001
15	0.000	0.000	1	0.000	
16	0.004	0.000	1	0.008	
23	0.067	0.072	1	2.783	
24	0.030	0.014	1	0.541	
25	0.005	0.000	1	0.017	
26	0.060	0.058	1	2.234	
34	-0.074	0.087	1	3.359	
35	0.047	0.035	1	1.374	
36	-0.043	0.030	1	1.155	
45	0.005	0 000	1	0.014	
46	0.048	0.037	1	1.435	
56	0.090	0.129	1	5.011	P < 0.05
Average	0.256				
Error		1.082	42		
Total		4.479	63		

(1-Period, 2-Segment Length, 3-Angle of Turn, 4-Preview Length 5-weight, 6-Threshold)

It can be seen that period, preview length and their interaction have the largest effect on performance. Different weighting functions also affect performance. In addition, RMS error is affected by the magnitude of turns and various interactions. Fraction of time spent on control is affected by the threshold. Higher threshold values reduce this fraction.

Though the interaction of mean segment length and threshold affects the RMS error, segment length alone does not affect either of the performance measures. This could be due to the constant forward speed in all cases, whereas the mean segment length is scaled by the time constant. For slower process, for a given threshold any error that may result takes a longer time to reduce to zero. Since the 'vehicle' would stay away from the trajectory for a longer time, higher RMS error results.

Relatively high workload as well as higher RMS error is observed for the slower process with longer preview. Once the threshold is exceeded, the model applies an appropriate amount of control. However, due to the slow response, the magnitude of error remains near the threshold for some time. But, the error could change sign as new points come into view, and might call for a different control action. Due to longer preview the error changes sign quite frequently resulting in increased control action. This again results in the error remaining near the threshold. Thus, behavior similar to a limit cycle results which, interestingly, has been observed when naive subjects control slow processes. This could possibly be avoided by having one threshold above which control is actuated, and a lower threshold below which control is made zero.

CONCLUSIONS

The next phase of this work will involve development of an experimental situation for use with human subjects. Non-control tasks will be included to simulate a multitask environment. Simple arithmetic tasks may be used. Multiplication tasks with keyboard entry of results are a possibility. Complexity and the rate at which these are presented could be varied, so control task error criterion (i.e., the threshold) may perhaps be manipulated.

The possibility of developing analytical models using the min-max approach [7],[8],[9],[10], satisfaction approach [11], and fuzzy sets [12] will be pursued. An attempt will be made to cast our problem in a form suitable for analysis using the above methods, with possible modifications where necessary. Especially interesting in this regard is the satisfaction approach. It may be possible to formulate our problem in this framework, and obtain a heuristic-based solution with the addition of a few conditions related to the problem structure. With these models available, a more realistic experiment will be developed using the General Aviation Trainer II (GAT II). Along with the control task, the non-control tasks will be made more realistic.

In summary, a simple heuristic model for the control task was presented. Simulation results for a set of conditions describing various trajectories were given. The controller part assumes perfect internal model. Only the threshold must be determined to yield intermittent control. The period and the preview length were found to be the most important parameters affecting performance. This will form the basis for proposed experiments with humans. The model will be refined to take into account the results of these experiments and then, will be used along with a queueing model for non-control tasks, to model the overall multitask situation.

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