MODELING HUMAN OPERATOR INVOLVEMENT IN ROBOTIC SYSTEMS

P.H. Wewerinke
Department of Applied Mathematics, Systems and Control Group
and Mechatronics Research Centre Twente,
University of Twente
P.O. Box 217, 7500 AE Enschede,
The Netherlands

Abstract — In this paper a modelling approach is presented to describe complex manned robotic systems. The robotic system is modelled as a (highly) nonlinear, possibly time-varying dynamic system including any time delays in terms of optimal estimation-, control- and decision theory. The role of the human operator(s) is modelled varying from supervisor of the automated (part of the) system to controller in terms of the various functions involved to perform goal-oriented tasks.

It may be expected that the model is capable of answering questions related to reliability and efficiency, design alternatives, function allocation, automation, etc.

1. INTRODUCTION

Robotic systems are more and more applied in many areas. Examples of industrial operations are part assembly, material transfer, repair of parts and inspections. In addition, robotic systems play an important role in many teleoperations, e.g. in space applications (space stations, serviceable sattelites, material processing platforms) and operations in a risky or unaccessible environment.

Autonomous systems can meet the safety, reliability and especially economic requirements for specified tasks, but many operations involve the interacting contribution of both human operator(s) and robotic system(s). This concerns especially complex, non-standard operations in an unstructured environment. One example is shared compliant control, especially in applications with tele-manipulators where time delays are considerable.
The role of the human operator(s) may vary from direct controller to supervisor of the automated (part of the) system. This depends on the goals to be achieved and the related functions to be fulfilled.

In the next section manned robotic systems are discussed in more specific terms. One approach to design and analyze a manned robotic system is based on mathematical models of this complex man-machine system. This is contained in section 3. The paper is concluded with some remarks about how the model can be utilized.

2. MANNED ROBOTIC SYSTEMS

In general the task to be performed with a manned robotic system can be described in terms of the various components involved. This is indicated in the block diagram of Fig. 2.1.

The first important aspect of the task are the goals to be achieved under given boundary conditions. Realistic operations may involve a complex goal hierarchy (interrelated, or even conflicting goals, subgoals, procedures, etc.). These goals dictate the tasks to be performed. The complexity of the task hierarchy will correspond with the complexity of the goal hierarchy. The defined task will be affected by the operational environment.
Next, the functions can be derived to perform the defined task. The motives to fulfill these functions originate from the goals to be achieved. The human operator (HO) will perform these functions utilizing the available resourses, being separate items or elements of the system.

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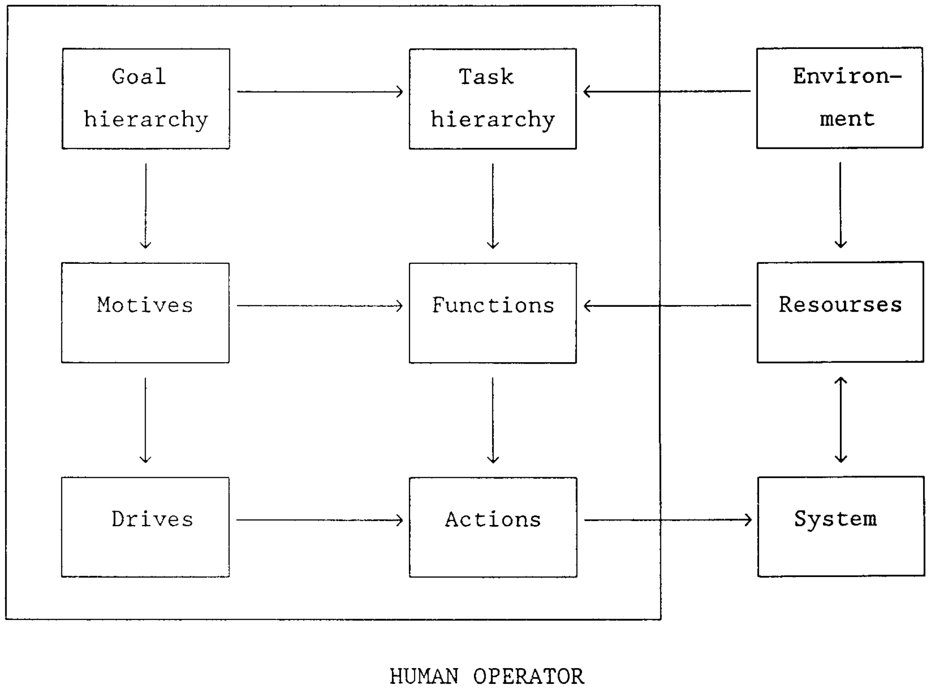

Fig.2.1 Manned robotic system components

These functions are the result of a function allocation procedure to the man and the machine, taking into account the human capabilities and limitations and the possibilities of the system.

Finally, the result of HO functions are actions, taken on the basis of drives (derived from his motives, etc.). Simple stimulus response behavior takes place at this level only. The actions affect the system resulting in a certain system behavior. Based on performance criteria and measures of this behavior, total system behavior can be evaluated with respect to the goals to be achieved.

More specifically, a manned robotic system can be analyzed or designed based on the assumption that a goal-oriented operation can be defined, e.g. controlling the robot from A to B, with given constraints (due to robot dynamics, control limits, environment, etc.) in a given (disturbance) environment. Furthermore, the robotic system is described as a (highly) nonlinear, possibly time-varying dynamic system including any transport or communication time delays.
The role of the HO may vary from supervisor of the automated (part of the) system to controller, or combinations. This involves HO functions such as perception of sytem outputs provided by (e.g.) displays and /or the visual scene, information processing to assess the task- and system variables of interest, decision making involved in monitoring the autonomous (sub)system and involved in intermittent control, and control. In this context, control is used in a broad sense including planning and compensatory actions.

There are various ways to analyze a manned robotic system.
One approach utilizes a variety of system

performance and HO measures obtained in an experimental situation. The drawback of an experimental approach is that it involves per se comlex man-in-the-loop simulation. This implies that experiments mainly serve to verify system performance rather than to predict the performance of new systems. This limits their utility, especially early in the design stage.

An alternative method to describe manned robotic system behavior is the use of mathematical models. The main advantage of mathematical models is that they provide a precise (quantitative) formulation of task aspects such as goals and system dymanics and basic concepts of HO functioning. Therefore, models potentially have a predictive capability, rendering a basis for selecting design alternatives. Furthermore, models provide a powerful tool to analyze operational problems of existing robotic systems systematically.

In the next section a model structure is presented describing the foregoing manned robotic system.

3. MODEL STRUCTURE

3.1 General

In this section a model of the manned robotic systems discussed in section 2 is presented. For details the reader is referred to Ref.1. Basically, the task considered is to control the robotic system from an initial state X_0 at time $k = 0$ to a final state X_n at time $k = N$ following a given desired trajectory $X_d(k)$.

As indicated before, the role of the HO may vary from supervisor of the automated (part of the) robotic system to controller. In this paper the manual control task will be assumed. The human functions involved include supervising. So the supervisor task is a special case of the manual control task. This will be discussed in the following.

The following elements are included in the model as indicated in the block diagram of the manned robotic system model shown in Fig. 3.1. The HO perceives (e.g. via a TV-camera/monitor system) the outputs of the system state (characteristic system variables such as position, velocity, attitude, etc.), which is perturbed by external disturbances. The HO utilizes these (inaccurate) observations of the state to estimate the state recursively. Based on this estimate and the task specifications a control input is selected and executed, resulting in a closed loop manual control.

In addition, the future desired state is observed (e.g. from pictorial information) and estimated. Based on this estimate and the system dynamics a pre-programmed control is selected. The resulting open

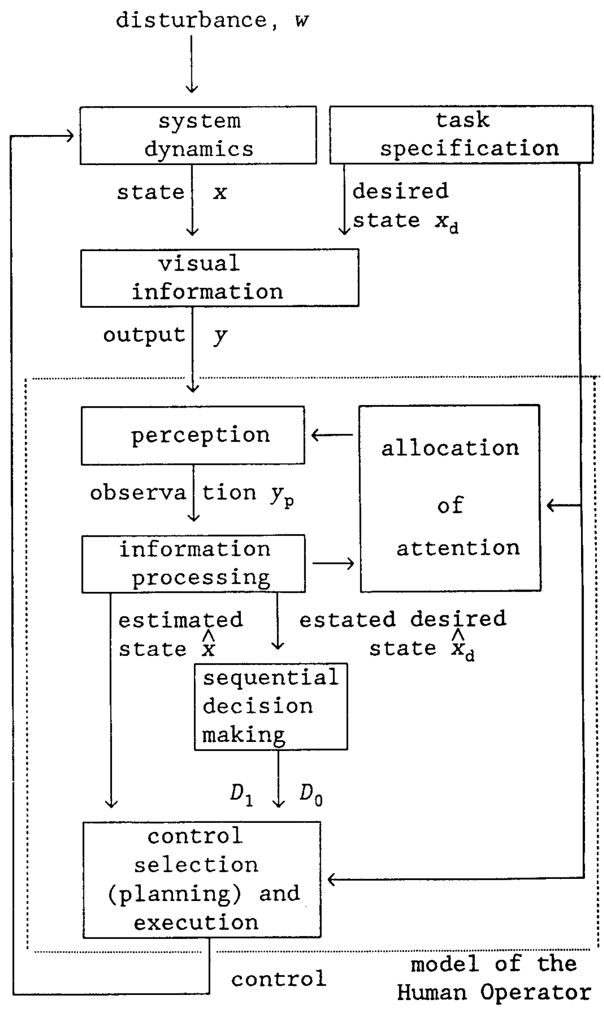

Fig. 3.1 Block diagram of the Manned Robotic System model

loop control is combined with the feedback control to compensate for deviations from the planned trajectory due to random disturbances.

3.2 System dynamics

A robotic system may be represented as a nonlinear, time-varying dynamic system. The standard procedure is followed to describe the nonlinear system behavior X in terms of a state reference X_0 and a "small" perturbation x around this reference; thus $X = X_0 + x$, outputs $Y = Y_0 + y$, etc. This linearization scheme yields a time varying reference model and a time-varying **linear** system description

$$x(k) = \Phi x(k-1) + \Psi u(k-1) + \Gamma w(k-1) \tag{1a}$$

$$y(k) = Hx(k) \tag{1b}$$

with $\Phi = \Phi(k,k-1)$ being the state transition matrix, etc.; u is the control and w is assumed to be a zero mean, Gaussian, purely random sequence, with covariance matrix R, representing disturbances and other system uncertainty.

This linearization scheme holds for relatively small x, u and w. This fact dictates the update rate of the reference and, therefore, of the various system matrices.

3.3 Control task

The task considered is to control the system state x of eq (3a) over some fixed interval of time $[0,N]$, so as to follow the desired state x_d, by realizing a control sequence $\{u(k),\ k = 0,1,\ldots,N-1\}$ that minimizes the performance index

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

$$+ u'(i-1)Q_u(i-1)u(i-1)\} \tag{2}$$

where Q_x and Q_u are weighting matrices.
The solution of this optimal control problem is discussed in the following subsection dealing with human control behavior.

3.4 Human observer and controller

The model of the HO comprises various functional aspects, which are shown in the block diagram of Fig. 3.1.

Perception

The perceptual model describes how the system outputs y are related to the perceived variables y_p. It is assumed that the HO perceives these system outputs with a certain inaccuracy and with a certain time delay

$$y_p(k) = y(k-i) + v(k-i) \tag{3}$$

Here v is an independent, Gaussian, purely random observation noise sequence, representing the various sourses of human randomness (unpredictable in other than a statistical sense). Each element v_j, therefore, is specified by its covariance V_j. This covariance is functionally related to the signal level, human attention allocation and threshold phenomena.
The lumped time delay i can be associated with the HO's internal time delays related to perceptual, central processing, and neuromotor pathways. For systems with relatively large time constants, these delays can be neglected. Also system-related delays, for instance the communication or transport delays of remotely controlled systems may be modelled as a lumped equivalent "perceptual" time delay involved in eq(3).

Information processing

Based on the perceived data y_p up to time k (corresponding to data y up to $k-i$) and the known (learned, thus assuming that the HO is well-trained) dynamics of the system, the best (minimum variance) estimate $\hat{x}$ of the system state x can be made corresponding to time $k - i$. The resulting Kalman-Bucy filter equations are given in Ref. 1.

The best estimate of x at time k, $\hat{x}(k)$, is obtained on the basis of $\hat{x}(k-i)$ and the known system dynamics by means of an optimal linear prediction process. The resulting prediction equation becomes

$$\hat{x}(k/k-i) = \Phi^i\hat{x}(k-i) + \sum_{\ell=0}^{i-1}\Phi^{i-1-\ell}\Psi u(k-i+\ell) \qquad (4)$$

Perception and estimation of the future desired state x_d is described in a similar way. It is assumed that visual cues y_0 can be observed that are related to the difference between the present state and the future desired state. Estimation of the future desired state is depending on the assumed a priori knowledge that the HO may have about x_d.

Sequential decision making

After the finite time interval for which the control task defined in subsection 3.3 has been performed, the decision has to be made about what to do next. This amounts to the binary decision as to whether the system behaves according to the small perturbation model of eq(1), 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 this system 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.
It might be necessary to update the sytem model more often. The extreme is to update the system model each time step. The reference is adjusted based on the estimated state (deviation from the old reference). This is known as the extended Kalman filter.

The comparison of system behavior as observed by the HO in terms of y_0 and the expected behavior on the basis of the present system model is made by the HO in terms of the innovation sequence n_0 (the difference between the observed and the estimated variables.). A systematic deviation of the zero mean 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. 1).
This can be tested by comparing (the log of) a generalized likelihood ratio with a threshold T according to

$$L(k) \underset{D_0}{\overset{D_1}{\gtrless}} T \qquad (5)$$

with

$$L(k) = L(k-1) + \frac{1}{2}\,\tilde{n}_0'(k)N_0^{-1}(k)\tilde{n}_0(k) \qquad (6)$$

and

$$T = \ell n((1-P_M)/P_F) \qquad (7)$$

where $\tilde{n}_0$ is a moving average of n_0, N_0 is the covariance of n_0 and P_M and P_F are the decision error probabilities ("miss" and "false alarm").

Human control behavior

The control task discussed in subsection 3.3 is defined in terms of $J_N(u)$ of eq(2). Optimal human control corresponds to the minimal J_N. The resulting optimal control sequence $\{u(k),\ k = 0,1,\ldots,N-1\}$ is derived in Ref. 1. The resulting control is composed of two parts: a feedback control operating on the state estimate and a feedforward (open loop) control operating on the estimate of the desired state x_d and computed recursively backwards in time.

3.5 Constraints

So far, the estimation and control problem of the nonlinear system is solved by linearizing the nonlinear system around an estimated reference yielding a linear estimation and control problem. Control comprises permanent feedback control and intermittent open loop control based on sequential decision making.
Several constraints may play a role in a given task. Control is, in principle, constrained because of limited control authority, hardware limits, etc. Generally these constraints have to be included a priori in formulating and solving the optimal control problem.
Secondly, it may be necessary to consider (hard) constraints in the state space. Examples are the requirement to realize precisely a final destination of the system state (apart from stochastic effects), and the limited space available

to go from A to B (e.g. due to fixed and moving obstacles).

Both types of constraints can be handled in a similar way. Conceptually, the procedure is (as discussed in Ref. 2) to "adjoin" the constraints to the performance index J_N, given by eq(4), by a set of (socalled Lagrange) multipliers, which are chosen in such a way, that an optimal control is obtained (corresponding with an minimal J_N) given the constraints. Such optimization problems with constraints are conceptually straightforward. Numerical solutions, however, can require considerable computational cost.

This can be aggrevated if the control problem is stochastic by nature. In that case the state has to be estimated requiring the solution of a nonlinear estimation problem (e.g. based on an extended Kalman filter).

For example, the solution of the optimal control task inclusive collision avoidance of moving obstacles requires:

- estimation of own system state and the state of relevant obstacles;
- definition of the constraints that have to be met in terms of the estimated states (e.g. the estimated distance to obstacles);
- computation of the optimal control while meeting the constraints. A more simple (engineering) approach to solve this and similar problems is given in Ref. 3.

4. CONCLUDING REMARKS

In this paper a model structure is presented of manned robotic systems in terms of optimal estimation-, control- and decision theory. The resulting model can be utilized to analyze, design and evaluate these systems by establishing the effect of task variables of interest on model outputs.

In case the model is used in a time simulation mode, the results are in terms of time histories (sequences) of interesting system- and HO- related variables. For the linearized model version, statistical measures can be obtained (i.e. ensemble mean values, covariances and probabilities) of all variables of interest. In the latter case the model provides a very cost-effective tool to assess the performance and reliability of manned robotic systems.

It may be expected that the model is capable of answering questions related to design alternatives, function allocation, automation, system reliability and efficiency, etc.

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