MODEL OF LARGE SCALE MAN-MACHINE SYSTEMS WITH AN APPLICATION TO VESSEL TRAFFIC CONTROL

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ABSTRACT

This paper deals with models of large scale man-machine systems. In general this implies a multi-function, multicrew process, implying interrelated subsystems. In the paper it is assumed that only the subsystems are interrelated.
For this reason human operators have to estimate the state of their own subsystem and of all pertinent other subsystems, and the relationships between them. This nonlinear filter problem is solved by means of linearized and extended Kalman filters. Based on these estimates, human operators control their own subsystem and decide and react to avoid unacceptable subsystem interference.

The model is applied to the concrete problem of vessel traffic control. This implies a number of ships in a confined area. The navigation of each ship is based on a planned route. In addition, collision avoidance is modeled. This involves perception, (non-linear) estimation, decision making and standardized control. Also the supervising role of a vessel traffic service is considered.

It is anticipated that the model structure is sufficiently general to be used for many complex large scale man-machine systems such as vessel (air, road) traffic and process control systems.

MODELING LARGE SCALE MAN-MACHINE SYSTEMS

The complexity of manned large scale systems requires a systematic approach to describe the components of the total system and their mutual interaction. In this paper, mathematical models are discussed to deal with complex large scale dynamic man-machine systems such as (vessel, air, road) traffic systems and process control systems.
Typically this implies a multifunction, multicrew process, comprising (many) interrelated subsystems.

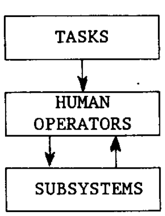

Fig. 1 Large scale system components

The interaction between these system components: tasks, human operators and subsystems, is summarized in Fig. 1.

Different tasks can be performed by different human operators, being related to different subsystems. Furthermore, subsystems can be more or less coupled and there can be more or less interaction and communication between human operators.

In this paper, a model approach is discussed to describe the components of large scale man-machine systems. Basically, only the interaction between sub-systems is considered. Both random system disturb-ances and human randomness is included. The task considered is to control the (sub)system to follow a desired state, involving perception, information processing, decision making and controlling. The result is a stochastic, nonlinear, estimation and control problem.
In the following, the system components an discussed in more detail. An accompanying block diagram of these components and their interrelationships is presented in Fig. 2.

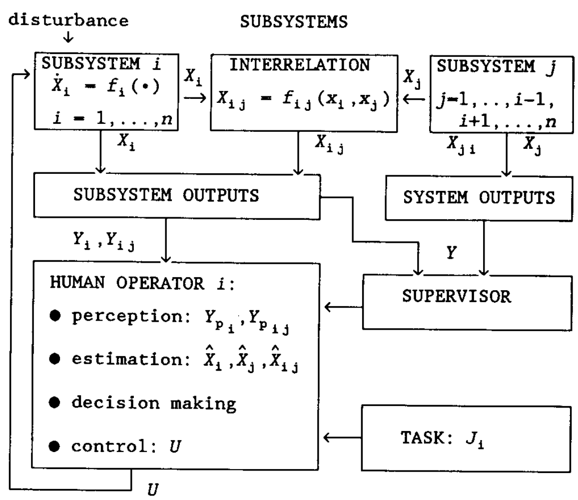

Fig. 2 Block diagram large scale man-machine system

Subsystems

In general, the (N) subsystems are assumed to be nonlinear and can be described by a nonlinear system model

$$\dot{X}(t) = f(X(t),U(t),W(t),t) \quad (1a)$$

$$Y(t) = g(X(t),U(t),t) \quad (1b)$$

with state $X \in \mathbb{R}^n$, control $U \in \mathbb{R}^k$, system output $Y \in \mathbb{R}^m$ and $W \in \mathbb{R}^\ell$ represents a Gaussian white noise process with power spectral density matrix $W(t)$.
Formally, this model cannot be developed within the traditional framework of stochastic calculus because the right side of eq (1a) is not (mean square Riemann) integrable. Two approaches can be followed to circumvent this problem.
One approach is to formulate the model and the nonlinear filter problem in the context of Itô calculus, treating white noise as a time derivate of an Brownian motion process and providing the mathematically correct rules for integrating eq. (1a). This formal approach is followed in Ref. 1. Another, engineering, approach is discussed in Ref. 2, considering W as a bandlimited (nonwhite) process having a bounded mean squared value.

The extent to which the subsystems are dynamically interrelated is determined by the vector function f. In case one, or more, of the subsystems (i) is independent of the others, the subsystem model is given by

$$\dot{X}_i(t) = f_i(X_i(t),U_i(t),W_i(t),t) \quad (2a)$$

$$Y_i(t) = g_i(X_i(t),U_i(t),t) \quad (2b)$$

with $X_i \in \mathbb{R}^{n_i}$, such that $n = \sum_{i=1}^{N} n_i$, and $Y_i \in \mathbb{R}^{m_i}$.
This will be the case for the vessel traffic application where the subsystems represent a number of ships, which are assumed to be hydrodynamically uncoupled.

Task

Consider the task of controlling the total system state X of eq. (1a) over some fixed interval of time $[0,T]$, so as to follow the desired system state X_d, by realizing a control history $\{U(t), t \in [0,T]\}$ that minimizes the cost functional

$$J(U) = E\{\left((X(T)-X_d(T)\right)'Q_x(T)\left(X(T)-X_d(T)\right) + \int_0^T \left[\left(X(t)-X_d(t)\right)'Q_x(t)\left(X(t)-X_d(t)\right) + U'(t)Q_u(t)U(t)\right]dt\} \quad (3)$$

where Q_x and Q_u are weighting matrices.
In general, subsystems can be more or less dynamically coupled (e.q. a ship with tug boats). At the other hand, certain controls may affect only certain subsystem states and human operators may have different performance measures. This can result in a complex decentralized control problem, which is not addressed in this paper. In case the subsystems are uncoupled, like in the following vessel traffic process, the task can be split up in N separate control tasks, defined by J_i. (corresponding with eq. (2a)), with

$$J = \sum_{i=1}^{N} J_i \quad (4)$$

Human operators

In the paper, the human operator (*HO*) is assumed to be involved in perception, attention allocation, and information processing, to control the process as specified in eq. (3). In this context control has a broad mean, involving planning, sequential decision making and compensation for unpredictable affects.

Perception

It is assumed that the *HO* derives information about the subsystems from instruments, the outside world and personal communication. This is described by the vector function g. To allow for intermittent observations, perception is decribed in discrete time. The system outputs are perceived with a given inaccuracy

$$Y_p(t_k) = Y(t_k) + V(t_k) \quad (5)$$

with $V(t_k)$ a linear independent, Gaussian, white noise observation process with power spectral density matrix V that is dependent on the output magnitude, perceptual threshold and *HO* attention (Refs. 3 and 4). Observations that are only related to subsystem i (see eq. (2b)) are given by

$$Y_{p_i}(t_k) = Y_i(t_k) + V_i(t_k) \quad (6)$$

In eqs. (5) and (6) it is assumed that the *HO*'s internal time delays associated with perceptual, central processing, neuromotor pathways and communication and transport delays are negigibly small compared with the process time constants. Otherwise, a pure time delay can be assumed in eqs. (5) and (6), for which delay the *HO* has to compensate to obtain an estimate of the present state.

Estimation

Based on the perceived information the *HO*'s have to make an estimate of (part of) the system state. One extreme is that each *HO* has to estimate only his subsystem state X_i, in other words the estimation process is uncoupled and the coupling is only in terms of the control task.
In general, however, each *HO* will have to estimate not only his own subsystem state X_i but also (certain, say N_{ir} relevant) other subsystems X_j. In addition, it is assumed that *HO*'s make decisions based on given interactions between subsystems. The (n_{ij}) relationships between subsystem i and j will be indicated with X_{ij} and will have to be estimated because X_{ij} is a stochastic process, related to X_i and X_j.

The reason for distinguishing between the estimation of X_i, X_j and X_{ij} is that each category is typified by different conditions, which require different procedures to describe the nonlinear estimation process.

More specifically, it is assumed that the *HO* knows the nominal state (or 'setpoint') of his own subsystem. Thus, the estimation of the nonlinear subsystem X_i can be described in terms of Kalman filter of the linearized system model (around the system reference). For this purpose, the standard procedure is followed to describe the nonlinear system behavior X_i in terms of a state reference X_{0_i} and a 'small' pertubation x_i around this reference; thus $X_i = X_{0_i} + x_i$, $U_i = U_{0_i} + u_i$, etc. This linearization scheme yields a time-varying reference model (assumed to be known to the *HO*) and a time-varying linear system model given by

$$\dot{x}_i(t) = A_i x_i(t) + B_i u_i(t) + E_i w_i(t) \tag{7a}$$

$$y_i(t_k) = C_i x_i(t_k) \tag{7b}$$

where $A_i = A_i(X_{0_i}(t),t) = \frac{\partial f_i}{\partial X_i}\Big|_{X_{0_i},U_{0_i},W_{0_i}}$, being the Jacobian matrix of f_i with respect to X_i, is the state transition matrix, etc. and w_i, is assumed to be an independent Gaussian white noise process with power spectral density matrix W_i.

For the (standard) filter equations the reader is referred to (e.q.) Ref. 2. The result, which is based on the assumption that the *HO* knows the system dynamics, the control u_i and the noise covariances W_i and V_i, is an estimate of X_i given by $\hat{X}_i = X_{0_i} + \hat{x}_i$.

The estimation of the (other) subsystems X_j can not be treated in a similar way if it is assumed that the *HO* of subsystem *i* does not know the nominal behavior of subsystem *j*. In other words, it is not possible to specify a reference state and follow the foregoing linearization scheme. In addition, the *HO* generally does not know the other subsystem inputs U_j. Furthermore, the assumption is that HO_i can perceive quantities Y_{ij} that are related to both his own subsystem *i* and X_j, thus

$$Y_{ij}(t_k) = g_{ij}\left(X_i(t_k), X_j(t_k), U_i(t_k), t_k\right) \tag{8}$$

There are many approaches to solve this general nonlinear filtering problem, all involving approximations of the optimal nonlinear filter. Moreover, there does not seem to be a straightforward way to make a theoretical comparison of the estimation qualities of the various nonlinear filter techniques. For this reason, in this paper a minimum variance estimation procedure is followed, corresponding with the conditional mean (Ref. 2). A maximum - likelihood estimator could be considered, because the nonlinear system is generally not Gaussian, but the resulting optimal nonlinear filter will have to be approximated leading to similar results as obtained with the minimum variance procedure (Ref. 5).

This procedure is based on the same linearization scheme as discussed before about some reference solution, for which the previous state estimate is being used. The state estimate is updated by adding the estimated state deviation to the previous state estimate, etc. The resulting filter equations, which are given in (e.q.) Refs. 2), are indicated with the extended Kalman filter.

There are several ways to adapt for the unknown control inputs U_j. One can increase the system disturbance covariance so as to increase the filter gain and emphasize the measurements, one can estimate U_j, or one can do both (Refs. 1 and 6).

The quality of the filter (convergence, accuracy, etc.), which is neither linear nor optimal, depends (among others) an the initial state estimate. This feature is conceptually similar to how *HO*'s function: more a priori uncertainty requires more time to obtain an accurate estimate.

The third category of estimates concerns the variables X_{ij} that describe the interactions between subsystems. These variables are given by

$$X_{ij}(t) = f_{ij}(X_i(t), X_j(t)) \tag{9}$$

These nonlinear relationships imply a non-Gaussian probability distribution of X_{ij}. Instead of trying to find (approximated) filter equations based on this conditional probability distribution, in this paper the approach is taken to derive stochastic differential equations for X_{ij} and to obtain a minimum variance estimate of X_{ij} in terms of an extended Kalman filter. This is the same approach as taken for the estimation of other subsystems (X_j) as, again, no state reference can be specified a priori. Thus, an initial estimate of X_{ij} is used to obtain a linearized model yielding a revised estimate, etc.

In summary, the resulting filter model consists of

$$n_t = n + \sum_{i=1}^{N} \sum_{\substack{j=1 \\ j\neq i}}^{N_{ir}} n_{ij}$$

stochastic differential equations of $X_t = \text{col}\,(X, X_{ij})$, with, possibly $N_{ir} \ll N$.

Control and decision making

It is assumed in this paper that the *HO* controls his own subsystem given by eq (2) by minimizing J_i, similar to eq (3). This represents a standard stochastic *LQG*-control problem. The solution is contained in many references (e.g. Ref. 7).

The resulting control is composed of two parts: a feedforward (open loop) control U_m operating on the desired state X_d, computed recursively backwards in time, and a feedback control U_r utilizing the estimated state.

In case X_d is relatively constant, one can consider to describe the control process on the basis of the steady-state solution. This amounts to only the (now stationary) feedback control U_r.

In case the desired state X_d is not known to the *HO*, X_d has to be estimated also. This amounts to the binary decision as to whether the system behaves according to the small perturbation model of eq. (7), corresponding to a given state reference, or a systematic discrepancy between both necessitates a correcting action of the *HO* and an update of the system model. In the first case, the *HO* continues to control the system (e.g.) steady-state. In the second

case the *HO* initiates another maneuver to track the systematic deviation X_d over some fixed interval of time, after which the *HO* updates his system model, being involved in a new decision cycle.
This finite time control case with unknown X_d is addressed in Ref. 4.

Finally, it is assumed that decisions are made based on subsystem interactions described by X_{ij}.
Many decisions can be formulated in terms of a (multiple) comparison of X_{ij} with a reference ("if X_{ij} exceeds a given value, then ...").
As the probability distribution of X_{ij} is generally unknown and non-Gaussian, it is not possible to construct a likelihood ratio test. However, a reasonable approach to mimic (describe) *HO* behavior is to test realistic (i.e. estimated) values of X_{ij} against corresponding thresholds. These threshold values are now model parameters, which may be selected based on task considerations.
Both *HO*'s of subsystems and central (supervising) services (e.g. a traffic service) may be involved in this type of decisions. Examples of possible subsequent actions are given in the second part of this paper.

A MODEL OF VESSEL TRAFFIC CONTROL

Background

The foregoing general model structure is applied to the concrete problem of vessel traffic control. This implies a number of ships, with a given destination, in a given confined area.
The navigation of each ship is based on a planned route, which is updated via information of the visual scene (containing aids to navigation), instruments and the vessel traffic services (VTS). Important disturbances are current and wind.

Normal operation amounts to tracking the planned route. Abnormal operation involves the detection of a possible conflict, i.e. a collision or grounding, and the subsequent actions taken by the ship(s) involved, i.e. the collision avoidance maneuvers. Both the collision situations and the standard avoidance maneuvers are strongly determined by procedures and rules.
This collision risk is recognized on board but also the VTS is considered in it's (possible) role of monitor, conflict detector and advisor of the total vessel traffic system.

The ultimate criteria of the traffic process are safety and economy. Derived measures for these are collision risks (probabilities) and traffic flows, which are related to (among others) the following aspects: ship dynamics, on board navigation instruments, *HO* functioning, visibility conditions, navigational aids, environmental conditions, number of ships and their planned route, traffic area, procedures and rules, information available to the VTS, role of the VTS.

A model of the vessel traffic process, which is presented in the following, must contribute to answering questions related to: safety, in terms of statistical measures of relative ship positions, the effect of *HO* functioning on safety, necessary information to perform the tasks (by the crews of the ships and the VTS), communication between ships and VTS, optimization of procedures, automation issues of the total vessel traffic process, etc.

Ship control

The nonlinear ship dynamics can be represented in a simplified form assuming no drift (lateral ship velocity) yet decribing the main response characteristics (Ref. 8). Referring to eq. (2a), the resulting vectors and matrices are (dropping for the moment the subscript *i* indicating ship *i* and the index *t* indicating the time-dependance)

$$X = \mathrm{col}(U,R,\Psi,X,Y)$$

$$U = \mathrm{col}(\Delta U_c,\delta)$$

$$W = \mathrm{col}(W_1,W_2) \qquad (10)$$

$$f = \begin{bmatrix} aU & + b\Delta U_s & \\ -\frac{1}{T}R & + \frac{K}{T}\delta & \\ R & & \\ U\cos\Psi & & + W_1 + \dot{X}_s \\ U\sin\Psi & & + W_2 + \dot{Y}_s \end{bmatrix}$$

where U is the longitudinal speed relative to the water, R is the rate of turn, Ψ is the heading, X and Y are the earth-fixed coördinates, ΔU_c is the commanded speed change, δ is the rudder angle, $W_{1,2}$ represent the random system disturbances, and $\dot{X}_s$ and $\dot{Y}_s$ represent the current components.

It is assumed that the navigator may observe variables provided by instruments (radar, compass, log, etc.) and by the visual scene (buoys, leading lights conspicuous points, distance a_{ij} and direction φ_{ij} of an other ship, etc.).
These observations are perceived with a given inaccuracy as described by eqs (5) and (6).

Based on these perceived data the *HO* estimates his own ship related state ($\hat{X}_i$) in order to track his planned route as indicated before. In addition, the state of other neighbouring ships are estimated ($\hat{X}_j$) and the variables that are involved in the collision avoidance process ($\hat{X}_{ij}$). In order to describe this complex nonlinear estimation process, the minimum variance estimation procedure, as described before, is followed resulting in an extended Kalman filter.

These estimates ($\hat{X}_j$ and $\hat{X}_{ij}$) are used to decide about the possibility of a collision, hazard or grounding. Such a situation is simply indicated with collision avoidance and will be discussed in the next section.

Collision avoidance

During navigation in congested waters, a principal task of the navigator is to avoid collisions with other ships or fixed objects. For this purpose, the *HO* has to observe his environment in order to recognize in time the occurrence of an encounter with

(e.g.) an other ship. In this context, encounter is defined as a risky situation requiring an action of (one of) the navigators involved.
Based on the 'Rules of the Road' of the International Maritime Organisation (Ref. 9) and referring to Ref. 10, the encounter situation and the required collision avoidence can be structured in the following way.

An encounter is defined as the situation in which all following variables are smaller than a reference value:

1. The distance a_{ij} between ship i and ship j.
2. The closest point of approach (CPA) c_{ij}. This is defined as the distance between the vector of the relative velocity (between the ships) and ship i.
3. The time T_{ij} to reach the closest point of approach.

The mathematical relationships between these variables and the state of the ships involved are derived in Ref. 1 and clarified in Fig. 3.

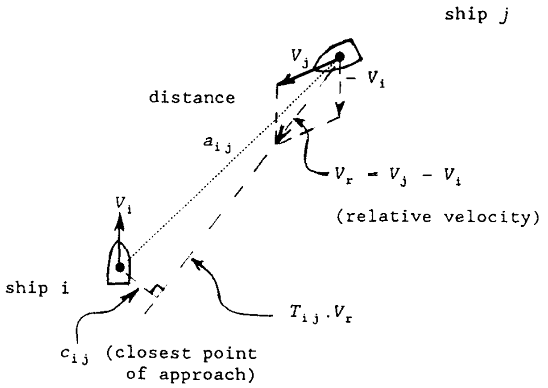

Fig. 3 Geometry of an encounter

The result is presented in the form of eq. (9)

$$X_{ij} = \mathrm{col}(a_{ij}, c_{ij}, T_{ij}) \tag{11a}$$

$$f_{ij} = \begin{bmatrix} ((X_j - X_i)^2 + (Y_j - Y_i)^2)^{1/2} \\ \dfrac{(U_j \cos\Psi_j - U_i \cos\Psi_i)(Y_j - Y_i) - (U_j \sin\Psi_j - U_i \sin\Psi_i)(X_j - X_i)}{(U_j^2 + U_i^2 - 2U_j U_i \cos(\Psi_j - \Psi_i))^{1/2}} \\ \dfrac{(U_j \cos\Psi_j - U_i \cos\Psi_i)(X_j - X_i) - (U_j \sin\Psi_j - U_i \sin\Psi_i)(Y_j - Y_i)}{U_j^2 + U_i^2 - 2U_j U_i \cos(\Psi_j - \Psi_i)} \end{bmatrix} \tag{11b}$$

So we have an encounter, if all elements of X_{ij} are smaller than the corresponding elements of the criterion $X_{c_{ij}}$.

Three types of encounters can be distinguished, each requiring a specific avoidance action:

1. **meeting**; both ships are burdened (to make an evasive maneuver to starboard, corresponding with a given lateral displacement);

2. **overtaking**; the overtaking ship is burdened (to realize a given lateral displacement), the other ship is privileged (having right of way, maintaining course and speed);

3. **crossing**; the starboard ship is privileged, the port ship is burdened. If possible, the evasive maneuver is towards starboard otherwise a port maneuver must be made. The maneuver corresponds to a given heading change and a given lateral displacement.

The precise classification is depending on the relative positions and orientations of both ships. For details the reader is referred to Refs. 1 and 10. Although both the encounter situation and the appropriate response may involve more than two ships, it is assumed in this paper that a collision avoidance situation can be described as an encounter of two ships (i and j) at the time. The situation that more than two ships are involved is considered as a sequence of encounters between two ships. Discussions with nautical experts support such an approach.

The navigator is assumed to decide about the occurrence of an ecounter by comparing X_{ij} with $X_{c_{ij}}$. However, because X_{ij} is a stochastic process, he is using an estimate of X_{ij}. This estimate is compared with the criterion value $X_{c_{ij}}$. If all elements of X_{ij} are smaller than the corresponding criterion value the decision D_1 is made, followed by an action if ship i is burdened. Thus

$$\hat{X}_{ij} \underset{D_1}{\overset{D_0}{\gtrless}} X_{c_{ij}} \tag{12}$$

The evasive maneuver is characterized by a given lateral displacement and a given (specified or reasonable) heading change. This standard maneuver is uniquely realized by a bang-bang control sequence with a given maximum rudder angle. The switching times are determinded by the (linearized) ship dynamics. For details the reader is referred to Ref. 1. It is assumed that the evasive maneuver is followed by a symmetric maneuver to resume the originally planned route.

Vessel traffic services

In congested areas (rivers, ports, etc.) a VTS can be helpful to minimize the risk of collisions. Although presently a VTS normally plays only an advisory role (only after the occurrence of an accident a VTS can give commands) it's role may change in the future, comparable to the air traffic control development. At any rate, it will be useful to guide and support such a development with a model of vessel traffic control, in which the role of the VTS may include monitoring and conflict detecting to advise or command the total vessel traffic system.

The simplest way to model a VTS is to assume that the navigator receives given (extra) observations (from the VTS). These observations will affect the estimation process and, therefore, the traffic process. Any communication uncertainty can be accounted for in terms of the observation noise level.
A more advanced role of the VTS can be modelled by assuming that the VTS will have the information to make an estimate of the total vessel traffic process and use this to detect any conflict. Based on this the VTS can feedback any advise or command to the navigator(s). It can be assumed that this feedback is taken into account with a given time delay. This approach will increase the model complexity considerably (not conceptually, as the same model elements as before will be involved).

CONCLUDING REMARKS

In this paper, mathematical models are discussed to deal with complex large scale man-machine systems, such as vessel (air, road) traffic and process control systems. Only interrelationships between subsystems are assumed. Each subsystem is controlled by a corresponding *HO*. Because of the interaction between subsystems, the *HO* has to estimate the state of all (relevant) subsystems and the relationships between them, based on which he can decide and react. This nonlinear filter problem is solved by means of both a linearized Kalman filter and an extended Kalman filter (in case state references are unknown and have to be estimated).

The general model structure is applied to the concrete problem of vessel traffic control. Apart from the control of each ship, this involves collision avoidance between ships. Also a vessel traffic service is considered in the role of supervising and conflict detection.

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