Proceedings of 25th Conference
on Decision and Control
Athens, Greece • December 1986

FA3 - 12:00

MODEL OF THE HUMAN CONTROLLER OF A DYNAMIC SYSTEM

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General.

In de last two decades considerable research effort has been devoted to the study of human involvement in dynamic systems. Especially human control behavior has been investigated, but in the restricted sense of continuous regulating against random disturbances, so as to minimize the system state deviation from a given reference state.
This paper deals with a model of the human controller of a dynamic system involving not only regulating (- short term, continuous, closed loop -), but also tracking (- often long term, intermittent, open loop -) a desired finite trajectory in some optimal sense. The latter concerns control behavior at a higher mental level involving planning (pre-programmed, open loop control) and decision making (to determine sequentially whether or not such a maneuver has to be initiated and/or stopped).
In this paper it is assumed that the Human Operator (HO) derives information about the system from instruments and/or the outside world; this pictorial information provides the HO (directly or via a TV-camera/monitor system) with visual cues related to the present system state and the present and future desired system state.
The model describes both this complex visual information process (including an optimal scanning strategy) and the control and decision making behavior in terms of stochastic optimal estimation, control and decision theory, providing an integrated framework of all important and inter-related aspects of the aforementioned humen control task. This is the subject of the following sections.
It is anticipated that the model will be useful to investigate a variety of man-machine systems (nonlinear systems are represented by linearized, time-varying systems) e.g., in the increasingly important area of robotics and in the handling of ships.

Description of the task

In general, it is assumed that the HO deals with a linear, time-varying dynamic system. Nonlinear systems can be linearized in terms of a time-varying reference and a (time-varying) linear (small perturbation) model. Furthermore, the overall effect of instruments and the outside world is described in terms of visual cues (y) which are linearly (or linearized), but time-varying, related to the present state (x(k)) and the future desired state ($x_d(k+N)$)

$$y(k) = Hx(k) + H_d x_d(k+N) \tag{1}$$

Background and details of this representation are given in reference 1. The task is to achieve a desired trajectory, i.e., controlling the state x over some fixed interval of time [0,N] by realizing a control sequence, $\{u(k),\ k = 0,1,\dots,N-1\}$, which minimizes the performance measure

$$J_N(u) = E\Big\{\sum_{i=1}^{N} \big(x(i) - x_d(i)\big)' Q_x(i)\big(x(i) - x_d(i)\big) + u'(i-1)Q_u(i-1)u(i-1)\Big\} \tag{2}$$

In case x_d is given this control problem is known (e.g., given in reference 2), In our case, however, x_d has to be derived (estimated) from the perceived visual cues. This is treated in the next section.

Human control model

Following the optimal control model (of continuous regulating control) formulation (Ref. 3), it is assumed that the HO perceives the visual cues corrupted by (observation) noise (v), and utilizes this information and the (learned) system dynamics to estimate the state of the system ($\hat{x}$).
One part of the control task is to regulate (continuously) against random disturbances. The resulting control is given by (Ref. 3) $u_r(k) = S(k)\hat{x}(k)$, which is the standard solution of the LQG-control problem, minimizing eq. (2) with $x_d = 0$.

Sequential decision making

In order to follow, intermittently, given desired trajectories, the HO has to decide when this is relevant. This decision process is described in sequential decision theoretical terms, assuming that the HO utilizes his innovation sequence (n) to determine whether a systematic deviation of the zero-mean system process is apparent (due to the incipient desired trajectory). This systematic deviation results in a non-zero mean innovation sequence, which is estimated by the HO by a 'local' sample mean $\bar{n}$ which is included in the state estimator according to

$$\tilde{\hat{x}}(k) = \Phi\tilde{\hat{x}}(k-1) + \Psi\tilde{u}(k-1) + K\tilde{n}(k) \tag{3.a}$$

$$\tilde{n}(k) = H\tilde{x}(k) - H\Phi\tilde{\hat{x}}(k-1) + H_d\tilde{x}_d(k+N) + \tilde{v}(k) \tag{3.b}$$

with

$$\bar{n}(k) = \frac{1}{M}\sum_{i=k-M+1}^{k} n(i) \tag{3.c}$$

Assuming that $\tilde{x}(k)$, $\tilde{u}(k-1)$ and $\tilde{v}(k)$ are small, $\tilde{n}(k)$ can be used to detect $\tilde{x}_d(k+N)$ and to estimate $x_d(k)$ and to respond to this desired trajectory.
As shown in reference 4, a generalized likelihood ratio test can be performed using a recursive expression for the (log of the) likelihood ratio

$$L(k) = L(k-1) + \frac{M}{2}\bar{n}'(k)N^{-1}(k)\bar{n}(k) \tag{4}$$

where N(k) is the covariance of the innovation sequence, by comparing this ratio with a decision threshold which can be related to the accepted (or assumed) risk. This sequential decision algorithm, which has been shown in several experimental programs to describe adequately this type of decision making behavior, is used to describe (in terms of detection times) the intermittent control behavior of tracking the desired system state.

Open loop maneuvering

Once the decision to track the desired state $x_d(i)$, $i = k,\dots,k+N$, is made, the HO makes an optimal (i.e., minimal performance index of eq. (2)) maneuver, using $\tilde{n}(k)$, which can be conceived as a planned stategy to follow $x_d(i)$ and reach $x_d(k+N)$. In system theoretical terms this amounts to backwards integration of the desired control response (from k+N to k) and then generating (forward in time) $u_m(k)$ (see, e.g., reference 2). In formula

$$u_m(k) = A(k)u_m(k+1) + B(k)\tilde{n}(k-N) \tag{5}$$

with

$$u_m(k+N) = -B(k+N)\tilde{n}(k)$$

The ensemble mean of $\tilde{n}(k)$ follows from eq. (3.b)

$$\bar{\tilde{n}}(k) = H_d\tilde{x}_d(k+N) + H\bar{\tilde{p}}(k-) \tag{6}$$

where p(k-) is the estimation error at time k before the observation at time k is included. It can be shown that the accuracy with which this mean value (and thus $\bar{x}_d$) is known is given by the ensemble covariance of $\tilde{n}(k)$, which is (shown in reference 1 to be)

$$\operatorname{cov}(\tilde{n}(k)) = \tilde{N}(k)/M \doteq N(k)/M \tag{7}$$

with

$$N(k) = HP(k-)H' + V(k) \tag{8}$$

and P and V the covariances of p and v, respectively. Combining eqs. (5), (6) and (7) yields the (ensemble) average maneuver and the ensemble covariance of the maneuver (variability)

$$\bar{u}_m(k) = A(k)\bar{u}_m(k+1) + B(k)\bar{\tilde{n}}(k) \tag{8.a}$$

$$U_m(k) = A(k)U_m(k+1)A'(k) + B(k)\,\frac{N(k)}{M}\,B'(k) \tag{8.b}$$

with which the mean and covariance of the system performance can, straightforwardly, be computed.

After the maneuver (at time k+N), the system reference and the small perturbation model are updated. Also the decision is made whether another (part of a) maneuver has to be executed or regulating only is required.

Visual scanning

Visual scanning is assumed to be based on the total system uncertainty U, according to

$$U(k) = \operatorname{tr}[QP(k)] \tag{9}$$

The minimization of this criterion is general in the sense that it represents also the minimal regulating cost (by an appropriate choice of the weightings Q, as shown in reference 3) and also optimal decision behavior (minimum detection time), which is shown in reference 5. It can be shown that the effect of looking at time k is given by

$$\Delta U(k) = \operatorname{tr}[G(k-)N^{-1}(k)] \tag{10}$$

with

$$G(k-) = HP(k-)QP(k-)H' \tag{11}$$

look independent.

Now, indicating the look sequence with $\delta_i(k)$: $\{0,1\}$ and writing for the observation noise covariances (Ref. 5)

$$V_j(k) = V_{0_j}(k-)/\delta_j(k) \tag{12}$$

with V_0 the noise level corresponding with 'full attention', for eq. (10) can be written (Ref. 1)

$$\Delta U(k) = \sum_{i=1}^{NY} g_{r_i}(k-)\delta_i(k) \tag{13}$$

with

$$g_{r_i}(k-) = g_{ii}(k-)[P_{j_{ii}}(k-) + V_{0_i}(k-)]^{-1} \tag{14}$$

and $p_{j_{ii}}$ a diagonal element of HPH'.

Thus the maximum reduction in uncertainty is obtained for δ_j with max g_{r_j}.

The (ensemble) average effect of looking is

$$E\{\Delta U\} = \sum_{i=1}^{NY} E\{g_{r_i}\}P_i \tag{15}$$

with P_i the probability of attending to i. So the optimal allocation of attention can be computed via an optimization procedure (e.g., steepest descent) with gradient expression

$$\frac{\partial E\{\Delta U\}}{\partial P_i} = E\{g_{r_i}\} \quad i = 1,\dots,NY \tag{16}$$

or, by assuming a 'reasonable' (suboptimal) scanning strategy:

$$P_i = E\{g_{r_i}\} / \sum_{i=1}^{NY} E\{g_{r_i}\} \quad i = 1,\dots,NY \tag{17}$$

With respect to maneuvering it is assumed that the HO looks ahead as frequently as necessary to 'reconstruct' the desired trajectory. This determines the scan frequency of the pertinent cue(s) and thus (assuming an ergodic process) of the probability (P_m) of attending to the 'maneuvering' cue(s).

The remaining attention (or rather, the probability of attending, $1-P_m$) is divided optimally among the other visual cues according to (e.g.) the scanning strategy of eq. (17).

Concluding remarks

This concludes the most important aspects of the model of the human controlling a dynamic system. The main feature of the model is the intermittent control behavior during finite time intervals, thus involving decision making and planning. Another central element is that control is based on the perceived visual information from instruments and visual scene, including a model for visual scanning. In reference 1, it is discussed to what extent the model has been validated and how the remaining characteristics of the model will be validated in the context of a ship control task.

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