Cognition, Technology & Work (2001) 3:4–21

Cognition
Technology &
Work

Risk Analysis of Ship Navigation by Use of Cognitive Simulation

K. Itoh[1], T. Yamaguchi[1], J. P. Hansen[2] and F. R. Nielsen[3]

[1]*Department of Industrial Engineering and Management, Tokyo Institute of Technology, Tokyo, Japan;* [2]*IT University of Cophenhagen, Copenhagen, Denmark;* [3]*Systems Analysis Department, Risø National Laboratory, Roskilde, Denmark*

Abstract: This paper presents a cognitive simulation approach to risk analysis for maritime operations. For this purpose, a ship navigator's cognitive model was constructed for simple course-tracking task based on cognitive task analysis of experimental navigation sessions using a maritime simulator. It describes the dynamic interaction between the navigator's cognitive processes and the states during manoeuvring. In addition to performance modelling of normal operations, the model is equipped with a navigator-error generating process to simulate identification error of vessel position and heading and look-ahead error of the future track. The cognitive model was examined in terms of its descriptive and predictive abilities of ship motion and navigator's behaviour through simulation runs using identical scenarios for the experimental navigation sessions. Many varieties of simulation were then performed with different navigation scenarios changing the navigator's individual factors and manoeuvring conditions to identify critical risk factors at sea. Based on these results, we discuss the possibility of applying the cognitive simulation approach to risk analysis in ship navigation.

Keywords: Cognitive modelling; Cognitive simulation; Cognitive task analysis; Human error; Risk analysis; Ship navigation

1. INTRODUCTION

Human cognitive processes play a crucial role in the safety of large-scale, complex technological systems such as nuclear power plants and aircraft cockpits (Mosneron-Dupin et al. 1997; Hollnagel 1996). This is evident from the fact that human factors were deemed to be the root cause of major disasters at Chernobyl, Three Mile Island, Piper Alpha, Zeebrugge, Bhopal, etc. (Broadbent et al 1990; Kletz 1994). Besides these catastrophic accidents, it is also found that human errors appear among the causes of most accidents in aviation and nuclear power plants (Miller and Swain 1987; Wiener and Nagel 1988). The percentage of human contribution to the accident rate is conjectured to rise higher in the future due to system complexity and the operator's role in the control loop as well as increasing reliability of mechanical and electronic components (Cacciabue 1998b).

Maritime operations on a ship bridge share many of the above-mentioned characteristics of high-tech human–machine operations. Most marine accidents are also known to be caused by humans (Hee et al 1999; Margetts 1976). In particular, it has been suggested that the crew's competence is of considerable importance to manoeuvring and decision making, when environmental conditions confine the safety margins (Schuffel 1986). Therefore, safety and reliability analyses of human functions are required in large-scale, complex systems (Hollnagel 1993). Sound and thorough investigation of human factors makes an essential contribution to safety assessments and risk analysis of ship navigation as in other highly developed technological systems (Cacciabue 1997).

Manoeuvring of a large-scale ship is performed by a team of people with a specialised set of tools and functions (Hutchins 1990). A navigator manages all the navigation processes and is supposed to cope with any kind of control problem on board (Hansen and Clemmensen 1993). He plans the ship's course and speed in advance, gives commands to a helmsman during the voyage according to the prescribed plan, and reacts to changes in the environment. The helmsman mainly serves as an executor of the control commands given by the navigator, and in most modern vessels his functions are often substituted by an autopilot. Accordingly, it has been of primary interest to understand the navigator's tasks and his performance for the safety at sea (Papenhuijzen 1988).

Among several methodological frameworks for reliability and safety analyses, simulation of the operator's cognition has been accepted as an appropriate and feasible approach in the high-tech human–machine field (Cacciabue 1998b). This approach is utilised for the purpose of safety assessment and design of human–machine interfaces and decision support tools mainly due to its advantage of cost and time savings. For example, simulation models have been developed to predict human behaviour in aeroplane cockpits (e.g., Bautsch et al 1997; Kirlik et al 1993; Valot et al 1991) and control rooms of nuclear power plants (e.g., Cacciabue et al 1990, 1992; Smidts et al 1997). Again, in the maritime field, the simulation approach has also been applied to investigate risks under specific manoeuvring conditions (e.g., Papenhuijzen 1988; Salski et al 1988). Ship motion and navigator's behaviour can be simulated under specific conditions without any experimental studies. However, most of the existing ship-handling models are based on control theoretical approaches (e.g., Hearn et al 1997; Parsons et al 1995; Zhang et al 1996) rather than on the cognitive performance of actual human navigators. This is due to little explicit knowledge available on the ship handler's skill (Gardenier 1981) and the difficulty of analysing and modelling navigator's cognitive processes which are characterised as skill- and rule-based performance (Rasmussen 1986).

The greatest advantage of the cognitive simulation approach, compared to the control theoretical approach, is its possibility to obtain flexibility and a more 'human-like' representation of cognitive processes for the benefit of rich rules, knowledge and logical connections between tasks, goals and observation of system performance (Cacciabue 1998a). This approach allows us to exploit an operator's states such as workload and risk evaluation in performing real system control activities. However, such advantages also exhibit a major weak point of this approach. It requires extensive work of detailed and accurate task analysis. If the aspects of task analysis and the development of a sound and vast amount of built-in rules and knowledge are not properly elicited, reliable results cannot be obtained from this approach (Cacciabue, 1998a).

In the simulation approach, modelling of human behaviour and cognition is of primary interest. The main focus is to develop an appropriate model which represents behaviour and process for each component of the human–machine system, i.e., operator cognition, system behaviour and their interaction, in a specific level of description depending on the model's purpose. There are two levels of description detail or simplicity for the cognitive model. At a higher level, only the major elements of human cognition are described. This type of model is suitable to understand overall characteristics of the operator's activities during task performance. The SMoC (Simple Model of Cognition) (Cacciabue and Hollnagel 1995) falls into this category. At a lower level, major cognitive elements must be further defined, and ideally their interaction processes with the system and environment are described as functions of the task context. This type of model is required for specific applications to safety and reliability management of the human–machine system (Cacciabue, 1998b). CES (Cognitive Environment Simulation Model) (Roth et al 1991, 1992), COSIMO (Cognitive Simulation Model) (Cacciabue et al 1990, 1992) and IDA (Information, Diagnosis/Decision, Actioni) (Smidts et al 1997; Shen et al 1997) are typical examples of this class.

For the application of the simulation approach to safety and reliability analyses, Hollnagel (1996) suggested two requirements that a cognitive model should address:

- For one requirement, the model must have a predictive capability to estimate whether an operator is likely to fail. This requirement means an identification of situations where the information and the conditions lead to the choice of the wrong action or to the incorrect performance of an action, combined with the operator's present state and capabilities. This implies the necessity of human error processes, e.g., observation error, identification error of situation, and decision-making error, as well as definition of the operator's competence or skills built into the cognitive model.
- For the other requirement, the model should describe human variability on task performance, depending on task conditions, environment and situations. This requires thorough description of the dynamics of the interaction between the operator's action and the system and environment. As for the model requirement, Cacciabue (1997) also suggested the necessity of emulation capability of cognitive processes, including the features of observation and inference, which are the key contributors in a process of decision making. This may imply the importance of model building of human cognition based on thorough and dedicated task analysis.

Following the above-mentioned requirements suggested by Hollnagel (1996) and Cacciabue (1997), the modelling approach presented in this paper adopts a lower-level description of a ship navigator's cognitive performance which contains human error processes in observation, identification of situations and decision making. The model describes a dynamic interaction between the navigator's cognitive processes and the states of manoeuvre. Initially, a cognitive model of the ship navigator (Itoh et al 1998) was built to represent a process for a simple course-tracking task based on cognitive task analysis using a maritime simulator and without consideration of human errors (Itoh and Hansen 1995). Results from a series of task analyses (Itoh 1997; Itoh et al 1998) were used to improve the model, so that it could resemble more closely human cognitive processes. In addition, the present version of the cognitive model was also equipped with the navigator's error-generating processes for the purpose of its application to risk analysis.

The objectives of this paper are twofold. One is to develop a simulation model which represents the navigator's detailed course-tracking process based on the cognitive task analysis. The other objective is to present the simulation approach with cognitive modelling to risk analysis in ship navigation. For these objectives, the cognitive model is examined by comparing simulated ship motions and navigator's behaviours with those of the actual human navigator using identical scenarios to the experimental navigation sessions. We then apply the cognitive simulation approach to risk analysis by performing a series of simulation runs under various scenarios changing the navigator's individual factors and manoeuvring conditions.

2. NAVIGATOR'S COGNITIVE MODEL

2.1. Modelling Architecture

As mentioned in the previous section, the navigator's cognitive process was modelled to represent the dynamic interaction between his behaviour and the states of manoeuvre based on the cognitive task analysis (Itoh and Hansen 1995; Itoh et al 1998). The task analysis was performed using eye movement recording synchronised from the navigator's verbal protocols under the essential theories of 'eye–mind assumption' (Just and Carpenter 1980) and the 'process-monitoring hypothesis' (Rayner and McConkie 1976). The navigator's cognitive activities and processes were analysed according to Rasmussen's (1986) SL (step ladder) and SRK (skill-, rule- and knowledge-based) modelling paradigm.

The track plots of the sailing course and the navigator's cognitive/perceptive behaviour can be generated as simulation outcomes under a specific manoeuvring scenario. The overall simulation model comprises four sub-models, i.e., the navigator model, the helmsman model, the interaction model and the ship motion model, as depicted in Fig. 1. All these models are synchronised at the end of every gaze of the navigator model, which is described in the task network structure.

The ship motion model was originally developed by the Danish Maritime Institute, Lyngby, Denmark, and was adapted to link with the navigator's cognitive model. It concerns the numerical description of the ship behaviour, and controls any motion of the ship based on the present setting of the ship parameters. This model describes the ship's dynamics numerically by a set of differential equations, and represents the hydraulic forces and the moment in a non-dimensional form (e.g., Chislett and Wied 1985).

The interaction model generates all the interactions between the navigator model and the ship motion model, and it attempts to maintain all the environmental and system state variables. The helmsman model works only to transmit the helm order generated by the navigator model to the ship motion model via the interaction model.

The navigator model controls the simulation of the navigator's cognitive and behavioural process. It describes the navigator's cognitive process obtained from the task analysis and its behavioural implementation involves analytical expressions. The activity or behaviour of the navigator model is affected by the information perceived from the outside scene and control indicators, and by the error process built into the model. To control the navigator's behaviour mentioned above, the model con-

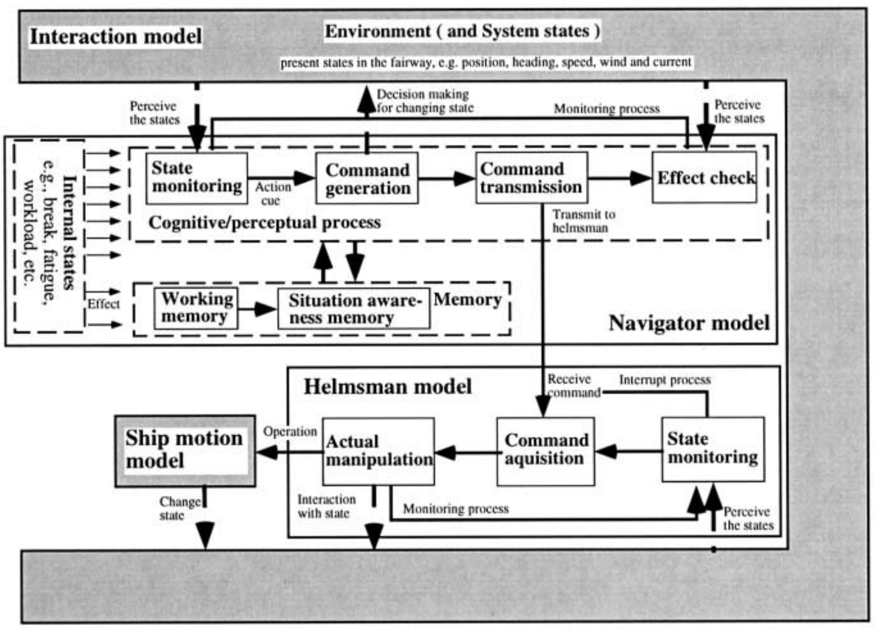

Fig. 1. Architecture for the cognitive model for ship navigation.

tains the cognitive process module and the memory module, as can be seen in Fig. 1. The cognitive process module performs the navigator's cognitive and perceptual functions, i.e., activation, observation, identification and formulation of procedures (Rasmussen 1986). The memory module retains the present states of manoeuvre and outcomes of the navigator's perceptual and cognitive functions, and it comprises the working memory (same as the short-term memory or STM) and the situation awareness memory (Itoh et al 1998). The latter is an intermediate memory of short-term and long-term memories to support situation awareness.

2.2. Outline of Modelled Cognitive Process

In this subsection, we briefly outline the modelled cognitive processes for the course-tracking task in a narrow fairway such as Øresund Channel between Denmark and Sweden. The navigator's processes during the task were conjectured based on the task analysis, and built its original cognitive model (Itoh and Hansen 1995; Itoh et al 1998). As mentioned in Section 1, the present version of navigator model was extended from the original model so that it can be applied to risk analysis by equipping the navigator's error-generating processes with several improvements for resembling more closely the human navigator's cognitive process.

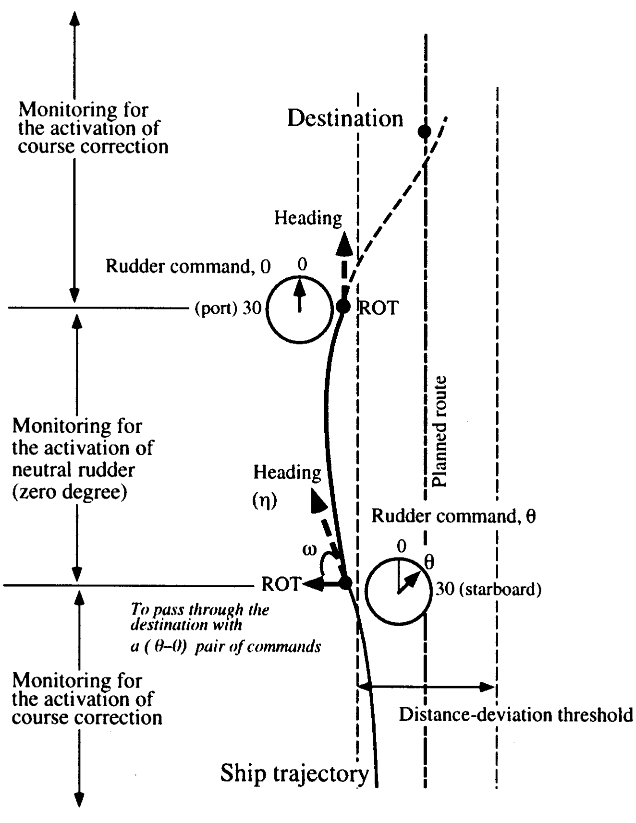

Fig. 2. Navigator's cognitive process in course tracking.

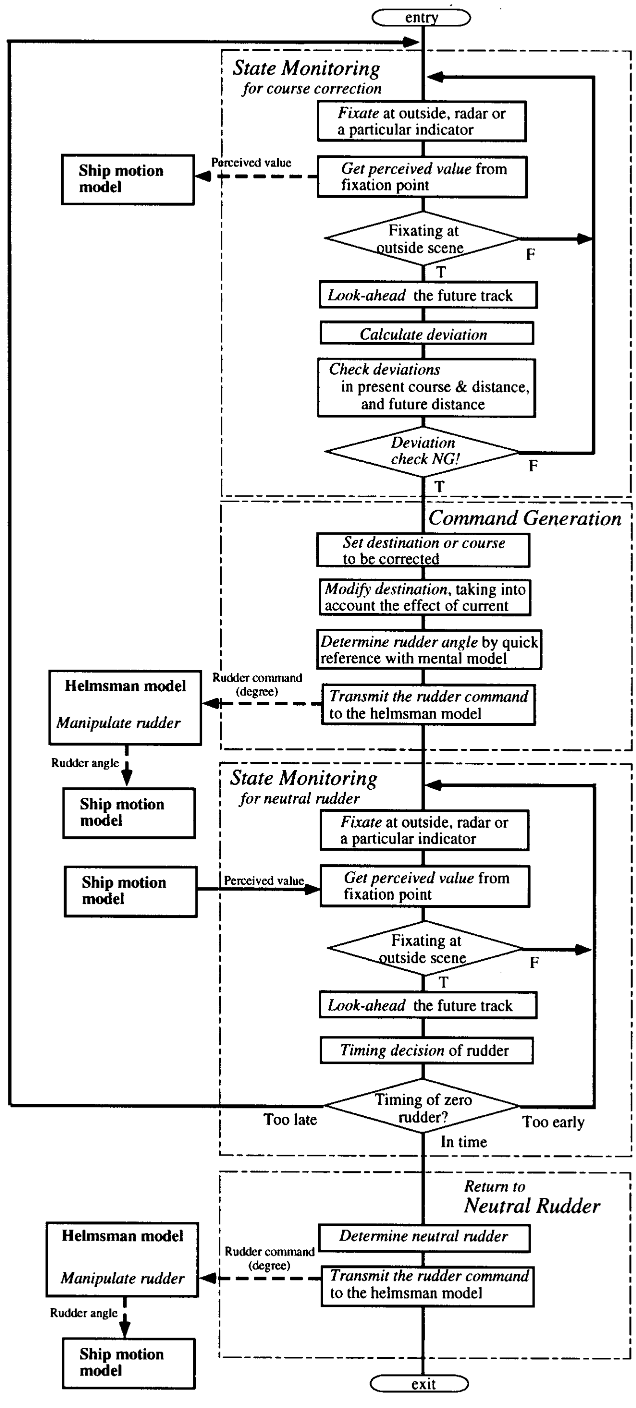

Fig. 3. Outline of cognitive flow diagram in the navigator model.

A schematic description of the modelled navigation performance is shown in Fig. 2. An outline flow diagram of the navigator's cognitive processes is also depicted in Fig. 3.

The navigator model controls state monitoring in manoeuvre using a sequential focal attention by which the present states are perceived from the outside, radar screen or indicators with or without observation errors.

During the state monitoring, the model frequently compares the present course or position with the planned route primarily based on the perceived states from the outside scene to check its deviation (deviation check). The model also performs a deviation check based on estimation of the future position, using the *look-ahead* function of the future states. If either one of these deviations is identified to exceed an allowance limit or threshold, a course correction operation is activated.

The navigator model tries to generate a pair of rudder commands, i.e., a non-zero rudder and a subsequent neutral rudder setting, for the present cue of course correction so that the ship sails smoothly to the destination for course correction with desirable heading and rate-of-turn (ROT).

For the required action of steering, the navigator is supposed to have a simplistic mental model of ship dynamics. A rudder setting for the first non-zero command is generated by quick reference to the mental model with the present state variables stored in the working memory and the situation awareness memory (command generation). Then, the navigator model transmits the command to the helmsman model, and the latter model manipulates the steering wheel accordingly.

Regarding the timing to return the rudder to the neutral position, the navigator model employs two strategies corresponding to the activation of course correction. In the case where operation was activated by a course deviation, the model determines the zero rudder timing by the present ROT indication when it looks at the indicator. When the ROT indication is in the range that the effect of rudder change is judged to be sufficient, then the model gives the neutral rudder. On the other hand, in case of activation by a distance deviation, the navigator model executes a look-ahead function to anticipate the future position, assuming that the helm should be returned to the neutral position at this point. Hollnagel (1996) also observed this kind of look-ahead function in complex human–machine systems in which 'operators are able to look ahead and react to things that have not yet happened'. The model repeatedly performs such a look-ahead process every time it looks at the outside scene until the timing decision of neutral rudder is initiated. When the expected position is on the destination within a safety margin, the model accepts the present timing to issue a zero-degree rudder command, and then the control of the model returns to the state-monitoring process.

Meanwhile, if the model determines the timing is too late to ease the helm, the control returns to the normal state-monitoring process. In such cases, the next helm operation has a non-zero rudder, instead of returning it to the neutral position.

Further details of the modelled process for each sub-activity will be mentioned in the following subsections.

2.3. Cognitive Behaviour in State Monitoring

The navigator model performs the state monitoring based on the eye gaze pattern, which was obtained from the task analysis (Itoh and Hansen 1995; Itoh et al 1998). This pattern represents transition probabilities between any two information sources and a distribution of gaze duration time at each source, both for state monitoring and for course correction operation. A gazed point and its gaze time are determined by the random digit according to their stochastic distributions in simulation.

The model obtains the present value from a gazed indicator. Also, when the outside scene or the radar picture is gazed at, the present position and heading are perceived with errors depending on the assumed navigator's competence, as will be further detailed in Section 2.7. Each of the state values obtained from looking outside or at the indicators is saved in the working memory, and then it moves to the situation awareness memory in a short while due to the limited duration of the working memory (Itoh et al 1998). These two memories differ in accuracy of stored information in the navigator model.

2.4. Activation of Course Correction

As mentioned in Section 2.2, the deviation check is performed on the basis of the present deviation and the future deviation. In the daylight condition, the deviation is checked every time the outside scene is attended to by the navigator model's 'eye'. The timing of the deviation check in the night-fog condition is modelled to take place whenever the radar picture or the compass is gazed during the state monitoring.

For the check on basis of the present state, the navigator model calculates the course deviation between the planned course and the perceived heading as well as the distance deviation from the planned route to the presently perceived position, as shown in Fig. 4(a). If either the course deviation or the distance deviation exceeds its threshold, a course correction operation is activated.

In the case of the deviation check on basis of the future state, only the distance deviation is taken into account. Sailing trajectory within the look-ahead time window is estimated by the look-ahead function. The navigator is assumed to have a simplistic mental model of ship dynamics, which is represented as a decision table in the cognitive model, as mentioned in Section 2.2. Thus, the look-ahead process can be modelled as the quick reference of the decision table with the present state variables stored in the working memory and the situation awareness memory. If the estimated future position is outside of the deviation threshold, a course correction operation is activated, as shown in Fig. 4(b).

Each threshold value varies depending on individual preference and competence among navigators, the

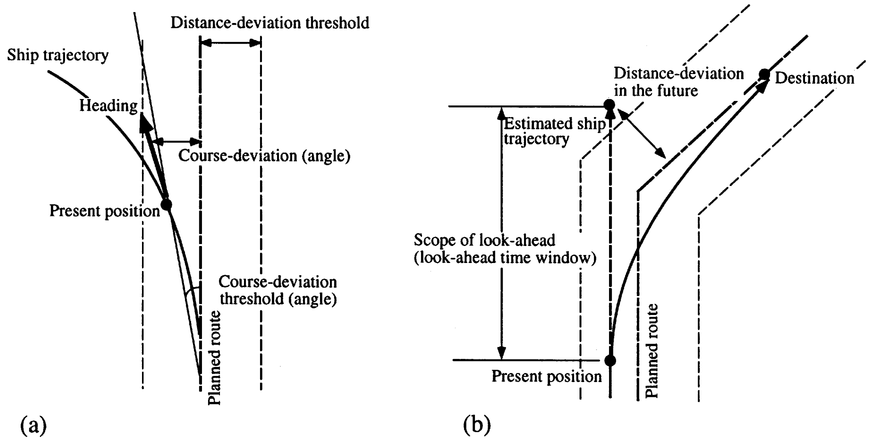

Fig. 4. Deviation check for activating a course correction action (a) by the present state and (b) by the future state.

environmental load, and the manoeuvrability of the particular ship. These values are treated as variables in the model and the course and distance thresholds in the simulation runs will be mentioned together with other individual parameters of the navigator in Section 3.2.

2.5. Helm Command Generation

When an operation is activated by the course deviation, the navigator model makes a rudder command so that the heading can be directed to the planned course. A rudder setting is generated with reference to required state values such as the course deviation, ROT and vessel speed, all of which are stored in the navigator model's memories. As mentioned previously, the model assumes that the navigator has a simplistic mental model of ship dynamics, and therefore this decision process is also implemented as a quick reference of the decision table like the look-ahead function.

In the case of activation by the distance deviation, its generation process is modelled as feed forward control, as depicted in Fig. 5. The generation process starts with setting a destination for the course correction. The navigator model decides the destination so that the ship can return onto the planned route in a particular time interval. This interval is closely related to the time window of how long the navigator searches for the future position in the fairway. To represent this time window, a straight line with a certain length, the pilot line, is introduced. This is also a variable in the model like the deviation thresholds. The model calculates the intersection of the pilot line originating from the present position and the planned route, and sets this point as the destination for the course correction.

The destination is modified, taking into account the effect of the wind and/or current. The present model treats only the current, and the navigator's perception error of current strength is also modelled, as will be mentioned in detail in Section 2.7. The modified destination is obtained by offsetting the distance vector, to which the ship is carried away by the perceived strength of current from the original destination. This modification enables the model to ignore the effect of the current in any successive processing of the command generation. This process was

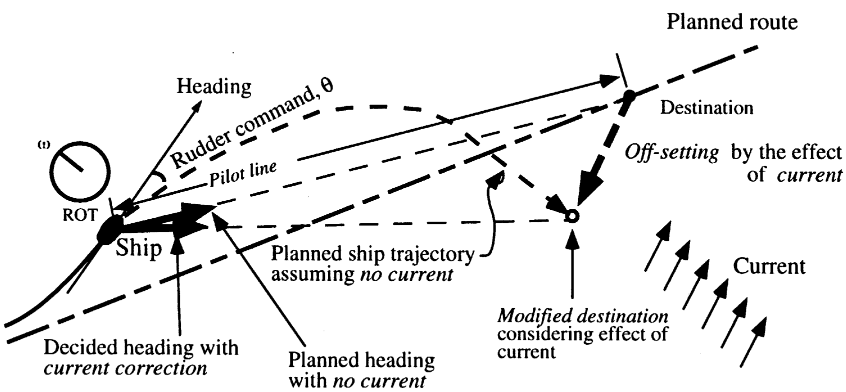

Fig. 5. Helm command generation process modelled for the course correction.

derived from the analogy of a golf player's putting process wherein an offset is determined based on the slope and the direction of grass, and the player putts in a direction adjusted by the distance of the offset from the real hole. In this application, the distance vector is calculated by the production of the identified current speed vector and the estimated time to the destination. For the modified destination calculated in this manner, the above-mentioned quick reference of simplistic ship dynamics is also applied to the decision process of rudder setting with necessary state variables.

2.6. Timing Decision of Neutral Rudder

The navigator model employs a 'generate and test' procedure (e.g., Winston 1984) for the timing decision on returning the rudder to the neutral position after a non-zero helm command. The schematic description of this process is shown in Fig. 6. The model generates the future track by applying a look-ahead function to the present state with the hypothesised helm operation to the neutral position. The predicted future position is tested by comparing it with the planned destination. The model accepts the present timing to issue a zero-degree rudder command when the expected course is on the destination within an allowance limit (look-ahead allowance). If the test is not satisfactory, then the future track is predicted again at the next time the navigator model's 'eye' fixates the outside scene. This process is repeated until a satisfactory timing is obtained.

When the generated future position on the planned route is much closer to the destination, the navigator model determines that the timing is too late to ease the rudder. Then, the control of the model returns to the normal state monitoring process. In this case, the next helm operation yields a value of non-zero degrees, instead of returning it to the neutral position.

2.7. Modelling of Human Errors

The present navigator model incorporates several human-error generating processes such as *misidentification* of the present position and heading, *look-ahead error* of the future track, and so forth. These errors are characterised in the model by probabilistic distributions which are largely dependent upon the navigator's competence and his mental states. This error-modelling approach can be applied to other aspects of human error such as generation of an inaccurate rudder setting and misreading of other indicators.

2.7.1. Identification Errors of Position and Heading. The modelled process of identification error of the present position is depicted in Figure 7(a). This error is characterised by a normal distribution having two parameters, i.e., N (b, σ^2). One parameter, b, represents a bias of identification as the navigator's error trend. A negative value of bias means that the navigator has an under-estimation trend in identifying the distance deviation from the planned route. In contrast, a positive value of b

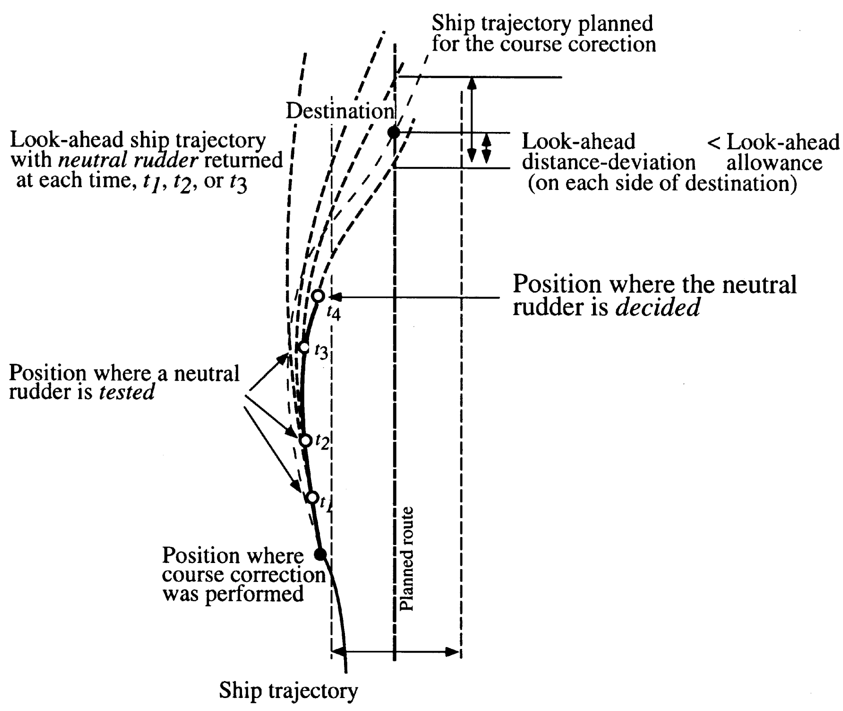

Fig. 6. Timing decision for returning the rudder to the neutral position.

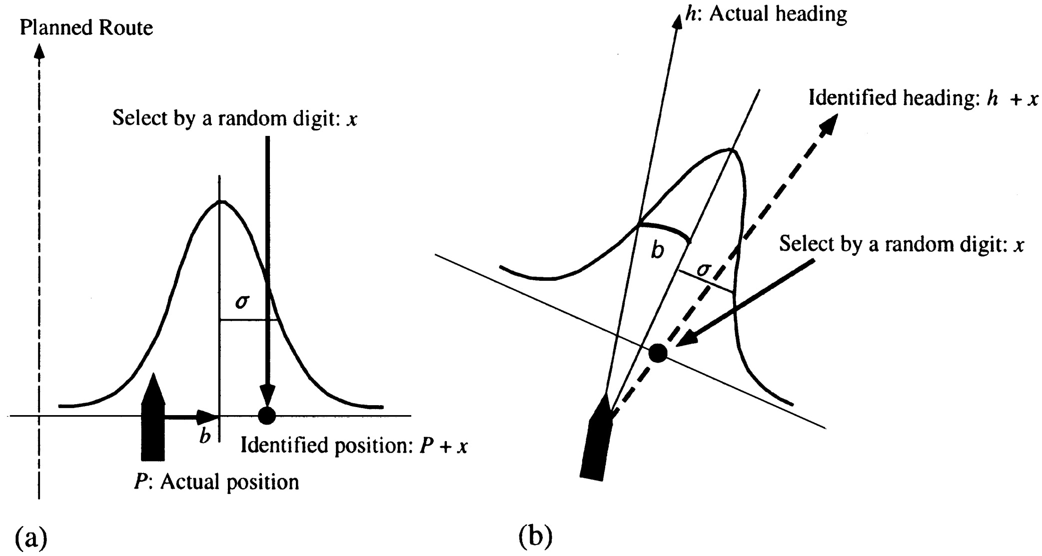

Fig. 7. Modelling of identification errors of (a) position and (b) heading.

indicates overestimation. For such a parameter setting, the navigator model is likely to perceive the present position with more deviation than the actual distance from the planned route. The other parameter, σ, represents a random error as the navigator's performance on position identification. In the simulation run, an identified position is determined by a random digit following the normal distribution of N (b, σ^2), as indicated in Fig. 7(a).

The heading perceived from the outside scene is generated in the same manner as the position identification mentioned above. The identification error of heading is also characterised by an error distribution having two parameters of bias and random error factors, as shown in Fig. 7(b). Assuming an actual heading, h, and a selected random digit, x, that follows the error distribution, N (b, σ^2), then the navigator model perceives the present heading as $h + x$.

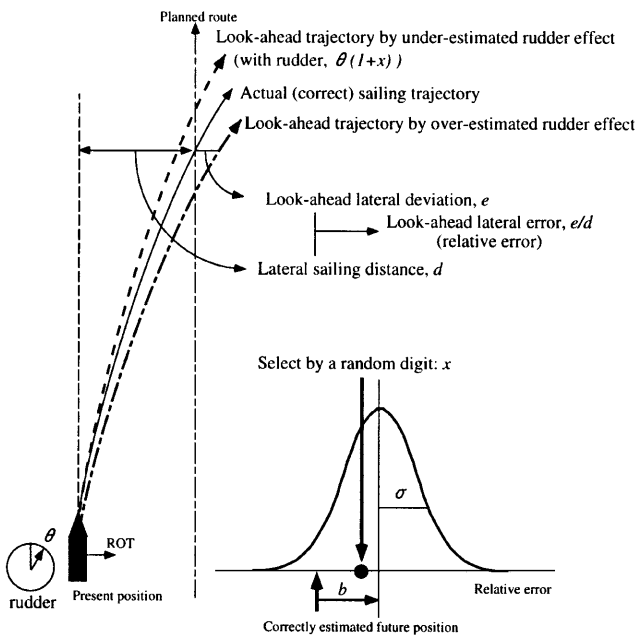

Fig. 8. Modelling of look-ahead error of the future track.

2.7.2. Look-Ahead Errors. A schematic description of look-ahead error of the future track is shown in Fig. 8. This error is also generated by a probabilistic distribution of bias and random error factors. Applying this error distribution for the look-ahead error, a relative error factor is determined as a selected random digit, while distributions of identification errors of the present states, i.e., position and heading, prescribe the absolute errors in metres and degrees. To produce a ship trajectory estimated with the relative error factor for the check of activation of course correction, the sailing track is obtained from the ship motion model, changing the rudder angle according to the selected random digit. Assuming that the ship is sailing with the rudder angle, θ, as indicated in Fig. 8, when a random digit, x, that follows the error distribution of N (b, σ^2) is selected, then a look-ahead ship trajectory is generated by the emulation of ship motion with the rudder angle of $\theta(1 + x)$. In case of a look-ahead for the timing decision of neutral rudder, the expected ship trajectory is produced by the emulation with the additional relative error factor of ROT, instead of the rudder angle.

If a relative error factor selected based on a random digit, which follows the normal distribution of N (b, σ^2), has a negative value, the turning rate is underestimated, as shown in a dashed line in Fig. 8. In contrast, a positive value of the error leads the navigator model to a steeper look-ahead that estimates a closer point to be reached than

Table 1. Look-ahead lateral errors and deviations produced by example error factors

(a) look-ahead for activation (by rudder)					(b) Look-ahead for timing decision (by ROT)				
Rudder position	Error factors	Look-ahead time interval			Rudder position	Error factors	Look-ahead time interval		
		60 s	120 s	180 s			60 s	120 s	180 s
5 deg.	−40%	−0.3 m	−6.1 m	−23.5 m	5 deg.	−80%	−1.5 m	−4.9 m	−10.9 m
		−51%	−48%	−45%	→ 0		−47%	−39%	−39%
	−20%	−0.2 m	−5.0 m	−11.1 m		−40%	−0.7 m	−2.5 m	−5.4 m
		−26%	−24%	−22%			−22%	−20%	−19%
	+20%	+0.2 m	+3.0 m	+10.6 m		+40%	+0.7 m	+2.5 m	+5.3 m
		+28%	+23%	+20%			+22%	+20%	+19%
	+40%	+0.3 m	+5.9 m	+20.5 m		+80%	+1.5 m	+4.9 m	+10.6 m
		+55%	+46%	+39%			+47%	+39%	+38%
Lat. sail. dist.		0.7 m	12.7 m	52.7 m	Lat. sail. dist.		3.2 m	12.5 m	28.2 m
10 deg.	−40%	−0.7 m	−11.0 m	−35.0 m	10 deg.	−80%	−3.1 m	−10.1 m	−20.9 m
		−46%	−41%	−36%	→ 0		−43%	−35%	−32%
	−20%	−0.4 m	−5.3 m	−16.1 m		−40%	−1.6 m	−5.0 m	−10.3 m
		−23%	−20%	−16%			−22%	−17%	−16%
	+20%	+0.4 m	+4.9 m	+13.6 m		+40%	+1.5 m	+5.0 m	+10.0 m
		+23%	+18%	+14%			+21%	+17%	+15%
	+40%	+0.7 m	+9.1 m	+25.0 m		+80%	+3.1 m	+9.8 m	+19.8 m
		+45%	+34%	+25%			+43%	+34%	+30%
Lat. sail. dist.		1.5 m	26.6 m	98.3 m	Lat. sail. dist.		7.2 m	28.8 m	66.3 m

Upper row: Look-ahead lateral deviation (m).
Lower row: Look-ahead lateral error (%).

the actual track. Table 1 indicates absolute anticipation errors (in metres) for the future track produced by example levels of the relative error factor in terms of a lateral deviation between the look-ahead and the actual position. This error relative to the lateral sailing distance is referred to as look-ahead lateral error, as shown in Fig. 8. In this table, look-ahead lateral errors are presented for some particular rudder settings, i.e., 5 and 10 degrees, when anticipating the future position in 60, 120 and 180 seconds. Supposing the navigator model performs a timing decision of neutral rudder from 5 degree rudder, and if the relative error factor of −40% is taken by a selected random digit, then −22% look-ahead lateral error is produced for anticipation of the future position in 60 seconds. The anticipation error is also affected by a look-ahead time window due to the time constant of the vessel.

2.7.3. Other Error Modelling. Some other forms were employed to describe human errors in the navigator model. In the present paper, we also model a vigilance problem as another type of human error to disable a particular cognitive/perceptual capability in a given specific time interval. For example, in case of fatigue or alcohol consumption, the process for modifying the target destination for a command generation is disabled in the model due to lack of awareness of current and wind forces. Effects of reduced perceptual capabilities can be also implemented with a change of attention allocation patterns, e.g., by removing a particular eye-gaze transition from the scan patterns.

As a similar type of human error process to the above-mentioned reduced capability, 'block-out' phenomenon is also built into the present model. This is represented as failure to take any part or all of the navigation process in due time due to sudden sickness or extremely high stress, for example. The length and timing of the block-out interval can be set in the model.

Several error-generating processes are also modelled by applying the stochastic error distribution approach mentioned above. For example, one of the most important risk factors is the navigator's perception error of current strength. Such incorrect current perception is generated by an error factor relative to the actual value. An inaccurate rudder setting is also produced by an error distribution, depending on the navigator's competence.

3. MODEL VALIDATION

3.1. Model Implementation

As mentioned in Section 2.1, the cognitive model is comprised of the four sub-models, each of which describes an individual operator's process, ship motion or their interaction in manoeuvre. The ship motion model, which controls the sailing process of the vessel, is synhcronised by the interaction model with the behaviour of the navigator model as well as with the helmsman model. All the modules comprising the cognitive model were programmed in standard C code, and implemented on a Macintosh PC.

In addition to process modelling of the ship crew, the simulation model includes some utility program modules. As indicated in a screen dump of the simulation window

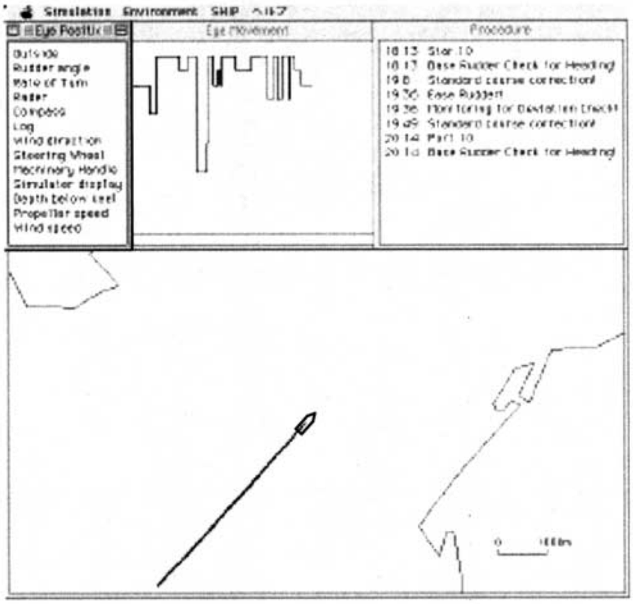

Fig. 9. Screen dump of simulation window.

shown in Fig. 9, a real-time display projects the progress of sailing trajectory simulated by the cognitive model. The navigator's simulated action sequences appear with time course in the simulation window. The transition of the navigator's attention, i.e., the fixation pattern, is also displayed in this window.

3.2. Task Network Simulation

To evaluate the cognitive model's descriptive and predictive capabilities, a task network simulation was executed using the identical scenarios as the experimental simulator sessions (Itoh and Hansen 1995; Itoh et al 1998). Results of the simulation also contribute to validating appropriateness of the cognitive task analysis. If simulated performance is similar to that by the actual human navigator in terms of operation sequence and rudder controls as well as vessel behaviour, it can be considered that the cognitive task analysis as well as modelling of the navigation performance were properly carried out. For this purpose, the navigator's ship-handling behaviour and track plots simulated by the cognitive model are compared with the observed performance by the human navigator in the above-mentioned experimental simulator sessions.

The vessel modelled in this study was a car carrier having 23,300 tons of displacement, 182 metres length, 32.2 metres breadth moulded, and 7.0 metres draught. The vessel was controlled with constant engine force by which it sailed at the speed of 6 knots with the neutral rudder under no-current condition. The ship was navigated by the constructed cognitive model in the narrow fairway of Øresund Channel between Denmark and Sweden under the following three conditions: daylight with no current,

Table 2. Parameter settings for competent and low-competence navigators

Parameters	Competent navigator	Low-comp. navigator
Competence-independent factors		
Present distance threshold		
in no current	60 m (for each side)	
in north-going current	40 m (port) 80 m (starboard)	
Present course threshold		
in no current	1.5 deg. (for each side)	
in north-going current	4.0 deg. (for each side)	
Future distance threshold		same as left
in no current	120 m (for each side)	
in north-going current	60 m (port) 180 m (starboard)	
Pilot line	800 m	
Look-ahead allowance	20 m	
Competence-dependent factors		
Position ident. error Bias (*b*)	0.0 m	−10.0 m
Random error (σ)	5.0 m	10.0 m
Headiing ident. error Bias (*b*)	0.0 deg.	−1.0 deg.
Random error (σ)	0..5 deg.	1.0 deg.
Current percept. error Bias (*b*)	30%	30%
Random error (σ)	0%	10%
Rudder generat. error Bias (*b*)	0%	−30%
Random error (σ)	0%	10%
Look-ahead error Bias (*b*)	0%	−20%
(by rudder) Random error (σ)	0%	20%
Look-ahead error Bias (*b*)	0%	−40%
(by ROT) Random error (σ)	0%	20%
Look-ahead time window	120 s	60 s

daylight with 0.55 m/s current (north-going) and night-fog with no current conditions. As mentioned in the previous section, the cognitive model used random digits to determine the values of several model aspects, including monitoring sequence of control indicators and outside scene, gaze duration during state monitoring as well as perceived errors for state identification and look-ahead. Therefore, simulation runs were executed 10 times with different seeds of the random digit for each manoeuvring scenario.

Some of the navigator's individual parameters used in the cognitive model were determined based on the subject's protocols obtained during the experimental sessions (Itoh and Hansen 1995) and the others were tuned on a 'trial-and-error' basis. The parameter settings decided for the simulation runs are shown in the leftmost column of Table 2.

3.3. Simulation Results

3.3.1. Simulated Sailing Course. In all the manoeuvring scenarios examined in the present paper, the ship was navigated by the cognitive model safely following the planned route. Figure 10 depicts an example track plot of manoeuvring in the no-current, daylight session. This figure includes points of rudder operations and their rudder settings in addition to the track plot. This track is similar to that obtained by the human navigator in the simulator

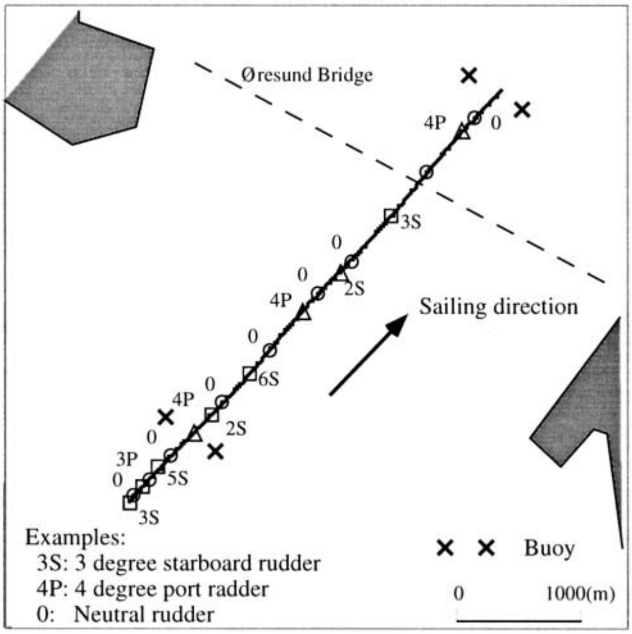

Fig. 10. Simulated track plot in the no-current daylight manoeuvring.

session in that the ship was sailing in the centre of buoys (Itoh et al 1998).

In addition, the simulated manoeuvring behaviour also resembles that of the actual human navigator not only in the number of commands and their rudder settings but also in the command sequence. It is seen from this figure that the cognitive model employed a *'return to neutral rudder'* strategy like the human navigator: after a non-zero, small rudder command (2–6 degrees) for course change, the helm was returned to the neutral position in almost all the operations, with only a few exceptions.

3.3.2. Timeline Comparisons. Time lines of the helm operations both by the human navigator and by the cognitive model are presented for all three sessions in Fig. 11 along with the rudder setting in each operation. The timeline produced by the cognitive model was selected on the basis of a typical operation sequence among all 10 simulation runs from each session.

In the daylight, no-current condition, the cognitive model took less time, i.e., approximately 19.5 minutes to

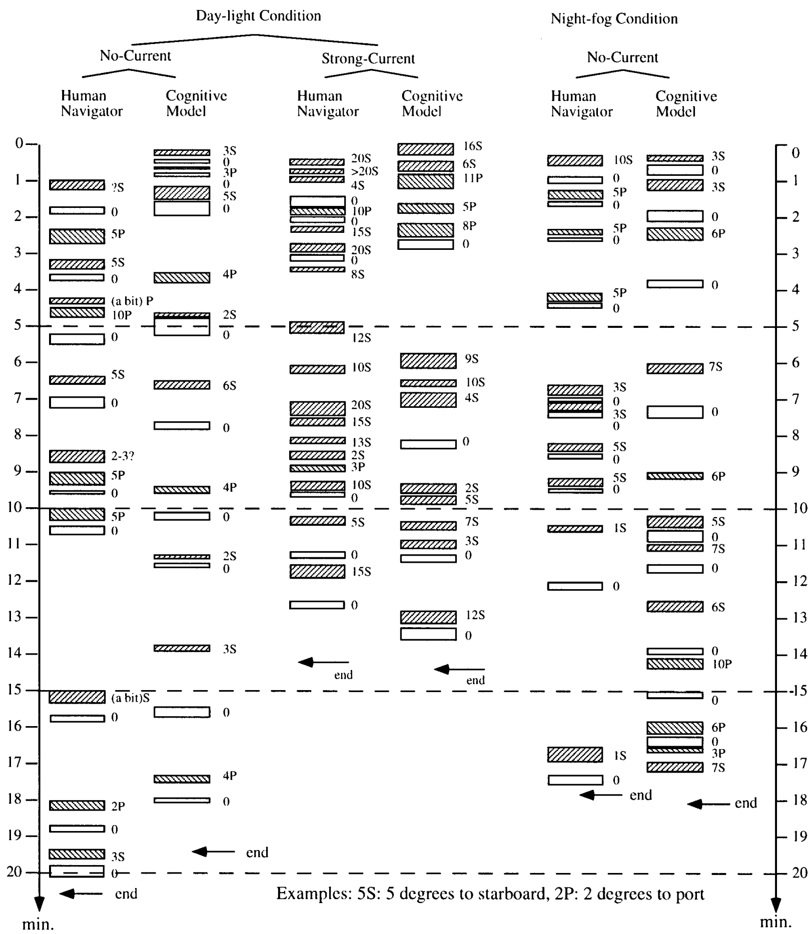

Fig. 11. Timeline of helm operations by the human navigator and the cognitive model.

terminate the course-tracking session. In the experimental session, the human navigator made some speed adjustment operations by controlling the engine force during the task (Itoh and Hansen 1995). In contrast, the present cognitive model does not involve a process of control operation of the engine force. For the other two conditions, the navigator performed no engine control operations during manoeuvring sessions, and there is little difference in the sailing times between the human and the model, as shown in Table 3.

There seems to be little difference in the number of performed helm operations between the human navigator and the model in all three sessions. The rudder settings generated by the cognitive model are also similar to those by the navigator for both directions of port and starboard. In no-current manoeuvring under both daylight and night-fog conditions, both the human navigator and the cognitive model proudced helm commands with small angles ranging between 0 and 6 degrees in most cases. In contrast, larger rudder angles were generated both by the model and the human under the strong current due to difficulty in controlling the ship against the current. In the simulation run shown in Fig. 11, the human navigator seemed to produce rudders with larger angles than the model. Further comparisons in some quantitative measures between the navigator and the model will be mentioned in the rest of this subsection, based on all the simulation results derived from all 10 repetitions for each case.

As mentioned in Section 3.3.1, both the human and the cognitive model employed the 'return to neutral rudder' strategy in principle under the no-current conditions both in daylight and night-fog sailing. However, it is seen that this strategy is violated in the strong current condition due to difficult operations both by the human navigator and by the cognitive model. Instead, a series of starboard rudder operations were generated with a few zero-degree rudders both by the human and by the cognitive model due to strong current from the vessel's port side.

3.3.3. Performance Comparisons. Simulation results of the cognitive model and the human navigator's performance are summarised in terms of several performance measures for all the three sessions in Table 3. These measures are the number of performed operations, mean angles of non-zero helm commands, sailing time, utilisation percentage of the 'return to neutral rudder' strategy, and percentage of time at the neutral rudder. In this table, the performance measures of the cognitive model are represented as mean values and standard deviations over 10 simulation runs for each condition.

From this table, it is seen that the number of rudder commands issued by the cognitive model is slightly smaller than that by the human navigator for each session. However, there seems to be little difference between the navigator and the model both in the mean angles of rudder setting and in the sailing minutes for all the sessions. Each of the two performance measures obtained from the human navigator falls within one standard deviation from the mean value produced by cognitive simulation.

Regarding the command sequence of helm orders, it is also found that the cognitive model can properly reflect the navigator's process. Under no-current conditions, both the navigator and the model keep the 'return to the neutral rudder' strategy with very high probability. In contrast, application frequency of this strategy falls down in the strong current both for the human and the model. Accordingly, the simulation result of the cognitive model matches that by the human navigator in total duration for which the rudder is at the neutral position.

Based on the results stated in this subsection, the cognitive model constructed in this study can be considered to have fair descriptive and predictive capability of the navigator's performance. Therefore, we decided that this model is sufficiently appropriate to apply to risk analysis.

4. RISK ANALYSIS BY COGNITIVE SIMULATION

4.1. Example Risks Examined

In order to apply the cognitive modelling approach to risk analysis, a series of simulation runs were conducted using various navigation scenarios, e.g., changing environmental

Table 3. Performance comparisons between the navigator and the cognitive model

	(1) Daylight and no-current			(2) Daylight and strong current			(3) Night-fog and no-current		
	Human navigator	Cognitive model		Human navigator	Cognitive model		Human navigator	Cognitive model	
		Mean	SD		Mean	SD		Mean	SD
No. of operations	21	17.9	3.1	23	21.0	2.1	20	16.1	2.2
Rudder angle (deg.)	4.7	4.3	0.8	11.0	10.3	2.7	4.4	5.1	0.8
Sailing minutes	20.5	19.3	0.11	14.0	14.8	0.37	18.0	17.9	0.12
% of applying RTN strategy[a]	81.8	90.2	17.4	35.3	28.6	5.2	100.0	83.3	9.5
% in time at neutral rudder	68.1	65.8	8.2	35.1	29.3	5.7	64.5	62.6	1.1

Averaged values over 10 simulation runs with different random digit seeds.
[a] RTN strategy: 'Return to neutral rudder' strategy.

conditions and navigator's individual factors. Example risks to be examined in this paper were strong current as an environmental factor and low competence as a navigator individual factor, specifically navigator's identification errors of present position and heading and look-ahead errors of the future states, as modelled in Section 2.7. The sailing route (Øresund Channel) and its direction (for north-east) were identical to those mentioned in Section 3.2.

The levels of current during manoeuvre were varied between zero and 1.0 m/s in the same direction (north-going). As a low-competence navigator, we considered one having an underestimated error trend toward position and heading identification and look-ahead of the future track and an overestimated current perception error. The parameter settings of this low-competence navigator's were shown in Table 2. In addition, to examine the effects both of identification error and of look-ahead error in more detail, further simulations were performed selecting several levels for identification error and look-ahead error and keeping the competent navigator's setting for all other error parameters.

4.2. Risk of Identification Errors

Track plots simulated both by the competent and the low-competence navigator models are shown in Fig. 12. As can be seen in Fig. 12(a), the ship was able to be navigated safely even by the low-competence navigator under the no-current condition. The effects of low competence in such an easy condition, however, were apparent in the more frequent generations of rudder commands required to follow the planned route.

In the strong current condition, a sailing track simulated by the low-competence navigator model was more deviated from the ideal route with more frequent command generation, for example, approximately 200 metres maximum distance deviation in the case shown in Fig. 12(b). It should be noticed that this result was not derived by any single error factor, but caused by the mixed or integrated effect of multiple forms of human error, i.e., identification error, look-ahead error, shorter look-ahead time window and current perception error. Thus, such poor competence may be a critical risk factor for losing control of the ship during manoeuvre under a strong current in a narrow fairway like Øresund Channel, taken up in this study. Such a strong current also impacted a competent navigator in that he issued helm commands 60% more frequently than in the no-current condition.

To examine closely the risk of poor identification of the present position and heading, a series of simulations was performed varying only the parameters on the identification error. Five levels of the identification error were selected, i.e., combination of slight/considerable tendency of errors and over-/underestimation, and competent navigator, as indicated in Table 4. In these simulation runs, the cognitive model took parameter settings of no look-ahead errors with 60 seconds look-ahead time window. Simulation results are given in Fig. 13, including maximum and mean deviations from the planned route, mean rudder setting and operation frequency in averaged values over 10 simulation runs for each level of the identification error as well as current conditions.

It is seen from this figure that the manoeuvring process is affected by the current for navigators having any level of position and heading identification ability. The distance deviation from the ideal route as well as the generated rudder setting increase with the strength of current. A

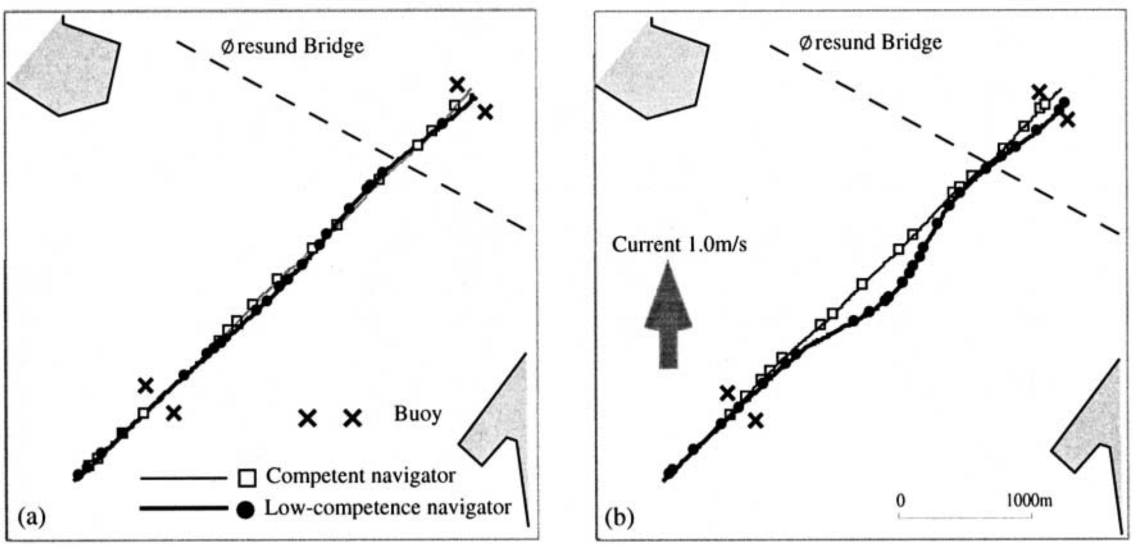

Fig. 12. Simulated track plots by competent and low-competence navigator models. (a) No-current condition; (b) strong current condition.

Table 4. Parameter settings for different levels of identification error

Parameters	(1) Competent navigator	(2) Slight overest.[a]	(3) Slight underest.[b]	(4) Considerable overest.	(5) Considerable underest.
Position identification error					
Bias (b)	0.0 m	+10.0 m	−10.0 m	+15.0 m	−15.0 m
Random error (σ)	5.0 m	10.0 m	10.0 m	15.0 m	15.0 m
Heading identification error					
Bias (b)	0.0 deg.	+1.0 deg.	−1.0 deg.	+1.5 deg	−1.5 deg.
Random error (σ)	0.5 deg.	1.0 deg.	1.0 deg.	1.5 deg.	1.5 deg.

[a] Overestimating navigator; [b] Underestimating navigator.

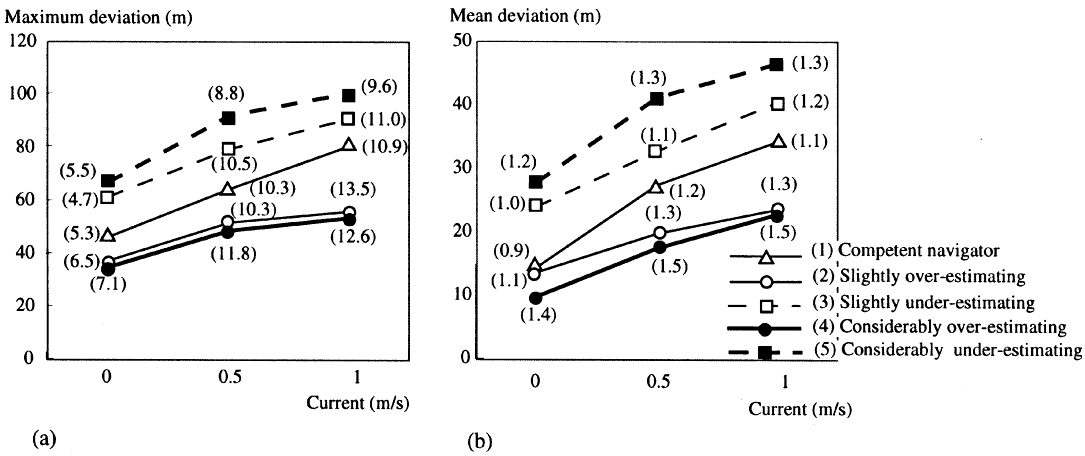

Fig. 13. Risk of identification error under different current conditions. (a) Maximum distance deviation (mean rudder angle in degrees); (b) mean distance deviation (mean operation frequency in /min).

navigator having a tendency to underestimate the distance and course deviation is the most critical of all the examined parameter settings even though it may not seem to be dangerous in terms of the maximum distance deviation, i.e., approximately 100 metres under 1.0 m/s strong current, in the absolute sense. The parameter settings examined here did not include a look-ahead error, as mentioned above, and the navigator model was able to estimate 60-second future position and heading correctly. Therefore, this result indicates that a dangerous situation caused by the navigator's low competence of position and heading identification may be avoidable by performing a look-ahead function of the future track appropriately.

In contrast, Fig. 13 indicates that a navigator who is likely to overestimate the deviation can follow the ideal route more closely even than the competent navigator. In the strong current condition of 1.0 m/s, the distance deviation produced by the slightly overestimating navigator was about 30% smaller than that by the competent navigator. The parameter setting of overestimated identification error can be interpreted as a navigator that is sensitive to course and distance deviation, and this setting detects an operation cue of course correction earlier according to its overestimated misidentification. This leads to more frequent operations, as can be seen in this figure. About 50% more operations were required due to overestimated deviation particularly in manoeuvre under the strong current, compared to the parameter setting of the competent navigator's.

4.3. Risk of Look-Ahead Errors

To investigate the effects of look-ahead error on manoeuvring performance, the navigator's command sequence and ship motion were estimated in the same manner as the risk prediction of identification error mentioned in the previous subsection. Five levels of parameter settings on the look-ahead error were chosen, as indicated in Table 5. The look-ahead time window was varied in three levels – 60, 120 and 180 seconds – and the other parameters were held constant at the setting for the competent navigator shown in Table 2. Ten simulation runs were carried out for each combination of look-ahead error levels and length of the look-ahead time window. Simulation results are indicated in terms of maximum distance deviations from the planned route and operation frequency in Table 6, as their mean values and standard deviations over 10 simulation runs for each condition. To analyse a risk of no look-ahead function involved in manoeuvre, these performance measures were also produced by simulation of the model from which this

Table 5. Parameter settings for different levels of look-ahead error

Parameters	(1) Competent navigator	(2) Slight overest.[a]	(3) Slight underest.[b]	(4) Considerable overest.	(5) Considerable underest.
Look-ahead error (by rudder)					
Bias (b)	0%	+20%	−20%	+40%	−40%
Random error (σ)	0%	20%	20%	30%	30%
Look-ahead error (by ROT)					
Bias (b)	0%	+40%	−40%	+80%	−80%
Random error (σ)	0%	20%	20%	30%	30%

[a] Overestimating navigator; [b] Underestimating navigator.

function was removed but which had the competent navigator's setting for the other parameters, and are shown in Table 7. This no-look-ahead model performed a deviation check and timing decision of neutral rudder based only on the present states with no anticipation of the future track.

As can be seen from Table 6(a), no significant difference ($F_0(4{,}405) = 0.76$) was observed in the maximum distance deviation between the five levels of navigator's competence of look-ahead. Regarding the operation frequency, there was a significant difference between the look-ahead error levels ($F_0(4{,}405) = 16.07$; $p<0.01$), but its absolute difference was small, as shown in Table 6(b). The largest difference in the operation frequency between the look-ahead error levels was less than 10% under the same levels of current conditions in most cases, while it varied about 50% between different levels of identification error. Therefore, the effect caused only by the look-ahead error on the sailing deviation from the ideal route may not be critical at least for the range shown in Table 5.

The largest look-ahead errors taken up in this study, i.e., parameter settings of (4) and (5) shown in Table 5, are not actually of great inaccuracy in the absolute sense. In the case of anticipation of the 120-second future position while

Table 6. Risk of look-ahead errors under different current conditions

(a) Maximum distance deviation (in metres)

Current level/Look-ahead time window		(1) Competent navigator		(2) Slight overest.[a]		(3) Slight underest[b]		(4) Considerable overest.		(5) Considerable underest.	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
No current	60 s	47.4	14.1	49.4	20.0	53.0	17.5	50.9	20.9	51.5	26.9
	120 s	45.7	13.9	46.9	14.7	52.4	15.8	48.1	14.9	49.8	17.0
	180 s	32.9	8.7	41.7	17.9	41.1	16.7	33.8	14.4	37.8	14.5
0.5 m/s	60 s	64.7	8.9	66.9	14.0	64.5	8.2	64.7	9.5	70.5	26.0
	120 s	42.8	6.4	45.5	8.4	41.0	4.9	38.4	3.7	42.6	6.2
	180 s	27.9	9.9	35.3	9.8	30.2	3.5	35.5	21.0	28.8	4.3
1.0 m/s	60 s	80.8	22.6	81.6	9.1	88.0	36.0	79.4	8.6	87.4	13.8
	120 s	56.3	13.0	52.6	2.8	52.9	8.3	52.9	7.2	54.1	13.1
	180 s	47.4	11.1	40.7	9.2	51.5	15.1	44.7	10.4	44.8	13.2

(b) Operation frequency (in min)

Current level/Look-ahead time window		(1) Competent navigator		(2) Slight overest.[a]		(3) Slight underest[b]		(4) Considerable overest.		(5) Considerable underest.	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
No current	60 s	0.86	0.15	0.85	0.15	0.86	0.10	0.80	0.18	0.85	0.18
	120 s	0.79	0.13	0.83	0.18	0.79	0.14	0.77	0.10	0.93	0.14
	180 s	0.86	0.22	0.91	0.14	0.91	0.20	0.84	0.17	0.91	0.13
0.5 m/s	60 s	1.18	0.21	1.15	0.16	1.16	0.09	1.13	0.16	1.32	0.18
	120 s	1.17	0.09	1.12	0.15	1.29	0.22	1.19	0.13	1.32	0.14
	180 s	1.38	0.12	1.32	0.13	1.38	0.23	1.36	0.21	1.47	0.16
1.0 m/s	60 s	1.08	0.17	1.22	0.17	1.24	0.17	1.16	0.16	1.47	0.17
	120 s	1.19	0.20	1.20	0.09	1.33	0.12	1.15	0.15	1.46	0.22
	180 s	1.43	0.14	1.32	0.18	1.41	0.11	1.38	0.16	1.50	0.16

[a] Overestimating navigator; [b] underestimating navigator.
Averaged values and SD over 10 simulaton runs with different random digit seeds.

Table 7. Navigation performance in case of no look-ahead functions

Current level	Max. deviation		Operation freq.	
	Mean	SD	Mean	SD
No current	53.8	20.2	0.82	0.12
0.5 m/s current	165.1	79.3	1.11	0.21
1.0 m/s current	212.1	71.0	1.22	0.20

sailing with 5 degrees rudder, the absolute look-ahead error produced by each of the worst parameter settings is about 6 metres, as can be seen in Table 1. This error is indeed not very large, compared to the future distance threshold, i.e., 120 metres set in the present model (cf. Table 2). The above-mentioned result on the effect of look-ahead error suggests that a future state look-ahead is an indispensable function in manoeuvring even if its accuracy is not high. This is also supported by the simulation results shown in Table 7 in that the sailing track simulated by the cognitive model excluding the look-ahead function was much more deviated from the ideal route particularly in strong current. The maximum distance deviation produced even by the lowest look-ahead competence navigator model, i.e., parameter setting of (5) in Table 6, with 60 seconds look-ahead time window, was significantly smaller by approximately 60% than that by the no-look-ahead model in 1.0 m/s current condition ($t_0(18) = 5.45$; $p<0.01$). There were also significant differences between these two models in 0.5 m/s current condition ($t_0(18) = 3.58$; $p<0.01$).

As another reason why the error level of look-ahead was not sensitive to the maximum distance deviation, there seems to be a dependency between the random-digit and the simulated navigation behaviour. For some manoeuvring conditions shown in Table 6, standard deviations of the maximum distance deviation are large relatively to their mean values, e.g., more than 20 metres SD. This indicates that the simulation result is dependent not only on the parameter settings of the navigator's individual factors but also on the random digit. This also suggests that more simulation runs are required for each navigation scenario to derive stable and sound conclusions from the risk analysis.

Regarding the look-ahead time window, strong effects on the sailing deviation were observed as significant ($F_0(2,405) = 148.06$; $p<0.01$). There was also a significant effect of the interaction between the current strength and the look-ahead time window ($F_0(4,405) = 15.92$; $p<0.01$). In particular, there existed highly significant differences in the maximum distance deviation between the 60 and 120-second look-ahead under 1.0 m/s strong current (e.g., $t_0(18) = 2.97, 9.63, 3.00, 7.47, 5.53$; $p<0.01$, for each parameter of the look-ahead error level). On average, the additional 60-second look-ahead available in 120-second look-ahead reduced the deviation by more than 30% (38.8% for 0.5 m/s current, and 33.1% for 1.0 m/s) in comparison to the 60-second look-ahead. Depending on the time constant of the vessel, at the shortest, a 120-second look-ahead is required to keep the sailing course safely for the ship taken in this study.

In contrast, under the no-current condition, there is less effect of the look-ahead time window on the sailing deviation. There were no significant differences in the maximum distance deviation between 60 and 120-second look-ahead in the no-current condition ($t_0(18) = 0.27, 0.32, 0.08, 0.34, 0.17$; $p>0.05$, for each parameter setting of the look-ahead error level). This is because most of the deviation checks and timing decisions of neutral rudder are initiated by the course deviation, not by the distance deviation. In these cases, there is no need to perform the look-ahead function for predicting the future track.

This phenomenon of no look-ahead demanding in the no-current condition also affects the difference in the sailing deviation between zero and 0.5 m/s current conditions with longer look-ahead time windows, i.e., 120 and 180 seconds. In these cases, the stronger current leads to shorter distance deviation due to more opportunities of applying look-ahead functions to estimating longer future track for timing decision of rudder.

5. CONCLUSION

In this paper, we presented a cognitive model of a ship navigator's course-tracking process based on the task analysis of simulator-manoeuvring sessions. Risk predictions for maritime safety have been conducted on a small scale for several years (Sand et al 1994) by letting real navigators produce a relatively small sample of tracks using ship simulators. The cognitive model in this study was constructed with the objective of performing man-in-the-loop simulation for risk analyses on a large scale. The great advantage of using cognitive models is to quickly perform these analyses for numerous scenarios by a number of batch processes of computer simulations. For this purpose, the cognitive model built in this study contained some forms of navigator-error generating processes in addition to his cognitive performance of course-tracking operations. The human behaviour for ship navigation and ship motions was simulated by the cognitive model under conditions identical to the experimental simulator sessions. From the simulation results, it was seen that the cognitive model constructed in this study produced similar performance to that by the human navigator, and therefore it can be considered to have proper capabilities to describe and predict the navigator's cognitive performance for applying to risk analysis.

Therefore, for this purpose, a series of cognitive simulations were conducted using this model with varying manoeuvring scenarios and navigator individual factors. As examples of risk-taking factors, low-competence navigator was examined under various levels of current through inclusion of identification errors of position and heading and look-ahead error of the future track. Based on these simulation results, it is found that the combined effects of multiple forms of error caused by the navigator's low competence is a critical risk for manoeuvre in strong current conditions. However, any single form of low competence, for example only identification error or look-ahead error, could not lead to a dangerous situation when other functions compensate for misidentification of the present position and heading or misanticipation of the future track. Risk predictions for other factors can be also examined, using the present cognitive model. For example, we can apply this model to other sailing courses and fairway conditions. As other aspects of navigator individual factors, it may be interesting to check the effect of deviation thresholds of course and distance as well as the effect of lack of normal cognitive or perceptual capabilities as a result of fatigue or sudden sickness.

To apply the cognitive simulation approach to human factors analysis, some other aspects are required to be built in the cognitive model. For example, it is of great importance to integrate prediction of the navigator's mental workload during task performance with the cognitive simulation. We believe it is possible to estimate the mental workload based on the calculated working memory states obtained from the cognitive model (Itoh 1998; Itoh and Enkawa 1991). In addition, to facilitate risk analysis using the cognitive simulation approach, it is necessary for the model to incorporate features for analysing the simulation data log. As such features, we are designing several automated analysis modules: calculation of mean square error of sailing track from the planned route, timeline analysis of navigator's action, operation sequence analysis and transition analysis of the navigator's attention.

Finally, the present cognitive model was programmed to control a ship only in a so-called single-ship situation. We plan to extend the model so as to navigate a ship in a more realistic, multi-ship situation. To cope with such a situation, the cognitive model must include a navigator's process of collision avoidance with other ships. We are anlaysing this process based on eye-movement data and verbal protocols recorded in ship simulator experiments. When these navigation processes are properly captured and modelled, human performance under more stressful, dangerous conditions with dense traffic scenarios can be analysed by a great number of overnight batch simulations.

Acknowledgements

This work was in part supported by Grant-in-Aid for Monbusho International Scientific Research Program (No. 80159871), the Japanese Ministry of Education, Science and Culture (Monbusho). Leif Løvborg and Steen Weber, Risø National Laboratory, and Jens Rasmussen, HEUR-ECON, all provided useful ideas to the project. We are deeply indebted to Jakob Buus Petersen, the Danish Maritime Institute, for his participation and suggestions. Special thanks to Shane J. Schvaneveldt, Weber State University, for his effort of language correction.

References

Bautsch SH, Narayanan S, McNeese DM (1997). Development and evaluation of a cognitive model of human-performance in fighter aircraft. In Proceedings of the IEEE international conference on systems, man and cybernetics, Part 3, pp 2109–2133.

Broadbent DE, Baddeley A, Reason JT (eds) (1990). Human factors in hazardous situations: Proceedings of a Royal Society discussion meeting, June 1989. Clarendon Press, Oxford.

Cacciabue PC (1998a). Modelling and simulation of human behaviour in system control. Springer, London.

Cacciabue PC (1998b). Modelling and simulation of human behaviour for safety analysis and control of complex systems. Safety Science 28(2):97–110.

Cacciabue PC (1997). A methodology of human factors analysis for systems engineering: theory and application. IEEE Transactions on Systems, Man and Cybernetics – Part A: Systems and Humans 27(3):325–339.

Cacciabue PC, Hollnagel E (1995). Simulation of cognition: applications. In Hoc JM, Cacciabue PC, Hollnagel E (eds). Expertise and technology: cognition and human–computer interaction. Erlbaum, Hillsdale, NJ, pp 55–74.

Cacciabue PC, Decortis F, Drozdowicz B, Kjaer-Hansen J (1990). A framework for cognitive simulation of human decision making and behaviour in complex work environments. In Andersen HB, Pedersen SA, Cacciabue PC, Reason JT (eds). Cognitive processes and resources: Proceedings of the second MOHAWC workshop, vol 1, Manchester, UK, December, pp 25–58.

Cacciabue PC, Decortis F, Drozdowicz B, Masson M, Nordvik JO (1992). A cognitive simulation model of human decision making and behaviour in accident management of complex plant. IEEE Transactions on Systems, Man and Cybernetics 22(5):1058–1074.

Chislett MS, Wied S (1985). A note on the mathematical modelling of ship manoeuvring in relation to a nautical environment with particular reference to currents. In Proceedings of the international conference on numerical and hydraulic modelling of ports and harbours, Birmingham, UK, April, pp 119–129.

Gardenier JS (1981). Ship navigational failure detection and diagnosis. In Rasmussen J, Rouse WB (eds). Human detection and diagnosis failures. Plenum Press, New York, pp 49–74.

Hansen JP, Clemmensen T (1993). Cognitive aspects of leaning and cooperation in simulated ship manoeuvring. In Proceedings of fuorth European conference on cognitive science approaches to process control, Frederiksborg, Denmark, September, pp 373–402.

Hearn GE, Zhang Y, Sen P (1997). Comparison of SISO and SIMO neural control strategies for ship track keeping. IEEE Proceedings of Control Theory and Applications 144(2):99–127.

Hee DD, Pickrell BD, Bea RG, Roberts RG, Williamson RB (1999). Safety management assessment system (SMAS): a process for identifying and evaluating human and organization factors in marine system operations with field test result. Reliability Engineering and System Safety 65:125–140.

Hollnagel E (1993). Human reliability analysis: context and control. Academic Press, London.

Hollnagel E (1996). Reliability analysis and operator modelling. Reliability Engineering and System Safety 52:327–337.

Hutchins E (1990). The technology of team navigation. In Galegher J, Kraut RE, Egido C (eds). Intellectual teamwork: social and technological foundations of cooperative work. Erlbaum, Hillsdale, NJ, pp 191–200.

Itoh K (1997). Data elicitation and task analysis for cognitive operations in ship navigation. In Proceedings of the international symposium on artificial intelligence, robotics and intellectual human activity support for nuclear applications: AIR & IHAS'97, Saitama, Japan, November, pp 161–174.

Itoh K (1998). A cognitive modeling scheme for task analysis and its application to computer editing task. International Journal of Cognitive Ergonomics 2(3):269–295.

Itoh K, Enkawa T (1991). Analysis and evaluation of cognitive tasks using an information transition model. In Bullinger HJ (ed). Human aspects in computing: design and use of interactive systems and work with terminals. Elsevier, Amsterdam, pp 646–650.

Itoh K, Hansen JP (1995). Cognitive task analysis of ship navigation by use of verbal protocols and eye-movement data. Report no 95–6, Tokyo Institute of Technology, Department of Industrial Engineering and Management.

Itoh K, Hansen JP, Nielsen FR (1998). A cognitive modelling of a ship navigator based on protocol and eye-movement analysis. Le Travail Humain 61(2):99–127.

Just MA, Carpenter PA (1980). A theory of reading: from eye fixation to comprehension. Psychological Review 87:329–354.

Kirlik A, Miller RA, Jagacinski RJ (1993). Supervisory control in a dynamic and uncertain environment: a process model of skilled human–environment interaction. IEEE Transactions on Systems, Man and Cybernetics 23:929–952.

Kletz T (1994). Learning from accidents. Butterworth-Heinemann, Oxford.

Margetts BD (1976). Human error in merchant marine safety. National Research Council, Washington, DC.

Miller DP, Swain AD (1987). Human error and human realiability. In Salvendy G (ed). Handbook of human factors. Wiley, New York, pp 219–250.

Mosneron-Dupin F, Reer B, Heslinga G, Sträter O, Gerdes V, Saliou G, Ullwer W (1997). Human-centered modeling in human reliability analysis: some trends based on case studies. Reliability Engineering and System Safety 58:249–274.

Papenhuijzen R (1988). On the modelling of the behaviour of a navigator: background and proposal for a control theoretic approach. In Patrick J, Duncan KD (eds). Training human decision making and control. Elsevier, Amsterdam, pp 189–203.

Parsons MG, Chubb AC, Cao Y (1995). An assessment of fuzzy logic vessel path control. IEEE Journal of Oceanic Engineering 20(4):276–284.

Rasmussen J (1986). Information processing and human–machine interaction: an approach to cognitive engineering. North-Holland, New York.

Rayner K, McConkie GW (1976). What guides a reader's eye movement? Vision Research 16:829–837.

Roth EM, Pople HE Jr, Woods DD (1991). Cognitive environment simulation: a tool for modelling operator cognitive performance during emergencies. In Apostolakis GE (ed). Proceedings of the international conference on probabilistic safety assessment and management (PSAM), Beverly Hills, CA, February, pp 959–964.

Roth EM, Woods DD, Pople HE Jr (1992). A cognitive simulation as a tool for cognitive task analysis. Ergonomics 35(10):1163–1198.

Salski A, Noback H, Stassen HG (1988). A model of the navigator's behaviour based on fuzzy set theory. In Patrick J, Duncan KD (eds). Training, human decision making and control. Elsevier, Amsterdam, pp 205–222.

Sand SE, Nielsen DS, Jakobsen VB (1994). Risk analysis of simulated ship approaches to port. Paper presented at PIAC, Copenhagen, Denmark.

Schuffel H (1986). Human control of ships in tracking tasks. Doctoral dissertation, University of Tillburg, The Netherlands.

Shen S-H, Smidts C, Mosleh A (1997). A methodology for collection and analysis of human error data based on a cognitive model: IDA. Nuclear Engineering and Design 172:157–186.

Smidts C, Shen SH, Mosleh A (1997). The IDA cognitive model for the analysis of nuclear power plant operator response under accident conditions. Part I: problem solving and decision making model. Reliability Engineering and System Safety 55:51–71.

Valot C, Amalberti R, Cibiel JY (1991). AIDE, A model of cognitive activity: features of reasoning for time and resource management. In Brehmer B, Leplat J (eds). Simulations, evaluations and models: Proceedings of the fourth MOHAWC workshop, vol 2, Bamberg, Germany, October, pp 28–41.

Wiener EL, Nagel DC (eds) (1988). Human factors in aviation. Academic Press, San Diego, CA.

Winston PH (1984). Artificial intelligence (2nd ed). Addison-Wesley, Reading, MA.

Zhang Y, Hearn GE, Sen P (1996). A neural network approach to ship track-keeping control. IEEE Journal of Oceanic Engineering 21(4):513–527.

Correspondence and offprint requests to: Kenji Itoh, Department of Industrial Engineering and Management, Tokyo Institute of Technology, 2-12-1 Oh-okayama Meguro-ku Tokyo 152-8552, Japan. Email: ken@ie.me.titech.ac.jp