MODEL OF THE HUMAN OBSERVER AND CONTROLLER OF A DYNAMIC SYSTEM

Theory and model application to ship handling

by P.H. Wewerinke *, J. Perdok **
and C. van der Tak **

ABSTRACT

The MMS model presented in this paper describes rather detailed human control of a dynamic system. The model is an integration and extension of previously developped (validated) (sub)models.

The model describes human control of a dynamic system, involving intermittent control behavior during finite time intervals and, therefore, decision making and planning and continuous regulating. Another central element is that the control is based on the perceived visual information from instruments and the outside world. Observing this visual scene is a complex process (e.g. involving preview) and intimately related to the control task. A model for visual scanning renders a useful insight in display- and navigational questions.

The model is being applied to the control of a ship entering a harbor. The preliminary results of this study show that the model adequately describes this complex control task.

It is anticipated that the MMS model is sufficiently general to be useful to investigate a variety of man-machine systems, e.g. in the important area of robotics and in the handling of ships, helicopters, etc.

Keywords

Human modeling, man-machine systems, human control, estimation theory, optimal control, ship handling.

INTRODUCTION

Human control of dynamic systems has been extensively investigated (modelled), but in the restricted sense of continuous regulating against random disturbances, so as to minimize the system state deviations from a given reference state. (Refs. 3, 4, 9, 10 and 11).
This paper deals with a model of the human controller of a dynamic system involving not only (short term, continuous, closed loop) regulating, but also (often long term, intermittent, open loop) tracking a desired finite trajectory in some optimal sense.

* University of Twente,
P.O. Box 217,
7500 AE, Enschede.
The Netherlands

** Maritime Research Institute MARIN,
P.O. Box 28,
6700 AA Wageningen.
The Netherlands

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).

The model, which will be indicated in the following with MMS (Man-Machine System) model, describes the 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 interrelated aspects of the aforementioned human control task.

The task considered is to control a dynamic system from state A to state B with a given desired state, based on perceived information about the present state and the future desired state from instruments and/or the outside world.
The various aspects of the task are: the task definition (minimization of a quadratic, finite time, cost functional), the linearized, time-varying dynamic system, the environment and human control behavior. The latter comprises: visual perception and state estimation, continuous regulating against random disturbances and intermittent maneuvering: once a systematic deviation of the given state reference is detected, the HO generates an open loop control sequence to track the desired trajectory and a closed loop control strategy to compensate for random disturbances. This is the subject of the following chapters.

TASK ENVIRONMENT

The HO has to fulfil the task utilizing the dynamic system, in a given environment.

A nonlinear, time-varying dynamic system can be represented by

$$X(k) = f(X(k-1),U(k-1),W(k-1),k) \quad (1a)$$
$$Y(k) = g(X(k),U(k),k) \quad (1b)$$

where $X(k)$ is the n-dimensional state vector at time k, f is the n-dimensional vector function, U is the k-dimensional control vector, W is the l-dimensional disturbance vector, Y is the m-dimensional system output vector and g is the m-dimensional vector function.

The standard procedure is followed to describe the nonlinear dynamic system behavior (X) in terms of a state reference (X_0) and "small" perturbations (x) around this reference; thus $X = X_0 + x$, etc. This linearization scheme yields a time-varying reference model and the following, time-varying, linear system discription.

$$x(k) = \Phi x(k-1) + \Psi u(k-1) + \Gamma w(k-1) \quad (2a)$$

$$y(k) = Hx(k) \quad (2b)$$

where the matrices Φ, Ψ Γ and H are time-varying (depending on X_0) and w is assumed to be a zero mean, Gaussian, purely random sequence with covariance W.

It is assumed that the HO derives information about the system from instruments and the outside world. The latter provides information (y_0, with dimension m_0) not only about the present state (x) but also about the future desired state (x_d) as explained in Ref. 1. Combined with eq. (2b) the resulting observation model is

$$y_e(k) = H_e x_e(k) \qquad (3)$$

with $y_e = \binom{y}{y_0}; H_e = \begin{pmatrix} H & 0 \\ H_0 & -H_0 \end{pmatrix} = (H_x \; H_{x_d}); x_e(k) = \binom{x(k)}{x_d(k+N)}$

and N indicates the looking time ahead.

The task considered is to achieve a desired trajectory (tracking task) in some optimal sense, i.e., controlling the state x over some fixed interval of time [0,N] by realizing a control sequence $\{u(k), k=0,1,\ldots,N-1\}$ which minimizes the performance measure

$$J_N(u) = E\{\sum_{i=1}^{N} (x(i)-x_d(i))'Q_x(i)(x(i)-x_d(i)) + u'(i-1)Q_u(i-1)u(i-1)\} \qquad (4)$$

This optimal control problem can be solved by rewriting eq (4) in terms of the extended state $x_e = \binom{x}{x_d}$. The results are given in Ref.(2) and used in the next chapter. In order to include $\dot{u}$-terms in eq (4) x_e can be augmented resulting (again) in the standard regulator control problem.

HUMAN CONTROL MODEL

The model of the HO comprises various functional aspects which are discussed in the following section.

Perception and State Estimation

It is assumed that the HO perceives the system outputs with a certain inaccuracy

$$y_{e_p}(k) = y_e(k) + v_e(k) \qquad (5)$$

With $v_e = \binom{v}{v_0}$ a linear independent gaussian, purely random observation noise sequence with covariances (Ref. 4)

$$V_{e_j}(k) = \frac{P_0 \, E\{y^2_{e_j}(k)\}}{\delta_j \, K(a_j, \sigma_{y_{e_j}})} \qquad (6)$$

with P_0 the 'full attention' noise ratio, $\delta_j\{0,1\}$ represents the look sequence (peripheral viewing neglected) and K the describing function gain (statistical representation of a threshhold a_j for a given signal level $\sigma_{y_{e_j}}$).

It is assumed that the HO utilizes the (learned) system dynamics and the observations y (eq (2b)) to estimate the state of the system. This estimation process is described by (Ref. 5)

$$\hat{x}(k) = \Phi\hat{x}(k-1) + \Psi u(k-1) + Kn(k) \qquad (7a)$$

with $n(k) = y_p(k) - H\Phi\hat{x}(k-1)$ (7b)

and $K(k) = P(k-)H'N^{-1}(k)$ (7c)

where P(k-) is the covariance of the estimation error p(k-), (k-) indicates the time k before the observation at time k is made, and N is the covariance of the innovation sequence n.

Perception and Estimation of the Future Desired State

Consider a sequence x_d which can be described by a deterministic process

$$x_d(k) = \Phi_d x_d(k-1) \qquad (8)$$

where $\Phi_d = \Phi_d(k,k-1)$ represents the complete knowledge about x_d.

Various assumptions can be made about the HO's prior knowledge about x_d. The corresponding internal models are discussed in Ref. 2. In this paper it is assumed the HO has no a priori knowledge of x_d. So the estimation of x_d has to be based solely on the observations.

The estimation of x_d is based on an internal process

$$x_i(k) = \Phi_i x_i(k-1) + w_i(k) \qquad (9)$$

where x_i is the 2n-dimensional vector containing x_{i_1} to be associated with the change in x_d per time step and x_{i_2} to be associated with x_d. $\Phi_i = \begin{pmatrix} I & 0 \\ \Delta I & I \end{pmatrix}$ representing a linear extrapolation from k-1 to k. w_i describes the change in x_{i_1}. This is clarified in figure 1.

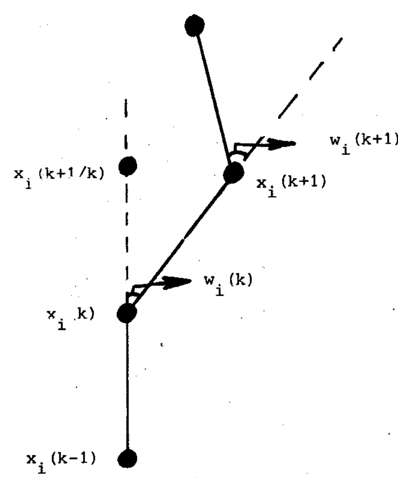

Fig. 1. Internal process

The estimation process is based on the aforementioned linear extrapolation corrected by the innovation sequence

$$\hat{x}_i(k) = \Phi_i \hat{x}_i(k-1) + K_i n_d(k) \quad (10)$$

with $n_d(k) = y_{d_p}(k) - H_i \Phi_i \hat{x}_i(k-1)$ (11)

and $y_{d_p}(k) = H_d x_d(k) + v_d(k)$ (12)

where $y_d(k) = y_0(k-N)$, $H_d(k) = -H_0(k-N)$ and $v_d(k+N) = v_o k) - H_0 p(k-)$, which is again a zero mean, Gaussian, purely random sequence (Ref. 2) and $H_i = (0\ H_d)$.

It can be shown (Ref. 2) that the optimal gain K_i (corresponding with the minimal mean-squared error of $p_d \equiv \binom{\dot{x}_d}{x_d} - \hat{x}_i$, MSp_d) is given by

$$K_i = MSp_d H_i' V_d^{-1} \quad (13)$$

However, the mean-squared error, MSp_d is unknown to the HO, so he, or she, has to make an estimate based on the innovation sequence.
The mean-squared innovation sequence can be estimated based on M past observations according to

$$\hat{MSn}_d(k) = \frac{1}{M} \sum_{i=k-M+1}^{k} n_d(i) n_d'(i) \quad (14)$$

With this result the optimal filter gains K_{i_2} related to the estimation of x_{i_2} (and thus x_d) can be obtained from (Ref. 2)

$$H_d K_{i_2} = \hat{MSn}_d \,(\hat{MSn}_d + V_d)^{-1} \quad (15)$$

if H_d has full rank (n) (thus $m_0 \geq n$).

However, in order to estimate all elements of K_i, it is also necessary to include observations of $\dot{x}_d$ (to be associated with x_{i_1}). A simpler approach, maintaining the original assumption that only x_d is observed, is to take $K_{i_1} = K_{i_2}/\Delta$. So, the estimate of the change in x_d is updated according to the update of the estimate of x_d, which is the best one can do, on the basis of only the observations y_{d_p}.

Sequential Decision Making

The control task defined in chapter 2 pertains to some fixed finite interval of time. This implies a decision to start this period (e.g. the decision that the present state reference corresponding with a straight path is followed by a curved trajectory)

This decision could be based on the estimate of x_d $\hat{x}_{i_2}$ (see before). An alternative is to utilize directly the innovation sequence n_o corresponding to observations y_o (of eq (3)).A systematic deviation of the zero-mean system sequence x, due to a change in the desired state (with respect to the present state reference) results in a non-zero mean innovation sequence (Ref. 6) This can be tested by the HO on the basis of a "local" sample mean according to

$$\tilde{n}_o(k) = \frac{1}{M} \sum_{i=k-M+1}^{k} n_o(i) \quad (20)$$

with M the number of samples used from the past. Combining eqs (20) and (7) (but now utilizing observations y_o) yields

$$\tilde{\hat{x}}(k) = \Phi x(k-1) + \Psi \tilde{u}(k-1) + K_o \tilde{n}_o(k) \quad (21a)$$

$$\tilde{n}_o(k) = H_o \tilde{x}_d(k+N) - H_o \tilde{p}(k-) + \tilde{v}_o(k) \quad (21b)$$

Assuming that $\tilde{p}$ and $\tilde{v}_o$ are small, $\tilde{n}_o$ can be used to "detect" $\tilde{x}_d(k+N)$ and to estimate $x_d(k)$ and to respond to this desired state. This estimate $\tilde{x}_d$ is an alternative for the estimate of x_d given in the foregoing.

A uniformly most powerful test (generalized likelihood ratio test) can be performed using the recursive expression for the (log of the) likelihood ratio

$$L(k) = L(k-1) + \frac{1}{2} \tilde{n}_o'(k) N_o^{-1}(k) \tilde{n}_o(k) \quad (22)$$

(with N_o the covariance of n_o) and compare this ratio with a threshold. Details of this test (detection time and decision error probabilities) are given in reference 6.

Once the decision is made that the desired state is systematically deviating from the present reference at time k_o, an (open loop) maneuver has to be executed to track this desired state. This is discussed in the next section.

Human Control Behavior

The optimal control of the finite time tracking task as discussed before is derived in Ref. 2. The resulting control sequence {u(k), k=0,1,...,N-1} is given by

$$u(k) = S(k)\hat{x}(k) + S_m(k) z(k+1) = u_r(k) + u_m(k) \quad (23)$$

with

$$S(k) = S_m(k) W(k+1) \Phi \quad (24a)$$

$$S_m(k) = -(\Psi' W(k+1) \Psi + Q_u)^{-1} \Psi' \quad (24b)$$

$$W(k) = Q_x(k) + \Phi' W(k+1) \Phi_c(k) \quad (24c)$$

$$\Phi_c(k) = \Phi(k) + \Psi S(k) \quad (24d)$$

and

$$z(k) = \Phi_c'(k) z(k+1) - Q_x(k) \hat{x}_d(k) \quad (25)$$

with $z(N) = -Q_x(N) \hat{x}_d(N)$, $k=N-1,\ldots,0$. (26)

So the control is composed of two parts: a feedback control, u_r, and a feedforward (open loop) control u_m, operating on (the estimate of) the desired state, x_d, obtained by backwards integration in time.

After the maneuver (at time $k_0 + N$) the system reference and the small perturbation model are updated according to

$$X_i(k_0+N) = X_{i-1}(k_0+N) + \hat{x}(k_0+N) \qquad (27a)$$

$$\Phi_i = \frac{\partial f}{\partial X}(X_i,U_i), \text{ etc.} \qquad (27b)$$

Visual Scanning

The HO is dealing with $m+m_0$ observations. m observations correspond to the estimation of the system state x and m_0 observations are necessary to estimate the future desired state. The question is, therefore, how the HO allocates his/her attention among these observations.

A visual scanning model is derived (Ref. 1) based on the assumption that the HO sequentially observes the visual cues (one at the time) optimally, i.e. minimizing the cost functional of eq (4). It can be shown (Ref. 2) that this implies that the HO is minimizing his total system uncertainly defined as

$$U(k) = tr[Q(k)P_e(k)] \qquad (27)$$

where Q(k) are given 'weightings' which can be expressed in the system variables and cost functional weightings given in eq (24), as shown in Ref. 2, and P_e is the (extended) estimation error 'covariance' comprising both the estimation error covariance of x(k) (P) and the mean-square estimation error of the future desired state $x_d(k+N)$ (MSp_e).

In order to obtain an optimal scanning strategy it is useful to describe the effect of one look at time k on the system uncertainty (ΔU). This is derived in Refs. 1 and 2 and given by

$$\Delta U(k) = tr[G_e(k-)N_e^{-1}(k)] \qquad (28)$$

with

$$G_e(k-) = H_eP_e(k-)Q(k)P_e(k-)H_e' \qquad (29)$$

look independent.

Now, indicating the look sequence with $\delta_j(k):\{0.1\}$ and writing for the observation noise covariance (Ref. 6)

$$V_{e_j}(k) = V_{e_{0_j}}(k)/\delta_j \qquad (30)$$

with V_{e_0} the noise level corresponding with 'full attention'. For eq (28) can be written (Ref. 1)

$$\Delta U(k) = \sum_{i=1}^{m+m_0} g_{e_{r_i}}(k-)\delta_i(k) \qquad (31)$$

with

$$g_{e_{r_i}}(k-) = g_{e_{ii}}(k-)[p_{e_{y_{ii}}}(k-) + V_{e_{o_i}}(k)]^{-1} \qquad (32)$$

and $p_{e_{y_{ii}}}$ a diagonal element of $H_eP_e(k-)H_e'$

Thus the maximum reduction in uncertainty is obtained for δ_j for which $g_{e_{r_i}}$ is maximal

This strategy can be implemented directly when the model is used in a (Monte Carlo) time simulation. In order to describe the process in (ensemble) statistical terms a statistical scanning strategy can be derived from eq (31) in terms of the probability of attending to observation i, P_i obtained from eq (31) by taking the expectation (over the ensemble) on both sides. Thus

$$E\{\Delta U(k)\} = \sum_{i=1}^{m+m_0} E\{g_{e_{r_i}}(k-)\} P_i(k) \qquad (33)$$

A "reasonable" (suboptimal) scanning strategy to optimize U is given by

$$P_i = E\{g_{e_{r_i}}\} / \sum_{i=1}^{m+m_0} E\{g_{e_{r_i}}\} \qquad (34)$$

resembling a first-order steepest descent gradient method to optimize U, and therefore J_N.

PERFORMANCE AND WORKLOAD MEASURES

For the present linearized, time-varying system with Gaussian inputs and outputs system performance can adequately be described in terms of the mean and covariance propagation (with time).

System performance is governed by the given disturbance input w and the control input (see eq (2)). The control input is composed of the regulator control u_r and the maneuver control u_m (see eq (23)). As the model is linear the effect of these two inputs on the system performance can be computed separately assuming that u_r and u_m are independent processes, implying that the observation process is uncorrelated for N time steps apart.
The resulting performance equations are derived in Ref. 8 and Ref. 2, respectively.

Furthermore, for many visual informational questions it is useful to establish the information contents of the visual cues (e.g. the effect of a given display, a navigation aid, visibility conditions, etc.). This can be investigated on the basis of the value of $E\{g_{e_{r_i}}\}$ indicating how system performance is improving by looking at observation i.

HO workload is described in terms of a workload model discussed in Refs. 9 and 10. This model involves the psychological notions 'attention' and 'arousal'. The model has been shown to correlate excellently with subjective ratings and psychological measurements in a variety of control tasks.

MODEL VALIDATION AND APPLICATIONS TO SHIP HANDLING

Model Validation

The MMS model has not been validated in total. That is the aim of an ongoing research program at MARIN (Maritime Research Institute Netherlands) of which the application of the model to the control of a ship entering an harbor is the first phase (this is discussed in the next section).

However, parts of the model have been supported extensively in previous studies (Refs. 4,9,10 and 11).

Comparison with real time simulation results

The model is applied to the manual control of a ship entering a harbor. The situation is visualized in Fig. 2.

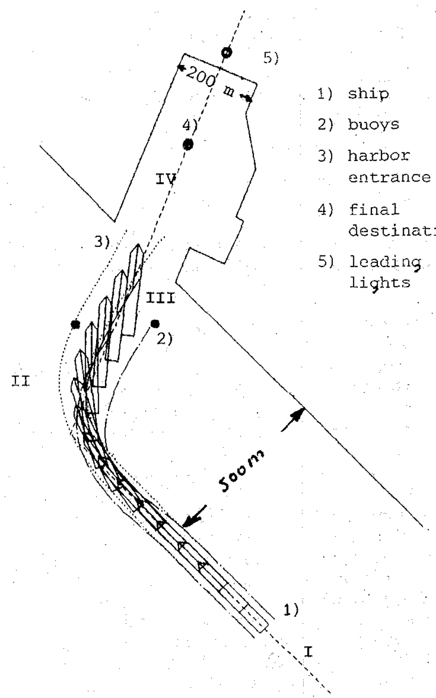

Fig. 2 Model predictions of ship control task

The ship is approaching the harbor with a velocity of 2.5 m/sec. (part I) on the basis of the coast line and the compass (heading).
At a given moment (corresponding with the position of the ship as indicated in the figure) a maneuver (part II) is initiated so as to pass the two buoys. The buoys provide the HO with heading information and, in principle, with track information on the basis of the inclination of the connection line between the buoys.
After the maneuver the harbor is entered (part III) based on the lateral deviation of the (292.5 deg) course line provided by leading lights at the end of the harbor and by the harbor entrance. The distance between the front and the rear light is 500 m and the heights of these lights are 19 m and 25 m, respectively. The visual cue used here is the bearing difference between the front light and the rear light which gives an indication of the lateral deviation of the centerline. Furthermore, the nominal heading is known and the actual heading is derived from the compass.
Finally, the terminal position (with zero velocity) has to be realized (part IV) based on the cues provided by the quay.

The ship is a coal carrier with a dead weight of 80.000 t (length of 235 m, width of 32 m and depth of 12 m). The disturbances which are simulated are a current of 1 m/s and variable wind. The harbor geometry and distances are indicated in the figure.

Model outputs are in terms of means and standard deviations of all system variables (the important ones are positions and heading). The effect of all navigational cues on system performance is also available in terms of a sensitivity parameter (see before). Finally a measure for the HO workload is provided by the model.

Model predictions are based on typical HO parameters. For specifics the reader is referred to Ref. 13, containing also a description of the control task in terms of the cost functional weightings.
The results shown in Fig. 2 pertain to the first two phases of the task (for a complete presentation of the results see Ref. 13) and are in terms of ship position and heading. In addition, a 99% probability interval is shown of the bow and stern of the ship. It will be clear from the figure that the probability of hitting the buoys is about one percent which is operationally unacceptable. This is partly due to the strong current for which the navigator has to compensate with a relatively large heading angle. So the model predicts that the task is difficult to perform at an acceptable level.

The experimental results of a simulation program are shown in Fig. 3. The results are averages of 12 simulation runs. Also the experimental runs show an average trajectory very similar to the model prediction. The variability in terms of the 99% probability interval of the bow and stern of the ship is close to (just a little bit larger than) the predicted performance confirming the poor task performance predicted by the model.
So this preliminary comparison between the model and experimental results show that the model is capable to predict adequately the complex navigation task performance.

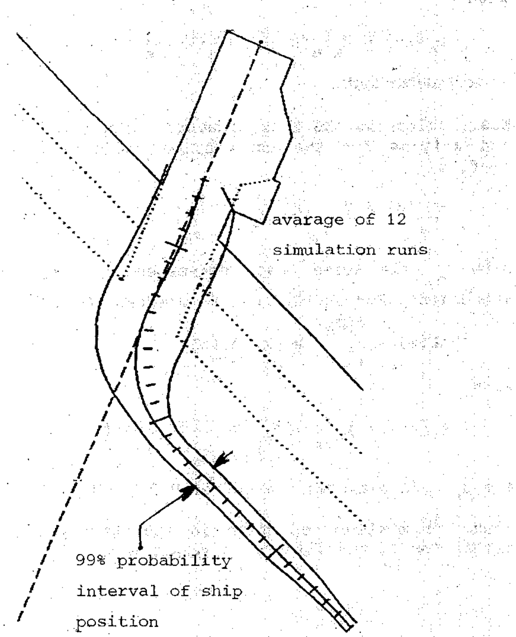

Fig. 3. Experimental results ship control task

Effects of aids to navigation

The model enables the investigation of the influence of aids to navigation on maneuvering performance. This is especially important in port design studies which are aimed at finding the minimum required dimensions of fairways. Since a trade-off exists between the required fairway dimensions and the accuracy of position information systems considerable savings on dredging costs can be achieved by improvement of position information. An example is shown in figure 4 in which two straight approach maneuvers are compared in the same port configuration as in the previous example. One maneuver is carried out by using the buoys for position information. The other maneuver is carried out by using the leading lights providing the lateral deviation of the course line, as indicated before. Again, the forward speed (through the water) of the ship is 2.5 m/s and the current velocity is 1 m/s in a direction parallel to the coast line. The heading associated with the equilibrium, correcting for the current, is a course of about 270 deg.

In figure 4 the (outer) solid lines along the track indicate the 99% probability interval for the maneuvers in which only use was made of the buoys and the compass to control the vessel. The (inner) dotted lines indicate the 99% probability for the maneuvers in which the leading lights were used in combination with the compass.
A comparison of the results shows a better performance, and hence less required maneuvering space, in the condition with leading line information. The explanation is that, in that case, the accurate position information substantially reduces the approach variability.

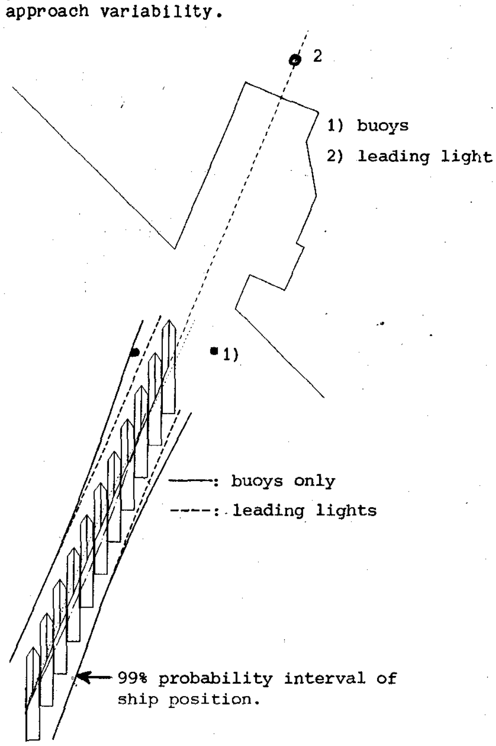

Fig. 4. Effect of aids to navigation on a straight approach.

CONCLUDING REMARKS

This paper describes the most important aspects of a model of the human controlling a dynamic system. The main new feature of the MMS 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 the visual scene, including a model for visual scanning.

The second part of the paper deals with an application of the MMS model to ship handling.
The model results and a comparison with experimental results show the predictive capability and the usefulness of the MMS model in describing and analyzing complex ship control tasks.

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